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TIME-VARYING RISK PREMIUMS AND CONDITIONAL MARKET RISK: EMPIRICAL EVIDENCE FROM EUROPEAN STOCK MARKETS

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ABSTRACT

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This study investigates the relationship between the time-varying risk premiums and conditional market risk in the stock markets of the ten member countries of Economy and Monetary Union. Second, it examines whether the conditional second moments change over time and are there asymmetric effects in the conditional covariance matrix. Third, it analyzes the possible effects of the chosen testing framework.

Empirical analysis is conducted using asymmetric univariate and multivariate GARCH-in-mean models and assuming three different degrees of market integration. For a daily sample period from 1999 to 2007, the study shows that the time-varying market risk alone is not enough to explain the dynamics of risk premiums and indications are found that the market risk is detected only when its price is allowed to change over time. Also asymmetric effects in the conditional covariance matrix, which is found to be time-varying, are clearly present and should be recognized in empirical asset pricing analyses.

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Tutkimus selvittää ajassa muuttuvien riskipreemioiden suhdetta ehdolliseen markkinariskiin kymmenen Euroopan talous- ja rahaliiton jäsenmaan osakemarkkinoilla. Lisäksi tutkitaan ovatko ehdolliset varianssit ja kovarianssit ajassa muuttuvia sekä löytyykö ehdollisesta kovarianssimatriisista epäsymmetrisiä varianssi- ja kovarianssiefektejä. Kolmantena tutkimuksen kohteena ovat valitun testausmenetelmän vaikutukset tuloksiin.

Empiirinen analyysi toteutettiin epäsymmetrisillä yhden ja usean muuttujan GARCH-M-malleilla olettaen kolme mahdollista rahoitusmarkkinoiden integraatiotasoa. Empiiriset tulokset päivittäisellä otoksella aikaväliltä 1999–2007 osoittavat, että ajassa muuttuva markkinariski ei itsessään ole riittävä selittämään riskipreemioiden dynamiikkaa. Löytyy myös viitteitä siitä, että markkinariskin havaitsemiseksi sen hinnan tulee antaa muuttua ajassa. Lisäksi tulokset osoittavat, että ehdollinen kovarianssimatriisi on ajassa muuttuva ja matriisista löytyy epäsymmetrisiä efektejä, jotka tulisi huomioida empiirisissä hinnoittelumallien analyyseissä.

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1. INTRODUCTION

1.1 Background

The expected risk premiums and conditional second moments have a key role in various financial theories and applications. Variance or standard deviation is generally used as a measure of risk and uncertainty for individual assets and covariance as a measure of comovements. Increasing amount of evidence supports time variations in expected risk premiums and conditional covariance matrices. Most importantly, many models assume a relationship between these components. Accurate estimates of time-varying covariances and risk premiums are seen as essential part for asset pricing and portfolio selection. From risk management's point of view, estimates have great importance for example in value at risk (VaR) calculations and for hedging purposes

From a theoretical perspective the relationship between stock excess returns and their conditional covariances with one or more pricing factors is in interest due the time-varying risk premiums. Uncertainty in stock returns varies over time, indicating that the expected risk premiums should also be varying. On the other hand, assumption about the prevailing degree of market integration is likely to impact this relationship. Treating market as a segmented, integrated or partially segmented can effect results considerably. To analyze risk-return relationship consistently it would be desirable that no large changes in degrees of market integration would occur during the test period. Also the need for the asset pricing model that could serve as a benchmark model is highlighted. Moreover, because the comovements of assets have potentially so great role for risk-return relations the model that can efficiently model covariances becomes essential. Models that are capable of modelling time-varying conditional second moments may be well suited for these purposes. Another interesting feature is that the existence of the leverage effects in the stock returns variance is generally accepted, but asymmetric effects in the time-varying covariance have gained considerably less attention. Allowing asymmetric effects in the time-varying comovements could enable the most robust analyses of risk-return relations and these asymmetries may have their own effects on the nature of the obtained results.

A number of papers have studied relationship between stock returns and their conditional covariance risk with the market assuming different degrees of market integration. Studies can be broadly divided into those concentrating on the time-varying risk-return relationship (e.g., French *et al.* 1987; Baillie and DeGennaro 1990; Nelson 1991; Glosten *et al.* 1993; Theodossiou and Lee 1995; De Santis and Imrohoroglu 1997; Balaban *et al.* 2001; Balaban and Bayar 2005) and those analyzing conditional asset pricing models (e.g., Bollerslev *et al.* 1988; Schwert and Seguin 1990; Ng 1991; Bodurtha and Mark 1991; Harvey 1991,1995; De Santis and Gérard 1997). Studies assuming segmented markets do not reach consensus about the nature of the conditional risk-return relationship whereas studies that assume some degree of integration are slightly more supportive for the relations existence. Asymmetric effects in the conditional covariance are studied and documented (e.g., Kroner and Ng 1998; Bekaert and Wu 2002) but asymmetric effects in the conditional covariance matrix are mainly considered or allowed in hedging or international market linkage contexts (e.g., Brooks *et al*. 2002; Cifarelli and Paladino 2005).

The number of studies analysing risk-return relationship among multiple markets and consistently reporting results from different degrees of assumed market integration is limited. Further, studies that in the international setting allow additionally asymmetric effects in the conditional covariance matrix are even more limited. After the launch of the Economy and Monetary Union’s (EMU) third stage in the beginning of the year 1999, countries that joined this stage offer well suited environment to consistently analyze these issues among multiple stock markets. Furthermore, according to author’s knowledge there is no publicized research combining these features and concentrating on the EMU member countries’ stock markets.

1.2 Objectives and methodology

The purpose of this thesis is to analyze a relationship between stock excess returns and conditional market risk in the EMU countries when different degrees of market integration are assumed. This is done to solve whether there exists time-varying risk premiums, in the sense of the increased expected rate of excess return required in response to an increase in the conditional covariance risk with the market. The asymmetric effects in the conditional second moments and the theoretical aspects of the testing framework are also analyzed. When markets are assumed to be completely segmented, the conditional first and second moments are modelled using asymmetric univariate Generalized Autoregressive Conditional Heteroskedasticity in mean (GARCH-M) model. For the rest of the analyses conditional moments are modelled with the asymmetric multivariate GARCH-in-mean (MGARCH-M) models. The research questions of this study are as follows:

Q1 What kind of relationship exists between the anticipated market risk and the expected risk premiums in the European stock markets? More precisely, is the conditional market risk itself able to explain the time-variations in risk premiums?

Q2 Are there asymmetric effects in the conditional covariance matrix and should these asymmetries be recognised when analyzing the conditional risk-return relationship?

Q3 Are conditional covariance matrices time-varying and is the conditional risk-return relationship affected when time-varying covariances are modelled differently between the MGARCH specifications?

Q4 How the different methodological choices can affect the testing framework when empirical analyses are conducted using GARCH models?

The question number one is first analyzed assuming full market segmentation. Second, assumption about full segmentation is relaxed and results are analyzed assuming different degrees of integration. The second and third questions can be seen as support questions for the first one in the sense that allowing asymmetric effects in the conditional second moments and recognising the possible effects of chosen statistical model can allow the most efficient testing of the first question. The fourth question rises from the need to understand the different aspects of the testing framework derived for the first question and it is answered throughout the model building.

1.3 Limitations

Although, the theoretical relationship concerning conditional risk and return is derived from the conditional version of the Capital Asset Pricing Model (CAPM), this study concentrates to analyze the nature of the relationship itself and not to test the original model's validity. Moreover, Roll (1977) points out that every test of the CAPM model that is performed with any other portfolio than the true market portfolio is really a test about the efficiency of the chosen proxy portfolio. The exact composition of the true market portfolio is unobservable and so all effort of this study is concentrated to investigate the risk-return relationship, which seems to be largely accepted to exist in both theory and practise.

Estimation procedures for MGARCH-M models are fairly demanding and set limits for the minimum amount of usable observations in data set. Since this research focuses on countries that joined the EMU's third stage at 1 January 1999 from there onwards, analyses cannot be conducted using monthly return interval data. As Baillie and DeGennaro (1990) mention there might be some advantages in using monthly data. Further, the sample period is rather short and limited to recent years so results may not be directly comparable to those studies using older monthly or weekly data.

However, all models in this study assume that the degree of integration stays unchanged through the estimation period, assumption that is not likely to be supported if much longer sample would be used, so limiting analysis to recent events is seen satisfactory. Luxemburg is omitted from the analyses because the Morgan Stanley Capital International (MSCI) calculated index is not available for the whole sample period and all data observations under study are wanted to keep consistently computed.

This study will also consider the case where the price of global market risk is allowed to be time-varying and markets are assumed to be fully integrated. This is done in order to demonstrate the possibility that the dynamics of risk premiums cannot be explained by the conditional risk alone and instead two time-varying components are needed. However, the relative importance of these components or the relative importance of asymmetric effects is not quantified. Further, these same issues could be of course additionally analyzed assuming fully segmented or partially segmented markets. Even though these issues are probably worth examining they are not covered within the limits of this study. Finally, this study does not cover the aspects of EMU as an organization and its member countries specific features. This is done because numerous sources provide information about these issues and the concentration was chosen to be directed onto main interests.

1.4 Structure

The rest of this thesis is organized as follows. Section 2 presents first the theoretical background of time-varying risk premiums. Second, the main elements of the GARCH models are treated especially from the financial markets perspective. Third, empirical models and hypothesis are developed. Fourth, previous studies and related aspects are discussed. Section 3 contains data description, properties of the sample distribution and its implications for the model building. Section 4 presents the empirical results. Finally, in section 5, the work is summarized.

2. THEORETICAL FRAMEWORK

2.1 Time-varying risk premiums

A. Risk premiums

The expected risk premium can be defined as the expected return on an asset minus the risk-free rate. It is the compensation required by risk averse economic agents for holding risky assets. Financial models like standard form CAPM of Sharpe (1964) and Lintner (1965) and other equilibrium models usually suggests that expected compensation should be positively related to the expected risk. More precisely, as Bollerslev *et al.* (1988) mention the CAPM model suggests that premium to induce economic agents to bear risk is proportional to the nondiversifiable risk measured by the covariance of the asset return with the market portfolio return. According to Engle *et al.* (1987) the uncertainty in asset returns varies over time. This suggests that covariances between asset returns are varying and so must also the risk premium vary. Engle *et al.* (1987) further argue that time series models of asset prices should therefore measure both risk and its movements over time and include it as a determinant of price.

The importance of accurate estimates of expected risk premiums reaches widely the financial field. Many applications and theories treat risk premiums as the basic fundamental ingredients. As we know, no theory can describe the real world exactly, making the need for useful benchmarks models important. Bodurtha and Mark (1991) argue that the CAPM might serve as such benchmark model for the relative asset returns. It offers simple and wide basic theory for risk and return, which is further quite easily extendable. Well known problems in the testing procedures cause that our tests of the CAPM model are really tests whether chosen market proxy is efficient or not. Further, because the original CAPM theory is derived in the static framework it will hold in an intertemporal environment only under restrictive assumptions. As Bodurtha and Mark (1991) mention, one such possible assumption is that investors have logarithmic utility functions. However, despite these problems the model can be used to gain essential information about the risk-return relationship that seems to be widely accepted to exist. Although nowadays many specifications have shown that in addition to the market risk the equilibrium expected returns may depend upon other sources of risk, Merton (1980) argues that for most common stocks the nondiversifiable market risk should remain as the dominant factor.

The level of market integration effects assumptions behind asset pricing models. At least two approaches can be used to define what is meant by the level of market integration. First, in the legal sense, following Vaihekoski (2007) markets can be interpreted to be integrated if there are no restrictions on capital movements. Meaning that domestic investors are free to invest internationally and foreign investors can freely invest in to local markets. On the other hand, if the risk is used as a measure, following Bekaert and Harvey (1995) markets can be seen as completely integrated if assets with the same risk, which refers to some common world or regional factor, have identical expected returns across markets. Vice versa, a segmented market's covariance with a common factor may have little or nothing to do when segmented markets expected returns are explained. Empirical results reported by Dumas and Solnik (1995) indicate that global equity and foreign exchange markets seem to be integrated. However, Bekaert and Harvey (1995) report time-varying integration for many emerging stock markets with the world stock markets. They also find some evidence that for the emerging markets the global market integration has even decreased over time. On the other hand, Alford and Folks (1996) report that for more developed countries the degree of integration has increased over time.

B. International conditional asset pricing

This study is interested about the expected risk premiums and not realized so the chosen estimation method should be forward looking. To illustrate ways for estimating risk premiums we select the international conditional CAPM and discuss related issues following Bekaert and Harvey (1995) and Vaihekoski (2007). First we assume that markets are completely integrated, the absence of exchange risk and that a risk-free asset exists. Now, let $R_{i,t}^{A}$ be the return on asset *A* in country *i* and $R_{w,t}$ the return on the global value-weighted market portfolio, measured as the nominal return on the local currency from time *t*-1 to *t*. Now, let $r_{i,t}^{A}$ and $r_{w,t}$ be their return in excess of the local risk-free asset, respectively. Further, let symbol Ω_{t-1} represent the information publicly available to agents at time *t*-1. The conditional version of the world CAPM in nominal excess return form can now be presented as

$$(1) \qquad E\left[r_{i,t}^{A}\middle|\Omega_{t-1}\right]=\beta_{i,t}^{A}E\left[r_{w,t}\middle|\Omega_{t-1}\right]$$

where

$$(2) \qquad \beta_{i,t}^{A}=\frac{Cov\left(R_{i,t}^{A},R_{w,t}\middle|\Omega_{t-1}\right)}{Var\left(R_{w,t}\middle|\Omega_{t-1}\right)}=\frac{Cov\left(r_{i,t}^{A},r_{w,t}\middle|\Omega_{t-1}\right)}{Var\left(r_{w,t}\middle|\Omega_{t-1}\right)}$$

and $\beta_{i,t}^{A}$ is the conditional beta for asset *A* in country *i*, $E[r_{w,t}|\Omega_{t-1}]$ and $E[r_{i,t}^{A}|\Omega_{t-1}]$ are the conditional expected excess returns on the global market portfolio and asset *A* in country *i* at time *t*, respectively. Similar, $Cov(r_{i,t}^{A},r_{w,t}|\Omega_{t-1})$ and $Var(r_{w,t}|\Omega_{t-1})$ are the conditional covariance between asset *A* in country *i* and the global market portfolio and the conditional variance of global market portfolio at time *t*. As Bodurtha and Mark (1991) mention the second equality in equation (2) follows because the nominal risk-free rate is included in Ω_{t-1}. Combining and modifying equations (1) and (2) further by replacing ratio $E[r_{w,t}|\Omega_{t-1}]Var(r_{w,t}|\Omega_{t-1})^{-1}$ by variable λ_{t-1} the equation for the nominal excess returns can now be presented in a following form

(3) $$E\left[r_{i,t}^{A}\middle|\Omega_{t-1}\right]=\lambda_{t-1}Cov\left(r_{i,t}^{A},r_{w,t}\middle|\Omega_{t-1}\right)$$

where λ_{t-1} can be interpreted as the conditionally expected world price of covariance risk. From the equation (3), it follows that for the global market portfolio the equilibrium pricing relation becomes as

(4) $$E\left[r_{w,t}\middle|\Omega_{t-1}\right]=\lambda_{t-1}Var\left(r_{w,t}\middle|\Omega_{t-1}\right)$$

It follows that the expected excess return on the market is proportional to λ_{t-1}, which measures the compensation representative agent must receive for unit increase in the variance of the market return. According to De Santis and Gérard (1997), because equations (3) and (4) both have to hold, λ_{t-1} can also be referred as the price of global market risk.

If markets are completely segmented and same kind of assumptions as before are made, the equation (3) becomes as

(5) $$E\left[r_{i,t}^{A}\middle|\Omega_{t-1}\right]=\lambda_{i,t-1}Cov\left(r_{i,t}^{A},r_{i,t}\middle|\Omega_{t-1}\right)$$

where $r_{i,t}$ is the excess return on the market portfolio in country *i* and $\lambda_{i,t-1}$ is the conditional price of local market risk. As can be seen, security *A* is now priced with respect to the local market portfolio in country *i*. Again, if the equation (5) is aggregated at the national level it becomes as

(6) $$E\left[r_{i,t}\middle|\Omega_{t-1}\right]=\lambda_{i,t-1}Var\left(r_{i,t}\middle|\Omega_{t-1}\right)$$

Under certain conditions and if representative investor with a constant relative risk aversion (CRRA) utility function is assumed, Merton (1980) argues that the price of market risk in equation (6) would be a constant $\lambda_{i,t-1} = \lambda_i$ and a measure of the representative investor's relative risk aversion. Although, we assume that the price of market risk is constant with most of our empirical models, the case were it is allowed to be time-varying is also considered. Usually in empirical studies, if the non-negativity restriction for the λ_{t-1} is incorporated, this is done by approximating the price of market risk with the exponential function $\lambda_{t-1} = \exp(\kappa' z_{t-1})$ where z_{t-1} is instrument set and κ is a vector of coefficients.

As Bekaert and Harvey (1995) mention, equations from (1) to (6) assumes either complete integration or segmentation. However, if the market is partially (mildly) segmented the local market risk should also be included in the pricing equation as an additional source of risk that matters. Further, this means that the conditional world CAPM is no longer enough. To handle this kind of situation, Errunza and Losq (1985) proposed a two-factor model for partially segmented markets. Under certain conditions the conditional two-factor model for partially segmented markets aggregated at the national level can be presented as

$$(7) \qquad E_{t-1}\left[r_{i,t}\right] = \lambda_{t-1} Cov_{t-1}\left(r_{i,t}, r_{w,t}\right) + \lambda_{i,t-1} Var_{t-1}\left(r_{i,t}\right)$$

where $Var_{t-1}(\cdot)$ and $Cov_{t-1}(\cdot)$ are short-hand notations for conditional variance and covariance, both conditional to Ω_{t-1}. It should be noted that the returns in equations from (1) to (7) should be real. However, according to Bekaert and Harvey (1995) nominal excess returns should offer reasonable approximation for real excess returns. In addition, De Santis and Gérard (1997) mention that usually a common currency (most commonly U.S. dollar) is used to measure all returns in an international framework. We follow these standard procedures and use nominal excess returns. Because this study is analysing EMU countries from the EMU investor's perspective the choice for a currency is naturally euro and the Euro interbank offered rate (EURIBOR) is used for the risk-free rate calculations.

The CAPM suggests that the market portfolio should include all kinds of assets including human capital. As Roll (1977) notice, in reality any empirical test has to be conducted using an incomplete market for assets. Attempts have been made to deal with this issue, for example Shanken (1987) has developed a technique that enables to test the CAPM model conditional on assumptions about the correlation between a proxy portfolio and the true market portfolio. In reality, without the exact knowledge of this correlation, the true market portfolio has to be still replaced by some market proxy. Furthermore, Elton (1999) points out that one big company can bias the market proxy substantially. At least for the smaller markets, this kind of situation can happen quite easily.

