

Université Catholique De Louvain
Faculté des Sciences Economiques, Sociales et Politiques
Département des Sciences Economiques
The Center for Operations Research and Econometrics

**Essays on Modeling International Stock Market Volatility
Spillovers Using Multivariate GARCH Models**

by Besik Samkharadze

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Contents

Chapter 1	5
1.1 Introduction	5
1.2 Overview of MGARCH models	7
1.3 Application of MGARCH models	15
1.4 Summary	19
Chapter 2	21
2.1 Introduction	21
2.2 Hedging	23
2.3 Methodology	24
2.4 Data	26
2.5 Results	30
2.6 Extensions	37
2.6.1 Other commodities	37
2.6.2 Mean-variance framework	39
2.7 Conclusions	41
Chapter 3	43
3.1 Introduction	43
3.2 Methodology	45
3.2.1 The model	45
3.2.2 Measuring unexpected changes of the target rate (news component)	47
3.3 Data	49
3.3.1 Monetary policy news	49
3.3.2 Stock return data	50
3.4 Results	53
3.4.1 Baseline results	54
3.4.2 Asymmetries	59
3.4.3 Sensitivity analysis	64
3.5 Conclusions	65
Chapter 4	67
4.1 Introduction	67
4.2 Methodology	69
4.3 Data and summary statistics	69
4.4 Empirical results	71
4.4.1 Causality in Variance	72
4.4.2 “Old members” group	75
4.4.3 “New members” group	77
4.4.4 Volatility spillovers between old and new EU members	79
4.4.5 Evolution of Conditional correlations over time	81
4.5 Summary and Conclusions	84
References	85
Appendix A	100
Appendix B	104
Appendix C	119

List of Tables

2.1	Goldman Sachs Commodity Price Index (SP GSCI) components and dollar weight (%)	27
2.2	Summary statistics of Log>Returns	29
2.3	OLS regression for dependent variable ΔS_t	30
2.4	Estimated Coefficients for BEKK-GARCH Model	31
2.5	Estimated Coefficients for Asymmetric BEKK-GARCH Model	32
2.6	Estimated nonlinear coefficients and standard errors for asymmetric BEKK-GARCH Model using Delta Method	33
2.7	In-sample forecasts: Variance and mean of Naive, OLS, BEKK and Asym-BEKK portfolios	33
2.8	Out-of-sample forecasts: Variance and mean of Naive, OLS, BEKK and BEKK-GJR portfolios	35
2.9	In-sample forecasts: Individual commodities	38
2.10	Out-of-sample forecasts: Individual commodities	39
2.11	In-sample forecast: portfolio “utility”	41
2.12	Out-of-sample forecast: portfolio “utility”	42
3.1	Descriptive statistics for monetary policy news and announcements.	50
3.2	Descriptive statistics, log-returns of all series.	53
3.3	Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-EZ/Europe.	55
3.4	Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-Eurozone countries.	56
3.5	Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-developed countries.	58
3.6	Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-BRIC countries.	59
3.7	Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-EZ/Europe.	60
3.8	Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-Eurozone countries.	61
3.9	Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-developed countries.	62
3.10	Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-BRIC countries.	63
3.11	Estimated results from BEKK-GARCH (1, 1) models: conditional mean equations.	64
3.12	Estimated results from BEKK-GARCH (1, 1) models: the effect of actual target rate changes	65
4.1	Descriptive statistics, close-to-close log-returns of all series	70
4.2	Unconditional correlations, all series	71
4.3	Wald test of restrictions on spillover parameters	74

4.4	Volatility spillovers: “Old members” group. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.	75
4.5	Volatility spillovers: “New members” group. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.	78
4.6	Volatility spillovers between “old” and “new” members. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.	79
4.7	Conditional covariances between “new members” and Germany. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.	80

List of Figures

2.1	Goldman Sachs Commodity Price Index	28
2.2	Spot and Futures Log-Return Series	28
2.3	In-sample forecasts - Optimal Hedge Ratios	34
2.4	Out-of-sample forecasts - Optimal Hedge Ratios	34
2.5	News Impact Surface of the Spot variance	36
2.6	News Impact Surface of the Futures variance	36
2.7	News Impact Surface of the Spot-Futures covariance	37
2.8	News Impact Surface of the Optimal Hedge Ratio	37
3.1	The “Timeline” for selected time zones	51
4.1	Estimated conditional correlations between old members.	76
4.2	Conditional correlation for Hungary.	81
4.3	Conditional correlation for Poland.	82
4.4	Conditional correlation for the Czech Republic.	82
4.5	Conditional correlation Romania-UK	83
4.6	Conditional correlation Bulgaria-UK	83
4.7	Conditional correlation Turkey-UK	84
4.8	Conditional correlation Croatia-UK	84

Chapter 1

Modeling Volatility Spillovers: An Introduction

1.1 Introduction

Time-varying volatility models have been extensively used in the finance literature since the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH by Engle, 1982) and later Generalized ARCH (GARCH by Bollerslev, 1986) models. The GARCH family models have become widespread tools for modeling volatility, since they cope with specific features found in the financial time series data. For example, the exponential GARCH (EGARCH) model addresses the asymmetry in the volatility, which is often attributed to the *leverage effect*, GARCH with t -distribution is well suited for modeling returns with “fat tails”, often found in financial data, e.g. equities.

Nevertheless, the question has been raised by researchers whether volatility of a particular times series should be analyzed in a univariate setup. A number of financial crises during the past decades showed that financial markets are highly interrelated. As the world becomes more globalized and technologies advance, interdependences between international financial markets become even more intense. Thus, a crisis originated in one market or country may rapidly expand to different geographical regions, giving rise to market fluctuations in these areas. Such transmissions or *volatility spillovers* have been a focus of interest for academics, policy-makers and financial market participants for a long time. In fact, the modern economic literature documents that volatilities tend to move in the same direction, i.e. volatility is transmitted across assets, markets and countries. Therefore, applying multivariate framework for modeling volatility dynamics of more than one series seems appropriate. The multivariate GARCH (MGARCH) models have been developed for studying such transmissions and represent a more effective way for estimating the interactions among volatilities of N different series. Due to the favorable properties MGARCH models quickly gained popularity among researchers and a large number of specifications has been proposed, which are comprehensively surveyed by Bauwens et al. (2006) and Silvennoinen and Terasvirta (2008).

Early research on international transmissions of stock market shocks, e.g. Eun and Shim (1989), has been mostly concentrated on modeling relationships in mean (first moment) among different markets/countries.¹ Later studies based on GARCH models proved

¹An extensive review of studies on volatility transmissions can be found in a survey by Soriano and

the importance of modeling transmissions in the second moment (variance). In the univariate setup volatility transmissions can be estimated in two stages. First, for each individual market an univariate GARCH model is estimated and, secondly, the squared residuals of the previous estimated models are used as regressors in the variance equation of the other market. In this way, one can evaluate the impact of the “volatility surprises” of one market on other market’s variance. A substantial number of authors have found significant volatility spillovers between international financial markets (Hamao et al., 1990, Engle et al., 1990, Ito et al., 1992, Koutmos and Booth, 1995, Booth et al., 1997). However, the univariate estimation does not take into account potential bi-directional causality between volatilities of different series. Moreover, it ignores the dynamics of the conditional covariance between these series.

Unlike their univariate counterparts, MGARCH models are particularly helpful in applications where, along with variances, estimating the covariance is of great practical importance. Examples of such fields include, but are not limited to, hedging, portfolio optimization, asset pricing and risk management.² However, in modeling variance-covariance structure, the MGARCH literature faces two major challenges: flexibility and parsimony. Here the flexibility of a model refers to its ability to comprehensively reflect the dynamics of and interactions between the conditional variances and covariances. On the other hand, flexible models with minimum restrictions may require estimating a substantially high number of parameters. While this might not imply significant estimation problems for small systems (including 3 to 5 variables), for larger systems the number of parameters to be estimated expands rapidly as the dimension of an MGARCH model increases, causing numerous issues (e.g. in the numerical optimization) and rendering the estimation of high-dimensional systems practically unfeasible. Thus, the main focus of the literature has been placed on finding the balance in the mentioned trade-off by imposing certain structure and/or restrictions on the variance-covariance dynamics. Furthermore, positive definiteness of the variance-covariance matrix in an MGARCH model should be guaranteed, which requires imposing restrictions on the parameters of the model.

The earliest study trying to impose the GARCH structure on the conditional variance-covariance matrix was the so-called VEC model of Bollerslev et al. (1988). This model is the most flexible specification, however it entails the estimation of a large number of parameters and requires specific restrictions to assure that the variance-covariance matrix is

Climent (2006). The authors provide a comprehensive list of papers, as well as methodologies employed in the analysis including GARCH and MGARCH models

²See section: Application of MGARCH models.

positive definite. For this reason it has not been used extensively in the empirical research. De Santis and Gerard (1997), among others, employ this model to test the conditional CAPM, while Ledoit et al. (2003) apply the diagonal version of the VEC model.

One specification that gained substantial popularity in the literature is the BEKK model proposed by Baba et al. (1990) and Engle and Kroner (1995). This model requires a lower number of parameters than the VEC specification and, by construction, it guarantees positive definiteness of the variance-covariance matrix. Karolyi (1995), among others, have found this model suitable for modeling volatility transmissions. Kearney and Patton (2005) employ three-, four- and five-variate BEKK models to estimate volatility spillovers among currencies of the European Monetary System. Other examples of application of this model include Darbar and Deb (1997), Brooks and Henry (2000), Tai (2004), among others.

Another model that has received attention in the literature is the Dynamic Conditional Correlation (DCC) model, developed by Engle (2002). It belongs to a class of MGARCH models that, instead of modeling variance-covariance matrix, are based on modeling of individual variances. At the first stage each of the conditional variances is assumed to follow a certain GARCH process, while at the second stage the structure of the conditional correlation matrix is specified. DCC specification is attractive as it significantly reduces the number of parameters compared to the BEKK model and at the same time it allows for time-varying dynamics of the conditional correlations, which is in contrast with the Bollerslev's (1990) Constant Conditional Correlation (CCC) model of the same class. The latter imposes a restrictive assumption of the conditional correlations being constant over time. More recent examples of studies using different extensions of the DCC model include Billio et al. (2003), Cappiello et al. (2006), Billio and Caporin (2005) and Pelletier (2006), among others.

In what follows we provide a more detailed overview of the above-mentioned MGARCH models and discuss the estimation strategy used throughout the following chapters.

1.2 Overview of MGARCH models

This section reviews some of the MGARCH models most used in the empirical literature on volatility transmissions. Let $\{y_t\}$ be an $N \times 1$ vector stochastic process. In financial applications, y_t mostly represents a vector of log-returns of N assets. y_t is usually assumed to be represented by the following equation:

$$y_t = \mu_t(\theta) + \varepsilon_t \quad (1.1)$$

where $\mu_t(\theta)$ is the conditional mean vector with θ being a vector of parameters and

$$\varepsilon_t = H_t^{1/2}(\theta)z_t \quad (1.2)$$

where H_t is the $N \times N$ conditional covariance matrix of y_t given the past information (I_{t-1}) up to time $t - 1$. The positive definite matrix $H_t^{1/2}$ is obtained by decomposition (e.g. Cholesky) of H_t and z_t is an *iid* vector error process such that

$$\begin{aligned} E(z_t) &= 0 \\ Var(z_t) &= I_N \end{aligned} \quad (1.3)$$

with I_N representing the identity matrix of N dimension.

The main challenge of the MGARCH literature has been specifying the variance-covariance matrix H_t , which according to different specifications follows different GARCH processes. In the rest of the section we review three of such specifications.³

The VEC-GARCH model of Bollerslev et al. (1988) is the most general form, since every conditional variance and covariance is a function of all lagged conditional variances and covariances, as well as lagged squared returns and cross-products of returns. The conditional variance-covariance matrix is specified as:

$$vech(H_t) = C + \sum_{i=1}^q A_i vech(\varepsilon_{t-i}\varepsilon'_{t-i}) + \sum_{i=1}^p B_i vech(H_{t-i}) \quad (1.4)$$

where $vech(\cdot)$ denotes an operator that stacks the columns of the lower triangular part of a square matrix (its argument). C is an $N(N+1)/2 \times 1$ vector of coefficients and A_i and B_i are $N(N+1)/2 \times N(N+1)/2$ coefficient matrices. The obvious advantage of this model

³Note that some classes of MGARCH models, such as Factor or semi-/non-parametric models, are not included in this review as we don't employ these models in our analysis and also because they are not so widely used in the empirical literature.

is its generality that makes it fully flexible for modeling interactions between conditional variances and covariances. However, such flexibility also implies estimating a large number of parameters which equals $(p + q)(N(N + 1)/2)^2 + N(N + 1)/2$. In practice, when N is large, estimation of such systems is hard to implement. For this reason this model has not been very popular in the literature. Bollerslev et al. (1988) also propose a diagonal version of the VEC model, where A_i and B_i are diagonal matrices. In this specification the number of parameters is reduced significantly, however the restriction makes this model inappropriate for analyzing the spillover effects.

The BEKK-GARCH specification developed by Engle and Kroner (1995) offers the same benefits in terms of flexibility as the VEC model, as it allows all the conditional variances and covariances to interact with each other. Yet, the attractive property of this model, also known as a positive definite parameterization, is that the conditional covariance matrices are positive definite by construction (due to the quadratic forms). Dropping the sum operators for simplicity, the variance equation in the BEKK-GARCH(1,1) model can be written in the following form:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \quad (1.5)$$

where A , B and C are $N \times N$ coefficient matrices, with C being an upper triangular matrix.

In more general form equation (1.5) can be rewritten as BEKK-GARCH(p, q) process, where p and q indicate the lag length of the regressors. With $p = q = 1$ the number of parameters to be estimated, excluding those in the conditional mean equation, becomes $2N^2 + N(N + 1)/2$, which is lower than that in the VEC model. To further facilitate application to large-dimensional systems, Ding and Engle (2001) proposed two restricted specifications. In the first, the scalar BEKK, the coefficient matrices A and B represent scalar matrices: $A = \alpha I$ and $B = \beta I$, where I is an identity matrix and α and β are scalars. In the second specification, diagonal BEKK, A and B are diagonal matrices. Such parameterizations substantially reduce the number of estimated parameters, however for obvious reasons the model becomes less suitable for modeling interactions among all the elements of the H_t matrix.

Statistical and asymptotic properties for the BEKK-GARCH model have been investigated by a number of authors. Engle and Kroner (1995) discuss the parameter constraints to ensure stationarity and identification. Identification of the parameters in model (1.5) is achieved by requiring that the diagonal elements of C and elements a_{11} and b_{11} of A and

B respectively, are positive.

Further, the stationarity of the BEKK model is ensured if the matrix H_t is positive definite and all the eigenvalues of

$$\sum_{i=1}^p (A_i \otimes A_i) + \sum_{i=1}^q (B_i \otimes B_i) \quad (1.6)$$

are less than one in modulus, with $\otimes$ denoting the Kronecker product. If this is the case, the unconditional covariance matrix is given by

$$E(\epsilon_t) = [I - (A_1 \otimes A_1)' - (G_1 \otimes G_1)']^{-1} \text{vec}(C_0' C_0), \quad (1.7)$$

where I is an identity matrix and $\text{vec}(\cdot)$ operator stacks the columns of a square matrix.

Rahbek, et al. (2002) provide conditions for geometric ergodicity of the BEKK representation of the multivariate ARCH(q) model. Hafner (2001) proved existence of the fourth moment. The fourth moment is an important measure in finance since it determines the “thickness” of tails of a distribution assumed for return innovations.

Comte and Lieberman (2003) provide results for asymptotic normality and strong consistency of the Quasi-Maximum Likelihood Estimator (QMLE) of BEKK, assuming the existence of the eighth order moment. In turn the authors rely on the conditions outlined in Jeantheau (1998). Hafner and Preminger (2009) consider asymptotic properties of the BEKK model as a special case of the VEC model. The strong consistency of the QMLE is established under the assumption that the second moment of the innovations is finite. It is important that the integrated GARCH process is also allowed. For the asymptotic normality of the QMLE the existence of the sixth moment is required. In addition the paper provides sufficient conditions for geometric ergodicity of the VEC model. Pedersen and Rahbek (2012) propose the variance-targeting estimator (VTE) for the BEKK-GARCH model and derive the asymptotic properties. This two-step estimation procedure is performed by first estimating the (unconditional) variance of the observed process using the method of moments, and second, the QMLE is obtained for rest of the parameters. For the consistency of VTE the second moment is assumed to be finite, while the asymptotic normality can be shown under the finite sixth-order moment. Finally the consistency and asymptotic normality results given above can be also extended to Scalar and Diagonal BEKK.

Another widely used specification is the Dynamic Conditional Correlation (DCC) model of Engle (2002), which has the following form.

$$H_t = D_t R_t D_t \quad (1.8)$$

with

$$D_t = \text{diag}(h_{11,t}^{-1/2} \dots h_{NN,t}^{-1/2}) \quad (1.9)$$

where each individual variance $h_{ii,t}$ follows some univariate GARCH process. Further,

$$R_t = \text{diag}(q_{11,t}^{-1/2} \dots q_{NN,t}^{-1/2}) Q_t \text{diag}(q_{11,t}^{-1/2} \dots q_{NN,t}^{-1/2}) \quad (1.10)$$

and Q_t , with the elements $(q_{ij,t})$, is the $N \times N$ symmetric positive definite matrix, which is given with

$$Q_t = (1 - \alpha - \beta)S + \alpha \nu_{t-1} \nu'_{t-1} + \beta Q_{t-1} \quad (1.11)$$

where ν_t is the devolatilized error ($D_t^{-1} \varepsilon_t$), S is a constant (positive definite) matrix and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$.⁴

The DCC model can be estimated in two steps. First, a univariate GARCH model is estimated for individual variances and, secondly, the structure of the conditional correlation matrix is specified. This fact can be viewed as its advantage, since it requires estimating low number of parameters. Thus, if a GARCH(1,1) process is assumed for individual conditional variances, the number of parameters becomes $(N + 1)(N + 4)/2$, which is significantly lower than the parameter count in the BEKK or VEC models. Nonetheless, one drawback of the model is that it restricts all the conditional correlations to have the same dynamics (since α and β are scalars) and is limited in modeling volatility spillovers. The above specification is also referred to as the scalar DCC, reflecting the structure of the model. More general alternatives have been proposed in the literature. For example Generalized DCC suggested by Cappiello et al. (2006), is a fully parameterized model,

⁴Note that the above specification is based on so called *variance targeting* technique, which implies that the intercept is a function of the long-run variance-covariance matrix. It is common to use a consistent estimator of the unconditional covariance matrix for this purpose.

where the evolution Equation in (1.11) is modified to be (dropping the asymmetric term):

$$Q_t = (S - A'SA - B'SB) + A'\nu_{t-1}\nu'_{t-1}A + B'Q_{t-1}B \quad (1.12)$$

where S is a constant matrix and A and B are parameter matrices. Another generalization of the DCC of Engle (2002) is proposed by Hafner and Franses (2009) which is based on Hadamard product representation.

The asymptotic properties of DCC are somewhat limited. While reviewing the asymptotic results for DCC models, Caporin and McAleer (2010) conclude that the “purported asymptotic theory for DCC models has simply been stated without formal proofs.” Aielli (2008) showed that the two step estimation of the DCC model is inconsistent.⁵ In particular, the author demonstrated that the sample correlation estimator (used in place of S) is an inconsistent estimator of the long run correlation matrix in DCC. Therefore the QMLE conditional on the inconsistent estimator cannot be consistent. An alternative, consistent, specification has been suggested by the author, the so called cDCC model. However, Hafner and Reznikova (2012) argue that for high dimensions the problem remains in the Aielli (2008) specification too. Their suggested solution is using the shrinkage technique, which produces an asymptotically consistent estimator of the correlation matrix. Finally, Caporin and McAleer (2010) showed that the conditional correlation estimates in the Indirect DCC of Caporin and McAleer (2008), which is derived from the BEKK representation, are consistent.

Estimation strategy

Because the empirical issues of our interest, highlighted in the following chapters, demand high flexibility of the model, also because of the fact that high dimensionality is not a major problem in addressing those questions, we want to use a model that is as general as possible in terms of spillover effects. For most empirical purposes both DCC and BEKK models could be used interchangeably, i.e. each can perform the same task as the other. However, we make our choice in favor of the BEKK-GARCH model and in this we partly rely on the findings and suggestions outlined by Caporin and McAleer (2010), who compare the two models and draw important conclusions from the theoretical perspective. The paper reviews theoretical aspects such as, conditions for consistency and asymptotic

⁵This result is also extended to a range of DCC models.

normality, sufficient conditions for existence of moments, computational tractability, etc. All in all, the authors conclude that, from the theoretical viewpoint, the optimal model is BEKK. Further, to address specific empirical issues, we amend the specification of the conditional variance-covariance matrix in equation (1.5) in different ways; these changes and corresponding modifications of the estimation are discussed in each chapter.

In the BEKK parameterization presented above the coefficients a_{ij} and b_{ij} of A and B cannot be interpreted directly. This can be seen from the equations (1.13) through (1.15), which correspond to the conditional variances and covariance equations for the bivariate BEKK-GARCH model. We can examine the effect of the regressors on the dependent variables in detail. As shown, such effects are represented by nonlinear functions of the estimated coefficients. For example for interpreting the effect of $h_{1,t-1}$ on $h_{1,t}$ we calculate the function (b_{11}^2) .

$$\begin{aligned} h_{1,t} = (c_{11}^2) & \\ & + (a_{11}^2)\varepsilon_{1,t-1}^2 + (2a_{11}a_{21})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + (a_{21}^2)\varepsilon_{2,t-1}^2 \\ & + (b_{11}^2)h_{1,t-1} + (2b_{11}b_{21})h_{12,t-1} + (b_{21}^2)h_{2,t-1} \end{aligned} \quad (1.13)$$

$$\begin{aligned} h_{21,t} = h_{12,t} = (c_{11}c_{12}) & \\ & + (a_{11}a_{12})\varepsilon_{1,t-1}^2 + (a_{11}a_{22} + a_{12}a_{21})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + (a_{21}a_{22})\varepsilon_{2,t-1}^2 \\ & + (b_{11}b_{12})h_{1,t-1} + (b_{11}b_{22} + b_{12}b_{21})h_{12,t-1} + (b_{21}b_{22})h_{2,t-1} \end{aligned} \quad (1.14)$$

$$\begin{aligned} h_{2,t} = (c_{12}^2 + c_{22}^2) & \\ & + (a_{12}^2)\varepsilon_{1,t-1}^2 + (2a_{12}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + (a_{22}^2)\varepsilon_{2,t-1}^2 \\ & + (b_{12}^2)h_{1,t-1} + (2b_{12}b_{22})h_{12,t-1} + (b_{22}^2)h_{2,t-1} \end{aligned} \quad (1.15)$$

However, for conducting significance test we need to obtain both point estimates and standard errors of these nonlinear functions. The point estimates can be easily obtained by plugging values of the estimated parameters, whereas calculating the asymptotic standard errors of transformed parameters is not straightforward. For doing so we use the “Delta method”, described for example in Oehlert (1992) or Hayashi (2000), among others. The delta method is used to approximate the variance of a function $G(X)$ of a random variable X . It first applies the first-order Taylor approximation and then takes the variance. For

the multivariate case the final expression is given by

$$\text{Var}(G(\Theta)) = J\text{Var}(\Theta)J'$$

where $G()$ is a $n \times n$ differentiable vector-valued function, Θ is a $m \times 1$ vector of estimated parameters, $\text{Var}(\Theta)$ represents the $m \times m$ variance-covariance matrix of the estimated parameters and J is the $n \times m$ matrix of first derivatives of $G()$ with respect to the parameters, evaluated at the estimated parameters. Thus, the result is the $n \times n$ variance-covariance matrix of $G(\Theta)$.

The model is estimated with the Quasi-Maximum Likelihood Estimation (QMLE) method which produces a robust variance-covariance matrix of the estimated parameters (so called *Sandwich estimation* method). With the QML method a set of unknown parameters (θ_0) is estimated by maximizing the following Gaussian log likelihood function for T observations: $L(\theta) = \sum_{t=1}^T l_t(\theta)$, with

$$l_t(\theta) = -\frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln |H_t(\theta)| - \frac{1}{2} \varepsilon_t' H_t^{-1}(\theta) \varepsilon_t. \quad (1.16)$$

It has been shown (Bollerslev and Wooldridge, 1992, Comte and Lieberman, 2003) that if the conditional mean and variance equations are correctly specified, the QML estimates ($\hat{\theta}$) are consistent and asymptotically normally distributed even under non-normal distribution of innovations. The asymptotic distribution is described by

$$\sqrt{T}(\hat{\theta} - \theta_0) \xrightarrow{d} N(0, \Sigma),$$

where

$$\Sigma = J^{-1} G J^{-1} \quad (1.17)$$

with

$$G = E \left[\frac{\partial l_t(\theta)}{\partial \theta} \frac{\partial l_t(\theta)}{\partial \theta'} \right]$$

$$J = -E \left[\frac{\partial^2 l_t(\theta)}{\partial \theta \partial \theta'} \right]$$

where matrix G represents the expectation of the outer product of the score vector (also called the information matrix) and J is the negative expectation of the Hessian. Both matrices are evaluated at the true parameter vector (θ_0).

Because of the consistency of the QML estimate, the matrices G and J can be consistently estimated by

$$G = \frac{1}{T} \sum_{t=1}^T \frac{\partial l_t(\theta)}{\partial \theta} \frac{\partial l_t(\theta)}{\partial \theta'} \quad (1.18)$$

$$J = -\frac{1}{T} \sum_{t=1}^T \frac{\partial^2 l_t(\theta)}{\partial \theta \partial \theta'} \quad (1.19)$$

evaluated at $\hat{\theta}$. We estimate the derivatives involved in (1.18) and (1.19) numerically as opposed to using analytical expressions provided for example by Hafner and Herwartz (2003). More details on the Sandwich estimation method can be found in Davidson and MacKinnon (2004).

Finally, computations are performed by coding in Ox programming language using OxMetrics, version 6.01.⁶

1.3 Application of MGARCH models

Clearly the primary advantage of MGARCH family models lies in its ability to better reproduce the joint dynamics of the financial markets or individual securities. Abundant number of studies have carried out analysis for different asset classes and shown superior performance of the MGARCH models, depicted by diverse measures. A considerable amount of papers analyze volatility spillovers between *exchange rates* (e.g. Bollerslev, 1990, Ito et al., 1992, or Kearney and Patton, 2005, among others). While other authors study transmissions between *stock markets* and *exchange rates* (Caporale et al., 2002). Other authors, such as Edwards and Susmel (2003), Abad and Novales (2004) and Alonso and Blanco (2005) among others, employ MGARCH models for analyzing volatility transmissions among *interest rates*. As regards the frequency of the data, these studies are mostly based on high frequency data, daily or intraday. However, in some applications, for example regime switching models, weekly or lower frequency is preferred. In this section we discuss specific issues, which are addressed in the following chapters. We demonstrate how applying the Multivariate GARCH models can lead to the better understanding of a particular issue. Since the concept of *asymmetry* is equally important for all chapters that follow, below we briefly describe it before turning to the main issues analyzed.

⁶OxMetrics offers an integrated development environment for Ox programming. More information is available at: www.oxmetrics.net

The concept of asymmetry has drawn substantial attention in the literature and it has originated from the need to obtain a better model fit. Different interpretations of this concept have emerged. For example, some studies use the term asymmetry to describe differences in spillovers between markets, i.e. volatility spillovers are found in one direction but not in the other. However, without doubt, the most widespread concept of asymmetry has been proposed by Black (1976), which relates to the asymmetric response of the volatility to the past shocks of different sign, but of the same magnitude. Thus, according to Black's *leverage hypothesis*, a drop in the value of a stock increases financial leverage, which makes the stock riskier and increases its volatility - a feature that is known as the *leverage effect*. Modeling asymmetries has been popular in the GARCH literature. For the univariate case, most used models are so called EGARCH by Nelson (1991) and GJR-GARCH by Glosten et al. (1993). Engle and Ng (1993) propose useful specification tests such as the Positive Size Bias Test (PSBT), Negative Size Bias Test (NSBT) and Sign Bias Test (SBT). The authors analyze various asymmetric specifications and find supportive evidence for the GJR-GARCH when compared to EGARCH. As for the multivariate case, Kroner and Ng (1998) propose the asymmetric extension of several MGARCH models, including VEC and BEKK. In our analysis we rely on these extensions, which are further explained in the following chapters.

One important application in the empirical literature is that of volatility transmissions between *spot and futures* markets. Examples of authors who find significant spillovers, either one-directional or in both directions include Chan et al. (1991), Arag et al. (2003), Lafuente (2002), Meneu and Torro (2003), Koutmos and Tucker (1996), Tse (1999) and Fung et al. (2005). A related application is estimating the *Optimal Hedge Ratio*, used to minimize the risk of a portfolio where spot contracts are hedged using futures contracts for various assets (e.g. commodities). Examples of such studies include Baillie and Myers (1991), Kroner and Sultan (1993), Brooks et al. (2002) and Lien and Yang (2006), among other works.

It has been shown that hedge ratios based on the dynamic variance-covariance matrix can perform such hedging more accurately than those obtained from static models. However, potential misspecification of the model describing volatility dynamics in commodity data may stem from the failure to account for the asymmetry. Commodities are a good example for which the asymmetric effect is found. But unlike for equities, the response of the volatility is higher for the past positive shocks, which is also referred to as the *inverse leverage effect*. Theoretical arguments behind this effect are found in the *theory of*

storage, according to which the shortage in inventories drives the prices up and increases the volatility/anxiety in markets. Some papers model asymmetries by using the so called “basis”, which represents the difference between spot and futures prices. For example, Ng and Pirrong (1994) find that the basis (as a proxy of inventories) affects metal volatility asymmetrically. Other examples include Brooks et al. (2002) and Lien and Yang (2008). However, using the basis is not the only way to proxy the conditions of inventories. For example Gorton et al. (2007) suggest that spot return itself is an accurate measure of the state of inventories. In chapter 2 we propose an alternative way for accounting asymmetries by applying an MGARCH model, which includes an asymmetric term and thus is well suited for capturing the inventory effect. In Chapter 2 we illustrate the importance of accounting for the commodity inverse leverage effect in modeling the variance-covariance dynamics. By in- and out-of-sample forecast we show that a portfolio hedged using the asymmetric BEKK-GARCH model has lower variance than that optimized using the symmetric BEKK, OLS or naive models. The extension of the analysis, by considering the standard mean-variance utility function, also confirms the result.

Many authors incorporate *macroeconomic news* such as policy rate and/or inflation announcements in the MGARCH models to study related macro-financial linkages. Such a linkage is important twofold: first, asset prices represent one of the channels of the monetary transmission mechanism and the relationship has been the subject of interest of central banks and policy makers (e.g. Bernanke and Kuttner, 2005). Second, the hedging performance of a (MGARCH) model may improve after accounting for macro variables (e.g. Flavin and Wickens, 2003). A large body of literature documents the effect of the US monetary policy on US (Bredin et al., 2005) or foreign (Ehrmann and Fratzscher, 2006) equity returns, i.e. the first moment. Relatively less extensive are studies which explore the cross-border spillover effect on the stock market volatility, i.e. the second moment (Bredin et al., 2005). Finally, the evidence of the effect of the monetary policy news (expressed as the unexpected component of target rate announcements) on the conditional covariance/correlation is limited. Using a multivariate GARCH model Brenner et al. (2009) provide the evidence of the effect on both conditional variance and covariance between bond and stock markets, nevertheless the study is limited to the US market only. Chapter 3 contributes to the existing empirical literature by documenting such an effect at the international level, where the main goal is to investigate the cross-border effect of policy rate announcements on comovements of the world’s major stock markets. Analyzing daily stock market return series with a flexible Multivariate BEKK-GARCH model we find

that monetary policy announcements have significant impact on comovements of domestic, as well as foreign markets. The analysis reveals that a higher magnitude of the surprise component of the Fed and ECB announcements positively affects the US and Eurozone markets' conditional covariances with other developed markets. However, for a group of emerging markets this effect is statistically insignificant and in some cases significantly negative. In turn, reduced correlation between two markets (given unaffected variances) implies that the investors in one market will benefit from the reduction of risk by adding the stocks from the second market to their investment portfolio.

The MGARCH models have been widely applied for analyzing *volatility spillovers* between financial markets, by conducting analysis on stock market indices. The majority of these studies are focused on the developed markets: see e.g. Lin et al. (1994), Tse and Tsui (2002) and Bae et al. (2003). A relatively lower number of papers have analyzed volatility spillovers between developing countries: Scheiher (2001), Syllignakis and Kouretas (2006), among others. The results of the estimated volatility transmission effect is of high practical importance. On the one hand the high degree of integration implies higher vulnerability of a country's economy to the external economic/financial risk, especially during a crisis when market correlations increase substantially. On the other hand, the results have considerable implications for different financial market participants who are involved in hedging and/or managing their financial exposure through portfolio diversification.

Early economic papers have documented that the stock market integration within Europe has increased since the introducing of the European Monetary Union (EMU): Hardouvelis et al. (1999), Fratzscher (2002) and Kim et al. (2005). After the enlargement stage in 2004, several authors analyzed the linkage between the old EU markets and the newly accepted Central and Eastern European (CEE) markets (Scheiher, 2001 and Li and Majerowska, 2006). Chapter 4 aims to extend this empirical evidence and contribute to the existing literature by (i) using a fully flexible model that incorporates different features of the financial time series and is well suited for analyzing volatility spillovers, (ii) increased geographical coverage and (iii) sample period covering the latest enlargement stage in 2007. Particularly, we are interested to what extent and how fast the volatility transmission between newly accepted markets and the old (established) markets increases over time. We find that joining to the European Union has considerable impact on the financial integration of a new member. While we observe a high degree of financial integration for the old markets, the level of integration is found to be lower for the newly accepted members. In addition we find evidence of volatility spillovers among these two groups. These spillovers

are mainly unidirectional, i.e. volatility is transmitted from the old markets to the new markets. Finally, we find that spillovers are higher for the members that joined the union at earlier stages.

1.4 Summary

In this introductory chapter we concentrate on modeling international volatility spillovers and comovement in a multivariate framework. We provide an overview of the most widely used MGARCH models and discuss their application in different fields in the empirical literature.

