

Stock Index Futures Hedging in the emerging Malaysian Market

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Abstract

The paper investigates hedging effectiveness of dynamic and constant models in the emerging market of Malaysia where trading information is not readily available and market liquidity is lower compared to the developed equity markets. Using daily data from December 1995 to April 2001 and bivariate GARCH (1,1) and TGARCH models, the paper uses differing variance-covariance structures to obtain hedging ratios. Performance of models is compared in terms of variance reduction and expected utility levels for the full sample period as well as the three sub-periods which encompass the Asian financial crisis and introduction of new capital control measures in Malaysia. Findings show that rankings of the hedging models change for the in-sample period depending on evaluation criteria used. TGARCH based models provide better hedging performance but only in the period of higher information asymmetry following the imposition of capital controls in Malaysia. Overall, despite the structural breaks caused by the Asian financial crisis and new capital control regulations, out of sample hedging performance of dynamic GARCH models in the Malaysian emerging market is as good as the one reported for the highly developed markets in the previous literature. The findings suggest that changes in the composition of market agents caused by large scale retreat of foreign investors following the imposition of capital control regulations do not seem to have any material impact on the volatility characteristics of the Malaysian emerging market.

J.E.L Classification: G10, C53

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1. Introduction

Until 15 December 1995, investors in Malaysia had little choice but to hold diversified portfolios to manage the risk. Alternatively, they would hold mainly low beta stocks. If the risk of holding the portfolio changed unexpectedly, investors reacted by selling the higher beta stocks in their portfolios and investing in low risk securities, such as, fixed-income securities. However, this meant higher transaction costs. The introduction of stock index futures contracts in Bursa Malaysia for Kuala Lumpur Stock Exchange (KLSE) Composite Index in 1995 offered investors an alternative to manage the market risk of their portfolio without changing its composition. With the introduction of KLSE Index futures, fund managers holding a portfolio of stocks are able to hedge against the risk of any future decline in the value of the portfolio by selling the stock index futures contracts. In the event of a fall in the market value, the profits gained from shorting futures contracts compensates for any losses on the equity portfolio thus saving the inconvenience of portfolio reshuffling and the associated higher transaction costs.

Introduction of stock index futures in emerging markets like Malaysia have greatly facilitated risk hedging. However, investors are required to calculate the number of futures contracts (the hedge ratio) that they should short for hedging risk of a loss in their underlying equity portfolio value. There are several factors which influence the selection of optimal hedge ratios. These include basis risk, hedging duration, correlation between changes in the price of futures and the spot price, and the methods employed in estimating hedge ratios.

It is well documented that emerging markets are generally more volatile and historically have been exposed to financial crisis more often than the developed markets (see Mishkin, 2000). Besides, financial market regulations in emerging markets are still evolving and this process creates greater uncertainty amongst investors. In the recent past, Malaysian financial markets have experienced financial crisis caused by devaluation of Thai Baht in 1997 as well as dramatic changes in financial market regulations following the crisis. This study therefore seeks to suggest the best way of hedging risk of investing in the Malaysian stock market during the period characterised by the financial crisis and new capital control regulations that were subsequently imposed by the Malaysian government in 1998. Malaysian market has been chosen for this study since it provides an ideal testing ground as the Malaysian data allows us to rigorously test the performance of different hedging techniques under uncertainty and structural breaks caused by the financial crisis and imposition of capital control measures. To the best of our knowledge, this study is the first to analyse hedging performance of stock index futures in the emerging Malaysian stock market. Another motivation for selecting Malaysian emerging markets is that thus far most available empirical evidence on index futures hedging is based on data from developed markets where trading information is readily available, the timeliness of trading information is high and market liquidity is higher. Malaysian emerging market does not satisfy these conditions and therefore it is worthwhile to investigate whether index futures can be as effectively used in hedging portfolio risk as has been documented for other developed markets.¹

¹ See Pok & Poshakwale (2004)

