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**Volatility Dynamics in Foreign Exchange
Rates: Further Evidence from the Malaysian
Ringgit and Singapore Dollar**

by

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Volatility Dynamics in Foreign Exchange Rates: Further Evidence from the Malaysian Ringgit and Singapore Dollar

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Abstract

The evolution of volatility and correlation patterns of the Malaysian ringgit and the Singapore dollar are analyzed in this paper. Our approach can simultaneously capture the empirical regularities of persistent and asymmetric effects in volatility and time-varying correlations of financial time series. Consistent with the results of Tse and Tsui (1997), there is only some weak support for asymmetric volatility in the case of the Malaysian ringgit when the two currencies are measured against the US dollar. However, there is strong evidence that depreciation shocks have a greater impact on future volatility levels compared with appreciation shocks of the same magnitude when both currencies measured against the yen. Moreover, evidence of time-varying correlation is highly significant when both currencies are measured against the yen. Regardless of the choice of the numeraire currency and the volatility models, shocks to exchange rate volatility are found to be significantly persistent.

1.   Introduction

Following the seminal work of Engle (1982) and Bollerslev (1986), modelling the time-varying conditional volatility of financial time series by the generalized autoregressive conditional heteroscedasticity (GARCH) type of models has generated tremendous applications in the past two decades.   The GARCH-type models are important as they can successfully capture the stylized fact in finance that large changes in many asset prices tend to be followed by other large changes, while small changes are usually followed by other small changes.   This phenomenon is now commonly known as volatility clustering.   A voluminous literature has developed on the estimation and forecasting of volatility with GARCH-type models, and their specific applications in empirical asset pricing, financial risk management, and option pricing and hedging. Among others, some important papers include Bollerslev et al. (1988), Campbell and Hentschel (1992), Christoffersen and Diebold (2000), Duan (1995, 1997), French *et al.* (1987), Glosten *et al.* (1993), Maheu and McCurdy (2004), Pagan and Schwert (1990), and Schwert (1989).   Moreover, there are many survey articles that provide detailed discussion of GARCH-type models and their scope of research.   See, for example, Bollerslev *et al.* (1992), Bera and Higgins (1993), Campbell *et al.* (1997), Engle (2002), Li *et al.* (2002), and more recently Bauwens *et al.* (2006).

Other than asset pricing and risk management, GARCH-type models are also employed to analyze the volatility dynamics of foreign exchange rates. Among others, see Hsieh (1989a, 1989b, 1993), Bollerslev (1990), Baillie and Bollerslev (1994), Baillie, Bollerslev, and Mikkelsen (1996), Tse and Tsui (1997), Tse (1998) and Tsui and Ho (2004), respectively. Several well-established empirical regularities may be highlighted: [a] evidence of volatility clustering is detected in exchange rate returns; [b] unlike stock market volatility, asymmetric responses to positive versus negative shocks of the same

2

magnitude in exchange rate volatility are not common; and [c] exchange rate volatility may display significant persistence and dependence between observations, a phenomenon commonly described as long-range dependence or long memory. In particular, Tse and Tsui (1997) examine the conditional volatility of the exchange rates of the Malaysian ringgit and the Singapore dollar against the US dollar using the univariate asymmetric power ARCH model proposed by Ding, Granger, and Engle (1993). They find evidence of negative asymmetric effects in the Malaysian ringgit. More recently, Tsui and Ho (2004) detect evidence of asymmetric volatility in the Malaysian ringgit and the Singapore dollar using univariate fractionally integrated GARCH-type models. However, such established findings are based on univariate GARCH-type models and on the bilateral USD rates. Little work has been done on foreign exchange rates with different choice of numeriare currency and GARCH-type structures in a multivariate framework.

While the univariate GARCH-type models may appear reasonably adequate for capturing the volatility dynamics in exchange rates, they are not tailored to accommodate co-movements in foreign exchange volatility. Several academics and practitioners have noted that exchange rates are significantly correlated and these correlations can influence currency trading strategies (see Lien (2005, 2006), Jiang, Ma, and Cai (2007), Muniandy and Uning (2006), and Mizuno *et al.* (2006)). Therefore, it is imperative to understand how different pairs of currencies move with one other over time. By keeping track of these co-movements, traders can understand their exposure to exchange rate risk. An example given in Lien (2006) illustrates that an effective foreign exchange trader should understand his/her overall portfolio's sensitivity to market volatility. The main reason is that "currencies are priced in pairs, no single pair trades completely independently of the others." Once a trader knows about their correlations

and the pattern of changes over time, he/she can take advantage of them to control the portfolio's exposure.   As such, it is important to analyze currency volatility in a multivariate framework in order to accommodate the potential interdependencies between the exchange rates.

Moreover, it has been frequently argued that information transmission from one foreign exchange market to another can influence currency volatility.   In particular, Engle, Ito and Lin (1990) argue that volatility in one foreign exchange market is transmitted to other markets like a "meteor shower", while Ross (1989) shows that volatility in asset returns depends upon the rate of information flow.   Since the rate of information flow and the time used in processing that information varies with each individual market (sector), one should expect different volatility patterns across markets (sectors).   The increasing integration of major financial markets has generated strong interest in understanding the volatility spillover effects from one market to another. These volatility spillovers are usually attributed to cross-market hedging and change in common information, which may simultaneously alter expectations across markets. Apparently, a multivariate framework to capture such features is more appropriate.

Empirically there are limited studies on the volatility dynamics of exchange rates by the MGARCH-type models. The main obstacle is due to the computational difficulties in estimating the increased number of parameters and there is no guarantee of the positive-definiteness for the conditional variance-covariance matrix during optimization. Bollerslev (1990) proposes the constant-correlations (CC)-MGARCH model, which automatically guarantees the positive-definiteness of the variance-covariance matrix once convergence is achieved.   However, this approach is quite restrictive and has not been successful in several studies (see, for example, Tsui and Yu (1999), Tse (2000),

Engle and Sheppard (2001), Bera and Kim (2002), and McAleer *et al.* (2008)).   A multivariate version that is different from the CC-MGARCH model is previously proposed by Engle, Granger, and Kraft (1984), who derive the necessary conditions for the matrix of the model to be positive-definite; however, generalizing this model to higher dimensions is rather intractable. Alternatively, Bollerslev, Engle, and Wooldridge (1988) propose the vech-representation, which is an extension of the univariate GARCH representation to the vectorized conditional variance-covariance matrix.   However, conditions that guarantee the positive-definiteness of the variance-covariance matrix are difficult to sustain during optimization.   Moreover, Engle and Kroner (1995) introduce the Baba-Engle-Kraft-Kroner (BEKK) model, which automatically guarantees the positive-definiteness of the variance-covariance matrix once parameter estimates are obtained. Another approach looks into the conditional volatility of different assets as a factor model; see Diebold and Nerlove (1989), Engel and Rodrigues (1989) and Engle, Ng, and Rothschild (1990) for details. However, the shortcomings of the BEKK and factor models are that the parameters cannot be easily estimated and interpreted, and their net impact on the future variance and covariance are not readily observed. In addition, the increasing number of parameters to be estimated under the BEKK and factor-GARCH models exacerbates the difficulties of achieving convergence in parameter estimation. For example, Bera *et al.* (1997) report that the BEKK model does not perform well in the estimation of the optimal hedge ratios, and Lien *et al.* (2002) report difficulties in obtaining meaningful estimates of the BEKK model during optimization. For a detailed comparison of these MGARCH-type models, see Bauwens *et al.* (2006).

