Sun Yat-Sen Management Review
P41-71

Examining Multiple Volatility and Co-movement States as Well as Beta Coefficients of International Stock Markets

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Abstract

This study establishes and tests the following two hypotheses. First, both the world and individual market equity return shocks are subject to their own processes of volatility state switches. Second, in each individual equity market, the correlation with the world market and the β coefficient are different in various combinations of the world and the individual market volatility regimes. Our empirical results are consistent with the following notions. First, the greatest correlation was associated with the individual and world markets in high volatility regimes simultaneously. Second, the maximum β appears in the situation that the individual and world markets were in the high and low variances respectively. Third, the differential β settings from various combinations of volatility states may

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[1] Corresponding author, the authors gratefully acknowledge the financial support of National Science Council, Taiwan (NSC-91-2416-H-260-012) and the comments and suggestions from the two anonymous referees.

be one of drivers to the documented abnormal returns.

Keywords: Multi-β International Capital Asset Pricing Model, Equity Return Volatility, Correlation in International Equity Returns, Abnormal Returns, Markov-switching model

I. INTRODUCTION

This paper establishes and examines the following two hypotheses. First, both world and individual stock markets have their own volatility regime switch process. Second, there exist significant differences in the cross-market correlations and the β coefficients among various combinations of market volatility regimes.

Examining the realized stock market returns, one can easily observe that the returns are much more volatile during certain periods such as the occurrences of financial crises or particular political events. Unfortunately, the simplified settings with constant parameters could not picture the characters of various volatility regimes. Many prior studies including Li and Lin (2003), Ramchand and Susmel (1998a, b) adopted Hamilton and Susmel (1994)'s Markov-switching ARCH (hereafter SWARCH) to analyze the stock return volatilities and demonstrated that the behavior of separate high/low volatilities really existed in the international stock markets. Intuitively, one can refer the transition from the low to high volatility to the occurrence of economic or financial crisis especially towards the 1990s.[2]

Many contemporary studies assume that, as the economies become more closely integrated and cross-border financial flows accelerate, national capital markets become more highly correlated. Moreover, the IMF Economic Outlook 2000 and the Economist 2001 indicated that because of rapid growth in global fund transfers, cross-border activities of financial flow, international divisions in the electronic industry, and deregulations, the global market epidemic effect has been significantly increasing, especially during excitable periods. Such phenomenon may reduce the benefit of the international diversification, namely, the reduction or

[2] This was highlighted by the international financial crises, which occurred during the 1990s: the Mexico crisis in 1994, the Asian crisis in 1997, and the Russia crisis in 1998 as well as the U.S. market down turn in 2000.

even elimination of idiosyncratic risks. Nevertheless, because of the character of the relationship between market volatility and correlation, if one uses the full sample data to calculate one constant market correlation, then he will underestimate the true market correlation and overestimate the benefit of the international diversification during the volatile period. Briefly speaking, the consideration of the behavior of non-constant variance of the stock markets is one of the key points for the calculation of the market correlations and the β coefficients.

Many prior studies focus on the co-movements among the international stock markets. Kim and Roger (1994) analyzed the influence of foreign direct investment deregulation on South Korea stock market. They concluded that the deregulation had a positive effect on cross-market correlation between South Korea and USA stock markets. Koutmos and Booth (1995) adopted EGARCH (Exponential GARCH) to analyze the differences in stock market correlations among US, UK and Japan from bullish and bearish states. Bertero and Kelleher (1988), Kaplanis (1988), Karolyi and Stulz (1995), King and Wadhwani (1990), King, Sentana and Wadhwani (1994), Longin and Solnik (1995) as well as Ramchand and Susmel (1998a) analyze the differences in correlations for various periods. They concluded that the unstable (stable) periods are correlated with high (low) cross-market correlations.

There are also prior studies documenting non-single β settings with the stock returns. Bhardwaj and Brooks (1993) used bull/bear market perspective to analyze dual β setting. Pettengill et al. (1995) and Fletcher (2000) discussed dual β feature derived from the difference in market rise and market fall periods. Ramchand and Susmel (1998b) employed Hamilton and Susmel (1994)'s SWARCH model to analyze dual β property from the difference in high and low volatility states of domestic country market. They concluded that the high (low) volatility state of individual markets is associated with the bigger (smaller) β. Mark (1988) and Ng (1991) adopted the time series approach to test the time-varying β model.

In contrast with Ramchand and Susmel (1998a, b) and prior studies, one of the features of our paper is to incorporate the SWARCH model with the idea of international capital asset pricing model (ICAPM). Markowitz (1952) employed the mean-variance model and capital market line (CML) to build an internationally efficient portfolio and demonstrated the advantages of international investing[3]. The

[3] Sharp (1964), Lintner (1965a, 1965b) and Mossin (1966) followed Markowitz (1952) to establish the capital asset pricing model (CAPM). In the market equilibrium, the

ICAPM model adopted in our paper introduces the perspective of international portfolios, and takes each country's stock index return and world stock index as individual asset return and market return, respectively. The ICAPM model could provide investor with the theoretical price of each country's asset and one could also use the β coefficients derived form the ICAPM model to evaluate the market risk of each country's assets[4].

By adopting the concept of ICAPM, we divide the individual market return into two independent segments - the co-movement term with the global market and the individual residual term. In this paper, we assume that the two segments have their own dynamic process during the periods of high market volatility. Moreover, this paper aims to examine whether the greater market correlations or the greater market risk coefficients are mainly caused by the systematic factors from the world market or by the nonsystematic factors from the individual market or by the joint effects from the two factors. Moreover, many prior studies concluded that world markets seem to be the most in step with each other when the volatility is the greatest. The four possible volatility combinations of individual and world markets including (1) high volatilities for both series, (2) high and low volatilities, respectively (3) low and high volatilities, respectively and (4) low volatilities for both series. We aim at exploring the cross-market correlations and β coefficients are consistent corresponding to the above four possible combinations. We also aim at exploring the combination under which exist the greatest market correlations and the greatest β coefficients. The empirical results of this paper could also possibly benefit the abnormal stock return researches. Because of the model misspecification from the inappropriate non-single β settings, one might wrongly conclude some periods or events with positively or negatively abnormal returns. Lewellen and Shanken (2002) demonstrated that the model parameter uncertainty is one of the reasons for abnormal returns. In order to capture the behavior of the international stock market volatilities, we employ Hamilton and Susmel (1994)'s SWARCH model to objectively identify the high/low volatility periods of the international stock markets.

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expected returns of individual securities are the linear function of the market portfolio returns and β.

4 The ICAPM model only consider the influence derived from systematic risk on the each country's asset returns and assumes investor could achieve an effectively diversified portfolio to completely eliminate the individual asset's specific risk. Therefore, there only exist the market risk that could not be eliminated by diversification, and only the market risk could obtain risk premium.

Section 2 presents the model specifications in this paper including Hamilton and Susmel (1994)'s SWARCH and the ICAPM with single β and dual β and multiple β. Section 3 presents the empirical results and the explanations for our empirical findings. Section 4 presents the conclusions of this paper.

