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A time-varying perspective on the CAPM and downside betas

Hsiu-Jung Tsai [a], Ming-Chi Chen [b,*], Chih-Yuan Yang [c]

[a] Department of Finance, National Kaohsiung First University of Science and Technology, Taiwan
[b] Department of Finance, National Sun Yat-sen University, Taiwan
[c] Department of Finance, Tainan University of Technology, Taiwan

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ABSTRACT

In the current study, we focus on the capital asset pricing model (CAPM) beta and downside betas. The empirical results of market index returns in the international samples of 23 developed countries exhibit significant differences between the CAPM and downside betas, indicating that these models capture distinct risks. Considering autocorrelation variance, the DCC downside betas (HW-beta and HR-beta) more effectively explain the expected stock market returns than does the CAPM beta.

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1. Introduction

For over a half century, academics and practitioners have debated the merits of the capital asset pricing model (CAPM), focusing on whether beta is an appropriate measure of risk. In the CAPM framework, risk is measured using variance, which treats upside and downside movements of returns equally. However, variance identifies extreme gains as being as undesirable as extreme losses, which is unrealistic. Because investors are more sensitive to downside losses compared with upside gains, they require a premium for holding assets that covary strongly with the market when the market declines (Ang, Chen, & Xing, 2006). Estrada (2007) suggested that the variance of returns is a questionable measure of risk for at least two reasons: the symmetry and normality of the underlying return distribution. However, the empirical evidence calls both the symmetry and the normality of stock returns into question. Therefore, considering the aversion of investors to losses, the semi-variance (or downside beta) is more appealing as a measure of risk than is the variance (or the CAPM beta).

Another criticism of the CAPM beta is its ordinary least squares (OLS) regression, which assumes a constant beta risk (Fama & MacBeth, 1973). According to Klemkosky and Martin (1975) and Bollerslev, Engle, and Wooldrige (1988), however, the expectations of economic agents for future returns are conditional and therefore random variables rather than constants. This implies that the beta of a risky asset should be time-varying. Studies, such as Harvey (1989), Ferson and Harvey (1991, 1993), and

* Corresponding author at: Department of Finance, National Sun Yat-sen University, 70 Lien-hai Rd. Kaohsiung 804, Taiwan. Tel.: +886 7 525000x4826; fax: +886 7 5254899.
E-mail addresses: sharon0623@gmail.com (H.-J. Tsai), mcchen@finance.nsysu.edu.tw (M.-C. Chen), chikyang@gmail.com (C.-Y. Yang).

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Saleem and Vaihekoski (2010), have suggested that a constant beta estimated using OLS does not capture the dynamics of the beta. Furthermore, Jagannathan and Wang (1996), Lettau and Ludvigson (2001), and Beach (2011) show that the conditional CAPM with a time-varying beta outperforms the unconditional CAPM with a constant beta.

To obviate the deficiencies of previous studies, in the current study, we compare the CAPM beta and the downside betas, examining their levels of performance. To empirically examine the time-varying relationships between the CAPM beta and the downside betas, we sampled 23 developed markets from the Morgan Stanley capital indices (MSCI). The HW-beta and HR-beta were consistently higher than were the other measures. To enhance the empirical results, we employed the dynamic conditional correlation (DCC) model, excluding the existing serial autocorrelation of variance. The robust results show that the conditional HW-beta (HR-beta) is higher compared with the conditional CAPM beta. This paper is the first to use a DCC model to estimate the time-varying CAPM beta and downside betas, contributing a suitable methodological application for estimating time-varying risk to the existing literature. Our beta performance findings show that the DCC HW-beta and the DCC HR-beta outperformed the other betas in explaining expected stock market returns. The downside betas captured certain downside linkages between the market portfolio and individual equity returns; however, the CAPM beta cannot capture these linkages.

The paper is organized as follows: Section 2 defines the risk measures for the CAPM beta and the downside betas; Section 3 introduces the DCC method; Section 4 describes the data; Section 5 reports the empirical results; and our concluding remarks are offered in the final section.

2. Definition of the CAPM beta and downside betas

According to the capital asset pricing literature, the CAPM beta combines covariance and volatility, measuring the sensitivity of asset returns to market returns in addition to the correlated relative volatility. The CAPM beta is denoted by β_i^{CAPM}, which uses the following formula:

$$\beta_i^{\mathrm{CAPM}} = \frac{Cov\left[\left(R_{it}-R_{ft}\right)\cdot\left(R_{Mt}-R_{ft}\right)\right]}{Var\left[\left(R_{Mt}-R_{ft}\right)\right]} \tag{1}$$

where R_{it} and R_{Mt} are the returns of security i and market portfolio at time t, respectively, and R_{ft} is the risk-free rate. Therefore, $R_{it} - R_{ft}$ can be regarded as the abnormal return of security i and $R_{Mt} - R_{ft}$ as the excess return of the market portfolio.

We considered three measures of the downside beta proposed in the literature. The first was proposed by Hogan and Warren (1974), who considered a riskless asset as an opportunity cost in their interpretation of the CAPM in a downside framework, defining the downside beta (the HW-beta), denoted by β_i^{HW}, as

$$\beta_i^{\mathrm{HW}} = \frac{Cov\left[\left(R_{it}-R_{ft}\right)\cdot\min\left(R_{Mt}-R_{ft},0\right)\right]}{Var\left[\min\left(R_{Mt}-R_{ft},0\right)\right]}. \tag{2}$$

The numerator in Eq. (2) is referred to as the co-semi-variance of returns below R_{ft} on the market portfolio with returns in excess of R_{ft} on security i.

Harlow and Rao (1989) indicated that investors appeared to characterize risk as downside deviations below a target related to the average equity market returns rather than the risk-free rate.[1] Hence, they calculated the downside beta (the HR-beta) by employing the covariance of returns below the average returns on the market portfolio and the de-mean return on security i. Thus, the HR-beta denoted by β_i^{HR} can be expressed as follows:

$$\beta_i^{\mathrm{HR}} = \frac{Cov[(R_{it}-\mu_i)\cdot\min(R_{Mt}-\mu_M,0)]}{Var[\min(R_{Mt}-\mu_M,0)]} \tag{3}$$

where μ_i and μ_M are the average returns of security i and the market portfolio, respectively.

Estrada (2002) modified the HR-beta by defining the covariance of security i's returns with the covariance of the market portfolio in a downside framework as $E[\min(R_{it} - \mu_i, 0) \cdot \min(R_{Mt} - \mu_M, 0)]$. Generalizing the correlation asymmetry, Estrada (2002) calculated the correlation of doubly truncated bivariate distributions and the downside beta (the E-beta), denoted by β_i^{E}, as

$$\beta_i^{\mathrm{E}} = \frac{Cov[\min(R_{it}-\mu_i,0)\cdot\min(R_{Mt}-\mu_M,0)]}{Var[\min(R_{Mt}-\mu_M,0)]}. \tag{4}$$

Galagedera and Brooks (2007) highlighted that the E-beta focuses exclusively on negative returns and thus "cannot be linked to a well-behaved utility function." By contrast, the E-beta does not suffer from the measure-inconsistency problem, in which the covariance between securities i and j differs from that between securities j and i.

[1] Such a target can be interpreted as the threshold for the downside beta.