In estimating hedge ratios for managing stock investment risk, early studies employed constant models². However, Constant models are criticised because they assume that the hedge ratios remain stable over the sample period. However, it has been demonstrated that if the joint distribution of stock index and futures prices changes over time, estimations using a constant hedge ratio may not be optimal.³ Research has now been extended to finding optimal hedge ratios while incorporating not only time-varying conditional variances but also changing covariance of spot and futures returns. Available empirical evidence so far has shown that dynamic hedging models which account for the time-variation in the joint distribution of the changes in spot and futures prices perform better than the constant or traditional OLS models in terms of greater risk-reduction and higher expected utility. Thus far, the dynamic models seem to outperform the conventional models in markets where trading restrictions are minimal, trading information is more readily available, the timeliness of trading information is high and market liquidity is higher (see Park and Switzer, 1995; Lypny and Powalla, 1998; Gagnon and Lypny, 1997; Sim and Zurbruegg, 2001a; Pattarin and Ferretti, 2004; Chiu et al., 2005; and, Hatemi-J and Roca, 2006).

However, there is much less evidence on the hedging effectiveness of GARCH(1,1) and TGARCH(1,1) dynamic models and constant hedging models in an emerging market where many of the above conditions are not satisfied. To date there are only two studies, one by Sim and Zurbruegg (2001b) and another by Floros and Vougas (2004) that have examined the hedging performance using data from

² See for example, Figlewski (1984, 1985), Witt, Schroeder and Hayenga (1987), Herbst, Kare and Caples (1989), and Lindahl (1992).

³ See for example, Malliaris and Urrutia (1991a, 1991b).

emerging markets of South Korea and Greece respectively. Sim and Zurbrugg (2001b) focus on the impact of Asian financial crisis upon the hedging effectiveness of KOSPI 200 stock index and index futures by incorporating error correction components within the conditional mean and conditional variances of a standard GARCH process. Their results show that cointegrating time-varying hedging strategy performs better than constant hedging models. Floros and Vougas (2004) examine hedging in Greek stock index futures market using standard OLS, ECM and VECM models, as well as bivariate GARCH models. They find that the bivariate GARCH model (capturing time-variation) provides best hedging performance.

We study the hedging effectiveness of using stock index futures in the Kuala Lumpur Stock Exchange Composite (KLSE) Index, introduced on 15 December 1995 with the opening of the Malaysia Derivatives Exchange, MDEX (formerly known as KLOFFE). This study differs from previous studies since our dataset: (1) begins with the opening of the MDEX, so that we could investigate how quickly the actions of market agents could adapt to the new market situation, and how sophisticated they were in hedging risks (hereafter referred as pre-crisis period); (2) includes the financial crisis, and its impact on volatility within and across markets (hereafter referred the crisis period); (3) covers the period following the imposition of capital controls aimed at stabilising the economy and financial markets (hereafter referred after capital controls period); and, (4) permits us to consider how well the hedging models perform in the post financial crisis period.⁴ Further, besides using the

⁴ It is important to examine the performance of hedging models for three sub-periods which allows us to reflect on the possible influence of changes in the composition of market agents on the effectiveness of the dynamic and static hedging strategies. This is particularly relevant since according to Pok (2007), the first phase of futures trading was dominated by foreign institutional investors. Although the Securities Commission provided support to the local traders by making appropriate policy changes, the

conventional tests for equality of means and variances of the hedged portfolio, we also employ more recent techniques such as the semi-variance and LPM which have figured in some recent literature (see, for example, Cotter and Hanly (2006)).

Our findings suggest that for the overall in-sample period, the GARCH models provide the best performance. However, when we use tests of equality of means and variances and semi-variance and the LPM, there is no evidence that GARCH models are any better than other models and the rankings are identical with those based on variance reduction and expected utility criteria. The results are consistent for the overall sample period as well as the sub-periods. Nonetheless, for the out-of-sample predictions, the GARCH based dynamic models provide the best performance and significant changes in the volatility structure caused by structural breaks and changes in the composition of the market agents seem to be well captured by the dynamic GARCH models. The findings suggest that the changes in the composition of market agents caused by large scale retreat of foreign investors following the imposition of capital control regulations do not seem to have any material impact on the volatility characteristics of the Malaysian emerging market.