II. MODEL SPECIFICATIONS

In order to capture the correlations among national stock markets with high volatilities caused especially by the effect of capital's globalization and the accelerated cross-border capital and technique movement in recent years, this paper adopts Hamilton and Susmel (1994)'s SWARCH to partition the volatility states (including high and low volatility states) of individual markets and the world market at each time point and to examine the difference in market correlations among various corresponding volatility state combinations. Moreover, we adopt the indicator function approach to capture the interactive effects from market volatilities and market correlations and establish the nonlinear multi-β ICAPM. The multi-β ICAPM specifications established in this paper are presented as follows:

(1) Single-β ICAPM

According to ICAPM, the *i-th* country's stock index returns could be presented as follows:

$$E(R_i) = R_f + \beta_i \times \left(R_m - R_f\right) \tag{1}$$

where R_i is the *i-th* country's stock index returns, $E(R_i)$ is R_i 's mean return, R_f is risk-free asset return and R_m is the world stock market return[5]. ICAPM explains the relationship between individual country's expected returns and the world market returns when investors choose an effective diversification portfolio. Moreover, the β in ICPM could be used to compare individual market returns with world market returns. Specifically, if β of the *i-th* market is greater (smaller) than one, the risks and volatilities of this *i-th* market are greater (smaller) than the world market[6]. In the above traditional single-β model, the β coefficient is the regression

[5] Market return denotes the return of a representative benchmark portfolio.
[6] For proposing the active investment strategies, investors should invest the securities with the high (low) β value during the bull (bear) market periods.

coefficient in the following linear regression setting:

$$R_{i,t}^{*} = a_i + \beta_i \times R_{m,t}^{*} + e_{i,t}$$

$$\beta_i = \frac{Cov(R_i^{*}, R_m^{*})}{Var(R_m^{*})} = \frac{\sigma_{i,m}}{\sigma_m^2} = \rho_{i,m} \times \frac{\sigma_i}{\sigma_m} \tag{2}$$

where R_i^* and R_m^* denote the excess returns of the *i-th* country's stock index and the world stock index, respectively. $COV(R_i^*, R_m^*)$ and $Var(R_m^*)$ are the covariance of R_i^* and R_m^* and the variance of R_m^*, respectively. σ_i and σ_m are the standard deviations of R_i^* and R_m^*, respectively. $\rho_{i,m}$ is the correlation coefficient between R_i^* and R_m^*.

Some economists find that the volatilities of stock returns are substantially greater (or less) than the average during some periods. Thus, one cannot take the overall sample period variance as a constant. Engle (1982) and Bollerslev (1986) established the ARCH (auto-regressive conditional heteroskedasticity) models and the GARCH (Generalized ARCH) models to capture the non-constant variances of macroeconomic and financial time series data[7]. In this paper, we use the GARCH model to capture the non-constant variances of stock returns to establish the following empirical models:

$$R_{i,t}^{*} = \alpha_i + \beta_i \cdot R_{m,t}^{*} + e_{i,t}$$

$$e_{i,t} = \sqrt{h_{i,t}} \cdot u_{i,t}, \quad u_{i,t} \sim N(0,1)$$

$$h_{i,t} = \gamma_0 + \gamma_1 e_{i,t-1}^2 + \lambda h_{i,t-1} \tag{3}$$

(2) Non-single-β ICAPM

Considering the relationship between the market volatilities and the market correlations, this paper brings the concepts of the difference in high and low market volatilities into the ICAPM.

Step 1:

[7] Engle's (1982) ARCH and Bollerslev's (1986) GARCH are the most commonly used methods to characterize the stock return volatilities.

We adopt Hamilton and Susmel (1994)'s SWARCH model to analyze individual market returns and world market returns to identify the volatility states of the market at each time point. Denoting R_t^* as the excess returns of stock index (including $R_{i,t}^*$ and $R_{m,t}^*$), Hamilton and Susmel (1994)'s SWARCH models are presented as follows:

$$R_t^* = \phi_0 + \phi_1 R_{t-1}^* + \cdots + \phi_p R_{t-p}^* + e_t$$

$$e_t = \sqrt{g_{s_t}}\, u_t$$

$$u_t = \sqrt{h_t}\, v_t$$

$$h_t = a_0 + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + \ldots + a_q u_{t-q}^2 , \tag{4}$$

where v_t is a Gaussin distribution with unit standard error, s_t is an unobservable state variable with possible values: 1, 2,…, k. For the two volatility states setting, s_t=1 (s_t=2) represents the stock market being at low (high) volatility states. The transition probabilities for state variables are presented as follows:

$$\begin{aligned} &p(s_t = 1 \mid s_{t-1} = 1) = p_{11}, \quad p(s_t = 2 \mid s_{t-1} = 1) = p_{12} \\ &p(s_t = 2 \mid s_{t-1} = 2) = p_{22}, \quad p(s_t = 1 \mid s_{t-1} = 2) = p_{21} \end{aligned} \tag{5}$$

where $p_{11}+p_{12}=p_{21}+p_{22}=1$[8].

As in Hamilton and Susmel (1994)'s SWARCH model, u_t is a standard ARCH(q) setting. When s_t=1 (s_t=2), e_t equals u_t multiplying by $\sqrt{g_1}$ ($\sqrt{g_2}$), and so on. Without losing the generalization principle, we set g_1 =1, and g_i>1 for $i=2,3\ldots k$. This means that the volatilities of state i is g_i times of state 1. Moreover, the ARCH(q) models are the SWARCH(q) models with the restrictions, $g_1=g_2=\ldots=g_k=1$. It is worth noting that, although the regime variable s_t in the

[8] For satisfying $1>p_{ij}>0$, i (j)=1 or 2, we use the following probability settings :

$$p_{11} = \theta_{11}^2/(1+\theta_{11}^2), \qquad p_{12} = 1 - p_{11} = 1/(1+\theta_{11}^2)$$
$$p_{22} = \theta_{22}^2/(1+\theta_{22}^2), \qquad p_{21} = 1 - p_{22} = 1/(1+\theta_{22}^2)$$

SWARCH model is unobservable, one can still use the data to estimate the specific regime probabilities at any time point[9].

Theoretically, one could use the multivariate SWARCH to simultaneously capture the volatility states of the various stock markets. Nevertheless, it is worth noting that SWARCH process becomes complicated when one extends the analysis to estimating the higher dimensional system. Specifically, this paper sets two outcomes of the discrete state variable s_t to represent high and low volatility regimes. Thus one needs to consider $2^8 = 256$ possible states for deliberating eight stock returns together at each date. As to the perspective of ICAPM from the financial theories, one can divide the investment risk into *distinct* systematic and nonsystematic risk. Specifically, the systematic risk is the component in an individual market return variance that is correlated with the international portfolio. In contrast, the nonsystematic risk is the component in an individual market return variance that is unique to that individual country's assets. The word, *distinct,* means each of them has its own random process. Following the above line of thought, in this paper, we use single-variate SWARCH model to *separately* identify the volatility states of the stock returns of the individual stock market and the global stock market.

Step 2:

We use the estimated smoothing probabilities of the specific regime from the step 1 and the indicator function approach to establish the following multi-β ICPM models.

Model 1: Dual -β ICAPM by Various Individual Stock Market Volatility State

$$R_{i,t}^{*} = \alpha_i + \beta_{i,1} R_{m,t}^{*} \cdot (1 - ID_1) + \beta_{i,2} \cdot R_{m,t}^{*} \times ID_1 + e_{i,t}\,,$$

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9 When the information set for estimation includes signals dated up to time t, the regime probability is $p(s_t|y_t, y_{t-1},\ldots)$ or *filtering probability.* On the other hand, one could also use the overall sample period information set to estimate the state at time t: $p(s_t|y_T, y_{T-1},\ldots)$, or *smoothing probability*. In contrast, a *predicting probability* denotes the regime probability for an ex ante estimation, with the information set including signals dated up to the period t-1: $p(s_t|y_{t-1}, y_{t-2},\ldots)$.

$$e_{i,t} = \sqrt{h_{i,t}} \cdot u_{i,t} \,,$$

$$h_{i,t} = \gamma_0 + \gamma_1 e_{i,t-1}^2 + \lambda h_{i,t-1} \tag{6}$$

In Equation (7), ID_1 is an indicator function with the following setting:

$$ID_1 = ID_1\left\{p(s_{i,t} = 2 \mid R^*{}_{i,T}, R^*{}_{i,T-1}, R^*{}_{i,T-2}, \cdots) > 0.5\right\} \tag{7}$$

where $s_{i,t}$ is the state variable of the *i-th* stock market. The features of model 1 are that by using SWARCH model to estimate the smoothing probabilities of the specific volatility regime of individual stock market and using 0.5 to be a threshold value, we conclude the individual stock market is at the high (low) volatility state when the estimated probabilities of state 2 (state 1) are greater than 0.5. Specifically, by using $ID1$=1 (=0) for probabilities of state 2 being greater (smaller) than 0.5, the β coefficient of the *i-th* country's stock market is $\beta_{i,2}$ ($\beta_{i,1}$).

