VOLATILITY TIMING OF FUNDS UNDER CPF INVESTMENT SCHEME: A GARCH MODEL APPROACH

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SUMMARY

Busse (1999) applies the conditional volatility generated by an EGARCH model to capture the volatility-timing ability of US mutual funds. However, researches on the volatility-timing performance of Singapore-based funds are rarely available. In this thesis, I examine the volatility-timing ability of funds under CPF Investment Scheme and non-CPF funds. I improve Busse model by including the currency risk effect on internationally managed funds. Modified factor models are applied to capture the response of funds to the market abnormal conditional volatility. The univariate GARCH or EGARCH models with the day of the week effect are used to derive the effective conditional volatility. The SMB and HML factors for non-US based funds have to be constructed from stock market data to exclude the contribution of size effect and BE\ME effect. This study reveals volatility timing is one of the factors that contribute to the excess return of funds. However, funds' volatility-timing seems to be country-specific. In the case of Japan equity funds and global equity funds under CPF Investment Scheme, most funds are found to have the ability of volatility timing, as they decrease the market exposure when market is extremely volatile. However, the empirical researches on Asian ex-Japan funds and Greater China funds fail to support the existence of the funds' volatility-timing behavior in both CPF side and non-CPF side. Moreover, most funds under CPF Investment Scheme do not have a group behavior of better volatility timing except Japan equity funds.

Key words: volatility timing, GARCH, weekday effect, currency risk exposure

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CHAPTER 1: INTRODUCTION

The performance measure of funds has been an important topic in the past four decades. Historically, researchers measure the performance of funds by calculating their absolute returns. Although this method directly measures the loss and gain of funds' investors, it fails to take into account the relation between funds' performance and their risk exposure to the market. Funds' reward-to-risk ratios (see Sharpe, 1966) become a good alternative, but it cannot distinguish the contribution of markets to funds' performance from that of fund managers. Therefore, to find a measurement method which can justify the active portfolio management becomes the main concern of researchers. The funds' ranking method developed by Jensen (1967) is the excess return of funds, so-called "Jensen's alpha". This method can clearly measure the contribution of fund managers' active management to the performance of funds. Meanwhile, other methods of performance measure are widely used in the industry[1]. For example, gain/loss ratio measures the proportion of funds' positive returns to negative returns. The higher gain/loss ratio it is, hence the better the performance of funds. Similarly to the reward-to-risk ratio, information ratio can be a risk-adjusted measure which evaluates how well funds perform relative to their peers. Since the late 20th century, the conditional models on return and volatility have been introduced into the funds' performance measure by Ferson, Schadt, Busse, Tsui and etc. However, these models have rarely been applied to Asian-based funds. One of the reasons is lack of adequate data which can be applied to American-based models. Moreover, American-based models for funds' performance measure may need great adjustment in the Asian context. The goal of this research is to explore a conditional method of measuring the performance of Singapore-based mutual funds under Central Provident Funds (CPF funds).

[1] Common methods for funds' performance measure are summarized from information available on the website of CPF Investment Scheme, http://mycpf.cpf.gov.sg/Members/GenInfo/FAQ/Investment/INV-Asset-Enhance.htm

The Central Provident Fund[2] (CPF) investment scheme was introduced in 1986 by Singapore government in order to enhance CPF members' funds for retirement. CPF members usually withdraw money for house purchase, while male and high income earners involve in more risky investment with their CPF saving. (see Koh, Mitchell, Tanuwidjaja and Fong, 2007) There are two accounts under the current CPF Investment Scheme, Ordinary Account (OA) and Special Account (SA). Through OA and SA, CPF members can invest insurance, unit trust, exchange traded funds (ETFs), fixed deposits, bond, treasury bills, fixed deposits, shares, property funds and gold. The investible products under CPF-OA and CPF-SA are different, as only selected unit trusts, ETFs and investment-linked insurance products can be invested under CPF-SA. The instruments under CPF-SA are usually regarded to have higher risk than those under CPF-OA. To become a member of CPF Investment Scheme, investors are required to have 20,000 SGD in CPF-OA or 20,000 SGD in CPF-SA. When the CPF Investment Scheme was first introduced, members were allowed to invest up to 20% of their saving in CPF-OA. In order to decrease risk, detailed investible ratios are allowed for different asset classes, while the investible ratio has increased gradually. Under current CPF-OA, investible ratio for shares, property funds and corporate bonds are up to 35%; investible ratio for gold ETFs and other gold products are 10%.

CPF board sets up strict admission criteria for investment products, especially for funds which tend to enter the CPF Investment Scheme. Fund management companies with intention to enter the CPF Investment Scheme must have at least S$500 million fund managed in Singapore with minimum three fund managers. One of fund managers must have at least five year experience in fund management. Moreover, foreign funds recognized by MAS are allowed to apply for the inclusion of CPF Investment Scheme. But they should become a member of Investment Management Association of Singapore and also have to submit a representative agreement of foreign funds or their mangers. 28 fund management companies

[2] The information about CPF funds is summarized from information available on the website of CPF Investment Scheme, http://mycpf.cpf.gov.sg/Members/GenInfo/FAQ/Investment/INV-Asset- Enhance .htm.

under the current CPF Investment Scheme are shown in Table A.1. Insurers can also provide members with investment-linked products if they fulfill similar important admission criteria. 11 insurers under CPF Investment Scheme are shown in Table A.2. Moreover, since 1st February 2006, the revised benchmark requires new-entry funds to be above the top 25% by ranking their performance among their global peers. Compared with the existing funds within the risk level under CPF Investment Scheme, new funds are also required to have lower-than-median expense ratio. A good historical performance for at least three years is desirable. In addition, sales charges for fund under CPF Investment Scheme must be less than 3% from 1st Jul 2007.

Considering the strict entry criteria of CPF funds, CPF members may automatically believe CPF funds imply "safer and better performed funds". However, whether people's common belief is true is the research question I wish to answer in this paper. Instead of using the common measures such as absolute return, information ratio and reward-to-risk ratio, I focus on evaluating the volatility-timing ability of CPF funds. In short, this thesis attempts to explore whether there is any difference in the performance of volatility-timing between funds under CPF Investment Scheme and non-CPF funds. This research shows its significance in three aspects following.

First, the volatility-timing ability of CPF funds will provide CPF board with a new method for risk classification. CPF board ranks funds' cumulative return within the same risk classification. The risk classification of CPF funds follows: 1) higher risk which includes funds investing in equities; 2) medium to high risk which includes funds investing in a mix of equities and bonds; 3) low to medium risk includes funds investing in income products and bonds; 4) low risk includes funds investing in money market products[3]. However, this method is too board to evaluate how well fund mangers of CPF funds time the change in market risk,

[3] The category of CPF funds' risk is from semiannual report of CPF funds available on the website http://www.fundsingapore.com/SG/xml/dsp_search_quick.xml.

as the exposure to the market risk will influence funds' risk and thus their return. In this thesis, modeling the volatility-timing ability of funds is to analyze the contribution of fund managers by testing their control in funds' volatility. This method becomes a new perspective to justify active fund management.

Second, this thesis is the first research which adjusts the advanced models for measuring the performance of Asian-based funds and fills the blank of the research on CPF funds. For a long time, economic researches about CPF Investment Scheme are rarely available. The research topics of CPF funds are limited too. Koh et al. (2007) analyze investment pattern of members in the CPF system. Their study summarizes sales load and expense ratios for unit trust under CPF Investment Scheme in Table 1. The study reveals that higher default rates for saving in OA or SA with high expense ratio of fund investing keep members' saving in default account.

Table 1
Summary of sales load and expense ratios for funds under CPF Investment Scheme

Risk Category	Fund Type	Funds	Average Sales Load	Average Expense Ratios
Higher risk	Equity	167	4.90%	2.07%
Medium-high	Balanced	26	4.80%	1.93%
Low-medium	Income	39	2.10%	1.12%
Lower risk	Cash	3	0.10%	0.71%
Total N funds		235		

Source: Koh, Mitchell, Toto & Fong (2007)

However, no research focuses on the performance measure of CPF funds itself, which in turn makes CPF members' common belief that CPF funds are "safer and better funds" unjustified. In this thesis, models from GARCH family are first applied to the performance measure of Singapore-based funds. Currency risk is included in the models to capture the characteristics of internationally managed funds. Moreover, this thesis is also the first study which explores the difference of performance between CPF funds and non-CPF funds.

Third, byproducts of this research will promote data innovation for the research about Asian financial markets. Adequate data is a problem which has vexed researchers who are interested in Asian financial markets for a long time. For example, it is easy to obtain indices of small-size stocks in the U.S. However, almost no index vendors offer indices of small-size stocks for Asia or individual Asian countries, because these indices are not marketable to global fund managers whose investment targets are big or medium size stocks in Asia. In this thesis, country or regional indices for small-size stocks, growth stocks and value stocks in Asia are created with adjustment of Asian accounting rules. These indices can be useful benchmarks for other researches about Asian markets such as Greater China and ex-Japan Asia.

The rest of this thesis is organized as follows. Literatures about funds' performance measure are reviewed in Chapter 2. In Chapter 3, the research methodology is briefly introduced. It includes both the GARCH-type and factor models. The model specification, data challenge and empirical analysis are discussed in Chapter 4. Chapter 5 summarizes the research results and discusses the implication of main findings.

CHAPTER 2: LITERATURE REVIEW

A lot of literature have discussed about the performance measure of funds. Generally, the performance measure of funds focuses on several aspects. Treynor and Mazuy (1965) first raise a market-timing model to capture whether mutual funds can outperform the market. Their model is based on the assumption that fund managers will shift to less-volatile assets when the market is bad and shift to more-volatile assets when the market is good. Therefore, a fund which can consistently outperform the market will have a "characteristic line" with steep slope when the market return is positive, or with a smooth slop when the market is negative. The slope of characteristic line describes the effective volatility of funds, which in turn contributes to the high return of funds. However, none of the 57 mutual funds in their sample is found to outperform the market. The Treynor-Mazuy model is basically a regression with a quadratic term described as below,

$$R_{pt+1} = a_p + b_p r_{mt+1} + r_{tmu}[r_{m,t+1}]^2 + v_{pt+1} \quad (1)$$

, where r_{tmu} measures the market-timing of funds; $r_{m,t+1}$ measures the market; R_{pt+1} is funds' return; b_p describes funds' exposure to the market; a_p is constant; v_{pt+1} is the residual.

Sharpe (1966) later on applies Treynor and Mazuy's model to an empirical test, thereby introducing reward-to-risk ratio. The numerator is the reward measured by the difference between funds' return and the risk-free rate. The denumerator describes the variability of funds' return. Reward-to-risk ratio measures funds' return in face of the risk. Sharpe also strives to explain the persistence of funds' performance by applying pre-1954 data to predict funds' performance from 1954 to 1963. The empirical results fail to indicate any correlation between past performance and future. An alternative market-timing model is proposed by Merton and Henriksson in 1981. The main assumption their model is that fund managers predict when they believe market return will excess the risk-free rate. Thus, the model becomes,

$$R_{pt+1} = a_p + b_p r_{mt+1} + r_u Max(0, r_{m,t+1}) + v_{pt+1} \tag{2}$$

, where $Max(0, r_{m,t+1})$ is "the payoff to an option on the market portfolio with exercise price equal to the risk-free asset" (Ferson and Schadt, 1996); R_{pt+1} is funds' return; b_p describes funds' exposure to the market; r_u is the coefficient of the market-timing payoff; a_p is constant; v_{pt+1} is the residual.

Instead of market-timing, Jensen (1967) measures funds' performance by evaluating the stock selection ability of fund managers. He defines performance of funds as fund managers' forecasting ability. Different from Sharpe who focused on the relative performance measure, Jensen relies on an absolute benchmark to measure performance. Jensen develops his model from traditional CAPM model (see Sharpe, Linter, Treynor), which he believes that a fund manager with good forecasting ability could tend to generate a positive extra return in (3) through stock selection.

$$\tilde{R}_{jt} - rf_t = \beta\left[\tilde{R}_{mt} - rf_t\right] + \tilde{e}_{jt} \tag{3}$$

$$\tilde{R}_{jt} - rf_t = \alpha_{jt} + \beta\left[\tilde{R}_{mt} - rf_t\right] + \tilde{e}_{jt} \tag{4}$$

, where $\tilde{R}_{jt}$ is the return of funds, rf_t is the risk-free rate, $\tilde{R}_{mt}$ is the market return, β is funds' exposure to the market and $\tilde{e}_{jt}$ is the residual. Therefore, we can expect a positive α_{jt} for fund managers with good forecasting ability in (4). Meanwhile, a random buy and hold policy is expected to have a zero or even a negative α_{jt}. However, Jensen's empirical results on 115 US mutual funds do not support that funds can outperform naive buy-and-hold random portfolios on average.

Ferson and Schadt (1996) extend Jensen's model, the Treynor-Mazuy market timing model and the Merton-Henriksson market timing model to a conditional basis. The rationale behind conditional models is that fund managers usually rely on trend information to manage assets.

A conditional beta with a consistent part and a conditional part responded to predetermined information variables is derived by Taylor rules. A regression about the conditional Jensen's model is "a regression of managed portfolio excess return on the market factor and the product of the market factor with the lagged information." Similarly, despite the quadratic term in the traditional Treynor-Mazuy market timing model, a conditional term which describes funds respond to public information is included. In the conditional Merton-Henriksson model, fund managers will choose an upside beta when they predict that the market risk premium is positive, a downside beta when the market risk premium is negative. The empirical results about 67 mutual funds from 1968 to 1990 indicate that "conditional information is both statistically and economically significant". Based on the conditional market timing model, Becker et al. (1999) further refine the model by estimating "parameters that describe the public information environment, the risk aversion of the fund manager and the precision of the fund's market-timing signal." The results about 400 US mutual funds in the period of 1976-94 confirm the effectiveness of conditioning public information in model specification.

Since the inception of ARCH model by Engle in 1982, researchers have begun to link GARCH models with the performance measure of funds. Models from GARCH family can be applied to generate conditional volatility and conditional beta. The category volume of future contracts and its volatility are found to have ARCH effect by Wiley and Daigler (1999). The conditional market-timing model is further extended by including GARCH risk measure by Coggins et al. (2006). Their established model allows "both condition on the expected market premium and the beta of funds". The later is realized by the condition generating process of the covariance between portfolio return and market return, variance of portfolio return and variance of market return. In this model, daily data is estimated by a bi-variate BEKK parameterization. The results confirm that conditional measure on fund manager's ability has advantage on the unconditional measure. Lim (2005) introduces a multi-factor model with time-varying beta. The advantage of this model is that it can analyze the contribution of factor to excess return of equity in two moments: "first moments via the time-varying factors" and "second moments via the time-varying betas" with M-GARCH specification. Besides the market-timing ability of funds, researchers also focus on the performance measure related to funds' volatility. Volatility-timing strategy is found to outperform its unconditional counterparts with the same target expected return and volatility by Fleming et al. (2001) This study focuses on the impact of predicable change in volatility on the short-term performance of assets. Instead of using the ARCH and GARCH models, they apply a non-parametric approach developed by Foster and Nelson (1996). In the US future data, it is found that "predictability captured by volatility modeling is economically significant". Busse (1999) constructs a volatility-timing model with conditional variance input. The empirical result of US funds supports that fund managers have the ability to predict the market volatility while decrease funds' exposure to the volatile market.

Besides the conditional measure, many researchers have discussed the appropriate specification for funds' performance and choice of benchmarks. Sharpe (1992) explains the impact of asset allocation on performance of funds by raising a multifactor asset class model in 1992. He defines 12 asset classes, the return of which is constructed by a "market capitalization-weighted index on a large number of securities". He finds that the variability of annual equity return greatly depends on the selection of asset classes, in which the asset class of small cap stocks is more volatile in return and the asset class of value stocks is the least volatile. He proposes a concept of "style analysis". This analysis is to find a set of the best asset classes which conforms to the funds' investment policy. The return of funds which cannot be captured by style analysis is contributed by stock selection. Based on funds' type, Sharpe analyzes the style of US mutual funds from 1985 to 1989. This research provides investors with an alternative method of fund-selecting by understanding funds' style. Although Jenson's measured based on factor model is widely used, Roll (1978) criticizes the sensitivity to the choice of the benchmark portfolio. In order to avoid the problematic part of benchmark, Grinblatt and Titman (1993) use portfolio holding to evaluate the performance of

US mutual funds between 1976 and 1985. Aggressive growth funds are found to have positive abnormal returns in the research results.

CHAPTER 3: RESEARCH METHODOLOGY

The properties of GARCH and EGARCH models are discussed in this chapter. The GARCH model is adopted because of its parsimonious advantage over the ARCH. The EGARCH model can capture the asymmetry in the financial time series. The estimation method of the GARCH models is also discussed. In addition, the theoretical background of a factor model is introduced to explain the relation between factors' sensitivity and market volatility.

3.1. GARCH

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is proposed by Bollerslev (1986) to extend the successful ARCH model pioneered by Engle (1982).

$$\varepsilon_t = \sigma_t e_t \tag{5}$$

$$\sigma_t^2 = a_0 + \sum_{i=1}^{m} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} b_j \sigma_{t-j}^2 \tag{6}$$

, where $a_0 > 0$, $a_i \ge 0$, $b_j \ge 0$ and $\sum_{i,j}^{\max(m,s)} (a_i + b_j) < 1$

In (6), ε_t^2 is the unconditional variance generated by the mean equation. ε_t can be assumed to follow a normal, t or generalized error distribution. σ_t^2 is the conditional variance generated by its lagged term and the lagged term of unconditional variance. First, the non negative constraint on the estimates of e_t^2 and σ_t^2 indicate that a larger e_{t-1}^2 or σ_{t-1}^2 leads to a larger σ_t^2 , which confirms "volatility clustering behavior in financial time series."(Tsay, 2002) Second, the last constraint on $a_i + b_i$ implies the finite unconditional variance and the evolution of conditional variance over time. It is also a sufficient condition for strict stationarity. Third, if $1 - 2a_1^2 - (a_1 + b_1)^2 > 0$, the left side hand in (7) should be bigger than 3 in GARCH (1,1) specification.

$$\frac{E(\sigma_t^4)}{\left[E(\sigma_t^2)\right]^2} = \frac{3\left[1-(a_1+b_1)^2\right]}{1-2a_1^2-(a_1+b_1)^2} > 3 \qquad (7)$$

Equation (7) implies that GARCH (1, 1) process should have a heavier tail than that of normal distribution.

Maximum likelihood method is commonly applied to the estimation of the univariate GARCH model (Bera and Higgins, 1993). If the conditional normality holds, the generalized likelihood function is given by

$$\ell(\partial) = -\frac{1}{2}\log 2\pi - \frac{1}{2}\frac{\varepsilon_t^2}{\sigma_t^2} - \frac{1}{2}\ln(\sigma_t^2) \qquad (8)$$

Engle (1982) indicates that the normal likelihood function is widely used because estimation of the mean and variance parameters can be separate from their testing.

Ljung-Box Q statistics is applied to check the autocorrelation in unconditional variance and conditional variance. The Q statistics is computed by

$$Q = T(T+2)\sum_{j=1}^{k}\frac{r_j^2}{T-j} \qquad (9)$$

, where T is the number of observation and r_j is the autocorrelation at j. The null hypothesis for testing autocorrelation up to lag order of k follows χ_k^2 distribution asymptotically. The Q statistics will be insignificant if there is no autocorrelation in the residual tested.

In a nutshell, the GARCH is employed as its parsimonious advantage over the ARCH. This advantage is more obvious in a GARCH (1, 1) model, whereas a low-order ARCH model fails to catch the volatility evolution process.

