VARIANCES AND COVARIANCES OF INTERNATIONAL STOCK RETURNS: THE INTERNATIONAL CAPM REVISITED

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ABSTRACT

In this paper, we examine a conditional version of the international capital asset pricing model (ICAPM) allowing for a time and state varying factor of proportionality or beta. Betas are allowed to change with an unobserved state variable. Return variances differ across the different states so that betas differ on account of differences in variance regimes of the return series. This method allows us to accommodate a non-linear relation between returns and variances. For six markets, we find that the world beta is a non-linear function of domestic volatility. In the Pacific and North American markets, we find strong evidence for a time and state varying beta coefficient. We find that for the European markets, with the exception of Switzerland, the world beta is not related to the state of the domestic market's volatility.

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I. Introduction

A variety of papers examine the international version of the capital asset pricing model. Solnik (1974), Agmon (1974) and Lessard (1974) use an international capital asset pricing model (ICAPM)with constant betas and find that both global and domestic factors influence asset returns. Mark (1988) uses an ICAPM model with time-varying betas to examine the forward premia on foreign exchange. Harvey (1991), Ferson and Harvey (1993) and, more recently, Bekaert and Harvey (1995) and Dumas and Solnik (1995) estimate models where the beta coefficient as well as the market premium are allowed to change. These papers differ in the way beta is modelled. For example, in Mark's (1988) model, betas are estimated using as inputs the time-varying conditional variances and covariances obtained from a multivariate ARCH specification. In Ferson and Harvey (1993) and Dumas and Solnik (1995) betas are specified as a function of exogenous variables. Although there are differences between all these methods, they all seek to capture the conditionality of betas as well as that of the risk factors.

Our aim in this paper is to also examine the conditional beta version of the ICAPM. Our point of departure lies in the way in which we model the conditionality of betas with respect to a world index. Our motivation is based on two strands in the existing literature. The first has to do with the evidence that industrial markets, in general, move more closely during unstable periods.[1] Correlations across markets hence, are higher during periods of greater volatility. Second, there is evidence that suggests that conditional returns are related to volatility. Campbell and Hentschel (1992), French, Schwert and Stambaugh (1987) for instance, report a positive relation between conditional means and variances; Fama and Schwert (1977), Nelson (1991) and Glosten, Jagannathan and Runkle (1993) on the other hand, find a negative relation.[2] These papers suggest that changes in the volatility of returns might affect the

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[1]See King and Wadhwani (1990), Bertero and Mayer (1990), Longin and Solnik (1995), Karolyi and Stulz (1995), Ramchand and Susmel (1997).

[2]See also Whitelaw (1994), Campbell (1987) and Harvey (1989).

proportionality between domestic and global returns.

Based on this literature, the parameterization in our model allows returns to depend on a world factor in such a way that the nature of the dependence is conditioned on the variability of returns. Our work is related to the model in Bekaert and Harvey (1995). They examine a conditional version of the ICAPM for emerging markets. The relation between domestic returns and a world index is conditioned on an unobservable state variable that takes on the value of zero or one. To estimate this unobservable state variable, they use a two-state Markov switching model. They link the resulting two states to the degree of the emerging market's integration with a world benchmark. Similar to Bekaert and Harvey (1995), beta in our model is modelled as state dependent. In particular, we permit the proportionality factor or beta to depend on the states of an unobservable variable. It turns out that this unobservable variable is linked to the volatility regime of the underlying return. Hence, our model generates a different beta for every state. It is in this sense that our parameterization captures a non-linear relation between domestic and world returns. Furthermore, since the determining factor is the variance state of local returns, the model also permits a non-linear relation between domestic returns and the underlying domestic variance.[3] In particular, our results show that, for a variety of countries, the unconditional version of the ICAPM with a constant proportionality factor is misspecified. For the North American and Japanese markets, the proportionality between domestic returns and a world benchmark portfolio depends on the state of the variance of each market. The factor of proportionality significantly changes across time, as a function of the variance of a country's returns series. For the European industrial markets, beta tends to be uncorrelated with higher domestic volatility. Our results are robust to the usual alternative specifications used in the literature. The rest of this paper is organized as follows: Section II reviews the underlying model used, Section III describes the data used, Section IV presents the results and Section

[3]In the literature cited above the relation between mean returns and variances is assumed to be linear and hence this constitutes another contribution of this paper.

V concludes the paper.

II. The Model

II.A The international capital asset pricing model (ICAPM)

If international capital markets are integrated, then the expected return of a security i, can be written in terms of the international capital asset pricing model (ICAPM) as:

$$(r_i^* - r_f) = \beta_i\,(r_w^* - r_f)$$
$$\beta_i = \frac{Cov\,(r_i^*\,,\,r_w^*)}{Var\,(r_w^*)} \tag{1}$$

where r_i^* is the expected real return on the asset i, r_f is a world wide risk-free interest rate, r_w^* is the expected real return on a value weighted portfolio of global assets and β_i is the world beta of the asset i that measures its covariance with the world market return standardized by the variance of the world market return. In the absence of exchange rate risk, empirical tests of the model used in the literature are based on the following regression:

$$R_i^* = \alpha + \beta_i\,R_w^* + \epsilon_i\,, \qquad \epsilon_i \sim N\,(0,\,\sigma^2)\;; \tag{2}$$

where R_i^* and R_w^* denote the excess return on the asset i and the world portfolio respectively. A simple procedure to introduce a time-varying beta in equation (2) is to specify β_i as a function of other variables. For example, Ferson and Harvey (1993) make β_i a linear function of variables such as dividend yields and the slope of the term structure. They find, however, that this formulation explains a small percentage of the predicted time variation of stock returns.[4]

[4]On the other hand, Ferson and Korajczyck (1995), using a similar model for the U.S. stock market, cannot reject the constant β_i model.

II.B An ICAPM with time-varying volatility

In recent years, a substantial body of literature has documented the importance of modeling time-varying volatility in financial time series. The autoregressive conditional heteroscedasticity (ARCH) model proposed by Engle (1982) and its variants including the generalized autoregressive conditional heteroscedasticity (GARCH) model have been successfully applied to model financial data. In the current context for instance, one could use the following GARCH (1,1) specification:

$$\begin{aligned} R^*_{i,t} &= \alpha + \beta_i R^*_{w,t} + \epsilon_i, \\ \epsilon_{i,t} | I_{t-1} &\sim D\,(0, h_t), \\ h_t &= a_0 + a_1\, \epsilon^2_{t-1} + b_1\, h_{t-1}. \end{aligned} \tag{3}$$

where the errors, conditional on the information set I_{t-1}, follow a distribution D with mean zero and variance h_t. In ARCH models, the distribution D is usually specified as normal or Student-t. The formulation in (4) incorporates the fact that the volatility of the returns series is changing over time. It also explicitly models the variance as a function of past variances and past squared disturbances.[5] In this ARCH framework, Engle, Lilien and Robins (1987) estimate a particular version of the CAPM. They propose the ARCH-in-mean, or ARCH-M, model, which introduces the time varying variance, h_t, into the mean equation. Mark (1988) and Ng (1991) also use a time-series approach and let β_i be time-varying. In their formulation,

$$\beta_{i,t} = \frac{Cov_t(R^*_i\,,\, R^*_w)}{Var_t(R^*_w)}, \tag{4}$$

where the covariance and variance terms are now time-varying. This model requires a model for the joint distribution of R^*_w and R^*_i. For example, Mark (1988) uses a simple multivariate diagonal ARCH(1) model. Mark (1988) and Ng (1991) find significant time-variation patterns in β_i. Braun, Nelson and

[5] More general specifications for the volatility generating process can be assumed.

