How big is the premium for currency risk? or: The quest for convergence

Hausarbeit im Rahmen des Hauptseminars
Topics in International Economics & Finance
von Prof. Dr. Joachim Grammig
im Sommersemester 2007

Betreuerin: Kerstin Kehrle

Heid, Benedikt
Melanchthonstr. 25
72074 Tübingen
International Economics, B. Sc.
6. Fachsemester

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"Life [...] is a tale told by an idiot,
Full of sound and fury,
Signifying nothing."

MACBETH, ACT V, SCENE IV
William Shakespeare

1 Introduction

In May 2007, Japanese car maker Honda announced to refrain from expanding its production of its British subsidiary until the United Kingdom joined the euro area. The reasons for this step, as given to the press, are not too high wages or taxes as the casual observer might be inclined to think but the exposure to the currency risk of the British Pound Sterling against the Euro, as the continental market is also served by the British Honda subsidiary.[1] Obviously, currency risk plays a major role in determining the worthiness of investment projects and influences optimal portfolio choices. Alas, classic portfolio theory as the Capital Asset Pricing Model (CAPM henceforth) does not bother to account for the fact that investors face investment opportunities and thus uncertain pay-offs denominated in different currencies.
Therefore, the aim of this paper is to present an amended international version of the CAPM which incorporates currency risk, confront the theory with data in order to check whether currency risk is priced in international financial markets and, if it is, how much one has to pay for it.
My econometric strategy is inspired by Santis and Gérard (1998) and follows a two-step approach: In a first step, covariances between different assets are generated using a parsimonious bivariate GARCH model. These are then used in a second step as regressors in OLS regressions of the international CAPM. Results of hypothesis tests are presented and the price of currency risk is plotted.

2 The model

I will introduce the international asset pricing model which was originally developed by Adler and Dumas (1983) and is the theoretical foundation of Santis and Gérard (1998).
Assume a world in which exist $L + 1$ countries and M risky assets apart the deposit in the measurement currency.

[1] `http://www.spiegel.de/wirtschaft/0,1518,484711,00.html`, 24/05/2007

With r_{it}, I denote the excess return on asset i denominated in the reference currency. The excess rate is obtained by subtracting the risk-free rate from the gross return. As risk-free rate, I use the short-term deposit rate of the reference currency.

In a world where Purchasing Power Parity (PPP) holds, exchange rate changes perfectly reflect relative changes in price levels between countries which implies that an investor can transform her return into the same amount of consumption, irrespective of her domestic currency. That is, every investor values the return of an asset equally. Therefore, exchange rate risk does not exist and is not priced as a consequence. The only risk premium which has to be paid to an investor is her exposure to the systematic market risk which cannot be diversified away. In terms of asset pricing restrictions, this translates into the textbook CAPM model given by

$$E_{t-1}(r_{it}) = \delta_{m,t-1}\text{cov}_{t-1}(r_{it}, r_{mt}), \quad i = 1, ..., M \tag{1}$$

where $E_{t-1}(\cdot)$ and $\text{cov}_{t-1}(\cdot)$ are conditional moments given the information available to the investor at $t-1$. $\delta_{m,t-1}$ can be interpreted as the price of market risk.

However, empirical evidence shows that even though PPP may hold in the very long-run, deviations from PPP are large and volatile [see Rogoff (1996) for an overview; new empirical evidence against PPP even in the long-run is given e.g. by Lopez, Murray, and Papell (2005)]. Therefore, PPP is no assumption which should be used for an international asset pricing model. As Adler and Dumas (1983) point out, if PPP is violated, then investors from different countries value returns differently as their respective purchasing power depends on their domestic price index. In order to account for this fact, the CAPM has to be amended by the covariances of an individual asset i with changes in PPP deviations. These can be seen as additional risk factors which will be incorporated in asset prices. Thus, the pricing restrictions for an asset i are given by

$$E_{t-1}(r_{it}) = \delta_{m,t-1}\text{cov}_{t-1}(r_{it}, r_{mt}) + \sum_{c=1}^{L} \delta_{c,t-1}\text{cov}_{t-1}(r_{it}, \pi_{ct}), \quad i = 1, ..., M \tag{2}$$

where π_{ct} denotes the inflation of country c expressed in terms of the measurement currency. In analogy to $\delta_{m,t-1}$, $\delta_{c,t-1}$ can be interpreted as the price of currency exchange risk of currency c. r_{mt} is the return on the market, i.e. world portfolio. In principle, deviations from PPP as measured by π_{ct} include not only differences in inflation rates across countries. As π_{ct} is given in the measurement currency, it also reflects exchange rate risk. In order to simplify the analysis, I assume that differences in inflation expectations are nonstochastic. As I use monthly returns for my empirical implementation, this assumption is not unduly restrictive. However, the gain from this is that in this case, the only random component in π_{ct} is the relative change in the exchange rate between the reference currency and the currency of country c. As deposit returns are denominated in domestic currency, their only random element is the variation in the exchange rate. Therefore, I replace π_{ct} with the return on eurocurrency deposits.

I arrange all equity and deposit returns in a vector r_t where the first q elements are excess returns on equity portfolios in the L countries, and the next L elements the excess returns on short-term deposits denominated in domestic currency but transformed into the measurement currency. The last element in r_t is the excess return on the world portfolio. Using this notation, the conditional international CAPM (ICAPM) can be represented as follows:

$$E_{t-1}(r_{it}) = \delta_{m,t-1}\text{cov}_{t-1}(r_{it}, r_{mt}) + \sum_{c=1}^{L} \delta_{c,t-1}\text{cov}_{t-1}(r_{it}, r_{q+c,t}) + \varepsilon_{it}, \qquad i = 1, ..., M \tag{3}$$

As is again indicated by the expectational operator, this formulation is a conditional version of the ICAPM as it uses all information available to the investor at time $t-1$. If investors behave rationally, they will hedge against any intertemporal expected variation in the investment opportunity set [see Merton (1973) for an intertemporal version of the CAPM.]. Thus, also covariances with the relevant variables which represent the state of the world should have to be included. However, this would complicate the empirical implementation significantly and is therefore not pursued further.

3 Empirical implementation

3.1 Approach from Santis and Gérard (1998)

As the above formulation of the ICAPM uses conditional covariances and variances, an econometric technique which takes account of the conditional heteroscedasticity is needed. Santis and Gérard (1998) use a multivariate version of a generalized ARCH (GARCH) process for their empirical implementation which can accommodate for the GARCH-in-mean feature of the ICAPM. For the sake of clarity in exposition, the estimated system of pricing restrictions which has to hold at every point in time is:

$$\begin{aligned}
E_{t-1}(r_{1t}) &= \delta_{m,t-1}\text{cov}_{t-1}(r_{1t}, r_{mt}) + \sum_{c=1}^{L} \delta_{c,t-1}\text{cov}_{t-1}(r_{1t}, r_{q+c,t}), \\
&\vdots \\
E_{t-1}(r_{q-1,t}) &= \delta_{m,t-1}\text{cov}_{t-1}(r_{q-1,t}, r_{mt}) + \sum_{c=1}^{L} \delta_{c,t-1}\text{cov}_{t-1}(r_{q-1,t}, r_{q+c,t}), \\
E_{t-1}(r_{q+1,t}) &= \delta_{m,t-1}\text{cov}_{t-1}(r_{q+1,t}, r_{mt}) + \sum_{c=1}^{L} \delta_{c,t-1}\text{cov}_{t-1}(r_{q+1,t}, r_{q+c,t}), \\
&\vdots \\
E_{t-1}(r_{q+L,t}) &= \delta_{m,t-1}\text{cov}_{t-1}(r_{q+L,t}, r_{mt}) + \sum_{c=1}^{L} \delta_{c,t-1}\text{cov}_{t-1}(r_{q+L,t}, r_{q+c,t}), \\
E_{t-1}(r_{q+L,t}) &= \delta_{m,t-1}\text{var}_{t-1}(r_{mt}) + \sum_{c=1}^{L} \delta_{c,t-1}\text{cov}_{t-1}(r_{mt}, r_{q+c,t}).
\end{aligned} \tag{4}$$

In principle, any subset $n < q$ of the pricing restrictions on the assets can be used in empirical work, however, only $q-1$ assets can be included at the uppermost. This is due to the fact

that as all M pricing equations hold, the last equation pricing the market portfolio would just be a linear combination of the last q equations for every period. To the contrary, all L currency risk terms have to be included in any subset of the assets as no currency risk factor can be omitted from the estimations. If an equity return index is used for each country, then $q-1=L$.
If only a subset $n<q-1$ of the assets is used, all in all $s=n+L$ pricing restrictions have to hold. Stacking all of these in one vector $\mathbf{r}_t$ yields

$$\mathbf{r}_t=\delta_{m,t-1}\mathbf{h}_{m,t}+\sum_{c=1}^{L}\delta_{c,t-1}\mathbf{h}_{n+c,t}+\boldsymbol{\varepsilon}_t,\quad \boldsymbol{\varepsilon}_t|\Im_{t-1}\sim N(0,H_t) \tag{5}$$

where $\Im_{t-1}$ is the set of conditioning information variables at time $t-1$. With H_t, I denote the $(s\times s)$ conditional variance-covariance matrix of asset returns. Accordingly, h_{n+c} is the $(n+c)$th column of H_t, and $h_{m,t}$ is the last column of H_t. Following the ordering from (4), the $(n+c)$th column of H_t contains the conditional covariances between each asset and the return on the currency deposit c, and therefore measures the exposure of each asset to the respective currency risk. Analogously, the last column of H_t contains the covariance of each asset with the world portfolio and thus measures its exposure to market risk. This only leaves the specification of H_t. Santis and Gérard (1998) use the multivariate equivalent of a GARCH(1,1) process which, under the assumption of covariance-stationarity, is specified as

$$H_t=H_0\circ(\iota\iota'-\mathbf{aa}'-\mathbf{bb}')+\mathbf{aa}'\circ\varepsilon_{t-1}\varepsilon_{t-1}'+\mathbf{bb}'\circ H_{t-1} \tag{6}$$

where H_0 is the unconditional variance-covariance matrix of the residuals, ι is a vector of ones, $\mathbf{a}$ and $\mathbf{b}$ are $s\times 1$ vectors of unknown parameters and $\circ$ denotes the Haddamard product, i.e. element-wise multiplication. This so-called diagonal GARCH has an immediate and intuitive appeal: The variance terms in H_t depend on the respective squared residuals and an autoregressive part, whereas the covariances depend on the respective cross-products and the autoregressive component. This parsimonious specification of the variance leaves $2s$ parameters to be estimated (s elements in a and b).
Assuming conditional normality of the error terms, parameter estimates can be obtained by maximizing the following log-likelihood function:

$$lnL(\boldsymbol{\theta})=-0.5ln(2\pi)-0.5\sum_{t=1}^{T}ln|H_t(\boldsymbol{\theta})|-0.5\sum_{t=1}^{T}\varepsilon_t(\boldsymbol{\theta})'H_t(\boldsymbol{\theta})^{-1}\varepsilon_t(\boldsymbol{\theta}) \tag{7}$$

As the normality assumption is often violated for financial time series, all test statistics should be calculated using the quasi-maximum likelihood approach to obtain robust variance-covariance matrices of the estimated parameters [For further details, see Santis and Gérard (1997).].