Model 2: Dual-β ICAPM by Various World Stock Market Volatility State

To take into account the difference in the volatility regimes of the world stock market, we replace the ID_1 in Equation (7) with the ID_2:

$$ID_2 = ID_2\left\{p(s_{m,t} = 2 \mid R^*{}_{m,T}, R^*{}_{m,T-1}, R^*{}_{m,T-2}, \cdots) > 0.5\right\} \tag{8}$$

where $s_{m,t}$ is the state variable for world market volatility. When the probabilities for the high (low) volatility state of the world market are greater than 0.5, ID_2=1 (=0) and the β coefficient is $\beta_{i,2}$ ($\beta_{i,1}$).

Model 3: Multi-β ICAPM by the Individual and World Stock Market Volatility States

To simultaneously capture the influence of the volatility state of both individual and world stock markets on the β coefficient in ICAPM, we incorporate ID_1 in Model 1 and ID_2 in Model 2 to establish the following setting:

$$R_{i,t}^{*} = \alpha_i + \beta_{i,1} R_{m,t}^{*} \cdot (1 - ID_1) \cdot (1 - ID_2) + \beta_{i,2} R_{m,t}^{*} \cdot (1 - ID_1) \cdot ID_2 \\ + \beta_{i,3} R_{m,t}^{*} \cdot ID_1 \cdot (1 - ID_2) + \beta_{i,4} R_{m,t}^{*} \cdot ID_1 \cdot ID_2 + e_{i,t},$$

$$e_{i,t} = \sqrt{h_{i,t}} \cdot u_{i,t},$$

$$h_{i,t} = \gamma_0 + \gamma_1 e_{i,t-1}^2 + \lambda h_{i,t-1} \tag{9}$$

The value of the β coefficient in Model 3 is $\beta_{i,1}$ for both individual and world market at the low volatility state (namely, ID_1 = 0 and ID_2 = 0), or $\beta_{i,2}$ for individual market at the low volatility state and for world market at the high volatility state (namely, ID_1 = 0 and ID_2 = 1), or β_{i3} for individual market at the high volatility state and world market at the low volatility (namely, ID_1 = 1 and ID_2 = 0), or$\beta_{i,4}$ for both individual and world market at the high volatility state (namely, ID_1 = 1 and ID_2 = 1).

In sum, this study discusses the single-β ICAPM and three types of multi-β ICAPM. Moreover, in the multi-β settings, we first use the simple SWARCH model to picture the specific volatility states of stock returns at each time point and then establish the multi-β ICAPM. Nevertheless, the main differences between SWARCH model and the ICAPM are that the former does not discuss the influences of the world market on the individual market. In the following section of empirical results, we will compare the forecast performances among the four types of ICAPM and the simple SWARCH model.

III. EMPIRICAL RESULTS

The stock market indices adopted in this paper include four major developed market indices including US S&P 500, Japan Nikkei, UK FTSE 100 and Germany DAX 30 and indices of four Asian emerging countries including Taiwan, South Korea, Malaysia and Thailand. The data are obtained weekly (Tuesday to Tuesday) from January 1980 to December 2000, totaling 1097 observations. We use weekly returns in US dollar for the eight stock indices. We employ the three-month US Treasury bill rate as the risk-free return and derive the excess returns by subtracting the bill rate from the raw returns. The data source is Data Stream Database.

3.1 How to establish an international portfolio?

There exist several alternative measures to proxy for the world factors. First, one can use the world index conducted by Morgan Stanley Capital International (MSCI). Unfortunately, the empirical results by using MSCI world index are not good (not reported)[10]. Moreover, MSCI world index is weighed by market capitalization, with significantly greater (less) weights for the developed (emerging) markets. Nevertheless, we believe an efficient international diversification should be a portfolio with large numbers of assets and also with balanced weight among various assets. Following the above line of thought, we average both developed and emerging market indices with equal weights to arrive at an equally weighted world (EWW) stock index as a replacement for the international portfolio.

In contrast with Ramchand and Susmel (1998b), in this paper the proposed international portfolio contains both developed and emerging market securities. To compare the differences between the two types of stock markets, we also average the four developed market indices and the four emerging market indices with equal weight to create an equally weighted developed market index (EWM) and an equally weighted emerging (EWE) market index, respectively. Table 1 presents the main descriptive statistics and correlation matrix for various index returns. It shows that the mean return of EWW (0.201) equals the average of EWM and EWE ((0.224+0.178)/2=0.201), but the standard error of EWW (2.033) is less than the average of EWM and EWE ((1.792+2.846)/2=2.319). The result is consistent with the notion that the internationally diversified portfolio can further reduce the variability of returns. Namely, risk that is systematic in the context of the mature economy may be unsystematic in the context of the global economy. This is one of the reasons why we incorporate both developed and emerging stock indices to generate EWW as the proxy of the world stock index. In contrast, Ramchand and Susmel (1998b) only weighed the developed markets.

3.2 The cross-market correlation analysis for various market volatility states

In this paper, we use Hamilton and Susmel (1994)'s SWARCH model to

[10] Although not reported in this paper, we use MSCI world index to re-estimate the model. But the empirical results with less significant parameter estimates and lower R^2 values.

analyze the eight index returns and EWW returns and partition the specific volatility states of the stock markets at each time point. In the estimation process, we set the order of auto-regression setting of the stock returns to be unity, namely, p=1, and the number of orders in ARCH to be two[11], namely, q=2, as well as the number of states to be two, namely k=2. (Please refer to Equation (4) in the above section for detailed discussions on the specifications of the SWARCH model). We use OPTIMUM, a package program from GAUSS, and the built-in BFGS[12] algebra to estimate the negative minimum likelihood function[13].

Quite impressively, the g_2 estimates are significantly greater than one for all cases (not reported). Take S&P500 index returns for example, the g_2 estimate is 3.109 with a standard deviation of 0.349. These results show that the volatilities of the US stock market for state 2 is 3.19 times the size of state 1. In the following sections, we take state 2 as the high volatility state and state 1 as the low volatility state.

Figure 1 presents the smoothing probabilities of high volatility state for the eight countries' stock markets and the world stock market. We conclude the market to be at a high–volatility regime if the associated smoothing probability is greater than 0.5; or otherwise, a low volatility regime. Specifically, if $p(s_t=2|R^*_{m,T}, R^*_{m,T-1},\ldots)>0.5$, then we conclude the market to be at a high volatility state at the time point t.

Table 2 presents the correlation coefficients between individual markets and the world market for the specific volatility states. The empirical results are consistent with the following notions. First, when considering only the differences in the volatility states of individual markets, the high volatility state of an individual market is associated with the greater correlation coefficient for all cases. Take S&P 500 index returns for example. The correlation coefficient between S&P500 and EWW is 0.581 for US S&P500 at the high volatility state in contrast to 0.211 for the low volatility state. Second, the high (low) volatility state of the world market is associated with the greater (smaller) correlation coefficients.