3. Dynamic conditional correlation (DCC)

Most financial time-series data exhibit strong autocorrelation behaviors, but certain studies have not considered this when estimating the CAPM beta. To ensure the thoroughness of our study, we used the DCC model[2] to estimate the CAPM beta and the three downside betas. Because the estimation procedure of dynamic conditional correlation also produces time-varying conditional variance and conditional covariance, we can easily compute the corresponding betas.[3]

The estimation of the dynamic correlation coefficients follows two steps. First, the parameters of the variance models are estimated. Scholars have agreed that GARCH (1, 1) is sufficient to capture the heteroscedasticity of stock and financial variables (Bollerslev, Chou, & Kroner, 1992). In accordance with Engle (2002) and using the conditional correlation coefficients and variances of two stock returns and market portfolios to parameterize the stock return covariance matrix H_t, we obtain:

$$H_t \equiv D_t R_t D_t \tag{5}$$

where R_t is the time varying correlation matrix and D_t is the 2×2 diagonal matrix of the time varying standard deviations from the univariate GARCH with $\sqrt{h_{it}}$ on the ith diagonal. As indicated, the elements in D_t follow the univariate GARCH process as follows:

$$h_{it} = b_0 + b_1 \varepsilon_{it-1}^2 + b_2 h_{it-1} \tag{6}$$

Engle (2002) suggested a two-step approach for estimating the DCC model by maximizing the following log-likelihood function:

$$\begin{aligned} L &= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi) + 2\log|H_t| + r_t' H_t^{-1} r_t\right) \\ &= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi) + 2\log|D_t R_t D_t| + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t\right) \\ &= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi) + 2\log|D_t| + \log(|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t\right) \end{aligned} \tag{7}$$

where $\varepsilon_t \sim N(0,R_t)$ are the residuals standardized by their conditional standard deviation. The term between the first capital brackets represents the volatility components that are the sum of individual GARCH likelihoods. Given the estimated parameters in D_t obtained using the first step, the correlation component of the likelihood function can be estimated in the second step.

Taking the estimation procedure of the HR-beta, we first employed the DCC model to estimate the dynamic conditional correlation between two types of returns such as returns that are below average compared with the market portfolio $[\min(R_{Mt} - \mu_M, 0)]$ and the de-mean return on security i $(R_{it} - \mu_i)$. The estimation procedure of dynamic conditional correlation simultaneously produces the time-varying conditional variance $Var[\min(R_{Mt} - \mu_M, 0)]$ and conditional covariance $Cov[(R_{it} - \mu_i) \cdot \min(R_{Mt} - \mu_M, 0)]$. As a result, we can easily compute the conditional HR-beta. The other betas can also be computed using this procedure.

4. Data description

The sample used in this study comprised 23 developed markets[4] of the MSCI. The data were collected from the Global Financial Database (GFD)[5] for the period from January 2, 1990 to May 31, 2009, including 5048 daily observations for each developed market. All the national stock price indices, presented in the local currency, represent the daily closing prices in each national market. The daily returns were calculated as the first difference of the natural log of each price index and expressed as percentages. When data were unavailable because of national holidays, bank holidays, or other reasons, the stock prices were assumed to be the same as those of the previous trading day.

In addition, the MSCI world index, which covers approximately 8500 securities, was selected as the proxy for the "market index." From the viewpoint of global portfolio management, the MSCI world index is a suitable benchmark for asset allocation because it consists of 45 country indices comprising 24 developed and 21 emerging market countries.[6] Finally, the yields on 3-month United States Treasury bills, which were converted into the daily interest rate, were collected as a proxy for the risk-free rate.

[2] Engle (2002) proposed a generalization of the Bollerslev (1990) constant conditional correlation model, making the conditional correlation matrix time dependent. This is called a DCC model.

[3] Bodurtha and Mark (1991) indicated that incorporating the time-varying conditional variance and covariance provides a convenient way to compute the conditional CAPM.

[4] These 23 developed markets comprise Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The Israeli market is not included in our sample because the MSCI Israel Index was re-classified to developed markets from emerging markets in May 2010.

[5] To ensure data validity, we consulted the Bloomberg database and found three controversial observations, including Greece (March 11, 2003), Portugal (March 5, 2007), and Singapore (June 19, 1998). These inconsistencies were corrected based on the records of regional stock exchanges.

[6] The included emerging market country indices were Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Morocco, Peru, the Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey.

Table 1 lists the statistics describing the daily returns of the world market and 23 developed markets. The corresponding stock indices for these markets are listed in Appendix I. Table 1 reveals that, out of the markets in these 23 developed countries, Hong Kong has the highest mean return, which is potentially a result of the economic rise of and policy support from China. Japan is the only market with a negative mean return, possibly resulting from its foam economy. The minimal daily return ranges from −17.403% to −7.322%, whereas the maximal return varies between 17.247% and 6.067%. The skewness ranges from −0.788 to 0.192, and the return distributions of most markets are negatively skewed. The world market return distribution is also negatively skewed and has 9.48 excess kurtosis and 0.011% mean return. In summary, most developed markets have positive average returns that are negatively skewed and peaked.

5. Empirical results and discussion

5.1. Estimating the CAPM beta and the three downside betas

This subsection presents estimations of the CAPM beta and downside betas. First, by using the formulae in Eqs. (1)–(4), we computed the CAPM beta and the three downside betas for each developed market by using the standard rolling one-year daily return. For example, we used the data from January 2, 1990 to January 1, 1991 to calculate the variance and covariance by using Eqs. (1)–(4), obtaining the corresponding value as the beta for January 2, 1991. Such computation rolls the daily return to the end, obtaining a series of time-varying betas. To avoid confusion with the following empirical process, we refer to the beta estimated using the formula as the rolling beta. Second, considering most financial time-series data with strong autocorrelation behaviors, we used the DCC model to calculate time-varying conditional variance and conditional covariance. The DCC betas were estimated in a two-step procedure. We first applied the GARCH (1, 1) to remove serial correlation of variance and used the filtered series to estimate the DCC model. Using standardized residuals from the first step, this estimation procedure also produced time-varying conditional variances and conditional covariances. Bodurtha and Mark (1991) suggested that the conditional CAPM provides a convenient way of incorporating time-varying conditional variances and covariances; thus, we used the conditional variances and conditional covariances given by Eqs. (1)–(4), computing the CAPM beta and the three downside betas for each market. To avoid confusion with the previous empirical process, we refer to the beta estimated by the DCC model as the DCC beta.

Using the daily returns of 23 developed markets, we computed the time-varying CAPM betas and the three downside betas. To avoid repetition, Fig. 1 depicts only the four types of time-varying rolling betas of six major industrialized countries; specifically, the United States was chosen as an example. Fig. 1(a) shows the time-varying rolling betas of the United States market. The average CAPM beta was 0.880. The highest beta (HW-beta) was 1.933, and the lowest beta (E-beta) was 0.243. The plots all exhibit time-varying patterns with volatility clustering, which justifies using the time-varying perspective in this study.

Table 1
Summary statistics of developed market daily returns.