3.2 Related work

The selling point of Santis and Gérard (1998) is that they can address the question of the size of the risk premia paid to international investors. This is the payoff they get from specifying explicitly the covariance matrix of returns H_t and a huge improvement compared to the approach of Dumas and Solnik (1995). They circumvent the specification of the conditional covariance matrix by estimating a pricing kernel representation of the model of Adler and Dumas (1983) instead of the direct asset pricing restrictions. This parsimony, however, comes at a cost: As they leave the second moment behaviour unspecified, they can only present time series of the *prices* of risk. In order to plot the risk *premia*, i.e. price of risk times the quantity of risk, they have to make the auxiliary assumption of time invariant market and currency risk. Santis and Gérard (1998), to the contrary, allow for the fact that both the *prices* of risk can vary, i.e. $\delta_{m,t-1}$ and $\delta_{c,t-1}$, and the *level* of risk, as measured by the $\text{cov}_{t-1}(\cdot)$ terms.

3.3 The *Kehrle* approach

For my own empirical implementation, I follow a different methodology than Santis and Gérard (1998) which was developed by Kerstin Kehrle.[2]
Santis and Gérard (1998) have to estimate their system of mean equations (4) jointly with their specification of the conditional covariance matrix H_t as their model features a GARCH in mean effect.
The *Kehrle* approach splits this system up in two steps. In a first step, series of the conditional covariances which are needed for the estimation of (4) are generated via a so-called BEKK model which is another specific form of a multivariate GARCH model. By this approach, the GARCH-in-mean feature can be circumvented. In a second step, one can then estimate the system of equations (4) by a simple OLS regression. The equality of coefficients in the system is simply imposed by stacking the equations in a single OLS regression. The remainder of this section will explain the two steps in more detail.

3.3.1 Step I: Estimating the covariances

In the first step, I fit bivariate ARCH models to generate series of the respective covariances needed for the estimation of the actual model (4). The specific form of the bivariate ARCH process I use is a modification of the BEKK model which was developed by Engle and Kroner (1995).[3]
As I only want to impose as much structure on the data as needed, I specify the mean equations of the returns as

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{m,t} \end{bmatrix} \tag{8}$$

or shorter

$$\mathbf{r}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t \tag{9}$$

[2] I am grateful to Kerstin Kehrle for hours of support and helpful comments.

[3] The acronym stems from an earlier draft of this paper which was presented by Baba, Engle, Kraft, and Kroner. Engle and Kroner kept this name as the model very rapidly became known by this catch phrase.

I only include a constant $\boldsymbol{\mu}$ in the mean for the sake of hoped-for numerical stability of the estimations.
Concerning the variance, I use a modified version of the so-called BEKK model

$$H_t = \Omega + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B \circ H_{t-1} \tag{10}$$

where $\circ$ again denotes the Haddamard product. Ω and B are both symmetric $(N \times N)$ parameter matrices, whereas A is a general $(N \times N)$ parameter matrix. In the bivariate case, i.e. $N = 2$, this implies

$$\begin{aligned} H_t \quad \equiv \quad & \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \\ \begin{bmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & \omega_{22} \end{bmatrix} \quad + \quad & \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \\ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad \circ \quad & H_{t-1} \end{aligned} \tag{11}$$

where $h_{12,t} = h_{21,t}$, $\omega_{12} = \omega_{21}$ and $b_{12} = b_{21}$.
For the sake of clarity, I write out the elements of H_t explicitly:

$$\begin{aligned} h_{11,t} &= \omega_{11} + a^2_{11}\varepsilon^2_{1,t-1} + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a^2_{21}\varepsilon^2_{2,t-1} + b_{11}h_{11,t-1} \\ h_{12,t} = h_{21,t} &= \omega_{12} + a_{11}a_{12}\varepsilon^2_{1,t-1} + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon^2_{2,t-1} + b_{12}h_{12,t-1} \\ h_{22,t} &= \omega_{22} + a^2_{12}\varepsilon^2_{1,t-1} + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a^2_{22}\varepsilon^2_{2,t-1} + b_{22}h_{22,t-1} \end{aligned}$$

where h stems from $vech(H_t) \equiv [h_{11,t}, h_{12,t}, h_{22,t}]'$. All in all, for every BEKK, 12 parameters have to be estimated (2 for the constant in the mean specification as in (8) and 9 for the actual variance specification).
The BEKK formulation has the general advantage that by construction, H_t is positive definite almost surely for all t. The BEKK model is also estimated by maximum likelihood. As above, I assume conditional multivariate normality. As the log-likelihood function only depends on the distributional assumption of the vector of residuals, it remains the same as specified in (7). This holds for any multivariate GARCH process. The different versions of GARCH only model the behaviour of H_t in a specific way; the likelihood function, however, remains oblivious to this explicit modeling as only H_t enters its calculation, irrespective of the underlying assumed data-generating process of H_t [see Bollerslev, Engle, and Nelson (1994)].
The programme I use for the estimation of the BEKK model was written by Ken Kroner and can be downloaded from his website.[4]
As the log-likelihood can only be maximized by iterative numerical optimization, starting values have to be provided. Therefore, I feed the BEKK models with the estimates of a univariate GARCH(1,1) process for the respective series which is estimated before the maximization of the actual BEKK likelihood. Specifically, I fit the conditional variance h_t for a univariate series with the mean specified analogously as in (8) as

$$h_t = \omega + \alpha_1\varepsilon^2_{t-1} + \beta_1 h_{t-1} \tag{12}$$

[4] `http://econ.ucsd.edu/publications/ARCH.shtml`

where ε_t is the residual from the mean equation.[5] Specifically, the estimates of ω are used to replace the diagonals of matrix Ω, the diagonals of A are filled with the respective estimates of α, and the estimates for β are used for the diagonals of B. For the off-diagonal values of the parameter matrices, no estimates are available, because they are specific to the multivariate GARCH process as they capture the cross-correlation behaviour of the variance-covariance matrix. Therefore, no guidance is available, and values between 0 and 1 are chosen.

In general, these starting values lead to convergence. However, in several cases, some of them had to be altered as convergence could not be reached with the generated values from the GARCH(1,1).

3.3.2 Step II: Estimating the ICAPM

Having obtained estimates for the covariances via the BEKK approach, I use these covariances as regressors in an ordinary OLS regression of the pricing restrictions. As theory implies the same risk premia for all six portfolios used in my investigation, I impose this restriction by stacking all the data for the s pricing restrictions. Thus, I estimate the following OLS regression with $s \times T$ observations:

$$r_{it} = \delta_m \text{cov}_{t-1}(r_{it}, r_{mt}) + \sum_{c=1}^{L} \delta_c \text{cov}_{t-1}(r_{it}, r_{n+c,t}) + \varepsilon_{it}, \qquad i = 1, ..., s \tag{13}$$

Note that in this framework, I model both the market risk premium as well as the currency premium as constant.

4 The data

4.1 Data used

Following Dumas and Solnik (1995) and Santis and Gérard (1998), I use monthly excess log returns on national equity indexes plus a value-weighted world equity index (as a proxy for the market portfolio) for the period of February 1975 to January 2007 (i.e. 384 observations) provided by Morgan Stanley Capital International (MSCI). My analysis includes stock markets from the US, the UK, and Germany which cover 50% of the MSCI world portfolio. It can only be hoped that this share is large enough so that any bias by not covering the whole portfolio can be negligible.

As measurement currency, I use US-$, i.e. I take the view of an investor residing in the US facing currency risk towards the German Mark and the British Pound Sterling.

For the calculations of returns I use time series of the actual price index without reinvested dividends. Dumas and Solnik (1995) actually use returns on these indexes with reinvested dividends; however, they do not clearly state whether they use gross or net returns (i.e. *ex* or *cum* withholding tax) for their estimations [see Morgan Stanley Capital International (2007) for details on index calculations]. Santis and Gérard (1998) do not even distinguish here either. However, their descriptive statistics of the data hint at total returns. Therefore, I tried

[5]For a thorough introduction to GARCH models for the univariate case, see Hamilton (1994), chapter 21.

to estimate the models with both pure price index returns and with total returns including dividends. However, convergence could not be achieved with the latter data series so that I use the pure price index data throughout my paper.
For measuring the exposure to currency risk of the British Pound Sterling and German Mark (Euros are transformed into Mark accordingly), I use monthly returns on the one-month euroDM and euro£ deposits. As risk-free rate, I follow Santis and Gérard (1998) and use the return on the one-month euroUS-$ deposit quoted on the first day of the month. All eurocurrency time series are provided by Financial Times, London.
Returns are calculated as log-returns and are measured in domestic currencies, i.e. they have to be transformed into returns in the measurement currency. For this, I use closing spot exchange rates calculated at 16:00 p.m. London time provided by WM/Reuters.
To sum things up, I have six asset pricing restrictions, i.e. $s = 6$ as defined in (13), with three equity return indexes, two eurocurrency deposits and the world portfolio.
Table 1 reports descriptive statistics for the used return series. Excess returns on the equity markets are considerably higher than returns on the Eurodeposits. Also, the standard deviation indicates higher volatility. This is in line with expectations from basic economic theory and with Santis and Gérard (1998). All series are leptokurtic, i.e. they have a kurtosis greater than 3 which is the kurtosis of the normal distribution; only the euroDM deposits come close to a mesokurtic behaviour. Consequently, for all series except the euroDM deposits the hypothesis of normally distributed returns can be rejected on any standard significance level. Evidence is even stronger for the returns on the UK equity index. I also find a very high value for the return of this index for January 1975 which is responsible for the high value of the Jarque-Bera statistic of 925.01.
Table 2 shows the autocorrelations of the respective return series. None of them turns out to be significant on the 5% level. This complete lack of autocorrelation indicates that there is no need to correct for spurious autocorrelation in the return series. This is again completely in line with Santis and Gérard (1998). In economic terms, this corroborates the fact that returns are not predictable by their own history, as past realizations do not convey any information about the return in the next period.
Nevertheless, I find significant autocorrelation in the squared returns for the German stock index and, even more prominently, for the British stock and euro£ series. This suggests that a GARCH parametrization for the conditional variance could be appropriate, at least for three of the six series. My results differ from Santis and Gérard (1998) in the respect that they find significant autocorrelations for the first lags for all their stock indexes, but none for the Eurocurrencies. The significant autocorrelations for all lags of the UK series is not found by Santis and Gérard (1998).