The remainder of the paper is organised as follows. Section 2 describes our data and the methodology. Empirical findings are presented in Section 3. The summary and conclusions are provided in Section 4.

foreign institutional investors continued to dominate the market even during the Asian financial crisis. Following the imposition of capital controls, the influence of foreign investors declined following large withdrawals of foreign funds from the Malaysian futures and spot markets.

2. Data and Methodology

2.1. Data

The spot market data consist of daily closing prices of KLSE Composite Index which is made up of 100 well established and largest stocks traded on the Main Board of Bursa Malaysia (formerly known as KLSE). The futures data corresponds to daily settlement prices for the nearby contracts. The spot data were obtained from *Datastream International* and the futures data from the KLOFFE (Kuala Lumpur Options and Financial Futures Exchange) website. The data begins on 15 December 1995 (the day the futures started to trade) and end on 31 July 2001.

Returns are calculated by computing the differences in the natural logarithm of price multiplied by 100. In total we get 1386 daily observations of which the first 1310 (from 15 December 1995 to 10 April 2001) observations are used for estimation purposes and the remaining 76 (from 11 April 2001 to 31 July 2001) observations are used for out-of-sample forecasting. As mentioned in Section 1, to take account of the financial crisis and introduction of the capital control regulations, we split the total sample into three sub-periods namely: Pre-crisis, 15 December 1995 to 31 July 1997 (observations 1 to 400); Crisis, 1 August 1997 to 14 September 1998 (observations 401 to 677); and, After Capital Controls, 15 September 1998 to 10 April 2001 (observations 768 to 1310).

Figure 1, provides support for the threefold division of the full in-sample period; as do the descriptive statistics discussed in the later sections of the paper. The unit root tests (not reported here but available on request) indicate that the returns are

$I(0)$ for all periods: full in-sample period; the in-sample sub-periods; and the out-of-sample period. Also, we note that the spot and futures prices are $I(1)$.

2.2 Methodology

2.2.1 Estimation of Optimal Hedge Ratios

We use GARCH (1,1) and TGARCH (1,1) for calculating the hedge ratios because they capture time-varying second moment effects in the joint distribution of spot and futures. Further, TGARCH is capable of capturing any possible asymmetric news effects.

The most general representation of the joint distribution of spot and futures returns used is:

$$y_t = \mu + \alpha EC + G\beta + V\gamma + \varepsilon_t; \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \quad (1)$$

Where: $y_t = (r_s, r_f)'$ is a vector of observations of the spot and futures rates of returns; μ, α, β and γ are column vectors of parameters; EC is the error correction term from any cointegrating relationship that may exist between the two rates of return; G is a 2×2 diagonal matrix with GARCH(1) terms on the diagonal; V is a row vector of lagged values of y_t and, $\varepsilon_t = (\varepsilon_s, \varepsilon_f)$ is a vector of residuals. In respect of the error correction term, it is argued in some of the literature that if spot and futures prices are cointegrated and the resultant error-correction term is not included in the equations for the mean returns, minimum variance hedge ratio estimates are biased downwards due to mis-specification (eg, Ghosh, 1993; Lien and Luo, 1993; and Lien, 1996).

The bivariate GARCH(1,1) model is represented as:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon_{t-1}'A' + BH_{t-1}B' \quad (2)$$

Hence:

$$(h_t = \text{vec}(H_t) = \text{vec}(CC') + (A \otimes A)\text{vec}(\varepsilon_{t-1}\varepsilon_{t-1}') + (B \otimes B)\text{vec}(H_{t-1})) \quad (2a)$$

where C , A and B are 2×2 symmetric parameter matrices. The conditional variance-covariance matrix H_t is estimated recursively from equations (1) and (2) and must be a positive definite matrix for all possible evaluations of $\varepsilon_{i,t-1}$. In addition, the GARCH process must be stationary.