Sunier (1995) also model time-varying betas using an ARCH framework. In addition, in their framework, betas respond asymmetrically to positive versus negative domestic or world news --in our notation, ϵ_i and ϵ_W. They find, however, no evidence of an asymmetric effect of negative news on β_i and therefore, no evidence for this particular time-variation of β_i.

Even though ARCH models are very popular in finance, several papers point out that they are very sensitive to changes in regimes. Diebold (1986) and Lamoreux and Lastrapes (1990) argue that the usual high persistence found in ARCH models is due to the presence of structural breaks. Nelson (1991), and Engle and Mustafa (1992) show that ARCH models are not able to account for events like the Crash of 1987.

II.C A state and time-varying ICAPM

Following Hamilton (1989), Cai (1994), Brunner (1991) and Hamilton and Susmel (1994) modify the ARCH specification to account for such structural changes in data and propose a Switching ARCH (SWARCH) model where the variance of the process is modeled as:

$$h_t = a_{0,s_t} + \sum_{j=1}^{j=q} a_{j,s_t,s_{t-j}}\, e_{t-j}^2 \quad ; \tag{5}$$

where the subscript s_t denotes the state of the economy at time t. The constant $a_{0,st}$, captures the structural shift parameters and the autoregressive coefficients, $a_{i,st,st-1}$,depend on the current or the lagged state of the economy. For instance, a shift from a low to a high volatility state, would be captured in a change in the a_i's. Given the evidence in Susmel (1996), we simplify the SWARCH specification and allow only the constant, a_0 to be state-dependent. Therefore, a sudden change to a high volatility state, for example, will increase the constant, but not the weights on past news. Following Hamilton (1989), maximum likelihood estimation is straightforward.

As a byproduct of the maximum likelihood estimation, Hamilton (1989) shows that we can make inferences about the particular state of the security at any date. The "filter probabilities," $p(s_t, s_{t-1} | y_t, y_{t-1}, ..., y_{-3})$, denote the conditional probability that the state at date t is s_t, and that at date t-1 was s_{t-1}. These probabilities are conditional on the values of y observed through date t. The "smooth probabilities," $p(s_t | y_T, y_{T-1}, ..., y_{-3})$, on the other hand are inferences about the state at date t based on data available through some future date T (end of sample). For a two state specification, the smooth probabilities at time t are represented by a 2x1 vector denoting the probability estimates of the two states. That is, the smooth probabilities represent the ex-post inference made by an econometrician about the state of the security at time t, based on the entire time series.

There is a growing literature that provides evidence that industrial markets move more closely during unstable periods.[6] Following this literature, in the context of an ICAPM model, we allow the beta coefficient to change according to the variance of the underlying domestic return. More specifically, the parameterization of our model makes beta a function of an unobservable state variable. This unobservable variable takes on two values, 0 and 1. The variance is allowed to change according to a SWARCH specification. This specification for the variance links the unobservable state variable to the variance state of domestic returns. The model we propose is:

$$
\begin{gathered}
R^{*}_{i,t} = \alpha + (\beta_{i,0} + \beta_{i,1} S_t) R^{*}_{w,t} + \epsilon_{i,t} , \\
\epsilon_{i,t} \sim D(0, h_t) , \\
h_t = a_{0,s_t} + \sum_{j=1}^{j=q} a_j \epsilon_{t-j}^2 ;
\end{gathered}
\tag{6}
$$

where the variable $S_t = 0$ or 1, depending on the state of the economy. Hence, the betas in the two states are β_0 when $S_t = 0$ and $\beta_0 + \beta_1$ when $S_t = 1$. This leads to a non-linear relation between local and world returns that depends on the underlying state S_t.

Chou, Engle and Kane (1992) also allow an unobservable variable to influence excess returns.

[6]See King and Wadhwani (1990) and Longin and Solnik (1995).

They use an ARCH-M model, where the ARCH-M coefficient, "the price of volatility," changes according to an unobserved state. Bekaert and Harvey (1995) use a GARCH-M approach where they allow "the price of volatility" to be multiplied by a parameter that takes on two values 0 or 1. This parameter's value is determined by by an unobservable variable, which they associate with the degree of integration.

The point of departure of our model is that it permits non-linearities in the relation between local and world returns in a manner that is determined endogenously based on the interaction between mean and variance states. The state variable, S_t, in our model is jointly determined based on both the mean as well as the variance of the local return. To see this, note that the system of equations in (6) is jointly estimated using maximum likelihood estimation. Hence, the states S_t are determined based on the intercept in the variance equation, $a_{0,st}$ as well as on the interactive term S_t in the mean equation. Our model, unlike the models cited above, does not require a model for the joint distribution of $R^*_{i,t}$ and $R^*_{w,t}$.[7] Hence, our model does not require a bivariate setting to model covariance, which might be difficult to estimate.[8] In this sense the model is similar to the univariate factor GARCH model used for the ten portfolios in Engle, Ng and Rothschild (1989).[9] However, while in the factor GARCH framework, the variance of the market return is modeled using a GARCH specification, in our case, the variance of the domestic return is modelled using a switching ARCH framework. In this sense, the local variance affects betas through the covariance between local and world returns, not through the variance of the market return. In addition, like in Mark's (1988), the specification we use does not require exogenous information variables

[7]Bekaert and Harvey (1995), for instance, impose a linear functional form for $R^*_{w,t}$ using variables in individuals' information sets such as dividend yields; Bodurtha and Mark (1991) use an AR(3) specification, and Ng (1991) uses an ARCH-M specification.

[8]Estimating this model in a multivariate SWARCH setting is computationally cumbersome. For instance, in a bivariate SWARCH model, the number of parameters to be estimated escalates to 26.

[9]See also King, Sentana and Wadhwani (199?).

to capture the conditionality of betas.

III. Data

We use weekly (Thursday to Thursday) U.S. dollar stock returns of major equity markets around the world compiled by Morgan Stanley Capital International Perspective. The indices adjust for stocks that are listed on more than one international exchange. The country indices account for at least 80% of each country's stock market capitalization. To convert returns to excess returns we subtract from the raw returns, the weekly Eurodollar deposit rate. The data cover the period January 1980 through the third week of April 1996 and are in terms of dollars, for a total of 849 observations. Table 1 reports univariate statistics for the various indices. The coefficients of skewness and kurtosis reveal nonnormality in the data. Moreover, a Jarque-Bera (1980) test (not reported) rejects normality for all the indices. The Ljung-Box Q-statistics, LB(5), for raw returns indicate significant autocorrelations in Canada, Australia, Hong Kong, and France. We also check for ARCH effects in the return series. We report a Ljung-Box Q-statistic, LBS(5), for squared raw returns and a standard ARCH test for filtered residuals. Both tests indicate significant ARCH effects for all markets except Switzerland and the U.K.