4.2 Data not used due to convergence problems

At the beginning, I wanted to closely follow Santis and Gérard (1998) and also include data for Japan, as it represents 31% of world market capitalization (ibd.). However, this was prevented by the fact that several of the BEKK models did not converge for the shorter

time period (Japanese data are only available from September 1979 onwards). The convergence problems, however, did not only arise with the Japanese return series but also for several BEKKs modeling the covariances with the market portfolio of other return series. Particularly the series for Germany and the US did not converge when Japan was included. Remember that *all* the covariances have to be estimated anew due to the new time period. It could well be that convergence is the harder to achieve the smaller the sample size as outliers in the data get harder to fit due to their higher relative weight.
Convergence problems such as these during non-linear optimization are quite common, though. Bond, Harrison, and O'Brien (2005) report similar problems using the GAUSS software. When implementing a recently proposed non-linear estimation technique, they document that even minor changes on the used data set like excluding a couple of the first or last observations can change convergence behaviour and even parameter estimates considerably (up to different results for significance of parameters). Even though their paper deals with a completely different estimation method, their convergence problems are still illustrative.

5 Empirical evidence

5.1 Step I: BEKK estimates

5.1.1 Description of results

As I need covariances between returns of all six assets (three equity markets, two eurocurrencies and the world portfolio), with the returns on the market portfolio as well as covariances of the asset returns with currency risk, I need 15 covariances. Because some of these terms in fact are equal and some are covariances between the same series of returns, i.e. they are actually variances, all in all only 12 BEKK models actually have to be estimated. Tables 4 to 15 present the estimation results of the bivariate BEKK models which I run to obtain estimates for the covariances between the different return series. Their specification is given by equations (8) and (11). The variance-covariance matrix of the estimated parameters is calculated by the inverse of the Hessian matrix [see Hamilton (1994), chapter 5.8 for statistical inference with maximum likelihood].
As the results of the BEKKs are of interest on their own concerning the modeled interdependence of volatilities of the respective return series, I describe the results of these estimations in quite some detail, even though technically, they are only used as the "data generating process" for the ICAPM.
The results show some broad similarities. First of all, the constant in the mean equation, i.e. the average or expected excess return on asset i, μ_1 and μ_2 respectively, is positive for all estimates except for the excess returns on the EuroDM deposit as estimated in Table 9. The highest estimate for μ_i is 0.35% [Table (9)] which is the estimated average excess return on the Euro£ deposit.[6] The lowest value is the negative average excess return from the same regression. One should not interpret too much into $\boldsymbol{\mu}$, though, as none of the estimated

[6] All estimations are run with actual percentage values, i.e. 0.1 equals 0.1%.

parameters in the mean equation are significant for any of the 12 BEKKs. *p-values* range from 14% in the best case (Table 11) to values as high as 98%.
Turning to the elements of Ω, i.e. the constant element in the variance H_t, I find that in only two cases (Tables 4 and 10), all three elements of Ω are significant, at least at the 10% level. At the opposite side of the spectrum, none of the elements in Ω are significant for the cases reported in Tables 14, 9, and 8. The remaining seven cases give a mixed result of the significance of the elements of Ω. The actual values of Ω are not of particular interest, as Ω represents a mere scaling factor which only shifts the overall level of the estimated conditional variances h_{11} and h_{22} and the covariance $h_{12} = h_{21}$, respectively.
Concerning the estimates of the elements of matrix A, which governs the influence of the squared residuals of the respective mean equation as well as the relative weight of their cross-products, I find that in none of the estimated BEKKs, all of the four estimated elements in A are significant. Yet, in eleven out of the twelve estimated BEKKs (exception is Table 7), the main diagonal elements of A turn out to be highly significant, in most of all cases at any standard significance level. As the residuals ε_{t-1} can be interpreted as new information hitting the market, one could conclude that news arriving at a market affect the estimate of its conditional variance to a higher degree than news (i.e. residuals) from the other market included in the BEKK estimation. This interpretation of the results is corroborated by the fact that the estimates for a_{11} and a_{22} are considerably larger than the estimates for the off-diagonal elements a_{12} and a_{21}. The only exception from this is again Table 7. A possible reason for the different behaviour of Table 7 could be the following: This case models the co-movement of volatility of US equity market returns with the world portfolio returns. As the US equity market has a weight of 35% in the calculation of the overall world portfolio return [see Santis and Gérard (1998)], it is not surprising that the weight of the cross-dependence of volatilities between the US and the world portfolio as measured by the parameters a_{12} and a_{21} is considerably higher than for all the other return series considered. Actually, the magnitude of the estimated coefficients just inverts its position: Here, the cross-correlation coefficients are considerably higher than the coefficients measuring the influence of the squared residuals of the same process. Furthermore, it could well be that the high influence of the cross-products takes away the otherwise significant effect of a_{11} and a_{22}.
The overall poor performance of the off-diagonal elements of A also fits into the descriptive statistics. Santis and Gérard (1998) note that there is hardly any evidence of cross-correlation in the return series, except for contemporaneous cross-correlation. It is for this reason that they adopt a diagonal parameterization of the covariance matrix which sets the influence of these non-contemporaneous cross-correlations equal to 0.
Finally, I turn to the elements of B, i.e. the part which captures the autoregressive behaviour of the variance. In all Tables except 4 and 12 which model the covariance of the German equity index with the world portfolio and the Euro£, respectively, all elements of B are highly significant. Still, even in the aforementioned two exceptions, the diagonal elements of B are highly significant. Only b_{12}, which governs the persistence behaviour of the covariance we are actually interested in, turns out to be insignificant. This does not imply, however, that

these covariances do not exhibit GARCH behaviour, as only the *generalized* part, i.e. the persistent element turns out to be insignificant. The ARCH part, to the contrary, is *alive and well*, i.e. its coefficients are significant even in these two cases. This means that both the conditional variances as well as the covariance clearly show GARCH behaviour. Moreover, as the significant coefficients are all close to 1 or at least as high as 0.511 (b_{11} in Table 11), I can conclude that the various return series show a high persistence in their conditional variances. This also corroborates the findings of Santis and Gérard (1998). For both their model of the ICAPM with constant as well as time-varying prices of risk they also find high values for the estimated elements of their vector $\mathbf{b}_i$ which are equally significant. Thus, even though different methodologies are used, conclusions about the high persistence of conditional variances and covariances is confirmed by both approaches.

5.1.2 Diagnostic checks

As a diagnostic check for the validity of the chosen parameterization of the conditional variance, I checked the residual diagnostics which are automatically computed by Kroner's programme. Short summaries of these statistics can be found at the bottom of Tables 4 to 15. The Ljung-Box Q-statistic for the standardized residuals (ε_t/h_t) I report checks the hypothesis of no autocorrelation up to lag 12 in the residuals. As can be expected from the preliminary descriptive statistics from above, I do not find autocorrelation in the residuals of the BEKK estimations. *p-values* are all well above the 10% level. Only twice (in Tables 6 and 5), I detect autocorrelation at the 10 % significance level. As for all the other cases *p-values* are far higher, I impute these two exceptions to chance.

The Q-statistic for the squared standardized residuals (ε_t^2/h_t) also checks the hypothesis of no autocorrelation up to lag 12. However, it does not check for autocorrelation in the mean equation but in the specification of the conditional variance. If the parametrization is correct, the standardized residuals should not exhibit any autocorrelation any more, as the used GARCH model takes account of it. If the Q-statistic nevertheless detects autocorrelation, then the conditional variance is misspecified as it cannot capture all of the autocorrelation of the data. Here, the general result is that the underlying covariance matrix specified by the BEKK model fits the data quite well. Only in three cases (Tables 6, 9, and 13), I find a rejection of the null at the 10% level. Especially in Table 6, the rejection is on any significance level with an *p-value* of 0.000. The most interesting fact is that all the rejections occur because of remaining autocorrelation in the conditional covariance, even though the descriptive statistics of the data hint at no cross-product autocorrelation. This is a finding contrary to Santis and Gérard (1998). It can only be speculated what the reason could be for this interesting fact.

I can conclude from this discussion that overall, the BEKK model specification fits the data quite well, albeit some problems with the model specification cannot be disputed away. Nevertheless, I use the covariance series generated by the several BEKK models in order to calculate the OLS regression for the ICAPM.

5.1.3 Estimated variances

An artefact of the BEKK specification I use throughout this paper is that I obtain five estimates of the variances of the world portfolio, the EuroDM and Euro£ deposits. Therefore, the question arises whether these estimated conditional variances behave in a similar way or not — what they should do as each of the five different series represents the same thing. Figures 1, 2, and 3 plot the time series of the five estimated conditional variances of the EuroDM, the Euro£ and the world portfolio, respectively. As can be seen by casual inspection of the graphs, in general, the variances behave "well", i.e. they all comove. The estimated variances of the Euro£ returns, depicted in 1, differ in the height of the peaks (May 1985 and December 1992), but are quite similar in their overall behaviour. The only exception is the variance estimated by the BEKK which includes the German equity index and the euro£ deposit. Here, the two peaks lose much of their impressive size, and the overall behaviour of the series is distinctly different. Still, some similar patterns remain.

For the variances of the euroDM deposits, the pictures is decidedly clearer: All the series behave quite similar.

Finally, turning to the variances for the world portfolio, one can see that the overall behaviour of the series is represented by each of the series. Still, differences are more pronounced than in the other two cases. Moreover, the variance from the BEKK using the German stock index and the world index returns has smaller peaks and is considerably smoother than the other estimated variances. Obviously, the German equity index behaves in a distinct way as the variances produced by the BEKK estimation it is involved in are considerably different from the rest. Still, even in this case, the series cannot deny its pedigree, i.e. it shares the common features of all the other variances. By and large, it seems to make only a minor difference which time series of the estimated variances of the respective returns is used for the ICAPM. Consequently, I arbitrarily choose the following variances: For the variance of the Euro£, I choose the series generated from the BEKK involving the returns on the world portfolio and the Euro£; for the euroDM, I chose the BEKK with the world portfolio and the euroDM deposit and finally the BEKK of the world portfolio and the German equity index for the variance of the world portfolio.

In principle, one could also come up with a more rigorous test of co-movement of the different time series of the estimated variances: If the variances really describe the same process, they should be pairwise cointegrated. Thus, an augmented Dickey-Fuller test or a KPSS test could be applied. I did not pursue this idea any further, though.