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11 Among all specifications, the third-order ARCH parameter estimate appears to be insignificantly different from zero. Therefore, for the specifications for ARCH, we only take into account the second order setting.

12 Boyden, Fletcher, Goldfarb, and Shanno (BFGS) algebra is effective for deriving the maximum value of the non-linear likelihood functions. See Luenberger (1984).

13 We randomly generate 50 sets of initial values and derive the ML function value for each of the 50 sets of initial values, respectively. The mapped converged measure of the greatest ML function value then serves to estimate the parameter.

Consider again S&P500, the correlation coefficient between US market and world market is 0.488 (0.449) when the world market is at the high (low) volatility state. Third, simultaneously consider the volatility states of the individual market and the world market, the value of the correlation coefficient for both individual and world markets at the high volatility states is the greatest among the four possible volatility states combinations[14]. Take S&P500 for example, the value of the correlation coefficient for both the US and the world markets at the high volatility state is 0.619 in contrast to 0.129 for the US market at a low volatility state and the world market at a high volatility state, 0.538 for the US market at the high volatility state and the world market at the low volatility state, and 0.301 for both the US and world markets at the low volatility state.

3.3 Examining the Multi-β Settings for Various Market Volatility States

Table 3 presents the empirical results of the parameter estimators and several statistic criteria for the single-β ICAPM. The β coefficients are significantly positive for all cases. Table 4 presents the results of the dual-β ICAPM by various individual stock market volatility states (or Model 1). Via LR statistics, AIC and Schwarz value serve as the model selection criteria, the dual-β settings in Model 1 significantly outperform the single-β ICAPM for all markets. Moreover, the β with individual market at the high volatility state (namely, $\beta_{i,2}$) is significantly greater than that with individual market at the low volatility state (namely, $\beta_{i,1}$). The significance could also be demonstrated by the fact that the 90% confidence levels of the two measures of β do not overlapping each other.

Table 5 presents the empirical results of Model 2: the dual-β ICAPM by various world stock market volatility states. These results show that the dual-β settings in Model 2 significantly outperform the single-β settings, except for Germany and South Korea. In contrast with Model 1, the magnitudes of the two measures of β are not consistent among various markets. Specifically in the US, Japan, UK and Malaysia markets, the β with the world market at the high volatility state (namely, $\beta_{i,2}$) is smaller than the β with the world market at the low volatility state (namely, $\beta_{i,1}$). In contrast with the Taiwan and South Korea stock markets, $\beta_{i,2}$ is greater than $\beta_{i,1}$.

Table 6 presents the results of Model 3: Multi-β ICAPM by various individual

[14] In contrast, in the three alternative combinations of volatility states, there are no consistent results for all markets.

and world market volatility states. Our empirical results indicated the multi-β settings outperform significantly the dual-β settings in Model 1 and Model 2 as well as the single-β setting. Furthermore, the 90% confidence level of the four measures of β does not overlap each other. The result demonstrates the significance of the setting with four measures of β established in this paper. Moreover, the maximum estimate of β appears when individual and world markets are at high and low volatility states respectively in all cases.

3.4 Examining the Abnormal Stock Returns for Various Market Volatility States

Our empirical results demonstrate that there exist very important relationships between the volatilities and correlations and we can conduct an ICPM setting with four types of β from the four groups of combinations of the individual country and world market volatility states. To analyze the influences of differential volatilities and the multi-β settings on the abnormal returns in the event study approaches, we use four types of ICPM settings and the simple SWARCH model to calculate the each country's normal stock returns, and then use the realized returns to minus the normal returns and then compute the abnormal returns.

Table 7 presents the averages of the absolute abnormal returns for the US, Japan and Taiwan stock markets. Our empirical results indicate that the maximum abnormal returns are connected with the individual country and world markets at the high and low volatility states, respectively, in contrast with the second maximum values being associated with both the individual country and world markets at the high volatility states. The third maximum values are associated with the individual country and world markets at the low and high volatility states, respectively; while the minimum values are associated with both the individual country and world markets at the low volatility states. These show that the difference in volatility states is one of the reasons for the abnormal returns. Comparing the abnormal returns of the competing models in this paper shows that the multi-β settings are associated with the minimum abnormal returns. This means that the improper β setting is one of the reasons for the abnormal returns[15].

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[15] Even though the absolute abnormal returns of multi-β setting established in this paper are less than the single-β setting, but the superiorities of the multi-β setting are not significant. Take US market for example, the difference between Model 1 and Model 4 at the situation that both individual country and world markets are at the low volatility states is only 0.007 and is not significant (the p-value=0.602). Nevertheless, the

3.5 Economic and Financial Explanations for Our Empirical Results

The foremost empirical results of this paper are the greatest correlations associated with both individual and world markets at the excitable states. Here we provide some appealing explanations for our findings. First, the volatile world market regimes constantly coincides the global financial or economic crisis. Moreover, the volatile individual market generally follows the recession economy (Please refer to Chen, Roll and Ross (1986), Schwert (1990), Chen (1991) and Hamilton and Lin (1996)). During both of the global crisis periods and the domestic recession periods, the world economic and financial the domestic (the domestic) the domestic would be the more (less) influential driver. Because all of the indices share similar elements from the world environments, the cross-market correlation would rise dramatically.

Moreover, the greatest β coefficient is not associated with both the individual and world markets at the high volatility states. By examining Equation (2) in the section 2, there exist three key factors for calculating the β coefficient including the individual market volatilities, the world market volatilities and the correlation between the individual and world markets. Furthermore, the β coefficient is positively related to the individual market variances and the correlation between the individual and world markets, but negatively related to the world market variances. Even though the greatest cross-market correlations exist when both individual and world market returns become more volatile and the correlations are positively related to the β value. Nevertheless, the greater world market volatilities would cause a negative consequence to the β value. These are the reasons why the maximum β is associated with the case, which the individual and the world market are at the high and low variance states, respectively.

The eventual empirical findings reveal that the multi-β ICAPM are associated with the minimum abnormal return. Analyzing the characters of the four types of ICAPM settings convey that the single-β settings did not deliberate the interactive functions from the variances and correlations. The absences of examination of volatility states in the single-β settings are the main reasons why the single-β setting processes the greater abnormal returns than the multi-β settings. In the other words, the superiorities of multi-β ICAPM model over the single-β ICAPM are the presences of discussion on the relationship between market volatilities and market

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superiorities of multi-β settings are consistent for all cases of Table 7(US, Japan and Taiwan cases).

correlations. The superiorities of multi-β ICAPM model over SWARCH model are the appearances of investigation on the effect of world market on the individual country market.

Finally, there exist two phenomena worth further studies with our results. First, the low volatility periods of both Thailand and the world markets did not overlap during the whole sample period. We believe that this is one of the potential reasons why the multi-β settings could not outperform the alternative models in the Thailand market. Second, event though we discuss both the developed and emerging markets, there exist insignificant differences between the two types of markets. One of the explanations is that we average the two types of market indices with *equal* weight to create the world index. The *equal* weight for the developed and the emerging market indexes in the world index may help explain our documented trivial differences between the emerging and developed markets.

IV. CONCLUSIONS

Possibly due to political and economic shocks from domestic or international economic and financial environments, the stock returns are much volatile during some periods than the others. The traditional single-β ICAPM does not consider the relationships between the market volatilities and the market correlations, and then assumes constant risk coefficient of individual country's stock asset. In this paper, we use the SWARCH models to identify the specific market volatility states at each time point, and then analyze the cross-market correlations, the multi-β ICAPM settings and the abnormal returns from the various volatility combinations from the individual and world stock markets. Our results are consistent with the following notions. First, the greatest returns correlations exist when both individual and world markets are at the high volatility states. Second, the maximum (minimum) β coincides with the individual and world markets at the high and low (low and high) volatility states, respectively. Third, the multi-β (single-β) settings are with the least (greatest) abnormal returns.