Brief overview about the empirical practices and findings concerning the choice of the market proxy can be given as follows. Studies using univariate time-series models like autoregressive conditional heteroskedasticity (ARCH) kind of specifications, usually utilise countries' equity indices as a market portfolio proxies. Multivariate and cross-sectional studies of financial valuation models often utilise different asset classes or portfolios grouped by some criteria. The choice made in particular situation in hand usually rises from theoretical or empirical motivations. Some widely used grouping techniques in the empirical literature are stock portfolios constructed based on ranked stock market betas, size, industry and book-to-market ratios to only mention few. From a theoretical point of view, the CAPM theory suggests that the proportion of asset in the market portfolio equals to its relative weight according to whole market. Foster (1978) reports evidence that as theory suggest, when a value-weighted market proxy is used in calculating risk-return relationship, results seem to hold more firmly than when equally weighted market proxy is used. Furthermore, Merton (1980) argues that specification like equation (1) should offer reasonable approximation for equilibrium expected returns at least for broad-based equity portfolios if not for individual assets.

Finally, it would be possible to try to measure the degree of integration before model building, but as Bekaert and Harvey (1995) mention it would be difficult in practise. To offer an extensive and consistent analysis we conduct our analyses assuming all different levels of integration discussed here. In addition, according to Nelson (1991) and French *et al.* (1987) there are more conditions besides those mentioned above, which should be satisfied in order for theoretical models shown here to hold. However, for purposes to examine time-varying risk premiums we choose to limit the theoretical discussion here.

C. Empirical mean model

De Santis and Gérard (1997) mention, that the model like equation (3) appears to be natural starting point to test relation between expected excess returns and conditional risk because it allows investors to update their expectations using newly acquired information for decision making. Following closely De Santis and Gérard (1997), with that exception that we use aggregation at the national level, we first notice that the conditional world CAPM requires that equation (3) holds for every asset and for the global market portfolio itself. Now, if we use local market portfolios as assets and there are *N* such risky assets, model requires that the following system of equations is satisfied, at each point in time.

(8)
$$
\begin{aligned}
E_{t-1}\left[r_{1,t}\right] &= \lambda_{t-1}Cov_{t-1}\left(r_{1,t}, r_{w,t}\right) \\
&\vdots \\
E_{t-1}\left[r_{N-1,t}\right] &= \lambda_{t-1}Cov_{t-1}\left(r_{N-1,t}, r_{w,t}\right) \\
E_{t-1}\left[r_{w,t}\right] &= \lambda_{t-1}Var_{t-1}\left(r_{w,t}\right)
\end{aligned}
$$

According to De Santis and Gérard (1997) the reason for system to include only (*N*-1) risky assets and the global market portfolio is that redundancies are avoided. They point out that if all risky assets were included the last equation would just be a linear combination of the formers. Further, they conclude that if in empirical work *N* is too large, any subset of the assets can be used. Of course, use of any subset means that information concerning cross-correlations is lost and the power of tests concerning restrictions imposed by the model are reduced.

When we move from the theoretical models to empirically testable specifications some additionally assumptions have to be made. For example, Vaihekoski (1998) argues that the complete and true information set Ω_{t-1} is not observable and therefore it has to be replaced by a subset of information. If we let a subset $Z_{t-1} \subset \Omega_{t-1}$ to be information set that is available to econometrician we can write the theoretical model conditional on Z_{t-1}. As Bodurtha and Mark (1991) mention if the CAPM holds conditioned on Z_{t-1} then the model holds for Ω_{t-1}, but the implication does not extend in the other direction so the model conditional on Ω_{t-1} need not to be rejected if the model conditioned on Z_{t-1} is rejected.[1]

Following the usual practise used for example Ferson *et al*. (1987) and Ng (1991) we assume that realized excess returns are unbiased estimates of investors' conditional expectations. Thus, conditional expected excess returns in system of equations (8) may be substituted by realized excess returns minus forecasting errors and now empirical formulation of system of equations (8) can be presented in alternative form as follows

$$
\begin{aligned}
&R_t = \left[r_{1,t}, \cdots, r_{N-1,t}, r_{w,t} \right]' : \\
&r_{i,t} = \lambda_{t-1} h_{iw,t} + \varepsilon_{i,t} \qquad \forall i = 1, \cdots, N-1 \\
&r_{w,t} = \lambda_{t-1} h_{ww,t} + \varepsilon_{w,t} \\
&\varepsilon_t \left| Z_{t-1} \sim N\left(0, H_t\right) \right.
\end{aligned} \tag{9}
$$

[1] As Bodurtha and Mark (1991) points out, this assumption holds unless additional assumptions are made (e.g. constant betas).

where R_t is the N x 1 vector of conditional mean equations for (N-1) risky assets and for the global market portfolio, $\varepsilon_t=[\varepsilon_{i,t},\ldots,\varepsilon_{N-1,t}, \varepsilon_{w,t}]'$ is the N x 1 innovation vector, which is here thought to follow a conditional multivariate normal distribution. Finally, H_t is the N x N conditional variance-covariance matrix. Notations $h_{iw,t} = Cov_{t-1}(r_{i,t}, r_{w,t})$ and $h_{ww,t} = Var_{t-1}(r_{w,t})$ are used for convenience throughout the rest of this study. If asset returns depend on multiple risk factors the relation (9) can be easily extended. We simply insert conditional mean equations for factor portfolios into R_t and add risk premium for each factor to the right-hand side of risky assets equations.

Equation (9) can be estimated and used to test equations (4), (6) and (7) after we select a model for the conditional covariance and for the conditional variance processes. In this study the conditional covariance matrix of asset innovations is assumed to follow different specifications of GARCH process, depending particular hypothesis tested. This choice follows from the fact that this approach is capable to capture empirical regularities found in equity returns. Furthermore, for example Bollerslev *et al.* (1988) state based on their results that any correctly specified intertemporal asset pricing model should take heteroscedastic nature of asset returns into account. In practice, our assumption means that agents are assumed to adjust their expectations of conditional mean and conditional covariance matrix of excess returns each period using latest innovations revealed in last period's excess returns and so, only information on returns is used by agents to learn about the changes in the covariance matrix. Of course, additional information that agents' could use to form expectations may exist. For example, Fama and French (1988) find evidence that lagged portfolio returns shown to be useful for predicting portfolio returns.

2.2 Univariate and multivariate GARCH models

A. Motivation

To complete empirically testable model, we use GARCH processes for the conditional second moments. In this section, theoretical motivation for this kind of models is first treated. Second, evolution of univariate and multivariate GARCH models is briefly summarized and the most important aspects of both kinds of models are discussed

Traditional econometric models are unable to explain number of typical features for financial data. Three of those features are treated here. First as Stenius (1991) points out evidence from stock markets usually indicate that returns have leptokurtic distributions rather than normal distribution. According to Watsham and Parramore (2002) one reason for this kind of distribution is for example discontinuous trading which products periodic jumps in asset prices. Markets are not continuously open and information may arrive during this time, this may result a jump in asset prices, which in turn results larger negative or positive returns than one would expect if markets were continuously open. The result is a leptokurtic distribution with fat tails and excess peakedness.

Second feature is volatility clustering first noted by Mandelbrot (1963). This refers to the tendency for volatility to appear in bunches. More specifically, large changes tend to be followed by large changes of either sign and the same applies with small changes. Third features are asymmetric variance and covariance effects. By an asymmetric volatility effect we mean a phenomenon that a negative (positive) return shock will lead to a higher following volatility than a positive (negative) return shock of the same magnitude. Interestingly, Kroner and Ng (1998) argue that with multivariate models, asymmetric effects in the covariance are likely if asymmetric effects exist in the variance.

B. Univariate GARCH models

Evolution of univariate GARCH models can be briefly summarized as follows. Engle (1982) introduced a univariate model that can deal with the first and second issues mentioned above. This model is called autoregressive conditional heteroskedasticity (ARCH) model. Traditional models assume that variance of errors is constant, also known as assumption about homoskedasticity. Situation where variance of errors is not constant is known as heteroskedasticity. Term autoregressive conditional heteroskedasticity is used about the process where variance of the errors changes over time as autoregressively conditional. The ARCH model allows the conditional variance of error term to change over time as a function of past errors leaving the unconditional variance constant. Bollerslev (1986) generalized the ARCH model (GARCH) by allowing past conditional variances in the current conditional variance equation. Engle *et al.* (1987) extended the ARCH to ARCH-in-mean (ARCH-M) model by allowing the conditional variance to enter into the conditional mean equation. Combining extensions concerning variance equation together and GARCH (*p*, *q*) model's equation for series *i*, when a zero mean process is assumed and *p*=*q*=1 can be presented as

$$h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1} \qquad (10)$$
$$\varepsilon_{i,t} \left| \Omega_{t-1} \right. \sim N(0, h_{ii,t})$$

where $h_{ii,t}$ is function of a constant term c_i, the ARCH term $\varepsilon_{i,t-1}^2$ and the GARCH term $h_{ii,t-1}$. Orders of terms are denoted as *q* for the ARCH terms and *p* for the GARCH terms. The error term $\varepsilon_{i,t}$ is here thought to follow conditional univariate normal distribution. Other distributions, like the *t*-distribution or the Generalized Error Distribution (GED) can also be used instead. To ensure that in equation (10) variance is stationary and non-negativity constrains are not violated should $c_i > 0$, $a_i \geq 0$, $b_i \geq 0$ and $a_i + b_i < 1$ be satisfied.

If we let $q=p=0$ the standard assumption that variance of errors is constant will be obtained. The original ARCH (q) model's conditional variance equation can be obtained by setting $p=0$. Bollerslev (1986) argues that with this kind of specification there are difficulties to set right lag structure and it will often lead to violation of the non-negativity constraints. The GARCH (p, q) specification can overcome partly these problems. This model can be seen as infinite order ARCH specification, which allows an infinite number of past squared errors to influence the current conditional variance. Day and Lewis (1992) argue that another advantage of (G)ARCH kind of model is that conditional variance is allowed to be a function of both exogenous and lagged dependent variables. This allows equation (10) to be further extended by adding regressors into conditional variance equation.

The equation (10) has still some drawbacks. It treats positive and negative volatility shocks symmetrically. This is because conditional variance is a function of squared lagged error terms and so signs of error terms are lost. Empirical results offers evidence that negative shocks may have a different impact than positive (e.g., Black 1976; Christie 1982; Nelson 1991; Glosten *et al*. 1993). More precisely, volatility tends to rise in response to situations where excess returns are lower than expected and fall when excess returns are higher than expected. Typically, these asymmetries are related to leverage effects after Black (1976). Explanation offered by a leverage effect is that a negative price shock increases the debt/equity ratio making the stock more risky and so increasing returns volatility.

An alternative explanation often presented in the literature is so called "volatility feedback". This explanation implies likewise a negative correlation between stock returns and future volatility. In this explanation it is thought that large quantity of news increases expected volatility, increasing the required rate of return, which in turn depresses the current asset price. This leads in the situation where the negative price effects of negative news are magnified and the positive price effect of positive news is mitigated. As Black and McMillan (2004) further mention, a consequence would also be that returns are characterised by negative skewness.

Two popular univariate models that are extended to capture asymmetric effects are the exponential GARCH (EGARCH) proposed by Nelson (1991) and the GJR model named after Glosten *et al*. (1993). According to Balaban *et al.* (2001) there exist arguments that when these two models are compared, the GJR model may better fit stock market data. With the GJR-GARCH (1, 1) model, the conditional variance for series *i* is modelled as follows

(11) $$h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1} + d_i \eta_{i,t-1}^2$$

where $\eta_{i,t-1} = \max[0, -\varepsilon_{i,t-1}]$ and d_i is the parameter for possible asymmetries. If parameter $d_i \neq 0$ then the impact is asymmetric and the leverage effects can now be tested by the hypothesis that $d_i > 0$. Non-negativity conditions for this specification are that $c_i > 0$, $a_i \geq 0$, $b_i \geq 0$ and $a_i + d_i \geq 0$. According to Wu (2006) constrain for the (1,1) process to be covariance stationary is that $a_i + b_i + ½ d_i < 1$. As can be seen equation (11) is a straightforward extension of equation (10), which only introduces asymmetric effects to the standard GARCH model. As Wu (2006) points out, the GARCH model is nested in the GJR-GARCH model or vice versa is restricted GJR-GARCH model where asymmetries are set to zero. For this reason we choose to use this specification throughout the study. More preciously, the GJR-GARCH should enable us to model conditional variance in ex post analysis at least as efficiently as its restricted version. We use asymmetric model without any prior specification test for model building. However, it should be noted that prior specification test could be done using a set of tests for asymmetry in variance, proposed by Engle and Ng (1993).

C. Multivariate GARCH models

When some degree of integration is assumed we need a multivariate model for our empirical analyses. In a more general level, integration of world financial markets has overall emphasised the need for multivariate models. It is clear that in the situation where markets or assets are dependent on each others one has to consider them jointly to understand relations between them. Models discussed in the previous section have two major limitations because their entirely univariate nature. First, if there are situations where volatility change in one market or asset tend to lead changes in volatility of another market or asset, situation also known as "volatility spillovers", the univariate model will be misspecified. Second, many applications and theories are interested about the covariance between series addition to variances themselves. Multivariate GARCH models can be used for modelling both conditional variances for the component series and conditional covariances between series. Obvious applications in finance for this kind of models are for example estimates of conditional betas and dynamic hedge ratios. Univariate volatility models have been generalized to the multivariate case by many authors. Some of the best known multivariate models are the diagonal VECH introduced by Bollerslev *et al*. (1988), the BEKK model developed by Engle and Kroner (1995), the constant correlation (CCORR) model and Dynamic Conditional Correlations (DCC) proposed by Bollerslev (1990) and Engle (2002), respectively.

There are two major problems with multivariate models. First, a variance-covariance matrix must be positive definite at each time period. This condition ensures among other things that variances are never negative and that the covariance between two series is the same irrespective of which of the two series is taken first. Second, the number of parameters to be estimated can grow quickly when the number of variables is increased and estimation becomes infeasible. When analysing multivariate models, the VECH parameterization serves as a natural starting point. Originally the model was developed by Bollerslev *et al.* (1988) and it can be presented as follows

(12)
$$\text{vech}(H_t) = C + A\text{vech}\left(\varepsilon_{t-1}\varepsilon_{t-1}'\right) + B\text{vech}(H_{t-1})$$
$$\varepsilon_t \left| \Omega_{t-1} \sim N(0, H_t) \right.$$

where H_t is a N x N conditional variance-covariance matrix, ε_t is a N x 1 innovation vector, C is a N x 1 parameter vector, A and B are N x N parameter matrices. The vech operator vech(·) takes a symmetric matrix and returns a vector with only its lower triangle. In equation (12) innovation vector ε_t is thought to follow a conditional multivariate normal distribution. Multivariate *t*-distribution can also be used instead, but with the GED distribution the estimation of the parameters gets very complicated.

Although, the VECH model allows full set of interactions between series the number of parameters to be estimated becomes quickly infeasible. To solve this problem Bollerslev *et al.* (1988) restricted A and B in equation (12) to be diagonal and the resulting diagonal VECH (DVECH) (1,1) model, which we use as a first multivariate base model, can now be presented as follows

(13)
$$h_{ii,t} = c_{ii} + b_{ii}h_{ii,t-1} + a_{ii}\varepsilon_{i,t-1}^2 \qquad \forall i = 1,\dots,N$$
$$h_{ij,t} = c_{ij} + b_{ij}h_{ij,t-1} + a_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1} \qquad \forall i \neq j$$

where c_{ij}, b_{ij} and a_{ij}, i = 1,…,N and j = 1,…,N are parameters. Each element in H_t follows the GARCH (1,1) process, where element depends only on its own lag and corresponding term in $\varepsilon_{t-1}\varepsilon_{t-1}'$. As Kroner and Ng (1998) points out, the DVECH is easy to understand and additionally individual coefficients are easy to interpret intuitively, which is not always the case. For example, due the quadratic nature of the BEKK model its individual coefficients may be hard to interpret.

The DVECH model has significantly less parameters compared to equation (12) or the BEKK model, but still too much if the number of series increases over few. In addition, Tsay (2005) argue that the DVECH model has two additional practical shortcomings. First, there is no guarantee that the model produces a positive definite conditional covariance matrix. Kroner and Ng (1998) mention that in order to solve this problem nonlinear inequality restrictions for the rates at which the weights are reduced for older observation should be imposed. The reason is that without these restrictions the covariance terms could become too big relative to the diagonal terms causing the nonpositive definite matrix. Second problem with the DVECH model is that the direct dynamic dependences between variance series are not allowed. The BEKK model would guarantee the positive definiteness but since our conditional mean equations are relative complex the estimation could become problematic. In addition, because we use the DVECH model only with the bivariate case the number of parameters stays acceptable and the probability to stumble with a non-positive definite matrix problem is not so serious that it otherwise could be. Most importantly, asymmetries are also in our interest and the DVECH model can be easily extended to allow asymmetries.

Bollerslev (1990) proposed a model that can be estimated even when relative large set of variables is considered. This specification is usually called as the constant correlation (CCORR) model. In this study, this model is used as a second multivariate base model. Let us assume that correlation coefficient $\rho_{ij,t} = \rho_{ij}$ is time-invariant and $|\rho_{ij}| < 1$. Now, ρ_{ij} is a constant parameter and the full conditional covariance matrix given by the CCORR model can be written as

(14) $$H_t = D_t \Gamma D_t$$

where D_t is a N x N time-varying diagonal matrix elements given as $\sigma_{1t},\ldots,\sigma_{nt}$ and Γ is the N x N time-invariant correlation matrix off-diagonal elements given as constant conditional correlation coefficients ρ_{ij}. According to Bollerslev (1990) it follows that necessary conditions for H_t to be almost surely positive definite are that Γ is positive definite and all *N* conditional variances are well defined. If conditional variances are modelled by an univariate GARCH (1,1) process as was with the DVECH model, then the elements of the conditional covariance matrix H_t follow the CCORR model as follows

$$h_{ii,t} = c_{ii} + b_{ii}h_{ii,t-1} + a_{ii}\varepsilon_{i,t-1}^2 \quad \forall i = 1,...,N$$
$$h_{ij,t} = \rho_{ij}\left(\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}\right) \quad \forall i \neq j \tag{15}$$

where the conditional covariance is now given by the product of the constant conditional correlation coefficient times the conditional standard deviations. This model allows us to further reduce the number of coefficients to be estimated. If the stationary conditions for individual conditional variances are satisfied then the model is covariance stationary. As with the DVECH model, again conditional variance processes are not allowed to be dynamically related.

However, because restrictions we impose, our multivariate and univariate models now model conditional variances exactly same way. This makes results more comparable and with the multivariate models differences in conditional covariance processes are highlighted. To illustrate these differences, as Kroner and Ng (1998) mention, with the DVECH model the shocks for series enter into covariance equation in the cross-product form implying that the covariance can be small or negative. With the CCORR model, the large shocks with both signs have their effect to the conditional covariance through standard deviation implying that the covariance will be large.

As with the univariate model, equations (13) and (15) handle positive and negative variance and covariance shocks symmetrically. Asymmetries in conditional variance were discussed in previous section. With the multivariate framework, Kroner and Ng (1998) argue that asymmetric effects in the covariance are likely if asymmetric effects exist in the variance. Following closely their interpretation at least two reasons can cause asymmetric effects in comovements. First, if the leverage effect discussed in previous section caused the asymmetric effect in the variance, then this change in the financial leverage in the firm should also influence the covariance between this particular firm's stock returns and stock returns of other firms that have not experienced changes in their financial leverage. Secondly, Ross (1989) shows that the rate of flow of information is related to the variance of price changes. Now, if an increase in the information flow following bad news has caused asymmetric effect in variance for one firm's stock returns and other firms have not experienced such changes in the rate of flow of information, then the covariance between stock returns should be influenced. This time the covariance is affected because the relative rate of information flow across firms is changed.