Country	Mean	Max	Min	SD	Skew	Kurt
World market	0.011	9.098	−7.322	0.944	−0.318	12.480
Australia	0.017	6.067	−8.554	0.908	−0.599	10.891
Austria	0.012	12.021	−10.253	1.357	−0.297	11.966
Belgium	0.010	10.323	−8.657	1.009	−0.103	13.473
Canada	0.019	9.370	−9.788	1.032	−0.788	15.353
Denmark	0.019	8.201	−10.583	0.971	−0.525	11.978
Finland	0.026	14.563	−17.403	1.789	−0.292	9.915
France	0.010	10.595	−9.472	1.394	−0.032	8.103
Germany	0.011	10.797	−9.881	1.464	−0.126	8.428
Greece	0.032	13.750	−10.214	1.681	0.061	8.365
Hong Kong	0.037	17.247	−14.735	1.683	0.014	12.958
Ireland	0.009	9.733	−13.964	1.221	−0.640	14.376
Italy	0.007	7.914	−9.723	1.226	−0.463	7.649
Japan	−0.028	13.235	−12.111	1.543	−0.016	8.808
Netherlands	0.014	10.568	−13.920	1.303	−0.405	13.516
New Zealand	0.001	9.175	−12.896	0.883	−0.598	17.657
Norway	0.031	9.186	−9.709	1.344	−0.529	10.689
Portugal	0.007	9.710	−10.379	1.024	−0.398	14.810
Singapore	0.014	14.869	−9.672	1.338	0.094	11.994
Spain	0.024	9.870	−9.680	1.259	−0.238	8.998
Sweden	0.026	11.023	−8.527	1.516	0.192	7.173
Switzerland	0.022	10.788	−8.299	1.201	−0.156	9.476
United Kingdom	0.012	9.384	−9.265	1.132	−0.085	9.992
United States	0.022	10.508	−8.201	1.110	−0.115	12.000

Notes: The return is computed as the change in logarithm of the closing prices and is expressed as a percentage. The sample covers the period from January 2, 1990 to May 31, 2009, and consists of 5048 daily observations for each developed market.

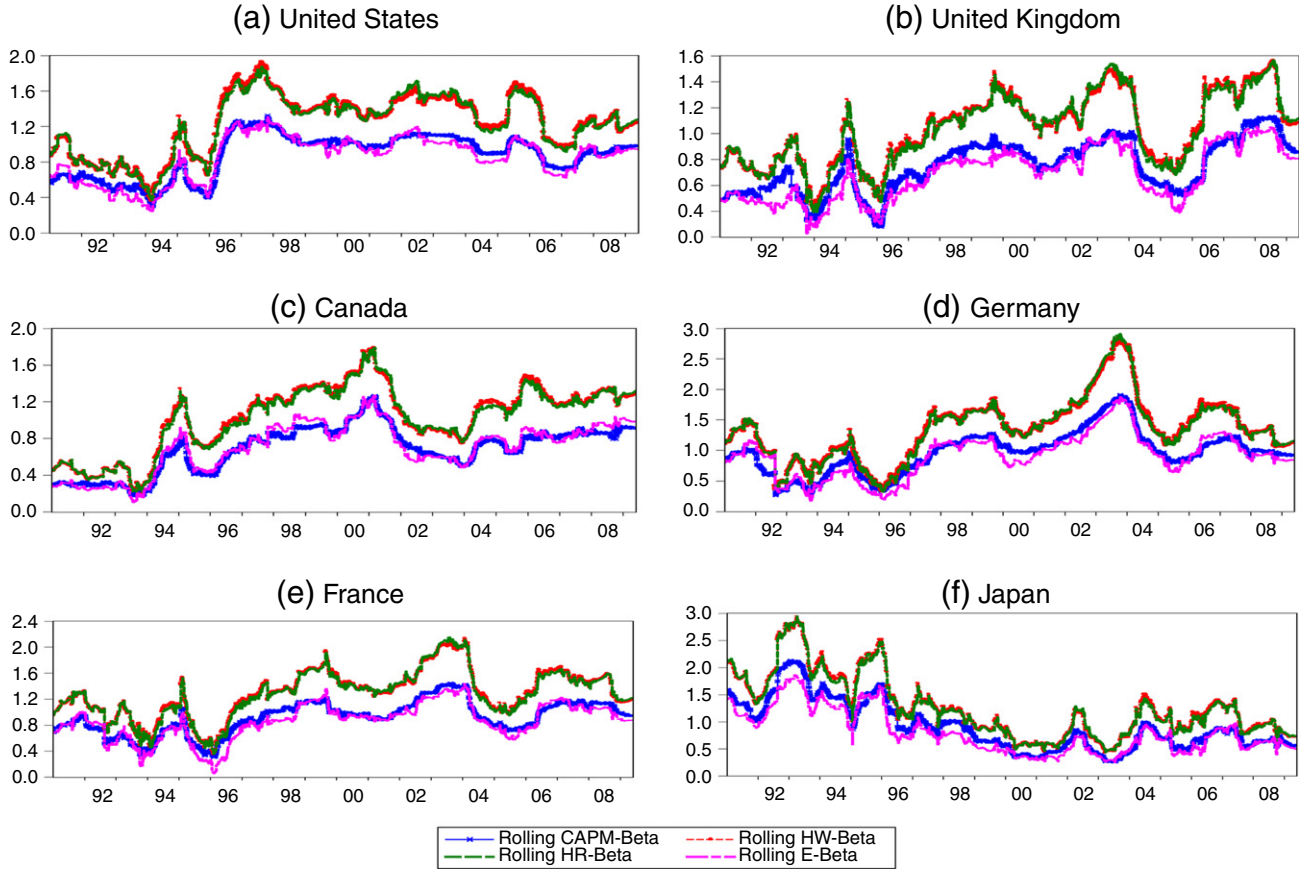


Fig. 1. The time-varying rolling CAPM beta and downside betas.