In this paper, we follow up on the study of asymmetric volatility of two currencies in the Asia-Pacific markets by Tse and Tsui (1997), namely the Malaysian ringgit and the Singapore dollar. To ensure consistency in comparison, we confine our investigation to

5

the GARCH-type models. Instead of using univariate APARCH models by Tse and Tsui (1997), we employ the MGARCH framework of Tse and Tsui (2002) to create a family of bivariate MGARCH models which can concurrently capture the stylized features of volatility asymmetry, long-range persistence in volatility, and time-varying correlations. The proposed models automatically ensure the positive definiteness of the conditional variance-covariance matrix once convergence is obtained. One added advantage of the Tse and Tsui approach is that the parameter estimates are relatively easy to interpret, as the univariate GARCH-type equations are retained. Unlike Bollerslev's (1990) constant correlation MGARCH model, the included time-varying conditional correlations in the proposed models can map out the time-path of conditional correlations between the two currencies. We also investigate the behaviour of long-memory persistence in volatility of the Malaysian ringgit and the Singapore dollar using fractionally integrated GARCH-type models. The fractionally integrated models help to distinguish between long persistence and exponential decay in the impacts of exchange rate volatilities.

Furthermore, we examine the robustness of the volatility dynamics of the two currencies against the Japanese yen as alternative numeraire currency besides the US dollar. We are motivated by several studies on the sensitivity of alternative numeraire currency. See, for example, Papell and Theodoridis (2001), Zambrano (2005), and Norrbin and Pipatchaipoom (2007), respectively. In particular, Papell and Theodoridis (2001) demonstrate that choice of different numeraire currency can have significant impacts on purchasing power parity (PPP). They find that PPP is stronger for European than for non-European base currencies, and the volatility of the exchange rate is one of the key determinants of such a finding. In addition, Schlossberg (2007) provides several examples in trading in cross rates where the Japanese yen is used as numeraire for the

6

Canadian dollar, the New Zealand dollar and the British pound, respectively. He argues that "trading in currency crosses can provide a multitude of profitable opportunities."

The rest of the paper is organized as follows. In Section 2, we present the methodology of synthesizing features of volatility asymmetry, long-memory and time-varying correlations in a bivariate GARCH framework. Section 3 briefly describes the data sets used and the estimation results. Section 4 provides some concluding remarks.

2.   Methodology

In what follows we first briefly describe the gist of the bivariate GARCH(1,1) model with time-varying conditional correlations (VC-GARCH) proposed by Tse and Tsui (2002). We then incorporate two different structures of asymmetric volatility and long memory into the conditional variance equations so as to synthesize the bivariate GARCH-type models.

Let $y_t = (y_{1t}, y_{2t})'$ be the bivariate vector of variables with time-varying variance-covariance matrix H_t, and let $\mu_{it}(\xi_i)$ be the arbitrary conditional mean functions which depend on ξ_i, a column vector of parameters. A typical bivariate GARCH(1,1) model can be specified as follows:

$$y_{it} = \mu_{it}(\xi_i) + \varepsilon_{it}, \qquad i = 1,2 \tag{1}$$

where $(\varepsilon_{1t}, \varepsilon_{2t})' \mid \Phi_{t-1} \sim (O, H_t)$ (2)

Note that Φ_t is the σ-algebra generated by all the available information up to time t. The random disturbance terms ε_{it} and the conditional variance equations h_{iit} are modelled as follows:

$$\varepsilon_{it} = \sqrt{h_{iit}} \, e_{it}, \quad \text{where } e_{it} \sim N(0,1) \tag{3}$$

$$h_{iit} = \eta_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{iit-1} \tag{4}$$

where (4) is the standard Bollerslev's (1986) symmetric GARCH(1,1) model.

Denote the ij-th element (i, j = 1, 2) in H_t by h_{ijt}. The conditional correlation

coefficients can be defined as $\rho_{ijt} = \dfrac{h_{ijt}}{\sqrt{h_{iit} h_{jjt}}}$. Essentially, Tse and Tsui (2002) assume

that the time-varying conditional correlation matrix $\Gamma_t = \{\rho_{ijt}\}$ is generated by the

following recursion

$$\rho_{12t} = (1 - \pi_1 - \pi_2)\rho_{12} + \pi_1 \rho_{12,t-1} + \pi_2 \psi_{12,t-1} \tag{5}$$

$$\psi_{12,t-1} = \frac{\sum_{a=1}^{2} e_{1,t-a} e_{2,t-a}}{\sqrt{(\sum_{a=1}^{2} e_{1,t-a}^2)(\sum_{a=1}^{2} e_{2,t-a}^2)}} \tag{6}$$

$$l_t(\theta) = -\frac{1}{2}\sum_{i=1}^{2} \log h_{iit} - \frac{1}{2}\log(1 - \rho_{12t}^2) - \frac{e_{1t}^2 + e_{2t}^2 - 2\rho_{12t}e_{1t}e_{2t}}{2(1 - \rho_{12t}^2)} \tag{7}$$

The conditional correlation equation in (5) inherits the prototype property of GARCH(1,1)

structure, and it nests Bollerslev's (1990) constant-correlations GARCH (CC-GARCH)

structure when $\pi_1 = \pi_2 = 0$. Hence, the likelihood ratio test can be readily applied to

compare the performance of both models.

Owing to computational difficulties, there are few empirical studies on long-range

temporal dependence. See Tse and Tsui (1997), Teyssiere (1997, 1998), and Brunetti

and Gilbert (2000), among others. These studies have mainly applied the multivariate

version of the fractionally integrated symmetric GARCH (FIGARCH) model of Baillie,

Bollerslev, and Mikkelsen (1996) to stock market and exchange rate data. However, they

8

often exclude the issue of asymmetric conditional volatility, and for convenience, they adopt the assumption of constant conditional correlations in the volatility structure. In what follows, we incorporate the structures of asymmetric volatility and long memory dynamics into the VC-GARCH model by modifying the symmetric conditional variance equation in (4). To maintain consistency in comparison, we choose two well-established asymmetric structures among the GARCH-type models. They include: the asymmetric GARCH (1,1) (AGARCH (1,1)) model proposed by Engle (1990) and the asymmetric power ARCH (1,1) (APARCH (1,1)) model of Ding, Granger, and Engle (1993), respectively. Indeed, Tse and Tsui (1997) use the APARCH (1,1) model to capture the possibly asymmetric effects of exchange shocks on future volatilities. In addition, these asymmetric GARCH-type models are less restrictive in assumptions and are more flexible to accommodate alternative variations. Their main features are briefly summarized as follows:

[a] Engle's (1990) asymmetric GARCH(1,1) (AGARCH(1,1)) model:

$$h_{iit} = \omega_i + \alpha_i (\varepsilon_{it-1} - \gamma_i)^2 + \beta_i h_{iit-1} \tag{8}$$

where γ_i is the asymmetric coefficient. When $\gamma_i = 0$, (8) becomes the GARCH(1,1) model and when $\beta_i = 0$, it becomes the prototype ARCH(1) model.