5.2 Step II: International conditional CAPM

5.2.1 International conditional CAPM with constant prices of risk

Having obtained estimates for the covariances which are used as regressors in (13), I can proceed to estimate this equation by OLS. Table 16 reports the results. Standard errors are calculated with the Newey-West covariance matrix estimator in order to control for possible autocorrelation in the residuals. Not surprisingly, $\bar{R}^2$ is 0.001, which means that practically nothing can be explained in the variations of the returns. However, anything else would be startling anyway, as returns should not be predictable. I obtain an estimated market risk premium of 0.010%, a negative currency risk premium of -0.045% for the German Mark, and a positive risk premium for the UK £.[7] Estimates of the coefficients are different from the results from Santis and Gérard (1998). Albeit I also find a negative currency premium for the German Mark, my estimate is more than twice as large. The same holds for the market risk premium. Having said that, one has to keep in mind, though, that all t-statistics report insignificant coefficients, if considered separately. Turning to the hypothesis of interest — namely: Is currency risk priced in international capital markets? — results are in the same spirit. The robust Wald statistic of the H_0: $\delta_{ger} = \delta_{uk} = 0$ is 2.503 and thus the H_0 cannot be rejected with a *p-value* of 0.286.[8] Thus the international version of the CAPM including currency risk is rejected in this setting. Even more so, also the joint hypothesis that all risk premia are equal to 0, i.e. H_0: $\delta_m = \delta_{ger} = \delta_{uk} = 0$, cannot be rejected either as it has a *p-value* of 0.177.

These results are in line with Santis and Gérard (1998), as they also report that currency risk is no significant factor in international asset pricing, at least if one assumes constant prices of risk as I do. Interestingly, this is a contrary finding to Dumas and Solnik (1995) who find evidence in favour of the ICAPM with constant prices of risk.

5.2.2 Robustness check: Market segmentation

In order to check for the robustness of my results, I mimic the robustness tests as proposed by Santis and Gérard (1998).

In a first step, I introduce the idea of some mild form of market segmentation by estimating a fixed effect model. This can be captured by including a different intercept δ_i for every asset. Technically, I do this by introducing five dummies while using the German equity index as the base category.

Economically, a significant δ_i could be interpreted as an average excess return for asset i. From a neoclassical perspective, this would imply a free lunch, as investors can reap an excess return even though they do not bear any risk for which they are compensated by the risk premia as represented by the last three terms of Equation (13). Nevertheless, reasons for a significant δ_0 are not difficult to think of. Examples could be differential tax treatment of the assets or a preferred habitat phenomenon [see Bollerslev, Engle, and Wooldridge (1988)]. In a more general way, all of the aforementioned facts can be reasons for market segmentation. Table 17 reports the results for this model specification. Only the dummy for the German equity index turns out to be significant at the 10% level; all the other dummies have *p-values* of at least 0.185. The joint hypothesis of no market segmentation, i.e. $H_0 : \quad \alpha_i = 0 \quad \forall \quad i$, cannot be rejected with a *p-value* of 0.550. Market risk is insignificant as well with a *p-value*

[7] As all variables enter the estimations as percentages, the parameters can be interpreted directly as percentage risk premia.

[8] I use the Newey-West covariance for the calculation of the Wald statistic. For computational details see Greene (2003), chapter 6.4.

of 0.507; but the currency risk premia are significant on the 5 and 10% levels for the euroDM and the euro£, respectively. The size of the estimates is different to the baseline model from Table 16: The German currency risk premium doubles its absolute value and becomes even more negative.

The most striking result, though, is the negative estimate of the market risk δ_m. As Santis and Gérard (1998) point out, δ_m cannot be negative by definition. This stems from the fact that theoretically, δ_m is a weighted average of the coefficients of risk aversion of all national investors. If all investors are risk-averse, then δ_m cannot be negative. Obviously, even this minimum requirement of the value of δ_m is violated by my estimations.

Having said that, I turn to the hypothesis of no priced currency risk, i.e. H_0: $\delta_{ger} = \delta_{uk} = 0$. It cannot be rejected, nor the null of no priced risk at all (*p-values* of 0.103 and 0.155, respectively).

As a further robustness check, I add the variance of the respective market as regressor. Contrary to Santis and Gérard (1998), however, I impose the restriction that all returns are affected by their respective variance in the same way, that is the coefficient is the same for all assets. I keep the fixed effects for comparison purposes. Thus, the estimated model becomes

$$r_{it} = \delta_i + \delta_m \text{cov}_{t-1}(r_{it}, r_{mt}) + \sum_{c=1}^{2} \delta_c \text{cov}_{t-1}(r_{it}, r_{n+c,t}) + \delta_{var} \text{var}_{t-1}(r_{it}) + \varepsilon_{it}, \qquad i = 1, ..., 6 \quad (14)$$

Results can be found in Table 18. Effectively, nothing changes compared to Table 17. Parameter estimates only vary in the second or third digit, and also the significance of parameters remains the same. The added regressor is highly insignificant with a *p-value* of 0.934. The robust Wald tests repeat the picture from Table 17, too. The hypothesis of no market segmentation (now also including δ_{var}) cannot be rejected with a *p-value* of 0.665. The same goes for the test of no currency risk premium and no risk premium at all, with *p-values* of 0.103 and 0.162, respectively.

To sum things up, it can be said that the used model specification of time-invariant prices of risk obviously fails to detect risk premia at all. This result also holds true for several robustness checks. These findings are completely in line with Santis and Gérard (1998). Obviously, prices of risk have to be modeled as time variant in order to detect risk premia in international asset prices.

5.2.3 The size of the risk premiums

In Figures 4–9, I plot graphs of the estimated total risk premium measured by

$$TP_{it} = \delta_m \text{cov}_{t-1}(r_{it}, r_{mt}) + \delta_{ecger} \text{cov}_{t-1}(r_{it}, r_{ecger,t}) + \delta_{ecuk} \text{cov}_{t-1}(r_{it}, r_{ecuk,t}) \quad (15)$$

and of the corresponding currency risk premium calculated as

$$CP_{it} = \delta_{ecger} \text{cov}_{t-1}(r_{it}, r_{ecger,t}) + \delta_{ecuk} \text{cov}_{t-1}(r_{it}, r_{ecuk,t}), \quad (16)$$

where the values of the estimated parameters are obtained from the baseline ICAPM results as reported in Table 16, i.e. with *time-invariant* prices of risk. Thus, these graphs differ from those as reported in Santis and Gérard (1998) as they use the estimates of their ICAPM with *time-varying* prices of risk. As a result, the graphs are not directly comparable; still, both depict the associated risk premia and their evolvement over time. Note that I can also plot the currency risk for the US equity market, even though the measurement currency is US-$. This is due to the fact that exchange rate risk is aggregated over the world population of investors who consume goods denominated in their domestic currency. Therefore, there also exists a premium for the US equity index.

Even though the dynamics of each premium are different for the various assets, some general observations can be made. First of all, all total and currency risk premia appear to be very similiar curves which are only moved up or down the vertical axis. This can be attributed to two features of the underlying estimates: On the one hand, it is an artefact of the very small value for δ_m, so that the influence of the market risk premium becomes very small. On the other hand, it is the direct result of *time-invariant* prices of risk. Therefore, the relative prices per unit of market or currency risk remain the same throughout the whole sample.

Another general result is that risk premia on equity and eurocurrency markets differ. Whereas in the latter case nearly the complete total risk premium consists of currency risk, market risk plays a far bigger role for the equity markets. This is in line with Santis and Gérard (1998) who find similar patterns, and also fits into economic theory: As eurocurrencies are fixed income securities, the importance of the covariance with market risk becomes a *quantité négigeable*. I also find that UK equities and euro£ essentially exhibit the same currency premium dynamics. Admittedly, Santis and Gérard (1998) can show this more prominently in their graphs than I can. But the similarity in the currency risk premia in Figures 5 and 9 is still striking. Again, the economics behind this finding are quite obvious: An invested US-$ bears the same currency risk, no matter in which asset it is actually invested in. German equity and eurocurrency risk premia (Figures 4 and 8) do not show this behaviour, however. Again contrary to Santis and Gérard (1998), I do not find negative currency premia for the period between January 1980 and December 1985. Only the German equity index and the EuroDM exhibit this feature. Furthermore, the German stock index premia somewhat resemble the those as depicted in Santis and Gérard (1998).

Despite this fact, similarities end here: The prominent spike in the risk premia of UK equity index and euro£ in December 1985, e.g., does not appear in the graphs of Santis and Gérard

(1998) even though it appears in all the estimated variances of the euro£ and obviously feeds through to the risk premia.
Even more striking, the risk premia estimated for UK equities resemble those for the world equity index, even though the UK only makes up for 11% of the total world portfolio.

6 Conclusion

The purpose of this paper is to tackle the question whether currency risk is priced in international capital markets using an international version of the CAPM and data from the US, the UK, and Germany from February 1975 to January 2007. Taking its inspiration from Santis and Gérard (1998), I motivate the *Kehrle* approach which consists of two steps: First, I estimate covariances of asset returns using bivariate multivariate GARCH models of the BEKK type. These covariances can then be used to estimate directly the CAPM asset pricing restrictions. The results are that there is no evidence in the data which backs the hypothesis of currency risk premia in international asset prices. However, these conclusions could well be an artefact of the chosen model specification which leaves prices for currency risk constant over time. This also corroborates the findings of Santis and Gérard (1998) who find similar results. In a next step, time-varying prices of market and currency risk which reflect the state of the world could be modeled using instrumental variables in order to check the robustness of the results of the findings of Santis and Gérard (1998). Furthermore, the inclusion of inflation risk premia could be a fruitful area of further research as it is obviously priced in capital markets [see Vassalou (2000)].
As a concluding afterthought, some remarks on model specification are warranted. A question which is hardly addressed in applied multivariate GARCH literature is the problem of model selection. Mostly, a GARCH(1,1) process is assumed as it arguably fits the data quite well, or at least not worse than more elaborate models, i.e. these which include higher lag orders. However, the overall *ad hoc* approach to model selection obviously is a weak point of most GARCH applications. Brooks and Burke (2003) present modified information criteria which can be used for model selection, however, they have to admit that there obviously exists no panacea for this problem. Given the fact that including GARCH terms of higher order inevitably complicates the convergence of the multivariate GARCH as even more parameters would have to be estimated, applying a rigorous model selection process is a formidable task in itself, and with doubtful success concerning an improvement of the representation of the actual data. Therefore, pragmatic econometricians often refrain from undergoing this painstaking process as the gains from it are presumably low comparing its implementational costs.
Obviously, the standard *top-down* Box-Jenkins approach of starting with a very high order of lags and then deleting out lags sequentially is ruled out by the difficulties of estimating non-linear models with such a high number of parameters. To the contrary, a *bottom-up* approach is indicated, i.e. starting with a simple model and adding more terms only if the remaining standardized residuals still contain GARCH behaviour. Inevitably, this makes di-

agnostic checks of the chosen model even more important. Here, classic portmanteau tests of standardized residuals and squared standardized residuals like the Ljung-Box test I report are very often used as they are easy to implement and have an intuitive appeal [see Li (2004) for an overview]. Yet, these tools should be used with care: It is not clear under which conditions they can actually be used as diagnostic tests. Therefore, some authors [e.g. Lüthkepohl (2005), chapter 16] do not use them altogether and prefer ARCH-LM tests instead as they maintain their validity under more general conditions.