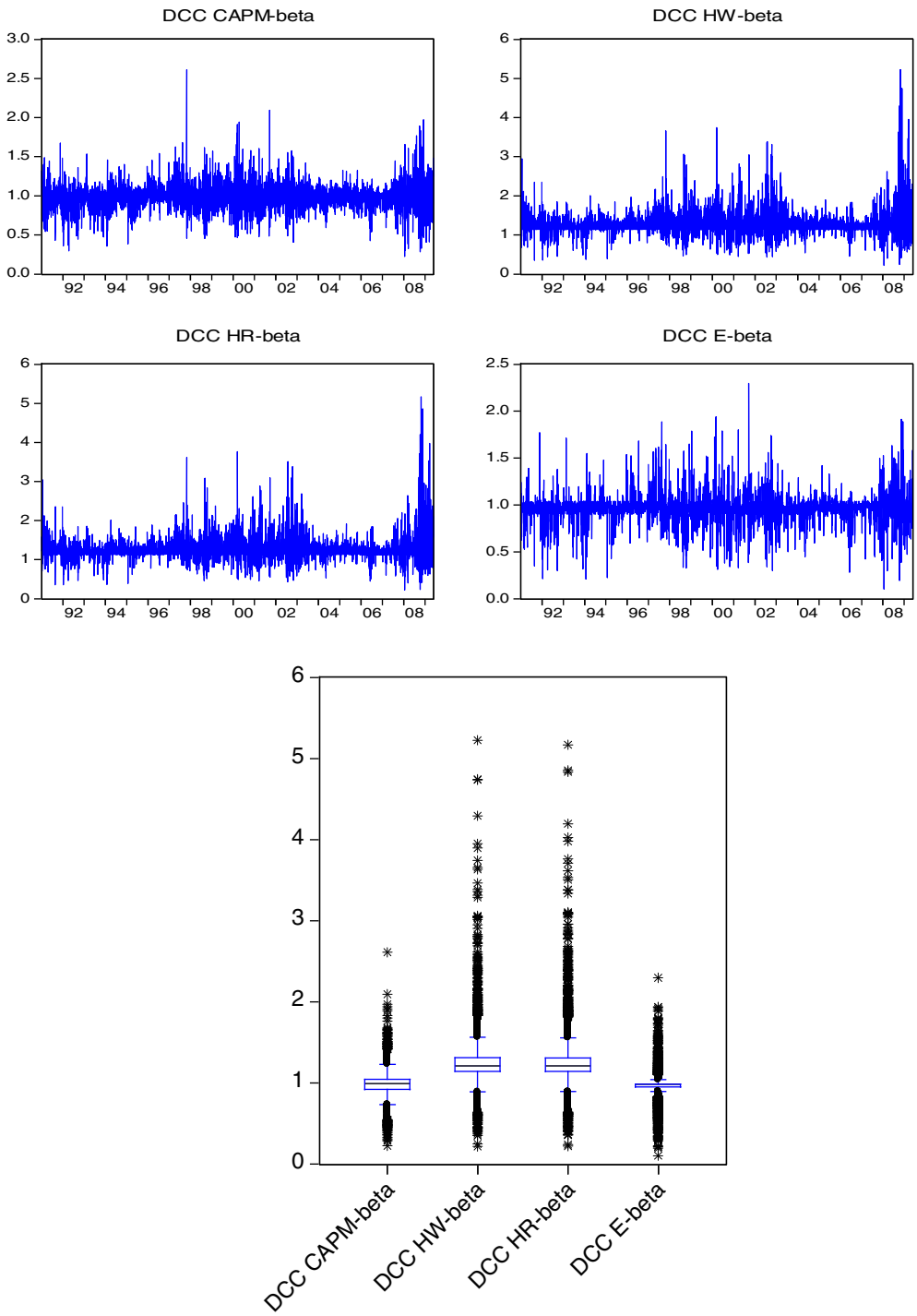


Fig. 2. The time-varying CAPM beta and downside betas under DCC model (The United States).

To control the autocorrelation behavior of stock returns, we employed the DCC model to produce time-varying conditional variance and covariances, thus computing the DCC beta. Fig. 2 depicts the four time-varying DCC betas of the United States.[7] The average DCC CAPM beta was 0.985. The highest beta was 5.228 (DCC HW-beta), and the lowest beta was 0.104 (DCC E-beta). As

[7] For ease of reading, only the United States figures are retained. The figures of the other G6 countries are listed in the Appendix II. The figures for the remaining countries are available from the authors.

Table 2
The mean of betas.

Country	CAPM-β^R	HW-β^R	HR-β^R	E-β^R	CAPM-β^{DCC}	HW-β^{DCC}	HR-β^{DCC}	E-β^{DCC}
Australia	0.350	0.531	0.523	0.326	0.345	0.462	0.458	0.340
Austria	0.596	0.881	0.869	0.593	0.690	0.961	0.948	0.728
Belgium	0.548	0.769	0.761	0.516	0.647	0.854	0.841	0.644
Canada	0.687	1.031	1.020	0.701	0.804	1.114	1.112	0.883
Denmark	0.464	0.691	0.688	0.464	0.586	0.818	0.805	0.628
Finland	0.905	1.299	1.291	0.851	1.072	1.405	1.391	0.997
France	0.915	1.289	1.280	0.860	1.066	1.371	1.366	1.022
Germany	0.967	1.352	1.347	0.910	1.114	1.413	1.407	1.048
Greece	0.429	0.694	0.685	0.456	0.586	0.834	0.804	0.568
Hong Kong	0.704	1.048	1.032	0.673	0.717	0.929	0.916	0.671
Ireland	0.551	0.805	0.797	0.537	0.684	0.952	0.925	0.721
Italy	0.588	0.866	0.862	0.589	0.640	0.868	0.855	0.645
Japan	0.906	1.268	1.254	0.798	0.767	0.981	0.983	0.666
Netherlands	0.762	1.088	1.080	0.745	0.935	1.230	1.217	0.959
New Zealand	0.173	0.266	0.261	0.144	0.153	0.246	0.230	0.152
Norway	0.637	0.957	0.947	0.642	0.778	1.085	1.066	0.822
Portugal	0.342	0.509	0.510	0.396	0.558	0.752	0.740	0.547
Singapore	0.536	0.760	0.751	0.509	0.556	0.728	0.713	0.515
Spain	0.768	1.095	1.085	0.735	0.896	1.181	1.174	0.870
Sweden	0.906	1.259	1.251	0.820	1.035	1.322	1.309	0.961
Switzerland	0.721	1.042	1.035	0.722	0.815	1.073	1.068	0.811
United Kingdom	0.748	1.038	1.030	0.685	0.864	1.105	1.100	0.842
United States	0.880	1.237	1.229	0.851	0.985	1.260	1.261	0.969

expected, this verifies the time-varying dynamic. The box plots show that the means of the CAPM beta and E-beta are lower compared with the means of the HW-beta and HR-beta. The HW-beta and HR-beta appear highly volatile.

To compare the CAPM beta and the downside betas, the means of these time-varying betas are summarized in Table 2, which shows relatively high means of the CAPM (downside) betas for Finland, France, Germany, and Sweden, revealing high (downside) systematic risk in these countries. By contrast, the systematic risk in the Australia and New Zealand markets is relatively low, which is partially a result of geographic location. The average values of the HW-beta and HR-beta in each market were higher than the other risk measures under the rolling formulae and the DCC model.

To illustrate these relationships graphically, we plotted the means of these CAPM betas and downside betas in Fig. 3. In the illustrations, the markets are presented in ascending order according to their CAPM beta. Fig. 3(a) and (b) shows that the means of the HW-beta and HR-beta are always higher than are the others. The high values of the HW-beta and HR-beta emphatically remind investors of the systematic risk involved in a downside market. The high values of the HW-beta and the HR-beta reflect more downside systematic risk when investors construct their investment portfolios. This concurs with Kaplanski (2004), who showed that investors in a depressed economy are highly concerned about downside risks, which are poorly captured by traditional betas.

5.2. Which beta most effectively explains the expected stock market returns?

The relationship between expected stock returns and downside risk is a worthy topic (Bali, Ozgur, & Levy, 2009; Demirer & Lien, 2003; Post & Vliet, 2006). Therefore, in this subsection, we investigate the cross-sectional relationship between the expected stock returns and time-varying betas. Table 3 presents the regression results for the expected stock returns and the four types of betas, which were calculated using the traditional (rolling) methods and the DCC model, respectively. For most markets, the rolling betas did not significantly affect the expected stock returns, implying that investors cannot obtain sufficient information to predict the dynamics of future stock prices.

For the time-varying DCC betas, we determined that the DCC HW-beta and the DCC HR-beta had more explanatory power for the expected stock market returns compared with the other betas. The DCC HW-beta and the DCC HR-beta capture certain downside linkages between market portfolios and expected stock returns; however, these linkages are unlikely to be captured by the CAPM beta. Because the DCC model considers the serial autocorrelation of variance, its calculated betas are close to the real financial environment.

In sum, we employed the rolling and DCC methods to estimate systemic risk and downside systemic risk. The results show that the downside beta is intuitively more appealing as a risk measure than is the variance (or CAPM beta). These results are consistent with Galagedera (2007, 2009). This paper also reinforces that a conditional beta with a time-varying beta outperforms an unconditional beta with a constant beta (Ferson & Harvey, 1991, 1993; Harvey, 1989).