Various parameterisations of the multivariate GARCH process have been proposed.⁵ We adopt the popular parameterisation introduced by Engle and Kroner (1995), henceforth the BEKK representation, which permits time variation in conditional correlations as well as the conditional variances. The BEKK ensures that the conditional covariance matrix is positive definite by defining C to be lower triangular, so that it is of full rank. Stationarity of the GARCH(1,1) process requires that the eigenvalues of $(A \otimes A) + (B \otimes B)$ be less than one in modulus, because from equation (2)(a) it follows that the unconditional covariance matrix is:

$$[I - (A \otimes A) - (B \otimes B)]^{-1}\text{vec}(CC') \quad (2b)$$

The system, obviously, can be estimated with no restrictions on H . Such an unrestricted version will be referred to as a full or general model. When the off-diagonal elements of A and B are restricted to be zero this version of the model will be

⁵ See Engle and Bollerslev, (1986). Bollerslev (1986), Baillie and Bollerslev (1990) and Kroner and Sultan (1993) adopt a constant conditional correlation parameterisation. Bollerslev, Engle and Wooldridge (1988) adopt a representation by assuming that the A and B matrices are diagonal.

referred to as the diagonal model; for which the stationarity condition from (2)(b) reduces to $a_{ii}^2 + b_{ii}^2 < 1, i = 1, 2$.⁶ In the static or constant model all elements of A and B are set to zero. Accordingly, the *static model* produces a *constant hedge ratio* equivalent to that obtained by using traditional OLS. The performance of models can be compared by likelihood ratio test since these models are nested models: constant within diagonal and diagonal within general.

For the TGARCH model, equation (2) becomes:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon_{t-1}'A' + BH_{t-1}B' + D(\varepsilon_{t-1}I_{t-1})(I_{t-1}\varepsilon_{t-1})'D' \quad (2c)$$

where $I_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise. The necessary amendments to equations (2)(a) and (2)(b) are immediate.

Under conditional normality, the log-likelihood function for a sample of T observations on spot and futures returns is:

$$L(\Theta) = -T \log(2\pi) - (1/2) \sum_{t=1}^T (\log |H_t(\Theta)| + \varepsilon_t(\Theta)H_t^{-1}(\Theta)\varepsilon_t'(\Theta)) \quad (3)$$

where Θ is the parameter vector to be estimated. The log-likelihood function is maximised subject to the constraint that the conditional variances be positive. Initial values are required for all the parameters and those found from the univariate GARCH model are used for this purpose.

⁶ This follows, of course, because the eigenvalues of a diagonal matrix are simply the elements along the diagonal; and the conditions detailed imply that all other diagonal elements are also less than 1 in absolute value.

2.2.2 Hedging effectiveness in-sample and out-of-sample

We evaluate the performance of models using both risk minimisation and expected utility maximisation criteria.

For the risk minimisation criterion⁷, the hedge ratios, b_{t-1}^* for the constant model is:

$$\frac{Cov(r_s, r_f)}{Var(r_f)}; \quad (4)$$

and, for the dynamic model it is:

$$\frac{Cov(r_{s,t}, r_{f,t} | \Omega_{t-1})}{Var(r_{f,t} | \Omega_{t-1})} = \frac{\hat{h}_{r_s r_{f,t}}}{\hat{h}_{r_{f,t}}} \quad (5)$$