Further, we outline number of applications where the MGARCH models may lead to the efficient resolution of a range of ongoing empirical issues. Consequently, we highlight our motivation and contribution in addressing these issues and provide a brief summary of the remaining chapters.

Chapter 2

The asymmetric Commodity Inventory Effect On The Optimal Hedge Ratio⁷

2.1 Introduction

Minimizing the investment risk through futures hedging is a technique widely used in many fields (currencies, stocks, commodities). Static regression techniques were first developed to estimate *OptimalHedgeRatios*, i.e. the ratio of futures and spot contracts that minimizes variance of returns (both positive and negative) on a given portfolio. Dynamic versions, computed with GARCH models, were then proposed and shown to perform better than the static ones (e.g. Baillie and Myers, 1991, Kroner and Sultan, 1993 and Lien et al., 2002, among others).

One shortcoming of these papers is that they overlook the potential asymmetries characterizing the dynamics of some assets' return volatility. This is the case of stock prices, for which the increase in the volatility is usually larger after a negative return shock than after a positive one of the same magnitude. The traditional explanation of this asymmetry is related to the balance-sheet effect; falling returns give rise to a deterioration of the debt-to-equity ratio, which raises the probability of default. This effect, originally put forward by Black (1976), is usually referred to as the "*leverage effect*". Commodity prices are another example of assets characterized by the asymmetric dynamics in the volatility. On the contrary to the stock leverage effect, positive shocks to commodity returns cause a larger rise of volatility than negative shock. This phenomenon was mentioned by Ng and Pirrong (1994) who, building on the theory of storage, find that inventory conditions, proxied by the basis (i.e. the spot-futures spread), affect metal prices volatility asymmetrically. Intuitively, shortage in inventories drives the prices up and increases the volatility/anxiety of the markets, while large inventories tend to put downward pressure on prices and decrease volatility.

Some papers take into account asymmetries in their dynamic optimal hedge ratio applications such as Lien and Yang (2006), for currency markets and Brooks et al. (2002), for stock returns. For commodities, Lien and Yang (2008) use a bivariate DCC model capturing the asymmetric inventory effect by adding a decomposition of the basis (into

⁷Chapter adopted from the paper with Jean-Francois Carpentier, resubmitted to the "Journal of Futures Markets" on March 15, 2012

negative and positive terms) in the variance equation. Their approach relies on the theory of storage as laid out by Ng and Pirrong (1994) and takes the basis as a proxy of the state of inventories.

However, the basis is not the sole possible proxy for inventories. As studied by Gorton et al. (2007), spot returns are also good indicators of the state of inventories. In addition, futures data is potentially more affected by speculation related to time-varying risk premium considerations. Since the asymmetries are related to the inventory data, spot returns are potentially less noisy and good alternatives to the basis. In this chapter we propose an alternative approach for introducing asymmetries by using an asymmetric BEKK-GARCH model, in which the asymmetric term captures the commodity inventory effect.

A different, but rather important approach to obtain the optimal hedge ratio is to use realized measures of volatility. Unlike the conditional volatility (e.g. from GARCH models), which can be seen as the ex-ante measure, the realized volatility is usually used as a proxy for the ex-post measure of volatility (since the latter cannot be observed in practice). Measures based on high-frequency data have gained popularity since the study by Andersen and Bollerslev (1998), who showed that the sum of squared intraday returns, i.e. the realized variance, provides an accurate measurement of daily volatility. Consequently a range of other estimators have been also developed, such as realized bipower variation, realized kernels and Markov chain estimators, see for example Barndorff-Nielsen and Shephard (2004a), Barndorff-Nielsen et al. (2008) and Hansen and Horel (2009) among others. A multivariate extension of realized volatility was suggested by Barndorff-Nielsen and Shephard (2004b), while Giot et al. (2010) decompose realized volatility into the continuously varying and discontinuous jump components. Related to OHR is the concept of Beta, in the context of Capital Asset Pricing Model (CAPM), which is a similar measure of linear dependence between two variables and which can also be estimated using time varying/realized variance measures (see e.g. Andersen et al., 2006). An interesting example is a recent paper by Hansen et al. (2012), which proposes a multivariate GARCH model and incorporates the realized variance into the GARCH structure of the conditional variance using the, so called, measurement equation. Using intraday stock index data, McMillan and Garcia (2010) compare hedging strategies based on different models, including realized hedge ratio and standard bivariate GARCH. They report that in terms of portfolio variance minimization the GARCH-based strategy outperforms the former, however when the portfolio mean and variance are considered simultaneously (based on Sharpe ratio) the realized hedge ratio is preferred. In this chapter we do not consider intraday data, there-

fore further extension of the analysis to cover the above mentioned issues might reveal practically useful results.

Our goal is thus twofold, first, we investigate and illustrate the relevance of taking into account the asymmetries in hedging techniques, second, through in-sample and out-of-sample forecasts we examine and compare the performance of our methodology in terms of portfolio variance minimization. This chapter is organized as follows: Section 2.2 introduces to hedging and derives the optimal hedge ratio, Section 2.3 presents the econometric methodology, while Section 2.4 describes the data. In Section 2.5 we present the results, Section 2.6 various extensions and robustness checks are provided and Section 2.7 concludes.

2.2 Hedging

A hedge against a spot position (short or long) is achieved by taking an opposite position in the futures so that losses (gains) incurred in one market are, to some extent, offset by gains (losses) in the other market. The number of futures contracts needed to be purchased depends on the covariance of the spot and futures contracts, as well as the variances of the two. The optimal hedge ratio, minimizing the variance of a hedged portfolio, is derived as follows.

Let S_t and F_t denote the logarithm of the spot and futures commodity prices, respectively. The return on a position in spot is $\Delta S_t = S_t - S_{t-1}$ and on a futures position is $\Delta F_t = F_t - F_{t-1}$. The expected return on a portfolio, R_t comprising one unit of the commodity and β units of the futures contracts would then be

$$E_{t-1}(R_t) = E_{t-1}(\Delta S_t) - \beta_{t-1}E_{t-1}(\Delta F_t), \quad (2.1)$$

where β_{t-1} is the hedge ratio for time t determined at $t - 1$. The variance of the portfolio is:

$$VAR(R_t) = VAR(\Delta S_t) + \beta_{t-1}^2 VAR(\Delta F_t) - 2\beta_{t-1} COV(\Delta S_t, \Delta F_t) \quad (2.2)$$

Combining the portfolio variance in a mean-variance utility function we get:

$$U(E_{t-1}(R_t), VAR(R_t)) = E_{t-1}(R_t) - \theta VAR(R_t) \quad (2.3)$$

where θ is the risk aversion parameter. Maximizing the utility $U(E_{t-1}(R_t), VAR(R_t))$ is equivalent to solve:

$$\begin{aligned} \max \quad & E_{t-1}(\Delta S_t) - \beta_{t-1} E_{t-1}(\Delta F_t) \\ & - \theta (VAR(\Delta S_t) + \beta_{t-1}^2 VAR(\Delta F_t) - 2\beta_{t-1} COV(\Delta S_t, \Delta F_t)) \end{aligned} \quad (2.4)$$

Solving equation (2.4) under the assumption that F_t follows a martingale process, i.e. $E_{t-1}(\Delta F_t) = 0$, yields the optimal hedge ratio β_{t-1}^* :

$$\beta_{t-1}^* = \frac{COV(\Delta S_t, \Delta F_t)}{VAR(\Delta F_t)} \quad (2.5)$$

$$= \rho_t \sqrt{VAR(\Delta S_t)/VAR(\Delta F_t)} \quad (2.6)$$

where ρ_t is the correlation between spot and futures returns.

2.3 Methodology

The simplest way to estimate the optimal hedge ratio laid out in equation (2.6) is to assume that spot and futures returns are perfectly correlated and the spot and futures variances equal to each other. Under these assumptions, the optimal hedge ratio is $\beta_{t-1}^* = 1$. This is the *naive* hedge, that we use as a comparison benchmark for more sophisticated models.

Another simplistic approach is to assume that the variances and covariance of spot and futures returns are constant over time. In this case, $\beta^* = \frac{COV(\Delta S, \Delta F)}{VAR(\Delta F)}$ is just the slope coefficient of a linear regression of the spot return on the futures return. This can be estimated by OLS in a regression of spot on futures return. We also use this approach later as a benchmark.

As reported by Baillie and Myers (1991), Kroner and Sultan (1993) and Lien et al. (2002), early models assuming that the variance-covariance matrix of returns is constant over time, proved to be too restrictive. Kroner and Sultan (1993) use the constant conditional correlation (CCC) model of Bollerslev (1990). The main weakness of this model is that conditional variances may vary over time but not correlations. As documented in Ng and Pirrong (1994), the correlation of spot and futures commodity returns tends to decrease when the inventories get low, according to the theory of storage. Therefore, this multivariate GARCH model is not well-suited for capturing this effect. Lien et al. (2002) use a DCC model, where the correlation is allowed to vary over time. Again, this model is rather restrictive in the sense that the correlation is only affected by its own lags and can-

not be affected, for example, by past shocks to the variances, where the theory of storage suggests that the past spot variance should affect negatively the conditional covariance.

Some authors use the BEKK-GARCH model for estimating the optimal hedge ratio (e.g. Baillie and Myers, 1991). As mentioned earlier, the advantages of the BEKK model is 1) the positive-definiteness of the variance-covariance matrix for all t is guaranteed (provided that H_0 is positive-definite), 2) the time varying structure of all its components (variances and covariance of spot and futures returns) and 3) the potential cross-variables influences of the spot and futures components (each depends on a constant, past variances of spot and futures, past covariance, past squared residuals and cross-products of past spot and futures shocks). We also include the BEKK model in our analysis to compare it with the asymmetric BEKK model.

As mentioned in the introduction, the theory of storage outlines different channels of influence of the inventories on the volatility. According to Gorton et al. (2007), the spot and futures shocks can be used as proxies of the state of the inventory, therefore an appropriate (asymmetric) multivariate GARCH model should capture the following features:

1. Spot variance is more responsive to past shocks than futures variances. As the inventories tend to stabilize over the long-run, the futures prices, especially those corresponding to longer maturities, will not be affected by the changed expectations of the state of the inventories (which is reflected by past shocks).
2. Spot and Futures correlation decreases when the spot variance increases. This is related to the previous point. Since the futures prices are less responsive to the state of the inventories (or expectations), the fluctuations in the futures returns does not match with those observed for the spot returns.
3. Positive shocks should have a larger impact on the volatility than negative shocks (the inventory effect). It is assumed that a reduction in the inventories affects the price positively and such a rise is regarded as the “bad” news by the investors. On the contrary, decrease in the price cannot be interpreted as the inventory shortage.

Thus, to measure and capture the inventory effect we use an extension of the BEKK model proposed by Kroner and Ng (1998) where the variance-covariance matrix not only depends on the magnitude of past squared return innovations and variance-covariance matrix but also on the sign of the past squared return innovations. The asymmetric BEKK model (Asym-BEKK) is the same as the BEKK model except that the variance-covariance matrix is specified as follows.

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\epsilon_{t-1}\epsilon'_{t-1}D \quad (2.7)$$

where D is a 2×2 matrix and ϵ_t , the asymmetric term, is defined as:

$$\epsilon_t = \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} = \begin{pmatrix} \max(\varepsilon_{1,t}, 0) \\ \max(\varepsilon_{2,t}, 0) \end{pmatrix} \quad (2.8)$$

Hence, the elements of D captures the effect of past (positively) signed innovations corresponding to the inventory effect. Note that in Kroner and Ng (1998) ϵ_t is defined as $\min(\varepsilon_t, 0)$, i.e. past negative shocks. In Chapter 1 we discussed the “Delta method” that we use for estimating the standard errors of the nonlinear functions of the estimated parameters. Table A.1 in Appendix A lists these functions for the asymmetric bivariate BEKK-GARCH specification given in equation (2.7).

Finally, as this model assumes the Gaussian distribution for the error term, the log-likelihood function excluding the constant takes the following form:

$$L(\theta) = -1/2 \sum_{i=1}^T (\ln |H_t| + \varepsilon'_t H_t^{-1} \varepsilon_t) \quad (2.9)$$

where T is the number of observations and N is the number of variables (series) in the system ($N = 2$ in this case).

2.4 Data

To illustrate the potential importance of the asymmetries for commodity hedging, we use daily data of the S&P GSCI Index (formerly the Goldman Sachs Commodity Index).⁸ The

⁸Note that it is important that the analysis is conducted for individual commodities, since the arguments brought forward by the Storage Theory may not equally apply to all commodities (e.g. storable vs. non-storable), moreover the empirical evidence is mixed (see for example FAO, 2011). However, reporting results only for those individual commodities for which the “Inverse Leverage Effect” is present should be avoided. Therefore, including the index in the analysis provides a good demonstration of the asymmetric effect for the whole asset class. Nevertheless, individual commodities are also considered in section 2.6. In turn, the choice of these commodities is based on data availability, as well as the results obtained by Carpentier (2010), who tested the “Inventory Effect” for a number of individual commodities using univariate GARCH models.

S&P GSCI index is traded at Chicago Mercantile Exchange and represents a benchmark measure of performance for the global commodity market. The weight of energy is by far higher than other constituents and it amounts to slightly more than 68% as of May 2010. Other components are: Industrial Metals (8.49%), Precious Metals (3.74%), Agriculture (13.7%), and Livestock (5.24%); overall, the index is composed of 24 commodities reported in Table 2.1. Because of the broad diversification the index is also interpreted as a measure of general price movements and inflation in the world economy. We use GSCI Spot Month and GSCI Three Month Future indices, which span the period from May 17, 1995 to April 15, 2010, resulting in 3978 observations. The data were collected from Datastream database under the respective codes CGSYSPT and GS3MSPT. The evolution of the two indices over the sample period is shown in Figure 2.1.

Table 2.1: Goldman Sachs Commodity Price Index (SP GSCI) components and dollar weight (%)

Energy	68.83	Industrial Metals	8.49	Precious Metals	3.74	Agriculture	13.7	Livestock	5.24
Crude Oil	35.35	Aluminium	2.67	Gold	3.35	Wheat	2.95	Live Cattle	2.83
Brent Crude Oil	14.44	Copper	3.79	Silver	0.39	Red Wheat	0.61	Feeder Cattle	0.5
RBOB Gas	4.59	Lead	0.44			Com	3.4	Lean Hogs	1.91
Heating Oil	4.56	Nickel	0.94			Soybeans	2.41		
Gas-Oil	5.78	Zinc	0.66			Cotton	1.38		
Natural Gas	4.1					Sugar	1.78		
						Coffee	0.77		
						Cocoa	0.39		

The choice of the data frequency is based on the empirical evidence and properties of commodity prices. For example FAO (2011) provides a comprehensive review of studies which considers various theoretical and empirical aspects of commodity prices, including the volatility. Most of the reviewed studies that investigate volatility are based on GARCH type models. Some of such papers employ low frequency data, e.g. Ramirez and Fadiga (2003) use quarterly data. In this context, an interesting model is the spline-GARCH model of Engle and Rangel (2008), which decomposes volatility into short and long-run components. This model has been applied by Roache (2010) to study the impact of macroeconomic variables on the volatility of commodity prices in the context of monthly data. However, GARCH models are most often fitted to high-frequency data (daily and intra-day). Examples include Kalev and Duong (2008) and Karali and Thurman (2010), Busse et al. (2011).

Summary statistics are presented in Table 2.2. As predicted by the theory of storage

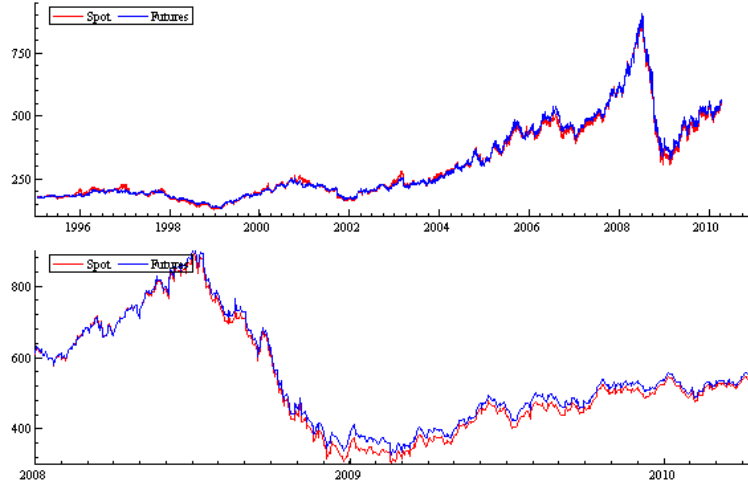


Figure 2.1: Goldman Sachs Commodity Price Index

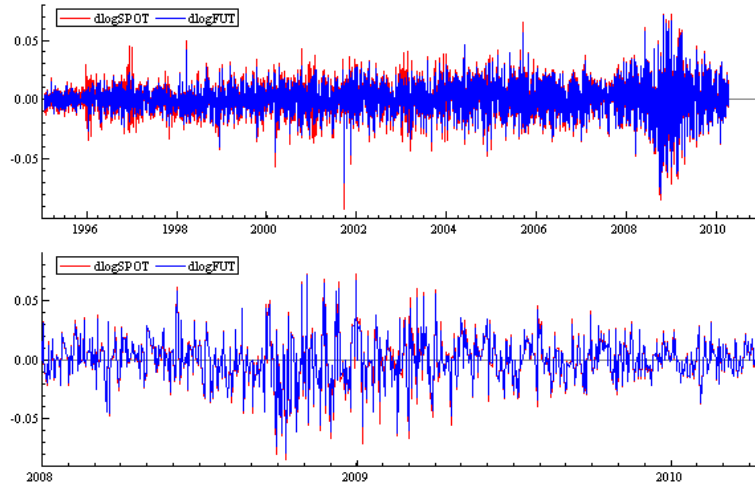


Figure 2.2: Spot and Futures Log-Return Series

and documented by Ng and Pirrong (1994), the standard deviation of spot returns is larger than for futures returns. The logic behind this argument is that when inventories are large, shocks affect both spot and futures volatility equally, but when stocks are low, spot volatility is more affected by a potential stock out than futures for which production has more time to adjust. The spot return also has more extreme values than futures, following the same logic. When tested for the presence of a unit root, using Augmented Dickey-Fuller (ADF) test,⁹ these series are found to be integrated of order one. However, after taking

⁹See Table A.2 in Appendix A

Table 2.2: Summary statistics of Log>Returns

	Spot	Futures
Mean	0.028438	0.028970
Standard Deviation	0.014473	0.012481
Minimum	-0.091451	-0.078958
Maximum	0.072147	0.070885
Normality test	725.58***	1089.8***
Unit Root test	-30.27***	-29.82***
$Q^2(20)$ test	2575.6***	3698.0***
LM test	42.85***	57.38***
Observations	3977	3977

Note: Log-Return of a variable x is defined as $\ln(x_t) - \ln(x_{t-1})$ and is multiplied by 100, i.e. is expressed in percentage. The null of the normality test is normality of the series. The null of the Unit Root test is the presence of the unit root in the series. The null of the Box-Pierce test ($Q^2(20)$) is the absence of autocorrelation in the squared series. The null of the Lagrange Multiplier (LM) test is the absence of ARCH effect in the series. *** stands for significance at 1%.

log-differences the data become stationary. The graph of these daily log-return series is given in Figure 2.2. Box-Pierce test on squared return series and Lagrange Multiplier test of Engle (1982), reported in Table 2.2, also indicate the presence of heteroskedasticity in the series, which together suggest that using GARCH models would be relevant.

It is well known that the equity and commodity time series are characterized with frequent jumps, which is also confirmed in Figure 2.2. In the presence of extensive outliers in the data the consistency of the QMLE estimates is adversely affected. Therefore, we underscore that one has to be careful when interpreting the QMLE results. To work around this problem, a number of authors have proposed robust estimation techniques. Some examples for univariate GARCH models include Franses and Ghijsels (1999), Park (2002), Peng and Yao (2003), Mancini et al. (2005) and Muler and Yohai (2002, 2007). In a recent paper Boudt and Croux (2010) propose a Robust M-Estimation for Multivariate GARCH models and give sufficient conditions for its consistency and asymptotic normality.

Further, using Monte Carlo simulations and by applying their model to empirical data the authors demonstrate good robustness (in the sense of Huber, 1981) of the estimator. Thus, conducting further analysis for detecting jumps and applying the above robust estimation technique is an important topic for potential extension of this study. To this end interesting results, especially in the context of Chapter 3, are found by Lahaye et al. (2011) who studied jumps and co-jumps (i.e. simultaneous jumps) across different asset classes. They employ Andersen et al. (2007) and Lee and Mykland (2008) test, with modification by Boudt, et al. (2008), to extract such jumps. In addition they also study the impact of macroeconomic news on the jumps and their findings suggest that news is a significant driver of the jump processes across markets.

2.5 Results

In this section we compare different models in terms of hedging performance and test if the asymmetric BEKK model delivers better results for hedging a (potential) position in the GSCI index. To do so, we estimate time-varying hedge ratios using two different specifications for the conditional variance-covariance matrix, which are then compared with the constant hedge ratio, obtained from the OLS regression and the naive hedge, i.e. the hedge ratio being equal to 1. Below we review the results obtained from estimation of these models.

The most basic estimate of the OHR is obtained from the OLS regression, where it represents simply an estimated slope coefficient. Table 2.3 shows that, for the full sample, the OHR estimated in this way is equal to 1.129, meaning that an investor interested in reducing the variance of a portfolio would have to sell (buy) 1.129 futures contracts for every spot contract in which (s)he has a long (short) position.

Table 2.3: OLS regression for dependent variable ΔS_t

Exog. Var.	Coef.	Std. Err.	t value	Prob.> t
ΔF_t	1.129678	0.004151	272.18	0
<i>Constant</i>	-1.8E-05	2.25E-05	-0.82	0.414

However, relaxing the assumption of a constant OHR and using time-varying variance-covariance matrices as an input for calculating OHR gives more flexibility. The parameter estimates for the multivariate BEKK-GARCH model are presented in Table 2.4. Panel A shows the results for the conditional mean equations, which are specified as AR(1) processes for both spot and futures series. P -values are presented in parenthesis and, as

can be seen, in both cases the lag coefficient is statistically different from zero, while the constant is insignificant.

Table 2.4: Estimated Coefficients for BEKK-GARCH Model

<i>Panel A</i> : Conditional Mean Equations (<i>P</i> -values in parenthesis)	
$y_{1,t} = 0.000040 + 0.102380y_{1,t-1} + \varepsilon_{1,t}$ $(0.6090) \quad (0.0000)$ $y_{2,t} = 0.000082 + 0.108843y_{2,t-1} + \varepsilon_{2,t}$ $(0.2307) \quad (0.0000)$	
<i>Panel B</i> : Conditional Variance-Covariance Matrix (<i>P</i> -values in parenthesis)	
$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$ $C = \begin{bmatrix} 0.000740 & 0.000439 \\ (0.0000) & (0.0000) \\ 0 & -0.000000 \\ & (0.0000) \end{bmatrix} \quad A = \begin{bmatrix} -0.851078 & -0.405689 \\ (0.0000) & (0.0000) \\ 1.031991 & 0.551631 \\ (0.0000) & (0.0000) \end{bmatrix}$ $B = \begin{bmatrix} 0.813052 & -0.070711 \\ (0.0000) & (0.0000) \\ 0.191031 & 1.067519 \\ (0.0000) & (0.0000) \end{bmatrix}$	

Panel B displays the coefficient estimates for the conditional variance-covariance matrix. The elements of A and B matrices represent the ARCH and GARCH effects respectively and C is an upper-triangular matrix representing the constant term. P -values in parenthesis suggest high statistical significance of both ARCH and GARCH effects. Lastly the eigenvalues of the matrix given in Equation (1.6) fall inside the [0.81 - 0.98] interval.

The results for the asymmetric BEKK-GARCH model, given in Table 2.5, suggest the presence of asymmetries in the conditional covariance dynamics. Particularly, all elements of matrix D are statistically significant even at 1% level.

However, as mentioned earlier, the BEKK specification does not allow direct interpretation of these elements as the impact of past variables on the contemporaneous volatility. Instead, we are interested in interpreting functions of these parameters, the results of which are reported in Table 2.6. The results confirm the presence of the inverse leverage effect, it can be clearly seen that positive innovations to spot and futures returns in period $t - 1$ have amplifying effect on the variances of both series in period t . The conditional covariance between the two series also responds positively and significantly to past positive

Table 2.5: Estimated Coefficients for Asymmetric BEKK-GARCH Model

<i>Panel A</i> : Conditional Mean Equations (<i>P</i> -values in parenthesis)	
$y_{1,t} = 0.000141 + 0.113007y_{1,t-1} + \varepsilon_{1,t}$ (0.4506) (0.0000) $y_{2,t} = 0.000262 + 0.116116y_{2,t-1} + \varepsilon_{2,t}$ (0.1051) (0.0000)	
<i>Panel B</i> : Conditional Variance-Covariance Matrix (<i>P</i> -values in parenthesis)	
$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\varepsilon_{t-1}\varepsilon'_{t-1}D$	
$C = \begin{bmatrix} 0.000734 & 0.000327 \\ (0.0000) & (0.0014) \\ 0 & -0.000003 \\ & (0.0000) \end{bmatrix}$	$A = \begin{bmatrix} -0.401618 & -0.045789 \\ (0.0000) & (0.1511) \\ 0.243888 & -0.127907 \\ (0.0004) & (0.0042) \end{bmatrix}$
$B = \begin{bmatrix} 0.921622 & -0.003593 \\ (0.0000) & (0.6909) \\ 0.066443 & 0.986246 \\ (0.0003) & (0.0000) \end{bmatrix}$	$D = \begin{bmatrix} -0.348236 & -0.206677 \\ (0.0002) & (0.0001) \\ 0.479650 & 0.328875 \\ (0.0000) & (0.0000) \end{bmatrix}$

shocks. The implied effect on the conditional correlation and the optimal hedge ratio can be also assessed. As the coefficient estimates suggest squared positive shocks of both series negatively affect the correlation, with the magnitude being slightly less than 0.8%.¹⁰ But the cross product of the shocks has about 3.62% positive impact. As for OHR, it positively responds to squared shock, while negatively to the cross product. Overall, the joint effect of all the past positive shock terms is positive, with the magnitude being about 0.0985% and 0.000048% for OHR and the correlation respectively. Lastly, it can be seen that all the asymmetric effects are statistically significantly different from zero.

Figure 2.3 graphs the time-varying OHRs for the BEKK- and asymmetric BEKK-GARCH models, as well as OLS and Naive hedge ratios. The average optimal hedge ratio for the asymmetric model is slightly lower than that obtained from the symmetric model (1.162967 and 1.16468 respectively) and both are higher than OLS hedge ratio. The two time-varying ratios are mostly above one, implying that more than one future contract should be traded for each spot contract.

¹⁰the effects given in percent terms represent the estimated coefficients expressed as a percentage of the average of the estimated variable to which they refer , e.g. a reported effect (coefficient) on the conditional variance can be expressed as a percentage of the sample average of this estimated variance.

Table 2.6: Estimated nonlinear coefficients and standard errors for asymmetric BEKK-GARCH Model using Delta Method

	Equation $h_{t,1}$		Equation $h_{t,12}$		Equation $h_{t,2}$	
	Coefficient	St. Error	Coefficient	St. Error	Coefficient	St. Error
C	1.0E-5***	1.3E-5	1.4E-7**	2.1E-7	2.9E-6	1.0E-6
ε_1^2	0.161***	0.045	0.018	0.015	0.002	0.003
$\varepsilon_1\varepsilon_2$	-0.196**	0.082	0.040*	0.022	0.012***	0.004
ε_2^2	0.059*	0.034	-0.031***	0.005	0.016	0.011
h_1	0.849***	0.030	-0.003	0.008	1.3E-6	6.5E-6
h_{12}	0.122***	0.031	0.909***	0.011	-0.007	0.018
h_2	0.004*	0.002	0.066***	0.019	0.972***	0.022
ϵ_1^2	0.121*	0.064	0.072**	0.033	0.043**	0.022
$\epsilon_1\epsilon_2$	-0.334***	0.149	-0.214**	0.086	-0.136**	0.064
ϵ_2^2	0.230***	0.088	0.158***	0.059	0.108**	0.050

Note: ***, ** and * represents significance at 1, 5 and 10 per cent levels respectively.

To compare in-sample hedging performance we use the full sample. The four OHRs are used to choose optimal positions in futures contracts over the sample period, then, the sample variance evaluated for the whole period is used as the measure of hedging performance. As illustrated in Table 2.7 employing time-varying OHR significantly reduces the portfolio variance. The symmetric BEKK model offers variance reduction of 26.62% compared to naive hedge. The asymmetric model performs even better, delivering additional reduction of 0.36%. Not surprisingly, the naive hedge is the worst, while the OLS hedge produces only 19.62% reduction.

Table 2.7: In-sample forecasts: Variance and mean of Naive, OLS, BEKK and Asym-BEKK portfolios

	Naive $\beta = 1$	OLS $\beta = 1.1296$	BEKK $\beta = h_{12,t}/h_{22,t}$	Asym-BEKK $\beta = h_{12,t}/h_{22,t}$
Variance	0.0133	0.0107	0.0097	0.0097
% of Variance	100.00%	80.38%	73.38%	73.02%
Mean	0.0232	-0.0247	-0.0085	-0.0104
% of Mean	100.00%	-106.21%	-36.54%	-44.71%

Note: For reporting purposes variance and mean are multiplied by 1000.

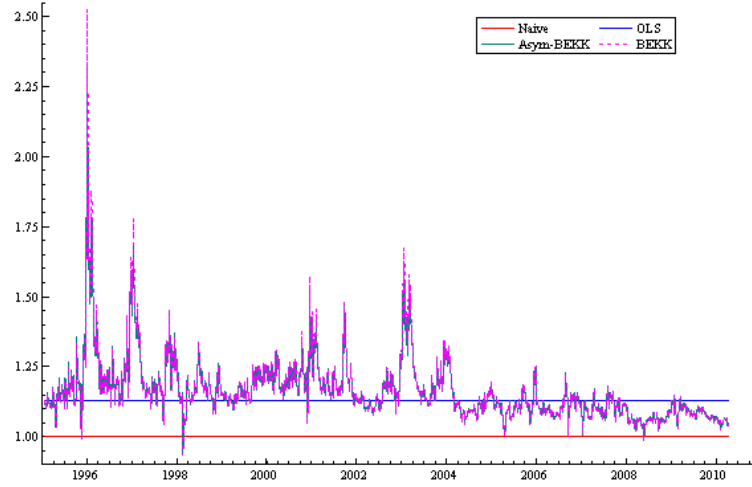


Figure 2.3: In-sample forecasts - Optimal Hedge Ratios

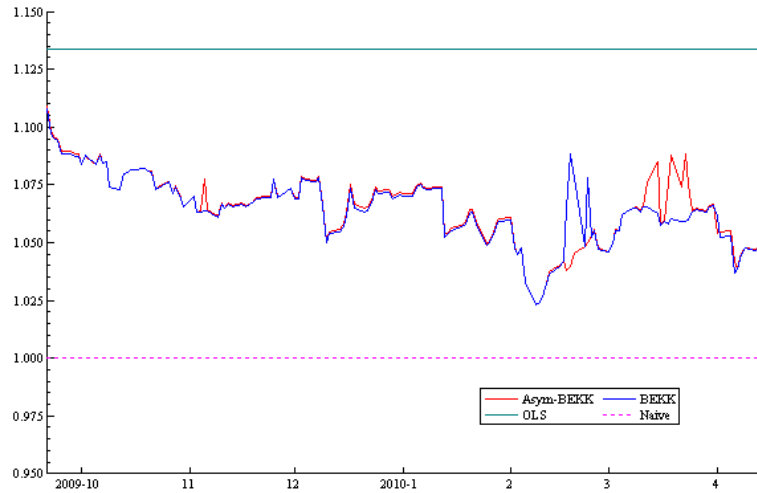


Figure 2.4: Out-of-sample forecasts - Optimal Hedge Ratios

Next we compare out-of-sample performance. One-day ahead forecasting is performed for 150 days (observations). We start at the 3830th observation and repeat the procedure until the 3977th observation. Each time the time-varying models are reestimated and the variance-covariance matrix (hence, OHR) forecasted. Additionally, at this stage, we also reestimate the OLS specification by adding one observation at every 150 steps. We use the obtained optimal hedge ratios to construct a portfolio consisting of spot and futures contracts and compute the variance of the portfolio returns. The generated series are illustrated in Figure 2.4.

The results demonstrate that the asymmetric model yields superior hedging performance relative to all other models. As can be seen from Table 2.8, the portfolio variance is reduced by 6.45% compared to the naive hedge. However, unlike the previous case, naively hedge portfolio is no longer the worst choice for a potential investor. Moreover, using the OHR measures based on OLS and symmetric BEKK models would be riskier than using naive hedge. Finally, the mean portfolio return is also highest for the portfolio hedged using the asymmetric model.

Table 2.8: Out-of-sample forecasts: Variance and mean of Naive, OLS, BEKK and BEKK-GJR portfolios

	Naive $\beta = 1$	OLS $\beta = 1.1335$	BEKK $\beta = h_{12,t}/h_{22,t}$	Asym-BEKK $\beta = h_{12,t}/h_{22,t}$
Variance	0.0010	0.0017	0.0011	0.0009
% of Variance	100.00%	176.86%	111.37%	93.46%
Mean	0.0372	0.0599	0.0412	0.0632
% of Mean	100.00%	160.86%	110.86%	169.89%

Note: For reporting purposes variance and mean are multiplied by 1000.

In their paper Brooks et al. (2002) suggest linking the concept of the optimal hedge ratio with the notion of the *News Impact Surface* developed by Kroner and Ng (1998). According to the authors changes in prices can be viewed as additional information available to the market. Therefore, innovations in prices, $S_t - S_{t-1} = \varepsilon_{S,t}$ and $F_t - F_{t-1} = \varepsilon_{F,t}$, represent a measure of news arriving to the market between periods t and $t - 1$. Consequently, the relationship between innovations in returns and the conditional variance-covariance structure is defined as the news impact surface. The optimal hedge ratio β_{t-1}^* , as defined in equation (2.6), can be linked to news by using news impact surfaces of futures variance and spot-futures covariance. The resulting news impact surface may be interpreted as the response of the optimal hedge ratio to arrival of the news.