6. Conclusion

Using a sample of 23 developed countries, we empirically computed the time-varying CAPM and downside betas, and further examined the relationships between these betas and the expected stock returns. Several conclusions can be drawn from the empirical results. First, the differences between the CAPM beta and the three downside betas are distinct. Whereas the downside

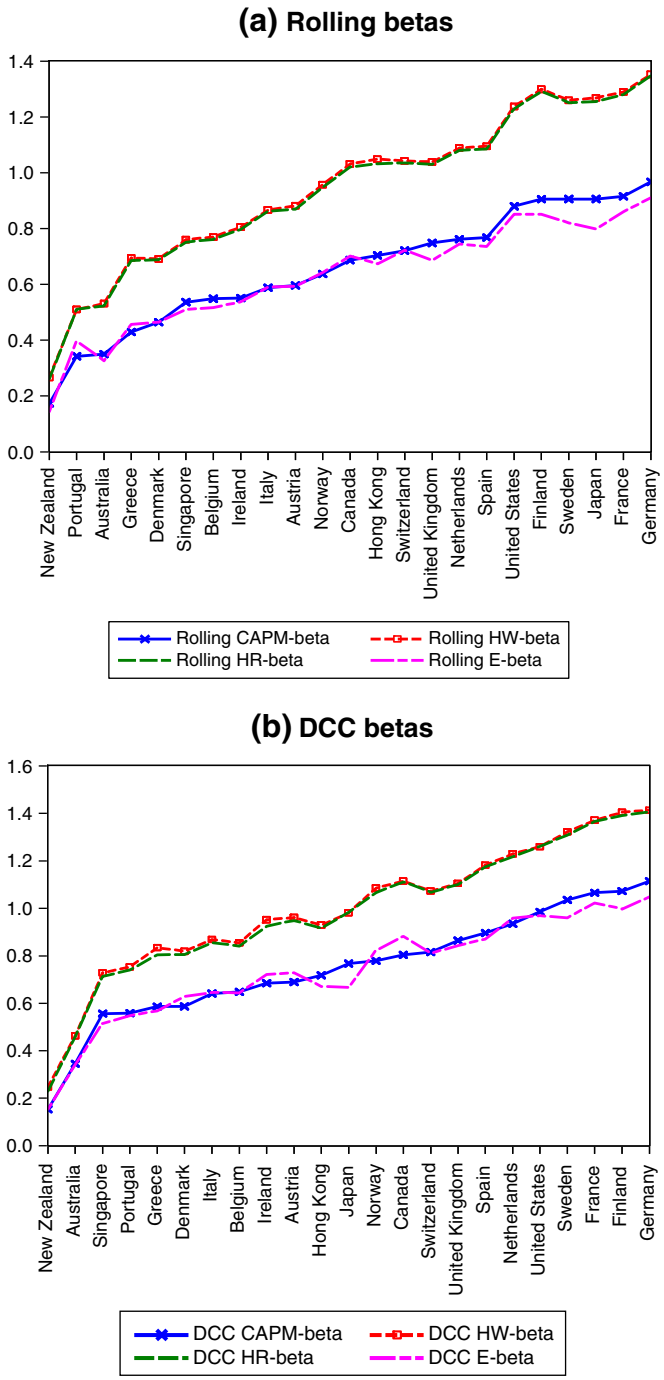


Fig. 3. The average betas of 23 developed markets (sorted by the CAPM beta).

beta captures certain downside linkages between the market portfolio and individual equity returns, these linkages likely cannot be captured by the CAPM beta. Second, among the risk measures in each developed country, the HW-beta and HR-beta are always higher than are the other betas. In a downside market, high HW-beta and HR-beta values can warn investors to pay attention to systematic risk. Third, because many studies have suggested that there are severe autocorrelation phenomena in stock returns and volatility, we examined the conditional CAPM and downside betas by using the DCC model. However, even after excluding the effect of autocorrelation, in most developed countries, the CAPM beta and the downside betas remain time-varying and distinct; thus, the results show that the conditional HW-beta (HR-beta) is higher than is the conditional CAPM beta. Finally, we investigated which beta most effectively explained the expected stock returns. The results demonstrate that the DCC HW-beta and the DCC HR-beta outperform the other betas in explaining the expected stock market returns.

Table 3
Cross-sectional analysis of between the expected stock returns and time-varying betas.

Country	CAPM-β^R	HW-β^R	HR-β^R	E-β^R	CAPM-β^{DCC}	HW-β^{DCC}	HR-β^{DCC}	E-β^{DCC}
Australia	1.236	0.820	0.255	0.394	0.110	0.823	0.833	0.561
Austria	2.089**	1.756*	0.708	0.492	0.188	2.440**	2.492**	−0.215
Belgium	1.260	1.388	0.924	0.788	−0.195	1.822*	1.877*	−0.125
Canada	1.436	1.241	0.974	0.888	2.707***	2.785***	2.680***	1.332
Denmark	2.550***	2.497**	1.894*	1.505	1.635	3.060***	3.164***	1.015
Finland	1.648*	1.980**	1.160	0.770	1.225	2.804***	2.750***	0.891
France	0.463	0.308	−0.025	−0.371	0.293	2.849***	2.887***	2.921***
Germany	0.628	0.357	0.011	−0.529	0.267	1.012	1.130	0.439
Greece	0.691	0.579	−0.144	−0.754	−3.288***	−2.035**	−1.939*	−3.040***
Hong Kong	1.426	1.699*	1.287	1.517	1.192	0.353	0.372	0.275
Ireland	4.230***	3.700***	3.386***	3.611***	2.000***	2.813***	2.729***	1.680*
Italy	−0.442	−0.996	−2.016**	−3.090***	−1.117	−0.293	−0.368	−0.958
Japan	−1.516	−1.724*	−1.915*	−1.983**	−1.111	−0.170	−0.304	−1.221
Netherlands	1.380	1.275	1.094	0.645	0.210	1.892*	1.891*	0.049
New Zealand	0.970	1.061	1.031	0.625	3.052	3.282***	3.192***	4.163***
Norway	1.362	1.410	0.752	−0.587	0.763	2.248**	2.364**	−0.867
Portugal	2.642***	3.003***	2.173**	2.171**	0.642	1.945**	2.172**	1.499
Singapore	0.764	0.825	−0.021	−0.162	−0.913	−1.230	−1.255	−1.485
Spain	1.430	1.407	0.518	0.116	1.457	3.129***	3.130***	0.944
Sweden	2.061**	1.977**	1.583	0.711	1.045	2.853***	3.012***	1.408
Switzerland	1.538	1.346	1.142	0.276	0.723	2.153**	2.316**	0.769
United Kingdom	1.594	1.273	1.084	0.926	0.316	2.946***	2.984***	1.869*
United States	0.578	0.458	0.169	0.023	3.606***	4.424***	4.097***	1.665*

