

Chapter 5

Conclusions and Discussion

In this chapter, the conclusions are presented and discussed from our study. The research objectives were as follows.

- (a) To describe the variation of banking shares in the stock market in Thailand during the six-year period 1994 to 1999.
- (b) To develop an appropriate statistical model for describing and forecasting the stochastic volatility of stock prices.

The banking share in this study comprise BAY, BBL, BOA, IFCT, KTB, SCB and TFB, running from 4 January 1994 to 30 December 1999, yielding 1468 observations on each series. Results for the distribution and trends of share prices, shown in the first section of the preliminary analysis in Chapter 3, suggested that the data need to be transformed. After trying various transformations, including logarithms and square roots, we found that the closing prices of the logarithms of the banking shares in Thailand had the most stable daily variability. The trend in first period (January 1994 to December 1995) was for the prices to increase on the whole, reversing from January 1996 to March 1998, and recovering to some extent in the final period from April 1998 to December 1999. But the prices at the end were still substantially below the levels in January 1994.

The second part of the preliminary analysis was concerned with the distribution and trends of share price returns. We found that the skewness coefficients were positive, but the histograms looked symmetric, and it was difficult to distinguish them from a normal distribution purely by looking at these graphs. But by looking at the distributions more carefully we saw that the returns have heavier than normal tails.

Next, we looked at the distributions of the returns over successive years. One-way analysis of variance was used to compare these distributions, and found no evidence of change between the years. However, the spreads of these distributions were not

constant, while the standard deviations in the last three years were more than three times higher than those in the first three years.

In the final section of the preliminary analysis we looked at the correlations between the share price returns from the different financial institutions.

Using principal components analysis, the largest component (PC1, based on summing the share returns from the seven banks) accounts for just over 67% of the variation. And the smallest component (PC7, based on the difference between the BBL and TFB share returns) accounts for just 2.8 % of the variance. The PC1 component thus corresponds to a portfolio with the highest investment risk, while a portfolio based on PC7 has the lowest risk.

In Chapter 4 we analysed the time series volatility based on the PC1 and PC7 components. The first section we compared the values of portfolios based on PC1 and PC7, and it found that the graphs of PC1 and PC7 showed different trends during the first three years, but had a stable relation over the last three years. The returns on PC1 and PC7 had constant volatility from 1994 to mid 1997, but fluctuated quite a lot during the period from mid 1997 to 1999.

In the second section we used GARCH (1,1) models to estimate the daily volatility series for each portfolio. We then saw that these volatility series needed to be transformed to stabilise their variances, and the best transformation was the natural logarithm. This enabled us to fit a time series model to the volatility series, and thus answer the second research objective.

The result of the time series analysis was described in the following terms.

It is well known that share price returns are essentially unpredictable. If they were predictable, traders using predictive models would be able to make profits at the expense of other traders, in violation of the arbitrage principle.

However, this principle does not necessarily apply to the volatility of a share price return. We have shown that for an equally weighted index of seven Thai banking shares with return u_t on trading day t , the volatility σ_t can be estimated as an exponentially weighted moving-average of the form

$$\sigma_{1,t}^2 = 0.059u_{1,t-1}^2 + 0.941\sigma_{1,t-1}^2$$

for PC1 and

$$\sigma_{7,t}^2 = 0.065u_{7,t-1}^2 + 0.935\sigma_{7,t-1}^2$$

for PC7.

These estimated volatilities are fitted by predictive time series models of the form

$$\ln(\sigma_{1,t}) = -3.683 + 0.725 \cos(2\pi t / 1467 + 1.320) + y_{1,t}, \text{ and}$$

$$\ln(\sigma_{7,t}) = -4.723 + 0.522 \cos(2\pi t / 1467 + 1.230) + y_{7,t},$$

where the $y_{j,t}$ ($j=1,2$) follow the ARMA (1,1) models

$$y_{1,t} = 0.975 y_{1,t-1} + z_{1,t} + 0.07 z_{1,t-1}$$

$$y_{7,t} = 0.979 y_{7,t-1} + z_{7,t} + 0.07 z_{7,t-1}$$

and $z_{1,t}$ is standardised white noise with standard deviation 0.048, and 0.055 for $z_{7,t}$

Note that

$$\sigma_{j,t} = s_j(t) \exp(y_{j,t}),$$

where $s_1(t)$ and $s_7(t)$ are specified sinusoidal waves each with period 6 years, and the $y_{j,t}$ have standard deviations as given in chapter 2, that is, $0.048\sqrt{\{1+0.07^2\}/\{1-0.975^2\}} = 0.217$ and $0.055\sqrt{\{1+0.07^2\}/\{1-0.979^2\}} = 0.271$. Given that these standard deviations are relatively small, it is reasonable to approximate $\exp(y_{j,t})$ by the first two terms in its Taylor series expansion, so that

$$\sigma_{1,t} = s(t) (1+y_{1,t}).$$

$$\sigma_{7,t} = s(t) (1+y_{7,t}).$$

The moving average component in each noise series is relatively small. If we ignore this term, each noise process is just a simple Markov process.

We arrived at these models by first fitting a GARCH (1,1) model to the series of returns, and then fitting a time series model to the resulting volatility series, after log-transforming it. An alternative (and statistically preferable) approach involves

simultaneous estimation of the parameters. In this method, the data are modelled as the system

$$u_t = s(t)(1 + y_t)w_t$$

$$y_t = a_1 y_{t-1} + z_t$$

where $s(t)$ is a specified parametric function and $\{w_t, z_t\}$ is a bivariate (possibly mutually correlated) white noise series.

Taylor (1986, 1994) proposed this model in the special case where $s(t)$ is constant, and in this case Stein & Stein (1993) obtained distributions when $\{w_t, z_t\}$ are mutually independent. Jirattivivat (1999) derived a joint moment generating function for the asymptotic process and used it to model currency exchange rates.

Note that two sets of parameters arise in the bivariate process. The parameters in the first set are those contained in the deterministic component of the volatility, $s(t)$. In the simplest case when $s(t)$ is constant, there is a single parameter σ , say. There are three parameters in the second set. These comprise δ , the level of stochastic volatility, a_1 , a measure of its elasticity or rate of mean-reversion, and ρ , say, the correlation coefficient between w_t and z_t .

Further analysis of this bivariate process, including the estimation of the underlying parameters, is of interest, but is beyond the scope of this research.

Discussion

In this study we focus on banking shares because a bank is a very important financial institution for the people and for the country's development. Banking is an indicator that can describe the health of the economy in Thailand. The results of this study could be used as a guide for an investor before making decisions to invest his money in the stock market.

However, while an investment in Thailand cannot be made by borrowing shares from brokers, the established model can be satisfactorily used to describe the stochastic volatility of stock prices. Other factors, for instance national policy, and national and world economic status, should also be taken into account.