Table 2, Panel A reports the correlations across markets for raw returns divided by time zones: the Far East (Pacific), Europe and North America. While in general, correlations are higher for countries that are geographically closer, we also find evidence of higher correlations for countries that might be integrated on account of other factors. For instance, the correlation between the Hong Kong and the Japanese markets is smaller than the correlation between the Hong Kong and the U.K. markets. We find, not surprisingly, the U.S., Japan, and the U.K. are highly correlated to the World Index. These high correlations are a reflection of the value-weighted composition of the World Index. Table 2, Panel B reports the correlations across markets for squared returns. We find that some of the squared returns correlations are higher than the returns correlations. Engle and Susmel (1993) find that this feature is related to common volatility between the series. For example, the correlations between European markets and North American markets tend to be higher for squared returns than for raw returns. In addition, the correlation between each market and the world index tends to be higher for the squared returns. The highest correlation of squared returns is between the U.S. and the World Index, which is almost .90.

IV. Results

In Table 3, we estimate a constant beta, constant variance ICAPM using the Morgan Stanley World Index as our proxy for the world market portfolio. In all cases, the beta coefficient is significant. The LBS(5) statistic is the Ljung-Box statistic for squared residuals which has a chi-square distribution. In all regressions, LBS(5) is significant suggesting that there is strong evidence for time-varying variance. For four stock markets, Australia, Germany, the UK and Canada, the LB(5) tests show evidence of mean autocorrelation. The autocorrelation coefficients (not reported), however, are quite small. The R^2s are high, especially for the three biggest markets, Japan, the U.K., and the U.S. These high R^2s are due in large part to the big weight of these markets in the world index. To see this, the R^2s of the ICAPM for the U.S. market when the Europe, Asia and Far East (EAFE) index is used to proxy for the world benchmark is .087, down from .620.[10]

To avoid results driven by the high correlation between the MSCI World Index and the three biggest markets, we estimate the model using an alternative measure to proxy for the world factor. Since the Morgan Stanley World Index is a value weighted index, we construct an equally weighted world index (EWW), using the ten indices that we have in this sample. The re-estimated beta coefficients are smaller, with the exception of the U.K., although still significant.[11]

[10]The EAFE Index includes all countries in the World Index except the U.S. and Canada.

[11]Although not reported here, we used several alternative proxies. For example, for the U.S. we re-estimate the model using the Europe, Asia and Far East (EAFE) index. Similarly, we re-estimate the model for Japan and the U.K. using the U.S. stock index as a proxy for the world factor. The

In Table 4, we report the results from the estimation of a ICAPM with a time-varying variance, using a simple GARCH(1,1) model as in equation (4). For brevity, we do not report the estimated coefficients for the conditional variance equation. For all markets there is a strong evidence for a Student-t distribution for the conditional errors, which is consistent with the usual heavy tails found in stock returns, as shown by Bollerslev (1987) and Baille and DeGennaro (1990). Therefore, in Panel A, we report the estimates from a GARCH(1,1)-t specification. These estimates reveal the usual high persistence of shocks --i.e., a_1+b_1 is close to one which might be a sign of parameter instability in the variance equation. The pricing errors, the α's, are small and, with the exception of Hong Kong, not significant. The columns labelled SK and EK report the coefficient of skewness (SK) and excess kurtosis (EK). Consistent with previous results in the literature, all series show significant evidence of non-normality of the error terms.

To check the adequacy of a GARCH(1,1)-t model, we also estimate (but do not report) other time-varying specifications: GARCH(1,1)-t-M, SWARCH, and SWARCH-t. In general, none of these alternative specifications significantly outperforms the GARCH(1,1)-t model. For example, the GARCH-t-M specification has a likelihood function very close to the likelihood from the GARCH-t specification.[12] Although not reported, the GARCH-t-M-mean coefficient was not statistically significant. We should point out, that, in general, among the switching models, there is evidence for a two-state formulation with a conditional t-distribution. Only for Australia and Hong Kong, after adjusting for degrees of freedom, a two-state formulation is statistically rejected in favor a three-state formulation, using standard chi-squared tests. In Table 4, Panel B of Table 4, we report the beta coefficient using the EWW as an alternative world benchmark for the three major markets. The parameter estimates are similar to the ones reported in Table 3.

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results are similar to the ones reported for the EWW, but with significantly lower R^2's.

[12] SWARCH-in-mean formulations produced likelihood functions similar to the above.

In Table 5, we estimate a state-dependent ICAPM with a SWARCH process, as specified in equation (6). For brevity, again, we only report the estimated coefficients for α, ß, and the a_{st}'s. Based on Bekaert and Harvey (1995) and the SWARCH results of Table 4, we use a two-state model[13]. We select the lags in the conditional variance equation using standard Wald-t tests. No more than two autoregressive lags are needed in the SWARCH estimation, with the exception of Canada, which needed three lags. With the exception of Germany, a conditional normal distribution is rejected in favor of a conditional Student-t distribution. In Table 5, we also report the LB(5) and LBS(5) for the standardized residuals for each country. The model passes these simple specification tests. We should note that the state-dependent beta formulation used in Table 5 improves over the GARCH and the simple beta models in Tables 3 and 4 in the several ways. One, this model substantially reduces the degree of non-normality of the conditional errors. Compared to the estimates in Table 4, there is a substantial reduction of skewness and excess kurtosis. Two, in all cases, except France, the likelihood functions of the state-dependent beta ICAPM are substantially higher than the likelihood functions from the models estimated in Table 4 and obviously those in Table 3. Three, this formulation results in R^2s that are considerably higher than those in Table 4 for the Swiss, Pacific and North American markets. For example, the non-linear interaction between variance and beta increases the R^2 for Canada and Australia by more than .10.

The states in this model are jointly determined based on the interaction between the mean and the variance of the local return. The coefficients of a_{01} and a_{02} suggest that for all the countries examined here, a two-state formulation for variance is significant. Furthermore, from Panel A of Table 5, the variance in the second state tends to be more than two times higher than the variance in the first state, getting as high as four times higher for France (14.808/3.687). The states obtained using model (6) are

[13] For Australia, we use a three-state model, since the second state in the two-state model is completely dominated by two observations in October 1987. This state seems to play the role of an intervention variable. In the terminology of Box and Tiao (1975), both observations are pure pulse variables. Therefore, in Table 5 we re-estimate the two-state model with two dummies in the mean equation.

very similar to the states obtained using the standard market model but with a SWARCH process for the variance as estimated in Table 4. This implies that beta is strongly influenced by the state of the domestic market volatility.