Conrad *et al.* (1991) and Kroner and Ng (1998) both report evidence that large-firm returns can affect the volatility of small-firm returns but not vice versa. This indicates that there exists an asymmetry between predictability of conditional variances. Kroner and Ng (1998) further find significant asymmetric effects in both variances and covariances. Their results show that bad news about large firms can cause volatility in both small-firm and large-firm returns and that the conditional covariance between small and large firms returns tend to be higher after bad news about large firms than good news. Results also show that the effect on the variances and covariances caused by news about small firms is minimal. If these kind of asymmetric effects exist, any model that does not capture these asymmetries can lead to wrong conclusions.

The DVECH and the CCORR models can be extended to take asymmetries into account using GJR approach developed by Glosten *et al*. (1993). Extensions are done following same kind of procedures as Kroner and Ng (1998). Let $\eta_{i,t}$ = max[0, -$\varepsilon_{i,t}$] and with GJR extensions the exact form of asymmetric models that we use throughout the study are as follows

Asymmetric DVECH:

(16)
$$h_{ii,t} = c_{ii} + b_{ii}h_{ii,t-1} + a_{ii}\varepsilon_{i,t-1}^2 + d_{ii}\eta_{i,t-1}^2 \qquad \forall i = 1,...,N$$
$$h_{ij,t} = c_{ij} + b_{ij}h_{ij,t-1} + a_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + d_{ij}\eta_{i,t-1}\eta_{j,t-1} \qquad \forall i \neq j$$

Asymmetric CCORR:

(17)
$$h_{ii,t} = c_{ii} + b_{ii}h_{ii,t-1} + a_{ii}\varepsilon_{i,t-1}^2 + d_{ii}\eta_{i,t-1}^2 \qquad \forall i = 1,...,N$$
$$h_{ij,t} = \rho_{ij}\left(\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}\right) \qquad \forall i \neq j$$

where d_{ii} and d_{ij} are parameters for asymmetries in conditional variance and covariance, respectively. As can be seen the asymmetric DVECH and CCORR both have exactly same variance functions with GJR extensions as the univariate model. In addition, the asymmetric DVECH allows also the cross-product term of the negative shocks enter into the conditional covariance equation. This means that when there is bad news for both firms the conditional covariance can be higher or lower depending of the sign of the coefficient d_{ij}. Now, if $d_{ij} \neq 0$ then asymmetric effects exist in the conditional covariance. For the asymmetric CCORR model, a possible asymmetric effect in the conditional covariance comes through intermediate of conditional variance functions.

2.3 Empirical models and main hypothesis

A. Full market segmentation

If markets are fully segmented, the domestic version of the conditional CAPM can be used separately for each country because the domestic market risk is thought to be the only source of risk that investors are interested. We follow the widely used practice in the empirical literature and use the country's market index as an approximation for the market portfolio. We also do additional modifications for the original model. First, we assume that the price of local market risk is constant. Second, we add intercepts and autoregressive (AR) components into conditional mean equations. AR(1) component is added only for those series that show autocorrelation in pre-specification tests. This is done to take the effect of non-synchronous trading into account and is widely used practise in empirical studies. For example, Akgiray (1989) mention that any realistic model for daily returns must recognise that time-series of returns exhibit significant first-lag autocorrelation. Alternative possibility would be the inclusion of moving average (MA) terms into mean equations. According to Nelson (1991) this is a somewhat trivial question and there is no significant difference between the choice of the AR term or either the MA term for these purposes.[2]

Although, the system of equations in (9) could be used for any set of assets within a country we only use one aggregate index for each market. Because of this, when the full segmentation is assumed the relation (9) reduces to a single equation and with discussed modifications the empirical conditional mean equation for the country *i* can be presented as

(18)
$$r_{i,t} = \omega_i + \delta_i r_{i,t-1} + \lambda_i h_{ii,t} + \varepsilon_{i,t} \,,$$
$$\varepsilon_{i,t} \left| Z_{t-1} \right. \sim N(0, h_{ii,t})$$

where λ_i is the time-invariant price of local market risk, ω_i and δ_i are constant and the AR(1) parameter for country *i*, respectively. Although the theoretical model does not include intercept term, Bollerslev *et al.* (1988) argue that nonzero ω_i might reflect the preferential tax treatments or a preferred habitat phenomenon. Informally, it can also be interpret as Jensen's (1969) measure. The conditional variance $h_{ii,t}$ of the market portfolio in country *i* is modelled as GJR-GARCH (1,1) process as described in equa-

[2] For example, De Santis and Imrohoroglu (1997) report that after replication of most tests using MA(1) term instead AR(1) term they find practically no differences in the results.

tion (11). The order (1,1) is chosen because lower order model is usually found to be enough to capture the empirical regularities found in financial data.

Hypothesis we test using the model consisting from equations (18) and (11) is that if financial markets are fully segmented and time-varying risk premium is induced by the conditional market risk then the coefficient λ_i should be positive and statistically significant. If $\lambda_i \neq 0$ it is interpreted as a direct evidence about time-varying risk premium driven by the conditional market risk. If $\lambda_i = 0$, the expected risk premium is unrelated to the variability of market portfolio returns. Another reasons to obtain $\lambda_i = 0$ can also be that markets are not fully segmented or that λ_i is not constant. From the theoretical conditional CAPM model's perspective, the reason for failure may also be that the chosen market proxy fails to be conditionally mean-variance efficient or that the model simply does not hold.

Our testing method, when full market segmentation is assumed, has one additional feature that needs to be recognized. Stenius (1991) points out that theoretically it should be the conditional covariance not the conditional variance that enters into equation (18) when the market proxy is used. If investors do not hold the market portfolio and they instead hold an incomplete set of assets due to taxes, transaction costs or restrictions etc. has Levy (1978) shown that the risk measure of an asset is not its beta (covariance with the market portfolio divided by the market variance), but instead its own variance. Because the purpose of this study is not to test CAPM, gives arguments above justification for using the variance and market proxy for our purposes. On the other hand, this means that there remains absence of distinction between components of risk that are seen as the basic elements of the portfolio theory. In fact, Bollerslev *et al.* (1988) in their multivariate GARCH-M study report that result from inclusion of the asset's own conditional variance into conditional mean equations in addition to conditional covariance risk is not found to be significant. They further conclude that this might be the reason why in many empirical studies that use univariate specification the time-varying measure of the own conditional variance is found to have poor explanatory power for the expected return on the equity market.

B. Completely integrated markets

Under the assumption that financial markets are completely integrated we need a multivariate system. First, as De Santis and Imrohoroglu (1997) mention, if the relation (9) is assumed to hold in international setting as such, we have to make assumption that investors do not cover their exposure to currency risk or that the price of currency risk is zero. Second, we make the same assumptions about constants and AR(1) terms as was when the segmented markets were assumed. Third, system's estimation becomes troublesome if we try to estimate it simultaneously for all countries and so we choose to estimate a series of bivariate models. Now, when full integration is assumed the relation (9) reduces to a system of two equations and can be presented as

$$\begin{aligned} r_{i,t} &= \omega_i + \delta_i r_{i,t-1} + \lambda_{t-1} h_{iw,t} + \varepsilon_{i,t} \\ r_{w,t} &= \omega_w + \delta_w r_{w,t-1} + \lambda_{t-1} h_{ww,t} + \varepsilon_{w,t} \\ \varepsilon_t \left| \mathrm{Z}_{t-1} \right. &\sim N\left(0, H_t\right) \end{aligned} \tag{19}$$

where the elements of the conditional covariance matrix H_t follow equation (16) when the asymmetric DVECH or alternatively equation (17) if the asymmetric CCORR is used.

With this specification hypotheses are studied in two stages. First, the price of global market risk in equation (19) is restricted to be constant $\lambda_{t-1}=\lambda$. Now, if financial markets are fully integrated and time-varying risk premiums are induced by the conditional covariance with the global market portfolio, the coefficient λ should be positive and statistically significant. Again, if $\lambda \neq 0$ it is interpreted as an evidence about the time-varying risk premium induced by the conditional global market risk. If hypothesis are not supported, it indicates either that the expected risk premiums are unrelated to the covariance risk, the price of global market risk is not constant or assumed level of market integration is wrong.

In the second stage with the equation (19) we allow the price of global market risk to be time-varying. The necessary step in forming empirically testable model is to choose how to model these dynamics. We choose the linear function form and model dynamics of the price of global market risk as follows

(20) $$\lambda_{t-1} = Z_{t-1}\kappa_w$$

where Z_{t-1} is the global instrument set and κ_w is a vectors of coefficients. Instrument set is described in the Data section. We do not restrict the price of market risk to be positive as suggested by the theory. There are two reasons for this. First, we choose not do such a restriction when we are at first stage testing models where the price of market risk is constant, so imposing restrictions at second stage would make results harder to compare. Second, we are testing time-varying risk premiums and not the conditional CAPM. In addition, De Santis and Gérard (1997) report that in their study such a restriction is not empirically supported. From the theoretical point of view, as Vaihekoski (2007) mentions, the choice how the dynamics of the price of global market risk is modelled means that we make assumptions that the information set is same through time and that due the time-invariant coefficients in κ_w the relation between information and expectations stays the same.

Hypothesis tested at the second stage are that the price of global market risk is time-varying and different from zero. With this specification the time-varying risk premium is induced by two conditional components that are the conditional price of global market risk and conditional covariance between particular country and global market portfolio. Failure of this specification can be again viewed as a rejection of assumed level of market integration or as a rejection of our model.

C. Partially segmented markets

Our last model is used when we make assumption that financial markets are partially segmented. Again, we assume that prices of market risks are constants and make the same assumptions about intercepts and AR(1) terms as previously and estimate a series of bivariate models. Also with this specification, the relation (9) reduces to a system of two equations and can be presented as follows

$$\begin{aligned} r_{i,t} &= \omega_i + \delta_i r_{i,t-1} + \lambda h_{iw,t} + \lambda_i h_{ii,t} + \varepsilon_{i,t} \\ r_{w,t} &= \omega_w + \delta_w r_{w,t-1} + \lambda h_{ww,t} + \varepsilon_{w,t} \\ \varepsilon_t \,|\, \mathrm{Z}_{t-1} &\sim N\left(0, H_t\right) \end{aligned} \tag{21}$$

where again the elements of H_t follow equation (16) in the case of the asymmetric DVECH or equation (17) in the case of the asymmetric CCORR. When operating with this specification a hypothesis is that time-varying risk premiums are induced by the global market risk λ and local market risk λ_i. Both coefficients should be statistically significant if this is true

Our multivariate models have some theoretical features that need to be recognised. As De Santis and Imrohoroglu (1997) mention, if we would analyze whether the conditional asset pricing model holds or what is the right level of market integration, then our bivariate testing method would be unsatisfactory. Simple reason for this is that in reality tests should not be independent pair-wise tests. Fortunately, for our conditional risk-return relationship analyses this independence assumption is not so restrictive. On the other hand, the bivariate testing framework raises questions how to model the price of global market risk. For example, Bekaert and Harvey

(1995) estimate their bivariate models in two stages essentially first restricting the price of global market risk to be same for each country, which of course is consistent whit the assumptions of the theoretical pricing model. However, as authors mention this approach is likely to lead in the situation where the usual standard errors are understated. Because, we are more interest about the risk-return relationship instead the conditional pricing model, we choose statistically more robust procedure and do not employ such a restriction for the prices of market risks.

Other features are restrictions we impose for processes generating H_t. First, according to De Santis and Gérard (1997) the CCORR type of model as equation (17) may be too restrictive. They mention that there have been suggestions that correlations would change along market conditions. Second, they also argue that the diagonal parameterization, as in both of our models may also be fairly restrictive. The reason for this are the cross-market dependencies in conditional volatility found in empirical studies. Rationality of the second restriction is analyzed in the Data section. It should be noted that Tse (2000) has proposed a test for constant correlations in multivariate GARCH model, which could be used to test the first restriction. However, because of the usual problems related to GARCH models the choice of particular model is always some sort of compromise, which in turn rises from the particular theoretical aspects in interest. To illustrate this, for example De Santis and Gérard (1997) mention that with their own parsimony MGARCH parameterization, which can handle quite many series simultaneously, the asymmetric effects in the conditional second moments can be hard to implement.

D. Estimation issues

For multivariate models, the log-likelihood function under the assumption of conditional normality is given as follows

(22)
$$L(\theta) = -\frac{TN}{2}\ln 2\pi - \frac{1}{2}\sum_{t=1}^{T}\ln\left|H_t\right| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t' H_t^{-1}\varepsilon_t$$

where *θ* is the vector of unknown parameters to be estimated. For the univariate model, the log-likelihood function is observed by modifying equation (22) by setting *N*=1, $\left|H_t\right| = h_{ii,t}$ and $\varepsilon_t' H_t^{-1}\varepsilon_t = \varepsilon_{i,t}^2 h_{ii,t}^{-1}$. Because financial time series often violate normality assumption, we follow standard procedures and estimate all our models and compute all our tests using the quasi-maximum likelihood (QML) approach proposed by Bollerslev and Wooldridge (1992). As mentioned by numerous authors, under some standard conditions the QML estimator is consistent and asymptotically normal and statistical inferences can be done using robust Wald or Lagrange multiplier (LM) statistics. Numerical maximization of the log-likelihood function $L(\theta)$ is done with the RATS (version 7) using BFSG algorithm. More details about used program and initial assumptions are given in Appendix 1.

2.4 Previous studies

Following Bekaert and Harvey (1995) asset pricing studies can be broadly classified into the three categories. First, studies assuming segmented markets are those that use one country's data to test models and restrictions. Second, there exists class of studies assuming that world capital markets are perfectly integrated. Third class of studies constitutes from those assuming partial market segmentation. Previous papers using same type of methodology like this study can additionally be broadly categorised according following aspects. First, studies use either univariate or multivariate specifications. Second, statistical methods used are usually either GARCH kind of models or the generalized method of moments (GMM). Third, studies' bases are in analyzing time-varying risk-return relationship or conditional asset pricing models. Fourth, according to used market, return interval and test assets. We present here results from some of these studies from our viewpoint, meaning that we concentrate our effort mainly to present important findings concerning risk-return relationship.

If markets are completely segmented the conditional CAPM model and restrictions it imposes as shown for example in equations (5) and (6) can be tested. Examples of papers studying a relationship between stock returns and their own conditional volatility using univariate models and ex post analyses in this context are summarized as follows. For the US market French *et al.* (1987) report a positive relationship between the expected volatility and the expected market risk premium and additionally a negative relationship between the unexpected volatility and stock market returns. On the other hand, Baillie and DeGennaro (1990) report very little evidence for a significant relationship between the own expected volatility and return. Finally, Nelson (1991) and Glosten *et al*. (1993) both allow asymmetric effects in conditional variance and find a negative relationship. Study analyzing several international markets is provided for example by Theodossiou and Lee (1995) how report a zero relationship for all ten industrialized countries under examination. Balaban *et al*. (2001) report a positive and significance relationship for three countries and insignificant relationship for 16 countries. Additionally, in their ex ante study Balaban and Bayar (2005) find only few significant negative or positive relations for 14 countries under investigation.

The conditional CAPM and completely segmented US markets using multivariate setting is tested by Bollerslev *et al.* (1988). Some of their results can be summarised as follows. First, study provides support for the conditional CAPM, supporting that time-varying risk premiums are induced by the conditional covariance with the market. Second, the conditional variance-covariance matrix is time-varying. Third, diagnostic test give some support for the conclusion that risk premiums are more influenced by conditional covariance with the market than by assets own conditional variances. Ng (1991) finds also support for the conditional CAPM using same kind of model with the difference that contrary to Bollerslev *et al.* (1988) the conditional mean equation in this study is a variant of zero-beta CAPM and the MGARCH-M specification assumes constant correlation between returns over time. For the beta-ranked portfolios results show support for the conditional CAPM model and indicate that the reward-to-risk ratio is positively correlated with the conditional market variance. However, for the size-sorted portfolios the model is rejected. Finally, Bodurtha and Mark (1991) also analyze the US markets but estimate their model by the GMM. They report some support for the conditional CAPM. Results suggest for example time-variation in the price of market risk, in the conditional first and second moments of stock excess returns and in the conditional covariance between the market return and portfolios' returns. Finally, Schwert and Seguin (1990) report evidence against the model.

In the case of completely integrated or partially segmented markets equations (3), (4) and (7) can be used as a basis for analyses. For example, Harvey (1991) studies the conditional world CAPM model using 17 countries. Results show, that for most countries a single risk factor seems to be enough to describe the cross-sectional variation in returns across countries, but not for every country. More specifically, time-varying covariances between the country return and the world stock return are able to partly explain the dynamic behaviour of the country returns. Giving some support for the view that risk premiums are induced by conditional covariances with the market. Further, the price of global market risk is found to be time-varying. Harvey (1995) studies emerging markets and rejects the conditional world asset pricing model for their returns. Although the model is rejected, the risk exposures are found to change through time for many emerging market suggesting the presence of time-varying risk premiums.

De Santis and Gérard (1997) test the conditional CAPM in international setting for world's eight largest equity markets. Empirical results from this study show support for most of the model's pricing restrictions. Further, results indicate that the price of global market risk is same for all countries and time-varying. With their partial segmented model they report that the price of local market risk is found to be zero supporting the view that international markets are integrated. Finally, De Santis and Imrohoroglu (1997) study emerging financial markets and risk-return relationship when markets are either fully segmented or integrated at a regional or global level. In the first case they find no relation. When regional and in particular global integrations are assumed the systematic risk is found to be priced in the Latin America but not in the Asia.

Dumas and Solnik (1995) using conditional international asset pricing model for world's four largest equity markets find evidence that in addition to market risk also the currency risk is priced. They also reject hypothesis that the price of global market risk and foreign exchange risks are time-invariant. Interestingly, the prices of market risks are find to vary almost the same way when estimated from the model with currency risk or alternative without currency risk. These result indicate that leaving the currency risk outside from analysis in the international framework, may be rather strong assumption for the theoretical model, but its effect for the price of market risk may be relative weak. The importance of the currency risk and time variations in prices of risks is further supported by De Santis and Gérard (1998). Another study concentrating to some related extensions compared to this study is Bekaert and Harvey (1995). They use a conditional regime-switching model, which allows the degree of market integration to change over time. Results indicate that integration is indeed time-varying and that the price of global market risk is found to be time-varying. It is therefore possible that empirical models where the level of assumed market integration is time-invariant may potentially be misspecified.

It is interesting to see how results differ according the particular choices made in each paper. Results from the studies using univariate model and assumption about segmented markets do not show any consensus about the nature of the conditional risk-return relationship. Based on a limited amount of empirical evidence the results from these previous studies indicate that when asymmetric models are used the conditional risk-return relationship may also have some tendency to appear as a negative one. However, segmented markets studies that use multivariate models show slightly clearer pattern and additionally find more support for the theoretical relationship. This may indicate that specifying wider market proxies can have significance for the results. On the other hand, if test portfolios are constructed using some empirically motivated characteristic, Lo and MacKinlay (1990) have shown that this may bias tests.