Table 1 The Summary of Main Descriptive Statistics and Correlation Matrix

(A) The Descriptive Statistics for Various Stock Markets

	S&P500	Nikkei	FTSE100	DAX30	Taiwan	South Korea	Malaysia	Thailand	EWM	EWE	EWW
Mean	0.254	0.103	0.253	0.267	0.300	0.211	0.190	0.132	0.224	0.178	0.201
S.E.	2.226	2.615	2.271	2.652	4.506	3.984	4.045	4.009	1.792	2.846	2.033
Kurtosis	15.014	3.891	14.561	3.604	2.952	2.958	8.480	6.815	15.656	2.165	4.618
Skewness	-1.292	-0.161	-1.253	-0.643	-0.158	0.235	0.200	0.616	-1.756	-0.218	-0.721
Maximum	10.215	14.476	11.194	12.419	22.152	19.938	33.064	32.101	6.368	14.278	9.892
Minimum	-24.701	-17.009	-23.343	-16.290	-21.579	-17.458	-27.910	-20.288	-19.767	-13.337	-13.997

(B) The Correlation Matrix

	S&P500	Nikkei	FTSE100	DAX30	Taiwan	South Korea	Malaysia	Thailand	EWM	EWE	EWW
S&P500	1.000	0.358	0.467	0.446	0.123	0.111	0.320	0.203	0.753	0.227	0.488
Nikkei		1.000	0.280	0.305	0.198	0.231	0.280	0.192	0.604	0.309	0.475
FTSE 100			1.000	0.457	0.130	0.168	0.287	0.283	0.780	0.259	0.523
DAX 30				1.000	0.258	0.147	0.303	0.285	0.768	0.344	0.589
Taiwan					1.000	0.156	0.214	0.223	0.237	0.807	0.724
South Korea						1.000	0.197	0.275	0.216	0.514	0.449
Malaysia							1.000	0.396	0.395	0.549	0.548
Thailand								1.000	0.327	0.546	0.533
EWM									1.000	0.380	0.709
EWE										1.000	0.909
EWW											1.000

Notes:

1. The data are provided from Data Stream database. The data are obtained weekly (Tuesday to Tuesday) from January 1980 to December 200, which include 1097 observations.
2. We average the four mature stock indices to conduct an equally weighted mature (EWM) stock index and the four emerging stock indices to conduct an equally weighted emerging (EWE) stock index as well as the eight stock indices with equal weight to conduct an equally weighted world (EWW) index for the proxy of world stock index.
3. We use weekly returns (Tuesday to Tuesday) in US dollar for all stock indices.

Table 2 Correlation Coefficients between the Individual and World Stock Markets for Various Volatility Regimes

(A) Volatility State of Individual Market

	Indl-LV	Indl=HV
US S&P500	0.211	0.581*
Japan Nikkei	0.355	0.507*
UK FTSE 100	0.415	0.734*
Germany DAX 30	0.395	0.688*
Taiwan	0.595	0.844*
South Korea	0.339	0.629*
Malaysia	0.381	0.692*
Thailand	0.082	0.566*

(B) Volatility State of World Market

	World=LV	World=HV
US S&P500	0.449	0.488*
Japan Nikkei	0.424	0.475*
UK FTSE 100	0.422	0.523*
Germany DAX 30	0.462	0.589*
Taiwan	0.555	0.724*
South Korea	0.392	0.449*
Malaysia	0.498	0.548*
Thailand	0.342	0.533*

(C) Volatility States of Individual and World Markets

	Indl=LV and World=LV	Indl=LV and world=HV	Indl=HV and World=LV	Indl=HV and World=HV
US S&P500	0.301	0.129	0.538	0.619*
Japan Nikkei	0.408	0.318	0.517	0.557*
UK FTSE 100	0.513	0.380	0.442	0.611*
Germany DAX 30	0.464	0.323	0.452	0.720*
Taiwan	0.514	0.676	0.600	0.794*
South Korea	0.366	0.360	0.458	0.473*
Malaysia	0.458	0.357	0.498	0.581*
Thailand	0.342	NA	0.457	0.597*

Notes:

1. * denotes the maximum value in the row.
2. Indl=LV (HV) denotes the individual stock market in the low (high) volatility state. World=LV (HV) denotes the world stock market in the low (high) volatility state.
3. The data source and other notations are same with Table 1.
4. NA denotes the not available values.

Table 3 Parameters Estimates and the Statistic Criteria for the Single-β ICAPM

	α_i	β_i	γ_0	γ_1	λ	*Log-Lik*	*AIC*	*Schwarze Value*
US	0.187**	0.475**	0.037	0.037**	0.952**	-2202.1	-2207.1	-2219.6
S&P500	(0.053)	(0.031)	(0.027)	(0.012)	(0.018)			
Japan	0.054	0.616**	0.143**	0.145**	0.839**	-2363.7	-2368.7	-2381.2
Nikkei	(0.052)	(0.034)	(0.052)	(0.024)	(0.025)			
UK FTSE	0.154**	0.581*	0.061	0.040**	0.940**	-1835.5	-1840.5	-1853.0
100	(0.054)	(0.03)	(0.038)	(0.014)	(0.023)			
Germany	0.161**	0.747**	0.165	0.079**	0.885**	-2332.5	-2337.5	-2350.0
DAX 30	(0.06)	(0.036)	(0.126)	(0.025)	(0.049)			
Taiwan	-0.051	1.402**	0.953**	0.149**	0.754**	-2723.9	-2728.9	-2741.4
	(0.058)	(0.056)	(0.269)	(0.031)	(0.049)			
South	0.006	0.698**	0.185*	0.089**	0.898**	-2793.7	-2798.7	-2811.2
Korea	(0.026)	(0.05)	(0.093)	(0.023)	(0.028)			
Malaysia	0.165*	0.872**	0.383**	0.136**	0.835**	-2766.7	-2771.7	-2784.2
	(0.084)	(0.052)	(0.134)	(0.027)	(0.031)			
Thailand	-0.054	0.695**	0.056*	0.114**	0.892**	-2704.2	-2709.2	-2721.7
	(0.075)	(0.056)	(0.03)	(0.025)	(0.021)			

Note:

1. The data source is same with Table 1. The values in the parenthesis are the estimates of the standard errors of parameter estimators.
2. ** (*) denotes the significance at 1％ (5%) level.
3. Please refer Equation (3) for the model specifications of the single-β ICAPM.
4. AIC＝ ML function value- N, N is the parameter numbers. Schwarz value = ML function value-(N/2)x ln(T), T is the sample numbers.