3.2 EGARCH

However, the symmetric GARCH model rules out the negative correlation between returns in assets and changes of returns volatility. (see Nelson, 1991) When market is melting down, investors are often found to behave as "rushing to the same door". This behavior causes returns in assets to be more volatile when "bad news" comes in, while volatility is more tolerant to "good news". In order to overcome this drawback of the GARCH, Nelson proposed the Exponential GARCH model (EGARCH) as follows.

$$\varepsilon_t = \sigma_t e_t \tag{10}$$

$$\ln(\sigma_t) = a_0 + \sum_{i=1}^{m} a_i \ln(\sigma_{t-i}) + \sum_{j=1}^{s} b_j g(e_{t-j}) \tag{11}$$

$$\text{, where } g(e_j) = \begin{cases} (\theta + \lambda)e_j - \lambda E(| e_j |), e_j > 0 \\ (\theta - \lambda)e_j - \lambda E(| e_j |), e_j < 0 \end{cases} \tag{12}$$

e_j is the error term in (10). In (12), $E(|e_j|) = \sqrt{2/\pi}$, if e_j follows normality; when e_j follows the student distribution, $E(|e_j|)$ is expressed as

$$E(|e_j|) = \frac{2\sqrt{\nu - 2}\Gamma((\nu + 1)/2)}{(\nu - 1)\Gamma(\nu/2)\sqrt{\pi}} \tag{13}$$

In Equation (11), the conditional variance follows a ARMA process with it lagged term and $g(e_j)$. Equation (12) is called as "weighted innovation" (Tsay, 2002), which catches the asymmetric response to positive and negative asset returns. θ represents the correlation between processed conditional volatility and the error term. If the leverage effect exists, we expect a negative θ and a positive λ. In this case, Equation $(\theta + \lambda)e_j - \lambda E(|e_j|)$ will process a lower conditional volatility if asset return is positive; Equation $(\theta - \lambda)e_j - \lambda E(|e_j|)$ will process a higher conditional volatility if asset return is negative.

Alternatively, EGARCH model can be described by Nelson as below:

$$\varepsilon_t = \sigma_t e_t \tag{14}$$

$$\ln \sigma^2{}_{mt} = a + \sum_{i=1}^{s} \alpha_i \frac{\left|\varepsilon_{m,t-i}\right| + \gamma_i \varepsilon_{m,t-i}}{\sigma_{m,t-i}} + \sum_{j=1}^{m} \beta_j \ln \sigma^2_{m.t-j} \tag{15}$$

Similar to (12), the conditional variance is generated by its lagged term and the leveraged ARCH effect in (15). A positive ε_t contributes $a_i(1+\lambda_i)|\varepsilon_i|$ to the conditional volatility, while a negative ε_t contributes $a_i(1-\lambda_i)|\varepsilon_i|$ to the volatility. λ_i is expected to be negative for series with leveraged effect in real application.

3.3 Factor Model

Besides the GARCH-type models, k-factor models have been used to capture the return of funds. It is described as follows:

$$R_{i,t+1} = \alpha_{it} + \sum_{j=1}^{k} \beta_{jit} R_{j,t+1} + \varepsilon_{i,t+1} \tag{16}$$

, where $R_{i,t+1}$ is the excess return of fund *i* at time t+1, α_{it} is the extra return which is usually regarded as "Jensen's alpha", β_{jit} is the exposure of fund *i* to the risk factor j at time t, $\varepsilon_{i,t+1}$ is the error term of fund *i* at time t+1. Assuming the error term is conditionally normal distributed, that is $E(\varepsilon_{i,t+1}) \mid \Phi_t = 0$ and $E(R_{j,t+1}\varepsilon_{i,t+1}) \mid \Phi_t = 0$, where Φ_t is the information set at time t. Based on (16) , the expected return of fund becomes

$$E_t(R_{i,t+1}) = \alpha_{it} + \sum_{j=1}^{k} \beta_{jit} E_t(R_{j,t+1}) \text{, where } E_t(\cdot) = E(\cdot) \mid \Phi_t \text{.} \tag{17}$$

Assuming that the factors from 1 to k are orthogonal, the conditional variance of fund *i* at time t is given by

$$\sigma_t^2(R_{i,t+1}) = \sum_{j=1}^{k} \beta_{jit}^2 \sigma^2_{j,t+1} + \sigma_t^2(\varepsilon_{i,t+1}) \text{.} \tag{18}$$

In this thesis, I shall apply Busse's volatility-timing idea of fund managers about decreasing funds' market exposure or factor risk exposure when the market is volatile. The objective of volatility timing is to maximize the expected utility of funds' shareholder. The utility function of funds' shareholders should be maximized as follows.

$$\max_{\beta_{1it},\cdots,\beta_{kit}} E_t[U_{t+1}(R_{i,t+1})]$$

$$\frac{\partial}{\partial \beta_{jit}} \max_{\beta_{1it},\cdots,\beta_{kit}} E_t[U_{t+1}(R_{i,t+1})]$$

$$= E_t[U'_{t+1}(R_{i,t+1})]E_t[R_{j,t+1}] + \text{cov}[U'_{t+1}(R_{i,t+1}), R_{j,t+1}]$$

$$= E_t[U'_{t+1}(R_{i,t+1})]E_t[R_{j,t+1}] + E_t[U''_{t+1}(R_{i,t+1})]\text{cov}[R_{i,t+1}, R_{j,t+1}]$$

$$= E_t[U'_{t+1}(R_{i,t+1})]E_t[R_{j,t+1}] + \beta_{jit}E_t[U''_{t+1}(R_{i,t+1})]\text{var}(R_{j,t+1})$$

$= 0$, where $j = 1,......,k$

$$=> \beta_{jit} = \frac{1}{a}\frac{E_t(R_{j.t+1})}{\sigma^2_{j,t+1}} \quad (19)$$

, where $a = -\frac{E_t[U''_{t+1}(R_{i,t+1})]}{E_t[U'_{t+1}(R_{i,t+1})]}$ is the Rubinstein (1973) measure of risk aversion regarded as a fixed parameter. Taking the optimal factor beta in (19) with respect to factor standard deviation, we have

$$\frac{\partial \beta_{jit}}{\partial \sigma_{j,t+1}} = \frac{1}{a\sigma^2_{j,t+1}}[\frac{\partial E_t(R_{j,t+1})}{\partial \sigma_{j,t+1}} - \frac{2E_t(R_{j,t+1})}{\sigma_{j,t+1}}], \text{ where } j = 1,......,k \quad (20)$$

$$=> \frac{\partial \beta_{jit}}{\partial \sigma_{j,t+1}} \le 0 \text{ , if } \frac{\partial E_t(R_{j,t+1})}{\partial \sigma_{j,t+1}} \le 0$$

The factor sensitivity would decrease with the factor standard deviation if the term $\partial E_t(R_{j,t+1}) / \partial \sigma_{j,t+1}$ is negative or small. Therefore, I expect a negative β_{ji} to σ_j if $\partial E_t(R_{j,t+1}) / \partial \sigma_{j,t+1}$ is negative or smaller than $2E_t(R_{j,t+1}) / \sigma_{j,t+1}$ and verse versa.

CHAPTER 4: EMPIRICAL ANALYSIS AND FINDING

The model specification will be discussed step by step in this chapter. First, market volatility is evaluated by the conditional variance generated by the GARCH or EGARCH models. Second, market conditional volatility is applied to the factor models to derive a coefficient which describes the volatility-timing ability of funds. Based on the theories, I expect a negative coefficient for funds with the good volatility-timing ability. Choice of variable will be described in the part of "data set". Finally, the empirical finding of 4 sample groups, Japan equity funds, global equity funds, Asian ex-Japan equity funds and Greater China equity funds will be presented.

4.1 Volatility-timing Coefficient

Factor models with a volatility-timing coefficient are applied in this paper. If the return of funds follows a single factor model, it is given by

$$R_{pt} = \alpha_p + \beta_{mp} R_{mt} + \varepsilon_{pt} \tag{21}$$

, where R_{pt} is the excess return of individual fund and R_{mt} is the excess return of market. Furthermore, a simplified Taylor series expansion is used in Busse's paper to transfer the market beta into a linear function of the difference between market volatility and it time-series mean:

$$\beta_{mpt} = \beta_{0mp} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m)\,. \tag{22}$$

By substituting (22) into (21), we can get the daily single-index volatility timing model as follows.

$$R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) R_{mt} + \varepsilon_{pt} \tag{23}$$

The volatility timing coefficient is γ_{mp}, which indicates the relation between market volatility and fund return contributed to fund manager's volatility-timing ability. If $\partial E_{t-1}(R_{mt}) / \partial \sigma_{mt} \leq 0$ or very small, where $E_{t-1}(R_{mt})$ is the expected return of market index conditioned on the information set at time t-1 and σ_{mt} is the standard deviation of market index, a negative γ_{mp} can be expected for the fund manager who is good at volatility timing. That is, when the market volatility is higher than its time-series mean, a fund manager good at volatility timing can predict the increasing market volatility in advance and then adjust the assets from high volatile securities to low volatile securities. In other words, the individual fund with good volatility timing would be more sensitive to the market when the market is less volatile, while it would be less sensitive to the market when the market is more volatile. This process generates returns for the fund. On the other hand, if $\partial E_{t-1}(R_{mt})/\partial\sigma_{mt} > 0$ for the market index, a positive volatility-timing coefficient is expected for a fund manager who is good at volatility timing.

4.2 Conditional Volatility

Instead of using the usual moving-average volatility, I apply the conditional variance generated from GARCH family to describe the market volatility. Busse (1999) uses an EGARCH model to get the conditional volatility estimates and then applies these volatility estimates to OLS regressions. The rationale behind is that models from GARCH family can govern the evolution of variance. Moreover, the conditional market volatility based on the past information is a usual benchmark for fund managers to adjust funds' volatility and thus improve funds' performance. Moreover, Yan (2000) finds that the estimation of funds' VAR heavily depends on the skewness and lepkurtosis of returns. In the GARCH model, the assumption of normality has a significant impact on the estimation of GARCH. This assumption also influences the performance measure of funds. As such, in this thesis, I adopt either a fitted EGARCH or GARCH with adjusted mean equation and assumed error term to generate the conditional variance for different benchmark series.

4.3 Currency Risk Exposure

For regionally or globally focused funds, the return is reported in a domestic currency on a daily basis while the actual investments denominated in foreign currencies are taking place in the foreign countries. The domestically reported return is exposed to the currency risk. Lim (2005) raises a "currency-adjusted nominal form of the international CAPM" in real form as follows:

$$E_t(R_{t+1}^{SG} - rf_{t+1}^{FC}) = \beta_t E_t(R_{mt}^{FC}) + E_t(\Delta s_{t+1}^{SG} - \Delta\pi_{t+1}^{SG})\,. \tag{24}$$

, where R_{t+1}^{SG} is the excess return of funds invested in foreign countries but reported in Singapore dollars. $\Delta s_{t+1}^{SG} = \ln(S_{t+1}^{SG}) - \ln(S_t^{SG})$ is the nominal change of exchange rate, S_{t+1}^{SG} is the spot exchange rate at time t+1, which is defined as the amount of Singapore Dollar per foreign currency. $\lozenge\pi_{t+1}^{SG} = \pi_{t+1}^{SG} - \pi_{t+1}^{FC}$ is the inflation differential, where π_{t+1}^{SG} and π_{t+1}^{FC} are the inflation rate at time t+1 for domestic country and foreign country respectively. This implied that "estimates of the market beta can be biased if account is not taken of the currency risk."(see Lim, 2005)

The proposed GARCH framework to estimate the volatility timing coefficients of funds are specified as follows:

Step 1: $R_{mt} = \phi_0 + \sum_{i=1}^{p}\phi_i R_{m,t-i} + \varepsilon_t - \sum_{i=1}^{q}\theta_i\varepsilon_{t-i}$ where $R_{mt} = r_{mt} - r_{ft}$ (25)

Step 2: $\varepsilon_{mt} \mid \varepsilon_{m,t-1}, \varepsilon_{m,t-2}, \ldots \sim N(0,\sigma_{mt}^2)$ or $t(0,\sigma_{mt}^2)$ (26)

$$\ln\sigma^2{}_{mt} = a_0 + \sum_{i=1}^{s}\alpha_i \frac{\left|\varepsilon_{m,t-i}\right| + \gamma_i\varepsilon_{m,t-i}}{\sigma_{m,t-i}} + \sum_{j=1}^{m}\beta_j \ln\sigma_{m.t-j}^2 \tag{27}$$

$$\text{Or , } \sigma_{mt}^2 = a_0 + \sum_{i=1}^{m} a_i\varepsilon_{m,t-i}^2 + \sum_{j=1}^{s} b_j\sigma_{m,t-j}^2 \tag{28}$$

Step 3: $R_{pt} = \alpha_p + \sum_{k=1}^{K}\beta_{kp}R_{kt} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m)R_{mt} + \beta_{ct}R_{ct} + \varepsilon_{pt}$ (29)

, where $k = 1,2,3$ and $R_{ct} = \Delta s_{t+1}^{SG} - \Diamond\pi_{t+1}^{SG} - r_{ft}$

Equation (25) is the typical autoregressive generating process for market index. Equation (26) assumes the error term follows a conditional normal distribution with zero mean and conditional variance σ_{mt}^2. Equation (27) and Equation (28) accommodate the conditional variance in a GARCH or EGARCH framework. The choice of GARCH or EGARCH depends on the fitness series. Equation (29) is the modified factor model to analyze the response of funds to abnormal market volatility. When k =1, the excess return of the market index is the only factor considered except the excess return of exchange rate change; when k=2, the excess return of the market and HML[5] are loaded factors; when k=3, the excess return of the market, SMB[4] and HML are included in the model besides the excess return of exchange rate change. (see Fama and French, 1993)

4.4 Data Set

4.4.1 Funds

The funds chosen for this study are confined to those available in Singapore fund market, whether they are managed offshore or managed locally. Time series data are obtained from Bloomberg, while the categories of regional, country and global funds are from IMAS Fund Information Service[5]. Only equity funds are considered because of unavailability of benchmarks about bonds. Newly launched funds after 2006 are excluded because of the short duration. The daily return of funds is obtained from (30)

$$R_{fund,t} = \frac{NAV_t - NAV_{t-1}}{NAV_{t-1}}. \qquad (30)$$

, where NAV_t is the daily net asset value. I do not include dividends as a part of return, because the funds' dividend is not easily available. Similarly to what I do for market return,

[4] SMB is the risk factor about stock's size. HML describes the risk factor about stock's book to market equity ratio.
[5] Please refer to the link, http://www.fundsingapore.com/SG/xml/dsp_search_quick.xml for details.

the daily returns of CPF funds are taken natural log to get the continuously compounded return. The excess return of CPF funds I use in regression is calculated by (31).

$$R_{pt} = \ln(\frac{NAV_t}{NAV_{t-1}}) - \ln(1 + rf_t) \qquad (31)$$

There are seven Japan equity funds under CPF Investment Scheme and six non-CPF Japan equity funds. Five Funds under CPF Investment Scheme and 4 non-CPF funds are included because of sufficient number of observations. There are 13 global equity funds under CPF Investment Scheme, while non-CPF global equity funds are 13. However, only nine global funds under CPF Investment Scheme and seven non-CPF funds started before 2000. I fail to find the concrete geographic investment segments for two funds among the nine CPF global funds, as they are closed in the early May. Therefore, the final dataset includes seven CPF global equity funds and seven non-CPF global equity funds. In the case of Asian ex-Japan equity fund, 15 funds are under CPF Investment Scheme while 10 are not. Only 10 CPF funds and four non-CPF Asian ex-Japan equity funds are included in my sample. Five out of eight CPF funds and two out of three non-CPF funds are included in the sample of Greater China equity funds. The duration for Japan equity funds, global equity funds and Asian ex-Japan equity funds is from 2000 to 2006 on daily frequency. The duration for Great China equity funds is from 2000 to 2007 on daily frequency.

4.4.2 Benchmark

As funds listed in Singapore are invested in different countries all around the world, it is unreasonable to use a single index to describe the market returns. The market indices I use to generate excess returns are categorized by the markets which funds are investing in. If the funds are a specific country fund, a stock index of that country will be chosen as the market index; if the funds hold equity regionally or globally, a regional or global index will be chosen. Furthermore, the main regional or global index used in the funds' factsheets has the priority to be chosen as the benchmark index of the invested market. Daily excess returns of markets are generated by (32):

$$R_{mt} = \ln(\frac{P_{mt}}{P_{m,t-1}}) \times 100 - \ln(1 + rf_t) \times 100 \quad (32)$$

, where P_{mt} is the daily index of the market. MSCI Japan, MSCI world, MSCI Asian ex-Japan and MSCI Golden Dragon are chosen to be the market benchmarks for Japan equity funds, global equity funds, Asian ex-Japan equity funds and Greater China equity funds, respectively.

4.4.3 SMB and HML

SMB is the risk factor about stock's size. HML describes the risk factor about stock's book to market equity ratio. (see Fama and French, 1993) Stock size is usually negatively related to the stock return while stocks' BE/ME (book to market equity ratio) and price usually have a negative correlation. Therefore, SMB and HML are introduced to exclude the contribution of size and BE/ME to stocks' return. SMB and HML are country-specific, as they describe the size effect and BE/ME effect of specific stock market. Here I use two methods to create country or regional SMB and HML indices because of the limitation on data. In the case of Japan Equity Funds, I generally follow Fama-French's method to create SMB and HML from overall stock prices of Japanese market. In the case of regional funds, I mimic the Fama-French method from available stock indices, as the standardized method should be built on a huge regional stock database which is unavailable to me.

Japan Equity Funds

I apply index-creating method of Fama and French (1993). Their study uses the data of US stock market to create common risk factors. However, I do not strictly follow Fama-French method of variable-choosing because of availability of financial and market data and even the different accounting rules between US and Japan.

The raw financial and market data of Japanese companies listed in Tokyo Stock Exchange are downloaded from PACAP database. Companies from both financial industries and other industries are all included. In year t, companies are categorized into 6 portfolios based on their financial data. The 6 portfolio characteristics are small size low BE/ME portfolio(S/L), small size median BE/ME portfolio(S/M), small size high BE/ME portfolio(S/H), big size low BE/ME portfolio (B/L), big size median BE/ME portfolio (B/M) and big size high BE/ME portfolio (B/H). Size is defined as the market capitalization of year t in a country stock market. The median size of a country stock market is then used to split the stocks in that country into two groups, small and big. In other words, companies with an upper 50% rank in market cap are regarded as big size stocks, while companies with a lower 50% rank in market cap are regarded as small size stocks.

BE/ME is the book to market equity ratio. This ratio is the book value of a company divided by its market cap. After ranking stocks' BE/ME in a country from top to bottom, we gain three breakpoints for, the bottom 30%, the middle 40% and the top 30%. These breakpoints are used to split the stocks by their BE/ME.

Considering the building blocks for creating BE and ME, I define BE as the book value of shareholders' equity[6] in the year which a company's fiscal month ends. For example, a company's fiscal year begins at March of year t-1 and ends at March of year t. Then the book value of shareholder's equity reported in March of year t is regarded as the book values of equity of year t. Companies with negative BE are excluded. Companies with an inactive status which means it is delisted are also excluded.

ME is the market cap of stocks. This variable is constructed by the product of shares outstanding at the end of fiscal month of year t[7] and closing price on the last trading day of year t. For some reasons such as public holiday and stock suspension, the closing price of

[6] According to Fama and French (1993), the book value of equity (BE) is defined as the formula below: the value of stockholders' equity + balance-sheet deferred taxes and investment tax credit-book value of preferred stock. As the last two terms in the formula are unusual in Japan equity market, I reduced the definition of BE to be the value of stockholders' equity in my study.

[7] I assume that shares outstanding do not change much from its fiscal month to the end of the year t.

some companies on the last trading day of year t may be missing. In order to better reflect the wholesome performance of a country's stock market, I impute the missing closing price at the last trading by replacing it with the closing price of closed pasted days. For example, if the closing price of a company on the last trading day is missing, the closing price on the day before last trading day is used; if the closing price on the day before the last trading day is again missing, the price on the day before it is used. In a nutshell, the non-missing closing price of past days within the last trading week can be used to substitute the closing price of the last trading day if the latter one is missing. Then companies with missing shares outstanding or missing closing prices within the last trading week in year t are excluded.