At the end of the day, it is a potential caveat of multivariate asset pricing models that they seem to be MUCH ADO ABOUT NOTHING.

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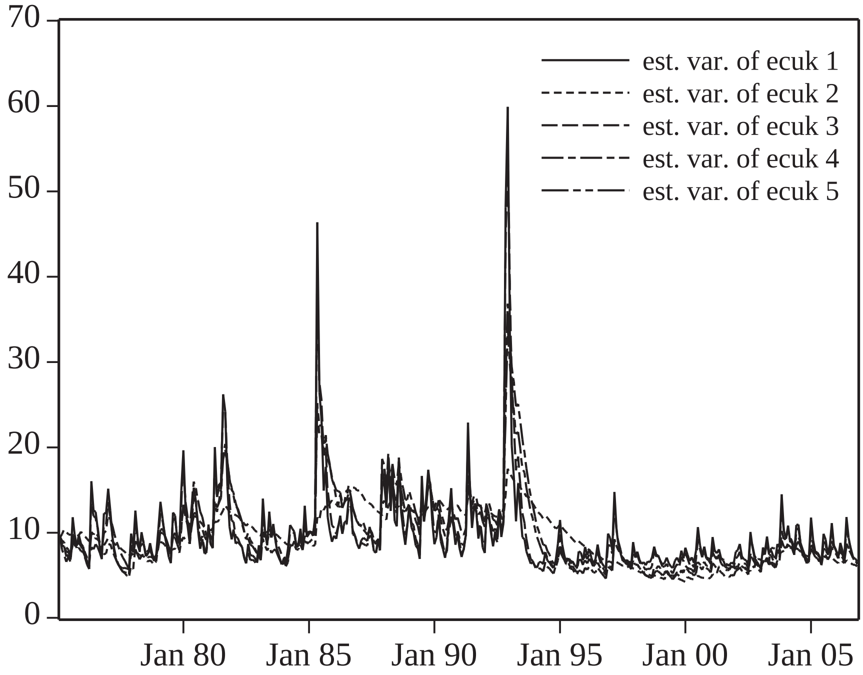
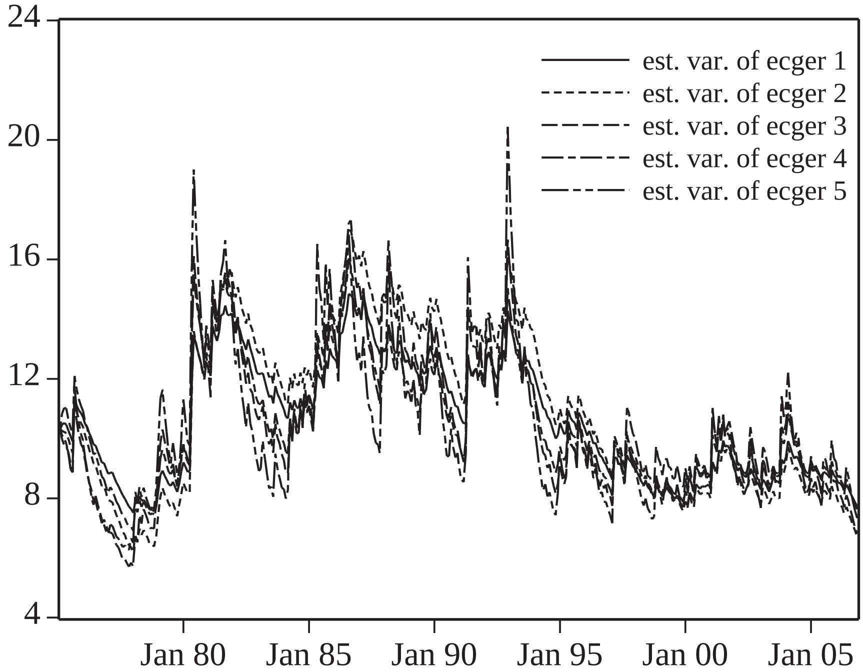
Figure 1: Estimated variances of euro£ returns



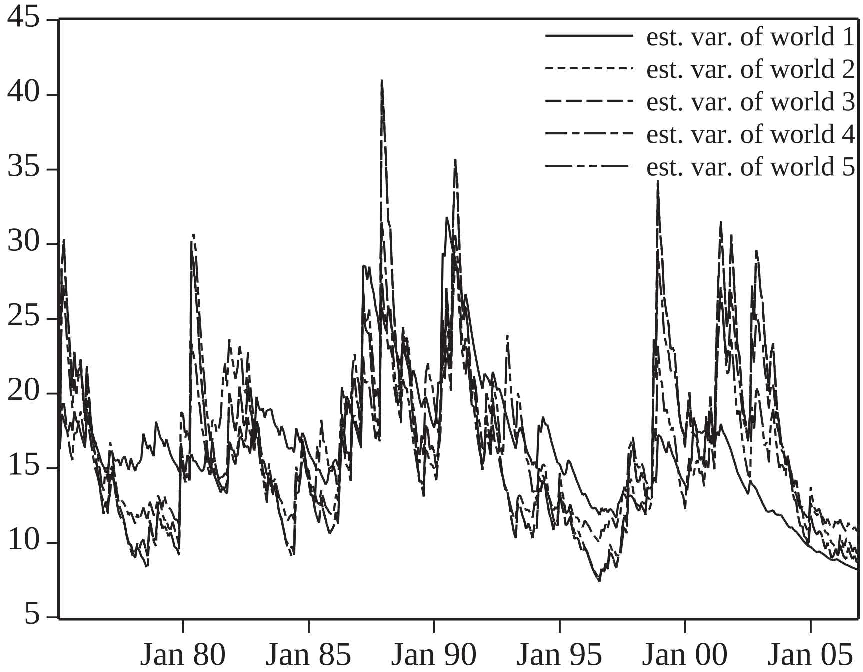
Graph depicts estimated variances of euro£ returns for the various bivariate BEKK models as specified in Equations (8) and (10). In all BEKKs, one of the series is the return on euro£, the other series are returns from:
Variance 1: world equity index
Variance 2: German equity index
Variance 3: UK equity index
Variance 4: US equity index
Variance 5: euroDM deposits
All returns are monthly excess log returns denominated in US-$. Excess returns are obtained by subtracting the euro$ deposit rate as a risk-free rate. Data range from February 1975 to January 2007 (384 observations).

Figure 2: Estimated variances of EuroDM returns



Graph depicts estimated variances of euroDM returns for the various bivariate BEKK models as specified in Equations (8) and (10). In all BEKKs, one of the series is the return on euroDM, the other series are returns from:
Variance 1: world equity index
Variance 2: German equity index
Variance 3: US equity index
Variance 4: UK equity index
Variance 5: euro£ deposits
All returns are monthly excess log returns denominated in US-$. Excess returns are obtained by subtracting the euro$ deposit rate as a risk-free rate. Data range from February 1975 to January 2007 (384 observations).

Figure 3: Estimated variances of world portfolio returns



Graph depicts estimated variances of world portfolio returns for the various bivariate BEKK models as specified in Equations (8) and (10). In all BEKKs, one of the series is the return on the world equity index, the other series are returns from:
Variance 1: German equity index
Variance 2: euroDM deposits
Variance 3: US equity index
Variance 4: UK equity index
Variance 5: euro£ deposits
All returns are monthly excess log returns denominated in US-$. Excess returns are obtained by subtracting the euro$ deposit rate as a risk-free rate. Data range from February 1975 to January 2007 (384 observations).

Figure 4: Estimated market and currency risk premia for German equity

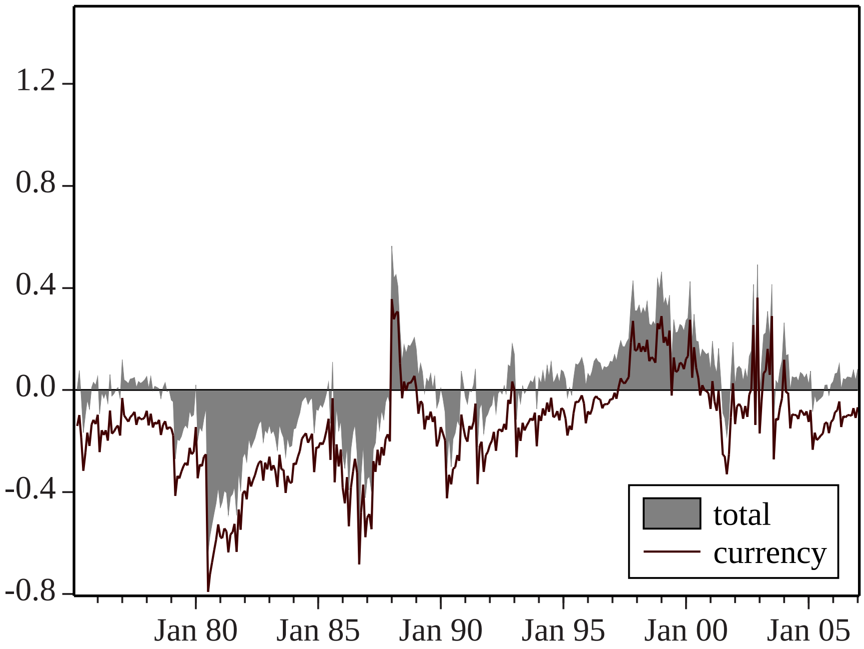


Figure depicts estimated total and currency risk premia for the German equity index as defined by Equations (15) and (16), respectively. Parameter values for the prices of market and currency risk are obtained from the ICAPM estimates reported in Table 16. Covariance series are obtained from respective BEKK estimations. Data range from March 1975 to January 2007 (383 observations).