Figures 2.5 through 2.8 plot the news impact surface for the conditional spot and futures variances, the conditional spot-futures covariance and the optimal hedge ratio, which are obtained from the asymmetric BEKK model. Each surface is evaluated in the region $\varepsilon_{j,t} = [-1, 1]$, with $j = Spot, Futures$.

The asymmetric response of variances and covariance is clearly seen from these Figures. Particularly, for higher positive values of innovations in spot and futures returns the conditional spot variance reaches higher levels in magnitude. This effect is especially

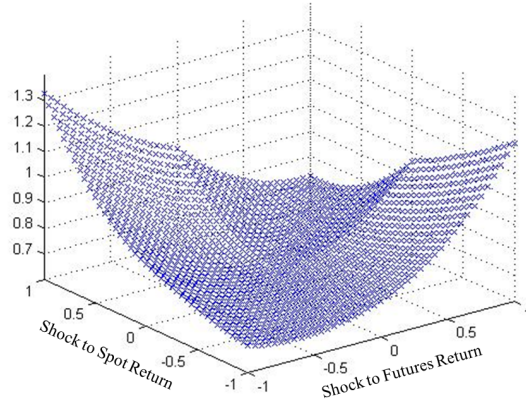


Figure 2.5: News Impact Surface of the Spot variance

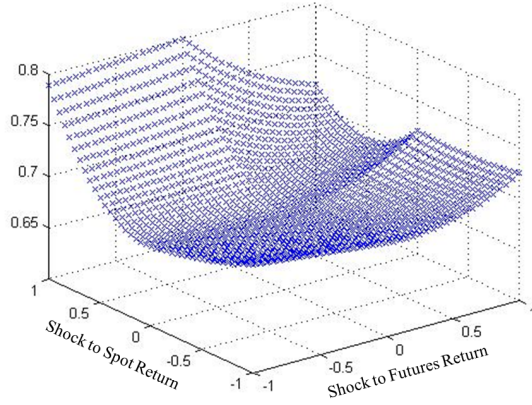


Figure 2.6: News Impact Surface of the Futures variance

strong for the high positive values of spot returns. A similar pattern is found for the news impact surface of the futures variance, i.e. stronger response of the variance is found for the region where return innovations are positive. The response of the conditional covariance to news is given in Figure 2.7. The higher response of the conditional covariance to the positive values illustrates the presence of the inverse leverage effect. Further, the impact of positive innovations in spot return on the covariance is higher compared with the effect of changes in futures return. This latter observation goes in line with the storage theory, which suggests that higher fluctuations in the spot prices are amplified by past positive shocks. Finally, Figure 2.8 shows the response of the optimal hedge ratio to news. It can be seen that the effect on OHR is quite stable, nevertheless in certain regions it displays jumps. However, the number of such jumps is limited.

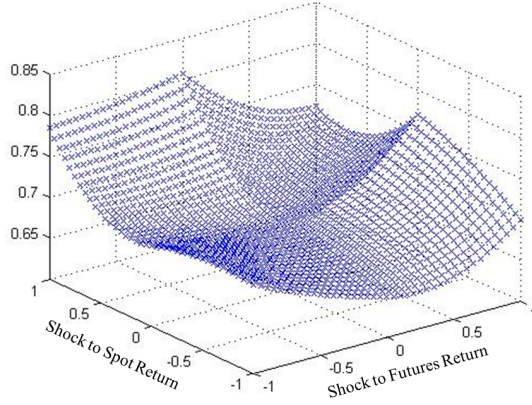


Figure 2.7: News Impact Surface of the Spot-Futures covariance

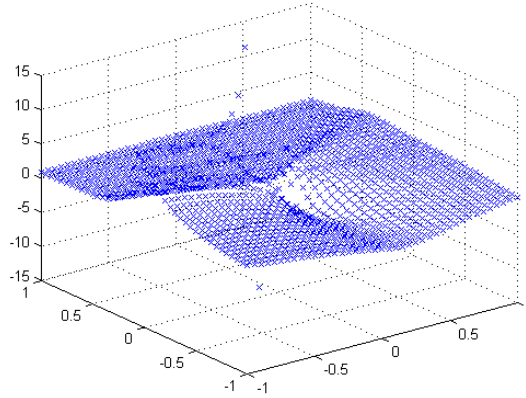


Figure 2.8: News Impact Surface of the Optimal Hedge Ratio

2.6 Extensions

We propose two extensions: first, we check if taking into account the inventory effect through an asymmetric BEKK model also improves the hedge performance for individual commodities. We then consider an alternative optimization framework not restricted to the variance reduction. More precisely we relax the assumption of F_t being a martingale and maximize the (quadratic) expected utility function by taking into account both the expected portfolio return and variance.

2.6.1 Other commodities

To check the relevance of using an asymmetric-BEKK model for estimating a dynamic optimal hedge ratio, we reiterate our in-sample and out-of-sample forecasts for 3 additional

commodities: lead, nickel and aluminium. Daily price series of these metals are available on Datastream under the following codes: LEDCASH and LED3MTH for lead, LNICASH and LNI3MTH for nickel and LAHCASH and LAH3MTH for aluminium. The suffix “CASH” and “3MTH” denote spot and futures prices respectively. The advantage of using these series, traded at the London Metal Exchange, is their availability in a continuous form (i.e. no need to compile successive futures contracts and correct for rollover discrepancies). Another advantage is their availability on the same time horizons as our benchmark S&P GSCI Index (spot and 3-month horizons). As before, we estimate two multivariate models for each of the three commodities. The results, that confirm the presence of the inventory effect, are provided in Tables A.3 through A.8 in Appendix A, similar to those presented in Tables 2.4 and 2.5.

Table 2.9: In-sample forecasts: Individual commodities

	Naive	OLS	BEKK	Asym-BEKK
Aluminium				
Variance	0.0108	0.0110	0.0112	0.0107
% of Variance	100.00%	102.11%	104.15%	99.45%
Lead				
Variance	0.0406	0.0399	0.0416	0.0397
% of Variance	100.00%	98.24%	102.92%	97.90%
Nickel				
Variance	0.0376	0.0376	0.0363	0.0364
% of Variance	100.00%	100.00%	96.47%	96.61%

Note: For reporting purposes variance is multiplied by 1000.

Further, Tables 2.9 and 2.10 compares the in- and out-of-sample performance of the asymmetric BEKK, BEKK, OLS and Naive models in terms of portfolio variance reduction. As shown by in-sample results the former outperforms all other models. The reduction of the portfolio variance by the asymmetric model is lowest for Aluminium (0.56%) and highest for Nickel (3.39%). Thus, in-sample performance of the asymmetric BEKK is better than its symmetric counterpart. The comparison of these two models shows that the variance obtained by the asymmetric BEKK model is lower for Aluminium and Lead by 4.46% and 4.57% respectively, while for Nickel it is higher by 0.28%. The difference between BEKK and asymmetric BEKK is even greater for out-of-sample results, where the

Table 2.10: Out-of-sample forecasts: Individual commodities

	Naive	OLS	BEKK	Asym-BEKK
Aluminium				
Variance	0.0244	0.0245	0.0339	0.0252
% of Variance	100.00%	100.31%	138.71%	103.28%
Lead				
Variance	0.0287	0.0296	0.0336	0.0277
% of Variance	100.00%	103.15%	117.17%	96.35%
Nickel				
Variance	0.0263	0.0260	0.0254	0.0260
% of Variance	100.00%	99.13%	96.55%	98.92%

Note: For reporting purposes variance is multiplied by 1000.

asymmetric model is far more effective.¹¹ For Aluminium and Lead the portfolio variance is lower by 25.67% and 24.32% respectively but, as before, is higher for Nickel (2.36%). Nevertheless, it must be noted that in both in- and out-of-sample forecast not BEKK, but Naive hedge is the second best for all commodities but Nickel. When we compare asymmetric BEKK with the Naive hedge, for both the index and individual commodities, in-sample variance improvement (of asymmetric BEKK over Naive) is higher than observed for the out-of-sample forecast. This is generally in line with the results found in the literature.

2.6.2 Mean-variance framework

The optimal hedge ratio depends on the particular objective function to be optimized. Minimizing the variance is the most widely used approach, but there exist alternatives. Lien and Tse (2002) and Chen et al. (2003) present a review of different theoretical approaches to optimal hedge ratios and discuss, as alternatives to the variance minimization, the mean-variance, the expected utility, the mean extended-Gini coefficient as well as the semivariance approaches. All these alternatives consider a priori that minimizing the variance is too restrictive and that the risk aversion or the expected return should be taken

¹¹It must be noted that the in-sample calculations are based on the full sample and the estimated variance-covariance matrix picks up the effect of the starting values (sample covariance matrix) in the beginning of the sample. For this reason the portfolio variance might be inflated (because of poor hedging in the beginning of the sample). Excluding first 200 observations and recalculating in-sample OHRs slightly reduces the portfolio variance, but not substantially and the difference remains.

into account. Actually, most of these approaches are equivalent to variance minimization under certain assumptions.¹²

A key assumption, used in Section 2.2 for derivation the optimal hedge ratio, was that the futures return follows a martingale, i.e. $E_{t-1}(\Delta F_t) = 0$. Under this assumption, the mean-variance framework (where the objective function to maximize is $E(R_p) - \theta Var(R_p)$, where θ is the risk aversion and R_p the portfolio return) is equivalent to the variance minimization. Even optimizing the expected-utility, where the objective function to maximize is $E(U(Wealth))$, turns out to be equivalent to the variance minimization if the utility function is quadratic (Kroner and Sultan, 1991).

Assuming that the futures return follows a martingale has some empirical grounds. Indeed, the constants in the mean equations reported in Tables 2.4 and 2.5 are not significant, this tends to give support to this assumption. Notwithstanding this empirical indication, we relax it to check the robustness of our results. The first reason is that the return on the portfolio hedged according to the asymmetric BEKK model does not outperform the return of the portfolio hedged using the BEKK model. In some cases, the portfolio return is even lower. Improving the risk performance in this case comes at the costs of lower return. The second reason of implementing the mean-variance framework is to implicitly check if the martingale assumption is reasonable. Radically different results, compared to those from Section 2.5 would seriously challenge the martingale assumption.

For convenience, we rewrite the quadratic utility function, which is maximized (see equation 2.4):

$$\begin{aligned} \max \quad & E_{t-1}(\Delta S_t) + \beta_{t-1} E_{t-1}(\Delta F_t) \\ & - \theta (VAR(\Delta S_t) + \beta_{t-1}^2 VAR(\Delta F_t) - 2\beta_{t-1} COV(\Delta S_t, \Delta F_t)) \end{aligned} \quad (2.10)$$

If we relax the martingale assumption for the futures return and solve this mean-variance optimization problem, we now find that the optimal hedge ratio, β_{t-1}^{**} , has an additional term:

¹²Chen et al. (2003) note that the extended mean-Gini coefficient hedge ratio would be the same as the minimum variance hedge ratio if the spot and futures returns were jointly normally distributed. The mean-generalized semivariance hedge ratio approach, based on lower partial moments, takes into account the mean and the asymmetric risk aversion (to better capture the portfolio managers focus on lower tail return distributions). Chen et al. (2003) note that this approach also provides the same results as variance minimization when futures price follow a martingale process.

$$\beta_{t-1}^{**} = \frac{COV(\Delta S_t, \Delta F_t)}{VAR(\Delta F_t)} - \frac{E_{t-1}(\Delta F_t)}{2\theta VAR(\Delta F_t)} \quad (2.11)$$

Following Lien and Yang (2008) and the empirical estimation of Chou (1988), we assume that θ , the degree of risk aversion, is equal to 4 and compare performance of different strategies.

Table 2.11: In-sample forecast: portfolio “utility”

	Naive	OLS	BEKK	Asym-BEKK
GSCI Index				
Utility	-0.13034	-0.13059	-0.13049	-0.13046
% of Utility	100.00%	100.20%	100.12%	100.10%
Aluminium				
Utility	-0.10419	-0.10421	-0.06213	-0.06188
% of Utility	100.00%	100.02%	59.63%	59.39%
Lead				
Utility	-0.15450	-0.15454	-0.07567	-0.07109
% of Utility	100.00%	100.03%	48.98%	46.02%
Nickel				
Utility	-0.11917	-0.11917	-0.06959	-0.06479
% of Utility	100.00%	100.00%	58.40%	54.37%

Note: Utility is defined as $E(R_p) - \theta Var(R_p)$. The OHR used is calculated as β_{t-1}^{**} (Equation 2.11).

We report our results in Tables 2.11 and 2.12, which show that, when we take into account the expected futures return, the utility increase can be achieved by using the asymmetric BEKK-GARCH model. As implied by the in-sample results, for all but the index series the utility is improved and for the latter it stays almost at the same level. The out-of-sample results further demonstrate the superiority of the asymmetric model. Along with the asymmetric one, BEKK also performs significantly better than other models, however it cannot beat the asymmetric model in any of the four cases.

2.7 Conclusions

Commodities are often found to exhibit the “inverse leverage effect”, in other words the response of the conditional variance to past negative shocks is weaker than the response to

Table 2.12: Out-of-sample forecast: portfolio “utility”

	Naive	OLS	BEKK	Asym-BEKK
GSCI Index				
Utility	-0.06137	-0.06150	-0.03305	-0.03302
% of Utility	100.00%	100.22%	53.87%	53.82%
Aluminium				
Utility	-0.05129	-0.05124	-0.01437	-0.01143
% of Utility	100.00%	99.89 %	28.03%	22.30%
Lead				
Utility	-0.06433	-0.06411	-0.01001	-0.00876
% of Utility	100.00%	99.66%	15.57%	13.63%
Nickel				
Utility	-0.05625	-0.05625	-0.02192	-0.01738
% of Utility	100.00%	100.00%	38.98%	30.90%
<i>Note:</i> Utility is defined as $E(R_p) - \theta Var(R_p)$. The OHR used is calculated as β_{t-1}^{**} (Equation 2.11).				

positive shocks of the same magnitude, i.e. opposite to the “leverage effect” documented for equity data in the empirical finance literature. This paper aims to show that addressing hedging problem in a multivariate setup that allows asymmetric response of the conditional variance-covariance matrix delivers a superior measure of optimal hedge ratio and reduces the risk that investors face when hedging their positions in spot contracts using futures contracts. To account for such asymmetries we estimate a flexible, asymmetric multivariate GARCH model in which the covariance structure is specified in a way that past positive and negative shocks have different effect on the conditional variances and covariance.

Our results confirm that such an asymmetric model yields improvements in both in-sample and out-of-sample forecasting and reduces the variance of returns on a portfolio consisting of spot and futures contracts on a broad commodity index (GSCI). These findings imply that using asymmetric multivariate models would be more effective in hedging compared with those that assume symmetric response to past innovations. In addition to hedging optimization, the results may have important implications for other widespread risk measures such as Value-at-Risk.

Chapter 3

Multivariate Modeling of the Global Spillover Effect of Monetary Policy Announcements on the Stock Market Volatility and Comovements

3.1 Introduction

The extent to which the monetary policy influences stock markets has been extensively studied by the theoretical and empirical economic literature. Asset prices represent one of the channels of the monetary transmission mechanism and theory suggests that in efficient markets new information is swiftly and fully absorbed and reflected in the dynamics of asset prices. Over the past decade several crisis periods demonstrated that financial markets' comovements across countries became more intensive and therefore the risk (volatility) contagion from one market to another is faster. The existing literature has explored the impact of the policy interest rate news on domestic, as well as foreign financial markets' returns (first moment) and volatility (second moment), while the evidence on the effect on market comovements (covariance) has not been documented at the international level.

On the other hand, such an effect on covariances is of great practical importance from the viewpoint of asset allocation and hedging (where the conditional covariance is modeled to be time-varying) since covariances, along with the return and variance, represent a fundamental input on which portfolio rebalancing decisions are based. Indeed, the advantage of employing a time-varying variance-covariance matrix in reducing a portfolio variance (i.e. the risk) is documented by a large number of empirical papers.¹³ Moreover, investors may directly incorporate macroeconomic news (including policy rate announcements) in their portfolio rebalancing decisions. For example Flavina and Wickens (2003) show that “taking account of inflation generates portfolio frontiers that lie closer to the origin and offers investors superior risk-return combinations.”

Numerous studies document a significant relationship between US monetary policy and US equity prices. For example Bernanke and Kuttner (2005) find that, on average, a hypothetical unanticipated 25 basis points (BPS) cut in the federal funds target rate is associated with about a 1 percent increase in broad stock indices.¹⁴ Other studies examine

¹³See, for example, Ledoit et al. (2003), Goeij (2004), Giotand and Petitjean (2005), Balasubramanyan (2005), Engle and Colacito (2006), Switzer and Omelchak (2009), Otranto (2010). Additionally, some recent examples of dynamic hedging using MGARCH models include Pandey (2008), Lee (2009), Moona et al. (2009), Jia and Fan (2011), among others.

¹⁴Other examples include: Bernanke and Blinder (1992), Kuttner (2001), Cochrane and Piazzesi (2002), Zettelmeyer (2003), Bomfim (2003), among others.

the relationship between US monetary policy and foreign equity prices. Ehrmann and Fratzscher (2006), find mostly a negative impact of the US monetary policy shocks on returns for fifty foreign equity markets. Using high-frequency data, Wongswan (2009) shows that, on average, an unanticipated 25 BPS cut in the federal funds target rate increases foreign equity indices by 2%.

A relatively lower number of papers provides evidence on the cross-border spillover effect on the stock market volatility. Bredin et al. (2005) analyze the effect of the Fed's target rate surprises on the Irish equity market volatility and find the calm before the storm effect, i.e., a decline in volatility on the day prior to a Federal Open Market Committee (FOMC) meeting and a subsequent increase on the day when an announcement is made. Kim and Nguyen (2009) found that unanticipated announcements by the Fed and the ECB significantly influence the volatility of twelve stock markets in the Asia-Pacific region. However, both papers rely on univariate models for estimating the spillover effect. This is a drawback, since such models do not account for interdependences of conditional variances and covariances and their relevance for analyzing market comovements is limited.

Finally, there is a limited evidence of the effect of the monetary policy news (expressed as the unexpected component of target rate announcements) on the conditional covariances. Brenner et al. (2009) employ an extended version of the multivariate GARCH-DCC model of Engle (2002) for modelling the spillover effect on the volatility and comovements of US equity and bond markets. We contribute to the existing empirical literature by documenting such an effect at the international level and, thus, providing comprehensive evidence on the linkage between monetary policy and financial markets globally.

The finance literature often finds an asymmetric response of the stock market volatility to unexpected negative and positive announcements. For example Bomfim (2003) found that unanticipated rises in the Fed funds target rate tend to have a larger effect on S&P volatility than unanticipated declines. Using a bivariate GARCH model, Gulley and Sultan (2003) find that US monetary policy shocks had an asymmetric effect on the stock market. Bredin et al. (2005) also provide evidence of the asymmetric response of the Irish stock market volatility to unexpected US monetary tightening. Such asymmetries go in line with the leverage effect documented in the finance literature (Black, 1976). The latter states that negative shocks to the stock returns in the previous period (usually regarded as "bad" news by equity investors) have higher impact on the current period volatility compared with the past positive shocks (which can be interpreted as "good" news). In this paper, we also test whether there is an asymmetric response of foreign volatility and comovements

to unanticipated tightening (“bad” news) and unanticipated expansion (“good” news).

Our results reveal the significant reaction of the conditional covariances to releases of unexpected monetary news. Further, we find that this effect varies according to the level of development of financial markets (developed versus emerging), as well as the information contents of the news (positive versus negative). Particularly, the findings suggest that the Fed and ECB announcements have positive effects on the conditional covariances between developed markets and negatively impact on the covariance between developed and emerging (BRIC)¹⁵ markets. Further, market comovements are more responsive to the negative news by the Fed, whereas for the ECB we don’t find significant differences between the effect of bad and good news.

One important application in the context of this chapter, which we do not consider but leave as a potential extension, is investigating the impact of news on the exchange rate volatility and volatility transmissions between exchange rates and equity. Examples of such studies include Fratzscher (2004) and Kim (1998) for major currencies, Fišer and Horváth (2010), Goyal and Arora (2010) for emerging currencies. Further Ben Omrane and Hafner (2011) use intraday data, while Lahaye et al. (2011) investigate the effect of macro news on jumps.

Finally, in Section 1.3 we discussed the use of intraday data for estimating the conditional variance-covariance matrix. Extending this study and conducting analysis on the intraday data may prove to be extremely important since the (intraday) impact of news on the covariance matrix may disappear within hours/minutes.

The rest of the paper is structured as follows. In Section 3.2 we present the econometric model and methodologies, in Section 3.3 we describe the data used in the analysis, Section 3.4 provides the summary of the results and in section 3.5 we conclude.

3.2 Methodology

3.2.1 *The model*

The econometric model used in this chapter is based on the BEKK specification described in Chapter 1, however we slightly modify the model in order to include the announcement effect. Thus, the conditional mean equation takes the following form:

$$Y_t = \alpha + \Theta Y_{t-1} + \Omega_1 News_{FED,t} + \Omega_2 News_{ECB,t} + \varepsilon_t \quad (3.1)$$

¹⁵By the term BRIC we refer to a group of countries: Brazil, Russia, India and China.

where $News_{FED,t}$ and $News_{ECB,t}$ represent the unexpected components of the changes in the monetary policy rate for the Fed and the ECB respectively (assumed to be exogenous) and Ω_1 and Ω_2 are $(N \times 1)$ vectors of coefficients, where N is the number of variables in Y_t . Further, the conditional variance equation also includes two exogenous variables, represented by the matrix $NEWS_t$ in the following equation:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + ZNEWS_tZ' \quad (3.2)$$

The matrix $NEWS_t$ is a $(K \times K)$ diagonal matrix of exogenous variables in the variance equation and K equals the number of exogenous variables in the model. Z represents an $(N \times K)$ matrix of coefficients.

We consider two specifications for the conditional variance equation. In the baseline specification, we are interested in evaluating the effect of the magnitude of news. Even though the rate changes might be correctly anticipated, the magnitude (size) of the change may still be surprising for the market participants. Therefore, in this specification, the matrix $NEWS_t$ includes only the absolute value (or modulus) of the news component (thus the elements of $NEWS_t$ are $|News_{FED,t}|$ and $|News_{ECB,t}|$ on its main diagonal, i.e. $K = 2$). On the other hand, as discussed in Section 3.1 the investors may react differently to the “good” and “bad” news. Thus, the information content, i.e. the sign of the unexpected news component is important. To test for such an asymmetric effect, in the second specification we drop the absolute values of the news component and instead decompose it into positive and negative components. The matrix $NEWS_t$ then becomes a diagonal matrix with $News_{FED+,t}$, $News_{ECB+,t}$, $News_{FED-,t}$ and $News_{ECB-,t}$ on its main diagonal with the subscripts “+” and “-” indicating positive and negative news respectively. In this case K is equal to four.

It is worth noting that in this setup the final term in Equation 3.2 is a quadratic term in Z , which in turn implies imposing certain restrictions on the effect of news variables. In particular Tables B.1 and B.2 show that the (nonlinear) coefficients of news in the conditional variance equations are restricted to be positive. This might be a drawback, since in the empirical literature a negative effect of news on the volatility has been found (e.g. Kim and Nguyen, 2009), known as the market calming effect. However, the theory is not prescriptive in this regard and the sign of the news effect will depend only on the information content that particular news conveys to a particular market – i.e. whether the news adds or resolves uncertainty in the market. The use of quadratic forms in the

BEKK model (excluding the last term of Equation 3.2) is a way of achieving positive definiteness of the H_t matrix for all $t = 1, \dots, T$. Nonetheless, imposing a similar restriction on the news term ($Z'NEWSZ$) does not necessarily guarantee its positive definiteness, since the elements of NEWS may be negative. For this reason the quadratic form might be substituted with more flexible term, which would impose minimum or no restrictions on the coefficients. However, we find that using the quadratic form produces much more stable results during the numerical optimization. Additionally, it already implies the equality of the effects of the news variables on h_{ij} and h_{ji} , for $i \neq j$. On the other hand, the choice of the above specification does not restrict the effects of news on the conditional covariances, it can be seen from Tables B.1 and B.2 that they can become negative. Thus, there is still some flexibility in the model, since the negative effect on covariances might be transmitted to variances via the second lag.

As before, we calculate nonlinear functions of the estimated coefficients. Tables B.1 and B.2 in Appendix B list the corresponding functions for the bivariate and 3-variable BEKK-GARCH(1,1) models with four exogenous variables.¹⁶

Finally, assuming the normal distribution of the error term, the log-likelihood function (excluding the constant) takes the following form:

$$L(\theta) = -1/2 \sum_{i=1}^T (\ln |H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \quad (3.3)$$

where T is the number of observations and N is the number of variables (series) in the system.

3.2.2 *Measuring unexpected changes of the target rate (news component)*

To measure the impact of the monetary policy it is necessary to model the news, or the unexpected component of a target rate announcement. Different measures have been used in the economic literature. A number of earlier studies employed survey-based variables, from which proxies of expectations for changes in the policy rate are obtained (e.g. Reinhart and Simin, 1997). However, more recent studies have instead relied on market price-based proxies. Krueger and Kuttner (1996) showed that the Fed funds futures rate is an efficient predictor of the Fed funds target rate and, therefore, an appropriate measure of policy expectations. Later Kuttner (2001) used Fed funds futures rate to derive the unanticipated

¹⁶ When the model includes two exogenous variables, the nonlinear functions correspond to those shown for the first two variables (X_1 and X_2).

component of changes in the Fed funds target rate. A recent study by Kim and Nguyen (2009) relies on the same methodology. Authors who show the Fed funds futures rate to be an efficient predictor of Federal Open Market Committee’s (FOMC) target rate changes are Grkaynak et. al. (2002), Bomfim (2003), Wongswan (2006) and Piazzesi and Swanson (2008), among others.

The measure of expectations of the ECB’s policy also varies across researchers. In the earlier studies the Euro Overnight Index Average (EONIA) has been used (Gaspar et al., 2001). More recently, Bernoth and Von Hagen (2004) suggested that the three-month EURIBOR futures rate is an unbiased predictor of the euro area policy interest rate changes. This choice was also confirmed by Kim and Nguyen (2009) who used the three-month EURIBOR futures contracts traded on the EUREX. Thus, the recent literature suggests that using market-based futures rates would give a more accurate measure for predicting the upcoming policy interest rate changes. In this paper, we follow Kuttner (2001)’s approach to extract unanticipated news component. We use the current-month Fed funds futures contracts traded on the Chicago Board of Trade (CBOT) and the three-month EURIBOR futures contracts traded on the EUREX to construct the news measure for the two central banks.

According to Kuttner (2001) the news component of the Fed’s target rate (and the ECB’s target interest rate – Main Refinancing Operations) announcement on day d of month m can be derived from the implied change in the price of the futures contract and is calculated as:

$$\Delta i^u = \frac{D}{(D-d)}(f_{m,d}^0 - f_{m,d-1}^0) \quad (3.4)$$

where Δi^u is the unexpected target rate change, $f_{m,d}^0$ is the current month Fed funds futures rate for the Fed and three-month EURIBOR futures rate for the ECB, $f_{m,d-1}^0$ is the futures rate on the day prior to the announcement. $D/(D-d)$ is a scaling factor. D is the number of days in the month and $D-d$ is the number of days in the month affected by the announcement. The Fed funds futures settlement price is based on the monthly average of the spot Fed Funds rate therefore it has to be scaled back, to account for the number of days affected by the announcement. The three-month EURIBOR futures settlement price is based on the EURIBOR, so there is no need of scaling the news variable.

Bernanke and Kuttner (2005) discuss the issue of endogeneity associated with the above measure. Potential sources of endogeneity might be a direct response of monetary policy

to stock market fluctuations or a joint response of both policy and the stock market to new information. Should there be such an issue, an instrumental variables approach would be necessary to obtain consistent estimates. However, according to the authors, a same-day response by the FOMC to new information is highly unlikely and there is a little probability of observing the problem for surprises measured at a daily frequency. Further, as noted by the authors, “to the extent that this endogeneity exists, it would tend to introduce a downward bias in the stock market’s estimated response to monetary policy. And in any case, our results do not depend on the assumption that the FOMC bases its decision on publicly released data”.

3.3 Data

3.3.1 *Monetary policy news*

The FOMC in the U.S. announces the Fed funds target rate after its regular, as well as ad hoc meetings at 2:00 pm US Eastern Standard Time (EST, GMT-5). For the ECB, the interest rate on the Main Refinancing Operations (MRO) represents the policy interest rate. The governing council meets twice a month, during which a press release announcing the decision on the key ECB interest rate is made at 1:45 pm Central European Time.

The frequency of the dataset used in the analysis varies across studies. Some researchers have chosen to employ low-frequency data in the estimation process (e.g. Durham, 2001). However, Wongswan (2009) argues that previous studies that use low-frequency data may “fail to detect responses that are incorporated very quickly”. The author refers to the study by Bailey (1990) and argues that his results, which showed weak evidence of foreign equity market responses to FOMC announcement surprises, could be due to the use of the low-frequency data. Indeed, employing the high-frequency data, the author found significant impact of the monetary policy on equity prices. Taking into account the fact that GARCH models perform better in the short-run, we follow the recent literature that suggests employing the high-frequency data and in our analysis we use the daily data of returns on stock indices.

The summary statistics of the monetary policy news variables for the Fed and the ECB are provided in Table 3.1. For the period from January 1999 through December 2010 there have been 115 announcements by the Fed, from which 20% were rate raises, another 20% rate cuts and the rest were no changes. As can be seen (the upper-left panel of the table), slightly less than 34% of all the announcements were anticipated correctly. From the unanticipated surprises 39 were positive and 37 – negative, which corresponds to 33.91%

and 32.17% of the total number of the Fed’s announcements. The mean value of positive rate changes is equal 0.25. This is due to the fact the Fed mainly increased the target rate by 25 BPS, while the rate cuts were of a larger magnitude, ranging from -25 to -75 BPS.

Table 3.1: Descriptive statistics for monetary policy news and announcements.

	Fed monetary policy surprises				Fed funds target rate (actual changes)			
	Total	Positive surprises	Negative surprises	No surprises	Total	Rate hike	Rate cut	No Change
Mean	-0,06	0,12	-0,32	0	-0,04	0,26	-0,46	0
Min	-1,95	0,01	-1,95	0	-0,75	0,25	-0,75	0
Max	0,93	0,93	-0,01	0	0,50	0,50	-0,25	0
St. Dev.	0,37	0,20	0,53	0	0,24	0,05	0,16	0
Skewness	-3,08	2,74	-2,20	0	-1,05	4,80	-0,18	0
Kurtosis	13,97	7,38	4,04	0	1,06	23,00	-0,46	0
Observations / Announcements	115	39	37	39	115	23	23	69
Proportions	100,00%	33,91%	32,17%	33,91%	100,00%	20,00%	20,00%	60,00%

	ECB monetary policy surprises				ECB target rate (actual changes)			
	Total	Positive surprises	Negative surprises	No surprises	Total	Rate hike	Rate cut	No Change
Mean	0,00	0,04	-0,04	0	-0,06	0,28	-0,43	0
Min	-0,19	0,00	-0,19	0	-0,75	0,25	-0,75	0
Max	0,28	0,28	0,00	0	0,50	0,50	-0,25	0
St. Dev.	0,05	0,05	0,03	0	0,38	0,09	0,15	0
Skewness	1,10	2,96	-2,30	0	-0,19	2,51	-0,09	0
Kurtosis	7,39	11,41	7,27	0	-1,62	4,90	-0,17	0
Observations / Announcements	177	81	71	25	177	16	15	146
Proportions	100,00%	45,76%	40,11%	14,12%	100,00%	9,04%	8,47%	82,49%

In comparison, only 14.12% of all ECB rate announcements were anticipated correctly. More than 45% of the total announcements were unexpectedly contractionary (positive) and about 40% were unexpectedly expansionary (negative). As for actual changes in the Main Refinancing Operations rate, sixteen times the ECB announced the rate hike and fifteen times took an expansionary decision (rate decrease). Finally, the variation of Fed news (0.37) was much higher than that of the ECB news (0.05), whereas it was the opposite for variation of the Fed funds target rate versus variation of the MRO rate. These datasets can be obtained from the websites of the two central banks.¹⁷

3.3.2 Stock return data

The dataset that we use covers the period from January 1999 through December 2010, thus corresponds to the monetary policy announcements data. We use daily log returns: $\ln(r_t) - \ln(r_{t-1})$, where r_t is the return on day t , computed on stock price indices in local

¹⁷The datasets are available at <http://www.federalreserve.gov/FOMC/calendars> for the Fed, and <http://www.ecb.int/stats/monetary/rates/html/index.en.html> for the ECB.

currencies.¹⁸ Only simultaneous trades are considered, i.e. we filter out the data to exclude all the observations when at least one market (in the model) was not operating. In addition, we follow Kutter (2001) and Bernanke and Kuttner (2005) to exclude the observation on September 17, 2001, as it represents joint decline in policy rate and stock markets, due to the US terrorist attack of September 11, 2001. After such filtering, the actual number of observations decreases slightly.