Studies that assume some level of market integration give some reason to assume that markets are not fully segmented and additionally are more supportive for the theoretical asset pricing model. Results from these studies also strongly suggest that the price of global market risk is time-varying. This would mean that time-varying risk premiums are driven by two components that are variation in both covariance risk and the price of global market risk. Interestingly, non of the international studies presented here allow asymmetric effects in the conditional covariance matrix making it interesting to see what are this assumptions effects on results. In addition, because results do not unambiguously show the right level of market integration, in order to consistently analyze the conditional risk-return relationship empirical analyses should be conducted assuming that all levels are possible. Combining other findings together indicate that use of multivariate model with possibility for asymmetric effects in the covariance matrix may offer the most robust specification. The reasoning is that if asymmetric effects are allowed using model where symmetric model is nested, we should be able to model conditional moments at least as efficiently as with the symmetric model. This of course concerns only ex post analyses. Further, findings indicate that model where the price of global market risk is time-varying will be superior compared to time-invariant counterpart. Finally, some concern for the empirical results causes our rather strong assumption that the currency risk is not priced.

2.5 Other related aspects

A. Alternative conditional mean model

As De Santis and Gérard (1997) mention, there exists alternative formulations for the conditional mean equation than the one used in this study. Bollerslev *et al.* (1988) use one of these parameterizations in the MGARCH-M framework. To illustrate differences between their and this study's parameterizations, let us assume that global markets constitute only from *N* local market portfolios. Using same type of notations as before, let $r_t = [r_{i,t}]$ be the *N* x 1 vector of excess returns of all local market portfolios measured same way as before. Now, let $E[r_t | \Omega_{t-1}]$ and H_t be the *N* x 1 conditional mean vector and *N* x *N* conditional covariance matrix of these excess returns, conditional to Ω_{t-1}. Further, let ω_{t-1} be the *N* x 1 vector of markets value weights at the beginning of the period. Now excess return on the global value-weighted market portfolio can be specified as $r_{w,t} = r_t'\omega_{t-1}$ and the vector of covariances with the market is given simply as $H_t\omega_{t-1}$. The conditional world CAPM is now using matrix notations $E[r_t | \Omega_{t-1}] = \lambda_{t-1} H_t \omega_{t-1}$ or in the same form as relation (8) as follows

$$
\begin{aligned}
E_{t-1}\left[r_{1,t}\right] &= \lambda_{t-1}\left(Var_{t-1}\left(r_{1,t}\right)\omega_{1,t-1}+,\ldots,+Cov_{t-1}\left(r_{1,t},r_{N,t}\right)\omega_{N,t-1}\right) \\
&\;\;\vdots \\
E_{t-1}\left[r_{N,t}\right] &= \lambda_{t-1}\left(Cov_{t-1}\left(r_{N,t},r_{1,t}\right)\omega_{1,t-1}+,\ldots,+Var_{t-1}\left(r_{N,t}\right)\omega_{N,t-1}\right)
\end{aligned}
\tag{23}
$$

where $Var_{t\text{-}1}(\cdot)$ and $Cov_{t\text{-}1}(\cdot)$ are short-hand notations for conditional variance and covariance, both conditional to $\Omega_{t\text{-}1}$. With equation (23) we do not need to place the market portfolio as a last element of system as it was previously with equation (8) and now all *N* risky assets instead (*N*-1) risky assets and the market portfolio can be included. If we consider equation (8) with the value-weighted market portfolio where values are rebalanced at the time *t*-1, then the covariance between risky asset *i* and the market portfolio will be exactly same as a sum given in parenthesis for asset *i* in relation (23). In any other case, there are at least minor differences.

The fact, that if empirical analysis is conducted with the empirically testable version of equation (23) we do not need a market index, can be valuable in some circumstances. On the other hand, as De Santis and Gérard (1997) points out, there are at least two drawbacks with this equation. First, the market weights may simply not be available or if weights have to be estimated from multiple sources measurement errors may be introduced. Second, if asset returns depend on multiple risk factors this parameterization is harder to extend. The latter is in great importance because we use the partial segmented model. Further, if researcher wants to include currency risk in the international analyses, then models have to be also extended.

B. Conditional skewness and asset pricing

Harvey and Siddique (1999) present a new interesting methodology for estimating autoregressive conditional skewness. They call their model as GARCH with skewness. Essentially, it is extension of traditional GARCH model where the conditional second and third moments are modelled jointly using a non-central conditional *t*-distribution. They find significance presence of conditional skewness and results show that when conditional skewness is included asymmetric effects in the variance appears to disappear and conditional variance becomes much less persistent. Harvey and

Siddique (1999) additionally report evidence that first three conditional moments are also linked to frequency and seasonality in returns. Despite this, these results indicate that conditional skewness and asymmetries in conditional variance are linked. It seems that asymmetries in conditional variance can capture some of the variation of conditional skewness. From this point of view we can see asymmetric conditional variance at least as a rough proxy for the conditional skewness. Additionally, Harvey and Siddique (2000) using regression framework and inclusion of skewness into asset pricing tests report that systematic coskewness is find to be important. They also note that skewness might be related to variables such a firm size and that group of securities such as the smallest market-capitalized portfolios usually have the most skewed returns. Historically, traditional CAPM model has countered problems especially when trying to explain small firms' returns. Mean-variance framework may therefore be insufficient and should be complemented with skewness. From our point of view, if the first two moments are not enough our model is incomplete. On the other hand, by allowing asymmetries in the conditional covariance matrix we may be able to partly model conditional skewness indirectly.

C. Reasons for dependences in return series and volatility persistence

Generally linear dependence in return series can be incorporated to various reasons. To give few examples, the presence of a common market factor, thin trading and calendar day effects, only mentioning few. Non-linear dependences may be explained by the changing variances. Variance changes, on the other hand, may be explained by the rate of information arrivals, level of trading activity and corporate leverage decisions, which tend to affect the level of stock price. (Akigray 1989) For example, Lamoureux and Lastrapes (1990) used daily trading volume as a proxy for information arrival time and showed that it has significant explanatory power to the variance of daily returns. They also showed that this often leads ARCH effects to tend to disappear. Further, although the reasons behind dependences are not in our direct interest it is good to keep in mind that we use ARCH approach for modelling the conditional variances and covariances, so essentially assuming that lagged residuals contribute the information we need.

Persistence of volatility shocks has also great role for this study. Poterba and Summers (1986) find that shocks to volatility decay rapidly and suggest that volatility shocks can therefore have only a small impact on stock market prices. Their results lead them to doubt that volatility fluctuations and the movements induced by those fluctuations in equity risk premium could explain much of the variation in the stock market's price level. Nelson (1991) argues based on the formers study, that in opposite situation where volatility shocks would persist indefinitely, the whole term structure of risk premiums could move.

D. Model estimation procedures

The Flexibility and applicability of GARCH models makes this class of models attractive. However, these models have also less attractive features which need to be recognized in order to fully understand results. In addition to usual constrains and conditions placed on these models, we need nonlinear estimation techniques, common feature shared with many other sophisticated statistical technique. This means that even in the case of simplest univariate GARCH models different assumptions and choices we make can produce quite large differences in resulting coefficients and standard error estimates.

Surprisingly, consistency of GARCH models' estimates has not been studied much. One exception is provided by Brooks *et al.* (2001). They compare consistency of GARCH and EGARCH estimation and forecasting using number of different statistical programs. Results show that with default settings results can differ considerably between programs. Some reasons for these differences for example with the simple GARCH model are as follows. First, the conditional maximum likelihood estimation procedure needs starting values for the parameters and initialisation of the variance and squared lagged residual series, which are likely to influence results. Second, the optimisation is done using different algorithms (e.g. BHHH or Newton) or different convergence criterions. Although some programs can use analytical rather than numerical derivatives with the simplest case, in practise models become quickly so complex that numerical derivatives have to be used. Because of these potential differences, one needs to be careful when interpreting and comparing results from different studies. Brooks *et al.* (2001) argue that researchers should therefore provide information concerning model estimation. We follow this recommendation and provide description of used procedures in Appendix 1.

3. DATA

3.1 Data description

A. Excess returns and information variables

We conduct our study for the ten of the eleven countries that joined the Economic and Monetary Union's (EMU) third stage at 1 January 1999. For these countries local currencies were tied in euro with a fixed exchange rate from 31 December 1998 onwards. The sample period under examination comprises from 4 January 1999 to 31 December 2007 and the full data set constitutes from 2346 daily observations for every series. In addition for being in our direct interest because the EMU, the chosen sample period has three attractive features. First, because we are interest about the situation nowadays, limiting analysis to fairly fresh data should give us more detailed picture about the current existing situation. Second, as Vaihekoski and Nummelin (2001) mention, many countries have abolished ownership and investments restrictions in recent years. Because all our models assume fixed level of integration it is desirable that there are no large changes in these aspects during the estimation period. Third, some countries in our sample had historically quite variable and insignificance currencies. Our models do not regard the currency risk and it is likely that euro as more stable and significant currency can reduce the effects of this possible source of misspecification.

We take the view of an EMU investor and so all returns are measured in euro. The 1-month Euro interbank offered rate (EURIBOR) observed at time t is used as a proxy for the daily risk-free return calculations for $t+1$ period. All excess returns are calculated as a difference between continuously compounded index returns and risk-free return. The data on equity indices for 10 countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain) are calculated by the Morgan Stanley Capital International (MSCI) and obtained from the Datastream database. In addition, the MSCI world index is used as a proxy for the world market portfolio. All indices are value-weighted total return indices where gross dividends are reinvested back into market.[3] The eleventh country to be included would have been Luxemburg, but MSCI provided index is not available for the sample period and so it is omitted from the empirical analyses. We have chosen MSCI indices because they are widely used in earlier empirical studies and further because indices are consistently computed across countries they are directly comparable. As Vaihekoski (2007) mention country stock markets are not excluded from the global market index, which is potential source for multiconlinearity. However, most of our countries' proportion in global market index is minimal and for larger countries it still stays sufficient small, so multiconlinearity is not likely to be a serious problem.

Another data set used in this study constitutes from the conditioning variables. The instrument set we chose is mainly motivated by earlier studies for example those used by Harvey (1991) and Antell and Vaihekoski (2007). These variables are used for modelling time-variation in the price of global market risk. The global instrument set Z_{t-1} constitutes from a constant, the change in the US term premium (ΔUSTP), the US default premium (USDP) and interest rate difference (dINT). ΔUSTP is calculated same way as Antell and Vaihekoski (2007) and it is simply the first difference of the yield difference in annual percentage terms between 10 year constant maturity bond and 3-month T-Bill. USDP is the difference between Moody's Baa bond yield and Aaa bond yield. dINT is simply the difference between the US 3-Month T-bill and the 3-Month EURIBOR rate in annual percentage terms (dINT). This last instrument may partly reflect the exchange rate changes between the US dollar and euro. All data for instruments is also observed from the Datastream database.

[3] Official monthly MSCI total return index datatype is provided on daily basis after 1 January 2001. However, to enable smooth transition MSCI started to provide daily total returns earlier and the rebased daily history goes back to 31 December 1998. More information can be obtained from www.msci.com.

Most often empirical analyses like this study are conducted using monthly or weekly return intervals. However, for example Baillie and DeGennaro (1990) use daily and monthly and Balaban *et al*. (2001) use daily intervals, as we do. The choice of interval is not likely to be a trivial question. In addition to problems like non-synchronous trading, for example Bailie and DeGennaro (1990) argue that other institutional features may affect daily stock returns in away that in turn affect volatility generating processes. More preciously, features they reference are related to trade and settlement processes. On the other hand, as Hassan and Malik (2007) points out, when daily returns are used we have more usable observations meaning that estimates are more precise because of more degrees of freedom per estimated parameter of the covariance matrix. In addition to attractive statistical features, they further continue that forecast for longer periods can be generated using shorter interval data but the vice versa is not true. At least from the model's practical applications perspective this is likely to be an important point.

B. Descriptive statistics

A wide range of descriptive statistics for the excess return series and information variables are presented in Table 1. These include mean, standard deviation, skewness, excess kurtosis, the *p*-value for the Bera-Jarque (B-J) test statistics (distributed as $\chi^2(2)$) of the null hypothesis of normal unconditional distribution, autocorrelation coefficients and the *p*-value for the Ljung-Box (L-B) test statistics (distributed as $\chi^2(5)$) for the joint null hypothesis that autocorrelation coefficients from first- to fifth-order lags are all zero.

Summary statistics for excess return series are shown in Panel A in Table 1. Daily mean excess returns vary from minus 0.007% (Ireland) to 0.044% (Austria). Standard deviations range from 0.948% (Netherlands) to 2.464% (Finland). If these figures are annualized we clearly see that the

Table 1. Descriptive statistics for the daily excess returns and information variables[a]

The statistics are based on daily data from 4 January 1999 to 31 December 2007 (2346 observations). The daily euro nominated excess returns on the ten EMU countries' equity indices and the world index are calculated using MSCI (Morgan Stanley Capital International) indices which are all value-weighted total return indices. One-month EURIBOR rate is used as a proxy for the risk-free rate calculation. Information variables are: the change in the US term premium (ΔUSTP), the yield on Moody's Baa rated bonds less the yield on Aaa rated bonds (USDP) and the difference between the 3-month T-bill and 3-month EURIBOR rates (dINT). All information variables are lagged by one day. B-J is the *p*-value from the Bera-Jarque test for normality and Q(5) is the Ljung-Box statistic of order 5 *p*-value

	Mean (%)	Std.dev. (%)	Skewness	Excess kurtosis	B-J (*p*-value)	Autocorrelations ρ_1	ρ_2	ρ_3	ρ_5	Q(5)
Panel A. Asset excess return series										
Austria	0.044	0.995	-0.502*	2.958*	<0.001	0.023	0.018	0.015	0.018	0.648
Belgium	0.003	1.216	0.219*	5.888*	<0.001	0.107*	0.001	-0.074*	-0.046*	<0.001
Finland	0.026	2.464	-0.458*	6.893*	<0.001	-0.008	-0.001	-0.039	-0.021	0.437
France	0.016	1.339	-0.137*	2.813*	<0.001	-0.012	-0.022	-0.056*	-0.064*	0.002
Germany	0.014	1.495	-0.114*	2.938*	<0.001	-0.031	0.020	-0.025	-0.047*	0.069
Ireland	-0.007	1.201	-0.573*	4.208*	<0.001	0.076*	0.012	-0.004	-0.021	0.004
Italy	0.009	1.155	-0.191*	3.181*	<0.001	-0.015	0.015	-0.003	-0.064*	0.015
Netherlands	0.006	1.355	-0.179*	4.253*	<0.001	-0.020	0.006	-0.057*	-0.073*	<0.001
Portugal	0.009	0.948	-0.273*	2.340*	<0.001	0.086*	-0.021	0.025	-0.021	<0.001
Spain	0.025	1.301	-0.010	2.811*	<0.001	-0.015	-0.017	-0.045*	-0.030	0.143
World	0.003	1.025	-0.036	2.266*	<0.001	0.084*	0.000	-0.029	-0.033	0.001
Panel B. Information variables										
ΔUSTP	<0.001	0.066	0.308*	7.970*	<0.001	0.062*	-0.026	-0.088*	0.023	<0.001
USDP	0.917	0.195	0.849*	0.171	<0.001	0.995*	0.990*	0.984*	0.971*	<0.001
dINT	0.127	1.352	-0.071	-1.620*	<0.001	0.998*	0.996*	0.994*	0.990*	<0.001

[a] Usual approximations for standard errors are used (skewness √(6/T), kurtosis √(24/T), autocorrelation coefficients 1/√T) to create confidence intervals.
* Denotes significance at least at 5%-level.

chosen period has been quite volatile. Interestingly, although being very close, the world portfolio fails to be the least volatile excess return series. Eight countries exhibit negative skewness, which indicates that their unconditional distributions are more skewed to the left than the normal distribution. Not surprisingly, only one (Belgium) series shows significant positive skewness. Excess kurtosis is significant for every return series meaning that unconditional distributions have heavy tails. This is consistent for example with findings reported by De Santis and Imrohoroglu (1997) how uses weekly data. The B-J static *p*-values show that the null of normality is clearly rejected for every series.

The L-B static *p*-values indicate that if 5%-level is used the null is rejected for the seven of the eleven excess return series. Somewhat surprisingly only three countries and the world portfolio exhibit significance positive first-lag autocorrelation. All significant higher order terms that are found in six cases are negative. As Balaban *et al*. (2001) mention, these higher order terms imply mean reversion and reflect the correlation of five trading days. Akgiray (1989) points out, that in the situation where series are not normal may use of usual approximations in creating confidence intervals lead to understatements. Despite this, values reported here are generally sufficiently large/small to give confidence for our conclusions.

Overall, we can summarize some implications of these findings concerning return series as follows. First, the use of QML estimates is highlighted. Second, significant skewness may indicate that asymmetric effects in conditional second moments will be found. Third, for some series the use of AR-term is necessary. There remains possibility that with multivariate models the vector autoregressive (VAR) mean specification would be appropriate. However, we want to preserve comparability and simplicity and pass the test of this aspect. Finally, it should be noted that the proper final AR-lag structure could also be determined using information criteria like Akaike's or Schwarz's Bayesian information criterion, which in some cases would be preferred practise.

Summary statistics for the information variables are shown in Panel B in Table 1. For all series, the null for normality is clearly rejected and autocorrelations are strongly present. The mean of the US default premium (USDP) agrees with those reported by De Santis and Gérard (1997) and Antell and Vaihekoski (2007). However, it is not sensible to compare the US term premium change (ΔUSTP) directly, because of our daily calculations. Interest rate difference (dINT) has been quite variable in our sample period and changes its sign couple of times during the period. All correlations (not reported) between information variables are week indicating that they do not carry redundant information.

3.2 GARCH specification tests

Before estimating final GARCH models it is sensible first to make sure that chosen class of models is appropriate for the data. We use testing methodology for ARCH effects proposed by Engle (1982). To test the presence of ARCH effects in residuals, first least square regression with constant as an explanatory variable is run for every series and resulting error terms are saved. Second, resulted error terms are squared and regressed on q own lags. Value of the Lagrange multiplier (LM) test statistic is given in usual way as TR^2, where T is the number of observations and R^2 is obtained coefficient of determination from the auxiliary regression. Statistics is distributed as $\chi^2(q)$. The null hypothesis is a joint hypothesis that all from first- to q^{th}-order autocorrelation coefficients are zero.

Results from the test are show in Panel A in Table 2. All static are significant at least at 5%-level and generally values are sufficient large to give confidence for conclusions even in the case of lack of normality. Results show clear evidence of ARCH effects in all series. This indicates that ARCH type of models should be well suited for all series.

Table 2. Specification tests for GARCH models

This table reports ARCH effect test statistics and cross-correlations of squared excess returns between world and Country *i.* Estimation is based on daily euro nominated excess returns from 4 January 1999 to 31 December 2007 (2346 observations). The data for the countries and world indices is calculated by MSCI (Morgan Stanley Capital International). The risk-free rate is approximated using the 1-month EURIBOR for calculations.