[b] Ding, Granger, and Engle's (1993) asymmetric power ARCH(1,1) (APARCH (1,1)) model.

$$h_{iit}^{\delta_i/2} = \eta_i + \alpha_i (|\varepsilon_{it-1}| - \gamma_i \varepsilon_{it-1})^{\delta_i} + \beta_i h_{iit-1}^{\delta_i/2} \tag{9}$$

where γ_i is the asymmetric coefficient. When $\delta_i = 1$, equation (9) becomes the threshold GARCH(1,1) model, which includes an asymmetric version of the Taylor/Schwert (1986/1989) model and Zakoian's (1994) threshold ARCH model. When $\delta_i = 2$, it becomes the leveraged GARCH model, which nests the GJR model of Glosten,

Jaganathan and Runkle (1993). When δ_i approaches 0, Ding, Granger, and Engle (1993) show that (9) becomes the logarithmic GARCH(1,1) model, thereby incorporating an asymmetric version of the Geweke/Pantula (1986) model. We note in passing that although the APARCH structure nests 7 models together (see Ding, Granger, and Engle (1993) for details), it does not nest the AGARCH model.

Turning to the structure of long-memory dynamics in volatility, we may transform the conditional variance equations in (4), (8) and (9) so that they are fractionally integrated. We follow the methodology by Baillie *et al.* (BBM) (1996). Below is a summary of the conditional variance equations for three fractionally integrated (FI) GARCH-type models obtained by the BBM approach.

[a]Fractionally integrated GARCH(1,1) model (FIGARCH(1,d,1))

$$h_{iit} = \frac{\eta_i}{1 - \beta_i} + \lambda_i(L)\varepsilon_{it}^2 \tag{10}$$

where $\lambda_i(L) = \sum_{a=1}^{\infty} \lambda_{ia} L^a = 1 - (1 - \beta_i L)^{-1}(1 - \phi_i L)(1 - L)^{d_i}$.

[b] Fractionally integrated asymmetric GARCH(1,1) model ((FIAGARCH)(1,d,)) model

$$h_{iit} = \frac{\omega_i}{1 - \beta_i} + \lambda_i(L)(\varepsilon_{it} - \gamma_i)^2 \tag{11}$$

where $\lambda_i(L)$ is defined as in (10). Note that (11) is similar to the FIGARCH(1,d,1) model in (10), except that it allows past return shocks to have asymmetric effects on the conditional volatility.

[c] Fractionally integrated APARCH(1,1) model (FIAPARCH(1,d,1))

$$h_{iit}^{\delta_i/2} = \frac{\eta_i}{1-\beta_i} + \lambda_i(L)(|\varepsilon_{it}| - \gamma_i\varepsilon_{it})^{\delta_i} \qquad (12)$$

where $\lambda_i(L)$ is defined as in (10). Similar to the FIAGARCH(1,d,1) model in (11), (12) allows past shocks to have asymmetric effects on the conditional volatility. Details of the derivations are given in Tsui and Ho (2004).

The parameters of these bivariate fractionally integrated GARCH-type models can be estimated using Bollerslev-Wooldridge's (1992) quasi-maximum likelihood estimation (QMLE) approach. Appropriate assumptions for the start-up conditions are made to facilitate convergence of the QMLE optimization process. These include the computation of $\lambda_i(L)$, the number of lags, and the initial values. For instance, the response coefficients for each of the fractionally integrated GARCH-type models $\lambda_i(L) = \sum_{a=1}^{\infty} \lambda_{ia} L^a = 1 - (1-\beta_i L)^{-1}(1-\phi_i L)(1-L)^{d_i}$ are computed by adopting the following infinite recursions given in Bollerslev and Mikkelsen (1996):

$$\begin{aligned} \lambda_{i1} &= \phi_i - \beta_i + d_i, \\ \lambda_{ib} &= \beta_i\lambda_{ib-1} + [(b-1-d_i)/b - \phi_i]\zeta_{ib-1}, \qquad b = 2,...,\infty \end{aligned} \qquad (13)$$

where $\zeta_{ib} = \zeta_{ib-1}(b-1-d_i)/b$, with $\zeta_{i1} = d_i$

As can be observed from (13), when *b* approaches infinity, an adequate finite truncation is necessary to secure the long-memory dynamics. We have sampled the 1000 and 2000 lags, respectively; and found that the parameter estimates trimmed at 1000 lags are reasonably close to those trimmed at 2000 lags. To save the computational time, we truncate $\lambda_i(L)$ after the first 1000 lags.

On the choice of initial values, we set the pre-sample observations ε_{it}^2 to the unconditional sample variance for the FIGARCH(1,d,1) model. As for the bivariate FIAGARCH(1,d,1) model, the pre-sample observations of $g(\varepsilon_{it})^2 = (\varepsilon_{it} - \gamma_i)^2$ are equated to the sample mean of $(\hat{\varepsilon}_{it} - \hat{\gamma}_i)^2$, where $\hat{\gamma}_i$ is the estimate of γ based on the univariate FIAGARCH(1,d,1) model. In the case of the bivariate FIAPARCH(1,d,1) model, the pre-sample observations of $g(\varepsilon_{it})^{\delta_i} = (|\varepsilon_{it}| - \gamma_i \varepsilon_{it})^{\delta_i}$ are equated to the sample mean of $(|\hat{\varepsilon}_{it}| - \hat{\gamma}_i \hat{\varepsilon}_{it})^{\hat{\delta}_i}$, where $\hat{\gamma}_i$ and $\hat{\delta}_i$ are the estimates of γ_i and δ_i based on the univariate FIAPARCH(1,d,1) model.

We shall investigate 6 different model specifications, including 3 basic symmetric and asymmetric GARCH-type models and their extensions to the corresponding fractionally integrated GARCH-type models. We then apply these univariate models individually to the Malaysian ringgit and the Singapore dollar against the dollar or the yen, thereby obtaining 6 bivariate CC-MGARCH-type models and 6 bivariate VC-MGARCH-type models, respectively.

3. Data and Estimation Results

Our data sets consist of 2998 daily observations of the Malaysian ringgit (MYR) and the Singapore dollar (SGD), covering the period from 2 January 1986 to 30 June 1997. More recent observations are excluded to avoid the possible distortions caused by the outbreak of the 2-year Asian financial crisis since July 1997. The exchange rates against the US dollar (USD) are obtained directly from DataStream International and details of these series are discussed in Tsui and Ho (2004). Owing to the non-

availability of the bilateral Japanese yen (JPY) exchange rates for the period under study, we utilize the implied cross rates instead. They are obtained by dividing the exchange rate of a nation's currency against the US dollar with the Japanese yen-US dollar (JPY/USD) exchange rate.