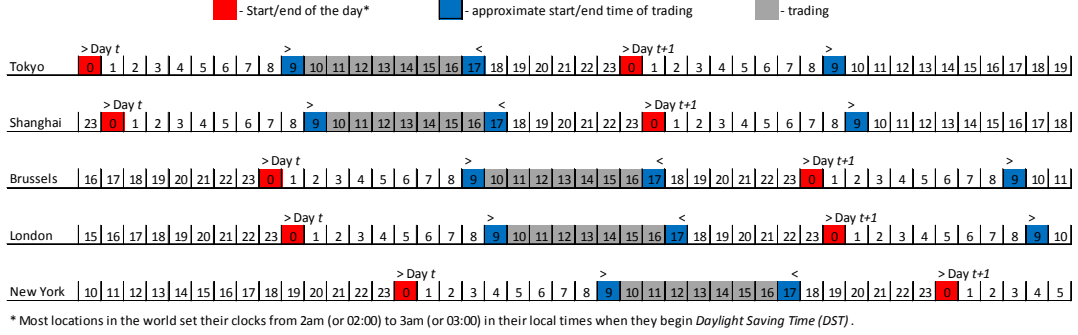


Figure 3.1: The “Timeline” for selected time zones

To circumvent the problem of non-simultaneous trading, stemming from time differences between the regions under consideration, we calculate returns over different time horizons. Due to the differences in trading hours in the regions under consideration, the problem of nonsynchronous trading may arise, with three possible cases: (i) total overlapping, (ii) no overlapping and (iii) partial overlapping. The first case does not imply any problem for the methodology of calculating daily returns, while for the second and third cases the issue gets more complex. In our analysis the last two cases are present. A very widespread solution to the asynchronous trading problem is using weekly data, for which this problem has very limited influence. This approach has been chosen by Aggarwal (1997), Martens and Poon (2001), Forbes and Rigobon (2002), Hyde et al. (2007), among others. However, in practice most financial applications (e.g. hedging) are important at a daily frequency, therefore we do not consider weekly data in this study. Another approach to deal with the issue would be to artificially synchronize daily returns data. One widely used method was suggested by Burns et al. (1998) and has been applied to empirical data by Martens and Poon (2001), Sun Y. (2008) and Hernandez et al. (2011). The authors give unconditional correlation between the synchronized and unsynchronized returns. It is noteworthy that about half of the reported correlations are not increased after applying the synchronization technique.¹⁹

¹⁸Expressing the stock price indices in their national currencies restricts their changes to the movements in the stock prices solely, avoiding distortions induced by exchange rate fluctuations (Voronkova, 2003).

¹⁹See Table 1, Table 2 and Table 3 respectively in the above references.

Other authors have used intraday data to circumvent the asynchronous trading problem, e.g. Gannon (2005) who uses the synchronously sampled data from real time records at 15 minute intervals for Hong Kong and US stock data. As mentioned earlier, our dataset consists of daily returns, what automatically excludes the possibility of using such techniques. Thus, rather than applying synchronization procedures, we calculate daily returns over different time horizons for different markets, as done for example in Hamao et al. (1990) and a large number of papers that are comprehensively reviewed by Soriano and Climent (2005), for example. These calculations are conducted as follows.

Unless otherwise specified, the daily returns for the US is calculated as open to close, i.e. the intraday return on day t . For the European countries we calculate open to open returns from day t to day $t + 1$. However, when the Asian markets enter the system alongside the European and the US markets, we use close to close return for the US, from day $t - 1$ to t and open to close return on day t for the European markets. Finally for the Asian markets we use open to open return from day t to day $t + 1$. Figure 3.1 illustrates that overlapping in trading is the highest for such a setup, in other words significant part of trading in different countries takes place simultaneously. Hence it is more likely that we observe comovements for these returns. We note that returns calculated in this way may still introduce a bias in estimated spillovers (e.g. due to the fact that opening price of one market will reflect the information during the period when it was closed but another market was open), but on the other hand these returns together span a period (slightly more than 24 hours) during which all markets would be responsive to the same set of external information, thereby reflecting movements due to the common factors.

The following stock market indices are employed in the analysis. For the United States - SP 500, Europe - FTSE Eurofirst 300, Eurozone - FTSE Eurofirst 300 Eurozone, France - CAC 40, Germany - DAX, Luxemburg - Luxemburg LuxX Index, Spain - IBEX 35, Belgium - BEL20, Finland - OMX Helsinki, the Netherlands - AEX Index, the United Kingdom - FTSE all share, Switzerland - Swiss Market Index (SMI), Sweden - OMX Stockholm 30, Japan - TOPIX, Korea - KOSPI Index, Brazil - BOVESPA, China - Shanghai Stock Exchange All Share Index, India - BSE-100, Russia - RTS Index. These countries were selected according to US holdings of foreign securities.²⁰

Descriptive statistics for the 19 series are summarized in Table 3.2. Returns have been multiplied by 100, so that they can be interpreted as percentage changes. The data reveals clear differences between the emerging and already established stock markets. Particularly,

²⁰See Table B.15 in Appendix B.

Table 3.2: Descriptive statistics, log-returns of all series.

	S & P 500 OC	Eurofirst 300 OC	Eurofirst 300 Eurozone OC	France OC	Germany OC	Luxemburg OC	Spain OC	Belgium OC	Finland OC	Netherlands OC
Mean	0.01	-0.01	-0.01	0.01	0.01	0.01	-0.01	-0.01	-0.02	-0.01
Min	-9.13	-8.24	-8.28	-11.98	-10.38	-30.05	-9.77	-11.81	-17.42	-12.02
Max	10.25	9.94	10.09	8.54	10.10	33.22	10.45	9.82	14.56	9.95
St. Dev.	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.01	0.02	0.02
Skewness	0.22***	0.08	0.07	0.19**	0.17**	-0.22***	0.11	0.17**	-0.34***	0.16**
Skewness t-stat.	2.89	1.02	0.97	2.54	2.24	2.92	1.39	2.26	4.52	2.16
Excess Kurtosis	2.12***	1.77***	1.1***	1.88***	1.33***	2.25***	0.57***	3.26***	3.99***	2.68***
Kurtosis t-stat.	13.92	11.63	7.22	12.33	8.72	14.79	3.75	21.39	26.23	17.60
Observations	2877	2877	2877	2865	2921	2931	2801	2874	2837	2938

	UK OC	Swiss OC	Sweden OC	Japan OO	Korea OO	Brazil OC	China OO	India OO	Russia CC
Mean	-0.01	-0.01	0.01	-0.02	0.04	0.07	0.02	0.03	0.11
Min	-10.91	-14.34	-7.51	-8.12	-11.52	-12.10	-11.06	-12.99	-21.20
Max	8.95	17.81	9.87	10.27	13.32	28.82	12.73	11.82	20.20
St. Dev.	0.01	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.03
Skewness	-0.04	0.02	0.21***	0.01	-0.2***	1.86***	0.57***	-0.65***	-0.29***
Skewness t-stat.	0.56	0.37	2.79	0.07	2.67	24.38	7.45	8.51	3.79
Excess Kurtosis	1.34***	4.05***	0.85***	0.66***	0.42***	24.52***	5.65***	3.71***	3***
Kurtosis t-stat.	8.82	26.64	5.61	4.35	2.77	161.11	37.09	24.35	19.69
Observations	2838	2901	2895	2647	2705	2872	2689	2659	2805

Note: For reporting purposes Mean, Min, Max and St. Dev. have been multiplied by 100, i.e. returns are in percentage.
OC, OO and CC denote open-to-close, open-to-open and close-to-close returns respectively. For Russia only close price data are available.
*, ** and *** denote significance at 10, 5 and 1% respectively.

while for all the developed markets the average return is close to zero, for emerging BRIC countries it is positive and at least twice as large as the highest positive values for developing countries. The highest mean return (0.11%) is observed for Russia. Given the high growth rates in emerging countries in the last decade, this observation does not seem surprising. As can be seen from Table 3.2, six out of nineteen calculated skewness coefficients are statistically insignificant. Whereas the excess kurtosis coefficients are significant for all returns series.

Finally, Figure B.1 in Appendix B provides the graphs of the 19 returns series. As anticipated, these graphs illustrate volatility clustering in the data. Furthermore, emerging markets are, on average, more volatile than established markets. more extreme values are typical for these markets, which is also consistent with the characteristics of emerging markets.

3.4 Results

This section summarizes the estimated results. Section 3.4.1 provides results for the baseline specification that relates the magnitude (absolute value) of the news to the conditional variances and covariances. In Section 3.4.2 we investigate the asymmetric response of the variance-covariance matrix to positive and negative news. Lastly in Section 3.4.3 we conduct a sensitivity analysis, by checking whether the methodology of extracting unexpected news makes a difference when compared with actual changes in the target rate. For brevity

only the estimated coefficients of the news component are reported,²¹ while full estimation results are included in Appendix B.

3.4.1 *Baseline results*

We start our analysis by exploring the effect of the magnitude of monetary policy announcements on volatility and comovements, which is performed by estimating the baseline specification of the model, where only absolute values of the news variables enter the conditional variance and covariance equations as exogenous variables. It is economically sensible to conjecture that, irrespective of their sign, higher unexpected surprises tend to increase uncertainty prevailing in the market and eventually result in higher volatility. Indeed, larger deviations from expectations of the market participants may alter their perception of the incoming information flow, intensify trade activity and give rise to fluctuations of asset prices. In Section 3.4.2 we come back to this question and consider the flip side of this assumption and decompose the news variables into positive and negative components, thus, focusing on the effect of the information contents rather than the absolute magnitude of the announcements.

The estimated results are given in Tables from 3.3 to 3.6. For brevity time indices have been removed from all “news” variables. As discussed in Chapter 1, we need to calculate nonlinear functions of the estimated coefficients, i.e. the elements of matrices A , B , C and Z from the BEKK model. Hence the coefficients reported in this section represent these functions. Further, to conduct statistical tests for significance we obtain standard errors of these nonlinear functions using the Delta method. Finally, alongside the coefficients we also report their P -values, while standard errors are reported only for the US-European model. Throughout the section by the term “statistically significant” we refer to statistical significance at 10% or lower levels. Additionally, we also report the effects on the conditional correlations which are derived from the BEKK model. These effects are included in Tables B.11 and B.14 in Appendix B and they include coefficients for both symmetric and asymmetric models.

Spillover effects between the US and Europe were estimated using the bivariate BEKK-GARCH model. We studied linkages between the US and the Eurozone (EZ), as well as between the US and broader Europe. Respectively Eurofirst 300 Eurozone and Eurofirst 300 indices were used as market proxies.²² The results are displayed in Table 3.3. Panels

²¹For reporting purposes, throughout the section, the coefficients are multiplied by 1000.

²²FTSEurofirst 300 Index consists of the 300 largest companies ranked by market capitalisation in the FTSE Developed Europe Index. The latter comprises large (45%) and mid (55%) cap stocks covering

Table 3.3: Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-EZ/Europe.

	S&P 500 - Eurofirst 300 Euro Zone			S&P 500 - Eurofirst 300		
	Coeff.	St. Dev.	P-value	Coeff.	St. Dev.	P-value
<i>Panel A</i> <i>Conditional Variance: US</i>						
$ News_{FED} $	0.0660	0.0230	0.00	0.0580	0.0230	0.01
$ News_{ECB} $	0.1710	0.0890	0.05	0.1970	0.0980	0.05
<i>Panel B</i> <i>Conditional Covariance: Europe - US</i>						
$ News_{FED} $	0.0040	0.0170	0.79	-0.0080	0.0130	0.53
$ News_{ECB} $	-0.2080	0.0460	0.00	-0.1600	0.0430	0.00
<i>Panel C</i> <i>Conditional Variance: Europe</i>						
$ News_{FED} $	0.0000	0.0020	0.89	0.0010	0.0040	0.77
$ News_{ECB} $	0.2520	0.1370	0.06	0.1300	0.0950	0.17

Note: for reporting purposes coefficients are multiplied by 1000.

A and C show the effect of the news variables on the conditional variance of the US and EZ/Europe respectively. The impact on the conditional covariance between the two markets is presented in panel B.

These results suggest that there is a considerable increase in uncertainty among market participants in response to releases of unexpected monetary policy news. Higher unexpected deviations from the expectations (absolute magnitude of the surprise component) are found to have positive and statistically significant effect on the US stock market volatility. Specifically, an increase in the Fed's news surprise of 100 BPS increases US volatility, on average, by 40.54% (which accounts for 0.29 standard deviation of the US conditional volatility). The ECB's news has even higher impact. As shown in Table 3.3, the coefficient of $|News_{ECB}|$ is significant at 5% level and increases the US volatility, on average, by 105.03% (0.74 St. Dev.). The difference may be a sign of higher credibility and consistency of the Fed, i.e. its surprises create less uncertainty in the market than those of the ECB.²³ The Eurozone volatility responds significantly only to the ECB's announcements with the effect equal to 122.91% (1.12 St. Dev.). Further, when we consider (geographically) broader Europe, represented by the Eurofirst 300 index, it is found that none of the central banks' announcements affect significantly the European volatility at the 10% level. This, at first sight, surprising "puzzle" is explained in the next section, where we turn our attention to the information contents of the announcements. It turns out that positive and negative news have different effect on the Euroblock and other developed non-eurozone

16 Developed markets in Europe and, in its turn, is derived from the FTSE Global Equity Index Series (GEIS), which covers 98% of the world's investable market capitalisation.

²³Note that while this may indicate the current state of the anticipation, but it does not explain its evolution over time. For example it might be possible that decisions of both central banks are better anticipated now than in the past. Similarly the situation may change in the future.

Markets.

The results shown in panel B of Table 3.3 reveal a negative and significant relationship between the conditional covariance and the ECB's monetary news. Such an effect is found for both Eurozone and broader European stock return indices. On the contrary, the coefficient of $|News_{FED}|$ is positive but not significant. However, the latter finding is not consistent with the results from the pair-wise country analysis, where we consider each country coupled with the US. The implied effect of the announcements on the conditional correlations is also negative (Table B.11), suggesting that on average the correlation would decrease after the decision has been announced.

Consistent with the existing literature, we find substantial financial interdependence between the US and European markets. As can be seen from Table B.3 volatility transmission from the US to Europe is higher than the other way around, indicating the dominant role of US financial markets. Contagion of European volatility to the US market takes place through lagged shocks to stock returns and covariance.²⁴

Table 3.4 highlights the results from bivariate GARCH models estimated for seven Eurozone countries. The index i is used to represent the own lagged variables for each country.

Table 3.4: Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-Eurozone countries.

	France		Germany		Luxemburg		Spain		Belgium		Finland		Netherlands	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>Panel A</i>														
<i>Conditional Variance: US</i>														
$ News_{FED} $	0.0770	0.01	0.1090	0.00	0.2290	0.00	0.0890	0.13	0.0340	0.99	0.0640	0.00	0.0790	0.01
$ News_{ECB} $	0.1760	0.22	0.1860	0.01	0.6010	0.03	0.2320	0.35	0.3340	0.01	0.1640	0.00	0.2210	0.00
<i>Panel B</i>														
<i>Conditional Covariance: Country i - US</i>														
$ News_{FED} $	0.0860	0.01	0.0860	0.00	-0.0740	0.00	0.0450	0.13	0.0000	0.99	0.1170	0.00	0.0720	0.01
$ News_{ECB} $	-0.0640	0.22	-0.1090	0.01	-0.1360	0.03	0.0890	0.35	0.2230	0.01	-0.2630	0.00	-0.1740	0.00
<i>Panel C</i>														
<i>Conditional Variance: Country i</i>														
$ News_{FED} $	0.0970	0.10	0.0680	0.02	0.0240	0.05	0.0230	0.38	0.0000	0.99	0.2140	0.00	0.0660	0.11
$ News_{ECB} $	0.0230	0.61	0.0640	0.33	0.0310	0.30	0.0340	0.60	0.1490	0.10	0.4210	0.00	0.1370	0.11

Note : for reporting purposes coefficients are multiplied by 1000.

As the results suggest, unexpectedly high surprises regarding the US Fed's target rate announcements are followed by a sizeable increase in the comovements between the US and the Euroblock stock markets. For five out of seven markets the estimated coefficient is statistically significant. From these the negative impact is observe for only Luxem-

²⁴However, due to the chosen methodology of calculating the US and European returns and the fact that the periods over which these returns were calculated do not overlap perfectly, the spillover effect of the European market might be underestimated. An intraday (high-frequency) data analysis that considers only the simultaneous trading period might unveil even higher spillovers between the two markets.

bourg, on average 144.09% (0.53 St. Dev.), while the lowest positive effect is observed for The Netherlands – 48.71% (0.31 St. Dev.). In terms of standard deviation (of the estimated conditional covariance), the US-Finland covariance has the largest response – 0.89 St. Dev., which corresponds to the average increase of 116.17%. The US-France and US-Germany conditional covariances increase, on average, by 59.94% (0.45 St. Dev.) and 71.38% (0.52 St. Dev.) respectively. Consistent with the results presented in Table 3.3, the ECB’s monetary policy news has a negative and significant effect on the comovements between the US and a majority of the seven Eurozone countries, with Belgium and Spain being exceptions. In comparison, the ECB’s surprising announcements have larger impact on the Eurozone countries: Finland (-261.13%; 2 St. Dev.) and Luxemburg (-279.80%; -1.03 St. Dev.) are among most affected markets and Germany (-90.47%; -0.65 St. Dev.) and The Netherlands (-117.72%; -0.75 St. Dev.) reveal weaker, though substantial responsiveness. The implied effect on the conditional correlations is shown in Table B.12. Five out of seven correlations are affected positively by the US news, whereas the ECB news increases the correlations in three cases.

The conditional volatility of five Eurozone markets increase significantly in response to the US Fed funds target rate surprises and only three markets are found to be significantly affected by the ECB’s monetary news. However, the magnitude of this effect is larger for the latter. For example the Dutch stock market volatility rises, on average, by 50.64% (0.37 St. Dev.) in response to the ECB’s news and by about half of that amount (24.40%; 0.18 St. Dev.) in response to the Fed’s news. Also, for Finland the ECB’s news effect is twice as high as the Fed’s – 102.21% (1.19 St. Dev.) versus 51.96% (0.60 St. Dev.).

Further, we analyze the effect of the two central banks’ monetary policy on the developed non-eurozone equity markets. The selected markets are well-established and are good representatives of their regions. The results are presented in Table 3.5. In panel D we report conditional covariances between country i and the US market, while Panel E highlights the results for the conditional covariance between country i and the Eurozone market. Panels A, C and F present the conditional variances of US, Europe and country i respectively. The derived effects on the conditional correlations are given in Table B.13.

All five covariances between the US and developed markets show significant response to the Fed’s news with the coefficient being positive in four cases. The response to the ECB news is mixed and less significant. All covariances, but one, between the EU and developed markets respond positively to both the Fed and ECB news, with the effect being higher for the latter. Interestingly, the correlation between the EU and developed markets

Table 3.5: Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-developed countries.

	UK		Switzerland		Sweden		Japan		Korea	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>Panel A</i>	<i>Conditional Variance: US</i>									
$ News_{FED} $	0.0380	0.09	0.0680	0.00	0.0840	0.00	0.1590	0.01	0.0920	0.00
$ News_{ECB} $	0.0870	0.16	0.1910	0.05	0.1290	0.12	0.0790	0.37	0.0060	0.72
<i>Panel B</i>	<i>Conditional Covariance: US – Eurozone</i>									
$ News_{FED} $	0.0090	0.51	-0.0010	0.95	0.0260	0.15	0.0290	0.32	-0.0220	0.14
$ News_{ECB} $	-0.1790	0.00	-0.1210	0.01	-0.1240	0.00	0.2500	0.13	0.0460	0.50
<i>Panel C</i>	<i>Conditional Variance: Eurozone</i>									
$ News_{FED} $	0.0020	0.71	-0.0010	0.98	0.0080	0.40	0.0050	0.57	0.0050	0.50
$ News_{ECB} $	0.3690	0.01	0.0770	0.34	0.1190	0.18	0.7870	0.00	0.3330	0.00
<i>Panel D</i>	<i>Conditional Covariance: Country i – US</i>									
$ News_{FED} $	0.0450	0.03	-0.0770	0.00	0.0850	0.00	0.1290	0.08	0.1200	0.00
$ News_{ECB} $	-0.0710	0.01	-0.1730	0.00	-0.2480	0.00	0.3420	0.12	0.0570	0.50
<i>Panel E</i>	<i>Conditional Covariance: Country i – Eurozone</i>									
$ News_{FED} $	0.0100	0.52	0.0010	0.95	0.0270	0.20	0.0240	0.40	-0.0290	0.14
$ News_{ECB} $	0.1460	0.13	0.1100	0.22	0.2380	0.08	1.0780	0.00	0.4160	0.00
<i>Panel F</i>	<i>Conditional Variance: Country i</i>									
$ News_{FED} $	0.0520	0.03	0.0870	0.02	0.0870	0.01	0.1040	0.26	0.1570	0.00
$ News_{ECB} $	0.0570	0.29	0.1570	0.20	0.4770	0.02	1.4760	0.00	0.5190	0.01

Note: for reporting purposes coefficients are multiplied by 1000.

would rise only following the ECB news (Panel B in Table B.13).

Studying the extent to which the Fed's and the ECB's monetary policy affects the covariance and the volatility of the BRIC countries is of great importance. Over the past decade the combined share of BRIC equity in the US holdings of foreign securities increased from 2.2% in 2001 to 9.7% in 2009 (Table B.15). This is a significant amount and implies larger financial interdependences and more intense capital flows to and from these countries. Therefore, while conducting monetary policy, the Fed and the ECB should be aware of the nature of reaction that these markets reveal in response to their policy actions. On the other hand, due to different economic structure (e.g. more export-oriented) and the fact that the economic and financial integration of these markets with already established ones is still low, we might expect significant differences in the responsiveness of BRIC and developed markets to the US and European monetary policy news. Table 3.6 confirms such differences. Although the effect is limited, findings suggests that the US news significantly decreases the US-Russia and Eurozone-Russia covariances and the ECB's news has a negative and significant effect on the covariance between Brazil and the US. As for the volatility, only the Russian market volatility responds significantly to the US news and rises after the Fed's announcements. Hence, the response of the comovements is opposite to the effect that we find for the developed markets. These findings coupled with the results for the conditional mean (discussed in the next section) and conditional volatility (the effect on the domestic

variance being larger than that on the foreign variance) imply that higher surprises by the Fed and the ECB create preconditions for switching capital from domestic to emerging equity. This is confirmed by the implied effect on the correlations between the EU and US on the one hand and the BRIC countries on the other (Table B.14), which shows that correlations mostly decrease as a result of Fed/ECB news (since negative correlation implies better diversification of portfolio risk).

Table 3.6: Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-BRIC countries.

	Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>Panel A</i> <i>Conditional Variance: US</i>								
$ News_{FED} $	0.0330	0.07	0.0300	0.20	0.0760	0.00	0.1840	0.00
$ News_{ECB} $	0.1990	0.02	0.2620	0.01	0.0540	0.32	0.2880	0.01
<i>Panel B</i> <i>Conditional Covariance: US – Eurozone</i>								
$ News_{FED} $	-0.0210	0.01	-0.0280	0.00	-0.0220	0.06	0.0510	0.00
$ News_{ECB} $	-0.0400	0.38	-0.1210	0.03	-0.0910	0.01	-0.0640	0.30
<i>Panel C</i> <i>Conditional Variance: Eurozone</i>								
$ News_{FED} $	0.0140	0.31	0.0270	0.20	0.0060	0.41	0.0140	0.07
$ News_{ECB} $	0.0080	0.69	0.0560	0.38	0.1520	0.21	0.0140	0.62
<i>Panel D</i> <i>Conditional Covariance: Country i – US</i>								
$ News_{FED} $	0.0080	0.68	-0.0130	0.58	0.0260	0.50	-0.1380	0.00
$ News_{ECB} $	-0.1690	0.01	0.0800	0.47	0.0020	0.98	0.0480	0.76
<i>Panel E</i> <i>Conditional Covariance: Country i – Eurozone</i>								
$ News_{FED} $	-0.0060	0.63	0.0120	0.58	-0.0080	0.52	-0.0380	0.00
$ News_{ECB} $	0.0340	0.53	-0.0370	0.52	-0.0030	0.98	-0.0110	0.72
<i>Panel F</i> <i>Conditional Variance: Country i</i>								
$ News_{FED} $	0.0020	0.82	0.0060	0.77	0.0090	0.73	0.1030	0.06
$ News_{ECB} $	0.1430	0.32	0.0250	0.72	0.0010	0.99	0.0080	0.88

Note: for reporting purposes coefficients are multiplied by 1000.

3.4.2 Asymmetries

As discussed in Section 3.2, various studies have shown that news can have asymmetric effect on the market volatility depending upon whether the market participants view the news as “good” or “bad”. We explore the asymmetric effect by decomposing the news variables into two components: positive, $NewsFED_+ = NewsFED$ if $NewsFED > 0$ and zero otherwise, and negative, $NewsFED_- = NewsFED$ if $NewsFED < 0$ and zero otherwise. We apply the same procedure for $NewsECB$. The positive sign of a central bank’s news can be understood as “unexpected tightening”, whereas the negative sign indicates that the monetary policy action has been more expansionary than anticipated. Hence, positive and negative news convey either a pessimistic or an optimistic outlook on

the economy. In what follows we use the terms “unexpected expansion” and “unexpected tightening” on the one hand and “good” and “bad” news on the other interchangeably.

Table 3.7: Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-EZ/Europe.

<i>Panel A. Conditional Variance: US</i>				
	S&P 500 -Eurofirst 300 Eurozone		S&P 500 - Eurofirst 300	
	Coeff.	P-value	Coeff.	P-value
$News_{FED+}$	0.038	0.34	0.021	0.72
$News_{ECB+}$	0.092	0.24	0.693	0.02
$News_{FED-}$	0.073	0.00	0.244	0.00
$News_{ECB-}$	0.381	0.03	0.216	0.36
<i>Panel B. Conditional Covariance: US - Europe</i>				
$News_{FED+}$	-0.071	0.03	-	0.31
$News_{ECB+}$	-0.239	0.00	0.212	0.30
$News_{FED-}$	0.021	0.32	0.188	0.00
$News_{ECB-}$	-0.074	0.51	-0.17	0.00
<i>Panel C. Conditional Variance: Europe</i>				
$News_{FED+}$	0.132	0.10	0.092	0.35
$News_{ECB+}$	0.618	0.01	0.065	0.53
$News_{FED-}$	0.006	0.59	0.144	0.04
$News_{ECB-}$	0.014	0.76	0.134	0.46

As can be seen from Table 3.7, the US-Eurozone covariance responds significantly to positive announcements of the two central banks. On the other hand the US-Europe covariance is affected by the negative announcements by the Fed and the ECB.

In the previous section we could not find the evidence of the US news having a statistically significant effect on the European volatility. However, Table 3.7 suggests that this effect is asymmetric. More specifically, in the “Eurozone specification” we find that the Eurozone market volatility increases following positive, rather than negative news. Yet, the results for the “Europe specification” indicate that uncertainty in the broader European market rises only after negative US announcements.

The individual country analysis reveals further evidence of asymmetries. Table 3.8 presents the results for the seven Eurozone countries. It can be clearly seen that for these markets unexpected expansionary announcements by the Fed are of greater importance than unexpected tightening. For six out of seven markets the conditional covariance responds significantly and positively to the negative US news, while the positive news affects significantly only two markets. With respect to the ECB announcements the results are mixed. In three out of seven cases the coefficient of the positive news is significant, while the coefficient of the negative news is significant in four cases. The corresponding effects

Table 3.8: Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-Eurozone countries.

	France		Germany		Luxemburg		Spain		Belgium		Finland		Netherlands	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>Panel A</i>														
<i>Conditional Variance: US</i>														
$News_{FED+}$	0.0580	0.31	0.0410	0.33	0.0430	0.28	0.1000	0.10	0.0960	0.07	0.0220	0.47	0.0970	0.17
$News_{ECB+}$	0.1610	0.11	0.0810	0.27	0.0700	0.53	0.1960	0.08	0.0840	0.37	0.1060	0.25	0.2160	0.08
$News_{FED-}$	0.0880	0.01	0.1130	0.00	0.0740	0.00	0.0810	0.01	0.0310	0.23	0.1020	0.01	0.0810	0.01
$News_{ECB-}$	0.2170	0.12	0.3780	0.02	0.2300	0.07	0.2960	0.06	0.0910	0.23	0.2850	0.04	0.1310	0.23
<i>Panel B</i>														
<i>Conditional Covariance: Country i - US</i>														
$News_{FED+}$	0.0350	0.57	-0.0430	0.03	-0.0910	0.06	-0.0460	0.18	0.0420	0.12	0.1160	0.17	0.0190	0.75
$News_{ECB+}$	-0.0630	0.31	-0.0940	0.01	-0.0290	0.83	0.0890	0.41	0.0870	0.10	-0.2660	0.01	-0.0850	0.14
$News_{FED-}$	0.1040	0.01	0.0910	0.00	0.0610	0.09	0.0610	0.09	-0.0020	0.92	0.1070	0.00	0.1100	0.00
$News_{ECB-}$	-0.0470	0.60	-0.0180	0.89	-0.2970	0.01	0.1220	0.46	0.2470	0.01	-0.2190	0.00	-0.2420	0.00
<i>Panel C</i>														
<i>Conditional Variance: Country i</i>														
$News_{FED+}$	0.0220	0.72	0.0440	0.38	0.1920	0.04	0.0210	0.58	0.0190	0.52	0.6160	0.00	0.0030	0.87
$News_{ECB+}$	0.0250	0.68	0.1020	0.37	0.0120	0.92	0.0400	0.63	0.0900	0.47	0.6670	0.00	0.0480	0.59
$News_{FED-}$	0.1240	0.10	0.0760	0.03	0.0510	0.36	0.0470	0.31	0.0000	0.96	0.1120	0.02	0.1290	0.04
$News_{ECB-}$	0.0100	0.81	0.0010	0.94	0.3840	0.20	0.0500	0.67	0.6660	0.00	0.1680	0.24	0.2250	0.07

Note: for reporting purposes coefficients are multiplied by 1000.

on the conditional correlations are given in Table B.12. The Fed news has mostly positive effect on the correlations (especially negative news), while the ECB news tends to decrease the correlations.

The results for developed non-eurozone stock markets are displayed in Table 3.9. The coefficient of the negative Fed's news is significant in covariance equations of all five markets. On the contrary, the positive announcements do not have significant effect on any, but the UK market. Additionally, the UK-US covariance responds negatively to an unexpected US tightening and positively to an unexpected expansion, with the magnitudes of these two effects being almost equal: on average, -91.61% (-0.55 St. Dev.) for positive news and 87.89% (0.52 St. Dev.) for negative. As the results suggest, the conditional covariance between the Eurozone and the five developed markets mostly respond to positive announcements by both central banks. For the ECB this effect is statistically significant for four markets, while for the Fed it is significant in three out of five cases. Not surprisingly the ECB's announcements have larger effect in absolute value too. Examining the effects on correlations in Table B.13 show that, in general, Fed and ECB announcements tend to have negative impact on the US-country i correlations, while the EU-country i correlations respond passively in most cases.

For the emerging BRIC markets we find little evidence of the asymmetric effect of the target rate announcements either by the Fed or the ECB (Table 3.10). One interesting finding is that, unlike in the case of the developed countries (including those from Eurozone), the covariances US-BRIC countries and EU-BRIC countries decrease following the

Table 3.9: Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-developed countries.

	UK		Switzerland		Sweden		Japan		Korea	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>Panel A</i>	<i>Conditional Variance: US</i>									
$News_{FED+}$	0.0990	0.11	0.0060	0.73	0.0090	0.67	0.1150	0.05	0.0380	0.39
$News_{ECB+}$	0.0000	0.97	0.1690	0.30	0.0170	0.67	0.1790	0.07	0.0450	0.48
$News_{FED-}$	0.0430	0.12	0.0370	0.15	0.0870	0.01	0.1240	0.00	0.1030	0.00
$News_{ECB-}$	0.4100	0.01	0.2050	0.19	0.3560	0.02	0.2520	0.05	0.1440	0.19
<i>Panel B</i>	<i>Conditional Covariance: US – Eurozone</i>									
$News_{FED+}$	-0.0780	0.00	0.0520	0.52	-0.0460	0.34	-0.0820	0.01	-0.1130	0.04
$News_{ECB+}$	-0.0100	0.93	-0.0240	0.81	-0.0860	0.34	-0.2060	0.00	0.1700	0.21
$News_{FED-}$	0.0040	0.75	0.0070	0.68	0.0390	0.10	0.0630	0.06	0.0140	0.59
$News_{ECB-}$	-0.1350	0.14	-0.1060	0.07	0.0290	0.78	-0.1610	0.01	-0.0910	0.07
<i>Panel C</i>	<i>Conditional Variance: Eurozone</i>									
$News_{FED+}$	0.0610	0.25	0.4590	0.00	0.2390	0.01	0.0590	0.29	0.3370	0.01
$News_{ECB+}$	0.6110	0.01	0.0030	0.91	0.4500	0.02	0.2370	0.05	0.6360	0.00
$News_{FED-}$	0.0000	0.87	0.0010	0.82	0.0170	0.31	0.0320	0.27	0.0020	0.78
$News_{ECB-}$	0.0440	0.54	0.0540	0.53	0.0020	0.88	0.1020	0.30	0.0570	0.47
<i>Panel D</i>	<i>Conditional Covariance: Country i – US</i>									
$News_{FED+}$	-0.0740	0.00	0.0440	0.51	-0.0430	0.36	-0.0090	0.75	0.0040	0.87
$News_{ECB+}$	-0.0880	0.02	-0.0600	0.56	-0.1120	0.36	0.3060	0.01	0.1570	0.23
$News_{FED-}$	0.0710	0.02	-0.0710	0.00	0.1030	0.00	0.1890	0.00	0.1510	0.00
$News_{ECB-}$	-0.0640	0.46	-0.2470	0.00	-0.2880	0.00	-0.1590	0.01	-0.0760	0.25
<i>Panel E</i>	<i>Conditional Covariance: Country i – Eurozone</i>									
$News_{FED+}$	0.0960	0.08	0.3880	0.00	0.2220	0.03	0.0060	0.78	-0.0130	0.85
$News_{ECB+}$	0.2880	0.08	0.0080	0.86	0.5830	0.01	-0.3530	0.00	0.5900	0.00
$News_{FED-}$	0.0290	0.26	-0.0140	0.63	0.0460	0.14	0.0960	0.06	0.0200	0.58
$News_{ECB-}$	0.0250	0.65	0.1270	0.34	-0.0230	0.75	0.1010	0.18	0.0480	0.48
<i>Panel F</i>	<i>Conditional Variance: Country i</i>									
$News_{FED+}$	0.0870	0.08	0.3280	0.01	0.2060	0.08	0.0010	0.88	0.0010	0.93
$News_{ECB+}$	0.1310	0.21	0.0210	0.78	0.7550	0.01	0.5250	0.01	0.5480	0.02
$News_{FED-}$	0.0900	0.01	0.1370	0.00	0.1220	0.01	0.2870	0.00	0.2220	0.00
$News_{ECB-}$	0.0120	0.74	0.2970	0.13	0.2330	0.20	0.1000	0.24	0.0410	0.65

Note: for reporting purposes coefficients are multiplied by 1000.

positive announcements of the two central banks. The limited asymmetric effect on the conditional volatility that we find is the positive impact of the Fed's negative announcements on the volatility of the Brazilian and the Russian markets. Nonetheless, compared with the developed markets, the absolute magnitude of these effects is considerably lower -34.66% (0.32 St.Dev.) and 19.75% (0.17 St.Dev.) respectively. As for the conditional correlations, Table B.14 shows that in majority of the cases these correlation would decrease as a result of Fed/ECB news.