The actual SMB and HML index in year t+1 used in the analysis are the composite daily returns of stocks from 6 portfolios of year t. The formulas for SMB and HML are following:

$$SMB_t = \frac{1}{3}(R_t^{S/L} + R_t^{S/M} + R_t^{S/H}) - \frac{1}{3}(R_t^{B/L} + R_t^{B/M} + R_t^{B/H}) \quad (32)$$

$$HML_t = \frac{1}{2}(R_t^{S/H} + R_t^{B/H}) - \frac{1}{2}(R_t^{S/L} + R_t^{B/L}) \quad (33)$$

, where R_t is the market cap weighted return within a specific portfolio. All the stock returns used to create market cap weighted return within a specific portfolio follow Equation (34).

$$R_i = \ln(\frac{P_{it}}{P_{i,t-1}}) \times 100 \quad (34)$$ [8]

, where R_i is the continuously compounded return of an individual stock.

Global Equity Funds

Based on the Fama-French method, the SMB index is generated by the difference between weighted-average return of small cap stocks and that of large cap stocks, while the HML index is created by the difference between weighted-average return of value stocks (high BM/ME) and that of growth stocks (low BM/ME). MSCI World value index and growth

[8] Dividend is not available in the database, so I exclude it from the calculation of returns.

index can be used to derive the return of global value stocks and growth stocks. Thus, global HML index is generated from the difference between return of MSCI World value index and that of MSCI World growth index. Similarly, MSCI Small Cap World index can be a good representative for global small cap stocks, from which the return of world small stock is derived. However, as it is very hard to get unpaid world large cap index from any index vendor, I create a composite world big cap index by weighting regional or country large cap indices available on Bloomberg. The large cap indices are Singapore STI, Japan NIKKEI 225, S&P Hong Kong Large Cap Index, Bloomberg European LC 500 and S&P 500. Their corresponding weights are 5%, 12%, 7%, 32% and 44%. The weights are determined by referring to average percentage of funds' geographic investment segments. Table E.1 [9] summarizes the actual average weights of funds' investment regions and determined weights.

Asian ex-Japan Equity Funds

HML index is created by weighting MSCI growth and value index of countries which funds are invested in[10]. The relevant regions are Hong Kong, Taiwan, China, India, Malaysia, Thailand, Korea and Indonesia. Their corresponding weights are 20%, 15%, 18%, 3%, 4%, 17% and 4%, which is determined by referring to the average percentage of funds' geographic investment segments and the weights of MSCI Asia ex-Japan. The detailed description of funds' investment segments is shown in Table E.2.

Greater China Equity Funds

HML index is created by weighting MSCI growth and value index of Hong Kong, Taiwan and China[9]. The relevant regions are Hong Kong, Taiwan, China and Singapore. Their

[9] In Table E.1, "determined weight 2" is used to generate composite inflation index, risk-free and world large cap index in order to decrease the use of series for countries with integrated economic condition like UK and Eurozone.

[10] As small cap indices for the relevant countries or region are not available or not long enough, I fail to mimic the SMB indices for Asian ex-Japan funds and Greater China funds. But I believe that exclusion of size indices will not affect the results much as asian funds usually invest in stocks with large or mid cap. Most of international funds are required to invest stock with a minimum market cap of 2 billion USD. This is one of reason why index vendors do not provides small cap indices for most Asian countries.

corresponding weights are 50%, 25%, 20% and 5%, which is determined by referring to the average percentage of geographic investment segments. Most of Greater China funds are based in Singapore and holding cash. Therefore, I regard Singapore as "implied investment region". The detailed description of funds' investment segments is shown in Table E.3.

4.4.4 Currency Risk

The currency risk is measured by its deviations from Purchasing Price Parity (PPP). (see Lim, 2005) All the funds' returns are reported in Singapore dollars, so the spot exchange rate at time t should be transferred to the amount of foreign currency per Singapore dollars. The continuously compounded rate about the change of exchange rate is captured by the formula:

$$\Delta s_{t+1}^{SG} = \ln(S_{t+1}^{SG}) - \ln(S_t^{SG}) \qquad (35)$$

, where S_t^{SG} is the spot exchange rate denominated in the amount of foreign currency per Singapore Dollar. The direct quotation between Singapore dollar and foreign currency is derived from the cross products of SGD against US quotation and foreign currency if it is not available. The inflation differential between foreign countries and Singapore are measured by the difference of their daily change of CPI indices, $\Diamond\pi_t = \pi_t^{SG} - \pi_t^{FC}$, where π_t^{FC} and π_t^{SG} are the change of CPI on daily basis for foreign countries and Singapore separately. The daily change CPI is transferred from monthly reported CPI index by the formula:

$$\pi_t = \ln[(CPI_{m+1} / CPI_m)^{1/22}]\,. \qquad (36)$$

, where CPI_m is the monthly CPI index at month m+1 and π_t is the daily continuously compounded CPI change. The excess return of currency risk defined as the difference between deviations from PPP and risk-free rate is applied in the regression as follows in (37).

$$R_{ct} = \Delta s_t^{SG} - \Diamond\pi_t^{SG} - rf_t^{FC} \qquad (37)$$

, where rf_t^{FC} is the risk free rate in the region or country in which funds are invested.

In the case of Japan equity funds, the spot exchange rate from 1 Jan 2000 to 31 Dec 2006 is obtained from DataStream. Monthly CPI index of Japan are obtained from CEIC and monthly CPI index of Singapore are gained from MAS. In the case of global equity funds, a composite series about world exchange rate change is derived by weighting the change of spot exchange rate in which funds' investment involves. Their corresponding weights are 18% for Euro, 10% for British Pound, 49% for US dollar[11], 12% for Japanese Yen, 1% for Switzerland Franc, 3% for Sweden Kronc and 1% for Canadian dollar[12]. Similarly, a composite series about global CPI change is derived by taking the weighted average of the change of regional CPI where funds' investment involves in. The weights are 7% for Hong Kong, 32% for European, 12% for Japan, 44% for US and 5% for Singapore[9]. In the case of Asian ex-Japan equity funds and Greater China equity funds, the composite index for CPI change of Greater China area is created by weighting relevant spots exchange rates. The detailed weights are shown in Table E.2 and E.3, respectively. The daily spot exchange rates are from Bloomberg, which regional or country monthly CPI series are from CEIC. As described, the inflation differential between foreign regions and Singapore is the difference between composite change in inflation and CPI change in Singapore.

4.4.5 Risk-free Rate

Different risk-free rates should be applied to funds focusing on different markets. As monthly rates can be easily accessed, I use the monthly rates and transfer the monthly risk-free rates into daily risk-free rates by (38).

$$rf_t^{FC} = \ln((rf_m^{FC} + 1)^{1/n} + 1) \times 100 \qquad (38)$$

, where rf_m^{FC} is the annualized monthly rate in which the funds are invested. n is defined to be 250, as it is the approximately trading days for a year. rf_t^{FC} is the daily continuously compounded risk-free rate for the funds' investment region.

[11] The weights for Hong Kong dollar is distributed to US dollar as it is pegged to US dollar.
[12] In Table E.1, "determined weight 1" is used to generate composite exchange rate change in order to catch regional currency risk change in detail.

In the case of Japan equity funds, 1-month deposit rate from Bank of Japan instead of government bond rate is used to be the risk-free rate, as Japan is in a liquid trap from 2000 and daily government bond rate would be almost zero. This rate is reported three times in a month, so I take the average rate reported in a month to the monthly risk-free rate for Japan. In the case of global equity funds, a composite world risk-free rate is constructed by taking the weighted average risk-free rates for relevant country or regions[9]. The raw data series are monthly exchange bill rate from Hong Kong Monetary Authority, monthly average rate of 3-month Euro currency from Bank of England, 1-month deposit rate from Bank of Japan and Singapore 3 month Treasury bill yield from Monetary Authority of Singapore. US risk free rate on daily basis is available on French data library[13]. The composite risk-free rates for Asian ex-Japan equity funds and Greater China equity funds are created by weighted risk-free rates of relevant countries. The risk-free rates referred are 1-montly time deposit rate for Taiwan, national interbank repurchase bond rate for China, 3-month cut off yield for India, monthly average yield on 91 CD for Korea, 3-month treasury bill discount for Malaysia, 3-to-6 month time deposit rate for Thailand, 3-month time deposit rate for Indonesia. All the weights referred are shown in Table E.1, E.2 and E.3, respectively.

4.5 Empirical Finding

4.5.1 Japan Equity Funds

The Dickey-fuller test is applied to test the stationarity of benchmark index. The t-statistics about excess return of MSCI Japan is -41.07, which indicates that there is no unit-root in both series. This series is described in Figure B.1.

As the day of the week effect may influence the Q-statistics (see Tsui and Yu, 1999), I apply the 5 dummy variables and autoregressive terms together to filter the raw series of excess return of market indices in (39).

[13] Please refer to website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for details.

$$R_{mt} = \sum_{j=1}^{5} d_j D_{jt} + \sum_{k=1}^{p} \phi_k R_{m,t-k} + \varepsilon_{mt} \quad (39)$$

In (37), R_{mt} is the excess return of market index. D_{1t} , D_{2t} , D_{3t} , D_{4t} and D_{5t} are dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday. D_{jt} is equal to 1 if the excess return of market index is from the j th day of the week, or else D_{jt} is equal to 0. d_j is the coefficients of D_{jt} to be estimated, while ϕ_k is the autoregressive coefficients for fitted lag-terms of R_{mt} . ε_{mt} is the residual series which will be used to generate GARCH model. The results about the mean-adjusted Equation with the day of the week effect for MSCI Japan are shown in the panel (b), Table 2.

To compare the effect of day of the week effect, I also apply the normal mean equation with autoregressive terms to filter the excess market return as follows.

$$R_{mt} = \sum_{k=1}^{p} \phi_k R_{m,t-k} + \varepsilon_{mt} \quad (40)$$

The results about the mean equation without the day of the week effect for excess return of MSCI Japan are shown in the panel (b), Table 2.

The Monday effect shows a negative coefficient while the coefficient of the Friday effect is positive in the series of excess return of MSCI Japan. This result is consistent with Dubois and Louvet’s research results, although it is not significance. (See Dubois and Louvet, 1996) The Q-statistics for residuals with day of the week effect are slightly lower than the residual without the day of the week effect. Q(9) for the with-day-week-effect residual is 6.372, while its Q(18) equals to 9.544. Q(9) for the without-day-of-week-effect residual equals to 6.559, while its Q(18) is 9.656. There is no evidence of significant serial correlation shown in both with-and-without the weekday effect residual. The description about standardized residuals with and without the weekday effect is given in Table D.1 and D.2, respectively.

Table 2
Autoregressive filter for the excess return of MSCI Japan

Series	d_1	d_2	d_3	d_4	d_5	ϕ_1	ϕ_{21}	ϕ_{22}
Panel (a): with the day of the week effect								
MSCI Japan		-0.0159 (0.0638)	-0.0451 (0.0638)	0.0522 (0.0637)	0.0746 (0.0747)	0.0360 (0.0236)	-0.0426 (0.0234)*	-0.0470 (0.0234)**
Panel (b): without the day of the week effect								
MSCI Japan						0.0359 (0.0235)	-0.0430 (0.0233)*	-0.0478 (0.0234)**
Note: (standard error is reported in parenthesis).** is at 5 % level of significance; * is at 10% level of significance								

Table 3
GARCH estimation for the excess return of MSCI Japan

Series	a_0	a_1	a_2	b_1	Log-likelihood	DW-Stat
Panel (a): with the day of the week effect						
MSCI Japan	0.0331 (0.00942)**	0.00397 (0.0188)	0.0909 (0.0209)**	0.886 (0.0155)**	-2807.349	1.997
Panel (b): without the day of the week effect						
MSCI Japan	0.0320 (0.00913)**	0.00577 (0.0191)	0.0889 (0.0211)**	0.887 (0.0153)**	-2807.937	1.997
Note: (standard error is reported in parenthesis).** is at 5 % level of significance; * is at 10% level of significance						

The large Q-statistics for all the residual series imply the GARCH effect. Therefore, both of residual series are estimated by a fitted GARCH model with normality error term. The fitted model is following.

$$\sigma^2{}_{mt} = a_0 + a_1\varepsilon^2_{m,t-1} + a_2\varepsilon^2_{m,t-2} + b_1\sigma^2_{m.t-1} \qquad (41)$$

In (41), ε_{mt} is the residual filtered by the adjusted-mean equation or mean equation. σ^2_{mt} is the conditional variance generated by the GARCH process. The results about a fitted GARCH (2, 1) model for excess return of the MSCI Japan with and without weekday effects are shown in Table 3.

In the series of the excess return of MSCI Japan, the estimates of with-and-without day of the week effect are similar. Although the ARCH coefficient a_1 is not significant, inclusion of it eliminates the serial correlation in the standardized residuals and the squared standardized residuals. The Q-statistics for standardized residuals filtered by both methods do not support the presence of serial correlation. However, the Q-statistics of the standardized residuals with day of the week effect are lower than that of the standardized residuals without day of the week effect. Q(9) and Q(18) of the standardized residual with the day of the week effect are 5.12 and 8.23, respectively. Q(9) and Q(18) of the standardized residual without the day of the week effect are 5.16 and 8.44, respectively. The Q-statistics for the squared standardized residuals filtered by both methods do not support the presence of serial correlation. However, the Q-statistics of the squared standardized residuals with day of the week effect are higher than that of the squared standardized residuals without day of the week effect. Q(9) and Q(18) of the squared standardized residuals with the day of the week effect are 8.84 and 18.19, respectively. Q(9) and Q(18) of the standardized residual without the day of the week effect are 8.74 and 18.02, respectively. The conditional volatility with and without weekday effects is described in Figure C.1.

Compared with the GARCH models with and without the day of the week effect, I find that the day of the week effect does not greatly affect the GARCH estimation. Furthermore, as the GARCH model without the day of the week effect yields lower Q-statistics for squared standardized residuals, I decide to apply the conditional variance generated by this model to the estimation of volatility-timing factor models.

The Dickey-Fuller test does not support the presence of unit-roots in funds' excess returns, SMB, HML and the excess return of real currency change. The description about the above series scheme is shown in Table D.3 and D.9, respectively. The correlation between conditional volatility and the return of MSCI Japan is 0.0257 with a t-statistic of 1.091. The correlation between ε_{mt}^2 and the excess return of MSCI Japan is -0.11 with a t-statistic of -4.695, which implies a negative correlation between the market return and the residuals. Therefore I expect a negative volatility-timing coefficient which shows funds can reduce the risk exposure to the volatile market.

I try four models to capture the volatility coefficient of funds: 1) single-index model without currency risk effect; 2) three-index model without currency risk effect; 3) single-index model with currency risk effect; 4) three-index model with currency risk effect. The single-index model is the market excess return of a traditional CAPM model. The single-index model with currency risk follows an international CAPM model which includes the market excess return and currency deviation to the excess return of funds. The three-index models with and without currency risk include SMB and HML as two additional factors. The four models are applied to both CPF funds and non-CPF funds. In order to exclude the possible multicollinearity among the explanatory variables, I orthogonalize SMB, HML and excess return of real currency change[14].

[14] I regress the SMB, HML and excess return of real currency change on the excess of market separately and derive the orthogonalized SMB, HML and excess return of real currency change by adding the constant to the corresponding regression residuals.

The results of Japan equity funds under CPF Investment Scheme are represented in Table 4. Most CPF funds show a negative volatility-timing coefficient, though the t-statistics are not significant in both the single-index and three-index models without currency risk effect. The t-statistics of Fund 4 show significance for volatility-timing coefficient in the three-index model with no currency risk effect, which means that this fund is more aggressive than other funds in volatility timing. Their volatility-timing coefficients, -0.155 and -0.173 also reveal they respond more to abnormal market volatility. When currency risk is included in the model specification, other four CPF funds show increasing response to the change of market conditional volatility by a more negative volatility-timing coefficient. Compared with the same model excluding currency risk effect, t-statistics of most funds increase greatly in the models with currency risk effect and without currency risk effect. Four out of five funds under CPF Investment Scheme show significance in the negative volatility timing coefficients in the three-index models including currency risk. This reveals that four funds will decrease their exposure to the volatile market, which can in turn contribute to the return positively. Only one fund shows a positive volatility-timing coefficient in the single-index model, thereby losing money from volatility-timing. But the t-statistics do not show any significance in this case.

Table 4
Volatility-timing coefficients for Japan equity funds under CPF Investment Scheme

Funds	Without currency risk		With currency risk	
	Single-index	Three-index	Single-index	Three-index
	γ_{mp}	γ_{mp}	γ_{mp}	γ_{mp}
Fund 1	-0.041	-0.048	-0.074	-0.082
	(0.95)	(1.10)	(1.77)	(1.96)*
Fund 2	-0.071	-0.077	-0.112	-0.121
	(1.54)	(1.70)	(2.57)*	(2.78)**
Fund 3	0.057	0.039	0.010	-0.011
	(1.30)	(0.90)	(0.25)	(0.27)
Fund 4	-0.155	-0.173	-0.128	-0.145
	(2.29)*	(2.55)*	(1.91)	(2.16)*
Fund 5	-0.060	-0.085	-0.106	-0.133
	(1.17)	(1.72)	(2.16)*	(2.84)**
$\bar{\gamma}_{mp}$	-0.155	-0.173	-0.109	-0.121
Group t-statistic	-1.592	-2.018	(3.331)*	(4.053)*
Note: (Absolute values of t statistics are in parentheses) * significant at 5%; ** significant at 1%				

The regression results about non-CPF funds are shown in Table 5. When currency risk is excluded, only one fund with volatility-timing coefficient of -0.09 is significant at 5% level in the three-index model. Although other three non-CPF funds have a negative volatility-timing coefficient in most cases, their t-statistics are far from the level to confirm the significant relation. Similarly, three funds out of four funds show increasing response to the change of market conditional volatility by a more negative volatility-timing coefficient, when the currency risk is included. Meanwhile, their increasing t-statistics result in the significance of two funds in the volatility-timing behavior. Fund 1 shows a negative volatility-timing coefficient -0.134 at 1% level of significance in the three-index model, while Fund 4 also shows a 5% level of significance in the single-index model and 1% level of significant in the three-index model.

Table 5
Volatility-timing coefficients for non-CPF Japan equity funds

Funds	Without currency risk		With currency risk	
	Single-index	Three-index	Single-index	Three-index
	γ_{mp}	γ_{mp}	γ_{mp}	γ_{mp}
Fund 1	-0.048	-0.080	-0.099	-0.134
	(0.83)	(1.50)	(1.79)	(2.64)**
Fund 2	-0.016	-0.054	-0.017	-0.057
	(0.41)	(1.55)	(0.44)	(1.61)
Fund 3	-0.032	-0.040	-0.031	-0.040
	(1.18)	(1.49)	(1.15)	(1.48)
Fund 4	-0.064	-0.090	-0.090	-0.118
	(1.52)	(2.19)*	(2.17)*	(2.93)**
$\bar{\gamma}_{mp}$	-0.040	-0.090	-0.090	-0.126
Group t-statistic	(3.87)*	(5.73)**	(2.87)*	(3.81)*

Note: (Absolute values of t statistics are in parentheses) * significant at 5%; ** significant at 1%

Though the t-statistics of some funds fail to be significant in their volatility-timing coefficients, I take the average of the significant volatility-timing coefficients in the group of CPF funds and non-CPF funds respectively to explore the group behavior funds. Average volatility timing coefficient for CPF funds is -0.155 and -0.173 in the single index and three-index models without currency risk respectively, which is lower than their non-CPF counterparts. However, the group t-statistics[15] for the average volatility-timing coefficient of CPF funds are not significant. All the group t-statistics for non-CPF funds are significant. The average volatility-timing coefficient of CPF funds with significant t-statistics increases to -0.109 in the single-index model with currency risk. Compared with the counterpart coefficients of non-CPF fund under the same model, CPF funds show a lower negative volatility-timing coefficient which reveals that CPF funds decrease their exposure to the volatile market more than non-CPF funds. As volatile market is usually accompanied by negative market return, a lower negative volatility-timing coefficient means CPF funds are stronger in risk management which can in turn generate positive return in the volatile market. As such, currency risk plays an important role in the model specification of international asset management. Inclusion of currency risk consolidates our conclusion about strong risk management of CPF Japan equity funds.