The daily nominal exchange rate returns expressed in percentage are computed on a continuously compounding basis as:

$$y_t = \log(\frac{S_t}{S_{t-1}}) \times 100 \qquad (14)$$

where S_t is the daily exchange rate. We assume that the conditional mean equation is captured by a lower-order autoregressive filter with lag order p:

$$y_{it} = \xi_0 + \sum_{a=1}^{p} \xi_{iat}\, y_{it-a} + \varepsilon_{it}, i = 1,2 \qquad (15)$$

Table 1 provides a summary of the descriptive statistics of y_t for the two currencies measured against the dollar or the yen. For a standard normal distribution, the skewness and kurtosis have values of 0 and 3, respectively. As can be observed from Panel A of Table 1, all differenced logarithmic series have kurtosis greater than 3. In particular, the MYR and SGD exhibit much higher kurtosis when they are measured against the dollar. Figures 1-2 present the plots of the exchange rates of the two currencies and their returns series against the dollar and the yen, respectively. It can be observed that the return series are centred about zero and the amplitude of the returns is changing. The magnitude of the changes is sometimes large (small) following the previous large (small) ones over the sample period, thereby reflecting the stylized fact of volatility clustering.

Figure 1. Malaysian Ringgit (MYR) and Singapore Dollar (SGD) against the US dollar (USD)
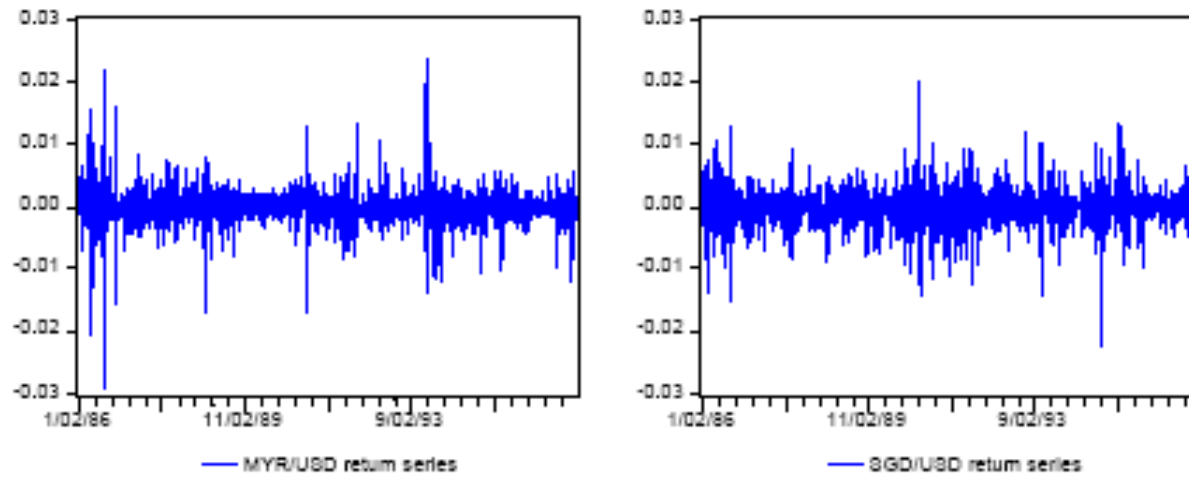
Figure 2. Malaysian Ringgit (MYR) and Singapore Dollar (SGD) against the Japanese Yen (JPY)
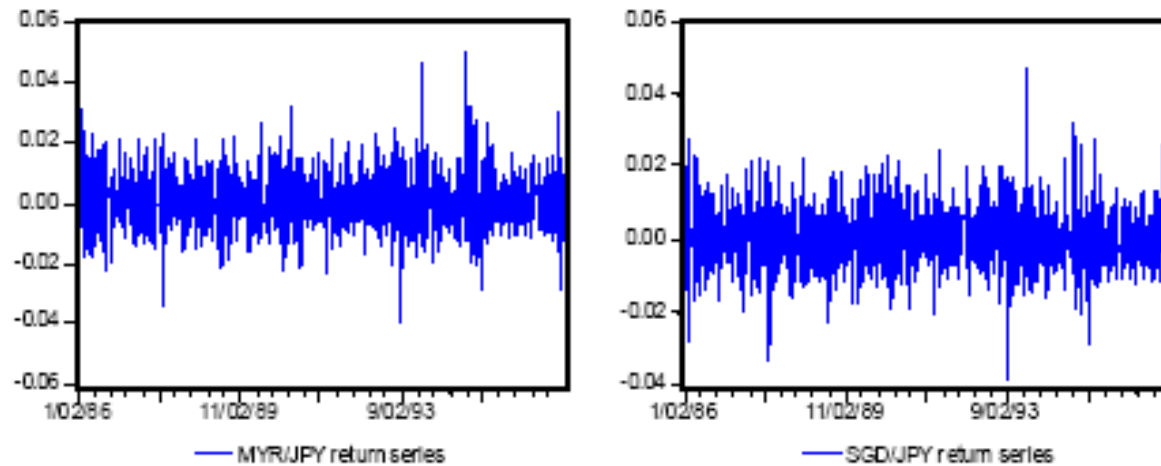
Table 1. Summary Statistics of Exchange Rates against the Japanese Yen and the US Dollar

Variable	MYR/JPY	SGD/JPY	MYR/USD	SGD/USD
Mean	0.0198	0.0053	0.0015	-0.0130
Median	0.0000	-0.0058	0.0000	0.0000
Maximum	4.9830	4.6842	2.3736	2.0232
Minimum	-3.9626	-3.8903	-2.9363	-2.2501
Std. Dev.	0.6822	0.6340	0.2555	0.2538
Skewness	0.4145	0.3571	-0.2254	-0.3627
Kurtosis	6.9749	6.6848	24.1763	10.3654
Observations	2997	2997	2997	2997
$Q_1(5)$	9.1017	10.6973	49.1369	68.9244
$Q_1(10)$	40.4815	37.4101	88.6244	79.6134
$Q_2(5)$	158.1128	27.4757	651.4362	181.8517
$Q_2(10)$	229.7626	38.9931	1196.7779	196.8995
$Q_3(5)$	32.9668	27.4292	447.1970	152.7907
$Q_3(10)$	43.1101	42.0719	592.3810	159.6123
BDS(e=3,l=1.5)	7.5261	6.3680	16.2961	14.0798
BDS(e=4,l=1.5)	9.0158	7.5216	16.7226	14.8928
BDS(e=5,l=1.5)	9.6963	8.0265	16.9930	15.4110
BDS(e=3,l=1.0)	7.8580	6.5282	15.8300	14.0291
BDS(e=4,l=1.0)	9.1719	7.5098	16.8401	15.7770
BDS(e=5,l=1.0)	10.0651	8.1987	17.7326	17.1760
R_1	3.8623	2.9018	0.4672	3.3028
R_2	-5.3707	-5.0340	-8.4397	-7.9397
R_3	-4.2167	-2.1550	-10.5792	-7.6008