Table 3.11 displays the results for the conditional mean equations. The mean equations were specified as AR (1) processes. Monetary news variables enter these equations as exogenous. We assume that for stock returns both the sign and magnitude of the news variables are important, therefore we include $News_{FED}$ and $News_{ECB}$ instead of their absolute values. In general the results are consistent with the literature. Particularly,

Table 3.10: Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-BRIC countries.

	Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
<i>Panel A</i> Conditional Variance: US								
News _{FED+}	0.0660	0.21	0.0530	0.26	0.0020	0.84	0.1780	0.06
News _{ECB+}	0.0320	0.57	0.1880	0.13	0.0000	0.99	0.0700	0.38
News _{FED-}	0.0500	0.05	0.0310	0.31	0.0780	0.00	0.1560	0.00
News _{ECB-}	0.4750	0.01	0.4140	0.02	0.2700	0.08	0.6970	0.00
<i>Panel B</i> Conditional Covariance: US – Eurozone								
News _{FED+}	-0.0560	0.01	-0.0620	0.01	-0.0200	0.67	-0.0410	0.26
News _{ECB+}	-0.0750	0.12	-0.1250	0.04	0.0030	0.98	-0.0870	0.04
News _{FED-}	-0.0080	0.53	-0.0180	0.06	0.0050	0.76	0.0490	0.00
News _{ECB-}	0.0320	0.74	-0.0800	0.42	-0.0180	0.88	0.1670	0.23
<i>Panel C</i> Conditional Variance: Eurozone								
News _{FED+}	0.0470	0.25	0.0730	0.18	0.2510	0.01	0.0100	0.62
News _{ECB+}	0.1790	0.25	0.0830	0.44	0.5620	0.01	0.1080	0.22
News _{FED-}	0.0010	0.78	0.0100	0.58	0.0000	0.88	0.0160	0.10
News _{ECB-}	0.0020	0.86	0.0160	0.72	0.0010	0.94	0.0400	0.51
<i>Panel D</i> Conditional Covariance: Country <i>i</i> – US								
News _{FED+}	-0.0690	0.06	0.0000	1.00	0.0120	0.71	-0.1610	0.06
News _{ECB+}	-0.0570	0.22	-0.0210	0.88	0.0000	0.98	0.1220	0.21
News _{FED-}	0.0850	0.03	-0.0320	0.31	0.0650	0.20	-0.1390	0.00
News _{ECB-}	-0.1580	0.24	0.1820	0.28	0.2660	0.23	-0.1790	0.56
<i>Panel E</i> Conditional Covariance: Country <i>i</i> – Eurozone								
News _{FED+}	0.0580	0.31	0.0000	1.00	-0.1540	0.14	0.0370	0.42
News _{ECB+}	0.1350	0.36	0.0140	0.88	0.0180	0.94	-0.1510	0.07
News _{FED-}	-0.0130	0.54	0.0180	0.40	0.0050	0.75	-0.0440	0.00
News _{ECB-}	-0.0110	0.70	-0.0350	0.60	-0.0180	0.88	-0.0430	0.50
<i>Panel F</i> Conditional Variance: Country <i>i</i>								
News _{FED+}	0.0720	0.46	0.0000	1.00	0.0950	0.43	0.1450	0.30
News _{ECB+}	0.1030	0.53	0.0020	0.94	0.0010	0.97	0.2120	0.39
News _{FED-}	0.1440	0.07	0.0330	0.53	0.0540	0.51	0.1240	0.09
News _{ECB-}	0.0520	0.62	0.0800	0.60	0.2620	0.55	0.0460	0.77

Note: for reporting purposes coefficients are multiplied by 1000.

the majority of the estimated coefficients are negative, implying that stock returns would decline following an unexpectedly tightening announcement. Similar results are found by other studies (e.g. Flavina and Wickens, 2003 and Brenner et al., 2009).

It is interesting to look at evolution of the estimated conditional covariances and correlations over the sample period. Figure B.2 in Appendix B includes graphs for 18 series. The dynamics of correlations and covariances provides support to the hypothesis that comovements of markets increase in crisis periods. It can be clearly seen from the graphs that the financial crisis of 2008 was accompanied by greater comovements, which decreased during the following period. Further, for the majority of developed stock markets we observe increased comovements over the sample period (excluding the crisis in 2008), with the exception of Belgium. The non-eurozone European markets are found to have higher correlation with the Eurozone market, which is an intuitively plausible result. On the

Table 3.11: Estimated results from BEKK-GARCH (1, 1) models: conditional mean equations.

<i>Conditional Mean</i>												
	Eurofirst 300		Eurofirst 300 EZ		France		Germany		Luxemburg		Spain	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.000	0.05	0.000	0.05	0.000	0.02	0.001	0.01	0.000	0.02	0.001	0.01
Coefficient AR (1)	-0.073	0.00	-0.078	0.00	-0.148	0.00	-0.077	0.00	0.020	0.29	-0.115	0.00
$News_{FED}$	-0.003	0.38	-0.003	0.35	-0.006	0.25	-0.006	0.20	-0.005	0.35	-0.007	0.10
$News_{ECB}$	-0.019	0.44	-0.024	0.25	-0.037	0.06	-0.021	0.29	0.023	0.24	-0.043	0.05
	Belgium		Finland		Netherlands		UK		Switzerland		Sweden	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.001	0.00	0.001	0.01	0.001	0.01	0.000	0.02	-0.002	0.02	0.000	0.04
Coefficient AR (1)	0.014	0.47	-0.008	0.63	-0.115	0.00	-0.066	0.00	0.782	0.00	-0.071	0.00
$News_{FED}$	0.006	0.04	-0.009	0.34	0.000	0.94	0.000	0.97	0.003	0.48	0.004	0.48
$News_{ECB}$	-0.025	0.13	-0.007	0.84	-0.018	0.17	0.001	0.94	-0.018	0.33	0.002	0.94
	Japan		Korea		Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.000	0.99	0.001	0.02	0.001	0.00	0.000	0.93	0.001	0.00	0.002	0.00
Coefficient AR (1)	0.042	0.01	-0.088	0.00	-0.047	0.00	-0.066	0.00	-0.031	0.10	0.095	0.00
$News_{FED}$	-0.003	0.66	0.001	0.89	-0.026	0.00	-0.002	0.84	-0.005	0.52	0.003	0.75
$News_{ECB}$	-0.023	0.25	-0.068	0.07	0.023	0.36	-0.034	0.32	0.009	0.79	0.016	0.65

contrary, two developed Asian markets (Japan and Korea) show higher correlation with the US market. Lastly, no clear pattern was found for the three markets from the BRIC group – Russia, India and, especially, China that confirms our expectations that the Fed’s and the ECB’s announcements may have different impact on developed and emerging markets and therefore underscores the importance of investigating the effect of the monetary announcements on such comovements.

3.4.3 Sensitivity analysis

Since the rate change may be anticipated by the markets, they may not respond to these predictable changes. Therefore it is interesting to conduct a sensitivity analysis and check whether the extracted unexpected news component really differs from the actual changes in the target rates. Such an analysis is performed by Kuttner (2001), for example. The author compares the effect of the expected and unexpected components, as well as the raw (actual) changes in the target rate, where the expected component is simply computed as the actual change minus the unexpected change. The effect investigated is that of Fed Funds rate on market interest rates of various maturities, starting from 3 months to 30 years. It is remarkable that the author reports nearly no response of interest rates to the actual and expected changes. This is especially evident for the long end of the yield curve (5 years and longer horizon), for which none of the coefficients are significant. For shorter maturities, the 3 month rate responds significantly, however the coefficients are found to

be much lower than that of the surprise component.

Table 3.12: Estimated results from BEKK-GARCH (1, 1) models: the effect of actual target rate changes

S&P 500 - Eurofirst 300 Eurozone			S&P 500 - Eurofirst 300 Eurozone - Asymmetric		
	Coeff.	P-value		Coeff.	P-value
<i>Panel A</i>			<i>Conditional Variance: US</i>		
$ News_{FED} $	0.0080	0.55	NewsFED+	0.0001	0.99
$ News_{ECB} $	0.0001	0.95	NewsECB+	0.0001	0.99
			NewsFED-	0.2690	0.01
			NewsECB-	0.0780	0.59
<i>Panel B</i>			<i>Conditional Covariance: Country US-Eurozone</i>		
$ News_{FED} $	-0.0160	0.10	NewsFED+	0.0001	0.99
$ News_{ECB} $	-0.0040	0.89	NewsECB+	0.0001	0.99
			NewsFED-	0.1100	0.09
			NewsECB-	0.0090	0.90
<i>Panel C</i>			<i>Conditional Variance: Eurozone</i>		
$ News_{FED} $	0.0320	0.25	NewsFED+	0.0030	0.96
$ News_{ECB} $	0.0440	0.38	NewsECB+	0.0001	0.99
			NewsFED-	0.0450	0.26
			NewsECB-	0.0010	0.95

Note: for reporting purposes coefficients are multiplied by 1000.

To check whether the extracted news component indeed reflects the information not foreseen by market participants we perform the same analysis as before, but news variables are now substituted with the actual changes in the Fed and ECB target rates. For demonstration purposes we only report the results for the model containing the US and Eurozone series. The results which are presented for both models, symmetric and asymmetric, are displayed in Table 3.12. It can be seen that the coefficients of the actual changes in both models are highly insignificant. Particularly for the symmetric model none of the coefficients are statistically significant at the 5% level, whereas for the asymmetric model only one significant coefficient is obtained. Thus, our results indeed provide support to the hypothesis that markets react only to the unanticipated information.

3.5 Conclusions

The link between monetary policy and financial markets is a topic of interest to monetary authorities, researchers and financial market participants. The importance of studying this issue increases as markets become globally integrated. Yet, the empirical literature mainly focuses on investigating the cross-border effect of monetary policy on stock returns (first moment) and, less extensively, the stock market volatility (second moment), while the evidence of the impact on market comovements (covariance) is limited.

This paper contributes to the literature by providing comprehensive empirical evidence on the cross-border effect of monetary policy announcements on the conditional covariances between the world's major stock markets.

The findings suggest that increases in the unexpected component of the Fed's news, in general, raise covariances between the US and developed stock markets, including the Eurozone countries. Yet, this effect is not confirmed for a group of emerging (BRIC) countries and for the latter we generally find a negative impact. Similar results are found for the ECB's announcements. Specifically, increases in the surprise component have positive impact on covariances between the Eurozone and developed markets but have negative or statistically insignificant effect on the BRIC countries. In addition, we report significant asymmetries in responsiveness of the conditional covariance to the different information contents of monetary announcements (positive versus negative surprises). Particularly, for the majority of markets unexpectedly expansionary news released by the Fed are of greater importance than unexpectedly tightening announcements. However, for the ECB, the results are mixed and vary across markets.

Our findings point out that the volatility and comovements, in addition to asset prices, have to be taken into account while conducting monetary policy. Secondly, the US and European monetary authorities would face heterogeneous responses from developed and emerging markets. Finally, it should be also taken into account whether the news surprise component is positive or negative, since markets react asymmetrically to "good" and "bad" news. These results highlight the complex nature of the linkage between monetary policy and financial markets. A worthwhile extension of this research would be examining the channels through which the spillovers take place, for example as done by Ehrmann and Fratzscher (2006) for the first moment (returns) and studying the effect on comovements between different asset classes (e.g. stocks and bonds).

Chapter 4

The Effect of EU Accession On The Stock Market Integration of New Members: A Multivariate GARCH Analysis

4.1 Introduction

Multivariate GARCH models have been broadly used to investigate volatility transmission and spillover effect across countries. The majority of these studies investigate the return and volatility linkages between developed markets. For instance, Hamao et al. (1990), Lin et al. (1994), Karolyi (1995), Tse and Tsui (2002) and Bae, Karolyi, and Stulz (2003) are among those who report the significant interdependence between established financial markets, such as the USA, the UK, Canada, Germany, Japan, etc. On the other hand, several studies explore the relationship between developed and emerging markets, though the work is less extensive.

A number of economic papers study the effect of introducing the European Monetary Union (EMU). For example, Hardouvelis et al. (1999), Fratzscher (2002) and Kim et al. (2005) all have shown that stock market integration within Europe was significantly driven by the introduction of the EMU. Later, after the EU enlargement in 2004, few papers analyzed the linkage between the old EU markets and the newly accepted Central and Eastern European (CEE) markets. For example Scheiher (2001) estimated constant conditional correlation (CCC) GARCH model for Hungary, Poland and Czech Republic. Their results suggest limited interaction of these CEE countries with the global market (the authors use the Financial Times (FT) or Standard & Poor's Actuaries World index as the proxy for the world equity portfolio). Although the CCC-GARCH model is in many respects an attractive parameterization, empirical studies have suggested that the assumption of constant conditional correlations may be too restrictive, see e.g. Silvennoinen and Terasvirta (2008). Syllignakis and Kouretas (2006) examine the short-and long-term relationships between the German, US and seven CEE markets. Using DCC models, they show that short-term interdependences between the CEE stock markets and the developed stock markets have strengthened during the Asian and Russian crises. The DCC model assumes the conditional correlations to be time varying, but this model does not incorporate cross effects of these conditional correlations, therefore the flexibility of the model is limited. Li and Majerowska (2006) employ a four-variate asymmetric BEKK model to examine the linkages between the emerging stock markets in Warsaw and Budapest and

the established markets in Frankfurt and the US. The results show evidence of return and volatility spillovers from the developed to the emerging markets, but the opposite effect is found to be weak. The implication is that investors in developed markets will benefit from the reduction of risk by adding, and therefore diversifying, the stocks of the emerging markets to their investment portfolios.

In this chapter we analyze the financial interdependences among the EU member, as well as the EU candidate countries. Our motivation is to contribute to the existing literature by using a fully flexible model, which incorporates different features of the financial time series. In addition to this, an increased geographical coverage and sample period should avoid misinterpretation of the results in the sense that we are not restricted to interpreting the interactions only among leading regional stock exchanges, but also include relatively less important markets. Particularly, we address the following issue: do the newly accepted members become more financially integrated with the old members after joining the EU? Two measures of financial integration are considered. Firstly, we estimate volatility spillover effects between old and new members; secondly we look at the evolution of the conditional correlations between the markets from the two groups over time. The results show clear evidence of a higher financial integration for the countries that joined the EU in 2004 compared with those which joined in 2007. This is reflected in both higher volatility spillovers and conditional correlations. In this chapter we do not consider potentially useful modeling choices such as the inclusion of dummy variables or introduction of a smooth transition mechanism in a GARCH specification, for example as done by Khemiri (2011). This decision is made largely due to model tractability issues. Yet such techniques may be helpful for modeling financial integration over time and therefore it would be worthwhile to extend our study in this direction.

The results are particularly important for those candidate countries, which will eventually become members of the Union. To a more general extent, the results have important implications for policy-makers. A high degree of integration renders a country's economy more vulnerable to external risks. On the other hand, the level of stock market integration is important for different financial market participants such as international investors, multinational corporations and portfolio managers, who are involved in minimizing and managing their financial risk through portfolio diversification.

4.2 Methodology

To estimate volatility spillovers we employ the GJR-BEKK-GARCH(1,1) model, which is a modified version of the BEKK specification outlined in Chapter 1. The conditional variance equation is specified as follows.

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\varepsilon_{t-1}\varepsilon'_{t-1}D \quad (4.1)$$

where the term $D'\varepsilon_{t-1}\varepsilon'_{t-1}D$ captures the asymmetric response of the variance-covariance matrix to the past negative shocks (the leverage effect). More precisely the vector of the negative shocks is specified as:

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \end{pmatrix} = \begin{pmatrix} \min(\varepsilon_{1,t}, 0) \\ \min(\varepsilon_{2,t}, 0) \\ \min(\varepsilon_{3,t}, 0) \\ \min(\varepsilon_{4,t}, 0) \end{pmatrix} \quad (4.2)$$

The nonlinear functions corresponding to the specification in equation (4.1) are given in Table C.1 in Appendix C. Lastly, we assume that the error term (ε_t) is Gaussian, hence the log-likelihood function excluding the constant term is given by

$$L(\theta) = -1/2 \sum_{i=1}^T (\ln |H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \quad (4.3)$$

with T denoting the number of observations.

4.3 Data and summary statistics

The data employed in this study consists of closing daily stock market price indices for the following countries. The old markets group: DAX (Germany), FTSE 100 (The United Kingdom), CAC 40 (France), IBEX (Spain), (SMI) Switzerland²⁵, AEX (The Netherlands), BEL20 (Belgium), MIBTEL (Italy), ATX (Austria), OMX Helsinki (Finland), OMX Stockholm (Sweden). The new markets group: BUX (Hungary), PX50 (Czech Republic), SBI (Slovenia), SAX12 (Slovakia), WIG (Poland), LNVILSE (Lithuania), RIGSEIN (Latvia), ESTALSE (Estonia), BET (Romania), SOFIX (Bulgaria). The candidates group: ISE

²⁵Although Switzerland is not in the EU, because of its historical linkages with other EU countries we include it in our analysis.

National-100 (Turkey), CROBEX (Croatia). We use daily log returns computed from the stock price indices, in local currency. The data were obtained from Datastream.

Table 4.1: Descriptive statistics, close-to-close log-returns of all series

	Germany	UK	France	Spain	Switzerland	Netherlands	Belgium	Italy
Mean	0.03	0.02	0.01	0.02	0.02	0.02	0.00	-0.01
Min	-13.71	-13.03	-10.14	-9.59	-11.11	-12.78	-8.32	-0.01
Max	10.80	9.38	10.59	10.12	10.79	11.18	9.33	6.81
St. Dev.	1.42	1.11	1.39	1.33	1.19	1.37	1.13	0.90
Skewness	-1.28***	-2.67***	-0.93***	-1.31***	-1.7***	-1.28***	-0.21***	-0.59***
(t-stat.)	16.79	35.07	12.19	17.21	22.25	16.76	2.70	7.72
Excess Kurtosis	13.82***	31.27***	10.66***	11.61***	18.17***	15.28***	8.59***	2.35***
(t-stat.)	90.79	205.42	70.02	76.29	119.35	100.37	56.45	15.47
# of Obs.	6587	6587	5669	5802	5413	6587	5021	1893
	Austria	Finland	Sweden	Hungary	Czech Rep.	Slovenia	Slovakia	Poland
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.11
Min	-0.10	-0.17	-0.09	-0.18	-0.16	-0.11	-0.12	0.00
Max	0.12	0.15	0.11	0.14	0.12	0.11	0.28	0.15
St. Dev.	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.02
Skewness	-0.29***	-1.79***	-0.62***	0.004	-0.47***	0.026	3.61***	-0.05
(t-stat.)	3.80	23.55	8.12	0.052	6.18	0.34	47.34	0.61
Excess Kurtosis	6.3***	43.28***	7.89***	8.01***	3.94***	3.24***	41.88***	2.42***
(t-stat.)	41.37	284.38	51.84	52.60	25.91	21.29	275.14	15.87
# of Obs.	6061	5803	6064	4760	3910	3978	4056	4686
	Lithuania	Latvia	Estonia	Romania	Bulgaria	Turkey	Croatia	
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Min	-0.14	-0.15	-0.22	-0.13	-0.21	-0.20	-0.13	
Max	0.12	0.09	0.13	0.12	0.21	0.18	0.17	
St. Dev.	0.01	0.02	0.02	0.02	0.02	0.03	0.02	
Skewness	-1.22***	-1.32***	-0.59***	0.13*	-0.46***	0.07	0.17**	
(t-stat.)	16.06	17.38	7.79	1.68	6.01	0.89	2.23	
Excess Kurtosis	17.66***	16.12***	8.24***	4.3***	25.16***	1.86***	6.67***	
(t-stat.)	116.03	105.89	54.12	28.28	165.32	12.20	43.84	
# of Obs.	2413	2412	3347	3008	2203	5542	3194	

Note: For reporting purposes Mean, Min, Max and St. Dev. have been multiplied by 100, i.e. returns are in percentage.
*, ** and *** denote significance at 10, 5 and 1% respectively.

Table 4.1 presents descriptive statistics for the 23 series under investigation, for different sample periods up to 2009. The period under consideration varies from country to country and ranges from 7 to 28 years, yielding 1893 to 6587 observations respectively. We only consider simultaneous trades, in other words, we filter out the data and exclude all the observations when at least one market was not open. After such filtering, the actual number of observations decreases slightly.

Table 4.2 reports the unconditional correlation coefficients between the examined markets. The table clearly shows the pattern of linear dependence among these markets. As we move from left to right and downward we observe the decreasing correlation coefficients. This highlights a higher degree of dependence among the old members than their counterparts from the emerging markets. Further, the correlations among emerging stock markets are small, indicating a low level of integration between these new members. Lastly, we observe low cross-group correlations between old and new members.

Table 4.2: Unconditional correlations, all series

	GER	UK	FR	SP	SWIS	Neth	BEL	IT	AUT	FIN	SWE	HUN
GER	1.00											
UK	0.80	1.00										
FR	0.88	0.91	1.00									
SP	0.82	0.85	0.90	1.00								
SWIS	0.79	0.85	0.87	0.83	1.00							
Neth	0.85	0.89	0.95	0.87	0.85	1.00						
BEL	0.77	0.83	0.87	0.81	0.81	0.88	1.00					
IT	0.68	0.74	0.75	0.73	0.72	0.72	0.71	1.00				
AUT	0.56	0.65	0.63	0.64	0.61	0.61	0.62	0.66	1.00			
FIN	0.72	0.74	0.79	0.75	0.72	0.77	0.70	0.69	0.57	1.00		
SWE	0.78	0.81	0.85	0.81	0.76	0.83	0.77	0.72	0.64	0.79	1.00	
HUN	0.45	0.50	0.50	0.49	0.47	0.48	0.46	0.50	0.54	0.46	0.49	1.00
CZ	0.46	0.56	0.53	0.54	0.52	0.52	0.51	0.59	0.66	0.49	0.54	0.56
Slvia	0.17	0.21	0.20	0.20	0.21	0.19	0.21	0.28	0.27	0.16	0.16	0.20
Slkia	0.02	0.02	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	-0.01
POL	0.47	0.52	0.51	0.52	0.49	0.50	0.47	0.56	0.57	0.48	0.51	0.57
Lithuania	0.17	0.21	0.20	0.20	0.21	0.21	0.21	0.32	0.29	0.18	0.19	0.22
Latvia	0.12	0.16	0.15	0.14	0.14	0.15	0.14	0.23	0.20	0.14	0.14	0.16
EST	0.24	0.25	0.26	0.26	0.26	0.28	0.28	0.37	0.30	0.26	0.25	0.26
ROM	0.23	0.29	0.25	0.26	0.27	0.25	0.25	0.32	0.37	0.20	0.22	0.28
BUL	0.12	0.14	0.13	0.13	0.13	0.12	0.12	0.19	0.18	0.11	0.12	0.11
TUR	0.36	0.40	0.38	0.39	0.34	0.36	0.35	0.43	0.43	0.35	0.39	0.38
CRO	0.31	0.35	0.33	0.36	0.36	0.34	0.31	0.36	0.40	0.29	0.31	0.28

	CZ	SLN	SLK	POL	LIT	LAT	EST	ROM	BUL	TUR	CRO
CZ	1.00										
SLN	0.30	1.00									
SLK	0.01	0.04	1.00								
POL	0.62	0.19	0.01	1.00							
LIT	0.32	0.29	0.03	0.23	1.00						
LAT	0.21	0.24	0.03	0.16	0.29	1.00					
EST	0.35	0.30	0.04	0.28	0.40	0.25	1.00				
ROM	0.40	0.30	0.00	0.30	0.26	0.19	0.26	1.00			
BUL	0.22	0.27	0.09	0.17	0.27	0.21	0.24	0.19	1.00		
TUR	0.44	0.17	0.03	0.45	0.16	0.14	0.20	0.26	0.14	1.00	
CRO	0.39	0.28	0.05	0.33	0.21	0.09	0.23	0.31	0.20	0.26	1.00

4.4 Empirical results

Ideally, we have to include all 23 series in one (global) model. But it is not feasible to estimate, as this would involve estimating 1910 parameters compared with 71 in our specification.²⁶ For this reason we concentrate on subsets of variables. In particular we use four variable submodels, which include markets from only one group when we investigate spillovers within a group and from both groups when the cross-group interactions are analyzed. We note that since no interactions are allowed between the four variables included in the model and those which are dropped, there is no formal relationship between such submodels and the (potential) global model. It is also possible to specify one global model and impose certain restrictions that would reduce the number of estimated parameters. Apart from explicitly restricting parameters, other methods have been also proposed. For example Billio et al. (2003) introduces a block-diagonal structure in the conditional variance

²⁶Including parameters in the conditional mean equation.

equation for DCC model of Engle (2002). It allows correlation dynamics to be different across blocks, however within blocks they are still restricted to be equal. Regardless of the method used for reducing the number of estimated parameters, this reduction will come at the price of losing the flexibility of the model. Since we are interested in modeling interactions among markets, it is important to maintain such generality. The choice of using submodels may not seem so restrictive, if we take into account the fact that in each group (old and new) we can identify the markets with the pivotal role. For example one can argue that, in general, signals and information coming from the German, UK and French markets mainly drive the rest of the European markets. For this reason we believe that, in the context of our study, increasing the number of variables in the model may be beneficial but not crucial. Therefore in the trade-off between the parsimony and flexibility the choice is made in favor of the latter.

One question that we have to answer is how to determine the number of representative markets from each group. For example we can estimate a BEKK model, which includes three old markets and one new market. Alternatively we might want to include two old and two new markets, if we believe that there are significant interdependences between them. To decide about the number of representative series from each group, we conduct formal tests of volatility spillovers within, as well as across, the two groups. Such causality tests can provide good intuition for balancing the number of old and new markets in the model. The results of the tests are presented in the following section.

4.4.1 *Causality in Variance*

Two main approaches of testing causality in variance have been used in the literature. One was introduced by Cheung and Ng (1996) and it is based on the cross correlation function (CCF). This uses a two-step procedure, which first obtains (squared standardized) residuals from the univariate (GARCH) estimation and consequently considers cross sectional correlations for testing the causality. Another methodology of testing causality in variance is based on the QML estimation. Namely a multivariate GARCH model is specified, which can be tested for noncausality by imposing zero restrictions on specific parameters and performing a standard Wald test. The BEKK model has been widely used for this purpose, for example by Hafner and Herwartz (1998), Herwartz and Lütkepohl (2000), Caporale et al. (2002), Beirne et al. (2009) and Grydaki and Bezemer (2012), among others. Comparing the two methodologies, Hafner and Herwartz (2004) show that the Wald test has better power properties. It is also robust to model misspecification (underestimation

of the BEKK order).

Following Hafner and Herwartz (2004) notations we compute the following Wald statistic:

$$W_T = T(Q\hat{\theta})'(Q\hat{\Sigma}_\theta Q')^{-1}(Q\hat{\theta}) \quad (4.4)$$

where Q is the $q \times k$ restriction matrix,²⁷ with q being the number of restrictions and k being the number of parameters in the conditional variance equations. $\hat{\theta}$ is the $k \times 1$ vector of the estimated parameters, with

$$\hat{\theta} = (\text{vech}(C)', \text{vec}(A)', \text{vec}(B)', \text{vec}(D)')'.$$

The $k \times k$ matrix $\hat{\Sigma}_\theta$ represents the robust variance-covariance matrix of the estimated parameters as given in Equations 1.17 through 1.19. Under the normal distribution of the QML estimates (demonstrated by Comte and Lieberman, 2003) the statistics W_T is distributed as χ_γ^2 , with γ denoting the degrees of freedom, which in our case is equal to 4 or 8.

We test two sets of hypothesis, one where unidirectional spillovers are tested and the other which tests the existence of bidirectional spillovers between two subgroups. For tractability purposes we consider only “representative” markets from each group. The results of the Wald test are presented in Table 4.3. For each hypothesis the corresponding four-variate BEKK model and restrictions are reported. For example, in case 1 the specified null hypothesis states that there are no spillovers between two subgroups consisting of the German and UK markets on the one hand and the French and Spanish markets on the other. We only test unidirectional spillovers when two subgroups belong to different groups (i.e. old and new).

As can be seen from the table the old markets’ group displays strong volatility spillovers, for which the H_0 of noncausality is rejected with very high confidence level. On the other hand the new markets also seem to be highly interrelated. This can be seen in case 2, where the hypothesis is also rejected at the significance level of 1%.

Further, we test the existence of spillovers between the old and new groups. Within the latter we differentiate two sets of countries, those which joined the EU in 2004 (here Hungary and Czech Republic) and others which joined at the latest stage in 2007 (Romania and Bulgaria). Cases 1 through 5 reveal interesting results, in particular the results suggest only unidirectional spillovers from the two old markets to the new markets, while

²⁷See the construction of the Q matrix in Appendix B in Hafner and Herwartz (2004)

Table 4.3: Wald test of restrictions on spillover parameters

Hypothesis	Wald statistics	χ^2 P-value	Degrees of Freedom
1. Model: $y = (\text{Germany, UK, France, Spain})'$ H_0 : No spillovers between y_1, y_2 and y_3, y_4 $(b_{13} = b_{23} = b_{14} = b_{24} = b_{31} = b_{32} = b_{41} = b_{42} = 0)$	488.46***	2.10E-100	8
2. Model: $y = (\text{Hungary, Czech Rep., Poland, Slovakia})'$ H_0 : No spillovers between y_1, y_2 and y_3, y_4 $(b_{13} = b_{23} = b_{14} = b_{24} = b_{31} = b_{32} = b_{41} = b_{42} = 0)$	36.06***	1.71E-05	8
3. Model: $y = (\text{Germany, UK, Hungary, Czech Rep.})'$ H_0 : No spillovers between y_1, y_2 and y_3, y_4 $(b_{13} = b_{23} = b_{14} = b_{24} = b_{31} = b_{32} = b_{41} = b_{42} = 0)$	19.26**	0.0137	8
4. Model: $y = (\text{Germany, UK, Hungary, Czech Rep.})'$ H_0 : No spillovers from y_1, y_2 to y_3, y_4 $(b_{13} = b_{23} = b_{14} = b_{24} = 0)$	15.46**	0.0038	4
5. Model: $y = (\text{Germany, UK, Hungary, Czech Rep.})'$ H_0 : No spillovers from y_3, y_4 to y_1, y_2 $(b_{31} = b_{32} = b_{41} = b_{42} = 0)$	1.38	0.8468	4
6. Model: $y = (\text{Germany, UK, Romania, Bulgaria})'$ H_0 : No spillovers between y_1, y_2 and y_3, y_4 $(b_{13} = b_{23} = b_{14} = b_{24} = b_{31} = b_{32} = b_{41} = b_{42} = 0)$	20.69***	0.0080	8
7. Model: $y = (\text{Germany, UK, Romania, Bulgaria})'$ H_0 : No spillovers from y_1, y_2 to y_3, y_4 $(b_{13} = b_{23} = b_{14} = b_{24} = 0)$	8.63*	0.0710	4
8. Model: $y = (\text{Germany, UK, Romania, Bulgaria})'$ H_0 : No spillovers from y_3, y_4 to y_1, y_2 $(b_{31} = b_{32} = b_{41} = b_{42} = 0)$	9.02*	0.0606	4

Note : ***, ** and * denote rejection of the null hypothesis at the 1%, 5% and 10% level respectively.

the opposite effect is statistically insignificant. With these results we would expect that spillovers from Romania and Bulgaria to the old markets are even more limited, however the noncausality hypothesis for these markets cannot be rejected at the 10% significance level. However, it must be noted that the dataset available for these markets is somewhat limited and spans a relatively shorter period from October 2000 to December 2008. For this reason the model may pick up the effect of the 2008 crisis, during which it is generally expected that market comovements increase.

Overall the tests demonstrate significant spillover effects within each group. However, when testing transmissions between the two groups, we mostly find unidirectional effect from old to new markets. Therefore, based on these results, it seems more appropriate that in the four-variate BEKK-GARCH models we include three developed and one emerging market. In what follows we present the estimation results for such models.

4.4.2 “Old members” group

We start our analysis with the old members group. Table 4.4 present the results of four-variate models, which include three major European stock markets, Frankfurt, London and Paris and a fourth market from the old group. Panel A shows all four conditional variances from the model that includes the Spanish market, while in Panel B only the conditional variances of the fourth series (countries in Panel B) are reported.