Figure 5: Estimated market and currency risk premia for UK equity

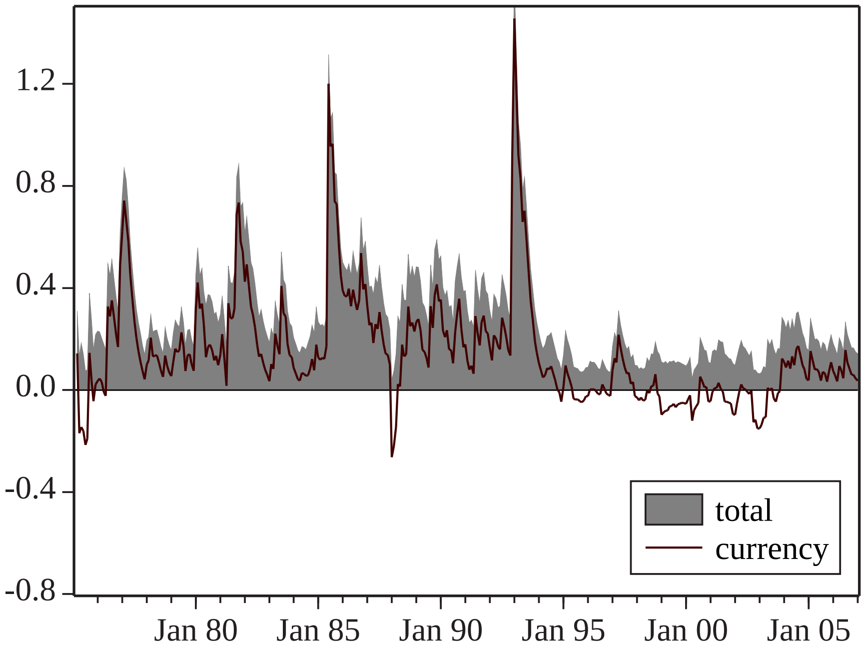


Figure depicts estimated total and currency risk premia for the UK equity index as defined by Equations (15) and (16), respectively. Parameter values for the prices of market and currency risk are obtained from the ICAPM estimates reported in Table 16. Covariance series are obtained from respective BEKK estimations. Data range from March 1975 to January 2007 (383 observations).

Figure 6: Estimated market and currency risk premia for US equity

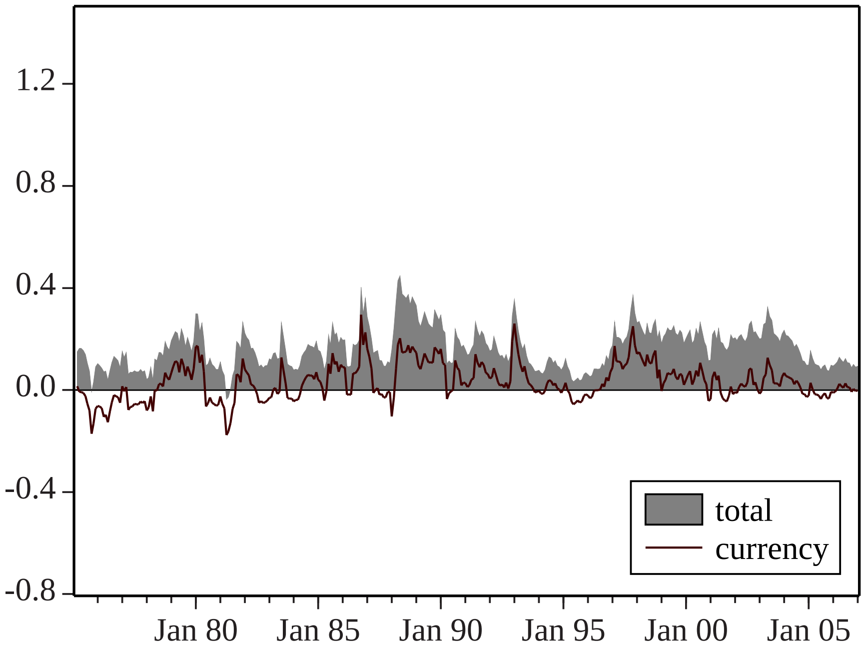


Figure depicts estimated total and currency risk premia for the US equity index as defined by Equations (15) and (16), respectively. Parameter values for the prices of market and currency risk are obtained from the ICAPM estimates reported in Table 16. Covariance series are obtained from respective BEKK estimations. Data range from March 1975 to January 2007 (383 observations).

Figure 7: Estimated market and currency risk premia for world equity

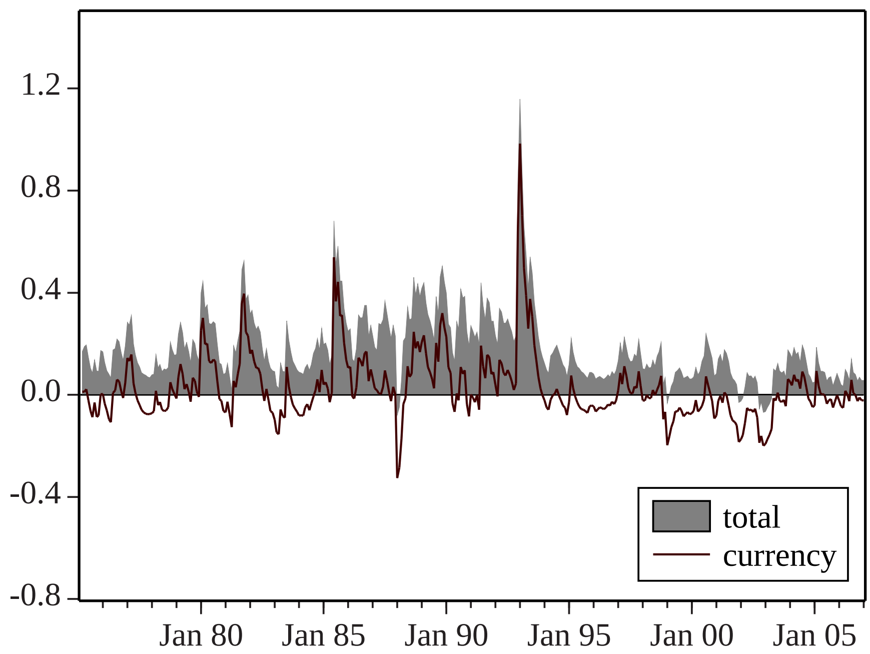


Figure depicts estimated total and currency risk premia for the world equity index as defined by Equations (15) and (16), respectively. Parameter values for the prices of market and currency risk are obtained from the ICAPM estimates reported in Table 16. Covariance series are obtained from respective BEKK estimations. Data range from March 1975 to January 2007 (383 observations).

Figure 8: Estimated market and currency risk premia for euroDM deposits

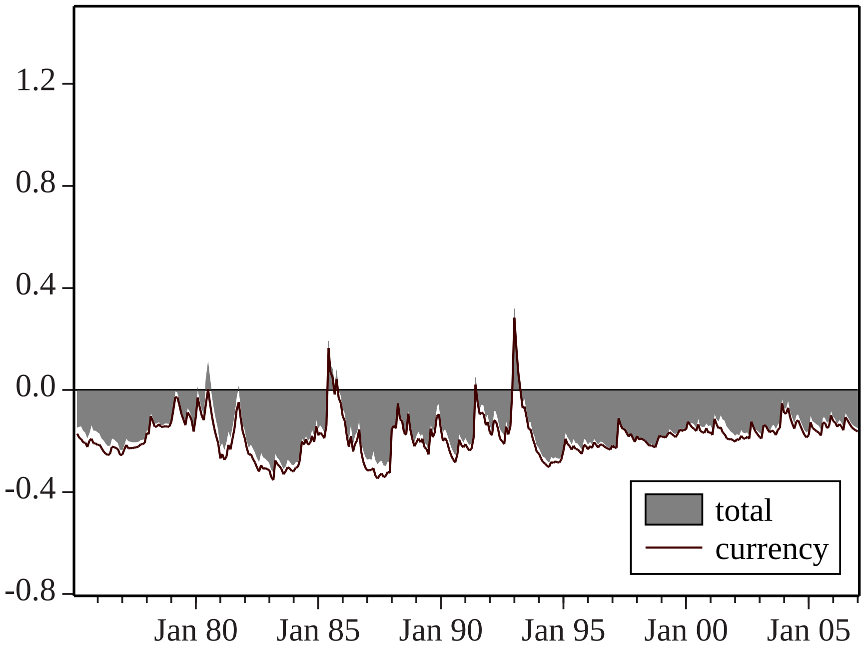


Figure depicts estimated total and currency risk premia for euroDM deposits as defined by Equations (15) and (16), respectively. Parameter values for the prices of market and currency risk are obtained from the ICAPM estimates reported in Table 16. Covariance series are obtained from respective BEKK estimations. Data range from March 1975 to January 2007 (383 observations).

Figure 9: Estimated market and currency risk premia for euro£ deposits

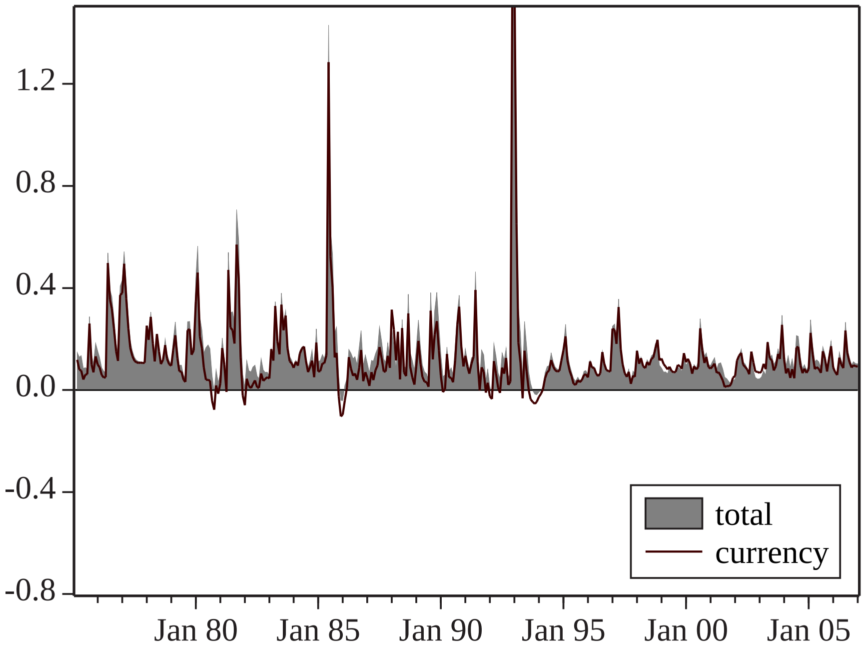


Figure depicts estimated total and currency risk premia for euro£ deposits as defined by Equations (15) and (16), respectively. Parameter values for the prices of market and currency risk are obtained from the ICAPM estimates reported in Table 16. Covariance series are obtained from respective BEKK estimations. Data range from March 1975 to January 2007 (383 observations).

Table 1: Descriptive statistics of excess returns

	Germany	*UK*	*US*	*EuroDM*	*Euro£*	*World*
mean	0.20	0.37	0.20	0.00	0.15	0.20
std.dev.	6.10	6.09	4.16	3.21	3.08	4.04
min.	-22.90	-25.94	-24.95	-10.84	-13.47	-17.53
max.	20.17	43.56	12.55	8.57	13.50	13.13
kurtosis†	4.44	10.46	6.26	3.26	4.76	4.39
J-B‡	44.43***	925.01***	202.83***	2.82	53.16***	42.53***

†kurtosis of the standard normal distribution is 3.

‡value of the Jarque-Bera test statistic, H_0 : series is standard normally distributed.