For the “expected utility” maximisation criterion⁸, there is an additional term, which describes the speculative demand for futures and the associated risk-aversion parameter of the investor (λ) such that b_{t-1}^* becomes:

$$\frac{Cov(r_s, r_f)}{Var(r_f)} - \frac{1}{2\lambda} \frac{E(r_f)}{Var(r_f)} \text{ for the constant model and} \quad (6)$$

$$\frac{Cov(r_{s,t}, r_{f,t} | \Omega_{t-1})}{Var(r_{f,t} | \Omega_{t-1})} - \frac{1}{2\lambda} \frac{E(r_{f,t} | \Omega_{t-1})}{Var(r_{f,t} | \Omega_{t-1})} \text{ for the dynamic model.} \quad (7)$$

The first ratio on the right-hand-side of each of these expressions is the variance minimisation hedge ratio, whilst the second is what is usually called as the

⁷ These are immediate from the minimisation of $Var(R)$ and $Var(R | \Omega_{t-1})$; with the variance being then equal to $Var(r_s)[1 - r_{s,f}^2]$, where r is the correlation between r_s and r_f .

⁸ Here we follow Kroner and Sultan (1993), who use the mean-variance representation of expected utility which is still so predominant in the *CAPM* and *APT* literature:

(i) $E[U(R)] = E(R) - \lambda Var(R)$, and

(ii) $E[U(R | \Omega_{t-1})] = E(R | \Omega_{t-1}) - \lambda Var(R | \Omega_{t-1})$

pure speculative demand which reflects the mean-variance trade-off in un-hedged futures positions as well as the investor's attitude to risk.

To assess the risk reduction potential of the two competing models, we adopt the traditional approach, similar to that proposed by Kroner and Sultan (1993). From the hedged portfolio return:

$$r_{P,t} = r_{s,t} - b_{t-1}^* r_{f,t} \quad (8)$$

we calculate the percentage reduction in the variance of the hedged portfolio over the unhedged portfolio:

$$\% \Delta = \frac{\sigma_{Hedged}^2 - \sigma_{Unhedged}^2}{\sigma_{Unhedged}^2}$$

where $\sigma_{Unhedged}^2 = Var(r_{s,t})$. The model that records the higher percentage variance reduction is considered as the most effective model. However, as we indicated earlier, we have specifically included the test of equality means and variances of the hedged portfolio to see if there is any significant change in means and variances of the hedged portfolio using different hedging models.

The expected utility comparison is secondary to that of variance reduction. The dynamic hedging models are superior to the constant hedge if they produce a higher value of:

$$E[U(R_i | \Omega_{t-1})] = E(R_i | \Omega_{t-1}) - \lambda Var(R_i | \Omega_{t-1}) \quad (9)$$

The subscript i defines the type of assumption made about the structure of H_t ; λ is the risk-aversion parameter.

In assessing the hedge effectiveness of the dynamic models in the *out-of-sample* period, the hedge ratios are computed using parameter estimates obtained from the in-sample estimation for the after capital controls period to up-date H_t ,

continuously. The out-of-sample hedge ratios are based, therefore, only on information that is available at the time each hedging decision is made; the information set Ω_{t-1} , contains the history of the two rates of return and the hedging returns from the start of the after capital controls period to the given current time during the forecast period. The predicted hedge returns, of course, are easier to obtain since the constant hedge ratio estimate from the in-sample after capital controls period is repeatedly used to forecast the following day return of the hedged portfolio.

The various dynamic models and the constant model are evaluated against each other and compared to the unhedged portfolio as in the in-sample periods. In terms of variance reduction, this is on an average basis over the whole of the out-of-sample period and at each day during that period. In terms of expected utility the comparison is based on the path of expected utility values over each day of the forecast period.