Notes:
1. JPY = Japanese Yen, MYR = Malaysian ringgit, SGD = Singapore dollar, USD = US dollar
2. Q(m) refers to the Ljung-Box Q-statistic with m degrees of freedom. Q_i for i = 1, 2, 3 denote the series y_t, $|y_t|$, and y_t^2 respectively.
3. For the BDS Test, e represents the embedding dimension whereas l represents the distance between pairs of consecutive observations, measured as a multiple of the standard deviation of the series. Under the null hypothesis of independence, the test statistic is asymptotically distributed as standard normal.
4. For the Runs Test, R_i for i = 1, 2, 3 denote the runs tests of the series y_t, $|y_t|$, and y_t^2 respectively. Under the null hypothesis that successive observations in the series are independent, the test statistic is asymptotically standard normal.

Table 2. Unit Root Tests

Exchange Rate	ADF Model	ADF Test Statistic	Q-statistic (20 lags)	PP Statistic
MYR/JPY	Case 3 (20)	-10.2777	0.4246	-57.8322
SGD/JPY	Case 3 (20)	-10.7728	0.4151	-58.1493
MYR/USD	Case 3 (20)	-11.1393	0.9246	-58.1271
SGD/USD	Case 3 (20)	-10.7799	0.5067	-63.4835

Notes:
1. ADF Model: Case 1 refers to the regression equation without any deterministic regressors; Case 2 refers to the equation with intercept; Case 3 refers to the equation with both the intercept and the deterministic time trend. The figure in parenthesis highlights the number of lagged difference terms.
2. For the PP test, both intercept and time trend are included and 8 truncation lags are chosen. It is found that the results are robust to different lag lengths.
3. Q statistic refers to the Ljung-Box Q-statistic with 20 degrees of freedom.

As displayed in Table 2, the augmented Dickey-Fuller and Phillips-Perron tests are all insignificant at the 5% level, thereby indicating that the return series of the MYR and SGD are stationary. However, the Ljung-Box Q-statistics and the BDS test statistics (Brock, Dechert, and Scheinkman (1996)) suggest that both foreign exchange series are not independently and identically distributed. In addition, as can be seen from Table 1, the highly significant Lung-Box Q statistics and the runs tests consistently indicate the presence of conditional heteroscedasticity in the return series. As such, the GARCH-type modelling of the volatility structures may be appropriate.

We shall estimate the conditional mean, variance and correlation components of the proposed bivariate GARCH-type models simultaneously using Bollerslev and Wooldridge's (1992) quasi maximum-likelihood estimation (QMLE) procedure coded in Gauss version 5.0. The QMLE approach provides consistent estimators even for non-normal errors with a thick-tailed distribution. For the mean equation, we find that the parsimonious AR(1) model is a reasonably adequate filter, taking into consideration of the log-likelihood values and the residual checks. To save space, we report only estimates of the conditional variance and correlation equations from the following models: the VC-GARCH, VC-AGARCH, VC-APARCH, VC-FIGARCH, VC-FIAGARCH and the VC-FIAPARCH, respectively. Except for the correlation coefficients and the log-likelihood values, most of the parameter estimates from the constant-correlation models are omitted. The complete set of estimation results is available upon request.

Tables 3-8 summarize the QMLE of the parameters of the bivariate VC-GARCH, VC-APARCH, VC-AGARCH, VC-FIGARCH, VC-FIAPARCH and VC-FIAGARCH models, respectively. We first discuss the evidence of asymmetric volatility. For the currencies against the dollar, only the Malaysian ringgit exhibits asymmetric volatility

under the VC-FIAPGARCH model, whereas there is no evidence of asymmetric effects for the SGD. Our results are consistent with the findings by Tse and Tsui (1997), and Tsui and Ho (2004), respectively. In particular, Tse and Tsui (1997) report that the depreciation shocks of MYR/USD generate greater future volatilities compared to appreciation shocks of the same magnitude. In contrast, when the yen is used as the numeraire currency, we detect significant evidence of negative asymmetric volatility for the SGD based on all of the GARCH-type models. As for the MYR, except for the VC-AGARCH model, we do not detect evidence of asymmetric volatility. Apparently, the support of volatility asymmetry is sensitive to the specification of the conditional volatility and to the choice of numeraire currency.

The estimated values of fractional differencing parameter (d) of various models are reported in Tables 6-8. Two interesting results are in order. First, all the estimates are statistically significantly different from 0 and 1, indicating that the impact of shocks to the conditional volatility displays a hyperbolic rather than exponential rate of decay. This result is robust to the choice of the numeraire currency and the models.   Second, most of the fractional differencing parameters for the MYR and the SGD are similar across the GARCH-type models for a given numeraire currency. For example, when the dollar is used as the numeraire, the estimated values of d for MYR and SGD are 0.4583 and 0.4428 respectively for the symmetric VC-FIGARCH model; 0.4217 and 0.5690 for the asymmetric VC-FIAPARCH model; and 0.4497 and 0.4470 for the asymmetric VC-FIAGARCH model, respectively.   Similarly, when the yen is used as the numeraire currency, the MYR and the SGD have consistently lower estimated values for d within the range of 0.20-0.30 than that of the corresponding GARCH-type counterparts under the dollar. Moreover, the likelihood ratio test statistics reported in Table 9 are all

significant at the 5% level, thereby indicating that the fractionally integrated models are more adequate than those without the long memory structure.

To assess the correlation dynamics of the two currencies, we apply the likelihood ratio (LR) test to the null hypothesis of $\pi_1 = \pi_2 = 0$ (see equation (5)). Under the null hypothesis, the LR test statistics follows an asymptotic chi-squared distribution with two degrees of freedom. Also, the significance of the estimated values of π_1 and π_2 are examined individually. As shown in columns 8-13 of Tables 3-8, all the LR tests indicate that the null hypothesis of constant conditional correlations is rejected at the 5% level of significance, thereby suggesting that the conditional correlations are time-varying. Such findings are robust across models. In contrast, almost all of the individual estimates of π_1 and π_2 are statistically insignificant when the MYR and SGD are measured against the dollar; and all individual estimates are significant at the 5% level when their exchange rates are based on the yen. This implies that the evidence of time-varying correlations between MYR/USD and SGD/USD is relatively weaker, and it is consistent with Tse's (2000) conclusion that the hypothesis of constant conditional correlation cannot be rejected for the MYR and SGD. However, we detect strong support of time-varying correlations between MYR and SGD when the Japanese yen is used as the numeraire currency. The reason as to why the asymmetric effects are not robust to exchange rates under different numeriare currency is still unknown to researchers. Apparently it is a challenging topic for future researchers.