Interestingly, we find that for the three biggest markets, the U.S., the U.K., and Japan, beta tends to decrease in the high variance state. A lower beta in the high variance regime implies that the required return is also lower when the variance of the underlying return is higher. At first glance, this finding is consistent with the documented negative relation between excess returns and volatility in the U.S.[14] Glosten, Jagannathan and Runkle (1993) explain such a finding. Periods of high variance may also coincide with periods when investors are more willing to bear risk so that the risk premiums required may not be high. We find, however, that the large relative weight of U.S. returns in the composition of the world index drives this result.[15] Similar results are found for Japan and, to a lesser extent, for the U.K., justifying our decision to use a different index to proxy for the world factor for those markets. Our basis for using an alternative index here is two-fold. One, given the high correlation between the World Index and the three biggest markets, the estimates of the average beta are biased towards 1. For instance, using the predicted probabilities of the two states and

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[14]See Fama and Schwert (1977), Campbell (1987), and Breen, Glosten and Jagannathan (1989).

[15]The smoothed probabilities estimated by (6) for the U.S. using the world index describes three periods of different volatility states. The U.S. market was in the low volatility state from 1980 until mid 1985 when the world beta was equal to 1.08. In mid 1985 there was a switch to the high volatility state which prevailed until mid 1994 and hence beta decreased to 0.68. Beyond 1994, the U.S. market switched back to the low volatility state and hence the high beta (1.08) until the end of the sample. These findings result from the high correlation between the U.S. and the world index. During the first low volatility regime which spans 1980-85 (the second is from 1994 to the end of the sample), the correlation between the U.S. and the world index is 0.91. Hence the residuals from the market model tend to be low and with low variance. A similar technical explanation holds for the other low volatility period. For the high volatility period, the correlation is 0.73 - in this period we observe relatively high levels for weekly returns in both the U.S. and the world index. As a result we obtain residuals with a relatively high variance. This results in a high variance state with lower covariance between the U.S. and the world index.

the betas in the two states, we arrive at average betas close to 1 for the U.S., Japan and the U.K. Two, this high correlation between local returns and the index also implies that the errors are low and, hence, a switching variance regression is really not justified. For example, as pointed out above, the high squared returns correlation between the U.S. and the World Index points to the existence of common volatility between the two series. Under these circumstances, a linear combination of the U.S. and World Index series, like the CAPM, might destroy time-varying volatility patterns, see Engle and Susmel (1993). To avoid this problem, we alter our choice of the world return and use the EWW index, constructed above, as a proxy for the world index.[16] The results are reported in Panel B of Table 5. We find that for the U.S. and Japan, beta now significantly increases with the variance of the domestic market. This finding is consistent with the literature that documents higher correlations between equity markets in periods of high volatility. On the other hand, for the U.K, there does not seem to be a relation between the world beta and U.K. domestic volatility.

The smoothed filtered probabilities from the state-dependent ICAPM are very similar to the estimated smoothed probabilities from the constant beta with SWARCH effects. Therefore, the states from the market model with a SWARCH process are very similar to the states as the states estimated using the state-dependent ICAPM. As an example, in Figure 1 we plot on the first panel the smoothed probabilities, $Prob(s_t=1 | r_T, r_{T-1}, \ldots)$ for the low volatility state for the U.S. The observations are classified using Hamilton's (1989) system wherein an observation belongs to state k if the smoothed probability is higher than 0.5. On the second panel of Figure 1, we plot the world-betas implied by the switching model. Given the specification of our

[16]We thank the referee for suggesting the equally weighted index as an alternative.

model, these switching betas mirror the first panel of Figure 1. The U.S. high volatility state is characterized by three short periods during the early 1980's and the mini-crash of 1990, and, therefore, the world-beta estimate increases from .574 to .938 for only brief periods of time. In addition, there is a long period of high volatility-high beta, around the market crash of 1987. The nature of the changes in betas are consistent with the literature of high correlations between international stock markets in periods of high volatility, see Longin and Solnik (1995). In particular they are consistent with the substantially higher correlations around the Crash of 1987 that lasts until April 1988, as documented by Bertero and Meyer (1989). On the last panel, we plot the time-varying betas, GARCH-betas, estimated using Mark's (1988) approach.[17]

In Figures 2 and 3 we do the same with respect to Japan and the U.K. but omit the second panel in these subsequent figures since they are mirror images of the first panels in all cases. Looking at the first panels in Figures 1, 2 and 3, Japan, as in Figure 2, is the market with the most changes of regime in the sample and, therefore, the Japanese world-beta switches the most. U.K. is the market with the most observations in the high volatility state. This market was in the high volatility state from 1980 till mid 1988. From then on, the U.K. market moves into a low volatility state for about a year, and then switches back into the high volatility state until late 1991. From then on, the U.K. market is in the low volatility state. The beta for the U.K. market, however, is not affected by this switch. The U.S. market is the market with the fewest observations in the high volatility state.

As can be seen from the last panels in Figures 1, 2 and 3, the GARCH-betas are quite unstable

[17]Strictly speaking the SWARCH model we present and a bivariate GARCH model with time-varying variances are not nested models and hence are not directly comparable. At the same time our results warrant comparison with other conditional variance models. Hence, we examine and compare the time-varying beta estimates resulting from the two models.

over time. For the U.S. and Japan, there is, however, a positive correlation between the higher than average GARCH-beta and the volatility states estimated in our model. This implies that the univariate SWARCH model we present generates beta estimates that are qualitatively consistent with the time-varying betas estimated using a bivariate GARCH model. The higher betas estimated in our model for the high volatility regime for the U.S., Japan and the U.K. are comparable to the higher than average betas estimated using the GARCH model.

The evidence presented suggests overall that previous findings in the literature of high correlation between stock markets during periods of high volatility has implications for returns. In particular, our results suggest that in most cases, these changes in correlations are priced. In the context of our conditional ICAPM we obtain betas that are significantly different across low and high variance states. For the North American, Pacific and Swiss markets, beta and hence expected returns increase when the local market is in the high volatility state. This evidence accords with earlier findings in the literature of higher correlation between markets during periods of greater volatility. Hence tests of the ICAPM must account for this nonlinear dependence of the beta on the variance regime of a country's returns.

V. Conclusion

In this paper, we examine the relation between stock returns and a world index for ten industrial stock markets. The world betas are allowed to change with an unobserved state variable. This state variable is allowed to have different variances in each state. For six markets, we find that the world-beta is a nonlinear function of domestic volatility. In the Pacific and North American markets, we find strong evidence for a time-varying beta coefficient. We find that for the European markets, with the exception of Switzerland, the world beta is not related to the state of the domestic market's volatility. The evidence presented here suggests that tests of the ICAPM should account for the change in betas over time and over the different variance states.

Reference List

Agmon, T (1974), "The Relations Among Equity Markets in the United States, United Kingdom, Germany and Japan," Journal of Finance, 28, 839-855.

Baillie, R.T. and R.P. DeGennaro (1990), "Stock Returns and Volatility," Journal of Financial and Quantitative Analysis, 25, 203-214.

Bekaert, G. and C. Harvey (1995), "Time-varying World Market Integration", Journal of Finance, 50, 2, 403-444.