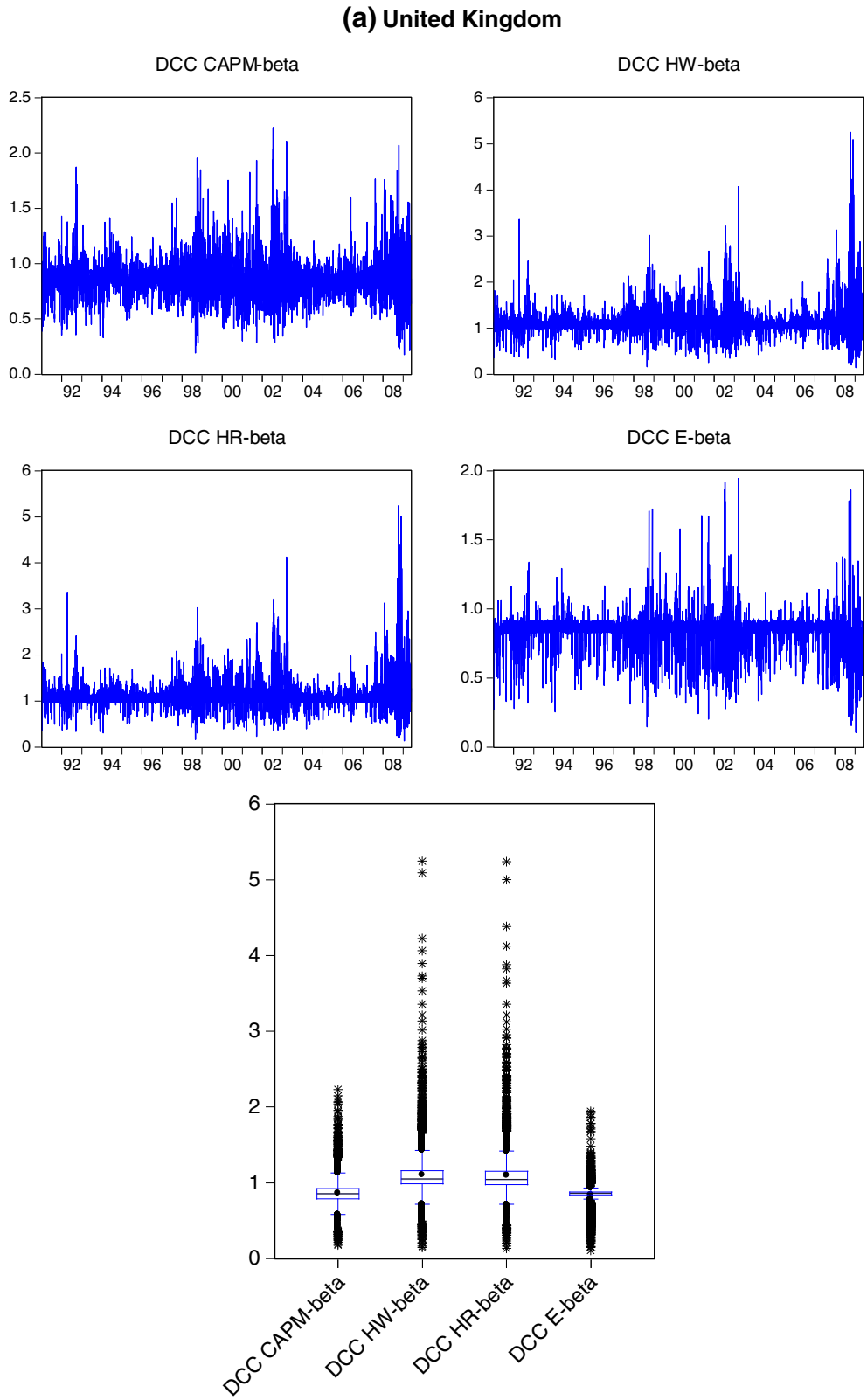
Note: Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.
Model: $E(R_{it} - R_t) = \alpha_{i0} + \alpha_{i1}\beta_{it} - 1 + \varepsilon_{it}$.

In sum, across the various computing methods, the resulting values of the downside betas were higher than were those of the CAPM betas. This indicates that the downside beta risk measure captures more downside systematic risk in a declining market (bear market). Investors should adopt hedging strategies to avoid potential investment losses. When building investment portfolios, we suggest that investors focus on the time-varying dynamic of downside systematic risk rather than traditional CAPM systematic risk. For a participant in the market, the time-varying downside risk can be used to measure potential risks that cannot be diversified by holding numerous assets or portfolios. Investors should pay attention to the CAPM systematic risk in addition to the time-varying downside risk when constructing their investment portfolios. The time-varying downside betas offer market participants a measure of the performances of their fund managers and also provide corporate financial managers with a helpful reference for capital structure decisions and investment evaluations.

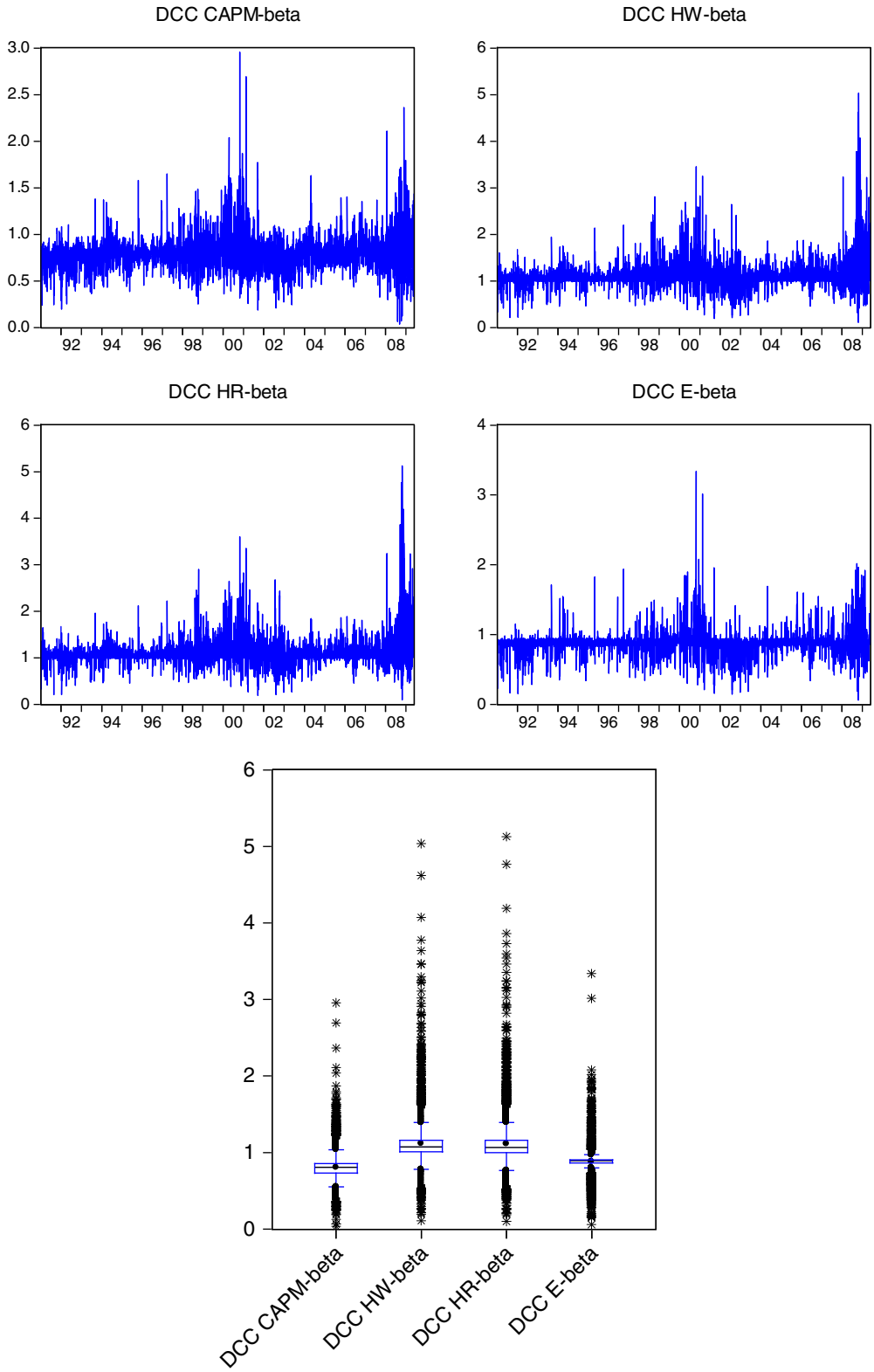
Appendix I. The major stock index for each developed market (country)