Panel A. ARCH effect test[a]

(q)	1	2	3	4	5	6	7
Austria	31.291*	61.164*	86.149*	146.979*	161.995*	162.166*	167.798*
Belgium	249.185*	295.817*	348.576*	357.465*	381.005*	398.657*	412.063*
Finland	21.183*	30.716*	39.594*	43.015*	54.907*	66.234*	67.478*
France	95.540*	213.881*	300.688*	324.872*	355.425*	435.381*	452.067*
Germany	78.878*	218.999*	337.287*	410.740*	433.666*	463.955*	498.152*
Ireland	34.412*	84.539*	127.735*	132.090*	138.886*	140.336*	142.964*
Italy	80.750*	175.515*	285.103*	331.070*	354.964*	399.760*	423.178*
Netherlands	139.776*	263.864*	431.648*	454.672*	537.659*	571.255*	590.048*
Portugal	85.999*	134.016*	171.790*	191.205*	197.883*	204.046*	208.237*
Spain	65.408*	162.502*	252.879*	304.234*	311.022*	363.332*	454.717*
World	19.610*	81.788*	140.646*	169.438*	191.824*	218.647*	235.460*

Panel B. Cross-correlations of squared excess returns - World and Country[b]

Lag	-3	-2	-1	0	1	2	3
Austria	0.096*	0.025	-0.006	0.127*	0.020	0.070*	0.054*
Belgium	0.161*	0.238*	0.143*	0.520*	0.157*	0.125*	0.203*
Finland	0.063*	0.067*	0.051*	0.290*	0.082*	0.071*	0.071*
France	0.195*	0.219*	0.142*	0.664*	0.146*	0.161*	0.208*
Germany	0.198*	0.178*	0.145*	0.673*	0.109*	0.249*	0.213*
Ireland	0.128*	0.127*	0.052*	0.243*	0.091*	0.097*	0.084*
Italy	0.169*	0.156*	0.166*	0.537*	0.108*	0.167*	0.170*
Netherlands	0.196*	0.223*	0.137*	0.630*	0.168*	0.171*	0.248*
Portugal	0.132*	0.124*	0.131*	0.301*	0.100*	0.116*	0.147*
Spain	0.166*	0.229*	0.127*	0.552*	0.175*	0.183*	0.190*

[a] $\chi^2(q)$ 5%-critical values for 1…q are 3.841, 5.991, 7.815, 9.488, 11.070, 12.592 and 14. 067, respectively.
[b] Usual approximation +/-1.96*1/√T is used for cross-correlations confidence interval.
* Denotes significance at least at 5%-level.

Neither of our MGARCH models allows cross-market dependences in volatility. Justification of this assumption, between the world and the country *i*, can be tested by analyzing cross-correlations of squared excess returns at different leads and lags. Results are shown in Panel B in Table 2. Excluding Austria, for all other countries all cross-correlations turn out to be significant at least at 5%-level. This indicates that our diagonal GARCH parameterizations may be too restrictive. However, because of other desirable features of our models we choose not to adjust our models further. Based on the limited evidence, diagonal GARCH models may be better suited for longer interval data. For example, De Santis and Gérard (1997, 1998) using monthly data, do not find significance cross-correlations excluding few exceptions.

Overall, findings support the use of chosen class of models. At least for the most of the countries, when the bivariate analysis is considered, the assumption that the country shock do not affect the world variance process, should not be theoretically too restrictive. Empirical results reported by Conrad *et al.* (1991) and Kroner and Ng (1998) how both find evidence that large-firm returns can affect the volatility of small-firm returns but not vice versa further supports this view. However, the assumption that the world shock does not affect the country variance process is stronger and should be recognised when analyzing results.

4. EMPIRICAL RESULTS

4.1 Segmented markets

We first begin our empirical analysis considering the situation where markets are fully segmented, meaning that investors do not diversify their portfolios internationally. This leads into situation where investors should be rewarded for the local risk only. We also assume that the price of local market risk is constant. As De Santis and Gérard (1997) mention, this means from the theoretical asset pricing perspective that although the conditional risk-free rate and mean-standard deviation frontier can change from period to period, the slope stays fixed. Empirical model constitutes from conditional mean equation (18) and conditional variance equation (11). Hypothesis and empirical model are considered more detailed in Section 2.3.

Panel A in Table 3 contains QML estimates of the parameters from the GJR-GARCH-M model. The point estimates for the price of local market risk λ_i varies from -0.061 for Portugal to 0.016 for France and the Netherlands. For half of the countries its value stays negative. However, coefficient λ_i turns out to be insignificant for every country. AR(1) parameter δ_i is positive and significant for all countries for which it is included (Belgium, Ireland and Portugal). This is just what was expected from the AR(1) term for these countries based on pre-specifications. For these countries this coefficient takes account the positive autocorrelation in the returns induced by the non-synchronous trading.

For every country, the estimated parameters for the GARCH process clearly show that the variance is time-varying, in all cases b_i are significant at 1%-level and a_i at least at 5%-level for four countries (Finland, Germany, Ireland and Portugal). De Santis and Imrohoroglu (1997) points out concerning their results, that because the GARCH term coefficients turn

Table 3. The GJR-GARCH(1,1)-M estimation results

Quasi-Maximum Likelihood (QML) estimates are based on daily euro nominated excess returns from 4 January 1999 to 31 December 2007 (2346 observations). Index data for the countries is calculated by MSCI (Morgan Stanley Capital International). The risk-free rate is approximated using the 1-month EURIBOR for calculations. The GJR-GARCH-M model's conditional mean equation (18) relates the index excess return to its conditional market risk $h_{ii,t}=Var_{t-1}(r_{i,t})$ and the conditional variance is parameterized as in eq. (11)

(18) $r_{i,t} = \omega_i + \delta_i r_{i,t-1} + \lambda_i h_{ii,t} + \varepsilon_{i,t} \quad \varepsilon_{i,t} | Z_{t-1} \sim N(0, h_{ii,t})$ and (11) $h_{ii,t} = c_i + a_i \varepsilon^2_{i,t-1} + b_i h_{ii,t-1} + d_i \eta^2_{i,t-1}$ where $\eta_{i,t}$ = max[0, $-\varepsilon_{i,t}$]

Skewness and excess kurtosis of standardized residuals are given as m_3 and m_4, respectively. B-J denotes Bera-Jarque statistics for normality and LLF log likelihood function. QML standard errors are reported in parenthesis.

	Austria	Belgium	Finland	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain[a]
Panel A. Parameter estimates										
ω_i	0.099**	0.027	0.129**	0.002	0.026	0.046	0.006	-0.006	0.070**	0.031
	(0.038)	(0.027)	(0.041)	(0.032)	(0.029)	(0.033)	(0.024)	(0.027)	(0.026)	(0.030)
δ_i		0.058**				0.047*			0.065**	
		(0.022)				(0.023)			(0.025)	
λ_i	-0.048	-0.002	-0.016	0.016	0.001	-0.031	0.007	0.016	-0.061	0.007
	(0.042)	(0.030)	(0.010)	(0.024)	(0.017)	(0.026)	(0.024)	(0.020)	(0.035)	(0.026)
c_i	0.054**	0.022**	0.003	0.022**	0.025**	0.071*	0.019**	0.021**	0.012	0.017**
	(0.011)	(0.006)	(0.002)	(0.007)	(0.007)	(0.031)	(0.005)	(0.006)	(0.007)	(0.006)
a_i	0.004	0.025	0.029**	0.013	0.022*	0.026*	0.010	0.001	0.039*	
	(0.016)	(0.015)	(0.005)	(0.015)	(0.009)	(0.013)	(0.009)	(0.015)	(0.017)	
b_i	0.866**	0.884**	0.981**	0.917**	0.908**	0.852**	0.900**	0.922**	0.917**	0.932**
	(0.020)	(0.020)	(0.006)	(0.012)	(0.010)	(0.034)	(0.014)	(0.012)	(0.030)	(0.014)
d_i	0.140**	0.140**	-0.019	0.105**	0.109**	0.141**	0.143**	0.117**	0.060	0.106**
	(0.026)	(0.024)	(0.012)	(0.026)	(0.020)	(0.046)	(0.024)	(0.024)	(0.032)	(0.022)
Panel B. Diagnostic tests										
m_3	-0.312**	-0.281**	-0.400**	-0.319**	-0.200**	-0.635**	-0.299**	-0.382**	0.004	-0.243**
m_4	1.303**	0.844**	4.030**	0.818**	0.567**	4.227**	0.789**	1.267**	2.305**	1.049**
B-J	204.198**	100.397**	1649.776**	105.152**	47.015**	1903.477**	95.710**	213.857**	518.956**	130.683**
LLF	-3142.120	-3213.752	-4959.699	-3606.213	-3817.480	-3552.002	-3245.820	-3490.150	-2947.533	-3547.841

[a] After restricting coefficient $a_i \geq 0$ to ensure the non-negativity of conditional variance, it was found that coefficient is zero and the final model was estimated without it.
** and * denotes significance at least at the levels of 1% and 5%, respectively.

out to be considerably larger than the ARCH terms it means that large market shocks induce relative small revisions in future variance, the same conclusion can be done for all countries in our case. Asymmetry coefficient d_i is significant and positive for all countries except for Finland and Portugal. This means that hypothesised leverage effects are clearly present in eight of the ten cases. These findings are consistent with those reported by Glosten *et al*. (1993) using different data set and partly consistent with those reported by Balaban *et al*. (2001) who find asymmetries in variance for Germany, France and Italy and no asymmetries for Finland, but contrary to our findings report none asymmetries for Austria, Belgium, the Netherlands and Spain. These differences are probably caused by the different conditional mean equation and the older data set used by Balaban *et al*. (2001).

Because $\lambda_i = 0$ we have to conclude for all countries that although the conditional variances are time-varying, time-varying risk premium is not induced by the conditional market risk, at least measured in this way. De Santis and Gérard (1997) argue that possible explanation for this kind of results may be due the assumption of constancy of the price of market risk. In the case where excess returns are considerably more variable than the conditional variance of the market, a model where λ_i is constant may not have enough power to explain the time variation of the risk premium. On the other hand, the observed insignificant relation between the expected risk premiums and country-specific risk is not so surprisingly since already the EMU membership itself speaks against the segmented markets assumption. Overall, our results considering insignificant λ_i widely agrees with empirical findings from various markets (e.g., Balaban *et al*. 2001; De Santis and Imrohoroglu 1997; Theodossiou and Lee 1995).

We conduct same kind of diagnostic checking for the standardized residuals as Akgiray (1989). If conditional variance equations are correctly specified ARCH effects in standardized residuals should have been disappeared. This is tested again with the Lagrange multiplier test. For six countries ARCH effects are not found. For Germany (lags 1,2,3 and 7), Italy (lag 1), the Netherlands (lags 3,4,5,6 and 7) and Spain (lag 7) there are still some significant effects left. For these countries higher order GARCH specification could be more proper alternative. If compared to the corresponding values for the excess returns we do not find many improvements in skewness in Panel B in Table 3. However, the excess kurtosis in standardized residuals has reduced considerably for all countries except for Ireland and Portugal. Despite reduction, excess kurtosis index stays statistically significant for all countries. The same is true for all Bera-Jarque test static. These results indicate that the use of conditional *t*-distribution could be more appropriate assumption.

Finally, we report that stationary condition $a_i + b_i + ½ d_i <1$ is satisfied for all countries, although due the rounding procedure, the Table 3 shows for example that the stationary condition for Finland would not be satisfied. Also conditions to ensure non-negativity of conditional variance are satisfied easily for the nine countries. For the Spain we have to impose restriction $a_i \geq 0$. After estimating model with this restriction it is found that this coefficient is zero and do not anymore affect functions value, so for the Spain the final specification is estimated without it.

4.2 Integrated markets

In this section we assume that markets are fully integrated. This means that the expected risk premium on asset should be proportional to the conditional covariance between the return on that asset and an international market portfolio. Empirical model constitutes from conditional mean equation (19) and conditional covariance and variance equations given as in equation (16) in the case of asymmetric DVECH and (17) in the case of asymmetric CCORR. Same way as in previous section, the price of market risk is assumed to be constant.

Panel A in Table 4 contains QML estimates of the parameters from the bivariate GJR-DVECH-M model for the world and country *i*. The point estimates for the price of global market risk λ varies from 0.010 for Finland to 0.045 for Ireland. In contrast to segmented markets results it also stays positive in every case as suggested by the theory. However, again for every country, coefficients λ turns out to be insignificant. Coefficient δ_i is significant only for Ireland and for both Portugal and world in their bivariate model. Results indicate for all other pair-wise analyses that the world portfolio would maybe not need the AR(1) term in it's conditional mean equation. However, after estimating most of the models without the AR term in the world portfolio's mean equation, it is found that results stay practically unchanged.

For every pair-wise comparison, the estimated parameters for the conditional variances clearly show that the variance is time-varying, all b_{ii} are significant at 1%-level and a_{ii} at least at 5%-level for Finland, France, Germany and Italy. Interestingly, if the model with Ireland is not considered, the coefficient a_{ii} stays always insignificant for the world portfolio. Conditional covariance process between country *i* and the world is also clearly time-varying and dominated by the b_{ij} term for every country. This means that also for covariances large shocks induce relative small revisions in future covariance.

Asymmetry coefficient d_{ii} for asymmetries in the conditional variances is significant and positive in all cases excluding Finland which has negative and significant coefficient and Portugal which have insignificant coefficient. Coefficient d_{ij} for asymmetries in the conditional covariance between the world and country *i* is also significant and positive for all countries excluding Austria and Finland which have insignificant coefficients. We also test the hypothesis that all asymmetry coefficients are jointly equal to zero. The robust Wald $\chi^2(3)$ static reported in Panel B shows that for all countries this hypothesis is rejected at least at 5%-level by the data.

Table 4. The bivariate GJR-DVECH(1,1)-M estimation results

Quasi-Maximum Likelihood (QML) estimates are based on daily euro nominated excess returns from 4 January 1999 to 31 December 2007 (2346 observations). The equity index data for Austria (AST), Belgium (BEL), Finland (FIN), France (FRA), Germany (GER), Ireland (IRE), Italy (ITA), the Netherlands (NET), Portugal (POR), Spain (SPA) and world (WOR) is calculated by MSCI (Morgan Stanley Capital International). The risk-free rate is approximated using the 1-month EURIBOR for calculations. The bivariate GJR-DVECH-M model's conditional mean equations relates the index excess return to its conditional market risk $h_{iw,t} = Cov_{t-1}(r_{it}, r_{wt})$ as

(19)
$$\begin{aligned} r_{i,t} &= \omega_i + \delta_i r_{i,t-1} + \lambda h_{iw,t} + \varepsilon_{i,t} \\ r_{w,t} &= \omega_w + \delta_w r_{w,t-1} + \lambda h_{ww,t} + \varepsilon_{w,t} \end{aligned} \qquad \varepsilon_t | Z_{t-1} \sim N(0, H_t)$$

where λ denotes the price of global market risk. The elements of conditional covariance matrix $H_t = [h_{ij,t}]$ follow the asymmetric DVECH parameterization as

(16)
$$\begin{aligned} h_{ii,t} &= c_{ii} + b_{ii} h_{ii,t-1} + a_{ii} \varepsilon^2_{i,t-1} + d_{ii} \eta^2_{i,t-1} \qquad \forall i \\ h_{ij,t} &= c_{ij} + b_{ij} h_{ij,t-1} + a_{ij} \varepsilon_{i,t-1} \varepsilon_{j,t-1} + d_{ij} \eta_{i,t-1} \eta_{j,t-1} \qquad \forall i \neq j \end{aligned}$$
where $\eta_{i,t} = \max[0, -\varepsilon_{i,t}]$

Skewness and excess kurtosis of standardized residuals are given as m_3 and m_4, respectively. B-J denotes Bera-Jarque statistics for normality and LLF log likelihood function. QML standard errors are reported in parenthesis. $\chi^2(3)$ denotes robust Wald-test statistics for the null of joint insignificance of the asymmetry terms.

	AST	WOR[a]	BEL	WOR	FIN[a]	WOR[a]	FRA	WOR	GER	WOR
Panel A. Parameter estimates										
ω_i	0.052*	-0.014	0.020	<0.001	0.075	0.007	-0.006	-0.017	0.011	-0.017
	(0.022)	(0.030)	(0.024)	(0.030)	(0.051)	(0.036)	(0.040)	(0.039)	(0.037)	(0.035)
δ_i		0.014	0.026	-0.011		-0.011		-0.018		0.022
		(0.022)	(0.019)	(0.019)		(0.019)		(0.016)		(0.015)
λ	0.027		0.018		0.010		0.036		0.035	
	(0.037)		(0.036)		(0.045)		(0.040)		(0.039)	
c_{ii}	0.056**	0.004	0.017**	0.006	0.002	0.003	0.021**	0.007	0.022**	0.008*
	(0.013)	(0.003)	(0.006)	(0.004)	(0.002)	(0.003)	(0.007)	(0.005)	(0.006)	(0.004)
a_{ii}	0.004		0.020	0.014	0.024**		0.014*	0.011	0.021**	0.010
	(0.013)		(0.012)	(0.008)	(0.005)		(0.006)	(0.006)	(0.008)	(0.007)
b_{ii}	0.875**	0.971**	0.914**	0.955**	0.986**	0.979**	0.931**	0.957**	0.925**	0.954**
	(0.022)	(0.009)	(0.020)	(0.015)	(0.006)	(0.009)	(0.012)	(0.014)	(0.009)	(0.012)
d_{ii}	0.114**	0.048**	0.094**	0.048**	-0.019**	0.032**	0.076**	0.047**	0.078**	0.052**
	(0.023)	(0.013)	(0.021)	(0.015)	(0.007)	(0.011)	(0.018)	(0.015)	(0.017)	(0.011)
c_{ij}	0.009		0.006		0.002		0.009*		0.008*	
	(0.005)		(0.003)		(0.002)		(0.005)		(0.003)	
a_{ij}	0.019*		0.016*		0.013*		0.016*		0.014*	
	(0.009)		(0.006)		(0.004)		(0.007)		(0.007)	
b_{ij}	0.941**		0.940**		0.982**		0.946**		0.946**	
	(0.018)		(0.015)		(0.004)		(0.013)		(0.009)	
d_{ij}	0.017		0.057**		0.005		0.047**		0.053**	
	(0.010)		(0.015)		(0.009)		(0.015)		(0.011)	
Panel B. Diagnostic tests and robust Wald-test										
m_3	-0.333**	-0.396**	-0.299**	-0.417**	-0.369**	-0.348**	-0.308**	-0.398**	-0.203**	-0.391**
m_4	1.344**	1.565**	0.889**	1.644**	3.681**	1.350**	0.724**	1.497**	0.519**	1.498**
B-J	220.0**	300.7**	112.2**	332.1**	1377.7**	225.2**	88.4**	281.0**	42.4**	278.8**
LLF	-6062.460		-5837.449		-7634.114		-5856.928		-6052.533	
$\chi^2(3)$	37.869**		24.317**		24.062**		19.340**		31.401*	

(*continued on next page*)

Table 4. (*continued*)

	IRE	WOR	ITA	WOR	NET	WOR	POR[a]	WOR[a]	SPA	WOR
Panel A. Parameter estimates										
ω_i	-0.009	-0.025	0.009	-0.013	-0.009	-0.019	0.019	-0.022	0.015	-0.021
	(0.026)	(0.025)	(0.032)	(0.041)	(0.031)	(0.034)	(0.018)	(0.036)	(0.028)	(0.031)
δ_i	0.073**	-0.007		0.026		-0.022	0.077**	0.041*		0.023
	(0.020)	(0.018)		(0.016)		(0.012)	(0.020)	(0.018)		(0.016)
λ	0.045		0.031		0.038		0.041		0.036	
	(0.029)		(0.048)		(0.039)		(0.042)		(0.036)	
c_{ii}	0.101**	0.017**	0.015**	0.007	0.017**	0.007	0.012	0.006	0.014*	0.006
	(0.035)	(0.004)	(0.006)	(0.005)	(0.006)	(0.004)	(0.010)	(0.005)	(0.006)	(0.004)
a_{ii}	0.026	0.017*	0.023**	0.014	0.001	0.008	0.028		0.006	0.007
	(0.015)	(0.008)	(0.008)	(0.008)	(0.007)	(0.005)	(0.015)		(0.009)	(0.010)
b_{ii}	0.833**	0.926**	0.925**	0.955**	0.939**	0.959**	0.931**	0.963**	0.946**	0.958**
	(0.034)	(0.011)	(0.015)	(0.016)	(0.012)	(0.011)	(0.036)	(0.015)	(0.019)	(0.018)
d_{ii}	0.128**	0.077**	0.069**	0.043**	0.088**	0.046**	0.050	0.057**	0.070**	0.054**
	(0.047)	(0.013)	(0.018)	(0.014)	(0.014)	(0.012)	(0.032)	(0.019)	(0.024)	(0.015)
c_{ij}	0.037**		0.007*		0.007*		0.003		0.006	
	(0.001)		(0.004)		(0.003)		(0.003)		(0.004)	
a_{ij}	0.019		0.029**		0.008		0.007		0.011	
	(0.013)		(0.008)		(0.006)		(0.011)		(0.010)	
b_{ij}	0.847**		0.940**		0.953**		0.953**		0.952**	
	(0.014)		(0.013)		(0.010)		(0.017)		(0.018)	
d_{ij}	0.077**		0.032*		0.049**		0.039*		0.048**	
	(0.024)		(0.013)		(0.012)		(0.017)		(0.018)	
Panel B. Diagnostic tests and robust Wald-test										
m_3	-0.619**	-0.408**	-0.303**	-0.383**	-0.371**	-0.392**	-0.009	-0.383**	-0.257**	-0.400**
m_4	3.984**	1.504**	0.859**	1.490**	1.067**	1.456**	2.310**	1.468**	1.064**	1.553**
B-J	1701.7**	286.4**	108.1**	274.4**	165.0**	267.3**	521.2**	268.0**	136.4**	298.4**
LLF	-6435.857		-5700.720		-5791.986		-5854.015		-6036.262	
$\chi^2(3)$	36.693**		24.901**		51.811**		9.075*		16.460**	

[a] To ensure the non-negativity of conditional variance we restrict $a_{ii} \geq 0$. If after imposing restriction it is found that coefficient is zero the final model is estimated without it.
** and * denotes significance at least at the levels of 1% and 5%, respectively.