4.5.2 Global Equity Fund

The t-statistic of the Dickey-Fuller test about the excess return of MSCI World is -37.10, which indicates the absence of unit-roots in the series. This series is described in the Figure B.2. The results about the mean equation with and without the day of the week effect for excess return of MSCI World are shown in the panel (a) and the panel (b) of Table 6, respectively. The coefficient for Monday effect is negative, but the coefficient for Friday effect is negative too. Both of the coefficients are not significant. The coefficient for Thursday effect is positive with a t-statistic close to the significant level. Similarly to the autoregressive result about the excess return of MSCI Japan, both autoregressive filters capture the movement of the series. However, the Q-statistics for residual with day of the week effect are slightly higher than the residual without the day of the week effect. Q(9) for the with-day-week-effect residual is 9.416, while its Q(18) equals to 15.762. Q(9) for the without-day-of-

[15] As the volatility-timing coefficients for different funds are independent, the formula for group t-statistic is following:

$$t = E(\gamma_i) / STD(\gamma_i) * \sqrt{n}$$

, where γ_i is the funds' volatility-timing coefficients and n is is the number of funds.

Table 6
Autoregressive filter for the excess return of MSCI World

Series	d_1	d_2	d_3	d_4	d_5	ϕ_1	ϕ_2	ϕ_5	ϕ_8	ϕ_{19}
Panel (a): with the day of the week effect										
MSCI World	-0.0246 (0.0436)	-0.0146 (0.0436)	-0.0380 (0.0436)	0.0680 (0.0436)	-0.0145 (0.0436)	0.147 (0.0234)**	-0.0441 (0.0235)*	-0.0403 (0.0232)*	0.0420 (0.0232)*	-0.0578 (0.0231)**
Panel (b): without the day of the week effect										
MSCI World						0.146 (0.0234)**	-0.0441 (0.0235)*	-0.0382 (0.0232)*	0.0417 (0.0232)*	-0.0582 (0.0230)**
Note: (standard error is reported in parenthesis).** is at 5 % level of significance; * is at 10% level of significance										

Table 7
GARCH estimation for the excess return of MSCI World

Series	a_0	a_1	b_1	Log-likelihood	DW-Stat
Panel (a): with the day of the week effect					
MSCI World	0.00556 (0.00225)**	0.0750 (0.0108)**	0.918 (0.0116)**	-2071.247	2.004
Panel (b): without the day of the week effect					
MSCI World	0.00519 (0.00215)**	0.0746 (0.0107)**	0.919 (0.0114)**	-2069.299	2.004
Note: (standard error is reported in parenthesis).** is at 5 % level of significance; * is at 10% level of significance					

week-effect resiual equals to 9.057, while its Q(18) is 15.025. Both of the residual series are described in Table D.1 and D.2, respectively.

The estimated results of a fitted GARCH (1, 1) for the excess return of MSCI World are given in the panel (a) and panel (b) of Table 7, respectively. The estimates with and without day of the week effect are also similar, while no serial correlation is shown in standardized residuals and squared standardized residuals based on the Q-statistics. The Q-statistics of the standardized residuals and the squared standardized residuals with day of the week effect are close to those of the standardized residuals without the day of the week effect. Q(9) and Q(18) of the standardized residual with the day of the week effect are 4.16 and 13.71, respectively. Q(9) and Q(18) of the standardized residual without the day of the week effect are 4.09 and 13.73, respectively. Q(9) and Q(18) of the squared standardized residual with the day of the week effect are 7.97 and 16.27, respectively. Q(9) and Q(18) of the squared standardized residuals without the day of the week effect are 8.10 and 15.79, respectively. Both of the series of conditional variance are plotted in Figure C.2.

As the day of the week effect does not show significant effect in the series of excess return of MSCI World, the conditional volatility without the day of the week effect is chosen to be the benchmark volatility. There is no evidence of unit-roots for excess return of funds, SMB, HML and excess return of real currency change, as the description of above series is presented in Table D.4, D.5 and D.10, separately. The correlation between return of MSCI World and its conditional volatility is 0.0294 with a non-significant t-statistics of 1.248. The correlation between the excess return of MSCI Japan and its corresponding ε_{mt}^2 is 0.0091 below its significant level. This implies that their correlation is not significantly different from zero. As such, a negative coefficient is expected for funds with good volatility-timing ability.

The results of CPF global equity funds are presented in Table 8. Except Fund 6 and Fund 5, most funds under CPF Investment Scheme show a negative volatility-timing coefficient, though the t-statistics are not significant in both single-index and three-index models without currency effect. Both Fund 5 and Fund 6 have a positive volatility-timing coefficient, which implies that they become more exposed to the market volatility and their investment strategy may overweight volatile index stocks. Only Fund 4 shows significant volatility-timing coefficients -0.172 and -0.181 in both the single-index and the three-index model without currency coefficient, which reveals they respond more to abnormal market volatility. When the model is corrected by including currency risk effect, the volatility-timing coefficients of most funds become more negative. The negative volatility-timing coefficient with Fund 1, Fund 3 and Fund 7 become significant in either single-index model or three-index model. Therefore, four out of seven CPF funds have the behavior of decreasing their exposure to volatile market, which can in turn contribute to the return positively. Fund 5 and Fund 6 keep

Table 8
Volatility-timing coefficients for global equity funds under CPF Investment Scheme

Funds	Without currency risk		With currency risk	
	Single-index	Three-index	Single-index	Three-index
	γ_{mp}	γ_{mp}	γ_{mp}	γ_{mp}
Fund 1	-0.047	-0.020	-0.093	-0.045
	(1.56)	(0.64)	(3.09)**	(1.50)
Fund 2	-0.060	-0.019	-0.067	-0.031
	(0.89)	(0.28)	(0.98)	(0.45)
Fund 3	-0.024	-0.058	-0.115	-0.095
	(0.49)	(1.15)	(2.36)*	(1.92)
Fund 4	-0.172	-0.181	-0.175	-0.182
	(3.33)**	(3.40)**	(3.32)**	(3.40)**
Fund 5	0.213	0.225	0.193	0.215
	(3.69)**	(3.77)**	(3.28)**	(3.60)**
Fund 6	0.211	0.113	0.112	0.084
	(5.03)**	(2.67)**	(2.74)**	(2.03)*
Fund 7	-0.056	-0.085	-0.127	-0.114
	(1.37)	(2.01)*	(3.12)**	(2.75)**
$\bar{\gamma}_{mp}$	0.084	0.0184	-0.0342	0.0075
Group t-statistic	0.17	-0.071	-0.75	-0.48
Note: (Absolute values of t statistics are in parentheses) * significant at 5%; ** significant at 1%				

a positive volatility-timing coefficient in the model specification with currency risk effect, which means this fund may lose money because of fail in volatility timing.

The regression results about non-CPF global funds are shown in Table 9. When the currency risk effect is excluded, only Fund 7 with volatility-timing coefficients of -0.124 and -0.156 is significant at the 5% level in both single-index and three-index model. Fund 3 shows a positive volatility-timing coefficient with the 5% significance level. Although other five non-CPF funds have a negative volatility-timing coefficient, their t-statistics are far from the level to confirm the significant relation. Similar to the result of non-CPF Japan equity fund, when the currency risk is included, most funds show increasing response to the change of market conditional volatility by a decreasing negative volatility-timing coefficient. However, their increasing t-statistics don't have any improvement. Fund 3 shows a negative volatility-timing coefficient -0.136 at the 5% level of significance in the three-index model with currency risk,

Table 9
Volatility-timing coefficients for non-CPF global equity funds

Funds	Without currency risk		With currency risk	
	Single-index	Three-index	Single-index	Three-index
	γ_{mp}	γ_{mp}	γ_{mp}	γ_{mp}
Fund 1	0.030	0.010	0.019	0.010
	(1.30)	(0.45)	(0.84)	(0.44)
Fund 2	0.044	-0.053	-0.124	-0.117
	(0.33)	(0.38)	(0.91)	(0.85)
Fund 3	0.136	-0.076	-0.068	-0.136
	(2.31)*	(1.33)	(1.25)	(2.49)*
Fund 4	-0.033	-0.018	-0.033	-0.031
	(1.53)	(0.78)	(1.53)	(1.41)
Fund 5	-0.118	-0.059	-0.103	-0.062
	(1.69)	(0.82)	(1.45)	(0.86)
Fund 6	-0.046	-0.010	-0.002	0.003
	(1.49)	(0.31)	(0.08)	(0.08)
Fund 7	-0.124	-0.156	-0.192	-0.183
	(3.13)**	(3.84)**	(4.87)**	(4.56)**
$\bar{\gamma}_{mp}$	0.006	-0.156	-0.192	-0.160
Group t-statistic	-0.45	(2.48)**	(2.57)**	(2.65)**
Note: (Absolute values of t statistics are in parentheses) * significant at 5%; ** significant at 1%				

while Fund 7 keeps negative volatility-timing coefficients with 1% level significance in both the single-index and the three-index models.

The average significant volatility-timing coefficients of CPF global equity fund is less negative that its non-CPF counterparts in both single-index and three-index models, although the negative volatility-timing coefficients of CPF global equity fund are insignificant. This is mostly because two funds with positive volatility-timing coefficients in CPF group increase the group coefficients. All the group t-statistics for volatility-timing coefficients of non-CPF funds are significant. Therefore, I cannot jump to the conclusion that CPF global equity funds show strong risk management from their group volatility-timing coefficients. However, there are more funds with negative volatility-timing coefficients in the CPF group.

4.5.3 Asian ex-Japan Equity funds

The t-statistic of the Dickey-fuller test about the excess return of MSCI Asian ex-Japan index is -41.27, which does not support the presence of unit-roots in the series. The excess return of MSCI Asian ex-Japan is described in Figure B.3.

I again apply the autoregressive filter to analyze whether the day of week effect has an impact on the mean equation. The results about the mean equation with and without the day of the week effect for excess return of MSCI Asian ex-Japan are shown in the panel (a) and (b) of Table 10, respectively. The Monday effect shows significance with a negative coefficient, while the coefficient of the Friday effect is positive in the mean equation of excess return of MSCI Asian ex-Japan. The t-statistics for both of the coefficients are significant, which confirms the research results of Dubois and Louvet (1996) that Monday has negative effect on the stock return, while Friday has a positive effect. Q(9) for the with-day-week-effect residual is 9.814, while its Q(18) equals to 13.565. Q(9) for the without-day-of-week-effect residual equals to 9.311, while its Q(18) is 13.612. The Q statistics for the with-day-week-effect standardized residual become smaller than those of the without-day-week-effect standardized

Table 10
Autoregressive filter for the excess return of MSCI Asian ex-Japan

Series	d_1	d_2	d_3	d_4	d_5	ϕ_1	ϕ_3	ϕ_9	ϕ_{13}	ϕ_{18}
Panel (a): with the day of the week effect										
MSCI Asian ex-JP	-0.137 (0.0596)**	0.00639 (0.0596)	0.0743 (0.0596)	-0.000619 (0.0596)	0.110 (0.0596)*	0.114 (0.0224)**	0.0437 (0.0233)*	-0.0476 (0.0233)**	0.0516 (0.0233)**	0.0754 (0.0231)**
Panel (b): without the day of the week effect										
MSCI Asian ex-JP						0.111 (0.0233)**	0.0425 (0.0233)*	-0.0494 (0.0233)**	0.0505 (0.0233)**	0.0749 (0.0231)**
Note: (standard error is reported in parenthesis).** is at 5 % level of significance; * is at 10% level of significance										

Table 11
EGARCH estimation for the excess return of MSCI Asian ex-Japan

Series	a_0	a_1	λ_1	b_1	Log-likelihood	DW-Stat
Panel (a): with the day of the week effect						
MSCI Asian ex-JP	-0.0922 (0.0147)**	0.123 (0.0191)**	-0.0869 (0.0106)**	0.969 (0.00610)**	-2596.331	2.003
Panel (b): without the day of the week effect						
MSCI Asian ex-JP	-0.0903 (0.0143)**	0.122 (0.0185)**	-0.0884 (0.0102)**	0.970 (0.00570)**	-2594.638	2.002
Note: (standard error is reported in parenthesis).** is at 5 % level of significance; * is at 10% level of significance						

residual, when the lagged term increases. The Q-statistics of squared standardized residuals with-and-without weekday effect are large, which indicates that squared residuals contain the GARCH effect. There is no significant serial correlation shown in both with-and-without the weekday effect residual. The standardized residuals with and without the weekday effect are described in Table D.1 and D.2, respectively.

As the Jarque-Bera statistic indicates strong kurtosis in the residuals of the autoregressive filter, I apply a fitted EGARCH model with normally distributed error term as follows.

$$\ln \sigma^2_{mt} = a_0 + a_1 \frac{\left|\varepsilon_{m,t-1}\right| + \lambda_1 \varepsilon_{m,t-1}}{\sigma_{m,t-1}} + b_1 \ln \sigma^2_{m,t-1} \tag{42}$$

The results about a fitted EGARCH (1, 1) model for the excess return of MSCI Asian ex-Japan are shown in Table 11. The EGARCH estimates for residuals of with-and-without the day of the week effect are similar. The leverage coefficients λ_1 are -0.0869 and -0.0884 with the 5% level of significance in the series of residual with weekday effect and that without weekday effect respectively. The Q-statistics for standardized residuals do not support the presence of serial correlation. The Q-statistics of the standardized residuals and the squared standardized residuals with day of the week effect are close to those without day of the week effect. Q(9) and Q(18) of the standardized residual with the day of the week effect are 4.903 and 10.618, respectively. Q(9) and Q(18) of the standardized residual without the day of the week effect are 5.341 and 11.392, respectively. Q(9) and Q(18) of the squared standardized residuals with the day of the week effect are 7.850 and 14.093, respectively. Q(9) and Q(18) of the standardized residuals without the day of the week effect are 7.691 and 13.498, respectively. Both of the series of conditional variance are described in Figure C.3.

Compared with the EGARCH models with and without the day of the week effect, I find that the day of the week effect greatly affects the EGARCH estimation in the series of excess return of MSCI Asian ex-Japan. Therefore, I decide to apply conditional variance generated with the day of the week effect to the estimation of volatility-timing factor models.

There is no evidence of unit roots for excess return of funds, SMB, HML and excess return of real currency change. (see Tables D.5, D.6 and D.11) The correlation between conditional volatility and excess return of MSCI Asian ex-Japan is -0.041 with a t-statistic of 1.741. The correlation between ε_{mt}^2 and excess return of MSCI Asian ex-Japan is -0.178 with a significant t-statistics of -7.682, which implies a negative correlation between the market return and residuals. In the case of the excess return of MSCI Asian ex-Japan, I can expect a negative volatility-timing coefficient which shows funds can reduce the risk exposure to the volatile market. The single-index and two-index models with and without currency effect are applied to Asian ex-Japan equity funds under CPF Investment Scheme and non-CPF funds[16].

The results of Asian ex-Japan funds under CPF Investment Scheme are represented in Table 12. Most funds under CPF Investment Scheme show a positive volatility-timing coefficient, though the t-statistics are not significant in both the single-index and the two-index models without currency risk. Fund 2 and Fund 3 shows negative volatility-timing coefficients in the two-index models with no currency effect, but they are far from significant. Fund 1, Fund 8, Fund 9 and Fund 10 have significant positive volatility-timing coefficients in both the single-index and the two-index models. This indicates they are bad performers in the turmoil market. A positive volatile-timing coefficient implies that increasing market exposure may contribute negatively contribute to the funds' return as market return is usually negative correlated with volatility. The signs of volatility-timing coefficients and their t-statistics do not change much when currency risk is included in the model specification. In all, four funds out of 10 under CPF Investment Scheme show significance in the positive volatility timing coefficient in two-

[16] Here I fail to apply the traditional Fama-French three-index model, because the SMB index for Asia ex-Japan cannot be constructed from available data. Based on my experience, the lack of SMB in the models will not have great impact on the estimation of volatility-timing coefficients, as international funds usually focus on big cap stocks.

index models with currency risk. This reveals that these four funds have the behavior of increasing their exposure to volatile market, which can in turn contribute to the return negatively.

Table 12
Volatility-timing coefficients for Asian ex-Japan equity funds under CPF Investment Scheme

Funds	Without currency risk		With currency risk	
	Single-index	Two-index	Single-index	Two-index
	γ_{mp}	γ_{mp}	γ_{mp}	γ_{mp}
Fund 1	0.082	0.08	0.081	0.079
	(3.16)**	(3.14)**	(3.14)**	(3.12)**
Fund 2	-0.06	-0.058	-0.061	-0.059
	-1.26	-1.22	-1.29	-1.26
Fund 3	-0.003	-0.004	-0.002	-0.003
	-0.1	-0.13	-0.07	-0.1
Fund 4	0.015	0.017	0.012	0.014
	-0.38	-0.43	-0.31	-0.35
Fund 5	0.02	0.022	0.017	0.018
	-0.68	-0.73	-0.6	-0.64
Fund 6	0.1	0.099	0.099	0.098
	(2.64)**	(2.61)**	(2.62)**	(2.60)**
Fund 7	0.035	0.037	0.033	0.035
	-0.89	-0.94	-0.85	-0.9
Fund 8	0.118	0.118	0.116	0.116
	(2.65)**	(2.65)**	(2.63)**	(2.62)**
Fund 9	0.059	0.061	0.058	0.06
	-1.43	-1.49	-1.4	-1.46
Fund 10	0.102	0.102	0.098	0.099
	(3.54)**	(3.57)**	(3.57)**	(3.59)**
$\bar{\gamma}_{mp}$	0.101	0.0998	0.0985	0.098
Group t-statistic	2.65**	2.72**	2.57**	2.64**
Note: (Absolute values of t statistics are in parentheses) * significant at 5%; ** significant at 1%				

The regression results of non-CPF Asian ex-Japan equity funds are shown in Table 13. When currency effect is excluded, Fund 1 with volatility-timing coefficients of 0.124 and is significant at the 1% level in both the single index and two-index models. Fund 2 shows a positive volatility-timing coefficient with the 5% significance level. Fund 3 also has a positive volatility-timing coefficient close to its 5% level of significance. Only Fund 4 has a negative coefficient, but its t-statistics is far from significant. Inclusion of currency risk does not improve the model specification in this case, as the coefficients of currency risk are not significant in three out of four funds[17].

Table 13
Volatility-timing coefficients for non-CPF Asian ex-Japan equity funds

Funds	Without currency risk		With currency risk	
	Single-index	Three-index	Single-index	Three-index
	γ_{mp}	γ_{mp}	γ_{mp}	γ_{mp}
Fund 1	0.124	0.124	0.121	0.121
	(2.65)**	(2.64)**	(2.62)**	(2.61)**
Fund 2	0.085	0.086	0.084	0.086
	(2.12)*	(2.16)*	(2.11)*	(2.16)*
Fund 3	0.057	0.058	0.057	0.057
	-1.69	-1.71	-1.68	-1.7
Fund 4	-0.017	-0.015	-0.017	-0.015
	-0.62	-0.56	-0.62	-0.56
$\bar{\gamma}_{mp}$	0.105	0.105	0.105	0.104
Group t-statistic	2.09	2.15*	2.10	2.16*
Note: (Absolute values of t statistics are in parentheses) * significant at 5%; ** significant at 1%				

The average significant volatility-timing coefficients of CPF Asian ex-Japan equity fund with significant group t-statistics is less positive than that its non-CPF counterparts in both the single-index and two-index models. In this case, both CPF and non-CPF funds fail to show any advantage in volatility-timing. However, non-CPF funds are even poorer in risk management, as a more positive volatility-timing coefficient implies the returns of non-CPF funds can be pulled down more by the negative market return than those of CPF funds with less positive coefficients.

4.5.4 Greater China Equity Funds

The t-statistic of the Dickey-fuller test about the excess return of MSCI Golden Dragon is -42.39, which indicates the absence of unit roots in the series. This series is described in Figure B.4.

[17] Please refer to Table F.17 in Appendix F for the regression results in detail.