Country	Major stock index
Australia	Australia ASX All-Ordinaries
Austria	Austria Trading Index (ATX)
Belgium	Brussels All-Share Price Index
Canada	Canada S&P/TSX 300 Composite
Denmark	OMX Copenhagen All-Share Price Index
Finland	OMX Helsinki All-Share Price Index
France	Paris CAC-40 Index
Germany	Germany DAX Price Index
Greece	Athens SE General Index
Hong Kong	Hong Kong Hang Seng Composite Index
Ireland	Ireland ISEQ Overall Price Index
Italy	Banca Commerciale Italiana Index
Japan	Japan Nikkei 225 Stock Average
Netherlands	Netherlands All-Share Price Index
New Zealand	New Zealand SE All-Share Capital Index
Norway	Oslo SE All-Share Index
Portugal	Oporto PSI-20 Index
Singapore	Singapore FTSE Straits-Times Index
Spain	Madrid SE General Index
Sweden	OMX Stockholm-30 Index
Switzerland	Swiss Market Index
United Kingdom	UK Financial Times-SE 100 Index
United States	Dow Jones Industry Average

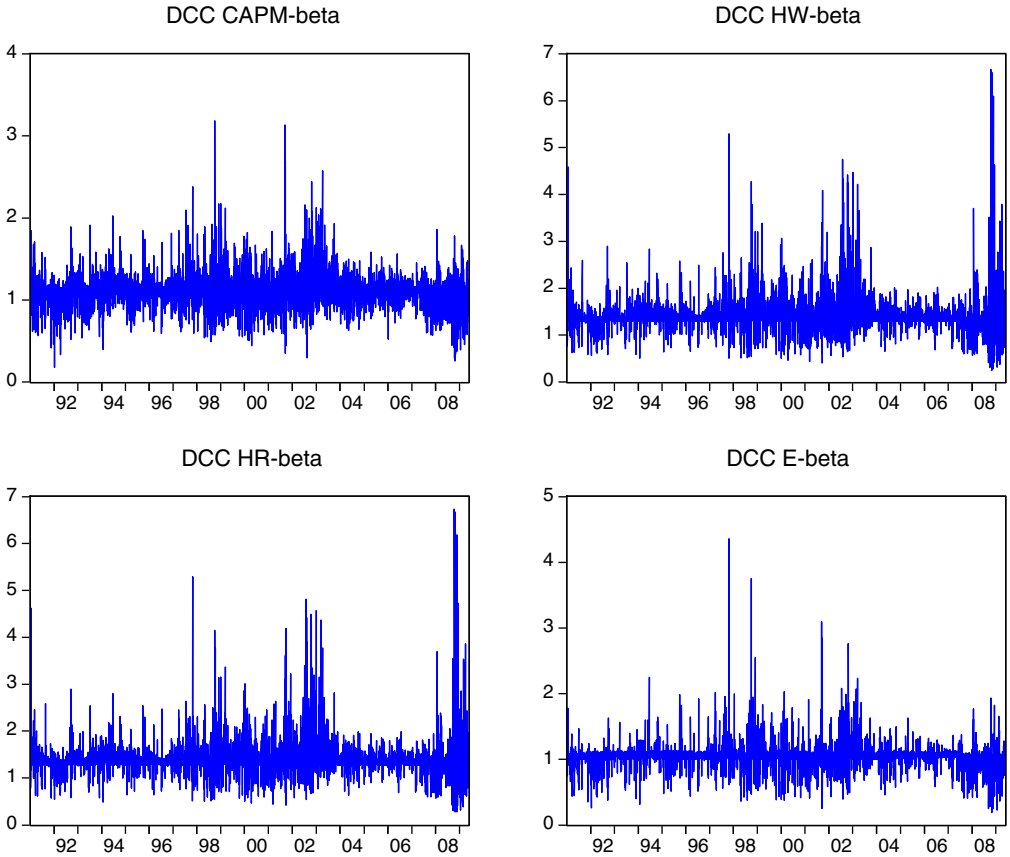
Appendix II. The time-varying CAPM beta and downside betas under DCC model