***denotes 1% significance level.

All returns are monthly excess log returns in percent, denominated in US-$. Excess returns are obtained by subtracting the euro$ deposit rate as a risk-free rate. Returns are calculated from time series of the German, UK, US, and world equity price index from MSCI and from euroDM and euro£ deposit returns from FT.

Data range from February 1975 to January 2007 (384 observations).

Table 2: Sample autocorrelations of r_{it}

Lag	*Germany*	*UK*	*US*	*EuroDM*	*Euro£*	*World*
1	0.00	0.05	0.03	0.03	0.09	0.07
2	0.02	-0.07	-0.03	0.10	0.03	-0.04
3	0.06	0.01	-0.01	0.03	-0.01	0.00
4	0.02	-0.01	-0.03	-0.03	0.01	-0.04
5	-0.01	-0.05	0.12	0.02	0.03	0.11
6	0.09	-0.03	-0.03	-0.03	-0.03	0.01
7	0.04	0.00	-0.01	0.08	-0.02	-0.04
8	0.04	0.00	0.03	0.04	0.04	0.06
9	-0.06	0.03	0.01	0.10	0.06	0.06
10	0.02	0.01	0.10	0.02	-0.05	0.10
11	0.07	0.04	-0.03	0.13	0.12	-0.02
12	-0.03	-0.04	0.00	0.01	0.00	0.01

Table reports autocorrelations up to lag 12 for monthly excess log returns in percent, denominated in US-$. Excess returns are obtained by subtracting the euro$ deposit rate as a risk-free rate. Returns are calculated from time series of the German, UK, US, and world equity price index from MSCI and from euroDM and euro£ deposit returns from FT.

Data range from February 1975 to January 2007 (384 observations).

Number of significant autocorrelations at 5% level: 0

Table 3: Sample autocorrelations of r_{it}^2

Lag	*Germany*	*UK*	*US*	*EuroDM*	*Euro£*	*World*
1	0.09	0.20**	0.10	0.04	0.21**	0.07
2	0.08	0.08**	0.03	0.02	0.04**	0.10
3	0.10*	0.06**	0.02	0.01	0.04**	-0.01
4	0.04*	0.02**	0.01	0.03	0.07**	-0.01
5	0.03	0.11**	0.02	0.03	0.06**	0.08
6	0.04	0.00**	0.02	0.04	0.07**	0.05
7	0.13*	0.04**	-0.03	0.03	-0.02**	0.02
8	0.02*	0.00**	-0.03	0.01	0.02**	-0.03
9	0.07*	0.02**	0.14	0.09	0.05**	0.09
10	0.05*	0.01**	0.04	0.08	0.02**	0.09
11	0.01*	0.01**	-0.01	0.01	0.00**	-0.01
12	0.04*	0.01*	0.02	0.01	-0.02*	0.00

Table reports autocorrelations up to lag 12 for squared monthly excess log returns in percent, denominated in US-$. Excess returns are obtained by subtracting the euro$ deposit rate as a risk-free rate. Returns are calculated from time series of the German, UK, US, and world equity price index from MSCI and from euroDM and euro£ deposit returns from FT.
Data range from February 1975 to January 2007 (384 observations).
* and ** denote statistical significance at the 5% and 1% levels, respectively.

Table 4: BEKK for estimating $\text{cov}_{t-1}(r_{gerpi}, r_w)$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.120	0.181	-0.664	0.507
μ_2	0.103	0.296	-0.348	0.728
ω_{11}	0.386**	0.154	2.516	0.012
ω_{12}	12.473**	6.113	2.040	0.041
ω_{22}	5.972***	2.124	2.812	0.005
a_{11}	0.231***	0.040	5.848	0.000
a_{12}	-0.082	0.105	-0.787	0.431
a_{21}	-0.111***	0.020	-5.661	0.000
a_{22}	0.240***	0.057	4.192	0.000
b_{11}	0.945***	0.017	54.191	0.000
b_{12}	0.195	0.385	0.507	0.612
b_{11}	0.786***	0.068	11.635	0.000
	ln(L)§ = -2174.985	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.109		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.219	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.203		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.667	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.603		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the German and world equity index for the estimation of their conditional covariance and the variance of the world portfolio as used for the ICAPM regressions reported in Tables 16–18. Standard errors are calculated from the inverse of the Hessian.
All returns are monthly excess log returns denominated in US-$. Excess returns are obtained by subtracting the euro$ deposit rate as a risk-free rate. Data range from February 1975 to January 2007 (384 observations).
§value of the log-likelihood at parameter values.
†*p-value* of the Ljung-Box statistic for autocorrelation in the standardized residuals up to lag 12.
‡*p-value* of the Ljung-Box statistic for autocorrelation in the squared standardized residuals up to lag 12.
*, **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: BEKK for estimating $\text{cov}_{t-1}(r_{ecger}, r_w)$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.237	0.190	-1.243	0.214
μ_2	0.003	0.162	-0.021	0.983
ω_{11}	0.740*	0.426	1.736	0.083
ω_{12}	0.136	0.251	0.542	0.588
ω_{22}	0.124	0.241	0.512	0.609
a_{11}	0.290***	0.051	5.682	0.000
a_{12}	0.018	0.030	0.586	0.558
a_{21}	0.016	0.057	0.280	0.780
a_{22}	0.145**	0.067	2.162	0.031
b_{11}	0.868***	0.039	22.228	0.000
b_{12}	0.866***	0.068	12.703	0.000
b_{11}	0.966***	0.037	26.107	0.000
	ln(L)§= -2051.148	$Q_{12}(z^2)^‡$ *for* h_{11}=0.552		
	$Q_{12}(z)^†$ *for* r_1=0.160	$Q_{12}(z^2)^‡$ *for* h_{12}=0.997		
	$Q_{12}(z)^†$ *for* r_2=0.091	$Q_{12}(z^2)^‡$ *for* h_{22}=0.969		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on euroDM deposits and the world equity index for the estimation of their conditional covariance and the variance of the euroDM deposits as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 6: BEKK for estimating $\text{cov}_{t-1}(r_{gerpi}, r_{ecger})$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.109	0.271	-0.401	0.688
μ_2	0.100	0.158	-0.628	0.530
ω_{11}	1.460	0.975	1.497	0.134
ω_{12}	0.448*	0.265	1.690	0.091
ω_{22}	0.001	0.088	0.010	0.992
a_{11}	0.338***	0.049	6.959	0.000
a_{12}	0.004	0.010	0.359	0.719
a_{21}	-0.137	0.088	-1.553	0.121
a_{22}	0.171***	0.036	4.736	0.000
b_{11}	0.864***	0.039	22.450	0.000
b_{12}	0.911***	0.021	42.879	0.000
b_{11}	0.971***	0.015	62.829	0.000
	ln(L)§= -2168.410	$Q_{12}(z^2)^‡$ *for* h_{11}=0.984		
	$Q_{12}(z)^†$ *for* r_1=0.551	$Q_{12}(z^2)^‡$ *for* h_{12}=0.000		
	$Q_{12}(z)^†$ *for* r_2=0.093	$Q_{12}(z^2)^‡$ *for* h_{22}=0.948		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the German equity index and euroDM deposits for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 7: BEKK for estimating $\text{cov}_{t-1}(r_{uspi}, r_w)$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.283	0.192	-1.470	0.142
μ_2	0.192	0.202	-0.950	0.342
ω_{11}	0.236	0.201	1.172	0.241
ω_{12}	0.442**	0.206	2.149	0.032
ω_{22}	1.055***	0.400	2.636	0.008
a_{11}	-0.065*	0.039	-1.689	0.091
a_{12}	0.177***	0.047	3.782	0.000
a_{21}	0.236***	0.052	4.510	0.000
a_{22}	0.004	0.059	0.065	0.948
b_{11}	0.948***	0.012	78.231	0.000
b_{12}	0.938***	0.012	81.379	0.000
b_{11}	0.907***	0.019	48.994	0.000
	$ln(L)^{\S}$= -1884.797	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.514		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.246	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.463		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.373	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.561		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the US and world equity index for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 8: BEKK for estimating $\text{cov}_{t-1}(r_{uspi}, r_{ecger})$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.232	0.183	-1.272	0.203
μ_2	0.021	0.161	-0.130	0.897
ω_{11}	0.227	0.221	1.028	0.304
ω_{12}	0.064	0.167	0.381	0.703
ω_{22}	0.271	0.287	0.946	0.344
a_{11}	0.305***	0.040	7.671	0.000
a_{12}	-0.018	0.031	-0.578	0.563
a_{21}	-0.039	0.053	-0.737	0.461
a_{22}	0.218***	0.053	4.148	0.000
b_{11}	0.897***	0.021	42.139	0.000
b_{12}	0.828***	0.074	11.223	0.000
b_{11}	0.926***	0.039	24.084	0.000
	$ln(L)^{\S}$= -2065.352	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.800		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.452	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=1.000		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.129	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.982		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the US equity index and euroDM deposits for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 9: BEKK for estimating $\text{cov}_{t-1}(r_{ukpi}, r_{ecger})$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.354	0.257	-1.374	0.169
μ_2	-0.011	0.160	0.070	0.944
ω_{11}	0.468	0.293	1.596	0.110
ω_{12}	0.511	0.551	0.927	0.354
ω_{22}	0.282	0.353	0.798	0.425
a_{11}	0.192***	0.063	3.031	0.002
a_{12}	0.010	0.020	0.525	0.600
a_{21}	0.096	0.113	0.853	0.393
a_{22}	0.178***	0.065	2.757	0.006
b_{11}	0.933***	0.023	39.834	0.000
b_{12}	0.789***	0.120	6.596	0.000
b_{11}	0.939***	0.049	19.111	0.000
	$ln(L)^{\S}$= -2189.057	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.906		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.982	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.090		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.112	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.984		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the UK equity index and euroDM deposits for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 10: BEKK for estimating $\text{cov}_{t-1}(r_{ukpi}, r_w)$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.233	0.192	-1.215	0.225
μ_2	0.288	0.231	-1.248	0.212
ω_{11}	1.132*	0.655	1.728	0.084
ω_{12}	0.830*	0.444	1.869	0.062
ω_{22}	0.373*	0.216	1.726	0.084
a_{11}	0.272***	0.055	4.950	0.000
a_{12}	-0.003	0.046	-0.075	0.940
a_{21}	-0.033	0.027	-1.240	0.215
a_{22}	0.174***	0.042	4.124	0.000
b_{11}	0.869***	0.046	18.882	0.000
b_{12}	0.906***	0.025	35.599	0.000
b_{11}	0.951***	0.017	57.741	0.000
	$ln(L)^{\S}$= -2103.256	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.511		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.157	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.752		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.988	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.853		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the UK and world equity index for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 11: BEKK for estimating $\text{cov}_{t-1}(r_w, r_{ecuk})$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.257	0.187	-1.378	0.168
μ_2	0.210	0.141	-1.493	0.135
ω_{11}	0.727*	0.395	1.839	0.066
ω_{12}	-0.072	0.279	-0.258	0.797
ω_{22}	2.756**	1.096	2.515	0.012
a_{11}	0.238***	0.047	5.062	0.000
a_{12}	0.004	0.039	0.114	0.909
a_{21}	0.135***	0.046	2.954	0.003
a_{22}	0.460***	0.077	5.989	0.000
b_{11}	0.875***	0.034	25.588	0.000
b_{12}	0.743***	0.073	10.127	0.000
b_{11}	0.511***	0.140	3.655	0.000
	$ln(L)^{\S}$ = -2020.214	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.559		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.248	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.995		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.591	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.925		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the world equity index and euro£ deposits for the estimation of their conditional covariance and the variance of the euro£ deposits as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 12: BEKK for estimating $\text{cov}_{t-1}(r_{gerpi}, r_{ecuk})$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.146	0.267	-0.548	0.584
μ_2	0.115	0.148	-0.776	0.438
ω_{11}	1.737*	0.960	1.809	0.071
ω_{12}	5.272***	1.994	2.644	0.008
ω_{22}	-0.011	0.103	-0.104	0.917
a_{11}	0.350***	0.050	6.988	0.000
a_{12}	0.053***	0.013	4.037	0.000
a_{21}	-0.039	0.093	-0.423	0.672
a_{22}	0.112***	0.037	3.017	0.003
b_{11}	0.840***	0.037	22.736	0.000
b_{12}	-0.383	0.348	-1.101	0.271
b_{11}	0.971***	0.016	59.238	0.000
	$ln(L)^{\S}$ = -2174.458	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.992		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.708	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.127		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.677	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.813		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the German equity index and euro£ deposits for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 13: BEKK for estimating $\text{cov}_{t-1}(r_{ukpi}, r_{ecuk})$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.326	0.245	-1.329	0.184
μ_2	0.194	0.137	-1.413	0.158
ω_{11}	0.632*	0.337	1.876	0.061
ω_{12}	0.239	0.366	0.653	0.514
ω_{22}	1.540**	0.642	2.400	0.016
a_{11}	0.191***	0.048	3.965	0.000
a_{12}	-0.013	0.022	-0.592	0.554
a_{21}	0.199***	0.069	2.864	0.004
a_{22}	0.424***	0.066	6.481	0.000
b_{11}	0.908***	0.025	36.374	0.000
b_{12}	0.800***	0.055	14.619	0.000
b_{11}	0.672***	0.088	7.606	0.000
	$ln(L)^{\S}$= -2130.493	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.881		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.992	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.010		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.572	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.974		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the UK equity index and euro£ deposits for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 14: BEKK for estimating $\text{cov}_{t-1}(r_{uspi}, r_{ecuk})$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.237	0.185	-1.281	0.200
μ_2	0.160	0.143	-1.125	0.261
ω_{11}	0.236	0.235	1.004	0.315
ω_{12}	-0.074	0.206	-0.356	0.722
ω_{22}	0.300	0.621	0.484	0.629
a_{11}	0.291***	0.042	6.905	0.000
a_{12}	-0.023	0.031	-0.751	0.453
a_{21}	0.060	0.047	1.269	0.205
a_{22}	0.294**	0.116	2.530	0.011
b_{11}	0.902***	0.021	42.779	0.000
b_{12}	0.693***	0.200	3.467	0.001
b_{11}	0.883***	0.127	6.975	0.000
	$ln(L)^{\S}$= -2041.598	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.798		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.451	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.551		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.649	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.968		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on the US equity index and euro£ deposits for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 15: BEKK for estimating $\text{cov}_{t-1}(r_{ecger}, r_{ecuk})$