3. Empirical Results

3.1 Descriptive statistics

From Table 1, it does appear that the 1997 financial crisis (between August 1997 and September 1998) and the subsequent imposition of capital controls (on 1st September 1998, but these were not effective until 15th September 1998), particularly, generated the extreme values that significantly influenced the distribution of daily returns of the futures and the spot markets. The results indicate that the mean returns of the futures during the pre-crisis and after capital controls (respectively, 0.0053 and 0.0547) are lower than those of the spot (respectively, 0.0056 and 0.0581). Both futures and spot have higher volatility during the crisis. Nonetheless, during the crisis, futures (-0.3355) suffered marginally lower losses than the spot market (-0.3416). The

futures' standard deviation is correspondingly higher than that of the spot for all three sub-periods (being, respectively, 0.9626, 5.1124, 1.9868 vs. 0.8885, 4.0579, and 1.5979). The significantly reduced subsequent volatility can be ascribed to the introduction of capital controls, the absence of which had led to large withdrawals by foreign institutional investors. With respect to skewness of returns, during the pre-crisis, it is negative for both futures and spot (respectively, -0.4526 and -0.3207). However, during the crisis, the futures returns are negatively skewed (-0.4499) whilst the spot returns are positively skewed (0.6221). After the capital controls, the skewness of futures returns reverts back to positive (0.3739). As expected, the kurtosis is comparatively higher for periods during the crisis than during the pre-crisis and after capital control periods which consequently leads to high Jarque-Bera statistic. The distributional attributes of both the futures and spot markets have improved after the introduction of capital controls. Tests for autocorrelation and ARCH effects (not reported here but available on request) show that varying degrees of AR and ARCH effects are present in both spot and futures returns for the whole sample period as well as for sub-periods.

>Insert Table 1 here<

3.2 Model estimation

As we mentioned earlier, various specifications of the mean equations are estimated for a given structure of H_t .⁹ The results from the maximum likelihood estimation of

⁹ No cointegration was found. In the context of our estimation of GARCH and TGARCH structures, we note the suggestion made by Engle and Kroner (1995) that the BHHH optimization algorithm might be the most appropriate for estimation of multivariate GARCH models. We found that the estimations provided by Marquardt algorithm for the diagonal and constant models were identical to or better than those obtained by using BHHH. For those model structures, except for the final period i.e., after capital controls, the GARCH estimates dominated those from the TGARCH for the same reasons, no matter which optimisation algorithm was used.

H_t for the GARCH general, diagonal and constant models for the overall in-sample and the in-sample sub-periods—pre-crisis, crisis and after capital controls as well as LR statistics tests are reported in Tables 2-5, respectively. For the overall in-sample period, the mean returns are random. Effectively, the log of the spot and futures price levels follows a Martingale process. In the covariance structure, for the general model, except for c_{22} , b_{12} , and a_{12} (which are significantly different from zero at the 6.57% level) all estimated parameters are significant at the 5% level implying that the distributions of spot and futures returns are time-varying. For the diagonal and constant models, all parameters are significant in explaining the distribution of spot and futures. In terms of the Likelihood value and LR statistics the general model dominates the diagonal and the constant model. The constant model is also dominated by the diagonal model. However, we observe from the eigenvalues that both the general and diagonal specifications are not covariance stationary. Further the results suggest that the covariance structure is affected by the conditions surrounding the markets, which is captured by the compartmentalising the data in the three sub-periods.

Nevertheless, the comparison of the GARCH models over the three sub-periods via the likelihood ratios indicates that the constant model can be rejected and that the restrictions imposed on the general model in its diagonal version can be rejected. For the pre-crisis period, we observe that in the general model, three coefficients in the H_t specification are again insignificantly different from zero, but because these now include a_{11} and b_{21} , H_t becomes covariance stationary. In the other

two models, all parameter estimates are statistically different from zero. The same pattern is found for the crisis period except that, again as might be expected, the crisis has produced estimates of the structures of H_t that are not covariance stationary. The period following the introduction of capital controls reveals a similar pattern: 8 out of the 11 parameters in the general model's H_t are statistically significantly different from zero. For this sub-period, again as might be anticipated, both dynamic models are covariance stationary.