Given these results, asymmetric effects in the conditional variances and covariance are clearly present and should be recognised. In multivariate empirical analyses the parsimonious MGARCH parameterization is often chosen before other aspects and in the light of our results this may affect results in undesirable ways. Our findings contrast those test static reported by De Santis and Gérard (1997) how use different monthly data set and conduct diagnostic checking and find no asymmetries in conditional co-variance matrix. It is likely that longer return interval that they use explains these differences. However, this aspect has gained surprisingly little attention in empirical multivariate analyses concerning the conditional risk-return relationships.

As with the segmented markets results, we do the same conclusion that the time-varying risk premiums are not induced this time by the conditional covariance between the world portfolio and country *i*. Our findings of insignificant coefficients λ agree with findings of De Santis and Gérard (1997, 1998) and partly with De Santis and Imrohoroglu (1997). Given the earlier studies from various markets and results reported here, it is likely that the dynamics of the risk premiums cannot be explained with the time-variation of risk itself, at least measured in this way.

Diagnostic checking is done in a same way as before. As Tsay (2005) mention, the use of multivariate statistics would maybe be preferable practise in the multivariate contexts. However, we follow many earlier empirical studies and conduct diagnostics using only univariate statistics. ARCH effects in standardized residuals have disappeared for five countries and in all cases for the world. For Belgium (lags 1,2,3,4 and 5), Germany (lags 1 and 7), Italy (lag 7), the Netherlands (lags 3,4,5,6 and 7) and Spain (lag 7) there are still some statistically significant effects left. If Ireland and Portugal are excluded, the excess kurtosis in standardized residuals has again reduced considerably for all other countries and in all cases for the world. However, excess kurtosis index and Bera-Jarque test static stays statistically significant for all countries, indicating the possible need for the conditional multivariate *t*-distribution.

Although our model does not guarantee the positive definiteness, the implied conditional correlation between the country *i* and the world portfolio stays always between -1 and 1. Individual processes also satisfy stationary conditions, although for Finland we have to restrict coefficients to ensure stationary. Non-negativity ensuring conditions for the individual conditional variances are satisfied without restrictions in seven bivariate models for the world portfolio and country *i*. For Austria, Finland and Portugal we have to impose restriction $a_{ii} \geq 0$ for both the country's coefficient (excluding Austria) and for the world's coefficients. After estimating models with these restrictions, the coefficient a_{ii} in the world's conditional variance equation is found to be zero in all cases and the final bivariate models for these countries are estimated without it. It should be noted that when models are estimated without these restrictions results stay practically unchanged and examination of estimated conditional variances show that non-negativity is never violated. However, theoretically restricted estimations are more robust.

We also estimate the bivariate GJR-CCORR-M model for every country and the world portfolio. Results are reported in Appendix 2. The main difference compared to those reported above, is that the point estimates for the price of global market risk λ has some tendency to be smaller varying from <0.001 for Finland to 0.036 for Portugal. Other main results and conclusions based on those stay practically unchanged and are not treated further. As with the DVECH, for this model stationary conditions are satisfied for all individual processes, although for Finland we have to again impose restrictions. However, conditions ensuring non-negativity of conditional variance turn out to be harder to achieve than with the DVECH model. In six cases after imposing restrictions for the world portfolio's parameter a_{ii} it is found to be zero and excluded from the final models and in two cases this have to be done for country specific parameter as well. Diagnostic checking shows that ARCH effects are left in standardized residuals for Belgium (lag 1), Germany (lags 1,2 and 7), Italy (lag 7), the Netherlands (lags 3,4,5,6 and 7) and Spain (lags 6 and 7) which are same countries as was with the DVECH model, although lags are not exactly same. However, because the assumption about time-invariant conditional correlation may be rather restrictive we consider results from the DVECH specification as more robust.

4.3 Partially segmented markets

In this section we consider the third possibility and assume that markets are partially segmented. In this specification the expected risk premium for each country depends from both the conditional covariance with the world portfolio and also on the country-specific factor that is the conditional variance of the country's stock market. Empirical model constitutes from conditional mean equation (21) and equations (16) and (17) in the case of asymmetric DVECH or asymmetric CCORR, respectively. We follow the same assumption as earlier and assume that prices of global and local market risks are constant.

The QML estimates of the parameters from the bivariate GJR-DVECH-M model for the world portfolio and country *i* are reported in Table 5 in Panel A. The point estimates for the price of global market risk λ varies from 0.015 for Finland to 0.043 for Portugal. None of the coefficients λ turns out to be statistically significant. For the price of local market risk λ_i estimates vary from -0.071 for Austria to 0.004 for France and are in eight cases negative. None of these coefficients are significant either which agrees results reported by De Santis and Gérard (1997). As with the integrated markets, the AR term is significant only for Ireland and for Portugal and world in their bivariate model. This potential misspecification is again checked by estimating most models without the AR term in the world portfolio's mean equation. We find again that this have negligible effects for the results. After our third stage analysis we can conclude that the time-varying risk premium induced only by the conditional second moments is not present, regardless the assumption of prevailing degree of market integration. Of course there remains the possibility that the level of market integration is time-varying as suggested by Bekaert and Harvey (1995).

The conditional variance and covariance processes are again clearly time-varying in all cases. Because the estimated coefficients and their interpretations are almost the same as in the previous section they are not

Table 5. The bivariate GJR-DVECH(1,1)-M estimation results

Quasi-Maximum Likelihood (QML) estimates are based on daily euro nominated excess returns from 4 January 1999 to 31 December 2007 (2346 observations). The equity index data for Austria (AST), Belgium (BEL), Finland (FIN), France (FRA), Germany (GER), Ireland (IRE), Italy (ITA), the Netherlands (NET), Portugal (POR), Spain (SPA) and world (WOR) is calculated by MSCI (Morgan Stanley Capital International). The risk-free rate is approximated using the 1-month EURIBOR for calculations. The bivariate GJR-DVECH-M conditional mean equations relates the index excess return to its conditional global market risk $h_{iw,t} = Cov_{t-1}(r_{it}, r_{wt})$ and conditional country's local risk $h_{ii,t} = Var_{t-1}(r_{i,t})$ as

(21)
$$\begin{aligned} r_{i,t} &= \omega_i + \delta_i r_{i,t-1} + \lambda h_{iw,t} + \lambda_i h_{ii,t} + \varepsilon_{i,t} \\ r_{w,t} &= \omega_w + \delta_w r_{w,t-1} + \lambda h_{ww,t} + \varepsilon_{w,t} \end{aligned} \qquad \varepsilon_t \left| Z_{t-1} \sim N\left(0, H_t\right)\right.$$

where λ and λ_i denotes the price of global and local market risk, respectively. The elements of conditional covariance matrix $H_t = [h_{ij,t}]$ follow the asymmetric DVECH parameterization as follows

(16)
$$\begin{aligned} h_{ii,t} &= c_{ii} + b_{ii} h_{ii,t-1} + a_{ii} \varepsilon_{i,t-1}^2 + d_{ii} \eta_{i,t-1}^2 \qquad \forall i \\ h_{ij,t} &= c_{ij} + b_{ij} h_{ij,t-1} + a_{ij} \varepsilon_{i,t-1} \varepsilon_{j,t-1} + d_{ij} \eta_{i,t-1} \eta_{j,t-1} \quad \forall i \neq j \end{aligned}$$ where $\eta_{i,t} = \max[0, -\varepsilon_{i,t}]$

Skewness and excess kurtosis of standardized residuals are given as m_3 and m_4, respectively. B-J denotes Bera-Jarque statistics for normality and LLF log likelihood function. QML standard errors are reported in parenthesis. $\chi^2(3)$ denotes robust Wald-test statistics for the null of joint insignificance of the asymmetry terms.

	AST	WOR[a]	BEL	WOR	FIN	WOR[a]	FRA	WOR	GER	WOR
Panel A. Parameter estimates										
ω_i	0.108**	-0.016	0.032	-0.006	0.083	0.003	-0.009	-0.016	0.015	-0.020
	(0.039)	(0.029)	(0.025)	(0.028)	(0.045)	(0.033)	(0.037)	(0.035)	(0.036)	(0.035)
δ_i		0.015	0.024	-0.011		-0.011		-0.018		0.022
		(0.016)	(0.017)	(0.018)		(0.017)		(0.013)		(0.016)
λ	0.029		0.024		0.015		0.035		0.038	
	(0.036)		(0.035)		(0.039)		(0.044)		(0.041)	
λ_i	-0.071		-0.021		-0.004		0.004		-0.006	
	(0.040)		(0.018)		(0.012)		(0.016)		(0.013)	
c_{ii}	0.051**	0.004	0.016**	0.006	0.002	0.003	0.022**	0.007	0.021**	0.008
	(0.012)	(0.003)	(0.005)	(0.004)	(0.002)	(0.002)	(0.008)	(0.005)	(0.007)	(0.004)
a_{ii}	0.004		0.021*	0.014	0.024**		0.014*	0.011	0.021**	0.010
	(0.012)		(0.010)	(0.009)	(0.005)		(0.007)	(0.007)	(0.007)	(0.007)
b_{ii}	0.879**	0.971**	0.915**	0.955**	0.986**	0.980**	0.930**	0.957**	0.926**	0.953**
	(0.019)	(0.009)	(0.019)	(0.016)	(0.006)	(0.007)	(0.012)	(0.014)	(0.011)	(0.013)
d_{ii}	0.116**	0.048**	0.095**	0.048**	-0.020**	0.032**	0.076**	0.047**	0.078**	0.052**
	(0.023)	(0.013)	(0.019)	(0.014)	(0.007)	(0.009)	(0.018)	(0.013)	(0.018)	(0.012)
c_{ij}	0.009*		0.006		0.002		0.009*		0.008*	
	(0.004)		(0.003)		(0.001)		(0.004)		(0.004)	
a_{ij}	0.020*		0.016*		0.013**		0.016*		0.014*	
	(0.009)		(0.007)		(0.004)		(0.006)		(0.006)	
b_{ij}	0.940**		0.940**		0.982**		0.946**		0.946**	
	(0.019)		(0.016)		(0.004)		(0.012)		(0.009)	
d_{ij}	0.017		0.057**		0.005		0.047**		0.053**	
	(0.011)		(0.015)		(0.008)		(0.014)		(0.012)	
Panel B. Diagnostic tests and robust Wald-test										
m_3	-0.330**	-0.395**	-0.294**	-0.416**	-0.366**	-0.348**	-0.309**	-0.399**	-0.203**	-0.390**
m_4	1.321**	1.559**	0.907**	1.628**	3.672**	1.345**	0.723**	1.499**	0.522**	1.492**
B-J	213.2**	298.6**	114.1**	326.8**	1370.6**	224.2**	88.3**	281.8**	42.7**	277.1**
LLF	-6060.990		-5836.756		-7634.013		-5856.894		-6052.418	
$\chi^2(3)$	34.070**		31.281**		32.847**		22.118**		26.225**	

(*continued on next page*)

Table 5. (*continued*)

	IRE	WOR	ITA	WOR	NET	WOR	POR[a]	WOR[a]	SPA	WOR
Panel A. Parameter estimates										
ω_i	0.048	-0.013	0.010	-0.013	-0.004	-0.022	0.054	-0.025	0.013	-0.021
	(0.035)	(0.029)	(0.035)	(0.040)	(0.032)	(0.032)	(0.029)	(0.038)	(0.030)	(0.031)
δ_i	0.069**	-0.002		0.026		-0.021	0.074**	0.042*		0.023
	(0.020)	(0.014)		(0.014)		(0.014)	(0.020)	(0.018)		(0.016)
λ	0.032		0.032		0.041		0.043		0.036	
	(0.038)		(0.043)		(0.037)		(0.043)		(0.034)	
λ_i	-0.043		-0.003		-0.009		-0.059		0.002	
	(0.023)		(0.023)		(0.015)		(0.034)		(0.020)	
c_{ii}	0.062*	0.007	0.015*	0.007	0.016**	0.007	0.011	0.006	0.014**	0.006*
	(0.026)	(0.008)	(0.007)	(0.005)	(0.005)	(0.004)	(0.009)	(0.006)	(0.004)	(0.003)
a_{ii}	0.028*	0.006	0.023*	0.014	<0.001	0.008	0.027*		0.006	0.007
	(0.011)	(0.012)	(0.011)	(0.010)	(0.008)	(0.006)	(0.013)		(0.006)	(0.005)
b_{ii}	0.875**	0.955**	0.925**	0.955**	0.940**	0.959**	0.933**	0.963**	0.946**	0.958**
	(0.031)	(0.030)	(0.018)	(0.018)	(0.013)	(0.013)	(0.034)	(0.017)	(0.010)	(0.010)
d_{ii}	0.100*	0.059*	0.069**	0.043**	0.088**	0.046**	0.052	0.056**	0.070**	0.054**
	(0.041)	(0.025)	(0.024)	(0.015)	(0.016)	(0.013)	(0.032)	(0.020)	(0.014)	(0.012)
c_{ij}	0.010		0.007		0.007*		0.003		0.006**	
	(0.008)		(0.004)		(0.003)		(0.002)		(0.002)	
a_{ij}	0.009		0.029**		0.008		0.007		0.011*	
	(0.008)		(0.010)		(0.006)		(0.012)		(0.005)	
b_{ij}	0.938**		0.940**		0.953**		0.955**		0.952**	
	(0.033)		(0.016)		(0.012)		(0.017)		(0.009)	
d_{ij}	0.045		0.032		0.049**		0.040*		0.048**	
	(0.027)		(0.017)		(0.014)		(0.018)		(0.012)	
Panel B. Diagnostic tests and robust Wald-test										
m_3	-0.666**	-0.416**	-0.303**	-0.383**	-0.370**	-0.391**	-0.005	-0.382**	-0.257**	-0.400**
m_4	4.453**	1.604**	0.860**	1.489**	1.074**	1.448**	2.298**	1.462**	1.063**	1.554**
B-J	2111.1**	319.1**	108.1**	274.1**	166.2**	264.6**	516.1**	266.1**	136.3**	298.6**
LLF	-6425.958		-5700.710		-5791.584		-5852.622		-6036.255	
$\chi^2(3)$	10.476*		21.464**		45.661**		7.826*		33.789**	

[a] To ensure the non-negativity of conditional variance we restrict $a_{ii} \geq 0$. If after imposing restriction coefficient is found to be zero the final model is estimated without it.
** and * denotes significance at least at the levels of 1% and 5%, respectively.

discussed further. More interesting is to find again that the coefficient d_{ii} for asymmetric effects in the conditional variances is significant and positive in all cases excluding Finland which has negative and significant coefficient and Portugal which has insignificant coefficient. The coefficient d_{ij} for asymmetries in the conditional covariance is significant and positive in all cases excluding Austria, Finland and contrast to results in previous section Ireland and Italy which have also insignificant coefficients. Again, the robust Wald $\chi^2(3)$ static reported in Panel B shows that for all countries the null of joint insignificance of asymmetry terms is rejected at least at 5%-

level. Results further strength the view that asymmetric effects should be allowed in the conditional variance-covariance matrix.

ARCH effects in standardized residuals have disappeared for five countries and in all cases for the world. Again, for Belgium (lags 1,2,3,4 and 5), Germany (1 and 7), Italy (lag 7), the Netherlands (lags 3,4,5,6 and 7) and Spain (lag 7) there are still significant effects left. If Ireland and Portugal are excluded, excess kurtosis in standardized residuals has again reduced considerably for all countries and in all cases for the world portfolio. However, excess kurtosis index and Bera-Jarque test static stays statistically significant for all countries, indicating the possible need for the conditional multivariate *t*-distribution. If we compare log-likelihood function values from partially segmented markets models to integrated markets models, values have stayed practically unchanged. Although this is rather rude way to measure, this further indicates that we cannot reject the assumption about fully integrated markets in favour for partially segmented markets.

We have to again impose restrictions for Finland's conditional variance parameters to ensure its stationary. Non-negativity ensuring conditions are satisfied after imposing restrictions $a_{ij} \geq 0$ for the world's coefficient with Austria and Finland and in the case of Portugal for country as well. In all cases, the parameter for the world is found to be zero and excluded from the final models. For all countries, the estimated correlation coefficients stay always between -1 and 1.

Results from the bivariate GJR-CCORR-M model for every country with the world portfolio are reported in Appendix 3. In contrast to the results from the DVECH model, for Austria and Ireland the price of local market risk is found to be negative and significant. This demonstrates that the choice how to model the conditional covariance may impact the results. Other main results and conclusions stay again practically same as with the DVECH model and are not discussed further. Restrictions and conditions concerning coefficients and optimization procedures are satisfied in practically same way as with the integrated markets and the corresponding constant correlation model.

4.4 Time-varying price of global market risk

A. Asymmetric model

Given the empirical results in the last three sections it seems that the time-variation of risk alone cannot explain the dynamics of the risk premiums. The results from earlier empirical studies (e.g., Harvey 1991; Bekaert and Harvey 1995; De Santis and Gérard 1997, 1998) indicate that indeed the price of global market risk is time-varying itself. This possibility is considered based on earlier empirical studies following assumption about fully integrated markets. We could of course additionally conduct our analyses with assumptions of other two levels of integration. However, our main goal is to demonstrate the possibility that the price of market risk is time-varying and risk premiums are driven by two time-varying components, so we limit our analysis to integrated markets case. We use four information variables to approximate the price of global market risk. It is likely that additional use of information variables like for example excess dividend yield could improve our approximation. However, as De Santis and Gérard (1997) mention any parameterization of the price of market risk can be criticized being ad hoc, so it can be argued that scarce use of information variables is maybe favourable, at least when the only purpose is to demonstrate the possibility of varying price of market risk.