parameters	*estimates*	*s.e.*	*est./s.e.*	*p-value*
μ_1	0.021	0.147	-0.140	0.889
μ_2	0.182	0.140	-1.299	0.194
ω_{11}	0.776*	0.425	1.828	0.068
ω_{12}	0.494	0.303	1.631	0.103
ω_{22}	0.407	0.281	1.448	0.148
a_{11}	0.211***	0.080	2.641	0.008
a_{12}	0.083	0.052	1.594	0.111
a_{21}	0.063	0.077	0.812	0.417
a_{22}	0.239***	0.070	3.432	0.001
b_{11}	0.859***	0.052	16.495	0.000
b_{12}	0.823***	0.053	15.679	0.000
b_{11}	0.865***	0.047	18.282	0.000
	$ln(L)^{\S}$= -1834.310	$Q_{12}(z^2)^{\ddagger}$ *for* h_{11}=0.974		
	$Q_{12}(z)^{\dagger}$ *for* r_1=0.119	$Q_{12}(z^2)^{\ddagger}$ *for* h_{12}=0.985		
	$Q_{12}(z)^{\dagger}$ *for* r_2=0.615	$Q_{12}(z^2)^{\ddagger}$ *for* h_{22}=0.970		

Table reports estimation results from bivariate BEKK as specified in Equations (8) and (10) using returns on euroDM and euro£ deposits for the estimation of their conditional covariance as used for the ICAPM regressions reported in Tables 16–18.
For a detailed description of the reported statistics see caption of Table 4.

Table 16: Estimation results of ICAPM with constant prices of risk

parameters	*estimates*	*s.e.*†	*t-stat.*	*p-value*
δ_m	0.010	0.009	1.116	0.264
δ_{ger}	-0.045	0.030	-1.481	0.139
δ_{uk}	0.044	0.028	1.545	0.122

$\bar{R}^2$=0.001 R^2=0.002 obs=6×383=2298

Robust Wald coefficient tests:

H_0: No currency risk priced,
i.e. $\delta_{ger} = \delta_{uk} = 0 \Rightarrow \chi^2(2)$ =2.503, *p-value*: 0.286
H_0: No risk priced at all,
i.e. $\delta_m = \delta_{ger} = \delta_{uk} = 0 \Rightarrow \chi^2(3) = 4.932$, *p-value*: 0.177

Table presents OLS estimates of the ICAPM with constant prices of market risk δ_m and constant prices of currency risk δ_{ger} and δ_{uk} as specified in Equation (13). 6 asset pricing restrictions are considered (3 restrictions for the German, UK, and US equity price index; 2 for the euroDM and euro£ deposits and 1 for the world portfolio.) These restrictions are stacked in order to impose the equality of coefficients during the OLS estimation. Data range from March 1975 to January 2007 (383 observations per asset).
†Standard errors are calculated using the Newey-West covariance-matrix estimator.

Table 17: Estimation results of ICAPM with constant prices of risk and fixed effects

parameters	*estimates*	*s.e.*†	*t-stat.*	*p-value*
α_0	0.993*	0.524	1.894	0.058
α_1	-0.436	0.435	-1.004	0.316
α_2	-0.673	0.507	-1.326	0.185
α_3	-0.181	0.577	-0.314	0.754
α_4	-0.602	0.537	-1.122	0.262
α_5	-0.444	0.439	-1.011	0.312
δ_m	-0.016	0.025	-0.664	0.507
δ_{ger}	-0.109**	0.054	-2.022	0.043
δ_{uk}	0.055*	0.032	1.717	0.086

$\bar{R}^2$=0.000 R^2=0.004 obs=6×383=2298

Robust Wald coefficient tests:

H_0: No market segmentation,
i.e. $\alpha_i = 0 \quad \forall \quad i \Rightarrow \chi^2(6)$ =4.954, *p-value*: 0.550
H_0: No currency risk priced,
i.e. $\delta_{ger} = \delta_{uk} = 0 \Rightarrow \chi^2(2)$ =4.544, *p-value*: 0.103
H_0: No risk priced at all,
i.e. $\delta_m = \delta_{ger} = \delta_{uk} = 0 \Rightarrow \chi^2(3) = 5.238$, *p-value*: 0.155

Table presents OLS estimates of the ICAPM with constant prices of market risk δ_m and constant prices of currency risk δ_{ger} and δ_{uk} as specified in Equation (13) plus an asset-specific "fixed effect" reflecting mild market segmentation. 6 asset pricing restrictions are considered (3 restrictions for the German, UK, and US equity price index; 2 for the euroDM and euro£ deposits and 1 for the world portfolio.) These restrictions are stacked in order to impose the equality of coefficients during the OLS estimation. α_0 is a constant and the base category (German equity index) for the five dummy variables. α_1 to α_5 measure the impact of the dummy variables. Data range from March 1975 to January 2007 (383 observations per asset).
†Standard errors are calculated using the Newey-West covariance-matrix estimator.
* and ** denote statistical significance at the 10% and 5% levels, respectively.

Table 18: Estimation results of ICAPM with constant prices of risk and fixed effects and market variance

parameters	*estimates*	*std. errors*†	*t-stat.*	*p-value*
α_0	0.971*	0.568	1.710	0.087
α_1	-0.430	0.439	-0.978	0.328
α_2	-0.656	0.529	-1.239	0.215
α_3	-0.162	0.601	-0.270	0.787
α_4	-0.581	0.572	-1.015	0.310
α_5	-0.420	0.499	-0.843	0.399
δ_m	-0.018	0.029	-0.610	0.542
δ_{ger}	-0.109**	0.054	-2.027	0.043
δ_{uk}	0.054*	0.033	1.665	0.096
δ_{var}	0.001	0.015	0.083	0.934
$\bar{R}^2$=0.000	R^2=0.004	obs=6×383=2298		

Robust Wald coefficient tests:

H_0: No market segmentation,
i.e. $\alpha_i = 0 \quad \forall \quad i \quad \wedge \quad \delta_{var} = 0 \quad \Rightarrow \chi^2(7)$ =4.956, *p-value*: 0.665
H_0: No currency risk priced,
i.e. $\delta_{ger} = \delta_{uk} = 0 \Rightarrow \chi^2(2)$ =4.539, *p-value*: 0.103
H_0: No risk priced at all,
i.e. $\delta_m = \delta_{ger} = \delta_{uk} = 0 \Rightarrow \chi^2(3) = 5.137$, *p-value*: 0.162

Table presents OLS estimates of the ICAPM with constant prices of market risk δ_m and constant prices of currency risk δ_{ger} and δ_{uk} as specified in Equation (14), i.e. including an asset-specific "fixed effect" as well as the variance of the respective asset (δ_{var}) as factors representing market segmentation. 6 asset pricing restrictions are considered (3 restrictions for the German, UK, and US equity price index; 2 for the euroDM and euro£ deposits and 1 for the world portfolio.) These restrictions are stacked in order to impose the equality of coefficients during the OLS estimation. α_0 is a constant and the base category (German equity index) for the five dummy variables. α_1 to α_5 measure the impact of the dummy variables. Data range from March 1975 to January 2007 (383 observations per asset).
†Standard errors are calculated using the Newey-West covariance-matrix estimator.
* and ** denote statistical significance at the 10% and 5% levels, respectively.