The results about the mean equation with and without the day of the week effect for excess return of MSCI Golden Dragon are shown in panel (a) and panel (b) of Table 14, respectively. The t-statistic for a negative coefficient in the autoregressive filter of excess return of MSCI Golden Dragon is -1.436, which is close to its significance level. Similar to the Monday effect, a positive Friday effect has a t-statistics closer to its significance level. Q(9) for the with-day-week-effect residuals is 10.061, while its Q(18) equals to 22.807. Q(9) for the without-day-of-week-effect residuals equals to 9.766, while its Q(18) is 23.045. The Q statistics for the with-day-week-effect standardized residual become gradually smaller than the Q statistics for the without-day-week-effect standardized residual, when the lagged term is increasing. The Q-statistics for the squared standardized residuals with-and-without weekday effect are large, which indicates that squared residuals may contain the GARCH effect. However, I do not find evidence of serial correlation shown in both with-and-without the weekday effect residuals. The residual series are described in Table D.1 and D.2, respectively.

Considering the significant Jarque-Bera statistics indicates strong kurtosis in the residuals of autoregressive filter, an EGARCH model with t-distribution is applied to the residual series. The estimation results about a fitted EGARCH (1, 1) model for the excess return of MSCI Golden Dragon are shown in Table 15. The EGARCH estimates for residuals of with-and-without the weekday effect have slight difference. The coefficients for t-distribution error are 8.398 and 8.275, respectively, both of which are far above its 5% level of significance. This confirms that ε_{mt} follows conditional t distribution. The leveraged coefficients λ_1 are -0.0636 and -0.0657, respectively for with the weekday-effect residuals and without-the-weekday-effect residuals. The Q-statistics for standardized residuals do not support the presence of serial correlation. The significant t-statistics for λ_1 confirm the existence of leveraged effect in both residual series. The Q-statistics of the standardized residuals without day of the week effect are smaller than its counterparts with the day of the week, whereas Q-statistics for the standardized residual squared are slightly bigger. Q(9) and Q(18) of the standardized residual without the day of the week effect are 3.913 and 12.007, respectively. Q(9) and Q(18) of the standardized residual with the day of the week effect are 3.971 and 12.338, respectively. Q(9) and Q(18) of the squared standardized residuals without the day of the week effect are 4.063 and 20.89, respectively. Q(9) and Q(18) of the standardized residuals without the day of the week effect are 3.967 and 20.849, respectively. The conditional variances with weekday effect and without weekday effect are described in Figure C.4.

Conditional variance generated by the EGARCH without the weekday effect is applied to the factor model, as the weekday effect fails to be significant in the series of the excess return of MSCI Golden Dragon and the Q-statistics for standardized residual without the weekday effect is better. There is no evidence of unit-roots for the excess return of funds, SMB, HML and the excess return of real currency change. Those series are described in Table D.8 and D.12, respectively. The correlation between conditional volatility and return of MSCI Golden Dragon is -0.0142, which is below its significant level. The correlation between ε_{mt}^2 and excess return of MSCI Golden Dragon is -0.0404 with a t-statistics of -1.835. This implies a negative correlation between the market return and residuals. In the case of the excess return of MSCI Golden Dragon, I can expect a negative volatility-timing coefficient which shows funds can reduce the risk exposure to the volatile market.

Table 14
Autoregressive filter for the excess return of MSCI Golden Dragon

Series	d_1	d_2	d_3	d_4	d_5	ϕ_1	ϕ_3	ϕ_{13}	ϕ_{25}
Panel (a): with the day of the week effect									
MSCI Golden Dragon	-0.0962 (0.0669)	0.0127 (0.0669)	0.0237 (0.0669)	-0.00177 (0.0669)	0.0993 (0.0669)	0.0733 (0.0219)**	0.0596 (0.0219)**	0.0728 (0.0220)**	0.0544 (0.0220)**
Panel (b): without the day of the week effect									
MSCI Golden Dragon						0.0718 (0.0219)**	0.0594 (0.0219)**	0.0726 (0.0220)**	0.0569 (0.0219)**
Note: (standard error is reported in parenthesis).** is at 5 % level of significance; * is at 10% level of significance									

Table 15
EGARCH estimation for the excess return of MSCI Golden Dragon

Series	a_0	a_1	λ_1	b_1	t	Log-likelihood	DW-Stat
Panel (a): with the day of the week effect							
MSCI Golden Dragon	-0.0763 (0.0140)**	0.108 (0.019)**	-0.0636 (0.0118)**	0.981 (0.00511)*	8.398 (1.736)**	-3215.881	1.99
Panel (b): without the day of the week effect							
MSCI Golden Dragon	-0.0765 (0.0140)**	0.109 (0.019)**	-0.0651 (0.0119)**	0.981 (0.00514)*	8.275 (1.685)**	-3214.176	1.99
Note: (standard error is reported in parenthesis).** is at 5 % level of significance; * is at 10% level of significance							

The results of Greater China equity funds under CPF Investment Scheme are presented in Table 16. Three out of five CPF funds show positive volatility-timing coefficients with significant t-statistics in both the single-index and two-index models without currency risk. Fund 2 shows a negative volatility-timing coefficient in the two-index model with no currency effect. However, its t-statistic narrowly misses the significant level. When currency risk is included in the model specification, four out of five funds show a more positive volatility-timing coefficient in the same models, although the t-statistic of Fund 3 is still not significant. Compared with the same model excluding currency effect, the coefficient t-statistics of most funds increase greatly in both with-currency effect and without-currency effect model specification. In all, the results about regression of CPF fund reveal that three funds have the behavior of increasing their exposure to the volatile market, which can in turn contribute to the return negatively.

Table 16
Volatility-timing coefficients for Greater China equity funds under CPF Investment Scheme

Funds	Without currency risk		With currency risk	
	Single-index	Two-index	Single-index	Two-index
	γ_{mp}	γ_{mp}	γ_{mp}	γ_{mp}
Fund 1	0.109	0.106	0.11	0.107
	(3.37)**	(3.28)**	(3.41)**	(3.32)**
Fund 2	-0.055	-0.051	-0.054	-0.05
	-1.74	-1.64	-1.71	-1.6
Fund 3	0.024	0.021	0.026	0.023
	-0.77	-0.68	-0.87	-0.78
Fund 4	0.146	0.142	0.148	0.145
	(4.91)**	(4.81)**	(5.17)**	(5.09)**
Fund 5	0.119	0.116	0.119	0.116
	(4.09)**	(4.00)**	(4.08)**	(3.99)**
$\bar{\gamma}_{mp}$	0.0686	0.0668	0.0698	0.0682
Group t-statistic	1.85	1.87	1.89	1.90
Note: (Absolute value of t statistics in parentheses) * significant at 5%; ** significant at 1%				

There are only two non-CPF Greater China equity funds available in Singapore. The regression results are shown in the Table 17. When currency effect is excluded, Fund 1 with the volatility-timing coefficients of 0.179 and 0.181 is significant at the 1% level in both the single index and three-index models. Fund 2 shows a positive volatility-timing coefficient, but it is not significant. When the currency risk is included, the volatility-timing estimates do not have any change in Fund 1, as currency risk does not have any effect on the model. In Fund 2, inclusion of currency risk boosts the t-statistic up in both the single-index and two-index models, but it is still far from significant.

Table 17
Volatility-timing coefficients for non-CPF Greater China equity funds

Funds	Without currency risk		With currency risk	
	Single-index	Two-index	Single-index	Two-index
	γ_{mp}	γ_{mp}	γ_{mp}	γ_{mp}
Fund 1	0.179	0.181	0.179	0.180
	(3.22)**	(3.25)**	(3.22)**	(3.25)**
Fund 2	-0.022	-0.024	-0.02	-0.021
	-0.72	-0.75	-0.66	-0.68
$\bar{\gamma}_{mp}$	0.179	0.181	0.179	0.180
Group t-statistic	0.78	0.77	0.80	0.79

Note: (Absolute values of t statistics are in parentheses) * significant at 5%; ** significant at 1%

The average volatility-timing coefficient of CPF Greater China equity fund is less positive than that its non-CPF counterparts in both the single-index and two-index models, although none of their group t-statistics is significant. In this case, Greater China equity funds fail to show any advantage in volatility timing. However, more individual funds under CPF Investment Scheme have a less positive volatility-timing coefficient than non-CPF individual funds.

CHAPTER 4: CONCLUSION

In this thesis, I have applied the factor models with volatility-timing adjustment to funds available in Singapore. Instead of using the moving average volatility, I employ the conditional variance computed from GARCH or EGARCH models to capture the market volatility. In addition, the day of the week effect is captured in the GARCH specification. Moreover, it is found that currency risk has a significant impact on model specification, as most funds show a significant response to the currency risk premium[18].

When applying my models to non US-based funds, I have encountered difficulties in obtaining appropriate datasets. It is because the benchmarks and factor indices are hardly available for Asian funds. In order to overcome data problem, I follow the Fama-French method to generate SMB and HML indices for Japan with adjustment to Japan's accounting rule. In the case of global funds, Asian ex-Japan funds and Greater China funds, I also mimic the Fama-French approach by weighting size, growth and value indices available to me. As such, I manage to create composite indices to describe the funds' currency risk and risk-free rate by similar methods.

Although this thesis does not cover all funds available in Singapore because of data limitation, I find the evidence of volatility-timing ability in Japan and global equity funds. This implies that fund managers will decrease funds' exposure to the market volatility to increase their performance, when the market is volatile. Inclusion of currency risk exposure improves the model specification. It is found that the managers of CPF Japan equity funds show stronger ability in risk management, as their average volatility-timing coefficient is more negative than that of non-CPF funds. In addition, CPF global equity funds fail to show any advantage in risk management by their average volatility-timing coefficient. However, there are more

[18] The details about regression results for the factor models of different sample group are shown in the tables of Appendix F.

funds with negative volatility-timing coefficients in the CPF group. With positive volatility-timing coefficients, Asian ex-Japan funds and Greater China funds fail to indicate any volatility-timing ability. Those funds may increase market exposure when the market is volatile, which in turn decrease their performance. This may be mainly caused by the lack of diversification for regional funds in Asia. As international fund managers can only invest in funds with minimum 2 billion market capitalization, they have less qualified stocks to adjust their active portfolio.

My findings may have important implications to the risk classification of CPF Investment Scheme. Besides the normal risk description like standard deviation, fund's intrinsic risk can be described as funds' manager ability of risk control over the market. This may help investors to have a better understanding of the essence of funds' risk. However, this study can be further improved in several aspects. First, the results may be reliable with more adequate factor indices. Second, it will be more appropriate to apply the volatility-timing model to hedge funds which are usually more aggressively managed. As volatility timing may require active-trading (see Fleming, Kirby and Ostdiek, 2001), hedge funds may be more obvious in adjusting the volatility compared to mutual funds. Third, multivariate GARCH models can be applied to capture the conditional covariance, as the global market is more integrated in the last decades. There is evidence that inclusion of the time-varying correlation in the multivariate GARCH models can further improve the estimation of conditional volatility. (see Tse and Tsui, 2002)

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APPENDIX A

Table A.1
List of fund management companies under CPF Investment Scheme

Fund Management Companies
1. Aberdeen Asset Management Asia Ltd
2. ABN AMRO Asset Management (Singapore) Ltd
3. AIG Global Investment Corporation (Singapore) Ltd
4. AllianceBernstein (Singapore) Ltd
5. Allianz Global Investors Singapore Limited
6. APS Asset Management Pte Ltd
7. AXA Rosenberg Investment Management Asia Pacific Ltd
8. Capital International Research & Management Inc
9. Credit Agricole Asset Management Singapore Ltd
10. DBS Asset Management Ltd[19]
11. Deutsche Asset Management (Asia) Ltd
12. FIL Investment Management (Singapore) Limited
13. First State Investments (Singapore)[19]
14. Goldman Sachs (Singapore) Pte Ltd
15. Henderson Global Investors (Singapore) Ltd
16. HSBC Global Asset Management (Singapore) Limited[19]
18. Legg Mason International Equities (Singapore) Pte Ltd
19. Lion Global Investors Limited
20. NTUC Income Insurance Co-operative Ltd[19]
21. Prudential Asset Management (Singapore) Ltd
22. Schroder Investment Management (Singapore) Ltd[20]
23. SG Asset Management (Singapore) Ltd
24. State Street Global Advisors Singapore Ltd
25. Templeton Asset Management Ltd
26. UBS Global Asset Management (Singapore) Ltd
27. UOB Asset Management Ltd[19]
28. Western Asset Management Company Pte Ltd

Source: http://mycpf.cpf.gov.sg/Members/GenInfo/FAQ/Investment/INV-Asset-Enhance.htm

[19] Can only manage investment-linked insurance sub-funds under CPFIS unlike the rest of the FMCs, which can manage unit trusts, ILP funds/sub-funds, exchange traded funds, and fund management accounts under CPF Investment Scheme.
[20]FMCs which offer Fund Management Account services.

Table A.2
List of insurance companies under CPF Investment Scheme

Insurance Companies
1. American International Assurance Co Ltd
2. Aviva Ltd
3. AXA Life Insurance Singapore Pte Ltd
4. Great Eastern Life Assurance Co Ltd
5. HSBC Insurance (Singapore) Pte Ltd
6. Manulife (Singapore) Pte Ltd
7. NTUC Income Insurance Co-operative Ltd
8. Overseas Assurance Corporation Ltd
9. Prudential Assurance Co Singapore Pte Ltd
10. TM Asia Life Singapore Ltd
11. UOB Life Assurance Ltd

Source: http://mycpf.cpf.gov.sg/Members/GenInfo/FAQ/Investment/INV-Asset-Enhance.htm