Table 3. Estimation Results of Bivariate VC-GARCH(1,1) Model: $h_t = \eta + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}$; $\Gamma_t = (1 - \pi_1 - \pi_2)\Gamma + \pi_1\Gamma_{t-1} + \pi_2\Psi_{t-1}$

Variable	η	β	α	Γ	π_1	π_2	LL (VC)	Corr (CC)	LL (CC)	LR
MYR/USD	0.0031	0.7872	0.1705	0.3782	0.4309	0.1129	6327.2524	0.3591	6305.3816	43.7416
	(0.0012)	(0.0453)	(0.0349)	(0.0263)	(0.7034)	(0.0744)		(0.0229)		
SGD/USD	0.0029	0.8595	0.1011							
	(0.0016)	(0.0562)	(0.0381)							
MYR/JPY	0.0186	0.9013	0.0601	0.9408	0.8715	0.0351	2372.3197	0.9044	2214.5174	315.6046
	(0.0236)	(0.0952)	(0.0502)	(0.0087)	(0.0363)	(0.0077)		(0.9044)		
SGD/JPY	0.0147	0.9113	0.0540							
	(0.0133)	(0.0586)	(0.0293)							

Notes:
1. All standard errors (in parenthesis) are the heteroskedastic-consistent Bollerslev-Wooldridge standard errors computed based on the Quasi-Maximum Likelihood Estimation (QMLE) technique.
2. Log-likelihood value (VC) and Log-likelihood value (CC) refer to the likelihood values obtained from the VC-GARCH(1,1) and CC-GARCH(1,1) models respectively.
3. Correlations (CC) refer to the conditional correlation coefficient obtained from the CC-GARCH(1,1) model.
4. LR is the likelihood ratio statistic for H_0: $\pi_1 = \pi_2 = 0$ in the VC-GARCH(1,1) model. It is distributed as chi-squared with 2 degrees of freedom under H_0.

Table 4. Estimation Results of Bivariate VC-APARCH(1,1) Model: $h_t^{\delta/2} = \eta + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta h^{\delta/2}_{t-1}$; $\Gamma_t = (1 - \pi_1 - \pi_2)\Gamma + \pi_1\Gamma_{t-1} + \pi_2\Psi_{t-1}$

Variable	η	β	α	γ	δ	Γ	π_1	π_2	LL (VC)	Corr (CC)	LL (CC)	LR
MYR/USD	0.0035	0.8010	0.1627	-0.1106	1.8861	0.3784	0.4815	0.1069	6338.1878	0.3585	6316.497	43.38208
	(0.0019)	(0.0470)	(0.0358)	(0.0656)	(0.2646)	(0.0263)	(0.9150)	(0.1008)		(0.0228)		
SGD/USD	0.0075	0.8619	0.1178	0.0176	1.3827							
	(0.0054)	(0.0512)	(0.0359)	(0.0921)	(0.3099)							
MYR/JPY	0.0287	0.9031	0.0713	-0.1943	1.1206	0.9408	0.8670	0.0356	2394.499072	0.9045	2237.167	314.663888
	(0.0249)	(0.0659)	(0.0377)	(0.1117)	(0.2053)	(0.0089)	(0.0383)	(0.0080)		(0.0065)		
SGD/JPY	0.0244	0.9123	0.0646	-0.2139	1.1065							
	(0.0163)	(0.0425)	(0.0235)	(0.1132)	(0.1713)							

Notes:
1. All standard errors (in parenthesis) are the heteroskedastic-consistent Bollerslev-Wooldridge standard errors computed based on the Quasi-Maximum Likelihood Estimation (QMLE) technique.
2. Log-likelihood value (VC) and Log-likelihood value (CC) refer to the likelihood values obtained from the VC-APARCH(1,1) and CC-APARCH(1,1) models respectively.
3. Correlations (CC) refer to the conditional correlation coefficient obtained from the CC-APARCH(1,1) model.
4. LR is the likelihood ratio statistic for H_0: $\pi_1 = \pi_2 = 0$ in the VC-APARCH(1,1) model. It is distributed as chi-squared with 2 degrees of freedom under H_0.

Table 5. Estimation Results of VC-AGARCH(1,1) Model: $h_t = \eta + \alpha(\varepsilon_{t-1} - \gamma)^2 + \beta h_{t-1}$; $\Gamma_t = (1 - \pi_1 - \pi_2)\Gamma + \pi_1\Gamma_{t-1} + \pi_2\Psi_{t-1}$

Variable	η	β	α	γ	Γ	π_1	π_2	LL (VC)	Corr (CC)	LL (CC)	LR
MYR/USD	0.0030	0.7900	0.1670	-0.0136	0.3778	0.4186	0.1139	6329.32	0.3587	6307.53872	43.56184
	(0.0013)	(0.0459)	(0.0355)	(0.0236)	(0.0258)	(0.6992)	(0.0734)		(0.0227)		
SGD/USD	0.0027	0.8638	0.0997	0.0225							
	(0.0015)	(0.0535)	(0.0367)	(0.0306)							
MYR/JPY	0.0154	0.9132	0.0513	-0.1537	0.9400	0.8708	0.0354	2379.867	0.9041	2221.51303	316.70716
	(0.0154)	(0.0653)	(0.0341)	(0.0770)	(0.0089)	(0.0360)	(0.0079)		(0.0070)		
SGD/JPY	0.0127	0.9199	0.0467	-0.1503							
	(0.0097)	(0.0436)	(0.0219)	(0.0774)							

Notes:
1. All standard errors (in parenthesis) are the heteroskedastic-consistent Bollerslev-Wooldridge standard errors computed based on the Quasi-Maximum Likelihood Estimation (QMLE) technique.
2. Log-likelihood value (VC) and Log-likelihood value (CC) refer to the likelihood values obtained from the VC-AGARCH(1,1) and CC-AGARCH(1,1) models respectively.
3. Correlations (CC) refer to the conditional correlation coefficient obtained from the CC-AGARCH(1,1) model.
4. LR is the likelihood ratio statistic for H_0: $\pi_1 = \pi_2 = 0$ in the VC-AGARCH(1,1) model. It is distributed as chi-squared with 2 degrees of freedom under H_0.

Table 6. Estimation Results of Bivariate VC-FIGARCH(1,d,1) Model

Variable	η	ϕ	β	D	Γ	π_1	π_2	LL (VC)	Corr (CC)	LL (CC)	LR
MYR/USD	0.0026	0.3595	0.5467	0.4583	0.3920	0.0993	0.1482	6392.685	0.3694	6367.309	50.75224
	(0.0012)	(0.1215)	(0.1090)	(0.1481)	(0.0257)	(0.3147)	(0.0409)		(0.0236)		
SGD/USD	0.0020	0.5869	0.7797	0.4428							
	(0.0010)	(0.1357)	(0.1093)	(0.2290)							
MYR/JPY	0.0786	0.2130	0.3018	0.2153	0.9409	0.8659	0.0345	2394.589	0.9058	2243.902	301.3736
	(0.0365)	(0.2298)	(0.2411)	(0.0439)	(0.0080)	(0.0349)	(0.0079)		(0.0063)		
SGD/JPY	0.0365	0.5094	0.6175	0.2369							
	(0.0143)	(0.1093)	(0.0993)	(0.0574)							

Notes:
1. All standard errors (in parenthesis) are the heteroskedastic-consistent Bollerslev-Wooldridge standard errors computed based on the Quasi-Maximum Likelihood Estimation (QMLE) technique.
2. Log-likelihood value (VC) and Log-likelihood value (CC) refer to the likelihood values obtained from the VC-FIGARCH(1,d,1) and CC-FIGARCH(1,d,1) models respectively.
3. Correlations (CC) refer to the conditional correlation coefficient obtained from the CC-FIGARCH(1,d,1) model.
4. LR is the likelihood ratio statistic for H_0: $\pi_1 = \pi_2 = 0$ in the VC-FIGARCH(1,d,1) model. It is distributed as chi-squared with 2 degrees of freedom under H_0.