Panel A in Table 6 contains QML estimates of the parameters for the price of global market risk from the bivariate GJR-CCORR-M model for the world portfolio and country *i*. This time we use only the constant correlation model because with the DVECH model we encountered problems with convergence. The constant parameter, the US default premium (USDP)

Table 6. Integrated markets and time-varying price of global market risk. Results from the bivariate GJR-CCORR-M for the world and country *i*.

Quasi-Maximum Likelihood (QML) estimates are based on daily euro nominated excess returns from 4 January 1999 to 31 December 2007 (2346 observations). Equity index data for the countries and world is calculated by MSCI (Morgan Stanley Capital International). The risk-free rate is approximated using the 1-month EURIBOR for calculations. The bivariate GJR-CCORR-M model's conditional mean equations (19) relates the index excess return to its conditional global market risk $h_{iw,t} = Cov_{t-1}(r_{it}, r_{wt})$.The price of global market risk is a function of information set Z_{t-1}, including a constant (Const), the US default premium (USDP), the change in US term premium (ΔUSTP) and interest rate difference (DINT). The elements of conditional covariance matrix H_t =[$h_{ij,t}$] follow the asymmetric CCORR model as in equation (17).

$$(19)\quad \begin{aligned} r_{i,t} &= \omega_i + \delta_i r_{i,t-1} + \lambda_{t-1} h_{iw,t} + \varepsilon_{i,t} \\ r_{w,t} &= \omega_w + \delta_w r_{w,t-1} + \lambda_{t-1} h_{ww,t} + \varepsilon_{w,t} \end{aligned} \qquad \varepsilon_t | Z_{t-1} \sim N(0, H_t) \quad \text{and} \quad (17)\quad \begin{aligned} h_{ii,t} &= c_{ii} + b_{ii} h_{ii,t-1} + a_{ii}\varepsilon^2_{i,t-1} + d_{ii}\eta^2_{i,t-1} \quad \forall i \\ h_{ij,t} &= \rho_{ij}\left(\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}\right) \quad \forall i \neq j \end{aligned} \qquad \text{where } \eta_{i,t} = \max[0, -\varepsilon_{i,t}]$$

and $\lambda_{t-1} = Z_{t-1}\kappa_W$ denotes the price of global market risk. Skewness and excess kurtosis of standardized residuals are given as m_3 and m_4, respectively. B-J denotes Bera-Jarque statistics for normality and LLF log likelihood function. QML standard errors are reported in parenthesis. $\chi^2(4)$, $\chi^2(3)$ and $\chi^2(2)$ denotes robust Wald-test statistics for the null of zero price of risk, the constant price of risk and the joint insignificance of the asymmetry terms, respectively.

	Austria[a]	Belgium[a]	Finland[a]	France[a]	Germany[a]	Ireland[a]	Italy[a]	Netherlands[a]	Portugal[a]	Spain[a]
Panel A. Parameter estimates for the price of risk										
Const	-0.002	0.097	-0.104	0.108	0.043	-0.054	0.023	0.006	-0.022	0.060
	(0.107)	(0.096)	(0.130)	(0.097)	(0.104)	(0.103)	(0.102)	(0.093)	(0.098)	(0.097)
USDP	0.062	-0.029	0.118	-0.025	0.030	0.107	0.045	0.083	0.081	0.010
	(0.100)	(0.092)	(0.111)	(0.092)	(0.099)	(0.098)	(0.096)	(0.085)	(0.092)	(0.093)
ΔUSTP	0.117	0.079	0.234	0.042	0.006	0.094	-0.012	0.179	0.052	0.026
	(0.222)	(0.258)	(0.262)	(0.207)	(0.226)	(0.272)	(0.249)	(0.255)	(0.260)	(0.258)
DINT	0.027	0.039**	0.025	0.039**	0.050**	0.036*	0.042**	0.050**	0.025	0.039*
	(0.016)	(0.015)	(0.019)	(0.014)	(0.017)	(0.015)	(0.016)	(0.015)	(0.016)	(0.018)
Panel B. Robust Wald-tests										
$\chi^2(4)$	5.588	12.744**	2.642	13.478**	14.514**	6.778	11.038*	15.456**	3.915	9.254
$\chi^2(3)$	4.006	10.488**	2.513	12.732**	13.325**	6.071	9.418*	12.708**	2.380	7.840*
$\chi^2(2)$	29.579**	28.365**	12.389**	21.554**	17.212**	182.244**	16.214**	40.064**	6.701*	25.114**
Panel C. Diagnostic tests for country i										
m_3	-0.318**	-0.285**	-0.387**	-0.317**	-0.199**	-0.645**	-0.305**	-0.371**	-0.027	-0.253**
m_4	1.322**	0.842**	3.855**	0.807**	0.478**	4.234**	0.834**	1.034**	2.268**	1.072**
B-J	210.198**	101.153**	1511.436**	102.917**	37.758**	1914.259**	104.301**	158.374**	503.361**	137.429**
LLF	-6085.534	-5891.565	-7636.832	-5886.094	-6110.664	-6433.755	-5730.343	-5804.545	-5854.438	-6062.837

[a] Restrictions for the non-negativity ensuring constraint $a_{ii} \geq 0$ has been imposed. ** and * denotes significance at least at the levels of 1% and 5%, respectively

and the change in US term premium (ΔUSTP) for the price of global market risk are all insignificant in all cases. Furthermore, these estimates vary considerably between countries. On the other hand, the interest rate difference (dINT) estimates are quite similar between the countries and varies from 0.025 for Finland and Portugal to 0.050 for Germany and the Netherlands. It is significant predictor for the price of global market risk in the case of Belgium, France, Germany, Ireland, Italy, the Netherlands and Spain.

We also test hypothesis that the price of global market risk is zero and that price of risk is constant. The robust Wald $\chi^2(4)$ in Panel B rejects the joint insignificance of information variables for Belgium, France, Germany, Italy, the Netherlands at least at 5%-level, meaning that in these cases the price of global market risk is not zero. If we had use for example 6%-level the null would have been rejected for Spain as well (*p*-value 0.055). For these same countries the Wald $\chi^2(3)$ rejects the null hypothesis of the constant price of global market risk. In these cases results agrees with Harvey (1991), Bekaert and Harvey (1995) and De Santis and Gérard (1997, 1998) how also find that the price of global market risk is time-varying. Asymmetry terms in conditional variance equations (not reported) are positive and significant at least at 5%-level in all cases excluding Finland which have negative and significant coefficient and Portugal with insignificant parameter. Same way as in the two previous sections, the Wald $\chi^2(2)$ for the joint insignificance of asymmetry terms is also rejected for all countries.

Given these results and those reported in the three previous sections it seems that the dynamic risk premiums cannot be explained by using time-varying risk itself only and instead two components are needed. It is interesting that the interest rate difference turns out to be the most efficient predictor of the price of global risk because it may partly reflect the currency movements due the interest rate parity. This finding may indicate the importance of currency risk when explaining the time-varying risk premiums as suggested by results reported by Dumas and Solnik (1995) and De Santis and Gérard (1998).

The rest of the conditional variance and covariance parameters (not reported) are also practically unchanged compared to those reported in Appendix 2 for the case of fully integrated markets and constant price of global market risk. Also the diagnostics in Panel C in Table 6 are very much same as before. However, more ARCH effects in standardized residuals are now left for Belgium (lags 1,2 and 3), Germany (lags 1,2 and 7), Italy (lag 7), Netherlands (lags 3,4,5,6 and 7) and Spain (lags 6 and 7) and for the world portfolio (lags 4,5,6 and 7) when the model is estimated with Finland. This gives indication that when the price of global market risk is maid time-varying, GARCH processes are harder to model. Stationary of individual processes are achieved in all cases after imposing restrictions for Finland. Again, restrictions for the non-negativity of conditional variances ensuring constraint $a_{ii} \geq 0$ have to be imposed for the world's a_{ii} and for two countries for the same parameter. In most cases the parameter a_{ii} is found to be zero after restriction and it is excluded from the final estimation.

B. Symmetric model

Given previous results it seems that our last specification where the price of market risk is allowed to be time-varying is the most promising. Although this is not supported by our previous results concerning asymmetric effects, as our final specification we estimate the same model this time without allowing asymmetries. This is done in order to see possible effects for the results if asymmetries are not allowed. Bekaert and Wu (2000) mention that if asymmetric and symmetric models yield different conditional moments, their implication will be different too. Further, with our previous model, leverage effects in the conditional variances were present in eight cases, meaning that risk and the risk premiums can increase more in response to negative shocks than in response to positive shocks. Bekaert and Wu (2000) points out that the significance of these asymmetric changes in risk for risk premiums depends on the price of risk. Because we do not restrict the price to be same for symmetric model we cannot directly compare asymmetries significance. However, at least indicative conclusions can be drawn.

Results from this symmetric bivariate CCORR-M model for the world portfolio and country *i* are reported in Panel A in Table 7. This time information variable dINT is significant predictor of the price of global market risk only for Austria and the Netherlands and as before all other information variables turn out to be insignificant. Interestingly, the robust Wald $\chi^2(4)$ in Panel B in Table 7 does not this time reject the zero price of global market risk for any of the countries. Also the Wald $\chi^2(3)$ show that the null hypothesis of the constant price of global market risk is not rejected in any cases. These results clearly contrast with those from the asymmetric bivariate models. It is possible that because of our scarce use of information variables, the meaning of the conditional risk modelling for the risk premiums modelling is highlighted. Moreover, it seems that asymmetries can potentially have great role for risk-return relationship because the global market risk was priced previously in five cases when risk was allowed to response asymmetrically for negative and positive shocks. However, we cannot quantify the relative importance of two time-varying components or the importance of asymmetries with in the limits of this study. Despite this, we can conclude that at least these results show clearly those potential effects that the use of asymmetric or symmetric model can have for the empirical results if models are built without recognising asymmetry issues.

The diagnostics in Panel C in Table 7 are very much same as before. However, compared to corresponding asymmetric model, considerably more ARCH effects in standardized residuals are now left with the same countries as before and additionally in the case of France and Portugal.

Table 7. Integrated markets and time-varying price of global risk. Results from the bivariate CCORR-M for the world and country *i*.

Quasi-Maximum Likelihood (QML) estimates are based on daily euro nominated excess returns from 4 January 1999 to 31 December 2007 (2346 observations). Equity index data for the countries and world is calculated by MSCI (Morgan Stanley Capital International). The risk-free rate is approximated using the 1-month EURIBOR for calculations. The bivariate CCORR-M model's conditional mean equations (19) relates the index excess return to its conditional global market risk $h_{iw,t} = Cov_{t-1}(r_{it}, r_{wt})$.The price of global market risk is a function of information set Z_{t-1}, including a constant (Const), the US default premium (USDP), the change in US term premium (ΔUSTP) and interest rate difference (DINT). The elements of conditional covariance matrix $H_t = [h_{ij,t}]$ follow the symmetric CCORR model as in equation (15).

$$(19)\quad \begin{aligned} r_{i,t} &= \omega_i + \delta_i r_{i,t-1} + \lambda_{t-1} h_{iw,t} + \varepsilon_{i,t} \\ r_{w,t} &= \omega_w + \delta_w r_{w,t-1} + \lambda_{t-1} h_{ww,t} + \varepsilon_{w,t} \end{aligned} \qquad \varepsilon_t \left| Z_{t-1} \sim N\left(0, H_t\right) \right. \quad \text{and} \quad (15)\quad \begin{aligned} h_{ii,t} &= c_{ii} + b_{ii} h_{ii,t-1} + a_{ii} \varepsilon_{i,t-1}^2 \quad \forall i \\ h_{ij,t} &= \rho_{ij} \left(\sqrt{h_{ii,t}} \sqrt{h_{jj,t}} \right) \quad \forall i \neq j \end{aligned}$$

where $\lambda_{t-1} = Z_{t-1}\kappa_W$ denotes the price of global market risk. Skewness and excess kurtosis of standardized residuals are given as m_3 and m_4, respectively. B-J denotes Bera-Jarque statistics for normality and LLF log likelihood function. QML standard errors are reported in parenthesis. $\chi^2(4)$ and $\chi^2(3)$ denotes robust Wald-test statistics for the null of zero price of risk and the constant price of risk, respectively.

	Austria	Belgium	Finland	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain
Panel A. Parameter estimates for the price of risk										
Const.	-0.022	0.076	-0.035	0.041	0.045	-0.013	0.038	0.067	0.015	0.027
	(0.126)	(0.130)	(0.131)	(0.123)	(0.132)	(0.128)	(0.133)	(0.134)	(0.129)	(0.139)
USDP	0.083	<0.001	0.068	0.025	0.025	0.072	0.035	0.034	0.052	0.047
	(0.114)	(0.115)	(0.112)	(0.109)	(0.114)	(0.119)	(0.115)	(0.120)	(0.117)	(0.121)
ΔUSTP	0.172	0.197	0.256	0.247	0.148	0.129	0.139	0.290	0.091	0.229
	(0.283)	(0.277)	(0.262)	(0.270)	(0.278)	(0.252)	(0.257)	(0.238)	(0.236)	(0.257)
DINT	0.036*	0.034	0.029	0.026	0.029	0.033	0.028	0.039*	0.029	0.035
	(0.018)	(0.020)	(0.019)	(0.020)	(0.021)	(0.019)	(0.020)	(0.018)	(0.019)	(0.020)
Panel B. Robust Wald-tests										
$\chi^2(4)$	5.109	4.950	3.301	3.365	2.778	3.836	3.510	7.268	4.223	4.377
$\chi^2(3)$	4.301	3.930	3.245	2.677	2.140	3.528	2.276	5.529	2.547	3.860
Panel C. Diagnostic tests for country i										
m_3	-0.367**	-0.310**	-0.469**	-0.304**	-0.221**	-0.711**	-0.327**	-0.330**	-0.062	-0.282**
m_4	1.638**	1.048**	4.341**	0.759**	0.528**	4.923**	1.056**	0.839**	2.259**	1.275**
B-J	315.046**	144.817**	1927.909	92.303**	46.456**	2565.402**	150.832**	111.433**	500.165**	190.050**
LLF	-6132.112	-5940.629	-7665.797	-5928.707	-6146.162	-6470.983	-5770.067	-5856.299	-5879.986	-6109.409

** and * denotes significance at least at the levels of 1% and 5%, respectively.

This gives some indication that the symmetric model cannot model the GARCH processes as efficiently as its asymmetric counterpart and strengths the view that asymmetries role may be important when conditional risk is modelled. The fact that also obtained values for the skewness, excess kurtosis and Bera-Jarque static for the standardized residuals are better in most cases for the asymmetric model than with the symmetric model further strengths this view. Stationary of individual processes and non-negativity is achieved in all cases without any restrictions. This clearly shows the trade-off with more complicated multivariate GARCH models. Even with the bivariate case we had to impose restrictions with our asymmetric model limiting some of its applicability.

One obvious question rising from the results above has to remain unanswered because we have to limit our study. In order to see if the asymmetric model succeeds better to model the conditional covariance we could employ some measures like for example the mean squared error (MSE) or the mean absolute error (MAE) to evaluate model performance. However, there remains question how to measure the true realized covariance. The same question concerning variance has been answered by Andersen and Bollerslev (1998) how argue that the usual way to use daily squared returns as a proxy may be very noisy practise and that the use of intra-daily data would be more preferable, which of course also likewise concerns the covariance proxy issues. Further, Maukonen (2002) points out that the traditional error measures may yield inconclusive inferences. For example, Brailsford and Faff (1996) report differences in results according to used error statistics. For these reasons, we left this question unanswered and settle to conclude that the inclusion of asymmetries can have wide impact for the results and support for the use of asymmetric model is found.

4.5 Further interpretation of results

Conditional variances and covariance are clearly time-varying in stock market excess return generating processes. However, time-varying market risk itself is not enough to explain the dynamics of risk premiums regardless what the assumed degree of market integration is. Poterba and Summers (1986) have suggested that volatility shocks can have only a small impact on stock market prices. Their results lead them to doubt that volatility fluctuations and the movements induced by those fluctuations in equity risk premium could explain much of the variation in the stock market's level. Also Baillie and DeGennaro (1990) argue based on their empirical results that investors may consider some other risk measures than the market risk as being more important. After detailed analysis with the ten EMU countries' stock market data we have to join to formers opinion. This result has important implications for the theory and applications. To illustrate this, for example if markets are find to be inefficient assuming that the covariance with the market is the appropriate and sufficient risk measure, then our results indicate that this kind of results need not to be understand as evidence against efficiency.

However, when we let the price of global market risk to be time-varying in the case of fully integrated markets, we find indications for six countries that indeed the dynamics of risk premium is driven by both the time-variation of the price of global market risk and time-variations of conditional market risk. Bekaert and Harvey (1995) find the price of global market risk being highest at US economic troughs and lowest at US economic peaks. They further conclude that this is consistent with the view that risk premiums should be highest in recession to attract investors. Our sample period contains quite large stock market troughs and peaks and so there are, in addition to our results, reasons to believe that the price of global market risk is time-varying.

Our results strongly support the presence of asymmetric effects in the conditional variance and covariance processes. Further, when the price of global market risk is allowed to be time-varying and the same model is estimated without asymmetries we find that results and conclusion are affected considerably. This indicates that these asymmetric features should be recognised in empirical multivariate asset pricing analyses, where the parsimonious model parameterization is often chosen over these aspects. In addition, results from Harvey and Siddique (1999, 2000) indicate that skewness may have important role in asset pricing and that the traditional mean-variance framework may be not enough. Our results concerning the conditional risk-return relationship and asymmetric effects may indirectly support formers results and the view that also higher moments should be included in conditional asset pricing.

We have conduct our analyses assuming three different level of market integration. However, as Bekaert and Harvey (1995) mention, models like our, have one disadvantage because all of them assume fixed degree of integration through time. Formers find some empirical evidence that indeed some markets exhibit time-varying integration. It is possible that conditional regime-switching model like used by formers, would give more robust results. This kind of models could also be used to allow regime-switches in the conditional second moments and the argument that the case where excess returns are considerably more variable than the conditional covariance with the market, a model where the price of market risk is constant may not have enough power to explain the time variation of the risk premium, could be tested.

We have conducted most of our multivariate analyses using the asymmetric extensions of the diagonal VECH (DVECH) and the constant correlation (CCORR) models that both model the conditional variances exactly same way. Using these specifications, we do not find that different processes for the conditional covariance have much impact for the results. However, we report that for both models, our pre-specification tests indicate that restricting cross-market dependences in volatility may be too restrictive assumption at least when operating with the short return interval data. Further, with asymmetric models we have to impose parameter restrictions even with our bivariate models to ensure well defined processes. This issue is likely to be even more important if models are used for forecasting purposes. This demonstrates the difficulty of the choice for multivariate GARCH model when other aspects than parsimonious parameterization are also in interest.

5. CONCLUSION

This study examines the relationship between the stock market excess returns and time-varying market risk in the ten Economy and Monetary Union's (EMU) member countries using daily data from 4 January 1999 to 31 December 2007. The study takes the view of an EMU investor and all returns are expressed in euro currency. The study is conducted assuming three different possible degrees of market integration. Analysis is done to examine if there exists a time-varying risk premium whose variation in time could be explained by the conditional market risk measured using the conditional second moments. We also analyze whether there are asymmetric effects in the conditional covariance matrix and the effects on results if different processes for the time-varying covariance is chosen. These latter questions are examined to see the significance of these features for the empirical results concerning the conditional risk-return relationship.