Table 4.4: Volatility spillovers: “Old members” group. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	GER	UK	FR	SP		Neth	SWIS	IT	AUT	FIN	SWD
	coeff	coeff	coeff	coeff		coeff	coeff	coeff	coeff	coeff	coeff
Panel A					Panel B						
ϵ_1^2	5.109**	0.104	0.053	0.055	ϵ_1^2	0.029	0.167	0.24	0.151	0.009	0.069
$\epsilon_1\epsilon_2$	0.651	1.204	0.04	-0.177	$\epsilon_1\epsilon_2$	0.364	-1.413	-0.993	-0.123	-0.021	0.436
$\epsilon_1\epsilon_3$	-0.801	-0.112	0.757	0.21	$\epsilon_1\epsilon_3$	-0.261	0.992	0.771	-0.558	-0.058	-0.313
$\epsilon_1\epsilon_4$	-0.493	0.178	0.124	0.788	$\epsilon_1\epsilon_4$	0.794	-0.099	-3.055	-2.206	-0.269	0.992
ϵ_2^2	0.021	3.487***	0.008	0.144	ϵ_2^2	1.156*	2.985	1.028	0.025	0.013	0.693
$\epsilon_2\epsilon_4$	-0.051	-0.646	0.286	-0.34	$\epsilon_2\epsilon_4$	-1.658**	-4.192	-1.596	0.228	0.07	-0.996
$\epsilon_2\epsilon_3$	-0.031	1.028	0.047	-1.278	$\epsilon_2\epsilon_3$	5.036***	0.417	6.327	0.901	0.328	3.155
ϵ_3^2	0.031	0.03	2.715	0.202	ϵ_3^2	0.594*	1.472	0.62	0.517*	0.096	0.358
$\epsilon_3\epsilon_4$	0.039	-0.095	0.886	1.515	$\epsilon_3\epsilon_4$	-3.612**	-0.293	-4.913	4.087***	0.896*	-2.269
ϵ_4^2	0.012	0.076	0.072	2.843	ϵ_4^2	5.487***	0.015	9.739	8.074***	2.086***	3.592
h_1	52.675***	8.201	6.37	1.26	h_1	3.576	0.549	19.264	13.367***	1.889	8.179
h_{12}	-156.124***	38.478***	58.875**	-0.844	h_{12}	-1.383	-2.193	1.79	-12.758**	0.531	70.092*
h_{13}	-8.408	8.084	-45.88**	-1.434	h_{13}	-1.732	4.135	-30.502**	-20.988***	-3.831	10.079
h_{14}	-93.142*	-10.295	29.298**	21.063	h_{14}	31.806	10.647	-83.683**	-63.852***	-26.847**	-31.911
h_2	115.685*	45.133	136.037***	0.141	h_2	0.134	2.191	0.042	3.044	0.037	150.166***
h_{23}	12.461	18.965**	-212.02***	0.48	h_{23}	0.335	-8.261	-1.417	10.016***	-0.539	43.185**
h_{24}	138.033***	-24.151***	135.39***	-7.055	h_{24}	-6.15	-21.272**	-3.888	30.473***	-3.776	-136.734***
h_3	0.336	1.992	82.611***	0.408	h_3	0.21	7.787	12.074	8.238**	1.942	3.105
h_{34}	7.434	-5.074	-105.506***	-11.992	h_{34}	-7.703	40.103**	66.249***	50.128***	27.22**	-19.661
h_4	41.174	3.231*	33.687	88.053***	h_4	70.73***	51.632	90.879***	76.253***	95.384***	31.126
ϵ_1^2	14.103**	0.223	2.229	1.391	ϵ_1^2	0.407	1.114	0.15	0.007	0.013	1.631
$\epsilon_1\epsilon_2$	-8.176	-1.754	-4.477	-4.438	$\epsilon_1\epsilon_2$	2.553	1.004	0.363	-0.037	-0.137	-7.249
$\epsilon_1\epsilon_3$	-21.752**	-0.842	-1.188	1.997	$\epsilon_1\epsilon_3$	-2.302	-0.953	-1.005	-0.015	-0.166	-4.254
$\epsilon_1\epsilon_4$	-16.61***	-0.079	-6.365*	-6.995*	$\epsilon_1\epsilon_4$	-2.687	5.63	3.174	0.406	-0.365	-1.728
ϵ_2^2	1.185	3.447	2.249	3.539*	ϵ_2^2	4.006	0.226	0.221	0.048	0.372	8.056
$\epsilon_2\epsilon_3$	6.305	3.31	1.193	-3.185	$\epsilon_2\epsilon_3$	-7.226*	-0.43	-1.221	0.04	0.903**	9.455**
$\epsilon_2\epsilon_4$	4.815	0.312	6.393	11.157***	$\epsilon_2\epsilon_4$	-8.434*	2.539	3.855	-1.056	1.984**	3.84
ϵ_3^2	8.387*	0.795	0.158	0.717	ϵ_3^2	3.258*	0.204	1.689	0.008	0.548	2.774
$\epsilon_3\epsilon_4$	12.81***	0.15	1.696	-5.021	$\epsilon_3\epsilon_4$	7.606**	-2.409	-10.665	-0.439	2.407**	2.254
ϵ_4^2	4.891**	0.007	4.544**	8.792***	ϵ_4^2	4.439	7.116	16.834*	5.78*	2.645***	0.458

The dependent variables are the conditional variances in period t . Indices 1, 2, 3 and 4 represent Germany, UK, France and Spain respectively and the index i represents the own conditional variance/covariance. Estimated coefficient of the constant term is not reported. For reporting purpose coefficients are multiplied by 100.

***, ** and * denote significance at 1%, 5% and 10% respectively.

As expected the results reveal a high degree of financial integration of the old European stock markets. One general characteristic is observed from the results. The London and Frankfurt stock exchanges seem to be less affected by other markets. On the contrary, they have significant contagious effects on them. This result is quite intuitive as the importance of these two stock exchanges is by far higher than other relatively small ones. However,

despite its importance, the same is not true for the French stock market. As can be seen from Panel A, the CAC 40 index is significantly affected by the German, UK and Spanish stock markets both directly through past variances and indirectly through past covariances.

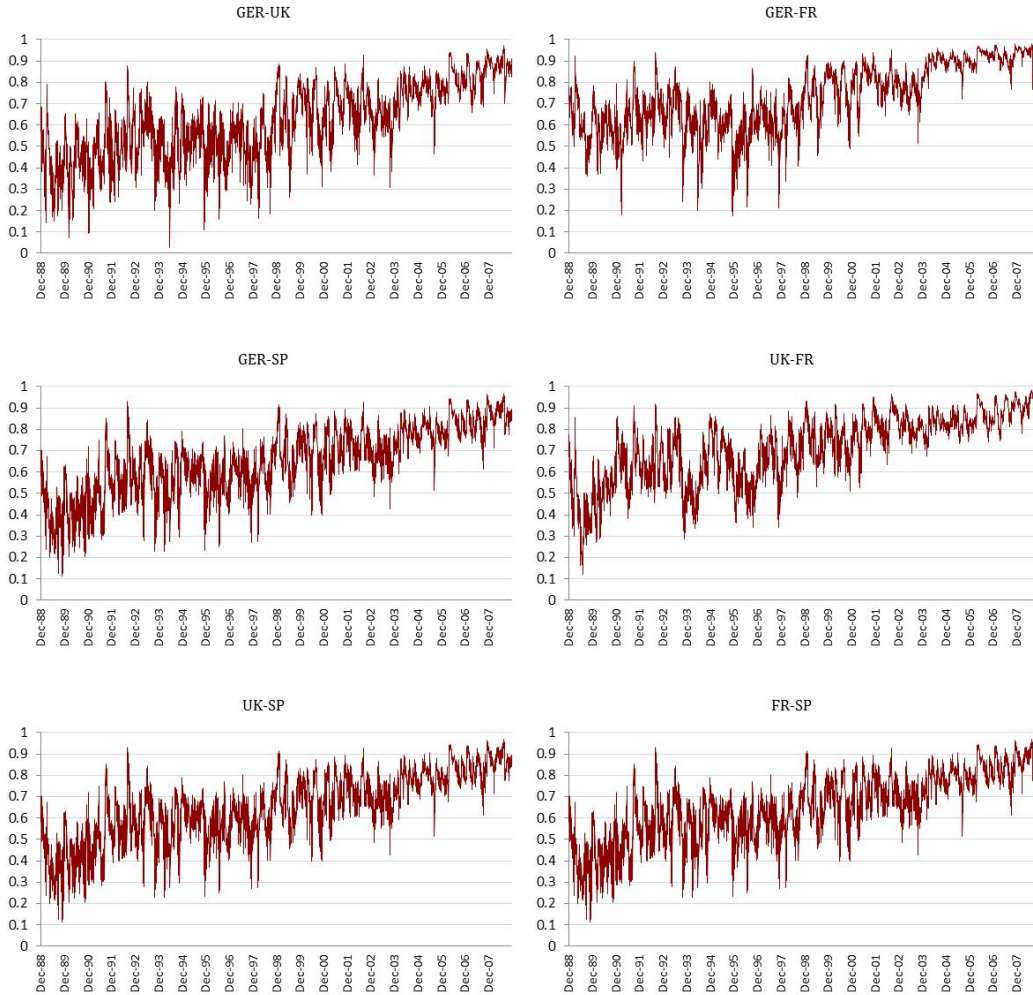


Figure 4.1: Estimated conditional correlations between old members.

The impact of the UK on the French market is significant, what is reflected in the high coefficient of past variances. The Spanish market also experiences significant spillovers from the three major European markets through the past variances and covariances. The leverage effect is also present for this market. Both the Spanish and French markets affect the German market indirectly (through covariances and squared shocks) and the Spanish market has a direct effect on the UK market.

Other European stock exchanges are presented in Panel B. The interaction of these

markets with the three major European markets is obvious, but is less than interaction among them. Most series presented in Panel B significantly respond to the past changes in own variances and squared residuals. All but Swiss and Austrian markets experience the leverage effect. German DAX has high and significant effect on the Austrian stock market via the variance and covariance. French market transfers volatility to the Swiss and Austrian market via the covariance and affects the Swedish market via the variance. Finally, in Appendix C we present the results for the conditional covariance equations. In general, the effect of past variables on the current covariances is slightly higher than the effects observed in Table 4.4, indicating strong interactions between these markets with the three major markets.

In Figure 4.1 we present the graphs of conditional correlations obtained by estimating the four variable model that includes the three major stock markets and Spain. The graphs for the other markets from the old group are provided in Appendix C.

As can be seen from Figure 4.1 the conditional correlations reflect increasing dependence over the studied period. In the final years of the sample the series are almost perfectly correlated, however when interpreting the conditional correlations we keep in mind that conditional correlations are expected to rise during crisis periods. The graphs show the rise of the conditional correlations throughout the sample period, with the increase being particularly evident in the second half. For example the correlation coefficients have been staying above 0.7 at least for the last five years.

In summary, our analysis reveals high interactions among the old European stock markets. The volatility is transmitted via past variances, covariances, past shock and past negative shocks. Furthermore, the estimated conditional time-varying correlations confirm the high degree of integration, in some cases being close to the maximum level.

4.4.3 “New members” group

Like in the previous part, we choose three major regional stock exchanges, include them in the four-variate model and estimate four variable models for each of the other markets, which are added one by one. To choose the appropriate exchanges we used their importance in the region (by daily trade volume), as well as unconditional correlations. The three chosen markets are Hungary, Czech Republic and Poland.

Table 4.5 presents the results for “new members” group. Panel A corresponds to the model with the Slovakian stock exchange as the fourth variable. As shown in the table the degree of volatility transmission is quite low. All series have significant ARCH and

Table 4.5: Volatility spillovers: “New members” group. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	HUN	CZ	POL	SLK		SLN	EST	LIT	LAT	ROM	BUL	TUR	CRO
t - 1	coeff	coeff	coeff	coeff		coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff
Panel A					Panel B								
ϵ_1^2	11.752***	0.016	0.66	0.078	ϵ_1^2	0.424	0.02	0.903	0.128	0.444	0.096	1.806*	0.85
$\epsilon_1\epsilon_2$	4.345	0.745	0.8*	-0.056	$\epsilon_1\epsilon_2$	-0.889	-0.03	-2.571	0.543	0.508	-0.536	1.209	-1.838
$\epsilon_1\epsilon_3$	0.993	0.027	2.471***	-0.148	$\epsilon_1\epsilon_3$	-0.56	-0.14	0.245	-0.65	-0.606	0.1	-0.262	1.38
$\epsilon_1\epsilon_4$	2.378	-0.013	0.271	0.829	$\epsilon_1\epsilon_4$	6.038**	-0.979	8.499	-2.899	5.945	-1.81	4.502***	-4.083
ϵ_2^2	0.402	8.826***	0.242	0.01	ϵ_2^2	0.466	0.011	1.83	0.576	0.146	0.744	0.202	0.995
$\epsilon_2\epsilon_4$	0.184	0.642	1.497**	0.053	$\epsilon_2\epsilon_4$	0.588	0.104	-0.349	-1.38	-0.347	-0.278	-0.088	-1.493
$\epsilon_3\epsilon_4$	0.44	-0.295	0.164	-0.296	$\epsilon_2\epsilon_4$	-6.336*	0.725	-12.1	-6.153	3.405	5.03**	1.507	4.418
ϵ_3^2	0.021	0.012	2.313**	0.07	ϵ_3^2	0.185	0.241	0.017	0.826	0.207	0.026	0.01	0.56
$\epsilon_3\epsilon_4$	0.101	-0.011	0.508	-0.786*	$\epsilon_3\epsilon_4$	-3.994	3.361	1.155	7.364	-4.056	-0.941	-0.327	-3.315
ϵ_4^2	0.12	0.003	0.028	2.197**	ϵ_4^2	21.518***	11.709***	19.998***	16.422***	19.907***	8.499***	2.806**	4.906
h_1	79.277***	0	0.055	0.078	h_1	0.002	0.034	0.182	0.097	0.031	0	33.725***	0.07
h_{12}	2.566	-0.172	0.022	-0.179*	h_{12}	-0.015	0.08	1.388	-0.151	-0.029	0.003	109.691***	-0.139
h_{13}	-0.304	-0.001	-4.579**	0.007	h_{13}	0	-0.364	0.616	-0.004	0.021	-0.005	32.16***	0.008
h_{14}	-0.236	0	-0.022	5.511***	h_{14}	-0.794	3.475	-6.982	-5.485	2.957	0.356	-106.252***	5.037
h_2	0.021	86.437***	0.002	0.102	h_2	0.027	0.047	2.646	0.059	0.007	0.004	89.192***	0.069
h_{23}	-0.005	0.472	-0.898	-0.008	h_{23}	-0.001	-0.429	2.35	0.003	-0.01	-0.017	52.301***	-0.008
h_{24}	-0.004	0.4	-0.004	-6.296***	h_{24}	2.857	4.1	-26.624	4.265	-1.385	1.256	-172.793***	-5
h_3	0	0.001	94.709***	0	h_3	0	0.977	0.522	0	0.003	0.017	7.667	0
h_{34}	0.001	0.001	0.905	0.253	h_{34}	-0.074	-18.649	-11.82	0.12	0.975	-2.457	-50.661***	0.287
h_4	0	0.001	0.002	96.898***	h_4	76.808***	89.033***	66.967***	77.481***	70.346***	91.283***	83.688***	90.683***
ϵ_1^2	4.273	0.14	0.646	0.013	ϵ_1^2	0.012	0.027	0.022	0.223	1.105	0.056	0.006	1.413
$\epsilon_1\epsilon_2$	-1.873	-1.703	1.802	-0.116	$\epsilon_1\epsilon_2$	-0.02	-0.2	0.549	-1.108	-2.695	0.034	0.238	-1.495
$\epsilon_1\epsilon_3$	0.367	-0.109	-3.702	-0.122	$\epsilon_1\epsilon_3$	-0.184	-0.47	-0.062	1.072	-3.11	-0.175	-0.038	-3.33
$\epsilon_1\epsilon_4$	-5.65	-0.238	-0.033	0.121	$\epsilon_1\epsilon_4$	0.542	0.499	0.397	2.136	4.109	-0.448	-0.057	-4.728
ϵ_2^2	0.205	5.186	1.256	0.253	ϵ_2^2	0.009	0.374	3.443	1.379	1.643	0.005	2.245	0.395
$\epsilon_2\epsilon_3$	-0.08	0.663	-5.162*	0.532	$\epsilon_2\epsilon_3$	0.156	1.755	-0.776	-2.667	3.792	-0.054	-0.714	1.761
$\epsilon_2\epsilon_4$	1.238	1.451	-0.047	-0.525	$\epsilon_2\epsilon_4$	-0.46	-1.863	4.986	-5.315	-5.01	-0.137	-1.078	2.501
ϵ_3^2	0.008	0.021	5.301**	0.28	ϵ_3^2	0.718	2.06	0.044	1.29	2.188	0.136	0.057	1.962
$\epsilon_3\epsilon_4$	-0.242	0.093	0.096	-0.553	$\epsilon_3\epsilon_4$	-4.237*	-4.374*	-0.562	5.143	-5.782	0.698	0.171	5.57*
ϵ_4^2	1.868	0.102	0	0.273	ϵ_4^2	6.25	2.322	1.805	5.124	3.819	0.895	0.129	3.954

The dependent variables are the conditional variances in period t . Indices 1, 2, 3 and 4 represent Hungary, Czech Republic, Poland and Slovakia respectively and the index i represents the own conditional variance/covariance. Estimated coefficient of the constant term is not reported. For reporting purpose coefficients are multiplied by 100.

***, ** and * denote significance at 1%, 5% and 10% respectively.

GARCH effects and only the Polish stock index experiences the leverage effect. The Polish and Slovakian markets are affected by the Hungarian and Czech markets, but the opposite effect is not observed.

Limited financial integration is confirmed by the results for other new member and candidate countries, provided in Panel B. From these eight markets Slovenia, Estonia, Bulgaria, Turkey and Croatia display limited interactions with the three markets mentioned above.

In appendix C we provide results for conditional covariance equations of all new member and candidate countries. These results are presented in Tables C.5-C.7. They show a higher degree of integration than the results for the variance equations reported in this section.

In summary, the analysis of financial interdependence among new member and can-

didate countries reveals a relatively lower level of volatility transmission. The volatility spillovers take place mainly through conditional covariances. Such results are consistent with the existing literature and are typical for the emerging markets.

4.4.4 Volatility spillovers between old and new EU members

As pointed previously, financial integration between the old markets is high, while the new markets reveal limited spillovers among each other. This fact justifies the use of the model that consists of three old markets and one new market, which is also supported by the results from Section 4.4.1.

Table 4.6 summarizes the result for ten new members and two candidate countries. The general picture is that the volatility spillovers between the two groups are higher through covariances than through variances.

Table 4.6: Volatility spillovers between “old” and “new” members. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	HUN	CZ	POL	SLK	SLN	EST	LIT	LAT	ROM	BUL	TUR	CRO
	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff
ϵ_1^2	0.575	0.015	0.135	0.008	0.297	0.013	0.163	0.075	0.667	1.559	3.286	0.48
$\epsilon_1\epsilon_2$	1.12	-0.001	0.77	0.037	-0.138	-0.505	0.342	-0.863	-0.144	4.833	-6.192	0.158
$\epsilon_1\epsilon_3$	-1.693	0.026	-0.381	0.009	-0.247	0.39	-0.482	0.499	-1.153	-7.972	-4.697	-0.358
$\epsilon_1\epsilon_4$	5.917	0.744	-1.637	-0.507	4.747	-0.968	-3.659	-2.03	-6.403	-7.168*	10.412	-3.921
ϵ_2^2	0.545	0	1.095	0.04	0.016	4.964	0.179	2.482	0.008	3.745	2.916	0.013
$\epsilon_2\epsilon_4$	-1.648	-0.001	-1.083	0.019	0.057	-7.656	-0.506	-2.869	0.125	-12.356	4.425	-0.059
$\epsilon_2\epsilon_4$	5.759	-0.034	-4.659	-1.115	-1.1	19.018*	-3.834	11.671	0.692	-11.11	-9.809	-0.645
ϵ_3^2	1.246	0.011	0.268	0.002	0.051	2.952	0.357	0.829	0.498	10.192*	1.679	0.067
$\epsilon_3\epsilon_4$	-8.708**	0.651	2.304	-0.265	-1.972	-14.665*	5.413	-6.746	5.537	18.327**	-7.442	1.463
ϵ_4^2	15.215***	9.483***	4.955***	7.695***	18.964***	18.215**	20.525***	13.72*	15.378***	8.239**	8.248**	8.013
h_1	0.25	0.04	0.186	0.344	1.344	0.016	2.671	0.125	0.019	1.05	0.898	0.643
h_{12}	0.119	-0.042	0.092	0.291	-1.96	-0.106	0.724	-0.46	0.166	0.734	4.033	1.523
h_{13}	-0.895	-0.022	-0.48	-0.774	-0.777	0.077	-5.265	0.188	-0.218	-2.453	-5.464	-2.71
h_{14}	-8.627	3.67**	8.256	-11.106	-20.537*	-2.296	26.371	6.284	-2.476	-19.542	-17.832	-14.978
h_2	0.014	0.011	0.012	0.062	0.714	0.173	0.049	0.422	0.357	0.128	4.528	0.901
h_{23}	-0.213	0.012	-0.119	-0.327	0.566	-0.251	-0.714	-0.346	-0.937	-0.857	-12.268	-3.208
h_{24}	-2.05	-1.92	2.049	-4.694	14.968	7.508	3.574	-11.541	-10.628	-6.83	-40.036	-17.732
h_3	0.8	0.003	0.31	0.435	0.112	0.091	2.595	0.071	0.616	1.433	8.309	2.855
h_{34}	15.434	-1.015	-10.656	12.481	5.936	-5.441	-25.993	4.728	13.971	22.83	54.237	31.561
h_4	74.416***	84.761***	91.615***	89.535***	78.436***	81.514***	65.097***	78.879***	79.219***	90.928***	88.503***	87.219***
ϵ_1^2	0.121	2.335**	2.298	0.211	0.031	0.874	1.119	0.02	0.074	3.904	8.513	11.182
$\epsilon_1\epsilon_2$	-1.72	-4.95**	-2.946	-0.959	0.036	-0.656	-5.606	-0.389	1.159	-8.18	-13.683	-3.769
$\epsilon_1\epsilon_3$	0.736	-0.901	-4.052	-0.151	-0.087	-1.852	3.144	0.256	-1.157	-1.702	-17.477	-22.782
$\epsilon_1\epsilon_4$	-1.389	-6.047**	-6.438	1.209	-0.942	-3.616	3.91	-0.646	1.269	-4.754	-4.274	-15.986
ϵ_2^2	6.099	2.623	0.944	1.091	0.01	0.123	7.02	1.912	4.537	4.286	5.498	0.318
$\epsilon_2\epsilon_3$	-5.222	0.955	2.597	0.343	-0.051	0.695	-7.875	-2.52	-9.063	1.784	14.045*	3.839
$\epsilon_2\epsilon_4$	9.855	6.409**	4.126	-2.748	-0.549	1.358	-9.794	6.35	9.934	4.981	3.435	2.694
ϵ_3^2	1.118	0.087	1.786	0.027	0.061	0.981	2.209	0.83	4.525	0.186	8.97	11.604
$\epsilon_3\epsilon_4$	-4.219	1.167	5.676	-0.432	1.331	3.832	5.494	-4.184	-9.921	1.037	4.388	16.285
ϵ_4^2	3.981	3.914	4.509*	1.731	7.217*	3.742	3.416	5.271	5.438	1.447	0.537	5.714*

The dependent variables are the conditional variances in period t . Indices 1, 2 and 3 represent Germany, UK and France respectively and the index i represents the own conditional variance/covariance. Estimated coefficient of the constant term is not reported. For reporting purpose coefficients are multiplied by 100.

***, ** and * denote significance at 1%, 5% and 10% respectively.

Table 4.7: Conditional covariances between “new members” and Germany. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	HUN	CZ	POL	SLK	SLN	EST	LIT	LAT	ROM	BUL	TUR	CRO
	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff
ε_1^2	0.186	0.027	0.81	0.232	-0.504	0.368	0.871	0.76	0.097	4.358*	1.859	1.479
$\varepsilon_1\varepsilon_2$	1.077	-0.17	1.849	0.43	0.776	-7.336**	0.429	-5.131	0.541	6.817	-2.304	-1.378
$\varepsilon_1\varepsilon_3$	-0.305	0.311	-1.388	0.068	0.525	5.269*	-1.82	2.515	-1.433	-14.591**	-0.278	-0.559
$\varepsilon_1\varepsilon_4$	1.331	0.742	-4.888	-7.063***	-3.996	-13.871***	-9.985	-10.31	-0.626	-10.093***	2.742	-6.099**
ε_2^2	0.872	0.008	-1.298	-0.18	-0.153	2.133	-0.508	4.388	-0.06	0.096	0.521	-0.267
$\varepsilon_2\varepsilon_4$	-1.348	-0.161	-0.062	-0.161	-0.347	4.345	0.16	-2.481	-0.331	-5.501	-0.594	0.603
$\varepsilon_2\varepsilon_4$	4.972*	-4.311**	2.807*	2.464	5.256	4.576	5.216	10.557	-2.631	-0.257	-0.685	6.615
ε_3^2	0.046	0.251	0.348	-0.028	-0.131	-4.618**	0.786	-0.032	1.167	8.815*	-0.751	0.003
$\varepsilon_3\varepsilon_4$	-0.712	7.365***	1.475	1.629	2.506	11.095**	6.265	-0.006	6.62	8.115**	1.809	0.05
ε_4^2	1.93*	1.248*	0.263	0.255	0.939	2.327*	0.561	0.774	0.17	-0.321	0.217	0.217
h_1	-3.619	1.842**	3.531	-2.459	7.298	1.293	-18.511*	-4.689	2.374	12.224	-8.634	-6.028
h_{12}	-0.013	-0.964	0.387	0.417	-24.544**	-6.445	-5.868	15.047	9.309	7.91	-18.652	-5.594
h_{13}	4.432	-0.442	-3.514	-1.765	-2.787	2.813	51.886*	-2.512	-15.739	-37.283	25.141	9.664
h_{14}	62.55***	85.103***	78.38	39.674**	-55.156***	-91.925***	-90.83	-117.731***	-151.975***	-113.844**	85.735*	70.253
h_2	0.201	0	-0.122	0.615	14.012	7.246	-0.455	-11.819	-3.787	1.272	1.645	1.826
h_{23}	-2	-0.035	0.891	-3.55	6.05	-4.427	7.87	2.977	-5.074	-12.29	-4.742	-6.847
h_{24}	-14.58***	0.011	-10.866	-23.464***	146.42***	157.641***	-16.51	161.592***	56.254***	-33.886*	-7.201	-17.907
h_3	3.655	-0.019	-1.348	5.088	0.196	-0.597	-33.159	0.764	13.214	26.873	3.406	6.401
h_{34}	35.044	3.115***	23.17	72.973***	5.003	17.663	165.538***	25.481	150.115***	214.165***	11.018	35.278
h_4	-1.921*	-0.288	0.12	-0.428	-4.51	6.633**	2.744	-0.436	3.003	0.843	-0.315	-0.569
ε_1^2	-1.091	-6.938***	-4.531	-0.312	-0.541	-1.705	4.31	-0.318	-0.17	-3.948	-9.426*	-7.83
$\varepsilon_1\varepsilon_2$	7.499**	7.014**	2.857	-0.203	-0.785	0.079	-7.671	2.445	0.313	-1.881	1.711	-0.619
$\varepsilon_1\varepsilon_3$	-3.096	4.313	2.758	-0.567	1.171	0.922	2.832	-1.596	0.63	2.873	16.138*	6.082
$\varepsilon_1\varepsilon_4$	6.259**	8.668***	6.882	-0.583	8.304***	3.518	7.713	5.1	-1.397	1.907	1.671	4.697
ε_2^2	1.682	0.36	0.03	2.074	-0.274	0.211	-7.825	6.656	12.85	6.306	4.712	0.327
$\varepsilon_2\varepsilon_3$	-2.253	-3.087*	0.834	1.869	0.9	0.927	12.462	-8.92	-18.288	-0.796	0.825	2.294
$\varepsilon_2\varepsilon_4$	1.299	0.773	-0.277	-3.316**	7.199***	1.166	5.003	11.866	14.517	4.185**	2.031	1.537
ε_3^2	0.656	-0.574	1.09	0.242	-0.575	0.938	-4.528	2.988	5.448	-0.439	-6.634	1.93
$\varepsilon_3\varepsilon_4$	-1.213	-3.79**	1.261	-2.054	-6.252*	1.843	-5.376	-8.067*	-6.422	-1.117	-0.909	2.271
ε_4^2	-0.049	0.407	-0.749	0.887*	-0.214	0.023	0.318	1.354*	0.493	0.303	0.175	0.643

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported. *, ** and *** denote significance at 10, 5 and 1% respectively.

The German stock market significantly affects Czech, Slovenian and Bulgarian conditional variances. The UK stock market has a significant impact on Czech, Estonian and Turkish variances. While only the Bulgarian and Turkish variances respond significantly to the French market.

Additionally, we are also interested in spillover through conditional covariances, which is summarized by Table 4.7 and by Tables C.8 and C.9 in Appendix C. As can be seen from the Table 4.7 these effects are highly significant. Each column corresponds to the equation of conditional covariance of the specified series with the German market. For example the 15th coefficient in the third column is interpreted as the effect of the covariance between the German and Czech stock markets in period $t-1$ on the covariance between the German and Czech markets in period t , or simply its own lag.

Among all conditional covariances the most affected is the covariance between the Czech and German markets. It is affected by all three major developed European stock

markets, it also exhibits leverage effect. In general, Hungarian, Czech, Polish, Slovakian and Slovenian covariances are highly affected, Estonian, Lithuanian, Latvian Romanian and Bulgarian covariances are effected less, while Turkish and Croatian covariances show very limited response to other markets. Further, the results for the covariances with the UK and French markets, presented in Appendix C, reveal similar pattern as observed in the case of Germany, suggesting that the new member and candidate countries can be categorized in groups, which differ according to the degree of integration with the three developed markets.

In summary, we find statistically significant spillovers between the stock markets of the old and new EU members and candidate countries. Such spillovers are realized mainly via conditional covariances. Among the stock exchanges, which have high degree of integration are Hungary, Czech Republic, Poland, as well as Slovakia and Slovenia. The Turkish stock market also seems well integrated with developed European markets, though the spillover is mainly unidirectional. Given the relatively long history of the Turkish stock market and its economic and financial ties with Europe, this result seems intuitive. Despite the short period after joining the EU, and in general short history of the Romanian and Bulgarian stock markets, they are significantly affected by the old members.

4.4.5 *Evolution of Conditional correlations over time*

In the previous section it was pointed out that the new members interact mainly though covariances. In this section we look at the estimated conditional and how they change over time, particularly we are interested if there is a difference for countries that joined the EU at different stages. Below we provide selected graphs of estimated conditional correlations, additional graphs for all new member and candidate countries are provided in Figures C.7-C.18 in Appendix C.

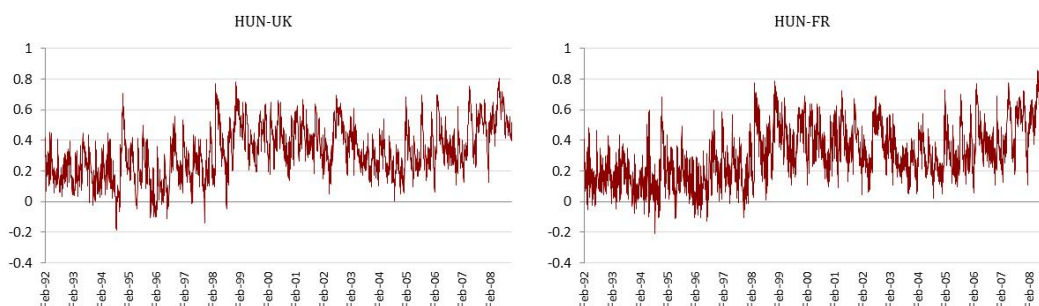


Figure 4.2: Conditional correlation for Hungary.

During the studied period there were at least three major financial crises that could have affected the correlations presented here. These are the Asian and Russian crises in 1997 and 1998 respectively and more recently the world financial crisis in 2008. From the graphs we clearly see that the correlations were high during all these periods.

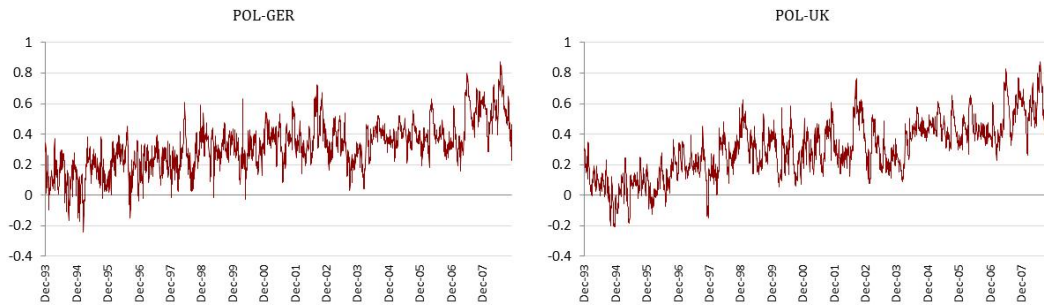


Figure 4.3: Conditional correlation for Poland.

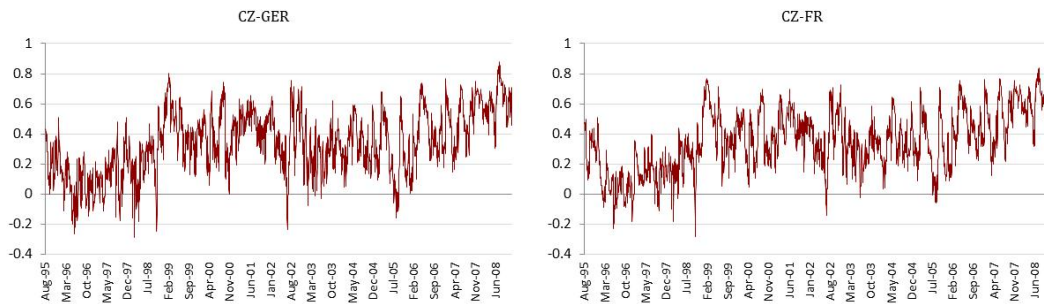


Figure 4.4: Conditional correlation for the Czech Republic.

Figure 4.2 illustrates conditional correlations between the Hungarian stock market and the UK and French markets. We see the clear pattern in both cases, starting from 1992 up to the end of 1996 these correlations were rather low, fluctuating within the limits from -0.2 to 0.6 with few exceptions. The period 1997-2002 can be characterized as the period of increased correlations and high fluctuations of the correlations with more frequent jumps. Starting from about 2004 we observe a gradual increase, which is followed by a sharp increase in 2008, after which it again drops rapidly at the end of the sample.

Figure 4.3 presents the conditional correlations of the Polish stock market and the UK and German markets. Again, we observe three periods, one with low correlation, the second with temporary high correlation and third with steady increase, starting in 2003. Considering the final value of the estimated correlation (about 0.4) the Hungarian

and Polish stock exchanges seem to be equally correlated with the three major developed European markets.

The third market, which exhibits similar pattern is the Czech stock market, presented in Figure 4.4. The main difference from the two markets discussed above is that the Czech market experienced several very large drops into the negative territory.