Bertero, E. and C. Mayer (1989), "Structure and Performance:Global Interdependence of Stock Markets around the Crash of October 1987", Center for Economic Policy Research, Discussion paper #307

Bodurtha James and Nelson Mark (1991), "Testing the CAPM with Time-Varying Risks and Returns", Journal of Finance, 46(4), 1485-1505

Bollerslev, T.P. (1987), "A Conditional Time Series Model for Speculative Prices and Rates of Returns," Review of Economics and Statistics, 69, 524-54.

Bollerslev, T., R. Y. Chou and K. F. Kroner (1992), "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence," Journal of Econometrics, 52, 5-59.

Box, G.E.P and G.C. Tiao (1975), Intervention analysis with implications to economics and environmental problems, Journal of the American Statistical Association, 70, 70-79.

Braun, P.A., Daniel Nelson and Alain Sunier (1995), "Good News, Bad News, Volatility and Betas," Journal of Finance, 50(5), 1575-1603

Brunner, A.D. (1991), "Testing for Structural Breaks in U.S. Post-war Inflation Data, unpublished manuscript, Board of Governors of the Federal Reserve System, Washington, D.C.

Cai, J. (1994), "A Markov Model of Unconditional Variance in ARCH", Journal of Business and Economic Statistics, 12, 309-316.

Campbell, J.Y. (1987), "Stock returns and the term structure", Journal of Financial Economics, 18, 373-

399.

Campbell, J.Y. and L. Hentschel (1992), "No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns", Journal of Financial Economics, 31, 281-318.

Chan, K.C., G.A. Karolyi and R.M. Stulz (1992), "Global Financial Markets and the Risk Premium on U.S. Equity", Journal of Financial Economics, 32, 137-167

Chou, R., R.F. Engle and A. Kane (1992), "Measuring Risk Aversion from Excess Returns on a Stock Index," Journal of Econometrics, 52, 201-224.

Davies, R.B. (1977), "Hypothesis Testing When a Nuisance Parameter is Present Only under the Alternative," Biometrika, 64, 247-254.

Diebold, F.X. (1986), "Modelling the Persistence of Conditional Variances: A Comment," Econometric Reviews, 5, 51-56.

Dumas, B. and B. Solnik (1995), "The World Price of Foreign Exchange Risk," Journal of Finance, 445-479.

Engle, R. F. (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K," Econometrica, 50, 987-1008.

Engle, R.F. and C. Mustafa (1992), "Implied ARCH Models from Options Prices," Journal of Econometrics, 52, 289-311.

Engle, R.F., D. Lilien and R. Robins (1987), "Estimating Time Varying Riks Premia in the Term Structure: The ARCH-M Model" Econometrica, 55, 391-407.

Engle, R.F., Victor Ng and Michael Rothschild (1990), "Asset Pricing with a Factor-ARCH structure: Empirical estimates for treasury bills", Journal of Econometrics 45, 213-237

Engle, R.F. and R. Susmel (1993), "Common Volatility in International Equity Markets," Journal of Business and Economic Statistics, 11,2, 167-176.

Fama, E. F., and G.W. Schwert (1977),"Asset Returns and Inflation", Journal of Financial Economics, 5, 115-146.

Ferson W.E. and C.R. Harvey, (1991), "The Variation of Economic Risk Premiums", Journal of Political Economy, 99, 2, 385-415.

Ferson W.E. and R. A. Korajczyk (1993), "The risk and predictability of international equity returns," Review of Financial Studies, 527-566..

Ferson W.E. and R. A. Korajczyk (1995), "Do Arbitrage Pricing Models Explain the Predictability of Stock Returns?," Journal of Business, 309-349.

French, K. R., G.W. Schwert and R.F. Stambaugh (1987), "Expected Stock Returns and Volatility", Journal of Financial Economics, 19, 3-30.

Glosten, L.R. and R. Jagannathan (1987), "Money, real activity and security prices," Unpublished manuscript, University of Minnesota

Glosten, L.R., R. Jaganathan and D. Runkle (1993), "Relationship between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," Journal of Finance, 48, 1779-1801.

Hamilton, J.D. (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," Econometrica, 57, 357-384.

Hamilton, J.D. (1996), "Specification Testing in Markov-Switching Time Series Models," Journal of Econometrics, forthcoming.

Hamilton, J.D. and G. Lin (1996), "Stock Market Volatility and the Business Cycle," Journal of Applied Econometrics, forthcomming.

Hamilton, J.D. and Susmel R. (1994), "Autoregressive Conditional Heteroscedasticity and Changes in Regime", Journal of Econometrics, 307-333.

Harvey, C. R. (1989), JFE, "Time-varying conditional covariances in tests of asset pricing models", Journal of Financial Economics, 24, 289-317

________ (1991), "The World Price of Covariance Risk," Journal of Finance, 44, 111-157.

Karolyi, A. and Stulz R.M.,(1995), "Why do Markets Move Together?", Working Paper, Ohio State University.

King, M. and Wadhwani S. (1990),"Transmission of Volatility Between Stock Markets", The Review of Financial Studies, 3, 5-33

King, M., E. Sentana and Wadhwani S. (1994),"Volatility and links between National Stock Markets", Econometrica, 901-934

Lamoreux, C.G. and W.D. Lastrapes (1990), "Persistence in Variance, Structural Change and the GARCH Model", Journal of Business and Economic Statistics, 5, 121-129.

Longin, F. and B. Solnik (1995), "Is the correlation in international equity returns constant: 1960-1990?," Journal of International Money and Finance, 14, 3-23.

Lessard, D. R. (1974), "World, National and Industry Factors in Equity Returns," *Journal of Finance*, 29, 379-391.

Makridakis, S. G. and S. C. Wheelwright (1974), "An analysis of the interrelationships among the major world stock exchanges," Journal of Business, Finance and Accounting, 1, 195-216.

Mark Nelson, (1988), "Time-Varying Betas and Risk Premia in the Pricing of Forward Foreign Exchange Contracts", Journal of Financial Economics, 22, 335-354

Nelson, D.B. (1991), "Conditional Heteroskedasticity in Asset Returns: A New Approach," Econometrica, 59, 347-370.

Ng Lilian, (1991), "Testing the CAPM with Time-Varying Covariances: A Multivariate GARCH Approach", Journal of Finance, 46 (4), 1507-1521

Pagan, A. and G. W. Schwert (1990), "Alternative Models for Conditional Stock Volatility," Journal of Econometrics, 45, 267-290.

Solnik, B.H. (1974), "The International Pricing of Risk: An empirical investigation of the world capital market structure", *Journal of Finance*, 29, 48-54.

Susmel, R. (1996), " Switching Volatility in International Equity Markets," unpublished manuscript, Dept. of Finance, University of Houston.

Whitelaw, R. F. (1994), "Time Variations and Covariations in the Expectation and Volatility of Stock Market Returns", Journal of Finance, 49, 2, 515-542.