Table 4 Parameter Estimates and the Statistic Criteria for the Dual-β ICAPM by Various Individual Stock Market Volatility State

	$\beta_{i,1}$ (Indl=LV)	$\beta_{i,2}$ (Indl=HV)	*Log-Lik*	*AIC*	*Schwarze Value*	*LR*
US S&P500	0.206	0.663	-2170.4	-2176.4	-2191.4	63.4**
	[0.14, 0.20]	[0.60, 0.73]				
Japan Nikkei	0.362	0.777	-2342.7	-2348.7	-2363.7	42.0**
	[0.28, 0.44]	[0.71, 0.84]				
UK FTSE 100	0.443	0.779	-1818.63	-1824.6	-1839.6	21.8**
	[0.38, 0.50]	[0.71, 0.85]				
Germany DAX 30	0.542	0.935	-2316.0	-2322	-2337.0	33.0**
	[0.46, 0.62]	[0.86, 1.01]				
Taiwan	1.054	2.295	-2644.4	-2650.4	-2665.4	159.0**
	[0.97, 1.14]	[2.18, 2.41]				
South Korea	0.515	1.936	-2747.4	-2753.4	-2768.4	92.6**
	[0.43, 0.60]	[1.72, 2.15]				
Malaysia	0.619	1.783	-2721.1	-2727.1	-2742.1	91.2**
	[0.53, 0.71]	[1.60,1.97]				
Thailand	0.115	1.222	-2634.2	-2640.2	-2655.2	140.0**
	[0.02, 0.21]	[1.12,1.33]				

Note:

1. The data source is same with Table 1.
2. Please refer Equations (6) and (7) for the model specifications of Model 1: the dual-β ICAPM by various individual stock market volatility state
3. The LR (likelihood ratio) statistics report the test of the null hypothesis of the single-β settings against the dual-β settings in Model 1 .The LR statistics follow the Chi-square distributions with freedom one.
4. The values in the square bracket are the 90% confidence intervals of the β estimates.
5. The other notations are similar with Table 3.

Table 5 Parameter Estimates and the Statistic Criteria for the Dual-β ICAPM by Various World Stock Market Volatility State

	$\beta_{i,1}$ (World=LV)	$\beta_{i,2}$ (World=HV)	*Log-Lik.*	*AIC*	*Schwarze Value*	*LR*
US S&P500	0.628 [0.54, 0.72]	0.413 [0.35, 0.47]	-2196.7	-2202.7	-2217.68	10.8**
Japan Nikkei	0.754 [0.65, 0.85]	0.550 [0.48,0.62]	-2359.8	-2365.8	-2380.78	7.8**
UK FTSE 100	0.761 [0.67, 0.86]	0.511 [0.45, 0.57]	-1829.0	-1835.0	-1849.98	13.0**
Germany DAX 30	0.695 [0.60, 0.79]	0.779 [0.70, 0.85]	-2331.8	-2337.8	-2352.78	1.4
Taiwan	1.180 [1.04, 1.32]	1.563 [1.44, 1.69]	-2718.2	-2724.2	-2739.18	11.4**
South Korea	0.785 [0.65, 0.92]	0.652 [0.55, 0.75]	-2792.8	-2798.8	-2813.78	1.8
Malaysia	1.176 [1.04, 1.32]	0.703 [0.61, 0.80]	-2756.4	-2762.4	-2777.38	20.6**
Thailand	0.441 [0.34, 0.54]	1.127 [1.00 , 1.26]	-2680.4	-2686.4	-2701.38	47.6**

Note:

1. The data source is same with Table 1. World=LV (HV) denotes the world stock market being at the low (high) volatility state.
2. Please refer Equations (6) and (8) for the model specifications of Model 2: the dual-β ICAPM by various world stock market volatility state
3. The LR (likelihood ratio) statistics report the test of the null hypothesis of the single-β settings against the dual-β settings in Model 2
4. The other notations are similar with Table 4.

Table 6 Parameter Estimates and the Statistic Criteria the Multi-β ICAPM by Various Individual and World Stock Market Volatility States

	$\beta_{i,1}$ (Indl=LV and World=LV)	$\beta_{i,2}$ (Indl=LV and World=HV)	β_{i3} (Indl=HV and World=LV)	$\beta_{i,4}$ (Indl=HV and World=HV)	*Log-Lik*	*AIC*	*Schwarze Value*	*LR*
US S&P500	0.347 [0.24, 0.45]	0.111 [0.02, 0.20]	1.055 [0.92, 1.19]	0.568 [0.50, 0.64]	-2153.3	-2161.3	-2181.3	34.2**
Japan Nikkei	0.547 [0.44, 0.65]	0.215 [0.12, 0.31]	1.274 [1.10, 1.45]	0.693 [0.62, 0.77]	-2323.9	-2331.9	-2351.9	37.6**
UK FTSE 100	0.754 [0.66, 0.85]	0.275 [0.21, 0.34]	0.809 [0.29, 1.33]	0.779 [0.70, 0.85]	-1796.7	-1804.7	-1824.7	43.8**
Germany DAX 30	0.678 [0.58, 0.78]	0.283 [0.15, 0.42]	0.95 [0.62, 1.28]	0.933+ [0.85, 1.01]	-2308.4	-2316.4	-2336.4	15.2**
Taiwan	1.112 [0.97, 1.25]	1.018 [0.91, 1.13]	4.664+ [4.06, 5.27]	2.288 [2.16, 2.42]	-2634.8	-2642.8	-2662.8	19.2**
South Korea	0.678 [0.54, 0.81]	0.422 [0.32, 0.52]	4.306 [3.21, 5.40]	1.778 [1.55, 2.00]	-2733.4	-2741.4	-2761.4	28.0**
Malaysia	0.993 [0.86, 1.13]	0.389 [0.28, 0.50]	3.104 [2.74, 3.47]	1.466 [1.25, 1.68]	-2688.1	-2696.1	-2716.1	66.0**
Thailand	NA	0.113 [0.02, 0.21]	1.373 [1.20, 1.55]	1.147 [1.02, 1.27]	-2632.7	-2640.7	-2660.7	-3.0

Note:

1. The data source is same with Table 1.
2. Please refer Equations (6) and (9) for the model specifications of Model 3: the multi-β ICAPM by various individual and world stock market volatility states
3. The LR (likelihood ratio) statistics report the test of the null hypothesis of the single-β settings against the multi-β settings in Model 4. The LR statistics follow the Chi-square distributions with freedom three.
4. NA denotes the not available values. The other notations are similar with Tables 4 and 5

Table 7 Means of the Absolute Abnormal Returns for Various Model Settings and Various Volatility States

(A) US S&P500

Model	Indl=LV and World=LV	Indl=LV and World=HV	Indl=HV and World=LV	Indl=HV and World=HV
Simple SWARCH	1.151	1.182	2.027	2.116
Single-β ICAPM	1.078	1.368	1.782	1.752
Dual (Multi)-β ICAPM				
Model 1	1.076	1.190	1.718	1.769
Model 2	1.101	1.306	1.728	1.769
Model 3	1.071*	1.187*	1.672*	1.748*

(B) Japan Nikkei 225

Model	Indl=LV and World=LV	Indl=LV and World=HV	Indl=HV and World=LV	Indl=HV and World=HV
Simple SWARCH	1.051	1.104	2.517	2.660
Single-β ICAPM	1.052	1.311	2.287	2.208
Dual (Multi)-β ICAPM				
Model 1	1.058	1.199	2.274	2.223
Model 2	1.066	1.240	2.258	2.218
Model 3	1.050*	1.042*	2.255*	2.212*

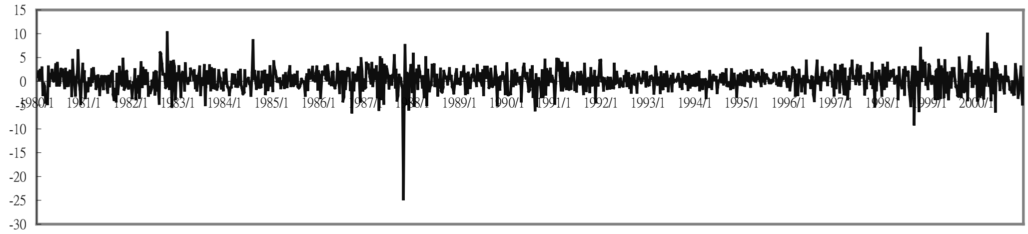
(C) Taiwan

Model	Indl=LV and World=LV	Indl=LV and World=HV	Indl=HV and World=LV	Indl=HV and World=HV
Simple SWARCH	1.975	2.988	6.604	5.957
Single-β ICAPM	1.844	2.258	4.963	3.444
Dual (Multi)-β ICAPM				
Model 1	1.836	2.196	4.475	3.068
Model 2	1.826*	2.408	5.214	3.214
Model 3	1.826*	2.134*	3.980*	2.693*