Figures 4.5 and 4.6 illustrate the estimated conditional correlations of Romania-UK and Bulgaria-UK. These are the new members, which joined the EU at the second stage (2007). As can be seen from the graphs, the correlation for Romania starts increasing from about 2006, while the correlation for Bulgaria is low and does not change significantly.

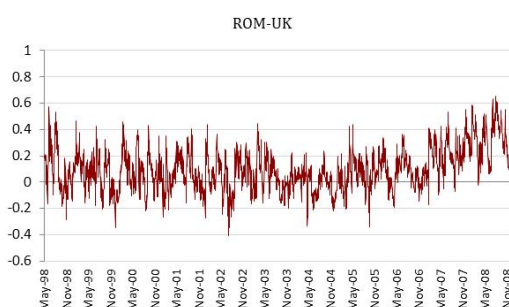


Figure 4.5: Conditional correlation Romania-UK

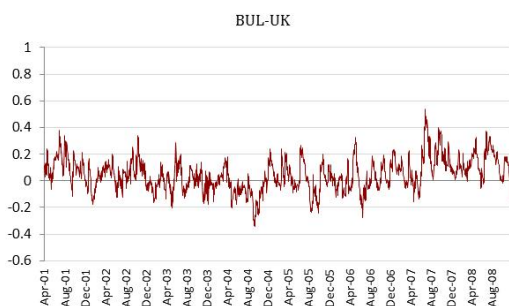


Figure 4.6: Conditional correlation Bulgaria-UK

Finally, we look at the interactions between the old members and the EU candidate countries. Figures 4.7 and 4.8 provide the graphs of the estimated conditional correlations of Turkey-UK and Croatia-UK. The correlation of Turkey has increased over the studied period, however this increase may reflect the development of the Turkish stock exchange and its economy over the sample period. On the other hand the Croatia-UK correlation was very low before 2006, but increases following that date.

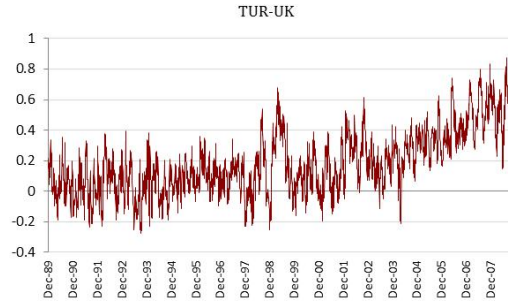


Figure 4.7: Conditional correlation Turkey-UK

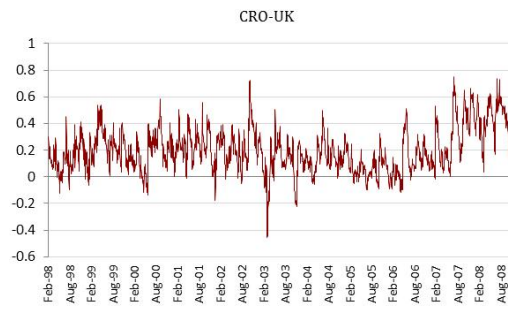


Figure 4.8: Conditional correlation Croatia-UK

4.5 Summary and Conclusions

In this chapter we analyze the volatility spillovers among stock markets of the old and new EU member countries. By estimating four variable BEKK-GARCH models we find a high degree of financial integration among the old members and lower level of interactions among the new member countries. In addition, we find evidence of volatility spillovers between these two groups. Moreover, these spillovers are mainly unidirectional, i.e. volatility is transmitted from the old markets to the new ones. Comparing two subgroups of the new members, which joined at different stages, reveals that such volatility transmission is higher for those markets that joined the EU in 2004 than for those which joined in 2007. Finally, there is a clear pattern of increasing correlations for the new members after the joining to the EU.

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Appendix A

Table A.1: Nonlinear functions of estimated coefficients for bivariate GJR-BEKK-GARCH(1,1) model.

	$h_{11,t}$	$h_{12,t} = h_{21,t}$	$h_{22,t}$
<i>Constant</i>	c_{11}^2	$c_{11}c_{12}$	$c_{12}^2 + c_{22}^2$
ε_1^2	a_{11}^2	$a_{12}a_{11}$	a_{12}^2
$\varepsilon_1\varepsilon_2$	$2a_{11}a_{21}$	$a_{12}a_{21} + a_{22}a_{11}$	$2a_{12}a_{22}$
ε_2^2	a_{21}^2	$a_{22}a_{21}$	a_{22}^2
h_1	b_{11}^2	$b_{12}b_{11}$	b_{12}^2
h_{12}	$2b_{11}b_{21}$	$b_{12}b_{21} + b_{22}b_{11}$	$2b_{12}b_{22}$
h_2	b_{21}^2	$b_{22}b_{21}$	b_{22}^2
ϵ_1^2	d_{11}^2	$d_{12}d_{11}$	d_{12}^2
$\epsilon_1\epsilon_2$	$2d_{11}d_{21}$	$d_{12}d_{21} + a_{22}a_{11}$	$2d_{12}d_{22}$
ϵ_2^2	d_{21}^2	$d_{22}d_{21}$	d_{22}^2

Table A.2: Augmented Dickey-Fuller test for unit root

OHR for BEKK-GARCH Model			
Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-7.398	-3.43	-2.86	-2.57
MacKinnon approximate p-value for $Z(t) = 0.0000$			
OHR for GJR-BEKK-GARCH Model			
Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-7.44	-3.43	-2.86	-2.57
MacKinnon approximate p-value for $Z(t) = 0.0000$			
The null hypothesis is the presence of unit root. The augmented Dickey-Fuller statistic lies outside the acceptance region at 1%, 5%, and 10% levels. Therefore, we reject the presence of unit root.			

Table A.3: Estimated Coefficients for Aluminium (BEKK-GARCH Model)

<i>Panel A:</i> Conditional Mean Equations (<i>P</i> -values in parenthesis)	
$y_{1,t} = 0.000006 - 0.120651y_{1,t-1} + \varepsilon_{1,t}$ (0.9714) (0.0000) $y_{2,t} = 0.000025 - 0.117683y_{2,t-1} + \varepsilon_{2,t}$ (0.8804) (0.0000)	
<i>Panel B:</i> Conditional Variance-Covariance Matrix (<i>P</i> -values in parenthesis)	
$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$	
$C = \begin{bmatrix} 0.001244 & 0.000867 \\ (0.0000) & (0.0000) \\ 0 & 0.000103 \\ & (0.0023) \end{bmatrix}$	$A = \begin{bmatrix} -0.476768 & -0.046696 \\ (0.0000) & (0.4343) \\ 0.634730 & 0.185678 \\ (0.0000) & (0.0031) \end{bmatrix}$
$B = \begin{bmatrix} 0.915819 & 0.000768 \\ (0.0000) & (0.9555) \\ 0.071633 & 0.987102 \\ (0.0139) & (0.0000) \end{bmatrix}$	

Table A.4: Estimated Coefficients for Aluminium (GJR-BEKK-GARCH Model)

<i>Panel A:</i> Conditional Mean Equations (<i>P</i> -values in parenthesis)	
$y_{1,t} = 0.000106 - 0.124773y_{1,t-1} + \varepsilon_{1,t}$ (0.5372) (0.0000) $y_{2,t} = 0.000112 - 0.122044y_{2,t-1} + \varepsilon_{2,t}$ (0.4959) (0.0000)	
<i>Panel B:</i> Conditional Variance-Covariance Matrix (<i>P</i> -values in parenthesis)	
$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\epsilon_{t-1}\epsilon'_{t-1}D$	
$C = \begin{bmatrix} 0.001526 & 0.001302 \\ (0.0002) & (0.0040) \\ 0 & 0.000266 \\ & (0.3952) \end{bmatrix}$	$A = \begin{bmatrix} -0.400325 & -0.001138 \\ (0.0000) & (0.9875) \\ 0.542842 & 0.122241 \\ (0.0000) & (0.1214) \end{bmatrix}$
$B = \begin{bmatrix} 0.933059 & 0.013103 \\ (0.0000) & (0.6387) \\ 0.040077 & 0.960979 \\ (0.1717) & (0.0000) \end{bmatrix}$	$D = \begin{bmatrix} 0.074625 & -0.108590 \\ (0.4754) & (0.1819) \\ 0.157953 & 0.333796 \\ (0.2333) & (0.0049) \end{bmatrix}$

Table A.5: Estimated Coefficients for Lead (BEKK-GARCH Model)

Panel A: Conditional Mean Equations (*P*-values in parenthesis)

$$y_{1,t} = 0.000126 - 0.166647y_{1,t-1} + \varepsilon_{1,t}$$

$$(0.5692) \quad (0.0000)$$

$$y_{2,t} = 0.000165 - 0.167800y_{2,t-1} + \varepsilon_{2,t}$$

$$(0.4180) \quad (0.0000)$$

Panel B: Conditional Variance-Covariance Matrix (*P*-values in parenthesis)

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

$$C = \begin{bmatrix} 0.002910 & 0.001273 \\ (0.0000) & (0.0000) \\ 0 & -0.000000 \\ & (0.0009) \end{bmatrix} \quad A = \begin{bmatrix} -0.694243 & 0.178799 \\ (0.0000) & (0.0005) \\ 0.848699 & 0.313452 \\ (0.0000) & (0.0000) \end{bmatrix}$$

$$B = \begin{bmatrix} 0.809674 & -0.032833 \\ (0.0000) & (0.1335) \\ 0.179680 & 1.022947 \\ (0.0012) & (0.0000) \end{bmatrix}$$

Table A.6: Estimated Coefficients for Lead (GJR-BEKK-GARCH Model)

Panel A: Conditional Mean Equations (*P*-values in parenthesis)

$$y_{1,t} = 0.000480 - 0.165828y_{1,t-1} + \varepsilon_{1,t}$$

$$(0.0000) \quad (0.0000)$$

$$y_{2,t} = 0.000410 - 0.166435y_{2,t-1} + \varepsilon_{2,t}$$

$$(0.0000) \quad (0.0000)$$

Panel B: Conditional Variance-Covariance Matrix (*P*-values in parenthesis)

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\epsilon_{t-1}\epsilon'_{t-1}D$$

$$C = \begin{bmatrix} 0.003280 & 0.001799 \\ (0.0000) & (0.0004) \\ 0 & 0.000001 \\ & (0.1373) \end{bmatrix} \quad A = \begin{bmatrix} -0.514071 & -0.143532 \\ (0.0000) & (0.0120) \\ 0.689060 & 0.285643 \\ (0.0000) & (0.0004) \end{bmatrix}$$

$$B = \begin{bmatrix} 0.829764 & -0.035877 \\ (0.0000) & (0.2124) \\ 0.140808 & 1.013492 \\ (0.0248) & (0.0000) \end{bmatrix} \quad D = \begin{bmatrix} 0.344528 & -0.074043 \\ (0.0012) & (0.2634) \\ -0.116299 & 0.275064 \\ (0.3338) & (0.0018) \end{bmatrix}$$

Table A.7: Estimated Coefficients for Nickel (BEKK-GARCH Model)

<i>Panel A:</i> Conditional Mean Equations (<i>P</i> -values in parenthesis)	
$y_{1,t} = 0.001056 - 0.183749y_{1,t-1} + \varepsilon_{1,t}$ $(0.0201) (0.0000)$ $y_{2,t} = 0.000879 - 0.180413y_{2,t-1} + \varepsilon_{2,t}$ $(0.0407) (0.0000)$	
<i>Panel B:</i> Conditional Variance-Covariance Matrix (<i>P</i> -values in parenthesis)	
$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$ $C = \begin{bmatrix} 0.001671 & 0.001218 \\ (0.0000) & (0.0028) \\ 0 & -0.000000 \\ & (0.2092) \end{bmatrix} \quad A = \begin{bmatrix} 0.248242 & -0.348764 \\ (0.0175) & (0.0245) \\ -0.109046 & 0.424299 \\ (0.2539) & (0.0005) \end{bmatrix}$ $B = \begin{bmatrix} 0.961257 & 0.131492 \\ (0.0000) & (0.0674) \\ 0.027146 & 0.860329 \\ (0.4530) & (0.0000) \end{bmatrix}$	

Table A.8: Estimated Coefficients for Nickel (GJR-BEKK-GARCH Model)

<i>Panel A:</i> Conditional Mean Equations (<i>P</i> -values in parenthesis)	
$y_{1,t} = 0.001056 - 0.195484y_{1,t-1} + \varepsilon_{1,t}$ $(0.0000) (0.0000)$ $y_{2,t} = 0.000886 - 0.191546y_{2,t-1} + \varepsilon_{2,t}$ $(0.0000) (0.0000)$	
<i>Panel B:</i> Conditional Variance-Covariance Matrix (<i>P</i> -values in parenthesis)	
$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\epsilon_{t-1}\epsilon'_{t-1}D$ $C = \begin{bmatrix} 0.001365 & 0.001761 \\ (0.0017) & (0.0000) \\ 0 & -0.000004 \\ & (0.0000) \end{bmatrix} \quad A = \begin{bmatrix} 0.490901 & -0.083505 \\ (0.0000) & (0.5905) \\ -0.352301 & 0.158567 \\ (0.0000) & (0.2164) \end{bmatrix}$ $B = \begin{bmatrix} -0.136157 & 0.677348 \\ (0.7524) & (0.0574) \\ 1.148693 & 0.293917 \\ (0.0082) & (0.4265) \end{bmatrix} \quad D = \begin{bmatrix} -0.181427 & 0.080674 \\ (0.2679) & (0.6277) \\ 0.333284 & 0.065307 \\ (0.0424) & (0.6956) \end{bmatrix}$	

Appendix B

Table B.1: Nonlinear functions of estimated coefficients for bivariate BEKK-GARCH(1,1) model with four exogenous variables.

	$h_{11,t}$	$h_{12,t} = h_{21,t}$	$h_{22,t}$
<i>Constant</i>	c_{11}^2	$c_{11}c_{12}$	$c_{12}^2 + c_{22}^2$
ε_1^2	a_{11}^2	$a_{12}a_{11}$	a_{12}^2
$\varepsilon_1\varepsilon_2$	$2a_{11}a_{21}$	$a_{12}a_{21} + a_{22}a_{11}$	$2a_{12}a_{22}$
ε_2^2	a_{21}^2	$a_{22}a_{21}$	a_{22}^2
h_1	b_{11}^2	$b_{12}b_{11}$	b_{12}^2
h_{12}	$2b_{11}b_{21}$	$b_{12}b_{21} + b_{22}b_{11}$	$2b_{12}b_{22}$
h_2	b_{21}^2	$b_{22}b_{21}$	b_{22}^2
X_1	z_{11}^2	$z_{11}z_{21}$	z_{21}^2
X_2	z_{12}^2	$z_{12}z_{22}$	z_{22}^2
X_3	z_{13}^2	$z_{13}z_{23}$	z_{23}^2
X_4	z_{14}^2	$z_{14}z_{24}$	z_{24}^2

Table B.2: Nonlinear functions of estimated coefficients for 3-variable BEKK-GARCH(1,1) model with four exogenous variables.

	$h_{1,t}$	$h_{12,t} = h_{21,t}$	$h_{13,t} = h_{31,t}$	$h_{2,t}$	$h_{23,t} = h_{32,t}$	$h_{3,t}$
<i>Constant</i>	c_{11}^2	$c_{11}c_{12}$	$c_{11}c_{13}$	$c_{12}^2 + c_{22}^2$	$c_{12}c_{13} + c_{22}c_{23}$	$c_{13}^2 + c_{23}^2 + c_{33}^2$
ε_1^2	a_{11}^2	$a_{12}a_{11}$	$a_{13}a_{11}$	a_{12}^2	$a_{13}a_{12}$	a_{13}^2
$\varepsilon_1\varepsilon_2$	$2a_{11}a_{21}$	$a_{12}a_{21} + a_{22}a_{11}$	$a_{13}a_{21} + a_{23}a_{11}$	$2a_{12}a_{22}$	$a_{13}a_{22} + a_{23}a_{12}$	$2a_{13}a_{23}$
$\varepsilon_1\varepsilon_3$	$2a_{11}a_{31}$	$a_{12}a_{31} + a_{32}a_{11}$	$a_{13}a_{31} + a_{33}a_{11}$	$2a_{12}a_{32}$	$a_{13}a_{32} + a_{33}a_{12}$	$2a_{13}a_{33}$
ε_2^2	a_{21}^2	$a_{22}a_{21}$	$a_{23}a_{21}$	a_{22}^2	$a_{23}a_{22}$	a_{23}^2
$\varepsilon_2\varepsilon_3$	$2a_{21}a_{31}$	$a_{22}a_{31} + a_{32}a_{21}$	$a_{23}a_{31} + a_{33}a_{21}$	$2a_{22}a_{32}$	$a_{23}a_{32} + a_{33}a_{22}$	$2a_{23}a_{33}$
ε_3^2	a_{31}^2	$a_{32}a_{31}$	$a_{33}a_{31}$	a_{32}^2	$a_{33}a_{32}$	a_{33}^2
h_1	b_{11}^2	$b_{12}b_{11}$	$b_{13}b_{11}$	b_{12}^2	$b_{13}b_{12}$	b_{13}^2
h_{12}	$2b_{11}b_{21}$	$b_{12}b_{21} + b_{22}b_{11}$	$b_{13}b_{21} + b_{23}b_{11}$	$2b_{12}b_{22}$	$b_{13}b_{22} + b_{23}b_{12}$	$2b_{13}b_{23}$
h_{13}	$2b_{11}b_{31}$	$b_{12}b_{31} + b_{32}b_{11}$	$b_{13}b_{31} + b_{33}b_{11}$	$2b_{12}b_{32}$	$b_{13}b_{32} + b_{33}b_{12}$	$2b_{13}b_{33}$
h_2	b_{21}^2	$b_{22}b_{21}$	$b_{23}b_{21}$	b_{22}^2	$b_{23}b_{22}$	b_{23}^2
h_{23}	$2b_{21}b_{31}$	$b_{22}b_{31} + b_{32}b_{21}$	$b_{23}b_{31} + b_{33}b_{21}$	$2b_{22}b_{32}$	$b_{23}b_{32} + b_{33}b_{22}$	$2b_{23}b_{33}$
h_3	b_{31}^2	$b_{32}b_{31}$	$b_{33}b_{31}$	b_{32}^2	$b_{33}b_{32}$	b_{33}^2
X_1	z_{11}^2	$z_{11}z_{21}$	$z_{11}z_{31}$	z_{21}^2	$z_{21}z_{31}$	z_{31}^2
X_2	z_{12}^2	$z_{12}z_{22}$	$z_{12}z_{32}$	z_{22}^2	$z_{22}z_{32}$	z_{32}^2
X_3	z_{13}^2	$z_{13}z_{23}$	$z_{13}z_{33}$	z_{23}^2	$z_{23}z_{33}$	z_{33}^2
X_4	z_{14}^2	$z_{14}z_{24}$	$z_{14}z_{34}$	z_{24}^2	$z_{24}z_{34}$	z_{34}^2

Table B.3: Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-EZ/Europe.

<i>Panel A. Conditional Variance: US</i>						
	S&P 500 - Eurofirst 300 Eurozone			S&P 500 - Eurofirst 300		
	Coeff.	St. Dev.	P-value	Coeff.	St. Dev.	P-value
Constant	0.0000	0.00	0.00	0.0000	0.00	0.00
ε_1^2	0.0487	0.01	0.00	0.0536	0.01	0.00
$\varepsilon_1\varepsilon_2$	0.0088	0.01	0.10	0.0004	0.01	0.96
ε_2^2	0.0004	0.00	0.50	0.0000	0.00	0.98
h_1	0.9392	0.01	0.00	0.9358	0.01	0.00
h_{12}	-0.0064	0.01	0.54	0.0018	0.01	0.88
h_2	0.0000	0.00	0.76	0.0000	0.00	0.94
$ News_{FED} $	0.0001	0.00	0.00	0.0001	0.00	0.01
$ News_{ECB} $	0.0002	0.00	0.05	0.0002	0.00	0.05
<i>Panel B. Conditional Covariance: US - Europe</i>						
	S&P 500 - Eurofirst 300 Eurozone			S&P 500 - Eurofirst 300		
	Coeff.	St. Dev.	P-value	Coeff.	St. Dev.	P-value
Constant	0.0000	0.00	0.10	0.0000	0.00	0.06
ε_1^2	-0.0213	0.00	0.00	-0.0133	0.00	0.00
$\varepsilon_1\varepsilon_2$	0.0687	0.01	0.00	0.0719	0.00	0.00
ε_2^2	0.0064	0.00	0.19	0.0002	0.01	0.96
h_1	0.0304	0.01	0.00	0.0215	0.01	0.00
h_{12}	0.9088	0.01	0.00	0.9109	0.01	0.00
h_2	-0.0031	0.01	0.54	0.0009	0.01	0.88
$ News_{FED} $	0.0000	0.00	0.79	0.0000	0.00	0.53
$ News_{ECB} $	-0.0002	0.00	0.00	-0.0002	0.00	0.00
<i>Panel C. Conditional Variance: Europe</i>						
	S&P 500 - Eurofirst 300 Eurozone			S&P 500 - Eurofirst 300		
	Coeff.	St. Dev.	P-value	Coeff.	St. Dev.	P-value
Constant	0.0000	0.00	0.00	0.0000	0.00	0.00
ε_1^2	0.0093	0.00	0.01	0.0033	0.00	0.10
$\varepsilon_1\varepsilon_2$	-0.0618	0.01	0.00	-0.0357	0.01	0.00
ε_2^2	0.1026	0.01	0.00	0.0964	0.01	0.00
h_1	0.0010	0.00	0.02	0.0005	0.00	0.06
h_{12}	0.0589	0.01	0.00	0.0418	0.01	0.00
h_2	0.8795	0.01	0.00	0.8867	0.01	0.00
$ News_{FED} $	0.0000	0.00	0.89	0.0000	0.00	0.77
$ News_{ECB} $	0.0003	0.00	0.06	0.0001	0.00	0.17

Table B.4: Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-Eurozone countries.

Panel A.														Conditional Covariance: country i – US													
France				Germany				Luxembourg				Spain				Belgium				Finland				Netherlands			
	Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value				
Constant	0.0000	0.00	0.0000	0.00	0.0000	0.04	0.0000	0.00	0.0000	0.00	0.0000	0.04	0.0000	0.00	0.0000	0.00	0.0000	0.00	0.0000	0.00	0.0000	0.00					
ε_i^2	-0.0267	0.00	-0.0128	0.00	0.0017	0.63	0.0016	0.72	-0.0071	0.00	0.0030	0.45	-0.0132	0.00													
$\varepsilon_i \varepsilon_i$	0.0813	0.00	0.0681	0.00	0.1071	0.00	0.0740	0.00	0.0393	0.00	0.0455	0.00	0.0842	0.00													
ε_i^2	0.0009	0.84	0.0011	0.77	0.0114	0.00	-0.0059	0.10	0.0331	0.00	0.0046	0.00	-0.0005	0.90													
h_i	0.0353	0.00	0.0148	0.01	0.0003	0.96	-0.0027	0.64	0.0358	0.00	-0.0045	0.31	0.0209	0.01													
h_{ii}	0.8923	0.00	0.9191	0.00	0.8394	0.00	0.9098	0.00	0.8801	0.00	0.9396	0.00	0.8912	0.00													
h_i	0.0028	0.59	-0.0016	0.69	-0.0086	0.00	0.0093	0.02	-0.0613	0.00	-0.0026	0.05	0.0061	0.21													
$ News_{FED} $	0.0001	0.01	0.0001	0.00	0.0001	0.00	0.0000	0.13	0.0000	0.99	0.0001	0.00	0.0001	0.01													
$ News_{ECB} $	-0.0001	0.22	-0.0001	0.01	-0.0002	0.03	0.0001	0.35	0.0002	0.01	-0.0003	0.00	-0.0002	0.00													
Panel B.														Conditional Variance: country i													
France				Germany				Luxembourg				Spain				Belgium				Finland				Netherlands			
	Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value				
Constant	0.0000	0.00	0.0000	0.00	0.0000	0.00	0.0000	0.00	0.0000	0.00	0.0000	0.04	0.0000	0.00	0.0000	0.04	0.0000	0.00	0.0000	0.00	0.0000	0.00					
ε_i^2	0.0142	0.00	0.0029	0.15	0.0001	0.81	0.0000	0.86	0.0046	0.02	0.0001	0.70	0.0032	0.17													
$\varepsilon_i \varepsilon_i$	-0.0865	0.00	-0.0313	0.01	0.0083	0.63	0.0040	0.72	-0.0572	0.00	0.0043	0.44	-0.0403	0.01													
ε_i^2	0.1320	0.00	0.0837	0.00	0.2561	0.00	0.0948	0.00	0.1783	0.00	0.0316	0.00	0.1287	0.00													
h_i	0.0013	0.02	0.0002	0.21	0.0000	0.98	0.0000	0.82	0.0013	0.00	0.0000	0.61	0.0005	0.18													
h_{ii}	0.0674	0.00	0.0291	0.01	0.0005	0.96	-0.0053	0.64	0.0657	0.00	-0.0093	0.31	0.0402	0.01													
h_i	0.8526	0.00	0.9045	0.00	0.7431	0.00	0.8968	0.00	0.8103	0.00	0.9640	0.00	0.8588	0.00													
$ News_{FED} $	0.0001	0.10	0.0001	0.02	0.0001	0.05	0.0000	0.38	0.0000	0.99	0.0002	0.00	0.0001	0.11													
$ News_{ECB} $	0.0000	0.61	0.0001	0.33	0.0002	0.30	0.0000	0.60	0.0001	0.10	0.0004	0.00	0.0001	0.11													

Table B.5: Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-developed countries.

<i>Panel A.</i> <i>Conditional Covariance: country i – US</i>										
	UK		Switzerland		Sweden		Japan		Korea	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.31	0.0000	0.00	0.0000	0.97	0.0000	0.00	0.0000	0.65
ε_1^2	-0.0207	0.00	0.0124	0.01	-0.0247	0.00	-0.0580	0.00	0.0150	0.02
$\varepsilon_1\varepsilon_2$	0.0050	0.12	-0.0308	0.00	0.0084	0.05	0.0095	0.09	-0.0075	0.11
$\varepsilon_1\varepsilon_i$	0.0480	0.00	0.0636	0.00	0.0545	0.00	0.0795	0.00	0.0400	0.00
ε_2^2	-0.0003	0.50	0.0190	0.00	-0.0006	0.21	-0.0004	0.38	-0.0027	0.01
$\varepsilon_2\varepsilon_i$	-0.0071	0.23	-0.0832	0.00	-0.0052	0.19	-0.0068	0.45	0.0126	0.00
ε_i^2	0.0224	0.00	0.0441	0.00	0.0093	0.00	0.0247	0.08	-0.0087	0.00
h_1	0.0255	0.00	-0.0158	0.01	-0.1459	0.00	0.0815	0.03	-0.0149	0.03
h_{12}	-0.0060	0.30	0.0201	0.01	0.7553	0.00	0.0387	0.37	0.0146	0.83
h_{1i}	0.9260	0.00	0.9306	0.00	0.3359	0.00	-0.4256	0.00	0.9194	0.00
h_2	-0.0001	0.21	-0.0001	0.30	0.1962	0.04	0.0010	0.58	-0.0024	0.97
h_{2i}	0.0129	0.02	-0.0061	0.32	-0.0577	0.31	-0.0281	0.31	-0.7207	0.00
h_i	-0.0213	0.00	-0.0154	0.00	-0.0530	0.01	0.1887	0.00	0.1858	0.00
$ News_{FED} $	0.0000	0.03	-0.0001	0.00	0.0001	0.00	0.0001	0.08	0.0001	0.00
$ News_{ECB} $	-0.0001	0.01	-0.0002	0.00	-0.0002	0.00	0.0003	0.12	0.0001	0.50
<i>Panel B.</i> <i>Conditional Covariance: country i – Eurozone</i>										
	UK		Switzerland		Sweden		Japan		Korea	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.00	0.0000	0.00	0.0000	0.44	0.0000	0.00	0.0000	0.85
ε_1^2	0.0079	0.00	-0.0034	0.00	0.0030	0.18	0.0082	0.17	-0.0061	0.01
$\varepsilon_1\varepsilon_2$	-0.0308	0.00	-0.0107	0.06	-0.0233	0.00	-0.0694	0.00	0.0216	0.00
$\varepsilon_1\varepsilon_i$	-0.0195	0.00	0.0023	0.81	-0.0068	0.17	-0.0326	0.04	-0.0175	0.00
ε_2^2	0.0031	0.56	0.0167	0.00	0.0053	0.21	0.0055	0.42	-0.0127	0.01
$\varepsilon_2\varepsilon_i$	0.0815	0.00	-0.0820	0.00	0.0533	0.00	0.1137	0.00	0.0488	0.00
ε_i^2	-0.0056	0.23	0.0725	0.00	-0.0008	0.83	0.0313	0.02	0.0004	0.80
h_1	0.0006	0.02	-0.0003	0.00	-0.0438	0.00	0.0007	0.63	0.0002	0.84
h_{12}	0.0247	0.00	-0.0151	0.01	0.2861	0.00	0.0813	0.02	0.0151	0.04
h_{1i}	0.0218	0.00	0.0156	0.00	-0.0516	0.22	-0.0340	0.12	-0.0228	0.76
h_2	-0.0062	0.26	0.0195	0.01	-0.2624	0.00	0.0363	0.40	-0.0031	0.97
h_{2i}	0.9031	0.00	0.9058	0.00	0.6836	0.00	-0.3974	0.00	-0.9363	0.00
h_i	0.0056	0.36	-0.0264	0.00	0.3092	0.00	0.1464	0.00	0.4573	0.00
$ News_{FED} $	0.0000	0.52	0.0000	0.95	0.0000	0.20	0.0000	0.40	0.0000	0.14
$ News_{ECB} $	□□□□	0.13	0.0001	0.22	0.0002	0.08	0.0011	0.00	0.0004	0.00
<i>Panel C.</i> <i>Conditional Variance: country i</i>										
	UK		Switzerland		Sweden		Japan		Korea	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.00	0.0000	0.00	0.0000	0.56	0.0001	0.00	0.0000	0.00
ε_1^2	0.0102	0.00	0.0040	0.12	0.0106	0.01	0.0723	0.00	0.0038	0.19
$\varepsilon_1\varepsilon_2$	-0.0021	0.56	-0.0091	0.05	-0.0050	0.23	-0.0115	0.43	-0.0056	0.15
$\varepsilon_1\varepsilon_i$	-0.0557	0.00	0.0342	0.00	-0.0503	0.00	-0.2359	0.00	0.0216	0.00
ε_2^2	0.0001	0.76	0.0052	0.07	0.0006	0.50	0.0005	0.68	0.0021	0.22
$\varepsilon_2\varepsilon_i$	0.0057	0.53	-0.0392	0.00	0.0118	0.16	0.0188	0.41	-0.0160	0.02
ε_i^2	0.0758	0.00	0.0737	0.00	0.0595	0.00	0.1925	0.00	0.0309	0.00
h_1	0.0007	0.01	0.0003	0.17	0.0256	0.01	0.0071	0.27	0.0003	0.28
h_{12}	-0.0003	0.32	-0.0007	0.16	-0.2777	0.00	0.0063	0.31	-0.0001	0.97
h_{1i}	0.0502	0.00	-0.0310	0.01	-0.1092	0.00	-0.0668	0.06	-0.0311	0.03
h_2	0.0000	0.58	0.0004	0.22	0.7535	0.00	0.0014	0.67	0.0000	0.98
h_{2i}	-0.0125	0.27	0.0391	0.01	0.5922	0.00	-0.0299	0.39	0.0063	0.97
h_i	0.9121	0.00	0.9105	0.00	0.1164	0.05	0.1581	0.00	0.9646	0.00
$ News_{FED} $	0.0001	0.03	0.0001	0.02	0.0001	0.01	0.0001	0.26	0.0002	0.00
$ News_{ECB} $	0.0001	0.29	0.0002	0.20	0.0005	0.02	0.0015	0.00	0.0005	0.01

Table B.6: Estimated results from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-BRIC countries.