TABLE 1. DESCRIPTIVE STATISTICS (1980-1996)

	Mean	S.D.	SK	EK	Max	Min	LB(5)	LBS(5)	ARCH(5)
AUSTRALIA	0.125	3.223	-1.897	16.794	8.83	-10.37	24.01*	169.60*	184.03*
HONG KONG	0.252	4.454	-1.596	12.906	15.28	-20.41	15.06*	14.85*	13.25*
JAPAN	0.257	3.095	-0.248	2.851	10.94	-10.77	4.88	70.51*	49.74*
FRANCE	0.180	2.899	-0.814	4.904	10.02	-12.22	16.31*	66.31*	61.16*
GERMANY	0.186	2.686	-0.317	1.926	8.10	-11.74	11.02	65.15*	55.14*
SWEDEN	0.331	3.090	-0.442	2.157	8.70	-13.13	4.98	71.75*	63.72*
SWITZER-LAND	0.216	2.510	-0.586	6.508	9.06	-8.50	8.13	9.63	7.33
U.K.	0.191	2.745	-0.851	6.961	8.62	-8.08	8.88	1.61	1.73
U.S.	0.203	2.034	-0.948	7.942	6.65	-7.82	4.88	19.19*	17.61*
CANADA	0.088	2.321	-0.674	6.046	7.62	-8.84	30.09*	66.75*	30.75*
WORLD	0.202	1.840	-0.874	6.502	5.28	-6.20	5.84	36.14*	25.40*

Notes:
Country returns are weekly returns obtained from Morgan Stanley Capital International and cover the period 1980:1-1996. WORLD is the Morgan Stanely world index. Mean and S.D. refer to the mean and standard deviation of the returns on each market.
* indicates significane at the 5% level.
SK is the skewness coefficient.
EK is the excess kurtosis coefficient.
Max is the largest observation.
Min is the smallest observation.
LB(5) is the Ljung-Box statistic, calculated with five lags, for raw returns.
LBS(5) is the Ljung-Box statistic, calculated with five lags, for raw squared returns.
ARCH(5) is the ARCH test, calculated with five lags, for residuals from an AR(5) regression on raw returns.

TABLE 2. CORRELATION MATRIX (1980-1996)

A.- RAW RETURNS

MARKET	AUS	HON	JAP	FRA	GER	SWED	SWIT	U.K.	U.S.	CAN	WORLD
AUSTRALIA	1.000	.356	.310	.255	.336	.344	.399	.400	.319	.428	.478
HONG KONG		1.000	.201	.185	.262	.237	.275	.261	.272	.279	.373
JAPAN			1.000	.353	.392	.332	.418	.354	.279	.215	.731
FRANCE				1.000	.536	.322	.523	.445	.336	.304	.535
GERMANY					1.000	.432	.687	.455	.334	.290	.575
SWEDEN						1.000	.460	.357	.320	.279	.474
SWITZERLAND							1.000	.525	.439	.406	.643
U.K.								1.000	.433	.429	.643
U.S.									1.000	.665	.787
CANADA										1.000	.617
WORLD											1.000

B.- SQUARED RAW RETURNS

MARKET	AUS	HON	JAP	FRA	GER	SWED	SWIT	U.K.	U.S.	CAN	WORLD
AUSTRALIA	1.000	.571	.163	.133	.544	.562	.608	.654	.615	.599	.689
HONG KONG		1.000	.052	.080	.358	.434	.116	.124	.084	.161	.211
JAPAN			1.000	.073	.252	.172	.192	.195	.191	.112	.390
FRANCE				1.000	.206	.137	.146	.151	.158	.142	.204
GERMANY					1.000	.515	.558	.469	.427	.377	.587
SWEDEN						1.000	.418	.370	.383	.314	.499
SWITZERLAND							1.000	.736	.726	.647	.776
U.K.								1.000	.756	.641	.804
U.S.									1.000	.743	.894
CANADA										1.000	.726
WORLD											1.000

TABLE 3. ICAPM ESTIMATION (1980-1996)

$$R_i^* = \alpha_i + \beta_i R_w^* + \epsilon_i , \qquad (7)$$
$$\epsilon_i \sim N(0, \sigma^2) ;$$

where R_i^* and R_w^* denote the excess return on the asset i and the world portfolio respectively.

PANEL A

	α_i	β_i	R^2	Likelihood	LB(5)	LBS(5)
AUSTRALIA	-0.070	0.841*	.231	-2083.0	12.78*	111.77*
	(0.10)	(0.05)				
HONG KONG	0.054	0.907*	.141	-2403.0	7.75	27.80*
	(0.14)	(0.08)				
JAPAN	0.043	1.229*	.536	-1833.4	7.48	47.27*
	(0.07)	(0.04)				
FRANCE	-0.015	0.844*	.287	-1961.4	7.21	60.82*
	(0.08)	(0.05)				
GERMANY	-0.001	0.843*	.335	-1867.0	16.04*	56.93*
	(0.08)	(0.04)				
SWEDEN	0.138	0.800*	.228	-2047.2	2.02	32.70*
	(0.09)	(0.05)				
SWITZERLAND	0.019	0.882*	.418	-1753.9	6.80	63.31*
	(0.07)	(0.04)				
U.K.	-0.010	0.956*	.412	-1832.5	18.96*	25.49*
	(0.07)	(.04)				
U.S.	0.007	0.869*	.620	-1395.12	3.76	65.57*
	(0.04)	(0.02)				
CANADA	-0.104	0.779*	.382	-1712.93	22.76*	120.24*
	(0.06)	(0.03)				

PANEL B

JAPAN-EWW	0.057	0.982*	.356	-2124.0	12.35*	46.40*
	(0.09)	(0.05)				
U.K.-EWW	0.009	1.021*	.489	-1771.7	27.86*	47.07*
	(0.07)	(.04)				
U.S.-EWW	0.014	0.683*	.399	-1586.6	13.75*	116.09*
	(0.05)	(0.03)				

Notes:

1. In Panel A, each country's returns R^*_i are regressed on the Morgan Stanley World Index, R^*_w while in Panel B, returns for Japan, the U.K. and the U.S. are regressed on an equally weighted index, EWW, constructed using the ten countries in our sample.
2. Likelihood is the value of the likelihood function resulting from maximum likelihood estimation.
3. Standard errors are in parantheses
4. *: significant at the 5% level; LB(5) and LBS(5) denote the Ljung Box statistic for the residuals and squared residuals respectively.

TABLE 5. ICAPM ESTIMATION WITH STATE DEPENDENT BETAS

$$R_{i,t}^{*} = \alpha_i + (\beta_{i,0} + \beta_{i,1} S_t) R_{w,t}^{*} + \epsilon_i , \quad \epsilon_{i,t}|I_{t-1} \sim D(0, h_t) , \quad h_t = a_{0,s_t} + \sum_{j=1}^{j=q} a_j \epsilon_{t-j}^2 ; \tag{9}$$

$S_t = 0$ or 1 and R_i^* and R_w^* denote the excess return on the asset i and the world portfolio respectively. D is a student-t distribution.