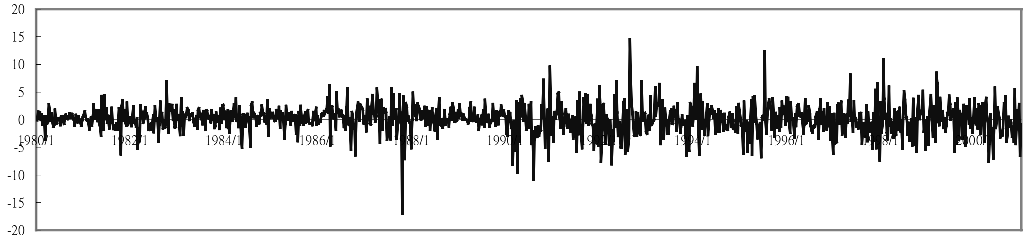
Note:

1. The data source is same with Table 1.
2. * denotes the minimum value in the column.
3. The other notations are similar with Tables 4 and 5

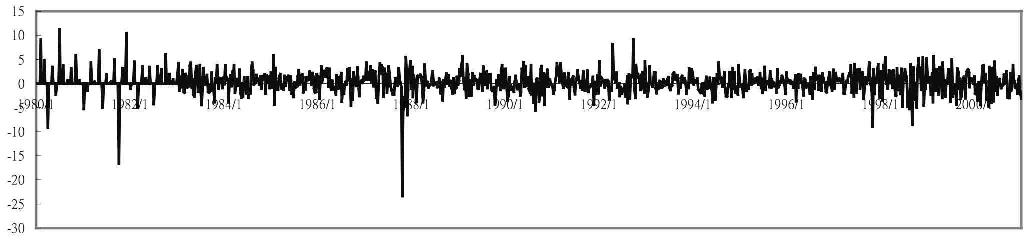
(a) US S&P 500



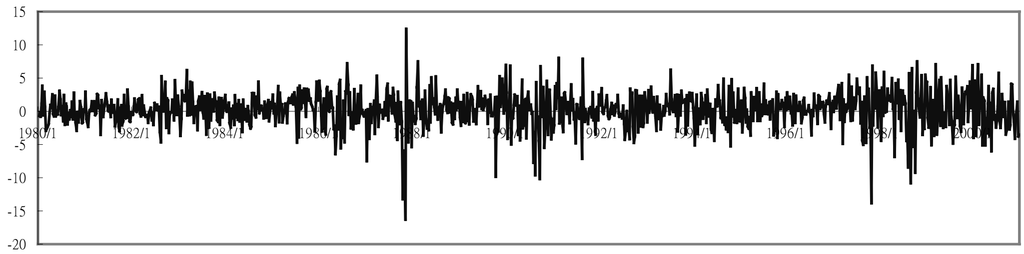
(b) Japan Nikkei



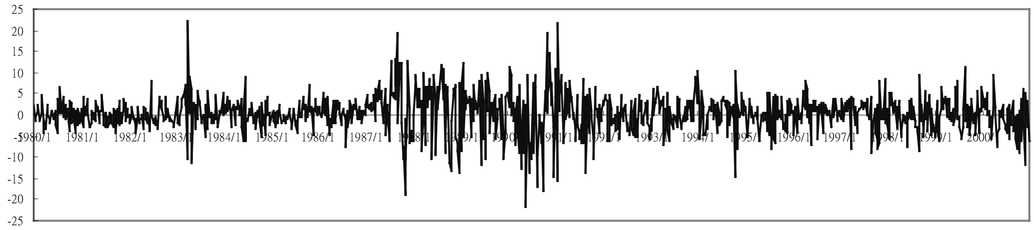
(c) UK FTSE100



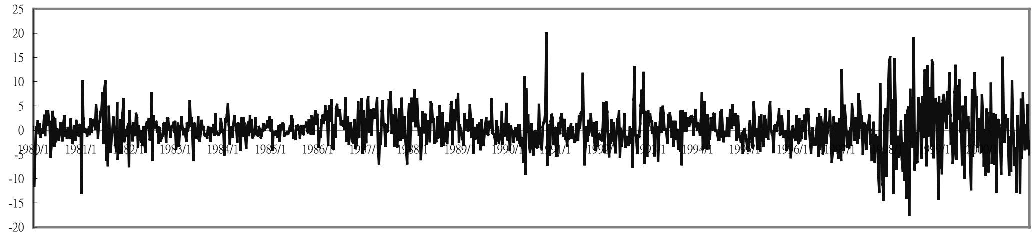
(d) Germany DAX30



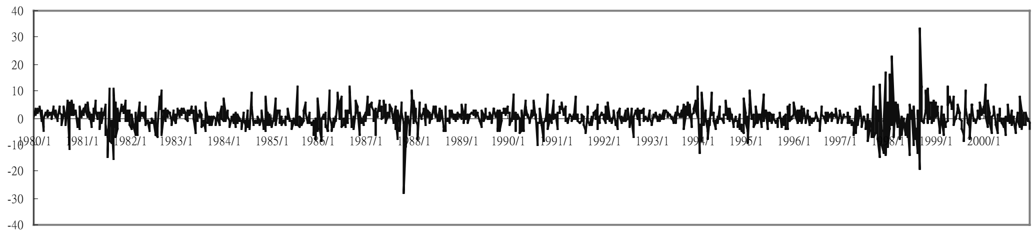
(e) Taiwan



(f) South Korea



(g) Malaysia



(h) Thailand

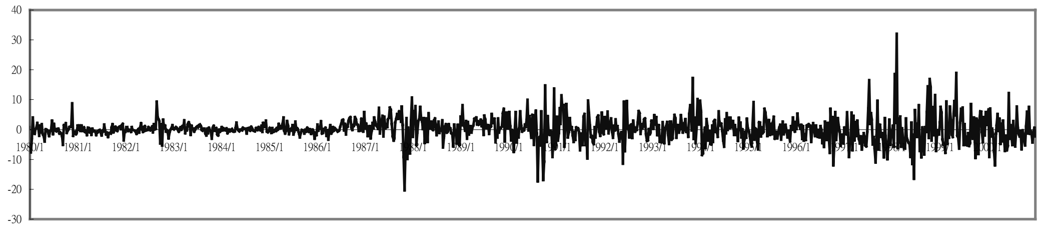
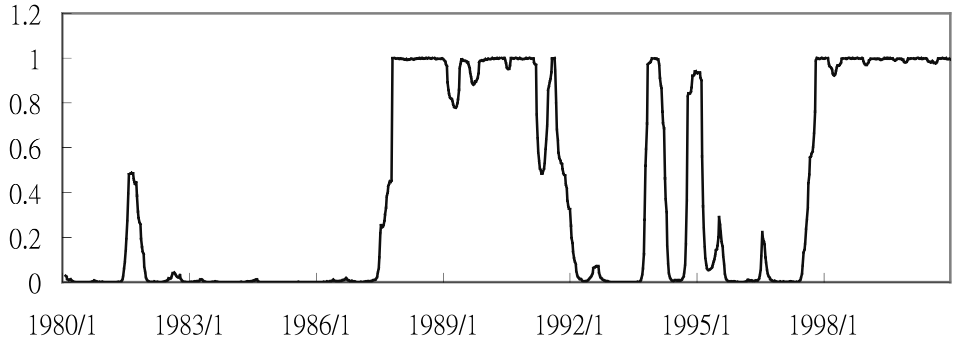
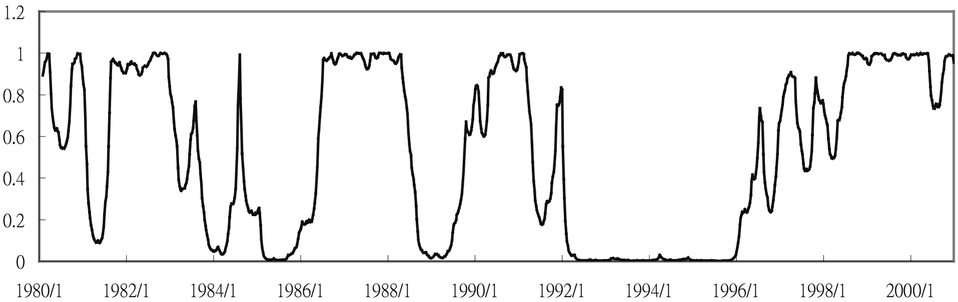