APPENDIX B

Figure B.1

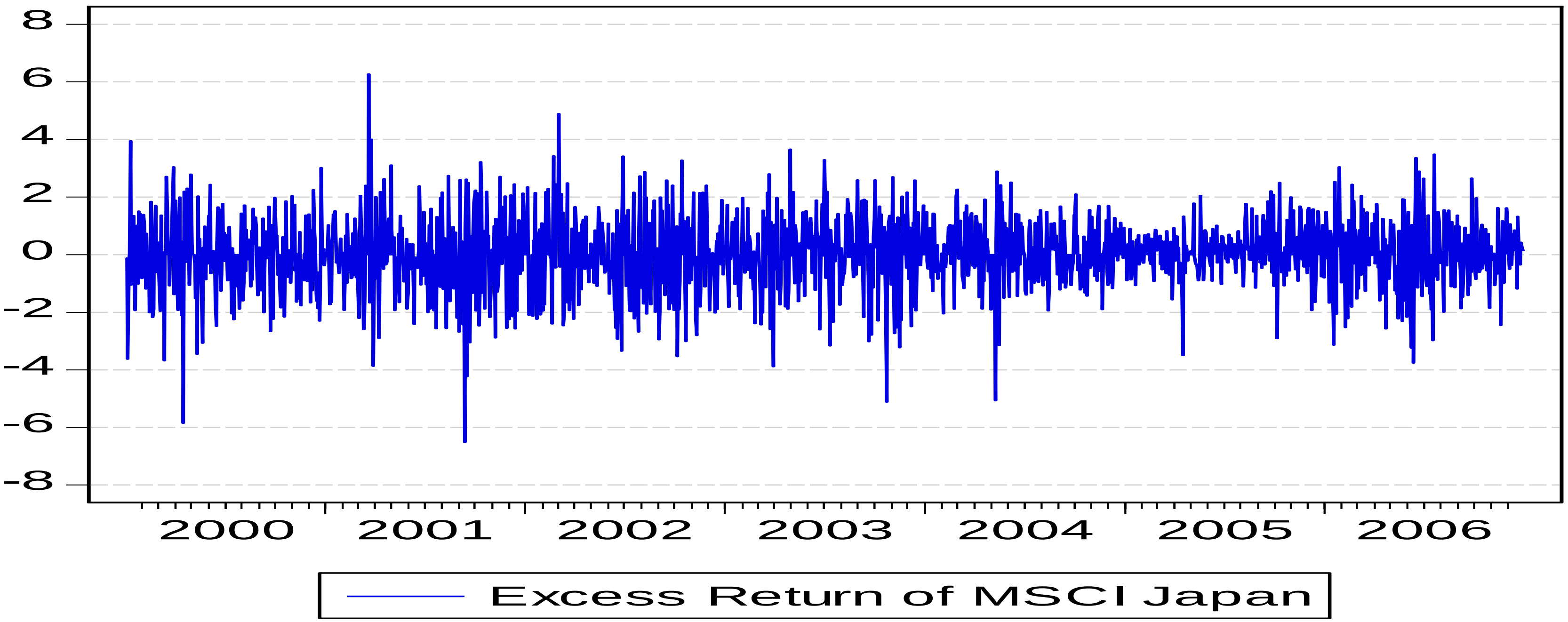


Figure B.2

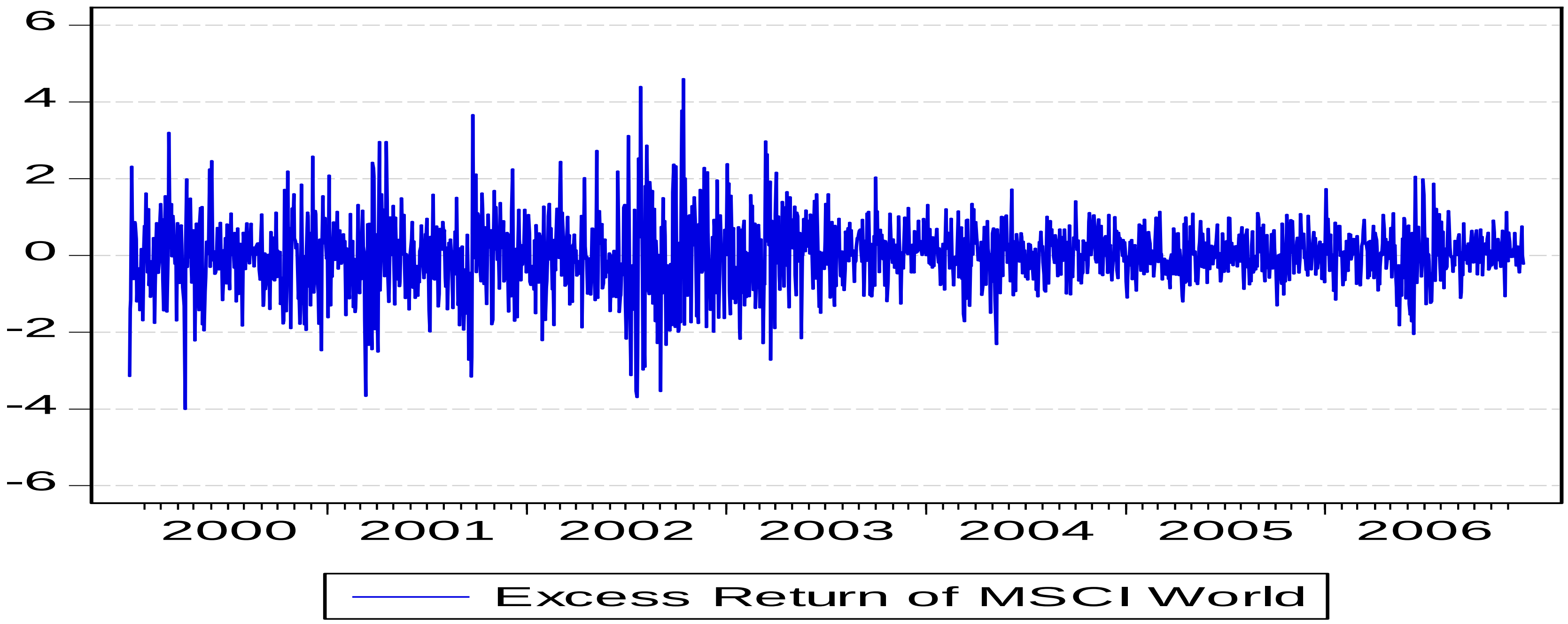

6
4
2
0
-2
-4
-6
2000
2001
2002
2003
2004
2005
2006
Excess Return of MSCI World

Figure B.3

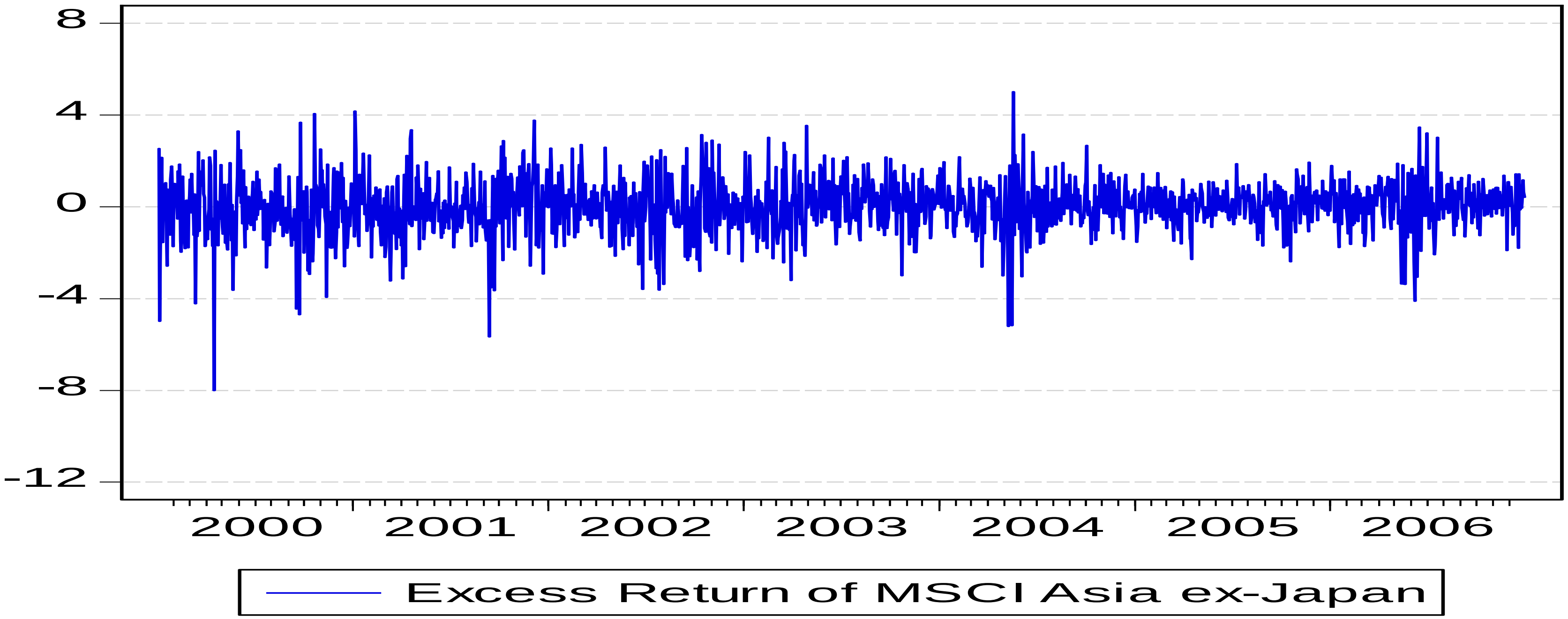
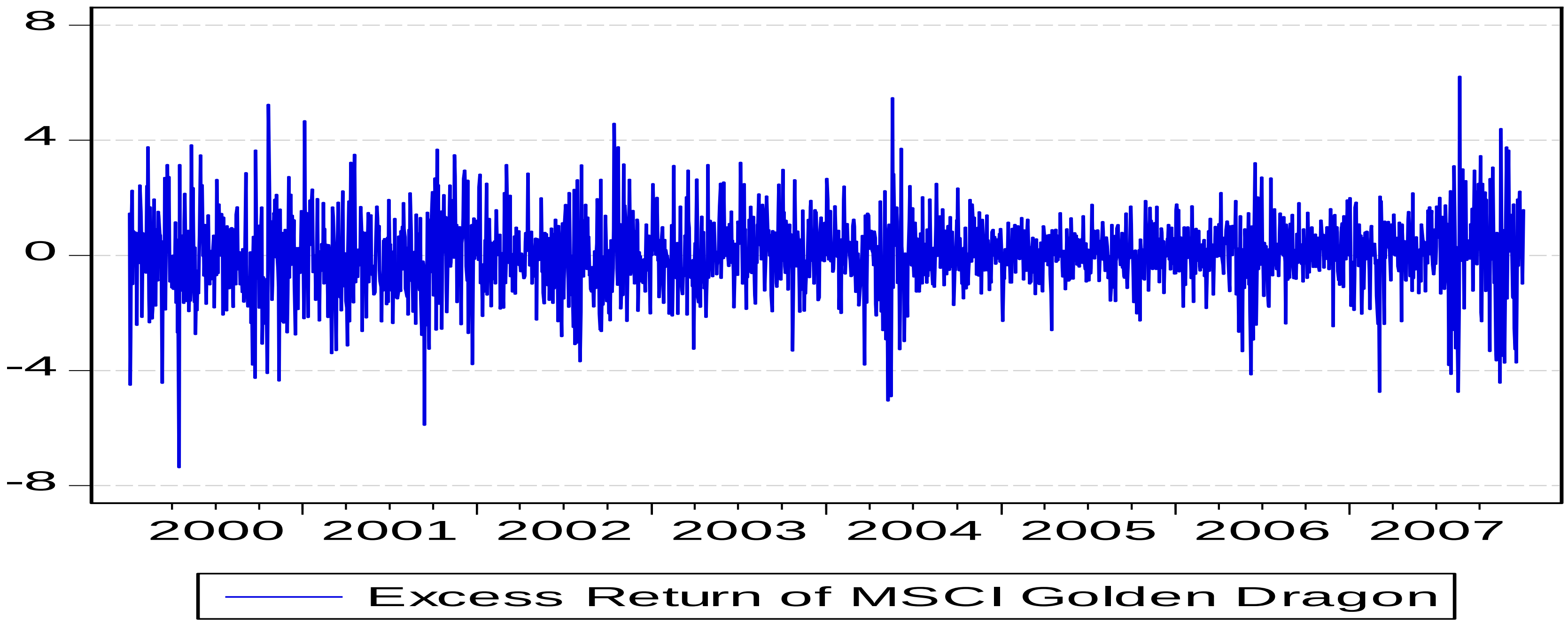
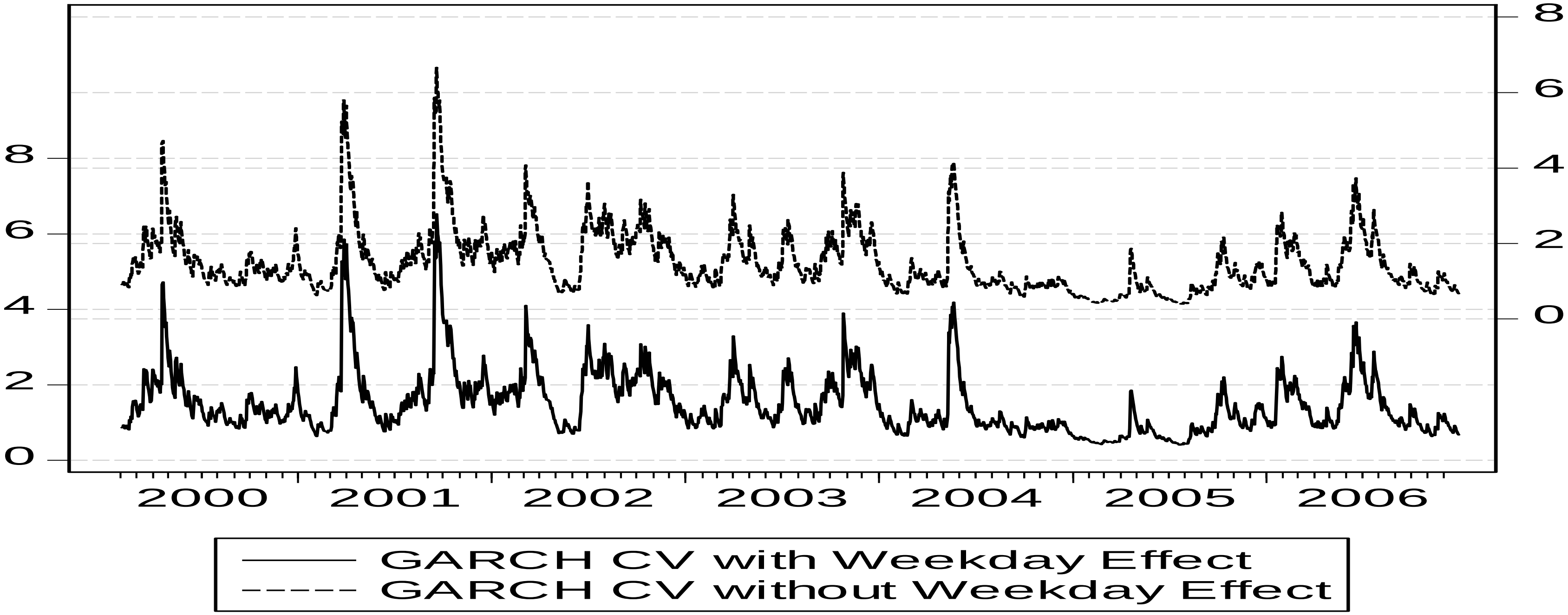

8
4
0
-4
-8
-12
2000
2001
2002
2003
2004
2005
2006
Excess Return of MSCI Asia ex-Japan

Figure B.4


8
4
0
-4
-8
2000
2001
2002
2003
2004
2005
2006
2007
Excess Return of MSCI Golden Dragon

APPENDIX C[21]

Figure C.1
Graph for conditional volatility with and without weekday effect for the excess return of MSCI Japan



[21] "CV" and "Weekday effect" are short for conditional variance and the day of the week effect, respectively in all the graphs of Appendix C.

Figure C.2
Graph for conditional volatility with and without weekday effect for the excess return of MSCI World

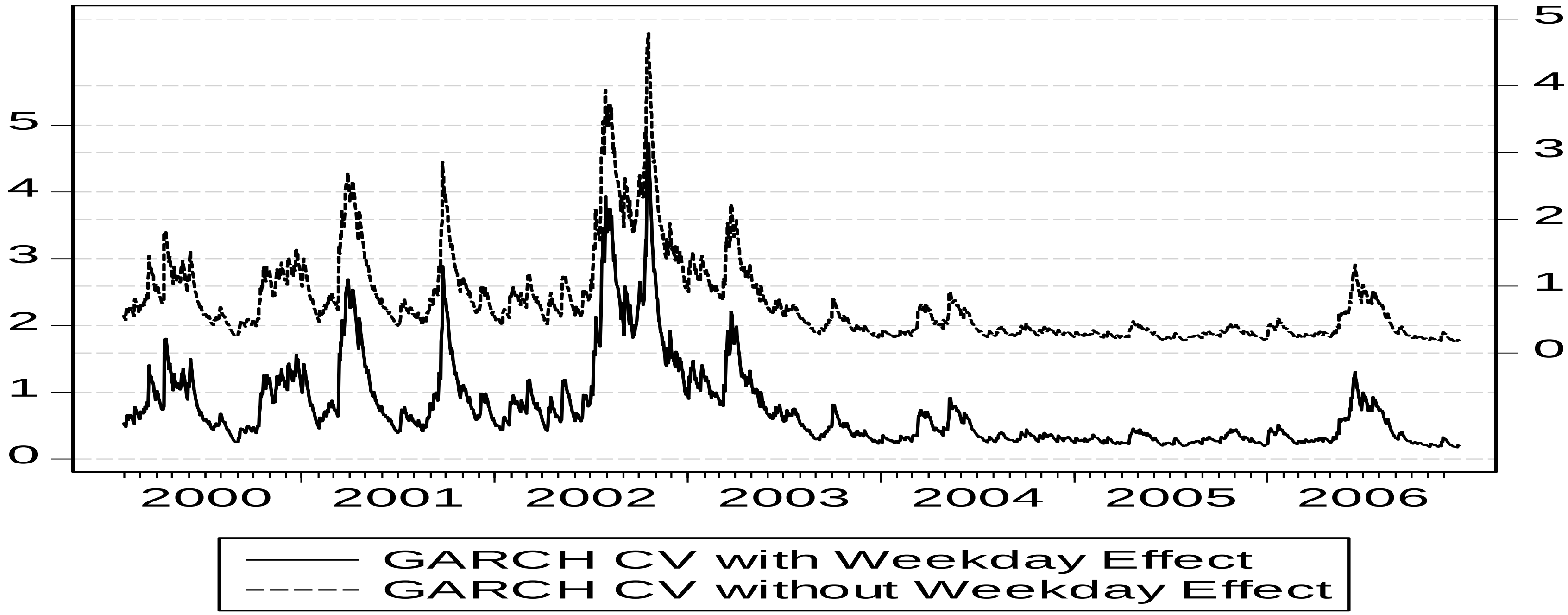


Figure C.3
Graph for conditional volatility with and without weekday effect for the excess return of MSCI Asian ex-Japan

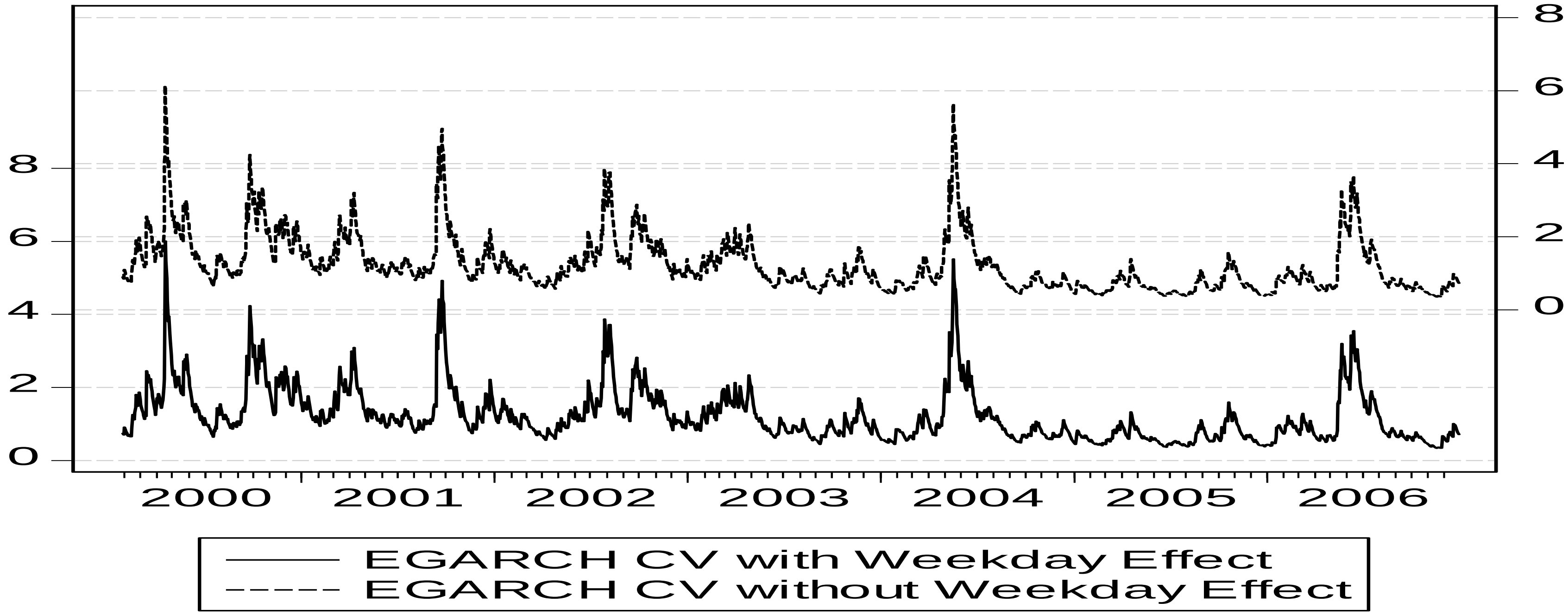
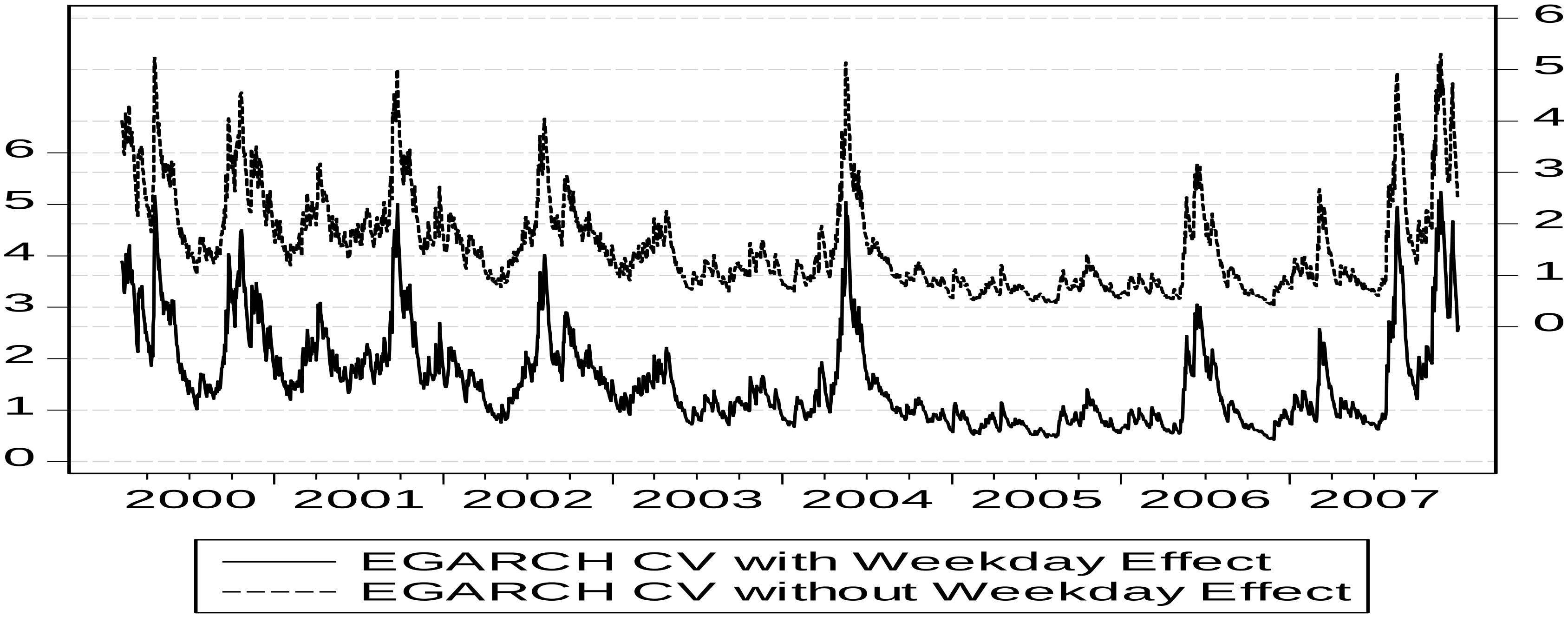


Figure C.4
Graph for conditional volatility with and without weekday effect for the excess return of MSCI Golden Dragon



APPENDIX D

Table D.1
Residuals of autoregressive filter without weekday effects

	Japan	World	Asian ex-JP	Greater China
Mean	0.000	0.000	0.000	0.000
Median	0.014	0.019	0.017	-0.026
Maximum	6.315	4.749	4.781	7.018
Minimum	-6.417	-3.774	-7.862	-6.875
Std. Dev.	1.207	0.864	1.110	1.259
Skewness	-0.199	0.044	-0.360	-0.027
Kurtosis	4.639	5.280	6.024	5.271
Jarque-Bera	213.504	391.583	727.174	443.033
Observations	1802	1805	1806	2060
Q(9)	6.372	7.132	9.8135	10.161
Q(18)	9.544	15.762	13.565	22.807
Q(9)^2	164.240	901.250	149.84	274.54
Q(18)^2	210.890	1164.600	193.910	377.92

Table D.2
Residuals of autoregressive filter with weekday effects

	Japan	World	Asian ex-JP	Greater China
Mean	0.002	-0.004	0.007	0.006
Median	0.012	0.013	0.032	-0.017
Maximum	6.267	4.730	4.837	6.914
Minimum	-6.465	-3.804	-8.030	-6.968
Std. Dev.	1.208	0.865	1.113	1.261
Skewness	-0.214	0.045	-0.408	-0.052
Kurtosis	4.647	5.291	6.201	5.302
Jarque-Bera	217.328	395.249	821.272	455.814
Observations	1802	1805	1806	2060
Q(9)	6.559	9.057	9.311	9.7666
Q(18)	9.656	15.025	13.612	23.045
Q(9)^2	164.740	909.490	146.640	273.13
Q(18)^2	211.370	1171.500	192.830	379.32