PANEL A

	α_i	β_{i0}	β_{i1}	a_{01}	a_{02}	R^2	Likelihood	SK	EK	LB(5)	LBS(5)
AUSTRALIA[1]	-0.015	0.395*	0.450*	3.798*	8.406*	.329	-2000.9	-0.13	0.13	9.89	7.93
	(0.08)	(0.07)	(0.10)	(0.48)	(0.74)						
HONG KONG	0.323*	0.690*	0.459*	6.325*	21.821*	.153	-2264.6	-1.15	7.19	9.27	9.75
	(0.11)	(0.11)	(0.20)	(0.92)	(3.32)						
JAPAN	-0.092	1.578*	-0.785*	3.127*	3.263*	.608	-1730.8	0.66	3.05	5.17	10.76
	(0.06)	(0.05)	(0.07)	(0.37)	(0.40)						
FRANCE	0.032	0.897*	-0.198	3.687*	14.808*	.292	-1879.7	-0.39	1.00	7.96	4.54
	(0.07)	(0.06)	(0.19)	(0.33)	(3.97)						
GERMANY[2]	-0.039	0.846*	-0.013	2.629*	7.553*	.334	-1831.4	-0.06	0.21	10.71	1.39
	(0.07)	(0.07)	(0.15)	(0.24)	(1.03)						
SWEDEN	0.159	0.537*	0.622	4.428*	10.016*	.281	-2017.1	-0.10	0.35	6.00	2.05
	(0.09)	(0.08)	(0.41)	(1.43)	(2.46)						
SWITZERLAND	0.025	0.511*	0.634*	2.413*	3.438*	.504	-1717.3	0.51	2.62	1.08	7.84
	(0.06)	(0.16)	(0.10)	(0.53)	(0.43)						
U.K.	-0.022	1.054*	-0.152	1.679*	5.368*	.415	-1773.3	-0.11	1.02	8.23	2.61
	(0.06)	(.06)	(0.08)	(0.23)	(0.52)						
U.S.	0.050	1.077*	-0.391*	0.815*	1.704*	.655	-1325.7	-0.30	1.07	2.91	9.15
	(0.04)	(0.04)	(0.05)	(0.09)	(0.21)						
CANADA	-0.066	0.449*	0.701*	1.883*	3.245*	.487	-1622.6	0.13	2.66	16.34*	5.19
	(0.05)	(0.04)	(0.06)	(0.21)	(0.46)						
PANEL B											
JAPAN-EWW	-0.018	0.745*	0.797*	1.535*	3.744*	.433	-1885.7	0.21	0.70	11.84	3.91
	(0.07)	(0.05)	(0.13)	(0.16)	(0.54)						
U.K.-EWW	-0.043	1.026*	0.023	0.815*	2.351*	.501	-1715.2	-0.06	0.34	6.10	7.98
	(0.06)	(.08)	(0.11)	(0.13)	(0.31)						
U.S.-EWW	0.044	0.574*	0.364*	1.650*	4.520*	.458	-1539.4	-0.12	0.08	10.24	5.18
	(0.05)	(0.05)	(0.09)	(0.19)	(0.92)						

Notes:

1. In Panel A, each country's returns R_i^* is regressed on the Morgan Stanley World Index, R_w^* while in Panel B, returns for Japan, the U.K. and the U.S. are regressed on an equally weighted index, EWW, constructed using the ten countries in our sample. In Panel A, for Australia, a two state model estimated with two October 1987 dummies is used. For Germany, since the estimated degrees of freedom were more than 30, we could not obtain convergence for the student-t model. Hence we report estimates under the assumption of a conditional normal distribution.
2. Likelihood is the value of the likelihood function estimated using maximum likelihood estimation.
3. Standard errors are in parantheses
4. *: significant at the 5% level; LB(5) and LBS(5) denote the Ljung Box statistic for the residuals and squared residuals respectively.
5. SK, EK, LB(5) and LBS(5) are as defined in Tables 3 and 4.

TABLE 4. ICAPM ESTIMATION WITH TIME-VARYING VOLATILITY (1980-1996)

$$R^*_{i,t} = \alpha_i + \beta_i R^*_{w,t} + \epsilon_i, \quad \epsilon_{i,t}|I_{t-1} \sim D(0, h_t), \quad h_t = a_0 + a_1 \epsilon_{t-1}^2 + b_1 h_{t-1}. \tag{8}$$

where R_i^* and R_w^* denote the excess return on the asset i and the world portfolio respectively.

A. GARCH-t ICAPM

	α_i	β_i	R^2	Likelihood	SK	EK
AUSTRALIA	-0.014	0.672*	.221	-2014.5	-0.58	2.95
	(0.08)	(0.05)				
HONG KONG	0.287*	0.761*	.135	-2267.9	2.34	23.88
	(0.10)	(0.06)				
JAPAN	-0.036	1.237*	.536	-1767.8	0.54	2.54
	(0.06)	(0.04)				
FRANCE	0.061	0.884*	.286	-1880.3	-0.57	2.50
	(0.07)	(0.04)				
GERMANY	-0.019	0.837*	.335	-1835.8	-0.07	0.82
	(0.07)	(0.04)				
SWEDEN	0.155	0.740*	.227	-2022.4	-0.22	0.76
	(0.09)	(0.05)				
SWITZERLAND	0.002	0.844*	.417	-1724.8	0.42	2.72
	(0.06)	(0.04)				
U.K.	-0.014	0.974*	.412	-1778.1	-0.04	1.70
	(0.06)	(.04)				
U.S.	0.029	0.900*	.619	-1358.1	-0.13	1.08
	(0.04)	(0.03)				
CANADA	-0.092	0.691*	.378	-1652.7	0.23	1.37
	(0.05)	(0.04)				
				PANEL B		
JAPAN-EWW	0.007	0.909*	.353	-1909.1	0.19	1.49
	(0.07)	(0.03)				
U.K.-EWW	-0.032	1.044*	.502	-1721.6	-0.07	1.19
	(0.06)	(.04)				
U.S.-EWW	0.034	0.650*	.411	-1545.0	-0.11	0.54
	(0.05)	(0.03)				

Notes:

1. In Panel A, each country's returns R^*_i are regressed on the Morgan Stanley World Index, R^*_w while in Panel B, returns for Japan, the U.K. and the U.S. are regressed on an equally weighted index, EWW, constructed using the ten countries in our sample.
2. Likelihood is the value of the likelihood function resulting from maximum likelihood estimation.
3. Standard errors are in parantheses
4. *: significant at the 5% level; LB(5) and LBS(5) denote the Ljung Box statistic for the residuals and squared residuals respectively.
5. SK is the coefficient of skewness and EK is the excess kurtosis measure