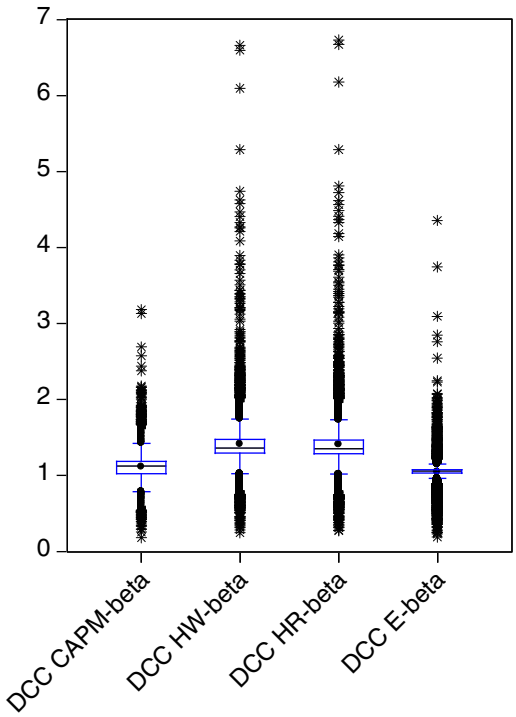


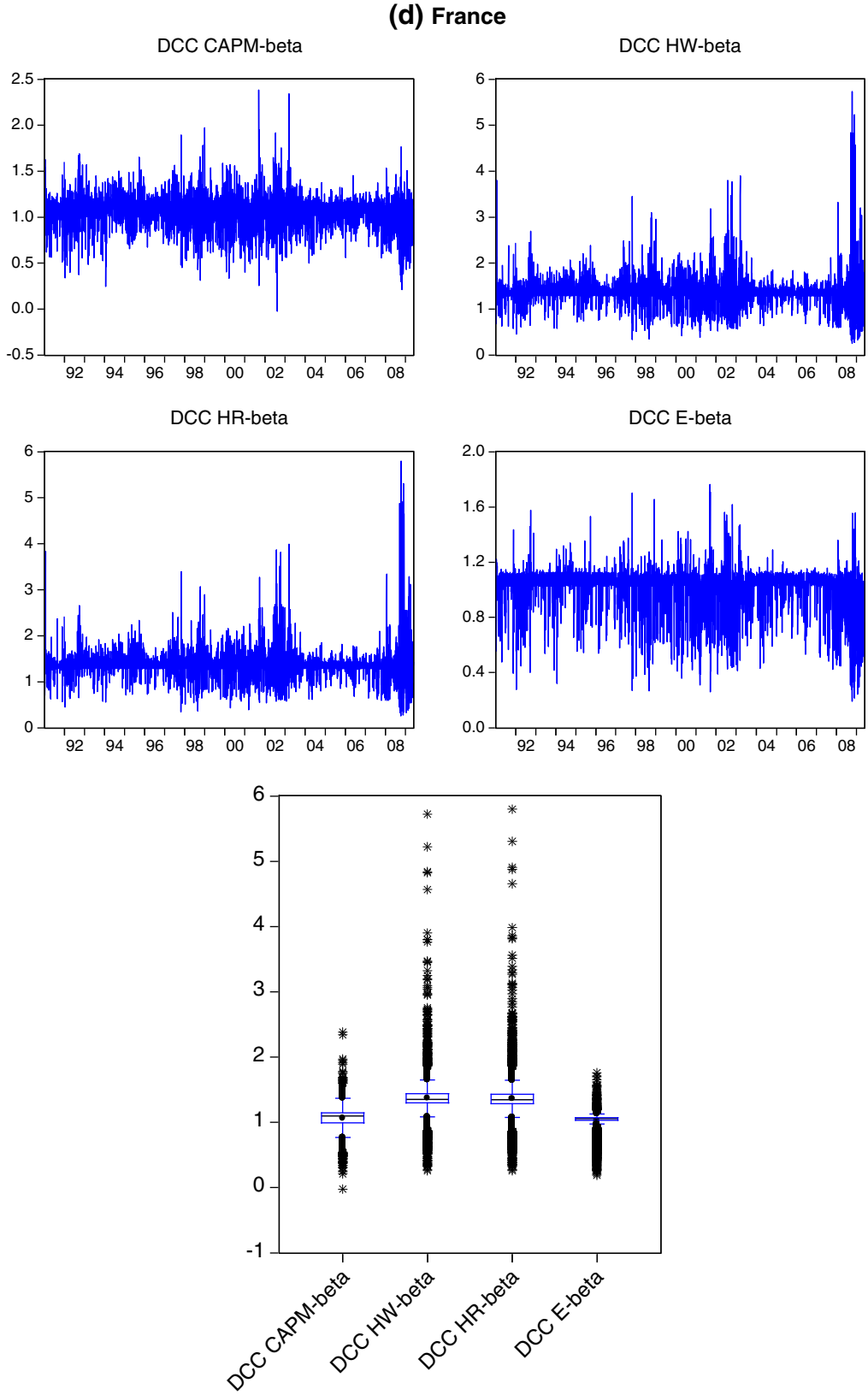
(b) Canada


DCC CAPM-beta
DCC HW-beta
DCC HR-beta
DCC E-beta
92 94 96 98 00 02 04 06 08
DCC CAPM-beta
DCC HW-beta
DCC HR-beta
DCC E-beta

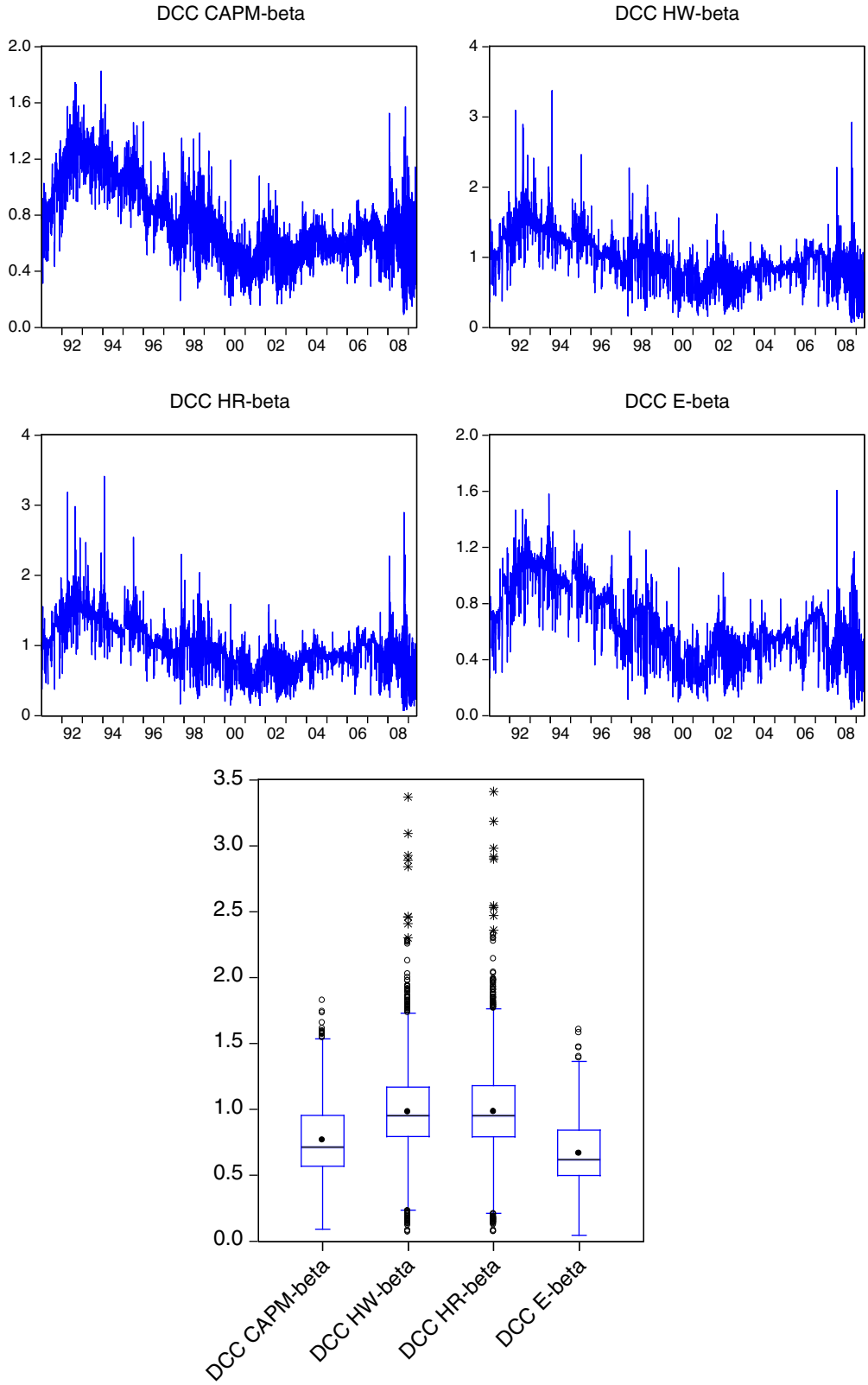
(c) Germany


DCC CAPM-beta
DCC HW-beta
DCC HR-beta
DCC E-beta
92 94 96 98 00 02 04 06 08


DCC CAPM-beta
DCC HW-beta
DCC HR-beta
DCC E-beta


(d) France
DCC CAPM-beta
DCC HW-beta
DCC HR-beta
DCC E-beta
92 94 96 98 00 02 04 06 08
DCC CAPM-beta
DCC HW-beta
DCC HR-beta
DCC E-beta

(e) Japan


DCC CAPM-beta
DCC HW-beta
DCC HR-beta
DCC E-beta
92 94 96 98 00 02 04 06 08
DCC CAPM-beta
DCC HW-beta
DCC HR-beta
DCC E-beta

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