Figure1 The weekly stock index returns for various stock markets

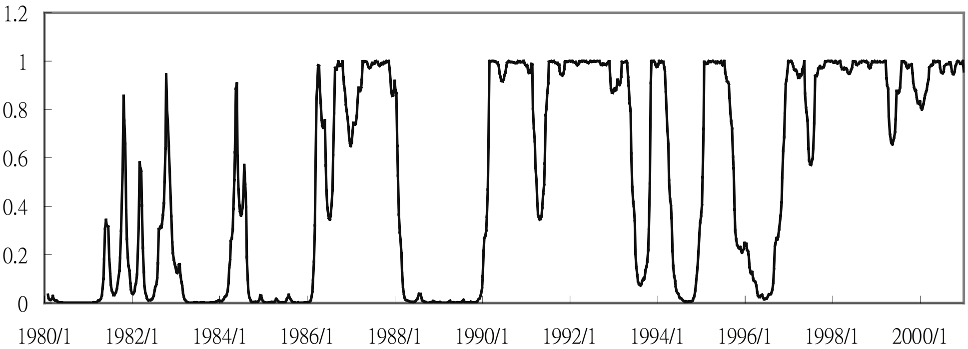
(a) EWW



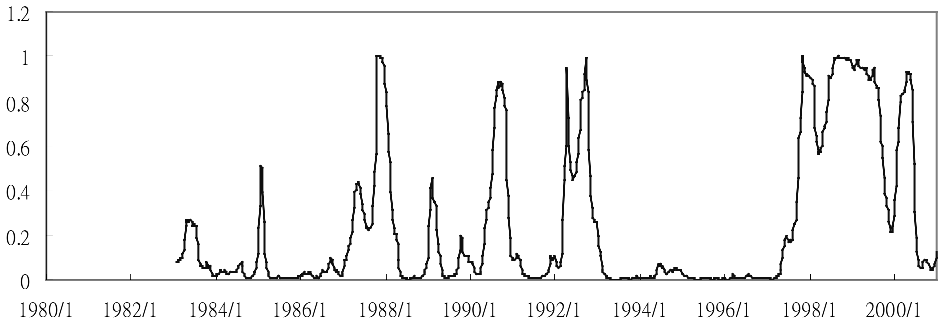
(b) US S&P500



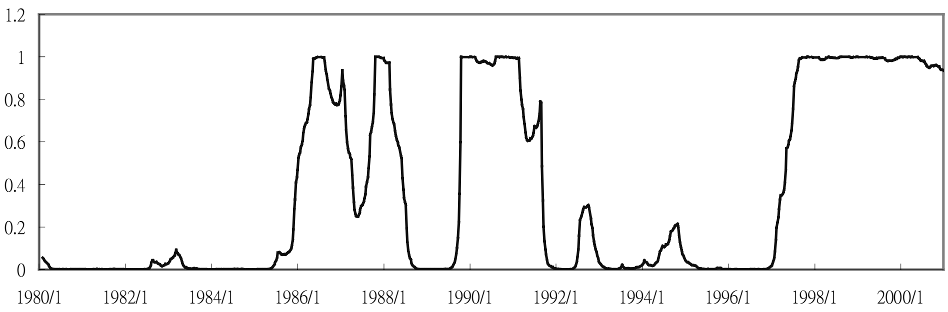
(c) Japan Nikkei



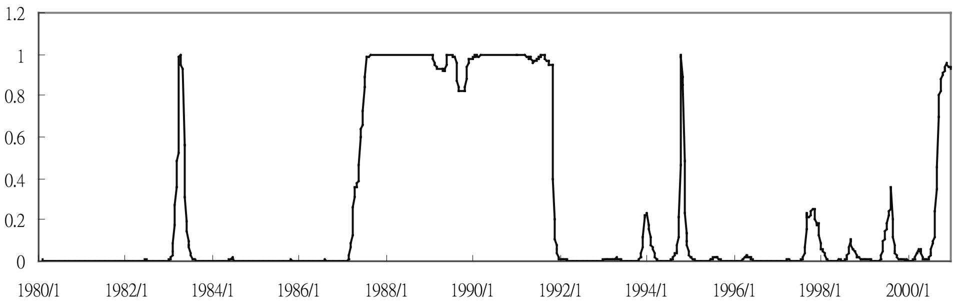
(d) UK FTSE100



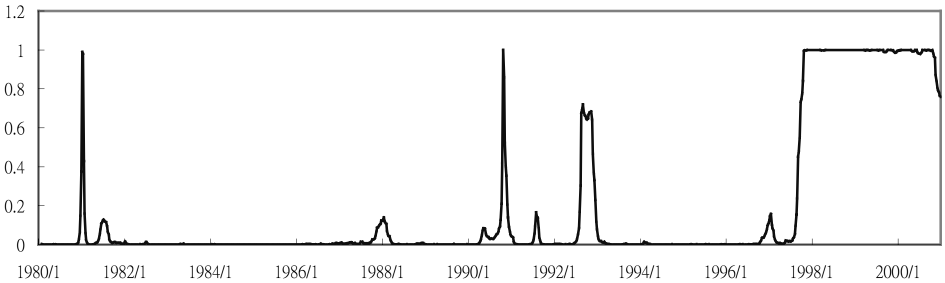
(e) Germany DAX30



(f) Taiwan



(g) South Korea



(h) Malaysia

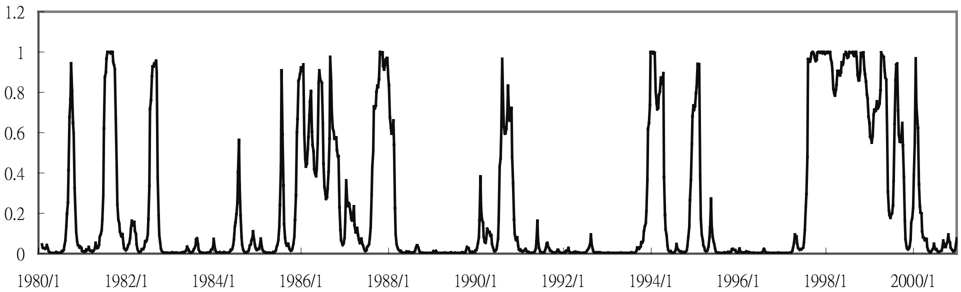


Figure2. The smoothing probabilities of high volatility state for various stock markets

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