Table D.3
Descriptions of the excess returns of Japan equity funds under CPF Investment Scheme and non-CPF Japan equity funds

	EX_CPF1	EX_CPF2	EX_CPF3	EX_CPF4	EX_CPF5	EX_NCPF1	EX_NCPF2	EX_NCPF3	EX_NCPF4
Mean	-0.017	-0.008	-0.025	-0.016	-0.002	-0.018	-0.021	0.002	-0.022
Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	5.561	5.849	6.952	17.450	5.999	5.914	7.434	5.899	6.971
Minimum	-5.615	-6.234	-6.233	-18.834	-8.976	-9.106	-9.682	-6.418	-8.073
Std. Dev.	1.216	1.318	1.394	1.524	1.287	1.278	1.422	1.104	1.380
Skewness	-0.072	-0.012	-0.071	-0.428	-0.415	-0.382	-0.570	-0.131	-0.298
Kurtosis	4.525	4.526	5.287	30.365	7.087	6.718	6.844	5.465	6.364
Dickey-Fuller Test	-43.065	-40.866	-40.149	-45.356	-37.650	-36.005	-37.435	-41.343	-38.054
Observations	1824	1824	1824	1824	1824	1824	1824	1824	1824

Table D.4
Description of the excess returns of global equity funds under CPF Investment Scheme

	EX_CPF1	EX_CPF2	EX_CPF3	EX_CPF4	EX_CPF5	EX_CPF6	EX_CPF7
Mean	0.005	-0.010	-0.010	-0.004	-0.031	-0.021	-0.003
Median	-0.004	-0.006	-0.006	0.052	-0.005	-0.008	-0.005
Maximum	4.775	5.511	6.612	6.825	5.603	6.990	7.871
Minimum	-5.809	-5.995	-6.913	-6.913	-6.834	-5.641	-9.924
Std. Dev.	1.047	0.974	1.099	1.049	1.085	1.070	0.877
Skewness	0.039	-0.080	-0.033	-0.158	-0.218	0.207	-0.861
Kurtosis	5.432	7.032	6.217	6.598	6.660	7.514	19.373
Dickey-Fuller Test	-38.696	-40.405	-38.795	-39.884	-37.258	-42.548	-38.743
Observations	1824	1824	1824	1824	1824	1824	1824

Table D.5
Description of the excess returns of non-CPF global equity funds

	EX_NCPF1	EX_NCPF2	EX_NCPF3	EX_NCPF4	EX_NCPF5	EX_NCPF6	EX_NCPF7
Mean	-0.023	-0.032	-0.015	0.022	-0.012	0.013	-0.009
Median	-0.005	-0.005	0.020	0.029	-0.006	0.029	-0.006
Maximum	4.849	45.328	4.886	3.259	5.809	4.182	3.665
Minimum	-4.576	-46.844	-7.675	-4.993	-5.894	-4.842	-6.973
Std. Dev.	0.981	1.914	1.117	0.591	1.039	0.768	0.866
Skewness	-0.047	-0.773	-0.245	-0.402	-0.110	-0.197	-0.402
Kurtosis	5.889	370.245	5.931	8.991	5.873	6.275	6.690
Dickey-Fuller Test	-37.647	-39.000	-42.275	-37.108	-41.031	-36.427	-38.399
Observations	1824	1824	1824	1824	1824	1824	1824

Table D.6
Description of the excess returns of Asian ex-Japan funds under CPF Investment Scheme

	EX_CPF1	EX_CPF2	EX_CPF3	EX_CPF4	EX_CPF5	EX_CPF6	EX_CPF7	EX_CPF8	EX_CPF9	EX_CPF10
Mean	0.040	0.006	0.017	0.015	0.013	0.021	0.008	0.017	0.016	0.018
Median	0.044	-0.006	0.010	-0.007	-0.002	-0.006	-0.006	-0.007	-0.007	-0.006
Maximum	3.557	5.921	4.877	5.284	7.405	5.017	10.923	5.384	5.399	5.185
Minimum	-6.549	-13.636	-7.552	-10.546	-8.666	-9.021	-12.441	-8.755	-8.087	-9.008
Std. Dev.	0.788	1.183	1.031	1.259	1.142	1.051	1.310	1.031	1.227	1.181
Skewness	-0.961	-1.147	-0.505	-0.563	-0.304	-0.742	-0.759	-0.787	-0.497	-0.523
Kurtosis	10.071	16.735	7.007	7.566	7.404	8.060	14.087	10.197	6.258	7.323
Dickey-Fuller Test	-38.247	-36.379	-37.137	-39.742	-39.837	-39.623	-41.522	-39.821	-39.077	-38.789
Observations	1824	1824	1824	1824	1824	1824	1824	1824	1824	1824

Table D.7
Description of the excess returns of non-CPF Asia ex-Japan funds

	EX_NCPF1	EX_NCPF2	EX_NCPF3	EX_NCPF4
Mean	0.018	0.004	0.006	0.013
Median	-0.007	-0.006	-0.006	-0.006
Maximum	6.468	5.528	6.378	7.062
Minimum	-12.579	-10.419	-9.111	-8.462
Std. Dev.	1.176	1.315	1.327	1.232
Skewness	-0.946	-0.415	-0.262	-0.285
Kurtosis	12.900	7.199	6.532	6.698
Dickey-Fuller Test	-39.934	-41.203	-37.223	-38.189
Observations	1824	1824	1824	1824

Table D.8
Description of the excess returns of Greater China funds under CPF Investment Scheme and non-CPF Greater China funds

	EX_CPF1	EX_CPF2	EX_CPF3	EX_CPF4	EX_CPF5	EX_NCPF1	EX_NCPF2
Mean	0.042	0.041	0.037	0.036	0.023	0.063	0.020
Median	-0.005	-0.003	-0.006	-0.005	0.024	-0.004	-0.006
Maximum	7.523	4.157	5.961	6.290	4.668	8.627	5.867
Minimum	-8.383	-8.729	-9.765	-10.466	-9.952	-8.482	-9.549
Std. Dev.	1.263	1.090	1.271	1.334	1.220	1.489	1.289
Skewness	-0.362	-0.580	-0.355	-0.538	-0.836	-0.327	-0.409
Kurtosis	7.065	6.853	6.926	7.820	9.085	7.303	6.733
Dickey-Fuller test	-41.684	-43.071	-41.284	-41.611	-41.247	-24.186	-42.026
Observations	2085	2085	2085	2085	2085	2085	2085

Table D.9
Description of the series about multi-factors for Japan equity funds

	EX_MSJP	EX_CUR	SMB	HML
Mean	0.002	0.008	0.003	0.086
Median	0.000	0.013	0.000	0.042
Maximum	6.272	1.819	3.362	5.255
Minimum	-6.512	-2.431	-3.192	-3.205
Std. Dev.	1.216	0.503	0.608	0.634
Skewness	-0.204	-0.342	-0.401	0.759
Kurtosis	4.702	4.654	5.113	10.053
Dickey-Fuller Test	-41.074	-46.230	-39.377	-37.437
Observations	1824	1824	1824	1824

Table D.10
Description of the series about multi-factors for global equity funds

	EX_MSCIW	EX_CUR	SMB	HML
Mean	-0.008	0.009	0.039	0.029
Median	0.019	0.005	0.059	0.019
Maximum	4.598	1.451	2.220	45.549
Minimum	-4.006	-1.157	-2.248	-44.008
Std. Dev.	0.882	0.269	0.529	1.561
Skewness	-0.009	0.015	-0.260	1.294
Kurtosis	5.451	3.923	4.399	744.474
Dickey-Fuller Test	-37.104	-40.123	-41.357	-31.156
Observations	1824	1824	1824	1824

Table D.11
Description of the series about multi-factors for Asian ex-Japan equity funds

	EX_AXJ	EX_CUR	HML
Mean	0.008	-0.015	0.019
Median	0.041	-0.015	0.014
Maximum	5.014	0.975	3.893
Minimum	-8.006	-0.849	-2.698
Std. Dev.	1.137	0.177	0.554
Skewness	-0.508	0.214	0.168
Kurtosis	6.267	5.589	7.448
Dickey-Fuller Test	-38.474	-45.044	-34.715
Observations	1824	1824	1824

Table D.12
Description of the series about multi-factors for Greater China equity funds

	EX_MXGD	EX_CUR	HML
Mean	0.008	-0.013	0.000
Median	-0.003	-0.018	0.000
Maximum	6.223	1.305	2.905
Minimum	-7.370	-1.098	-4.550
Std. Dev.	1.276	0.218	0.681
Skewness	-0.191	0.212	-0.264
Kurtosis	5.249	4.880	6.780
Dickey-Fuller test	-42.386	-45.440	-27.774
Observations	2085	2085	2085

APPENDIX E

Table E.1
Summary of geographic segments for global equity fund[22]

Fund Name	US	JP	UK	EU	HK	SG	SW	SED	CA	Cash	Other
AB Global Growth Trends A	54%	4%	7%					10%			25%
DBS Horizon Global Equity SGD	41%	13%	16%	22%							8%
DBS Shenton Global Opp	31%	4%		6%	10%	20%					29%
Fidelity Fds PS Global Growth A	45%	9%	8%	11%				4%		2%	21%
First State Global 100 Gth SGD	46%	8%	4%	31%						2%	8%
Schroder Global Enterpris	47%	10%	11%	14%	2%		3%	1%	4%		6%
UOB United Intl Growth	42%	7%	8%	5%				8%	5%	2%	24%
Allianz-dit Interglobal A	51%	9%	11%	8%	3%		5%		3%		11%
Fidelity Fds World A	24%	6%	7%	35%					3%	1%	24%
Franklin Mut Beacon A acc $	62%	0%	5%	13%				2%		9%	9%
HSBC GIF Gbl Equity AD USD	49%	4%	9%	12%	4%			7%		1%	14%
Templeton Global A Y-D $	28%	4%	19%	26%				3%		2%	18%
UOB United Glb Unifem SGD	31%	0%	6%	22%				8%		26%	6%
Average Weight	42%	6%	9%	16%	1%	2%	1%	3%	1%	4%	15%
Determined Weight 1	44%	12%	10%	18%	5%	6%	1%	3%	1%		
Determined Weight 2	44%	12%	32%		7%	5%					

[22] "US" is short for USA, "JP" for Japan, "EU" for Euro Zone, "HK" for Hong Kong, "SG" for Singapore, "SW" for Switzerland, "SED" for Sweden, "CA" for Canada.

Table E.2
Summary of geographic segments for Asian ex-Japan equity funds[23]

Fund Name	HK	TW	CN	SG	IN	MY	ID	TH	SK	AU	Others
Invesco Asia Opp Equity Fund	22%	23%	9%	8%	0%	5%	3%		19%		13%
DWS Asia Premier	12%	22%	26%	6%		3%	2%		22%		6%
Allianz Global	36%	5%	17%	10%		3%			15%		14%
Asian Growth Fund	30%	20%	9%	9%		5%	4%		18%		5%
LionGlobal Asia SE Asia Fund				38%		21%	13%				28%
United Asia Fund	16%	11%	32%	10%					18%		12%
Aberdeen Pacific Equity	21%			16%	13%	6%	6%		11%	9%	18%
Templeton Asian Growth Fund	4%	4%	28%		15%	1%	4%	25%	14%		10%
Shenton Aisa Pacific Fund	26%	21%	13%	8%			3%		18%		9%
HSBC GIF Asia ex Japan Equity	14%	21%	24%	6%		4%	2%		22%		8%
Legg Mason Asian Enterprise	19%	22%	16%	11%					22%		10%
Schroder IS Fund	16%	17%	19%	5%	10%		4%	3%	19%		8%
Shenton Twin City Fund	33%		12%	49%							5%
Average Weight	19%	13%	16%	14%	3%	4%	3%	2%	15%	1%	11%
MSCI Asian ex-JP	13%	17%	22%	7%	10%		3%	2%	21%		4%
Determined Weight	20%	15%	18%	16%	3%	4%	4%	3%	17%		

[23] "TW" is short for Taiwan, "CN" for China, "IN" for India, "MY" for Malaysia, "ID" for Indonesia, "TH" for Thailand, "SK" for South Korea, "AU" for Australia.

Table E.3
Summary of geographic segments for Greater China equity funds

Fund Name	HK	CN	TW	SG	Other
Fidelity Fds Greater China A	21%	33%	27%		19%
First State Regional China SGD	70%		26%		4%
Franklin Temp F-China	15%	59%	22%		4%
Lion Capital China Growth SGD	25%	46%	18%		11%
UOB United Greater China	20%	60%	14%		7%
DBS Shenton Greater China	43%	16%	35%		5%
Average Weight	32%	36%	24%		8%
Determined Weight	50%	20%	25%	5%	

APPENDIX F

Table F.1
Regression results for the factor model of Japan equity funds under CPF Investment Scheme without the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_{JP}	0.790	0.792	0.871	0.872	0.944	0.948	0.824	0.828	0.776	0.781
	(50.91)**	(51.00)**	(52.89)**	(53.35)**	(59.86)**	(60.65)**	(33.87)**	(34.14)**	(42.16)**	(44.03)**
γ_{mp}	-0.041	-0.048	-0.071	-0.077	0.057	0.039	-0.155	-0.173	-0.060	-0.085
	(0.95)	(1.10)	(1.54)	(1.70)	(1.30)	(0.90)	(2.29)*	(2.55)*	(1.17)	(1.72)
β_{SMB}		0.016		0.196		0.054		0.146		0.414
		(0.49)		(5.54)**		(1.59)		(2.78)**		(10.81)**
β_{HML}		-0.062		0.004		-0.169		-0.128		-0.109
		(2.01)*		(0.13)		(5.49)**		(2.68)**		(3.12)**
α	-0.015	-0.010	-0.006	-0.007	-0.024	-0.010	-0.015	-0.005	-0.004	0.005
	(0.88)	(0.57)	(0.32)	(0.35)	(1.36)	(0.54)	(0.57)	(0.17)	(0.19)	(0.25)
N	1802	1802	1802	1802	1802	1802	1802	1802	1802	1802
R^2	0.62	0.62	0.64	0.64	0.70	0.71	0.41	0.42	0.53	0.56
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.2
Regression results for the factor model of Japan equity funds under CPF Investment Scheme with the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_{JP}	0.796	0.798	0.878	0.880	0.952	0.957	0.820	0.823	0.784	0.789
	(53.08)**	(53.24)**	(56.10)**	(56.65)**	(64.97)**	(66.17)**	(33.97)**	(34.23)**	(44.73)**	(46.98)**
γ_{mp}	-0.074	-0.082	-0.112	-0.121	0.010	-0.011	-0.128	-0.145	-0.106	-0.133
	(1.77)	(1.96)*	(2.57)*	(2.78)**	(0.25)	(0.27)	(1.91)	(2.16)*	(2.16)*	(2.84)**
β_{c}	0.389	0.394	0.494	0.493	0.561	0.572	-0.320	-0.314	0.544	0.549
	(11.51)**	(11.65)**	(13.99)**	(14.09)**	(16.97)**	(17.53)**	(5.88)**	(5.79)**	(13.77)**	(14.48)**
β_{SMB}		0.010		0.188		0.045		0.151		0.406
		(0.32)		(5.61)**		(1.43)		(2.90)**		(11.19)**
β_{HML}		-0.079		-0.018		-0.195		-0.114		-0.134
		(2.69)**		(0.59)		(6.84)**		(2.40)*		(4.04)**
α	-0.019	-0.013	-0.011	-0.010	-0.030	-0.013	-0.012	-0.003	-0.009	0.002
	(1.15)	(0.74)	(0.62)	(0.54)	(1.81)	(0.80)	(0.45)	(0.10)	(0.47)	(0.08)
N	1802	1802	1802	1802	1802	1802	1802	1802	1802	1802
R^2	0.65	0.65	0.67	0.68	0.74	0.75	0.42	0.43	0.57	0.61

Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%

Table F.3
Regression results for the factor model of non-CPF Japan equity funds without the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4	
β_{JP}	0.659	0.665	1.018	1.027	0.825	0.827	0.944	0.949
	(31.60)**	(34.48)**	(74.46)**	(81.46)**	(84.72)**	(85.30)**	(62.48)**	(64.49)**
γ_{mp}	-0.048	-0.080	-0.016	-0.054	-0.032	-0.040	-0.064	-0.090
	(0.83)	(1.50)	(0.41)	(1.55)	(1.18)	(1.49)	(1.52)	(2.19)*
β_{SMB}		0.700		0.303		0.026		0.178
		(16.82)**		(11.13)**		(1.22)		(5.60)**
β_{HML}		-0.076		-0.294		-0.080		-0.207
		(1.99)*		(11.85)**		(4.19)**		(7.12)**
α	-0.015	-0.009	-0.020	0.005	-0.000	0.007	-0.018	-0.000
	(0.63)	(0.42)	(1.31)	(0.34)	(0.00)	(0.62)	(1.06)	(0.02)
N	1802	1802	1802	1802	1802	1802	1802	1802
R^2	0.39	0.48	0.78	0.81	0.82	0.82	0.71	0.73
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%								

Table F.4
Regression results for the factor model of non-CPF Japan equity funds with the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4	
β_{JP}	0.667	0.674	1.019	1.027	0.825	0.827	0.948	0.954
	(33.61)**	(37.02)**	(74.42)**	(81.45)**	(84.65)**	(85.23)**	(64.17)**	(66.47)**
γ_{mp}	-0.099	-0.134	-0.017	-0.057	-0.031	-0.040	-0.090	-0.118
	(1.79)	(2.64)**	(0.44)	(1.61)	(1.15)	(1.48)	(2.17)*	(2.93)**
β_c	0.611	0.612	0.013	0.028	-0.006	-0.002	0.306	0.317
	(13.64)**	(14.90)**	(0.43)	(0.98)	(0.27)	(0.07)	(9.18)**	(9.80)**
β_{SMB}		0.691		0.303		0.026		0.173
		(17.58)**		(11.12)**		(1.22)		(5.59)**
β_{HML}		-0.103		-0.295		-0.080		-0.221
		(2.87)**		(11.88)**		(4.18)**		(7.80)**
α	-0.021	-0.013	-0.020	0.005	0.000	0.007	-0.021	-0.002
	(0.94)	(0.63)	(1.32)	(0.33)	(0.01)	(0.62)	(1.27)	(0.15)
N	1802	1802	1802	1802	1802	1802	1802	1802
R^2	0.44	0.53	0.78	0.81	0.82	0.82	0.72	0.74
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%								

Table F.5
Regression results for the factor model of global equity funds under CPF Investment Scheme without the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_w	1.096	1.090	0.262	0.252	0.977	0.985	0.894	0.896	0.747	0.745
	(81.17)**	(80.97)**	(8.66)**	(8.26)**	(44.33)**	(44.46)**	(38.54)**	(38.27)**	(28.78)**	(28.47)**
γ_{mp}	-0.047	-0.020	-0.060	-0.019	-0.024	-0.058	-0.172	-0.181	0.213	0.225
	(1.56)	(0.64)	(0.89)	(0.28)	(0.49)	(1.15)	(3.33)**	(3.40)**	(3.69)**	(3.77)**
β_{SMB}		0.044		0.118		-0.106		-0.008		0.004
		(2.23)*		(2.65)**		(3.27)**		(0.23)		(0.11)
β_{HML}		-0.043		0.015		-0.022		0.024		-0.038
		(6.76)**		(1.07)		(2.12)*		(2.15)*		(3.11)**
α	0.012	0.011	-0.007	-0.012	-0.003	0.002	0.006	0.005	-0.027	-0.026
	(1.20)	(1.16)	(0.33)	(0.55)	(0.19)	(0.09)	(0.32)	(0.30)	(1.41)	(1.36)
N	1805	1805	1805	1805	1805	1805	1805	1805	1805	1805
R^2	0.84	0.84	0.05	0.05	0.60	0.61	0.52	0.52	0.43	0.43
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.6
Regression results for the factor model of global equity funds under CPF Investment Scheme without the effect of currency risk (continued)