>Insert Tables 2-5 here<

3.3 Descriptive statistics of the hedge ratios under risk-minimisation

The graphs of the hedge ratios (not included here, but available on request) show that throughout the period there is wide divergence between hedge ratios estimated using dynamic models (general and diagonal) and those estimated using the constant model. The time-varying conditional hedge ratios are, indeed, clearly changing as new information arrives. The hedge ratios for pre-crisis period are somewhat higher than those during the crisis and after the imposition of capital controls. During the crisis, the ratios fluctuate around the constant hedge and after capital controls the hedge ratios seem to swing to a lower level.

The descriptive statistics (not included here, but available upon request) for the hedge ratios of the three types of model for the overall in-sample and the three sub-periods indicate that the mean hedge ratio of the diagonal model exceeds that of the general model, which exceeds that of the constant model. Although the means appear to differ by very little, they do so according to “tests of equality”. The spread and standard deviations vary considerably, numerically as well as statistically. The standard deviation and kurtosis of the hedge ratios of the diagonal model are higher

than those of the general model for all sub-periods, and they also alter substantially during the crisis period.

The mean of the estimated hedge ratios of all three models has fallen consistently over the three sub-periods. This could imply that as markets integrate or mature, the size of hedge ratios also declines. We note further that ADF and PP unit root tests suggest that for the overall period and the three sub-periods, the time-varying hedge ratios are $I(0)$, at the 5% level, for the general model and also for the diagonal model except for the period after capital controls. This implies that the stock index hedge ratios are mean reverting and any impact of a shock to them eventually becomes negligible.

3.4. In-sample performance of hedging models

3.4.1. Variance reduction

Table 6 reports the variance reduction of the hedged portfolio returns compared with those obtained for the unhedged portfolio. For the overall in-sample, results in Panel A of Table 6 indicate that the general model is superior to the diagonal, but both are dominated by the constant model. From Panel B we see that the diagonal model is better than the general both of which are better than the constant model for the pre-crisis period. For the crisis and after capital controls periods the general model is again superior to the diagonal, but is inferior to the constant model in the crisis period. In the crisis and after capital controls periods the constant model is superior to the diagonal.

>Insert Table 6 here<

In Table 7 we report the variance reductions implied by the dynamic TGARCH structures (which suggest that asymmetric information is statistically

significant through d_{22} and/or d_{11}) for the period after the imposition of capital controls. Those reductions are almost identical with those for the GARCH specifications. Tests of equality of the variances of the hedge returns across the GARCH, TGARCH and constant models indicate that all models have identical variances (and means): and they are ranked identically in respect of variance reduction over the period after the imposition of capital controls.¹⁰

>Insert Table 7 here<

Table 8 summarises the rankings of the models. For all four periods, the general and constant models provide the same or lower variance reduction than does the diagonal model; and the choice between the general and constant models seems to be inconsequential. For the period after capital controls, the TGARCH diagonal model appears to be inferior to its GARCH counterpart. Overall, the GARCH models seem to do better than the T-GARCH models.

>Insert Table 8 here<

3.4.2. Expected utility maximisation

Results of the hedge ratios under this criterion (not reported here but available on request) are almost invariably identical with those under the risk minimisation criterion, except in those instances where the mean equations of the two rates of return contain intercepts. Even on those occasions where the latter is not the case, the expectation is effectively zero as the ranking of the models by means of $E(U)$ is conditioned by the variances of the hedge returns, no matter what value we set for the

¹⁰ Tests that at least one of the variances differs from the others confirm that they are all identical: Bartlett = 0.594[0.964]; Levene = 0.072[0.991]; and, Brown-Forsythe = 0.071[0.991].

risk-aversion parameter (λ). Accordingly, the rankings of the models are identical with those obtained under variance reduction criterion reported in Table 8.