Our empirical models are univariate and two multivariate GARCH-M specifications with the asymmetry extensions. Multivariate models are the diagonal VECH and the constant correlation parameterization, which are chosen because they can be easily modified for asymmetric effects and the differences in the covariance processes are highlighted. The conditional mean equations are derived from the simple conditional CAPM which is extended to take the non-synchronous trading effects account with the first order autoregressive component. Study uses MSCI country and world indices as a market proxy for countries and world stock markets. Hypotheses are tested in two stages. First, we restrict the price of market risk to be constant and estimate models assuming fully segmented, completely integrated and partially segmented markets, respectively. Second, we allow the time-varying price of global risk and estimate asymmetric and symmetric models assuming integrated markets.

The empirical results from the first stage show that although the conditional second moments are time-varying, the time-varying market risk itself is not enough to explain the dynamics of risk premiums. These results are in line with the previous studies. The possible reason is that the excess returns are considerably more variable than the conditional covariance with the market and a model where the price of market risk is constant may not have enough power to explain the dynamics of the risk premiums. Results suggest strongly that there exist asymmetric effects in the conditional covariance matrix. However, the different conditional covariance processes do not have much effect on the results.

In the second stage, the price of global risk is made time-varying approximating it with the four information variables. The results from the asymmetric model show indications for six countries that the price of global market risk is time-varying and priced. This finding is consistent with the earlier empirical studies. Results also support the fact that asymmetric effects should be allowed. Interestingly, when otherwise identical symmetric model is estimated, the hypothesis of the constant and zero price of global market risk cannot be rejected for any countries. These results indicate that allowing the asymmetric effect in the second moments may allow most efficient conditional risk modelling and result show clearly that these features can have wide impact for the results. The diagnostic testing conducted for the standardized residual gives also some support for the asymmetric specification.

Given these results, we conclude that the time-varying risk itself is not enough to explain time-varying risk premiums and instead there are indications that both the time-varying risk and time-varying price of market risk is needed to explain risk premiums. Because this means that the conditional covariance with the market is maybe not sufficient measure of risk as alone, developing some other risk measures may be necessary. Also the asymmetric effects in the conditional covariance matrix are clearly present and should be recognized in multivariate asset pricing analyses where they can have wide impact for the results. Found asymmetries can also indirectly indicate that the inclusion of skewness into conditional asset pricing could be appropriate.

Finally, it would be interesting to further investigate relations between the risk and returns using asymmetric conditional regime-switching model that would allow the degree of market segmentation or the conditional moments' processes to change through time. Further, asymmetric effects in the conditional covariance matrix and their role for risk-return relations deserve more research. Furthermore, the inclusion of currency risk in the asymmetric model and the use of longer return intervals and longer data could also affect results.

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APPENDICES

APPENDIX 1: Description of model estimation issues

Statistical program

RATS (Regression Analysis of Time Series) version 7.

RATS program

Program codes are built by modifying RATS code examples given in RATS User's Guide and in econometric textbook written by Brooks (2002).[4] We have proceed from the simplest to the more complex code and checked results in all stages against RATS built-in procedures as long as it stays possible. Modifications we have done concern mainly combining GARCH-in-mean and asymmetry terms in the same model.

Optimization issues

The BFGS algorithm is used for optimization. First, the linear OLS regressions are run to supply initial values for the part of the parameters and to initialize the residual vectors, conditional variance vectors and conditional covariance vector. For the rest of the coefficients we set values that are likely to be in reasonable range. With the multivariate models all initial parameter values are further refined using the simplex algorithm. In all cases convergence limit is set to 0.00001. If convergence is not achieved, we first add subiterations limit, try different initial values or start from the values from the last optimization.

[4] Brooks, C. 2002. Introductory econometrics for finance. Cambridge: Cambridge University Press.

APPENDIX 2: GJR-CCORR-M model and integrated markets

The bivariate GJR-CCORR(1,1)-M estimation results

Quasi-Maximum Likelihood (QML) estimates are based on daily euro nominated excess returns from 4 January 1999 to 31 December 2007 (2346 observations). The equity index data for Austria (AST), Belgium (BEL), Finland (FIN), France (FRA), Germany (GER), Ireland (IRE), Italy (ITA), the Netherlands (NET), Portugal (POR), Spain (SPA) and world (WOR) is calculated by MSCI (Morgan Stanley Capital International). The risk-free rate is approximated using the 1-month EURIBOR for calculations. The bivariate GJR-CCORR-M model's conditional mean equations relates the index excess return to its conditional global market risk $h_{iw,t} = Cov_{t\text{-}1}(r_{it}, r_{wt})$ as

$$(19)\qquad \begin{aligned} r_{i,t} &= \omega_i + \delta_i r_{i,t-1} + \lambda h_{iw,t} + \varepsilon_{i,t} \\ r_{w,t} &= \omega_w + \delta_w r_{w,t-1} + \lambda h_{ww,t} + \varepsilon_{w,t} \end{aligned} \qquad \varepsilon_t \left| Z_{t-1} \sim N\left(0, H_t\right)\right.$$

where λ denotes the price of global market risk. The elements of conditional covariance matrix $H_t = [h_{ij,t}]$ follow the asymmetric CCORR parameterization as

$$(17)\qquad \begin{aligned} h_{ii,t} &= c_{ii} + b_{ii} h_{ii,t-1} + a_{ii}\varepsilon^2_{i,t-1} + d_{ii}\eta^2_{i,t-1} \quad && \forall i \\ h_{ij,t} &= \rho_{ij}\left(\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}\right) && \forall i \neq j \end{aligned} \qquad \text{where } \eta_{i,t} = \max[0, -\varepsilon_{i,t}]$$

Skewness and excess kurtosis of standardized residuals are given as m_3 and m_4, respectively. B-J denotes Bera-Jarque statistics for normality and LLF log likelihood function. QML standard errors are reported in parenthesis. $\chi^2(2)$ denotes robust Wald-test statistics for the null of joint insignificance of the asymmetry terms.

	AST	WOR[a]	BEL	WOR	FIN[a]	WOR[a]	FRA	WOR	GER	WOR
Panel A. Parameter estimates										
ω_i	0.055*	-0.020	0.027	0.002	0.079	0.013	0.006	-0.009	0.024	<0.001
	(0.023)	(0.032)	(0.023)	(0.033)	(0.048)	(0.036)	(0.032)	(0.032)	(0.033)	(0.032)
δ_i		0.027	0.042*	0.013		-0.012		-0.015		0.021
		(0.020)	(0.020)	(0.020)		(0.018)		(0.018)		(0.018)
λ	0.033		0.008		<0.001		0.020		0.008	
	(0.039)		(0.037)		(0.042)		(0.041)		(0.038)	
c_{ii}	0.055**	0.004	0.020**	0.005	0.003	0.003	0.019**	0.006	0.025**	0.007
	(0.010)	(0.004)	(0.006)	(0.004)	(0.002)	(0.003)	(0.006)	(0.005)	(0.008)	(0.005)
a_{ii}	0.004		0.018	0.001	0.028**		0.010	0.001	0.025*	0.003
	(0.013)		(0.013)	(0.009)	(0.006)		(0.008)	(0.008)	(0.010)	(0.008)
b_{ii}	0.867**	0.968**	0.904**	0.966**	0.983**	0.976**	0.936**	0.965**	0.923**	0.963**
	(0.018)	(0.014)	(0.020)	(0.016)	(0.007)	(0.011)	(0.010)	(0.016)	(0.013)	(0.018)
d_{ii}	0.130**	0.054**	0.108**	0.054**	-0.020**	0.037**	0.076**	0.051**	0.067**	0.050**
	(0.023)	(0.020)	(0.019)	(0.014)	(0.008)	(0.014)	(0.018)	(0.014)	(0.022)	(0.017)
ρ_{ij}	0.375**		0.559**		0.568**		0.717**		0.711**	
	(0.019)		(0.014)		(0.020)		(0.011)		(0.012)	
Panel B. Diagnostic tests and robust Wald-test										
m_3	-0.317**	-0.410**	-0.285**	-0.395**	-0.386**	-0.355**	-0.311**	-0.380	-0.199**	-0.358**
m_4	1.325**	1.647**	0.853**	1.563**	3.882**	1.385**	0.759**	1.429**	0.470**	1.388**
B-J	211.0**	330.8**	102.9**	299.6**	1531.4**	236.8**	94.1**	256.0**	37.2**	238.5**
LLF	-6087.488		-5898.869		-7638.371		-5893.223		-6119.265	
$\chi^2(2)$	35.197**		37.226**		15.512**		20.043**		12.998**	

(*continued on next page*)

(*continued*)

	IRE	WOR[a]	ITA	WOR	NET[a]	WOR[a]	POR	WOR[a]	SPA[a]	WOR[a]
Panel A. Parameter estimates										
ω_i	0.004	-0.008	0.008	-0.004	-0.007	-0.020	0.018	-0.021	0.027	-0.005
	(0.027)	(0.032)	(0.025)	(0.032)	(0.030)	(0.035)	(0.018)	(0.031)	(0.028)	(0.034)
δ_i	0.076**	0.005		0.033		-0.023	0.073**	0.043*		0.028
	(0.022)	(0.019)		(0.018)		(0.017)	(0.022)	(0.019)		(0.018)
λ	0.020		0.017		0.031		0.036		0.014	
	(0.039)		(0.039)		(0.041)		(0.040)		(0.038)	
c_{ii}	0.080*	0.005	0.016**	0.006	0.019**	0.007	0.012	0.007	0.013**	0.004
	(0.035)	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.010)	(0.004)	(0.005)	(0.004)
a_{ii}	0.028*		0.021*	0.002			0.032			
	(0.014)		(0.009)	(0.009)			(0.017)			
b_{ii}	0.849**	0.966**	0.920**	0.964**	0.935**	0.963**	0.930**	0.962**	0.951**	0.972**
	(0.037)	(0.016)	(0.015)	(0.018)	(0.010)	(0.011)	(0.035)	(0.015)	(0.010)	(0.012)
d_{ii}	0.121**	0.054*	0.081**	0.051**	0.092**	0.054**	0.042	0.057**	0.073**	0.045**
	(0.043)	(0.022)	(0.021)	(0.016)	(0.013)	(0.014)	(0.027)	(0.020)	(0.014)	(0.013)
ρ_{ij}	0.431**		0.648**		0.705**		0.409**		0.634**	
	(0.018)		(0.012)		(0.013)		(0.020)		(0.014)	
Panel B. Diagnostic tests and robust Wald-test										
m_3	-0.643**	-0.395**	-0.300**	-0.368**	-0.368**	-0.388**	-0.024	-0.376**	-0.253**	-0.365**
m_4	4.223**	1.527**	0.816**	1.431**	1.070**	1.432**	2.275**	1.436**	1.047	1.436**
B-J	1904.6**	288.8**	100.3**	253.0**	164.8**	259.2**	505.9**	256.7**	132.1**	253.6**
LLF	-6436.650		-5735.601		-5812.622		-5855.742		-6068.777	
$\chi^2(2)$	12.844**		16.780**		51.130**		8.299*		30.759**	

[a] To ensure the non-negativity of conditional variance we restrict $a_{ii} \geq 0$. If after imposing restriction it is found that coefficient does not affect the value of function the final model is estimated without it.
** and * denotes significance at least at the levels of 1% and 5%, respectively.

APPENDIX 3: GJR-CCORR-M and partially segmented markets

The bivariate GJR-CCORR(1,1)-M estimation results

Quasi-Maximum Likelihood (QML) estimates are based on daily euro nominated excess returns from 4 January 1999 to 31 December 2007 (2346 observations). The equity index data for Austria (AST), Belgium (BEL), Finland (FIN), France (FRA), Germany (GER), Ireland (IRE), Italy (ITA), the Netherlands (NET), Portugal (POR), Spain (SPA) and world (WOR) is calculated by MSCI (Morgan Stanley Capital International). The risk-free rate is approximated using the 1-month EURIBOR for calculations. The bivariate GJR-CCORR-M conditional mean equations relates the index excess return to its conditional global market risk $h_{iw,t} = Cov_{t-1}(r_{i,t}, r_{w,t})$ and conditional country's local market risk $h_{ii,t} = Var_{t-1}(r_{i,t})$ as

(21)
$$\begin{aligned} r_{i,t} &= \omega_i + \delta_i r_{i,t-1} + \lambda h_{iw,t} + \lambda_i h_{ii,t} + \varepsilon_{i,t} \\ r_{w,t} &= \omega_w + \delta_w r_{w,t-1} + \lambda h_{ww,t} + \varepsilon_{w,t} \end{aligned} \qquad \varepsilon_t \left| Z_{t-1} \sim N\left(0, H_t\right)\right.$$

where λ and λ_i denotes the price of global and local market risks, respectively. The elements of the conditional covariance matrix $H_t = [h_{ij,t}]$ follow the asymmetric CCORR parameterization as follows

(17)
$$\begin{aligned} h_{ii,t} &= c_{ii} + b_{ii} h_{ii,t-1} + a_{ii} \varepsilon_{i,t-1}^2 + d_{ii} \eta_{i,t-1}^2 \quad \forall i \\ h_{ij,t} &= \rho_{ij} \left(\sqrt{h_{ii,t}} \sqrt{h_{jj,t}}\right) \quad \forall i \neq j \end{aligned}$$
where $\eta_{i,t} = \max[0, -\varepsilon_{i,t}]$

Skewness and excess kurtosis of standardized residuals are given as m_3 and m_4, respectively. B-J denotes Bera-Jarque statistics for normality and LLF log likelihood function. QML standard errors are reported in parenthesis. $\chi^2(2)$ denotes robust Wald-test statistics for the null of joint insignificance of the asymmetry terms

	AST	WOR[a]	BEL	WOR	FIN	WOR[a]	FRA	WOR	GER	WOR
Panel A. Parameter estimates										
ω_i	0.115**	-0.023	0.044	-0.003	0.091	0.008	0.005	-0.008	0.036	-0.004
	(0.031)	(0.029)	(0.026)	(0.029)	(0.053)	(0.035)	(0.036)	(0.032)	(0.040)	(0.035)
δ_i		0.028	0.039*	0.013		-0.012		-0.015		0.021
		(0.019)	(0.019)	(0.020)		(0.017)		(0.018)		(0.015)
λ	0.036		0.013		0.004		0.020		0.012	
	(0.035)		(0.036)		(0.041)		(0.039)		(0.042)	
λ_i	-0.079*		-0.028		-0.006		0.002		-0.013	
	(0.033)		(0.020)		(0.011)		(0.015)		(0.013)	
c_{ii}	0.050**	0.004	0.019**	0.005	0.003	0.003	0.019**	0.006	0.024**	0.007
	(0.008)	(0.003)	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.009)	(0.006)
a_{ii}	0.004		0.019	0.001	0.027**		0.010	0.001	0.025**	0.003
	(0.013)		(0.013)	(0.008)	(0.005)		(0.007)	(0.008)	(0.008)	(0.010)
b_{ii}	0.874**	0.968**	0.905**	0.965**	0.983**	0.976**	0.936**	0.965**	0.923**	0.963**
	(0.016)	(0.011)	(0.020)	(0.014)	(0.007)	(0.010)	(0.012)	(0.014)	(0.014)	(0.022)
d_{ii}	0.133**	0.053**	0.109**	0.054**	-0.021*	0.037**	0.076**	0.051**	0.068**	0.049**
	(0.022)	(0.014)	(0.021)	(0.017)	(0.010)	(0.013)	(0.018)	(0.014)	(0.019)	(0.015)
ρ_{ij}	0.377**		0.560**		0.567**		0.717**		0.711**	
	(0.019)		(0.017)		(0.016)		(0.011)		(0.011)	
Panel B. Diagnostic tests and robust Wald-test										
m_3	-0.317**	-0.409**	-0.277**	-0.395**	-0.385**	-0.355**	-0.311**	-0.380**	-0.198**	-0.358**
m_4	1.297**	1.637**	0.879**	1.552**	3.880**	1.379**	0.758**	1.430**	0.477**	1.382**
B-J	203.7**	327.2**	105.4**	296.2**	1530.1**	235.2**	94.0**	256.2**	37.5**	236.8**
LLF	-6085.598		-5897.977		-7638.170		-5893.218		-6118.888	
$\chi^2(2)$	41.593**		35.813**		15.615**		19.264**		15.789**	

(*continued on next page*)

(*continued*)

	IRE	WOR[a]	ITA	WOR	NET[a]	WOR[a]	POR	WOR[a]	SPA[a]	WOR[a]
Panel A. Parameter estimates										
ω_i	0.060	-0.010	0.012	-0.006	<0.001	-0.023	0.055*	-0.023	0.031	-0.006
	(0.033)	(0.035)	(0.030)	(0.038)	(0.025)	(0.027)	(0.025)	(0.032)	(0.033)	(0.038)
δ_i	0.069**	0.004		0.033		-0.023	0.071**	0.043*		0.028
	(0.020)	(0.018)		(0.019)		(0.015)	(0.021)	(0.019)		(0.017)
λ	0.023		0.018		0.035		0.037		0.015	
	(0.040)		(0.046)		(0.030)		(0.037)		(0.043)	
λ_i	-0.051*		-0.007		-0.011		-0.060		-0.005	
	(0.021)		(0.019)		(0.013)		(0.032)		(0.017)	
c_{ii}	0.076*	0.005	0.016*	0.006	0.018**	0.007*	0.011	0.007	0.012*	0.004
	(0.032)	(0.005)	(0.007)	(0.007)	(0.004)	(0.003)	(0.009)	(0.005)	(0.004)	(0.003)
a_{ii}	0.030*		0.020*	0.002			0.031			
	(0.012)		(0.009)	(0.011)			(0.018)			
b_{ii}	0.851**	0.966**	0.920**	0.964**	0.936**	0.963**	0.932**	0.962**	0.951**	0.972**
	(0.037)	(0.015)	(0.019)	(0.026)	(0.007)	(0.009)	(0.038)	(0.014)	(0.009)	(0.009)
d_{ii}	0.123**	0.054*	0.081**	0.051*	0.092**	0.054**	0.044	0.057**	0.073**	0.045**
	(0.040)	(0.019)	(0.028)	(0.023)	(0.010)	(0.012)	(0.032)	(0.018)	(0.013)	(0.011)
ρ_{ij}	0.432**		0.648**		0.705**		0.409**		0.634**	
	(0.021)		(0.012)		(0.013)		(0.019)		(0.013)	
Panel B. Diagnostic tests and robust Wald-test										
m_3	-0.638**	-0.394**	-0.299**	-0.367**	-0.366**	-0.388**	-0.018	-0.375**	-0.252**	-0.365**
m_4	4.205**	1.523**	0.818**	1.429**	1.078**	1.426**	2.264**	1.432**	1.049**	1.434**
B-J	1886.5**	287.3**	100.3**	252.3**	166.1**	257.4**	510.0**	255.4**	132.5**	253.0**
LLF	-6435.138		-5735.542		-5812.366		-5854.403		-6068.742	
$\chi^2(2)$	14.717**		8.580*		83.097**		11.086*		35.881**	

[a] To ensure the non-negativity of conditional variance we restrict $a_{ii} \geq 0$. If after imposing restriction it is found that coefficient does not affect the value of function the final model is estimated without it.
** and * denotes significance at least at the levels of 1% and 5%, respectively.