	Fund 6		Fund 7	
β_w	0.958	0.983	0.759	0.766
	(50.95)**	(53.19)**	(41.35)**	(41.40)**
γ_{mp}	0.211	0.113	-0.056	-0.085
	(5.03)**	(2.67)**	(1.37)	(2.01)*
β_{SMB}		-0.270		-0.077
		(10.03)**		(2.85)**
β_{HML}		-0.013		-0.002
		(1.48)		(0.23)
α	-0.015	-0.005	0.003	0.006
	(1.08)	(0.33)	(0.25)	(0.46)
N	1805	1805	1805	1805
R^2	0.70	0.71	0.56	0.57
Absolute value of t statistics in parentheses * significant at 5%; **				

Table F.7
Regression results for the factor model of global equity funds under investment scheme with the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_w	1.107	1.096	0.263	0.254	0.999	0.994	0.895	0.896	0.752	0.747
	(82.97)**	(83.84)**	(8.67)**	(8.35)**	(46.25)**	(45.86)**	(38.34)**	(38.24)**	(28.83)**	(28.56)**
γ_{mp}	-0.093	-0.045	-0.067	-0.031	-0.115	-0.095	-0.175	-0.182	0.193	0.215
	(3.09)**	(1.50)	(0.98)	(0.45)	(2.36)*	(1.92)	(3.32)**	(3.40)**	(3.28)**	(3.60)**
β_c	-0.298	-0.445	-0.047	-0.212	-0.588	-0.644	-0.018	-0.017	-0.134	-0.177
	(8.01)**	(10.65)**	(0.55)	(2.17)*	(9.75)**	(9.29)**	(0.28)	(0.23)	(1.84)	(2.12)*
β_{SMB}		0.160		0.173		0.062		-0.004		0.050
		(7.28)**		(3.38)**		(1.70)		(0.09)		(1.14)
β_{HML}		-0.042		0.015		-0.022		0.024		-0.038
		(6.93)**		(1.08)		(2.14)*		(2.15)*		(3.10)**
α	0.015	0.012	-0.007	-0.012	0.004	0.003	0.006	0.005	-0.025	-0.026
	(1.57)	(1.27)	(0.31)	(0.53)	(0.23)	(0.16)	(0.33)	(0.30)	(1.33)	(1.35)
N	1805	1805	1805	1805	1805	1805	1805	1805	1805	1805
R^2	0.84	0.85	0.05	0.06	0.62	0.63	0.52	0.52	0.43	0.43
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.8
Regression results for the factor model of global equity funds under CPF Investment Scheme with the effect of currency risk (continued)

	Fund 6		Fund 7	
β_w	0.982	0.990	0.777	0.773
	(54.18)**	(54.62)**	(43.02)**	(42.63)**
γ_{mp}	0.112	0.084	-0.127	-0.114
	(2.74)**	(2.03)*	(3.12)**	(2.75)**
β_c	-0.638	-0.506	-0.460	-0.514
	(12.62)**	(8.74)**	(9.14)**	(8.86)**
β_{SMB}		-0.138		0.057
		(4.55)**		(1.87)
β_{HML}		-0.012		-0.002
		(1.48)		(0.21)
α	-0.008	-0.004	0.009	0.007
	(0.58)	(0.28)	(0.64)	(0.53)
N	1805	1805	1805	1805
R^2	0.72	0.72	0.58	0.58
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%				

Table F.9
Regression results for the factor model of non-CPF global equity funds without the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_w	1.043	1.048	0.349	0.373	0.802	0.855	0.574	0.570	0.404	0.390
	(102.19)**	(102.71)**	(5.77)**	(6.12)**	(30.32)**	(33.96)**	(58.71)**	(57.85)**	(12.92)**	(12.36)**
γ_{mp}	0.030	0.010	0.044	-0.053	0.136	-0.076	-0.033	-0.018	-0.118	-0.059
	(1.30)	(0.45)	(0.33)	(0.38)	(2.31)*	(1.33)	(1.53)	(0.78)	(1.69)	(0.82)
β_{SMB}		-0.065		-0.250		-0.556		0.039		0.154
		(4.38)**		(2.81)**		(15.14)**		(2.73)**		(3.36)**
β_{HML}		-0.021		0.011		0.014		-0.004		-0.005
		(4.34)**		(0.40)		(1.17)		(0.86)		(0.36)
α	-0.015	-0.012	-0.030	-0.021	-0.013	0.008	0.026	0.025	-0.007	-0.013
	(1.99)*	(1.60)	(0.68)	(0.48)	(0.65)	(0.43)	(3.66)**	(3.46)**	(0.31)	(0.55)
N	1805	1805	1805	1805	1805	1805	1805	1805	1805	1805
R^2	0.89	0.90	0.03	0.03	0.44	0.50	0.72	0.73	0.10	0.11
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.10
Regression results for the factor model of non-CPF global equity funds without the effect of currency risk (continued)

	Fund 6		Fund 7	
β_w	0.731	0.722	0.789	0.797
	(52.76)**	(52.50)**	(44.41)**	(44.59)**
γ_{mp}	-0.046	-0.010	-0.124	-0.156
	(1.49)	(0.31)	(3.13)**	(3.84)**
β_{SMB}		0.120		-0.094
		(5.98)**		(3.59)**
β_{HML}		0.035		-0.011
		(5.42)**		(1.28)
α	0.020	0.014	-0.005	-0.001
	(1.95)	(1.44)	(0.39)	(0.10)
N	1805	1805	1805	1805
R^2	0.68	0.69	0.59	0.59
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%				

Table F.11
Regression results for the factor model of non-CPF global equity funds with the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_w	1.045	1.048	0.390	0.388	0.852	0.869	0.574	0.573	0.401	0.390
	(101.99)**	(102.60)**	(6.49)**	(6.42)**	(35.26)**	(36.26)**	(58.71)**	(59.07)**	(12.73)**	(12.37)**
γ_{mp}	0.019	0.010	-0.124	-0.117	-0.068	-0.136	-0.033	-0.031	-0.103	-0.062
	(0.84)	(0.44)	(0.91)	(0.85)	(1.25)	(2.49)*	(1.53)	(1.41)	(1.45)	(0.86)
β_c	-0.066	-0.003	-1.084	-1.127	-1.321	-1.057		-0.241	0.097	-0.064
	(2.32)*	(0.10)	(6.47)**	(5.84)**	(19.60)**	(13.80)**		(7.76)**	(1.10)	(0.64)
β_{SMB}		-0.064		0.044		-0.281		0.102		0.171
		(3.75)**		(0.44)		(6.97)**		(6.26)**		(3.23)**
β_{HML}		-0.021		0.012		0.014		-0.004		-0.005
		(4.34)**		(0.43)		(1.28)		(0.85)		(0.35)
α	-0.014	-0.012	-0.018	-0.020	0.002	0.009	0.026	0.025	-0.008	-0.013
	(1.89)	(1.60)	(0.41)	(0.44)	(0.13)	(0.54)	(3.66)**	(3.57)**	(0.36)	(0.55)
N	1805	1805	1805	1805	1805	1805	1805	1805	1805	1805
R^2	0.89	0.90	0.05	0.05	0.54	0.55	0.72	0.74	0.10	0.11
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.12
Regression results for the factor model of non-CPF global equity funds with the effect of currency risk (continued)

	Fund 6		Fund 7	
β_w	0.721	0.719	0.806	0.803
	(52.46)**	(52.59)**	(46.10)**	(45.74)**
γ_{mp}	-0.002	0.003	-0.192	-0.183
	(0.08)	(0.08)	(4.87)**	(4.56)**
β_c	0.282	0.219	-0.441	-0.467
	(7.36)**	(5.01)**	(9.05)**	(8.31)**
β_{SMB}		0.063		0.028
		(2.74)**		(0.95)
β_{HML}		0.035		-0.010
		(5.44)**		(1.27)
α	0.017	0.014	-0.000	-0.001
	(1.66)	(1.41)	(0.00)	(0.04)
N	1805	1805	1805	1805
R^2	0.69	0.70	0.61	0.61
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%				

Table F.12
Regression results for the factor model of Asian ex-Japan equity funds under CPF Investment Scheme without the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_{axj}	0.573	0.574	0.796	0.795	0.806	0.806	0.945	0.945	0.903	0.903
	(57.73)**	(58.76)**	(43.70)**	(43.86)**	(72.48)**	(72.70)**	(61.79)**	(62.12)**	(78.80)**	(79.25)**
γ_{mp}	0.082	0.08	-0.06	-0.058	-0.003	-0.004	0.015	0.017	0.02	0.022
	(3.16)**	(3.14)**	-1.26	-1.22	-0.1	-0.13	-0.38	-0.43	-0.68	-0.73
β_{HML}		0.149		-0.148		0.069		-0.14		-0.106
		(7.87)**		(4.21)**		(3.22)**		(4.78)**		(4.82)**
α	0.038	0.034	-0.003	0.001	0.014	0.012	0.008	0.012	0.005	0.007
	(3.76)**	(3.48)**	-0.14	-0.04	-1.22	-1.08	-0.55	-0.76	-0.44	-0.65
N	1806	1806	1806	1806	1806	1806	1806	1806	1806	1806
R^2	0.71	0.72	0.57	0.57	0.79	0.79	0.73	0.73	0.81	0.82
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.13
Regression results for the factor model of Asian ex-Japan equity funds under CPF Investment Scheme without the effect of currency risk (continued)

	Fund 6		Fund 7		Fund 8		Fund 9		Fund 10	
β_{axj}	0.723	0.723	0.998	0.997	0.614	0.614	0.891	0.89	0.934	0.933
	(49.88)**	(50.01)**	(65.74)**	(66.11)**	(35.96)**	(35.95)**	(56.19)**	(56.62)**	(85.04)**	(85.12)**
γ_{mp}	0.1	0.099	0.035	0.037	0.118	0.118	0.059	0.061	0.102	0.102
	(2.64)**	(2.61)**	-0.89	-0.94	(2.65)**	(2.65)**	-1.43	-1.49	(3.54)**	(3.57)**
β_{HML}		0.081		-0.141		0.001		-0.171		-0.048
		(2.90)**		(4.83)**		-0.03		(5.63)**		(2.27)*
α	0.017	0.016	0.003	0.006	0.017	0.017	0.009	0.013	0.013	0.014
	-1.2	-1.07	-0.17	-0.38	-0.97	-0.97	-0.6	-0.84	-1.19	-1.28
N	1806	1806	1806	1806	1806	1806	1806	1806	1806	1806
R^2	0.65	0.65	0.75	0.76	0.49	0.49	0.69	0.7	0.84	0.84
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.14
Regression results for the factor model of Asian ex-Japan equity funds under CPF Investment Scheme with the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_{axj}	0.574	0.574	0.797	0.796	0.805	0.806	0.946	0.946	0.904	0.904
	(57.93)**	(59.04)**	(43.84)**	(43.99)**	(72.66)**	(72.85)**	(63.21)**	(63.47)**	(81.85)**	(82.19)**
γ_{mp}	0.081	0.079	-0.061	-0.059	-0.002	-0.003	0.012	0.014	0.017	0.018
	(3.14)**	(3.12)**	-1.29	-1.26	-0.07	-0.1	-0.31	-0.35	-0.6	-0.64
β_c	0.196	0.226	0.339	0.311	-0.209	-0.197	0.767	0.742	0.74	0.722
	(3.48)**	(4.09)**	(3.29)**	(3.03)**	(3.33)**	(3.12)**	(9.03)**	(8.76)**	(11.81)**	(11.55)**
β_{HML}		0.154		-0.14		0.065		-0.123		-0.089
		(8.16)**		(4.00)**		(3.01)**		(4.27)**		(4.20)**
α	0.041	0.038	0.003	0.006	0.01	0.009	0.021	0.023	0.017	0.019
	(4.07)**	(3.84)**	-0.16	-0.31	-0.92	-0.81	-1.37	-1.54	-1.51	-1.67
N	1806	1806	1806	1806	1806	1806	1806	1806	1806	1806
R^2	0.71	0.72	0.57	0.57	0.79	0.79	0.74	0.74	0.83	0.83
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.15
Regression results for the factor model of Asian ex-Japan equity funds under CPF Investment Scheme with the effect of currency risk (continued)

	Fund 6		Fund 7		Fund 8		Fund 9		Fund 10	
β_{axj}	0.723	0.723	0.998	0.998	0.615	0.615	0.891	0.89	0.934	0.934
	(49.92)**	(50.06)**	(66.26)**	(66.58)**	(36.18)**	(36.17)**	(56.39)**	(56.78)**	(88.53)**	(88.55)**
γ_{mp}	0.099	0.098	0.033	0.035	0.116	0.116	0.058	0.06	0.098	0.099
	(2.62)**	(2.60)**	-0.85	-0.9	(2.63)**	(2.62)**	-1.4	-1.46	(3.57)**	(3.59)**
β_c	0.145	0.162	0.448	0.422	0.431	0.433	0.319	0.286	0.729	0.723
	-1.76	(1.97)*	(5.24)**	(4.95)**	(4.47)**	(4.48)**	(3.56)**	(3.21)**	(12.18)**	(12.05)**
β_{HML}		0.085		-0.131		0.011		-0.164		-0.031
		(3.03)**		(4.51)**		-0.33		(5.41)**		-1.54
α	0.02	0.018	0.01	0.012	0.024	0.023	0.015	0.018	0.025	0.025
	-1.35	-1.24	-0.64	-0.81	-1.37	-1.36	-0.92	-1.12	(2.32)*	(2.38)*
N	1806	1806	1806	1806	1806	1806	1806	1806	1806	1806
R^2	0.65	0.65	0.76	0.76	0.5	0.5	0.7	0.7	0.85	0.85
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.16
Regression results for the factor model of non-CPF Asian ex-Japan equity funds without the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4	
β_{axj}	0.757	0.757	0.977	0.977	1.052	1.052	1.014	1.014
	(42.21)**	(42.20)**	(63.77)**	(63.96)**	(81.30)**	(81.33)**	(97.99)**	(99.33)**
γ_{mp}	0.124	0.124	0.085	0.086	0.057	0.058	-0.017	-0.015
	(2.65)**	(2.64)**	(2.12)*	(2.16)*	-1.69	-1.71	-0.62	-0.56
β_{HML}		0.011		-0.109		-0.045		-0.143
		-0.32		(3.70)**		-1.79		(7.27)**
α	0.019	0.019	-0.001	0.002	-0.002	-0.001	0.006	0.009
	-1.07	-1.06	-0.03	-0.13	-0.13	-0.05	-0.53	-0.85
N	1806	1806	1806	1806	1806	1806	1806	1806
R^2	0.57	0.57	0.75	0.75	0.83	0.83	0.87	0.87
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%								

Table F.17
Regression results for the factor model of non-CPF Asian ex-Japan equity funds with the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4	
β_{axj}	0.758	0.758	0.977	0.977	1.052	1.052	1.014	1.014
	(42.69)**	(42.69)**	(63.75)**	(63.94)**	(81.30)**	(81.33)**	(97.96)**	(99.30)**
γ_{mp}	0.121	0.121	0.084	0.086	0.057	0.057	-0.017	-0.015
	(2.62)**	(2.61)**	(2.11)*	(2.16)*	-1.68	-1.7	-0.62	-0.56
β_c	0.623	0.628	0.03	0.008	0.069	0.061	-0.001	-0.029
	(6.19)**	(6.22)**	-0.34	-0.09	-0.94	-0.82	-0.01	-0.51
β_{HML}		0.026		-0.109		-0.043		-0.144
		-0.75		(3.68)**		-1.73		(7.28)**
α	0.029	0.029	0	0.002	-0.001	0	0.006	0.008
	-1.63	-1.6	0	-0.13	-0.04	-0.02	-0.53	-0.81
N	1806	1806	1806	1806	1806	1806	1806	1806
R^2	0.58	0.58	0.75	0.75	0.83	0.83	0.87	0.87
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%								

Table F.18
Regression results for the factor model of Greater China equity funds under CPF Investment Scheme without the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_{dg}	0.793	0.795	0.677	0.676	0.839	0.84	0.88	0.881	0.779	0.78
	(57.46)**	(57.79)**	(50.31)**	(50.44)**	(64.43)**	(64.70)**	(69.51)**	(69.94)**	(62.81)**	(63.12)**
γ_{mp}	0.109	0.106	-0.055	-0.051	0.024	0.021	0.146	0.142	0.119	0.116
	(3.37)**	(3.28)**	-1.74	-1.64	-0.77	-0.68	(4.91)**	(4.81)**	(4.09)**	(4.00)**
β_{HML}		-0.104		0.098		-0.085		-0.101		-0.087
		(4.45)**		(4.29)**		(3.84)**		(4.72)**		(4.12)**
α	0.036	0.036	0.036	0.036	0.029	0.029	0.029	0.029	0.021	0.021
	(2.34)*	(2.35)*	(2.42)*	(2.43)*	(1.98)*	(1.99)*	(2.02)*	(2.03)*	-1.53	-1.53
N	2060	2060	2060	2060	2060	2060	2060	2060	2060	2060
R^2	0.69	0.69	0.61	0.61	0.73	0.73	0.77	0.77	0.73	0.73
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.19
Regression results for the factor model of Greater China equity funds under CPF Investment Scheme with the effect of currency risk

	Fund 1		Fund 2		Fund 3		Fund 4		Fund 5	
β_{dg}	0.793	0.794	0.677	0.676	0.839	0.839	0.88	0.881	0.779	0.78
	(57.66)**	(57.97)**	(50.59)**	(50.74)**	(66.11)**	(66.34)**	(72.11)**	(72.49)**	(62.83)**	(63.15)**
γ_{mp}	0.11	0.107	-0.054	-0.05	0.026	0.023	0.148	0.145	0.119	0.116
	(3.41)**	(3.32)**	-1.71	-1.6	-0.87	-0.78	(5.17)**	(5.09)**	(4.08)**	(3.99)**
β_c	0.282	0.269	0.341	0.354	0.691	0.682	0.796	0.785	-0.095	-0.106
	(3.94)**	(3.77)**	(4.90)**	(5.11)**	(10.48)**	(10.36)**	(12.55)**	(12.41)**	-1.48	-1.66
β_{HML}		-0.1		0.102		-0.075		-0.091		-0.088
		(4.31)**		(4.52)**		(3.51)**		(4.38)**		(4.19)**
α	0.04	0.04	0.041	0.041	0.039	0.039	0.04	0.04	0.02	0.02
	(2.60)**	(2.60)**	(2.75)**	(2.77)**	(2.72)**	(2.72)**	(2.92)**	(2.92)**	-1.43	-1.42
N	2060	2060	2060	2060	2060	2060	2060	2060	2060	2060
R^2	0.69	0.69	0.61	0.62	0.74	0.74	0.78	0.78	0.73	0.73
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%										

Table F.20
Regression results for the factor model of non-CPF Greater China equity funds without the effect of currency risk

	Fund 1		Fund 2	
β_{dg}	0.652	0.652	0.866	0.866
	(27.52)**	(27.49)**	(64.99)**	(65.02)**
γ_{mp}	0.179	0.181	-0.022	-0.024
	(3.22)**	(3.25)**	-0.72	-0.75
β_{HML}		0.053		-0.033
		-1.31		-1.47
α	0.061	0.061	0.01	0.01
	(2.31)*	(2.31)*	-0.7	-0.7
N	2060	2060	2060	2060
R^2	0.35	0.35	0.72	0.73
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%				

Table F.21
Regression results for the factor model of non-CPF Greater China equity funds with the effect of currency risk

	Fund 1		Fund 2	
β_{dg}	0.652	0.652	0.865	0.866
	(27.51)**	(27.49)**	(67.27)**	(67.27)**
γ_{mp}	0.179	0.18	-0.02	-0.021
	(3.22)**	(3.25)**	-0.66	-0.68
β_{c}	-0.035	-0.028	0.813	0.81
	-0.28	-0.23	(12.16)**	(12.10)**
β_{HML}		0.052		-0.023
		-1.3		-1.03
α	0.061	0.061	0.022	0.022
	(2.29)*	(2.29)*	-1.53	-1.52
N	2060	2060	2060	2060
R^2	0.35	0.35	0.74	0.74
Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%				