3.5 Out-of-sample predictions

The parameter estimates of each model, from the after capital controls sub-period, were used to up-date H_t (except, of course, for the constant model) continuously throughout the 76 out-of-sample observations. The results are given in Table 9. Panel A provides the properties of the GARCH and constant models and Panel B for the TGARCH models. It is apparent that the variance reductions of all models are likely to be identical under equality tests, except for the TGARCH diagonal model. The tests confirm that TGARCH model is the exception. The test statistics for the equality of the other four variances being: Bartlett=0.485[0.922]; Levene=0.043[0.988]; and Brown-Forsythe=0.340[0.989].

>Insert Table 9 here<

The more useful comparison of the models, perhaps, is those between the time paths of the variance reductions of the different covariance specifications and between the time paths of expected utility. The calculations of these attributes of the models, we reiterate, are founded upon a day-by-day revision of the forecasts of variance reduction and of expected utilities if given sets of estimates of the conditional covariance matrix are used. Figure 2 portrays the time paths of the variance reductions expected to follow from the adoption in the next period of a hedging strategy based on a particular model. On that basis the GARCH diagonal model is the best model. It holds that status throughout the period and there is no need for any change in hedging strategy by an investor's switching between models. Indeed, except for some slight

changes in the ranking of the constant model and general variants of GARCH and TGARCH, the models are ranked uniquely, as listed in column three of Table 10.

>Insert Figure 2 here<

The time paths of expected utility are portrayed in Figure 3. For the reasons mentioned previously, these rankings are independent of the level of the risk-aversion parameter. Merely for the sake of convenience we have assumed that $\lambda = 1$. On this occasion, because we are now considering the time series of expected utilities, there is a slight alteration in the ranking of the models compared with that obtained from comparing their variance reductions over time.

>Insert Figure 3 here<

The rankings are summarised in Table 10. In Panel A, the best models are seen to possess the GARCH(1,1) dynamic structures. On the application of the “average” criteria of the results from the period after the imposition of capital controls, GARCH (1,1) shared first place jointly with the other models. The weakest model is uniquely the TGARCH diagonal; but leaving that on one side it is the constant model that is the inferior model. The rankings of the models by the *SV* and *LPM* metrics are given in Panel B. Once again, the distributions of hedge returns at zero or below are such that these rankings are identical. Finally, on the basis of equality tests the rankings are identical with those based on the variance reduction criterion.

>Insert Table 10 here<

4. Summary and Conclusions

The paper examines the hedging performance of dynamic and constant models in the emerging Malaysian market during the financial crisis and in a period characterised by major regulatory changes during 1995-2001. Despite the extreme conditions in which the various specifications of dynamic and constant models were examined, our

results are consistent with previous studies for the in-sample period. Amongst the three models, the general GARCH model outperforms other models and provides the best hedging performance during the normal period, financial crisis period, and in the period after imposition of capital controls. However, when we apply tests of the equality of mean and variance of the hedged portfolios, the rankings of the models change, except for the overall in-sample period. For the in-sample sub-periods, all models provide similar performance, except for the crisis sub-period, when the GARCH diagonal model is inferior to the other two models. Effectively, there is nothing to choose between the general GARCH and the constant models; and even between them and the diagonal model. Furthermore, our estimated systems are such that speculative demand has minimal impact on the construction of hedge ratios.

For the out-of-sample performance which tests the models for their predictive accuracies, the dynamic GARCH model outperforms constant model. However, TGARCH does not perform as well as GARCH until the period after the introduction of capital controls. We attribute this to the asymmetry in information impacts across the two markets following the imposition of capital controls in September 1998 that led to a significant drop in participation of the foreign institutional investors as explained in footnote 4.

Overall, the evidence presented in the paper suggests that despite lower liquidity, higher perceived information asymmetry, as well as structural breaks caused by financial crisis and introduction of capital controls in the emerging Malaysian market, out of sample hedging performance of general GARCH model is as good as the one reported for the highly developed markets in the previous literature. The findings suggest that changes in the composition of market agents caused by large scale retreat of foreign investors following the imposition of capital control

regulations do not seem to have any material impact on the volatility characteristics of the emerging Malaysian market.

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