20

Table 7. Estimation Results of Bivariate VC-FIAPARCH(1,d,1) Model

Variable	η	ϕ	γ	δ	β	D	Γ	π_1	π_2	LL (VC)	Corr (CC)	LL (CC)	LR
MYR/USD	0.0032	0.3598	-0.1400	1.9157	0.5401	0.4217	0.3856	0.0899	0.1441	6409.403	0.3644	6385.195	48.41536
	(0.0023)	(0.1167)	(0.0636)	(0.1685)	(0.1080)	(0.1332)	(0.0254)	(0.3452)	(0.0406)		(0.0232)		
SGD/USD	0.0057	0.4877	-0.0610	1.5333	0.8088	0.5690							
	(0.0036)	(0.1662)	(0.0814)	(0.1803)	(0.1102)	(0.2592)							
MYR/JPY	0.1427	0.2180	-0.1880	1.2189	0.3669	0.2675	0.9398	0.8570	0.0362	2419.755	0.9056	2270.288	298.9349
	(0.0720)	(0.2247)	(0.1004)	(0.1731)	(0.2517)	(0.0532)	(0.0080)	(0.0402)	(0.0087)		(0.0063)		
SGD/JPY	0.0790	0.4527	-0.2304	1.1728	0.6241	0.3007							
	(0.0295)	(0.0802)	(0.1012)	(0.1549)	(0.1004)	(0.0755)							

Notes:
1. All standard errors (in parenthesis) are the heteroskedastic-consistent Bollerslev-Wooldridge standard errors computed based on the Quasi-Maximum Likelihood Estimation (QMLE) technique.
2. Log-likelihood value (VC) and Log-likelihood value (CC) refer to the likelihood values obtained from the VC-FIAPARCH(1,d,1) and CC-FIAPARCH(1,d,1) models respectively.
3. Correlations (CC) refer to the conditional correlation coefficient obtained from the CC-FIAPARCH(1,d,1) model.
4. LR is the likelihood ratio statistic for H_0: $\pi_1 = \pi_2 = 0$ in the VC-FIAPARCH(1,d,1) model. It is distributed as chi-squared with 2 degrees of freedom under H_0.

Table 8. Estimation Results of Bivariate VC-FIAGARCH(1,d,1) Model

Variable	η	ϕ	γ	β	d	Γ	π_1	π_2	LL (VC)	Corr (CC)	LL (CC)	LR
MYR/USD	0.0026	0.3532	-0.0138	0.5371	0.4497	0.3915	0.0973	0.1478	6393.943	0.3692	6368.837	50.21296
	(0.0013)	(0.1215)	(0.0238)	(0.1118)	(0.1538)	(0.0257)	(0.3162)	(0.0411)		(0.0236)		
SGD/USD	0.0019	0.5911	-0.0082	0.7848	0.4470							
	(0.0011)	(0.1392)	(0.0312)	(0.1190)	(0.2368)							
MYR/JPY	0.0793	0.1602	-0.1289	0.2481	0.1968	0.9394	0.8611	0.0351	2405.644	0.9053	2257.234	296.8197
	(0.0316)	(0.2027)	(0.0703)	(0.2070)	(0.0387)	(0.0081)	(0.0388)	(0.0084)		(0.0063)		
SGD/JPY	0.0321	0.5403	-0.1638	0.6275	0.2066							
	(0.0151)	(0.1340)	(0.0692)	(0.1218)	(0.0489)							

Notes:
1. All standard errors (in parenthesis) are the heteroskedastic-consistent Bollerslev-Wooldridge standard errors computed based on the Quasi-Maximum Likelihood Estimation (QMLE) technique.
2. Log-likelihood value (VC) and Log-likelihood value (CC) refer to the likelihood values obtained from the VC-FIAGARCH(1,d,1) and CC-FIAGARCH(1,d,1) models respectively.
3. Correlations (CC) refer to the conditional correlation coefficient obtained from the CC-FIAGARCH(1,d,1) model.
4. LR is the likelihood ratio statistic for H_0: $\pi_1 = \pi_2 = 0$ in the VC-FIAGARCH(1,d,1) model. It is distributed as chi-squared with 2 degrees of freedom under H_0.

Table 9. Likelihood Ratio Test: Bivariate VC and VC-FI Models

Variable	VC-GARCH	VC-FIGARCH	LR	VC-APARCH	VC-FIAPARCH	LR	VC-AGARCH	VC-FIAGARCH	LR
MYR/USD SGD/USD	6327.2524	6392.6850	139.9132	6338.1878	6409.4027	142.4298	6329.3196	6393.9434	129.2474
MYR/JPY SGD/JPY	2372.3197	2394.5890	51.4773	2394.4991	2419.7554	50.5126	2379.8666	2405.6442	51.5552

Note: LR is the likelihood ratio test statistics

Another noteworthy finding is that the magnitude of the time-variant component of the correlation equation $\Gamma = \{\rho_{ij}\}$ is much higher when the Japanese yen is the numeraire. For example, the estimated correlations of the MYR/USD and SGD/USD (MYR/JPY and SGD/JPY) based on the VC-GARCH, VC-APARCH, VC-AGARCH, VC-FIGARCH, VC-FIAPARCH and VC-FIAGARCH models are 0.3782 (0.9408), 0.3784 (0.9408), 0.3778 (0.9400), 0.3920 (0.9409), 0.3856 (0.9398) and 0.3915 (0.9394); respectively. This also applies to the corresponding estimates for the CC-GARCH, CC-APARCH, CC-AGARCH, CC-FIGARCH, CC-FIAPARCH and CC-FIAGARCH models. They are: 0.3591 (0.9044), 0.3585 (0.9045), 0.3587 (0.9041), 0.3694 (0.9058), 0.3644 (0.9056) and 0.3692 (0.9053), respectively. Moreover, it can be seen that all estimates of the constant components of the conditional correlations are significant at the 5% level. However, for the same pair of exchange rates, the magnitude of correlation based on the time-varying correlation models is consistently higher than that under the constant correlation models.   This is consistent with the finding of Tse and Tsui (2002). Furthermore, the time-varying models are able to keep track of the time path of the conditional correlation between the two currencies across models.