Figure 1: U.S.-EWW: Low volatitilty state and GARCH betas

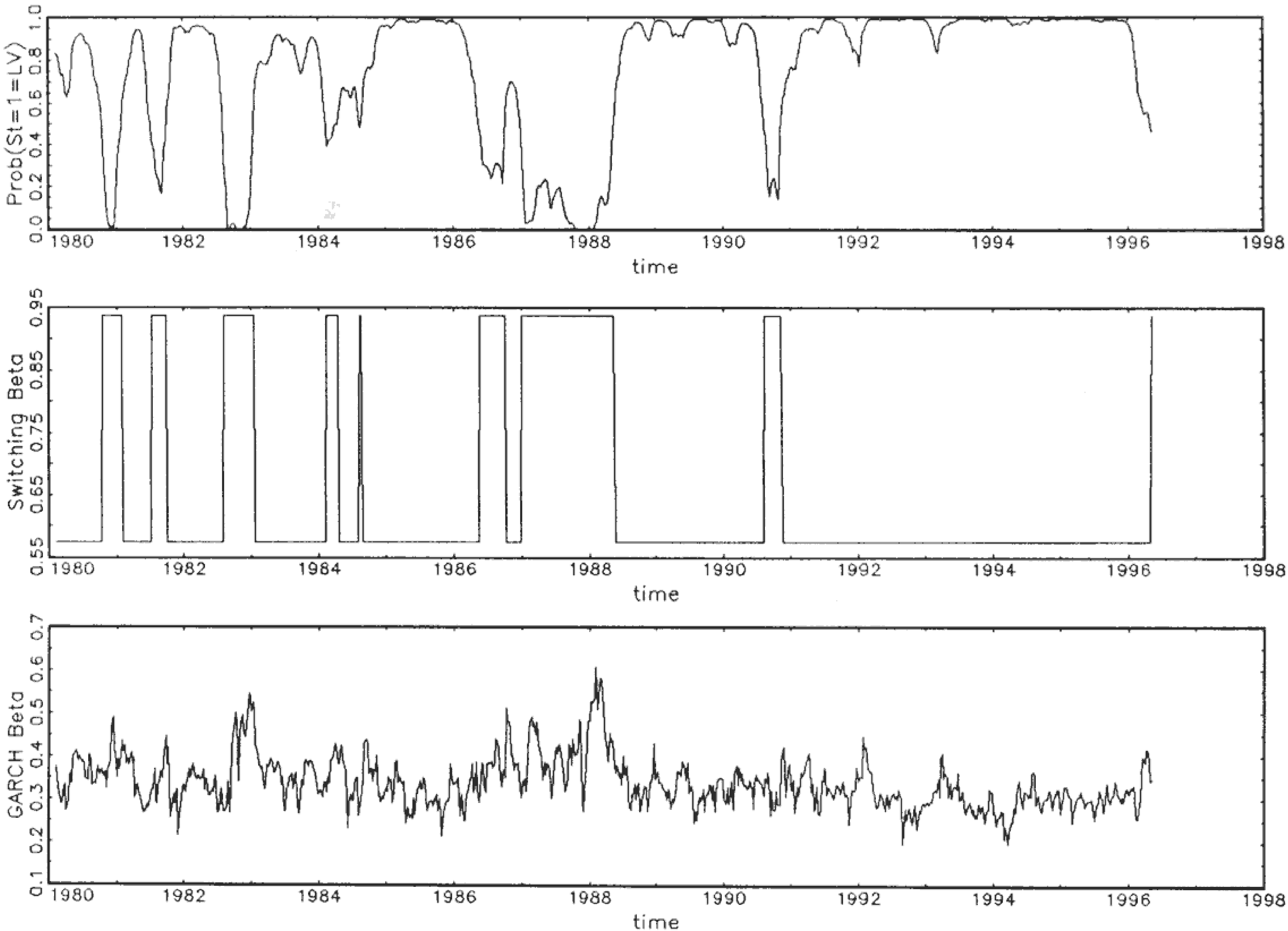

Figure 2: Japan-EWW: Low volatitilty state and GARCH betas

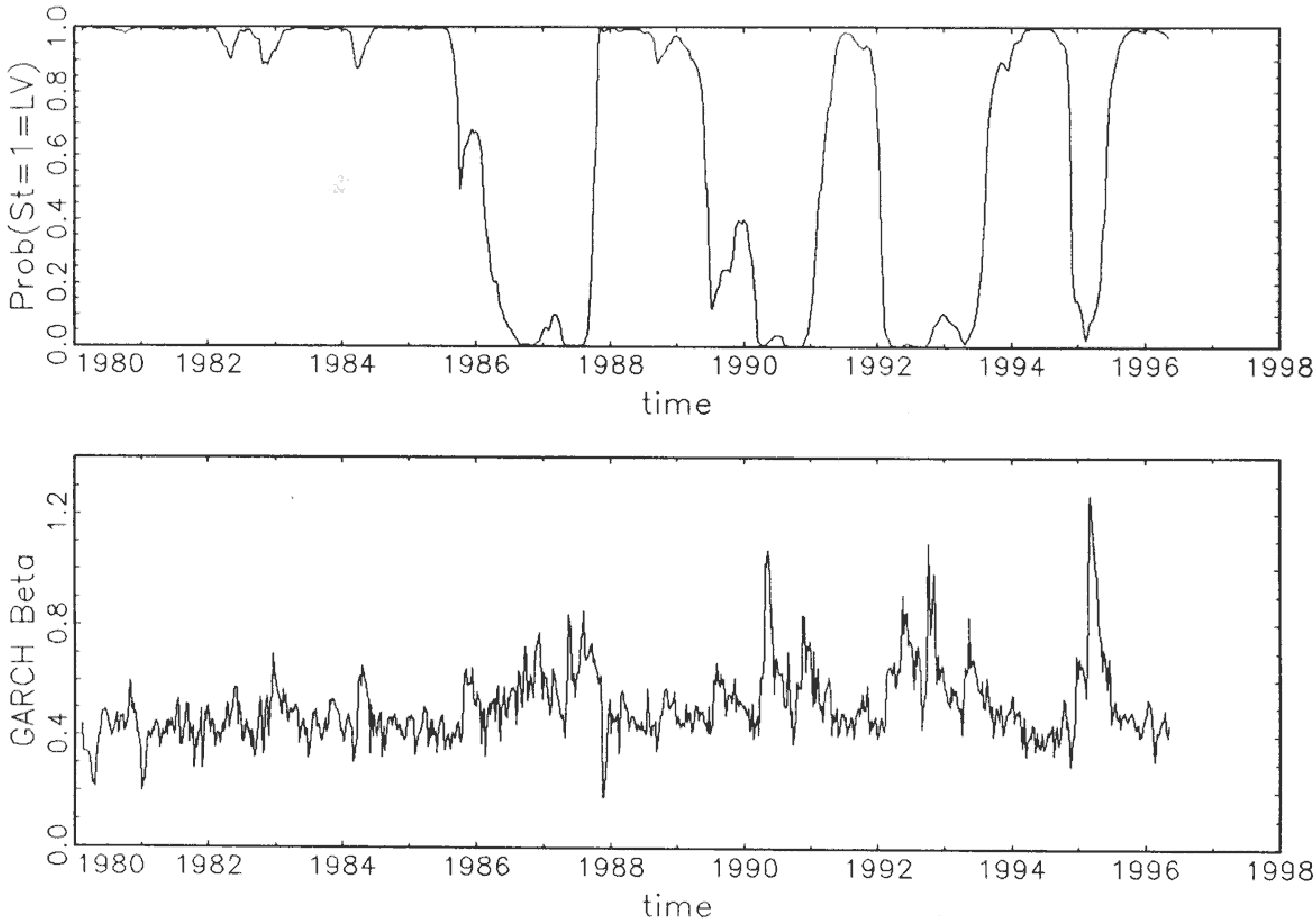

Figure 3. U.K.-EWW: Low volatility state and GARCH betas