Finally, we perform residual diagnostics for all the models. Most of the Ljung-Box Q-statistics and McLeod-Li test statistics of the standardized residuals are insignificant at the 5% levels. However, the BDS test statistics for the bivariate VC-APARCH model are still significant at the 5% level, suggesting that dependencies are still present for the

MYR/JPY and SGD/JPY series. But the BDS tests are less significant for residuals of the same series in the VC-FIAPARCH model. Apparently, the fractionally integrated model acts as a better variance filter than those without such a structure. We also apply the diagnostic tests to the cross-product of the standardised residuals. Under the null hypothesis of constant correlations, these residuals should be serially uncorrelated (Bollerslev (1990)).   Indeed, most of the Ljung-Box Q-statistics based on the cross product of the standardised residuals are insignificant at the 5% level, thereby suggesting the absence of serial correlation. This is corroborated by the BDS test results.   However, the time-varying models are preferred to the constant-correlation models as there is less evidence of serial correlation in the cross product of the standardised residuals. The complete test results are available from the authors upon request.

Indeed, the relationship between currency hedging and exchange rate volatility has been extensively discussed by many researchers, such as Grammatikos and Saunders (1983), Kroner and Sultan (1993), Glen and Jorion (1993), Tong (1996), Jong, de Roon, and Veld (1997), Gagnon *et al.* (1998), Bos *et al.* (2000), Brooks and Chong (2001), and Bollen and Rasiel (2003). In particular, Kroner and Sultan (1993) argue that neglecting time-varying volatility and the conditional distributions of the currency returns affects the performance of currency hedging strategies.   They estimate the risk-minimizing futures hedge ratios for several currencies using a symmetric GARCH framework with constant correlations, and find evidence of greater risk reduction in the GARCH model than those of the conventional models. Moreover, Bollen and Rasiel (2003) compare the option valuation model based on the GARCH framework with the standard "smile" model and note that the symmetric GARCH model outperforms the standard model in terms of hedging. Consistent with previous findings, our results have

implications for currency hedging in three ways. First, most of the previous research on currency hedging with GARCH-type models assumes that shocks to volatility do not have asymmetric effects. Since it is possible for currency volatility to be asymmetric under different numeraire currencies, a currency hedging model that does not incorporate asymmetries can potentially be biased. Second, as the conditional correlation of exchange rate volatility can be significantly time-varying, the optimal hedge ratio will most likely require frequent updating. The assumption of conditional correlations in previous research is clearly inadequate. Third, with the significant presence of high persistence in exchange rate volatility, a dynamic hedging strategy presuming that shocks to volatility subside in a relatively short period can underestimate the optimal hedge ratio over time. As noted by Baillie, Bollerslev and Mikkelsen (1996), "optimal hedging decisions must take into account any such long-run dependencies."

Regarding the implications for international portfolios, it is widely accepted that the issue of international diversification of portfolios cannot be separated from foreign exchange risk. De Santis and Gerard (1997) test the conditional capital asset pricing model (CAPM) for the world's eight largest equity markets by using a parsimonious GARCH parameterization. They show that the expected gains from international diversification for a US investor average 2.11 percent per year and have not significantly declined over the last two decades. However, their results are predicated on the assumption that the numeraire currency is the US dollar and investors do not cover their exposure to exchange rate volatility. Analyzing the case of incorporating exchange rate volatility in international portfolio diversification is beyond the scope of this paper, but our results may provide some preliminary evidence that the benefits of international diversification could be overstated if exchange rate volatility were ignored. In addition, investors in mutual funds based on foreign firms need to determine the risks of their

foreign exchange. However, most empirical regularities of exchange rate volatility and correlation are derived from the US dollar exchange rates. Our findings indicate that such a reliance on the US dollar as the numeraire currency could be rather restricted as the volatility and correlation properties of foreign exchange are dependent on the choice of the numeraire currency.

4.   Concluding Remarks

We have followed up the study of Tse and Tsui (1997) to examine the empirical evidence of asymmetric volatility and long memory of the Malaysian ringgit and the Singapore dollar in the Asia-Pacific markets using a family of bivariate GARCH-type models. The proposed models can concurrently capture the stylized features of long-range persistence, asymmetric conditional volatility and time-varying correlations associated with the exchange rate returns. Besides the possible gains in efficiency in joint estimation of parameters, the bivariate approach is capable of tracking down the time path of conditional correlations between the two currencies.

Consistent with previous studies by Hsieh (1993), Tse and Tsui (1997), and Tsui and Ho (2004), we find that in general the returns of the Malaysian ringgit and the Singapore dollar against the dollar do not exhibit asymmetric effects in their conditional volatilities. In contrast, we detect strong evidence of negative asymmetric volatility when the Singapore dollar is measured against the yen. This may imply an unbalanced degree of uncertainty induced by depreciation and appreciation of the Singapore dollar against the yen in the market. In addition, we detect evidence of long-range temporal dependence in volatility in the two currencies, regardless of the choice of the numeraire currency. It seems that the impacts of exchange rate shocks display much longer

persistence than the standard exponential decay. By comparing the log-likelihood values, we find that the bivariate fractionally integrated models generally outperform those models without the long-range dependent structures in the conditional variance. Moreover, we find significant evidence of time-varying conditional correlations in the two currencies against the yen. In contrast, the evidence of time-varying correlations among the bilateral USD rates is much weaker. The time-varying models help to map out interesting time paths of the correlation between the Malaysian ringgit and the Singapore dollar.

Overall, this study has shown that the choice of numeraire currency (either the US dollar or the yen) for both the Singapore dollar and Malaysian ringgit can affect the significance of volatility asymmetry and time-varying correlations. In addition, we have discussed the implications for currency hedging strategies and international investment portfolios. Our findings may also be useful for empirical researchers in several areas, including the computation of VaR (Value at Risk) as a way to measure the risks of portfolios involving multiple currencies; the pricing of options based on the GARCH framework; the hedging of portfolios involving derivative securities; and the analysis of the impact of foreign exchange intervention on currency volatility.

As noted by Tse and Tsui (1997), in their study of the Malaysian ringgit and the Singapore dollar against the US dollar, the ringgit exhibits asymmetric volatility whereas the Singapore dollar does not. They argue that the outcome probably depends on the particular market microstructure of each currency. They further suggest that, during the period of analysis, heterogeneous expectations and central bank intervention probably contribute to the significance of persistence and asymmetric effects in conditional volatility of the MYR/USD. More recently, McKenzie (2002) also finds evidence of

volatility asymmetry in the Australian dollar against the US dollar, and suggests that this may have to do with foreign exchange intervention operations conducted by the central bank. Moreover, Ramchander and Sant (2002) note that Fed intervention is associated with negative changes in the US dollar/Japanese yen volatility during the period from 1985-1993. An interesting topic for future research would be to investigate whether central bank intervention does consistently lead to significant asymmetries in the volatility of various currencies of developed and developing countries.

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