<i>Panel A. Conditional Covariance: country i – US</i>								
	Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.48	0.0000	0.00	0.0000	0.49	0.0000	0.95
ε_1^2	-0.0258	0.00	-0.0056	0.37	0.0064	0.22	-0.0399	0.00
$\varepsilon_1\varepsilon_2$	0.0301	0.00	0.0095	0.14	-0.0051	0.33	0.0358	0.00
$\varepsilon_1\varepsilon_i$	0.0408	0.00	0.0721	0.00	0.0740	0.00	0.0880	0.00
ε_2^2	-0.0085	0.00	-0.0010	0.25	0.0002	0.68	-0.0019	0.74
$\varepsilon_2\varepsilon_i$	-0.0291	0.00	-0.0096	0.04	-0.0026	0.61	-0.0751	0.00
ε_i^2	0.0091	0.00	-0.0109	0.00	0.0014	0.62	0.0034	0.10
h_1	0.0408	0.00	0.0033	0.65	-0.0078	0.28	0.0354	0.00
h_{12}	0.0648	0.48	-0.0091	0.25	0.0059	0.48	-0.0956	0.15
h_{ii}	0.8974	0.00	0.9123	0.00	0.9084	0.00	0.7936	0.00
h_2	-0.0595	0.28	-0.0001	0.38	0.0000	0.64	0.0645	0.51
h_{2i}	-0.5653	0.00	0.0069	0.16	0.0033	0.52	-1.0565	0.00
h_i	0.1462	0.00	0.0160	0.00	0.0007	0.81	0.2170	0.00
$ News_{FED} $	0.0000	0.68	0.0000	0.58	0.0000	0.50	-0.0001	0.00
$ News_{ECB} $	-0.0002	0.01	0.0001	0.47	0.0000	0.98	0.0000	0.76
<i>Panel B. Conditional Covariance: country i – Eurozone</i>								
	Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.89	0.0000	0.47	0.0000	0.90	0.0000	0.58
ε_1^2	0.0201	0.00	0.0003	0.52	-0.0009	0.25	0.0013	0.54
$\varepsilon_1\varepsilon_2$	0.0156	0.00	-0.0067	0.35	0.0085	0.21	0.0218	0.00
$\varepsilon_1\varepsilon_i$	-0.0493	0.00	-0.0033	0.46	-0.0102	0.02	-0.0108	0.04
ε_2^2	-0.0121	0.00	0.0098	0.13	-0.0060	0.33	-0.0012	0.74
$\varepsilon_2\varepsilon_i$	-0.0383	0.00	0.0769	0.00	0.0912	0.00	-0.0486	0.00
ε_i^2	0.0243	0.00	-0.0100	0.00	-0.0027	0.34	0.0178	0.00
h_1	0.0006	0.84	0.0000	0.65	-0.0001	0.28	-0.0080	0.02
h_{12}	-0.0377	0.00	0.0032	0.66	-0.0076	0.28	-0.0265	0.31
h_{ii}	0.0330	0.59	0.0110	0.01	0.0131	0.00	-0.1622	0.02
h_2	-0.0874	0.30	-0.0090	0.25	0.0059	0.48	0.0513	0.51
h_{2i}	-0.8074	0.00	0.9006	0.00	0.8902	0.00	-0.8502	0.00
h_i	0.4412	0.00	0.0115	0.00	0.0032	0.32	0.3407	0.00
$ News_{FED} $	0.0000	0.63	0.0000	0.58	0.0000	0.52	0.0000	0.00
$ News_{ECB} $	0.0000	0.53	0.0000	0.52	0.0000	0.98	0.0000	0.72
<i>Panel C. Conditional Variance: country i</i>								
	Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.00	0.0000	0.00	0.0000	0.00	0.0000	0.00
ε_1^2	0.0267	0.00	0.0006	0.65	0.0008	0.54	0.0190	0.01
$\varepsilon_1\varepsilon_2$	-0.0256	0.01	-0.0018	0.53	-0.0013	0.55	-0.0021	0.75
$\varepsilon_1\varepsilon_i$	-0.0951	0.00	-0.0146	0.37	0.0193	0.22	-0.0851	0.00
ε_2^2	0.0061	0.08	0.0014	0.45	0.0005	0.63	0.0001	0.87
$\varepsilon_2\varepsilon_i$	0.0455	0.00	0.0230	0.13	-0.0149	0.33	0.0048	0.74
ε_i^2	0.0846	0.00	0.0921	0.00	0.1124	0.00	0.0954	0.00
h_1	0.0017	0.02	0.0000	0.82	0.0001	0.59	0.0018	0.11
h_{12}	0.0078	0.31	-0.0001	0.73	-0.0001	0.65	-0.0050	0.46
h_{ii}	0.0759	0.00	0.0065	0.65	-0.0151	0.28	0.0812	0.00
h_2	0.0087	0.61	0.0001	0.56	0.0000	0.72	0.0034	0.74
h_{2i}	0.1699	0.29	-0.0178	0.25	0.0115	0.48	-0.1111	0.51
h_i	0.8283	0.00	0.8919	0.00	0.8766	0.00	0.8989	0.00
$ News_{FED} $	0.0000	0.82	0.0000	0.77	0.0000	0.73	0.0001	0.06
$ News_{ECB} $	0.0001	0.32	0.0000	0.72	0.0000	0.99	0.0000	0.88

Table B.7: Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-EZ/Europe.

<i>Panel A. Conditional Variance: US</i>						
	S&P 500 - Eurofirst 300 Eurozone			S&P 500 - Eurofirst 300		
	Coeff.	St. Dev.	P-value	Coeff.	St. Dev.	P-value
Constant	0.0000	0.00	0.00	0.0000	0.00	0.00
ε_1^2	0.0459	0.01	0.00	0.0910	0.01	0.00
$\varepsilon_1\varepsilon_2$	0.0116	0.01	0.04	-0.2750	0.02	0.00
ε_2^2	0.0007	0.00	0.35	0.2078	0.02	0.00
h_1	0.9406	0.01	0.00	0.9019	0.01	0.00
h_{12}	-0.0081	0.01	0.44	-0.2174	0.02	0.00
h_2	0.0000	0.00	0.70	0.0131	0.00	0.00
$News_{FED+}$	0.0000	0.00	0.34	0.0000	0.00	0.72
$News_{ECB+}$	0.0001	0.00	0.24	0.0007	0.00	0.02
$News_{FED-}$	0.0001	0.00	0.00	0.0002	0.00	0.00
$News_{ECB-}$	0.0004	0.00	0.03	0.0002	0.00	0.36
<i>Panel B. Conditional Covariance: US - Europe</i>						
	S&P 500 - Eurofirst 300 Eurozone			S&P 500 - Eurofirst 300		
	Coeff.	St. Dev.	P-value	Coeff.	St. Dev.	P-value
Constant	0.0000	0.00	0.25	0.0000	0.00	0.00
ε_1^2	-0.0237	0.00	0.00	0.0264	0.01	0.00
$\varepsilon_1\varepsilon_2$	0.0651	0.01	0.00	-0.1926	0.02	0.00
ε_2^2	0.0086	0.00	0.08	0.2308	0.02	0.00
h_1	0.0333	0.01	0.00	0.0084	0.01	0.29
h_{12}	0.9088	0.01	0.00	0.8133	0.01	0.00
h_2	-0.0039	0.01	0.43	-0.0982	0.01	0.00
$News_{FED+}$	-0.0001	0.00	0.03	0.0000	0.00	0.31
$News_{ECB+}$	-0.0002	0.00	0.00	0.0002	0.00	0.30
$News_{FED-}$	0.0000	0.00	0.32	0.0002	0.00	0.00
$News_{ECB-}$	-0.0001	0.00	0.51	-0.0002	0.00	0.00
<i>Panel C. Conditional Variance: Europe</i>						
	S&P 500 - Eurofirst 300 Eurozone			S&P 500 - Eurofirst 300		
	Coeff.	St. Dev.	P-value	Coeff.	St. Dev.	P-value
Constant	0.0000	0.00	0.00	0.0000	0.00	0.00
ε_1^2	0.0123	0.00	0.00	0.0077	0.00	0.02
$\varepsilon_1\varepsilon_2$	-0.0704	0.01	0.00	-0.0886	0.02	0.00
ε_2^2	0.1011	0.01	0.00	0.2563	0.02	0.00
h_1	0.0012	0.00	0.01	0.0001	0.00	0.59
h_{12}	0.0644	0.01	0.00	0.0151	0.01	0.29
h_2	0.8784	0.01	0.00	0.7352	0.02	0.00
$News_{FED+}$	0.0001	0.00	0.10	0.0001	0.00	0.35
$News_{ECB+}$	0.0006	0.00	0.01	0.0001	0.00	0.53
$News_{FED-}$	0.0000	0.00	0.59	0.0001	0.00	0.04
$News_{ECB-}$	0.0000	0.00	0.76	0.0001	0.00	0.46

Table B.8: Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-Eurozone countries.

Panel A.														Conditional Covariance: country i – US													
France				Germany				Luxembourg				Spain				Belgium				Finland				Netherlands			
	Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value				
Constant	0.0000	0.00		0.0000	0.00		0.0000	0.02		0.0000	0.00		0.0000	0.00		0.0000	0.00		0.0000	0.00		0.0000	0.00				
ε_1^2	-0.0269	0.00		-0.0129	0.00		0.0012	0.72		0.0015	0.72		0.0079	0.00		-0.0003	0.94		-0.0108	0.02							
$\varepsilon_1\varepsilon_2$	0.0812	0.00		0.0682	0.00		0.1056	0.00		0.0740	0.00		0.0335	0.00		0.0442	0.00		0.0849	0.00							
ε_2^2	0.0007	0.87		-0.0003	0.94		0.0117	0.00		-0.0061	0.09		-0.0364	0.00		0.0054	0.00		-0.0016	0.70							
h_1	0.0356	0.00		0.0167	0.00		0.0020	0.72		-0.0020	0.73		-0.0362	0.00		-0.0005	0.90		0.0179	0.03							
h_{1i}	0.8927	0.00		0.9188	0.00		0.8406	0.00		0.9091	0.00		0.8922	0.00		0.9406	0.00		0.8909	0.00							
h_i	0.0030	0.57		-0.0003	0.94		-0.0090	0.00		0.0097	0.02		0.0611	0.00		-0.0034	0.01		0.0072	0.14							
$News_{FED+}$	0.0000	0.57		0.0000	0.03		-0.0001	0.06		0.0000	0.18		0.0000	0.12		0.0001	0.17		0.0000	0.75							
$News_{ECB+}$	-0.0001	0.31		-0.0001	0.01		0.0000	0.83		0.0001	0.41		0.0001	0.10		-0.0003	0.01		-0.0001	0.14							
$News_{FED-}$	0.0001	0.01		0.0001	0.00		0.0001	0.09		0.0001	0.09		0.0000	0.92		0.0001	0.00		0.0001	0.00							
$News_{ECB-}$	0.0000	0.60		0.0000	0.89		-0.0003	0.01		0.0001	0.46		0.0002	0.01		-0.0002	0.00		-0.0002	0.00							
Panel B.														Conditional Variance: country i													
France				Germany				Luxembourg				Spain				Belgium				Finland				Netherlands			
	Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value		Coeff.	P-value				
Constant	0.0000	0.00		0.0000	0.00		0.0000	0.00		0.0000	0.00		0.0000	0.00		0.0000	0.01		0.0000	0.00		0.0000	0.00				
ε_1^2	0.0143	0.00		0.0030	0.14		0.0000	0.86		0.0000	0.86		0.0057	0.00		0.0000	0.97		0.0021	0.27							
$\varepsilon_1\varepsilon_2$	-0.0865	0.00		-0.0321	0.01		0.0060	0.72		0.0040	0.72		0.0585	0.00		-0.0004	0.94		-0.0323	0.04							
ε_2^2	0.1311	0.00		0.0847	0.00		0.2552	0.00		0.0952	0.00		0.1508	0.00		0.0331	0.00		0.1261	0.00							
h_1	0.0014	0.02		0.0003	0.16		0.0000	0.86		0.0000	0.86		0.0014	0.00		0.0000	0.95		0.0003	0.26							
h_{1i}	0.0680	0.00		0.0328	0.00		0.0035	0.72		-0.0039	0.73		-0.0674	0.00		-0.0010	0.90		0.0345	0.02							
h_i	0.8534	0.00		0.9021	0.00		0.7439	0.00		0.8953	0.00		0.8336	0.00		0.9608	0.00		0.8607	0.00							
$News_{FED+}$	0.0000	0.72		0.0000	0.38		0.0002	0.04		0.0000	0.58		0.0000	0.52		0.0006	0.00		0.0000	0.87							
$News_{ECB+}$	0.0000	0.68		0.0001	0.37		0.0000	0.92		0.0000	0.63		0.0001	0.47		0.0007	0.00		0.0000	0.59							
$News_{FED-}$	0.0001	0.10		0.0001	0.03		0.0001	0.36		0.0000	0.31		0.0000	0.96		0.0001	0.02		0.0001	0.04							
$News_{ECB-}$	0.0000	0.81		0.0000	0.94		0.0004	0.20		0.0001	0.67		0.0007	0.00		0.0002	0.24		0.0002	0.07							

Table B.9: Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-developed countries.

<i>Panel A.</i> <i>Conditional Covariance: country i – US</i>										
	UK		Switzerland		Sweden		Japan		Korea	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.26	0.0000	0.02	0.0000	0.92	0.0000	0.86	0.0000	0.57
ε_1^2	-0.0194	0.00	0.0098	0.02	-0.0223	0.00	0.0190	0.00	0.0157	0.01
$\varepsilon_1\varepsilon_2$	0.0035	0.26	-0.0287	0.00	0.0054	0.17	-0.0188	0.00	-0.0049	0.30
$\varepsilon_1\varepsilon_i$	0.0460	0.00	0.0584	0.00	0.0503	0.00	0.0375	0.00	0.0363	0.00
ε_2^2	-0.0001	0.67	0.0202	0.01	-0.0003	0.40	-0.0030	0.05	-0.0032	0.01
$\varepsilon_2\varepsilon_i$	-0.0055	0.36	-0.0945	0.00	-0.0033	0.42	0.0068	0.05	0.0146	0.00
ε_i^2	0.0216	0.00	0.0552	0.00	0.0105	0.00	-0.0023	0.34	-0.0080	0.00
h_1	0.0252	0.00	-0.0115	0.04	-0.1656	0.00	-0.0295	0.70	-0.0175	0.01
h_{12}	-0.0059	0.32	0.0218	0.01	0.7299	0.00	0.0544	0.43	0.0230	0.74
h_{1i}	0.9276	0.00	0.9387	0.00	0.3511	0.00	-0.9042	0.00	0.9220	0.00
h_2	-0.0001	0.24	-0.0009	0.00	0.2455	0.02	0.0004	0.87	-0.0073	0.89
h_{2i}	0.0110	0.05	-0.0385	0.00	-0.0719	0.26	-0.0535	0.57	-0.7130	0.00
h_i	-0.0197	0.00	-0.0130	0.00	-0.0688	0.00	0.8002	0.00	0.1839	0.00
<i>News_{FED+}</i>	-0.0001	0.00	0.0000	0.51	0.0000	0.36	0.0000	0.75	0.0000	0.87
<i>News_{ECB+}</i>	-0.0001	0.02	-0.0001	0.56	-0.0001	0.36	0.0003	0.01	0.0002	0.23
<i>News_{FED-}</i>	0.0001	0.02	-0.0001	0.00	0.0001	0.00	0.0002	0.00	0.0002	0.00
<i>News_{ECB-}</i>	-0.0001	0.46	-0.0002	0.00	-0.0003	0.00	-0.0002	0.01	-0.0001	0.25
<i>Panel B.</i> <i>Conditional Covariance: country i – Eurozone</i>										
	UK		Switzerland		Sweden		Japan		Korea	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.00	0.0000	0.01	0.0000	0.39	0.0000	0.95	0.0000	0.80
ε_1^2	0.0083	0.00	-0.0028	0.00	0.0028	0.20	-0.0084	0.00	-0.0063	0.00
$\varepsilon_1\varepsilon_2$	-0.0309	0.00	-0.0110	0.07	-0.0225	0.00	0.0318	0.00	0.0245	0.00
$\varepsilon_1\varepsilon_i$	-0.0203	0.00	0.0019	0.83	-0.0070	0.17	-0.0148	0.00	-0.0159	0.00
ε_2^2	0.0020	0.70	0.0170	0.01	0.0037	0.39	-0.0253	0.00	-0.0129	0.03
$\varepsilon_2\varepsilon_i$	0.0842	0.00	-0.0857	0.00	0.0539	0.00	0.0428	0.00	0.0518	0.00
ε_i^2	-0.0076	0.13	0.0718	0.00	0.0003	0.94	0.0045	0.12	-0.0004	0.79
h_1	0.0006	0.01	-0.0002	0.03	-0.0566	0.00	□□□□	0.51	0.0003	0.83
h_{12}	0.0242	0.00	-0.0106	0.04	0.3215	0.00	-0.0277	0.72	0.0174	0.02
h_{1i}	0.0231	0.00	0.0168	0.00	-0.0546	0.24	-0.0043	0.96	-0.0243	0.73
h_2	-0.0060	0.29	0.0203	0.01	-0.2552	0.00	0.0544	0.45	-0.0095	0.89
h_{2i}	0.8999	0.00	0.8943	0.00	0.6634	0.00	-0.9722	0.00	-0.9219	0.00
h_i	0.0077	0.22	-0.0222	0.00	0.3086	0.00	0.7736	0.00	0.4559	0.00
<i>News_{FED+}</i>	0.0001	0.08	0.0004	0.00	0.0002	0.03	0.0000	0.78	0.0000	0.85
<i>News_{ECB+}</i>	0.0003	0.08	0.0000	0.86	0.0006	0.01	-0.0004	0.00	0.0006	0.00
<i>News_{FED-}</i>	0.0000	0.26	0.0000	0.63	0.0000	0.14	0.0001	0.06	0.0000	0.58
<i>News_{ECB-}</i>	0.0000	0.65	0.0001	0.34	0.0000	0.75	0.0001	0.18	0.0000	0.48
<i>Panel C.</i> <i>Conditional Variance: country i</i>										
	UK		Switzerland		Sweden		Japan		Korea	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.00	0.0000	0.00	0.0000	0.53	0.0000	0.00	0.0000	0.00
ε_1^2	0.0100	0.00	0.0025	0.20	0.0103	0.01	0.0072	0.01	0.0045	0.15
$\varepsilon_1\varepsilon_2$	-0.0014	0.70	-0.0060	0.12	-0.0034	0.39	-0.0163	0.00	-0.0057	0.15
$\varepsilon_1\varepsilon_i$	-0.0557	0.00	0.0239	0.01	-0.0506	0.00	0.0292	0.00	0.0228	0.00
ε_2^2	0.0000	0.85	0.0036	0.16	0.0003	0.65	0.0092	0.01	0.0018	0.27
$\varepsilon_2\varepsilon_i$	0.0038	0.69	-0.0284	0.01	0.0084	0.35	-0.0330	0.00	-0.0143	0.03
ε_i^2	0.0774	0.00	0.0568	0.00	0.0618	0.00	0.0296	0.00	0.0286	0.00
h_1	0.0007	0.01	0.0001	0.29	0.0340	0.00	0.0009	0.85	0.0003	0.21
h_{12}	-0.0003	0.34	-0.0005	0.17	-0.3206	0.00	-0.0035	0.78	-0.0004	0.89
h_{1i}	0.0494	0.00	-0.0227	0.04	-0.1291	0.00	0.0594	0.70	-0.0365	0.01
h_2	0.0000	0.60	0.0005	0.17	0.7566	0.00	0.0032	0.70	0.0001	0.95
h_{2i}	-0.0122	0.30	0.0420	0.01	0.6095	0.00	-0.1098	0.45	0.0197	0.89
h_i	0.9113	0.00	0.9249	0.00	0.1227	0.04	0.9355	0.00	0.9654	0.00
<i>News_{FED+}</i>	0.0001	0.08	0.0003	0.01	0.0002	0.08	0.0000	0.88	0.0000	0.93
<i>News_{ECB+}</i>	0.0001	0.21	0.0000	0.78	0.0008	0.01	0.0005	0.01	0.0005	0.02
<i>News_{FED-}</i>	0.0001	0.01	0.0001	0.00	0.0001	0.01	0.0003	0.00	0.0002	0.00
<i>News_{ECB-}</i>	0.0000	0.74	0.0003	0.13	0.0002	0.20	0.0001	0.24	0.0000	0.65

Table B.10: Estimated asymmetric effects from BEKK-GARCH (1, 1) model: conditional variance-covariance matrix US-BRIC countries.

<i>Panel A.</i> <i>Conditional Covariance: country i – US</i>								
	Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.77	0.0000	0.00	0.0000	0.27	0.0000	0.92
ε_1^2	-0.0283	0.00	-0.0143	0.05	0.0005	0.92	-0.0327	0.00
$\varepsilon_1\varepsilon_2$	0.0235	0.00	0.0194	0.01	-0.0004	0.93	0.0237	0.03
$\varepsilon_1\varepsilon_i$	0.0554	0.00	0.0826	0.00	0.0696	0.00	0.0879	0.00
ε_2^2	-0.0037	0.16	-0.0030	0.05	0.0000	0.93	0.0023	0.69
$\varepsilon_2\varepsilon_i$	-0.0356	0.00	-0.0171	0.00	0.0025	0.63	-0.0725	0.00
ε_i^2	0.0063	0.03	-0.0121	0.00	-0.0003	0.93	0.0038	0.08
h_1	0.0370	0.00	0.0127	0.07	-0.0005	0.95	0.0328	0.00
h_{12}	-0.0538	0.54	-0.0172	0.02	0.0002	0.98	-0.0894	0.25
h_{1i}	0.9181	0.00	0.9038	0.00	0.9116	0.00	0.8515	0.00
h_2	0.0195	0.75	-0.0002	0.09	0.0000	0.98	0.0601	0.54
h_{2i}	-0.6284	0.00	0.0126	0.01	-0.0014	0.80	-1.0320	0.00
h_i	0.1514	0.00	0.0172	0.00	0.0016	0.62	0.2068	0.00
$News_{FED+}$	-0.0001	0.06	0.0000	0.99	0.0000	0.71	-0.0002	0.06
$News_{ECB+}$	-0.0001	0.22	0.0000	0.88	0.0000	0.98	0.0001	0.21
$News_{FED-}$	0.0001	0.03	0.0000	0.31	0.0001	0.20	-0.0001	0.00
$News_{ECB-}$	-0.0002	0.24	0.0002	0.28	0.0003	0.23	-0.0002	0.56
<i>Panel B.</i> <i>Conditional Covariance: country i – Eurozone</i>								
	Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.85	0.0000	0.54	0.0000	0.94	0.0000	0.58
ε_1^2	0.0070	0.03	-0.0023	0.11	-0.0001	0.92	-0.0019	0.22
$\varepsilon_1\varepsilon_2$	0.0266	0.00	-0.0098	0.09	0.0008	0.92	0.0202	0.00
$\varepsilon_1\varepsilon_i$	-0.0249	0.00	0.0152	0.00	-0.0180	0.00	-0.0016	0.76
ε_2^2	-0.0059	0.18	0.0147	0.01	-0.0006	0.93	0.0018	0.69
$\varepsilon_2\varepsilon_i$	-0.0558	0.00	0.0678	0.00	0.0920	0.00	-0.0562	0.00
ε_i^2	0.0217	0.00	-0.0123	0.00	-0.0043	0.15	0.0185	0.00
h_1	0.0002	0.95	0.0000	0.56	0.0000	0.95	-0.0036	0.16
h_{12}	-0.0371	0.00	0.0128	0.07	-0.0004	0.95	-0.0288	0.09
h_{1i}	0.0216	0.74	-0.0027	0.55	0.0183	0.00	-0.0791	0.25
h_2	0.0285	0.75	-0.0174	0.02	0.0002	0.98	0.0520	0.54
h_{2i}	-0.9252	0.00	0.9066	0.00	0.8862	0.00	-0.9021	0.00
h_i	0.4398	0.00	0.0140	0.00	0.0050	0.13	0.3437	0.00
$News_{FED+}$	0.0001	0.31	0.0000	0.99	-0.0002	0.14	0.0000	0.42
$News_{ECB+}$	0.0001	0.36	0.0000	0.88	0.0000	0.94	-0.0002	0.07
$News_{FED-}$	0.0000	0.54	0.0000	0.40	0.0000	0.75	0.0000	0.00
$News_{ECB-}$	0.0000	0.70	0.0000	0.60	0.0000	0.88	0.0000	0.50
<i>Panel C.</i> <i>Conditional Variance: country i</i>								
	Brazil		China		India		Russia	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	0.0000	0.00	0.0000	0.00	0.0000	0.00	0.0000	0.00
ε_1^2	0.0195	0.01	0.0030	0.31	0.0000	0.96	0.0131	0.03
$\varepsilon_1\varepsilon_2$	-0.0082	0.24	-0.0070	0.21	0.0000	0.96	0.0023	0.68
$\varepsilon_1\varepsilon_i$	-0.0806	0.00	-0.0334	0.05	0.0016	0.92	-0.0718	0.00
ε_2^2	0.0009	0.52	0.0041	0.20	0.0000	0.96	0.0001	0.84
$\varepsilon_2\varepsilon_i$	0.0170	0.19	0.0393	0.01	-0.0014	0.93	-0.0062	0.69
ε_i^2	0.0834	0.00	0.0942	0.00	0.1119	0.00	0.0981	0.00
h_1	0.0015	0.02	0.0002	0.37	0.0000	0.98	0.0014	0.10
h_{12}	-0.0022	0.74	-0.0005	0.27	0.0000	0.99	-0.0041	0.52
h_{1i}	0.0719	0.00	0.0251	0.07	-0.0009	0.95	0.0697	0.00
h_2	0.0009	0.87	0.0003	0.25	0.0000	0.99	0.0031	0.76
h_{2i}	-0.0553	0.75	-0.0342	0.02	0.0003	0.98	-0.1057	0.54
h_i	0.8864	0.00	0.8895	0.00	0.8756	0.00	0.8966	0.00
$News_{FED+}$	0.0001	0.46	0.0000	0.99	0.0001	0.43	0.0001	0.30
$News_{ECB+}$	0.0001	0.53	0.0000	0.94	0.0000	0.97	0.0002	0.39
$News_{FED-}$	0.0001	0.07	0.0000	0.53	0.0001	0.51	0.0001	0.09
$News_{ECB-}$	0.0001	0.62	0.0001	0.60	0.0003	0.55	0.0000	0.77

Table B.11: Derived effect on the conditional correlation: US-EZ/Europe.

	S&P 500 - Eurofirst 300 Euro Zone	S&P 500 - Eurofirst 300
	Coeff.	Coeff.
<i>Panel A</i> <i>Conditional Correlation: US - Europe</i>		
$ News_{FED} $	-0.0703	-0.1147
$ News_{ECB} $	-0.8436	-0.7309
<i>Asymmetric Model</i>		
<i>Panel B</i> <i>Conditional Correlation: US - Europe</i>		
$News_{FED+}$	-0.4491	-0.3187
$News_{ECB+}$	-0.8704	0.1469
$News_{FED-}$	-0.0074	0.2527
$News_{ECB-}$	-0.4870	-0.7528

Table B.12: Derived effect on the conditional correlation: US-Eurozone countries.

	France	Germany	Luxemburg	Spain	Belgium	Finland	Netherlands
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
<i>Panel A</i> <i>Conditional Correlation: Country i - US</i>							
$ News_{FED} $	0.0845	0.1024	-0.2560	0.0245	-0.0027	0.1889	0.0674
$ News_{ECB} $	-0.4443	-0.5644	-0.3541	0.0120	0.5124	0.0308	-0.7629
<i>Asymmetric Model</i>							
<i>Panel B</i> <i>Conditional Correlation: Country i - US</i>							
$News_{FED+}$	0.0170	-0.2810	-0.3072	-0.3328	0.1662	0.1087	-0.0757
$News_{ECB+}$	-0.4360	-0.5079	-0.1259	0.0367	0.3124	-0.6891	-0.5171
$News_{FED-}$	0.0972	0.1051	0.1343	0.0664	-0.0125	0.1692	0.1223
$News_{ECB-}$	-0.3995	-0.3215	-0.6396	0.0374	0.5108	-0.6151	-0.9421

Table B.13: Derived effect on the conditional correlation: US-developed countries.

	UK	Switzerland	Sweden	Japan	Korea
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
<i>Panel A</i> <i>Conditional Correlation: Country i – US</i>					
$ \text{News}_{\text{FED}} $	0.1088	-0.3170	0.1245	0.2582	0.1376
$ \text{News}_{\text{ECB}} $	-0.4606	-0.5394	-0.7955	0.2349	-0.0629
<i>Panel B</i> <i>Conditional Correlation: Country i – Eurozone</i>					
$ \text{News}_{\text{FED}} $	-0.1533	-0.1179	-0.1419	-0.0906	-0.1886
$ \text{News}_{\text{ECB}} $	0.3454	0.0557	0.0441	1.3768	0.9074
<i>Asymmetric Model</i>					
<i>Panel C</i> <i>Conditional Correlation: Country i – US</i>					
$\text{News}_{\text{FED}+}$	-0.4761	0.0414	-0.2815	-0.1308	-0.0394
$\text{News}_{\text{ECB}+}$	-0.5360	-0.2631	-0.5156	0.3571	0.1051
$\text{News}_{\text{FED}-}$	0.1680	-0.2978	0.1455	0.2994	0.1612
$\text{News}_{\text{ECB}-}$	-0.4491	-0.6564	-0.8542	-0.6709	-0.3759
<i>Panel D</i> <i>Conditional Correlation: Country i – Eurozone</i>					
$\text{News}_{\text{FED}+}$	0.0405	0.9820	0.5030	-0.0612	-0.0790
$\text{News}_{\text{ECB}+}$	1.0843	-0.1247	0.8449	-0.9730	1.1585
$\text{News}_{\text{FED}-}$	-0.1394	-0.1642	-0.1191	0.0489	-0.0804
$\text{News}_{\text{ECB}-}$	-0.3678	0.0151	-0.5138	0.1057	0.0281

Table B.14: Derived effect on the conditional correlation: US-BRIC countries.

	Brazil	China	India	Russia
	Coeff.	Coeff.	Coeff.	Coeff.
<i>Panel A</i> <i>Conditional Correlation: Country i – US</i>				
$ \text{News}_{\text{FED}} $	-0.0225	-0.0478	0.0684	-0.3559
$ \text{News}_{\text{ECB}} $	-0.6054	0.1778	-0.0001	-0.0056
<i>Panel B</i> <i>Conditional Correlation: Country i – Eurozone</i>				
$ \text{News}_{\text{FED}} $	-0.0517	0.0385	-0.0278	-0.2021
$ \text{News}_{\text{ECB}} $	-0.0742	-0.1035	-0.0123	-0.1612
<i>Asymmetric Model</i>				
<i>Panel C</i> <i>Conditional Correlation: Country i – US</i>				
$\text{News}_{\text{FED}+}$	-0.3246	-0.0036	0.0330	-0.3979
$\text{News}_{\text{ECB}+}$	-0.2758	-0.0652	-0.0001	0.2057
$\text{News}_{\text{FED}-}$	0.1030	-0.1112	0.1719	-0.3611
$\text{News}_{\text{ECB}-}$	-0.5796	0.3338	0.4493	-0.3707
<i>Panel D</i> <i>Conditional Correlation: Country i – Eurozone</i>				
$\text{News}_{\text{FED}+}$	0.0921	-0.0050	-0.4950	-0.0610
$\text{News}_{\text{ECB}+}$	0.3500	0.0248	0.0640	-0.4323
$\text{News}_{\text{FED}-}$	-0.1232	0.0558	0.0090	-0.2100
$\text{News}_{\text{ECB}-}$	-0.2052	-0.0880	-0.0443	-0.2608

Table B.15: US Holdings of Foreign Securities at the end of the year.

	2009	2008	2007	2006	2005	2004	2003	2001
UNITED KINGDOM	14.1%	13.7%	13.6%	15.6%	16.2%	17.8%	20.2%	21.7%
JAPAN	9.3%	12.6%	10.1%	12.6%	14.9%	12.9%	12.3%	10.6%
SWITZERLAND	7.5%	7.8%	5.3%	6.1%	5.8%	5.4%	5.7%	4.7%
CANADA	7.4%	6.6%	7.2%	6.9%	7.5%	7.0%	7.2%	5.6%
FRANCE	6.3%	7.7%	6.6%	7.1%	6.2%	6.4%	6.3%	7.0%
GERMANY	4.8%	5.8%	6.3%	5.1%	4.8%	4.8%	5.0%	4.5%
BRAZIL	4.5%	2.6%	3.3%	2.1%	2.1%	1.7%	1.5%	1.4%
CAYMAN ISLANDS	3.7%	3.5%	4.4%	3.7%	3.1%	2.7%	2.2%	2.2%
AUSTRALIA	3.2%	2.4%	2.6%	2.4%	2.1%	2.2%	2.7%	2.3%
BERMUDA	3.0%	5.2%	4.9%	4.4%	5.2%	6.0%	5.2%	7.4%
NETHERLANDS	2.7%	2.8%	2.9%	3.7%	4.0%	5.3%	5.6%	7.0%
CHINA, P.R.	2.5%	1.9%	1.8%	1.7%	0.8%	0.5%	0.6%	0.1%
HONG KONG	2.3%	2.2%	2.3%	2.0%	1.3%	1.4%	1.7%	1.9%
KOREA, SOUTH	2.2%	1.6%	2.5%	2.6%	3.3%	2.6%	2.4%	1.8%
SPAIN	2.2%	2.3%	2.0%	2.0%	1.9%	2.5%	2.1%	2.0%
IRELAND	2.0%	0.8%	0.9%	1.1%	1.0%	1.3%	1.1%	1.8%
TAIWAN	1.9%	1.5%	1.5%	1.7%	1.7%	1.3%	1.3%	1.2%
MEXICO	1.6%	1.7%	1.6%	2.0%	1.7%	1.5%	1.4%	1.6%
INDIA	1.6%	1.1%	1.6%	1.1%	1.0%	0.9%	0.9%	0.4%
ITALY	1.5%	1.7%	1.8%	2.1%	1.9%	2.2%	1.9%	2.1%
NETHERLANDS ANTILLES	1.4%	1.4%	1.7%	1.3%	1.4%	1.1%	1.1%	0.9%
SOUTH AFRICA	1.2%	1.1%	0.9%	0.9%	1.0%	0.8%	0.7%	0.4%
SINGAPORE	1.1%	0.9%	1.1%	1.0%	0.9%	0.9%	1.1%	1.3%
RUSSIA	1.1%	0.7%	1.4%	0.9%	0.6%	0.4%	0.6%	0.3%
ISRAEL	1.1%	1.1%	0.7%	0.6%	0.9%	0.7%	0.8%	0.8%
SWEDEN	1.1%	1.1%	1.1%	1.4%	1.2%	1.5%	1.3%	1.5%
LUXEMBOURG	0.8%	0.6%	0.8%	0.4%	0.3%	0.3%	0.3%	0.1%
FINLAND	0.7%	1.3%	1.7%	1.3%	1.3%	1.3%	1.7%	3.2%
BELGIUM	0.7%	0.6%	0.6%	0.7%	0.6%	0.7%	0.5%	0.5%
DENMARK	0.7%	0.7%	0.6%	0.5%	0.5%	0.6%	0.5%	0.5%
NORWAY	0.6%	0.5%	0.9%	0.7%	0.7%	0.7%	0.6%	0.5%
TURKEY	0.5%	0.4%	0.4%	0.3%	0.3%	0.2%	0.2%	0.1%
JERSEY	0.5%	0.4%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
PANAMA	0.4%	0.4%	0.5%	0.5%	0.6%	0.8%	0.7%	0.5%
INDONESIA	0.4%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%
THAILAND	0.3%	0.2%	0.3%	0.3%	0.3%	0.2%	0.3%	0.1%
MALAYSIA	0.3%	0.2%	0.3%	0.2%	0.2%	0.3%	0.2%	0.2%
GUERNSEY	0.3%	0.2%	0.3%	0.3%	0.2%	0.2%	0.2%	0.3%
AUSTRIA	0.2%	0.2%	0.4%	0.4%	0.3%	0.4%	0.2%	0.1%
GREECE	0.2%	0.3%	0.5%	0.3%	0.3%	0.3%	0.2%	0.2%
CHILE	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
BRITISH VIRGIN ISLANDS	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%
MARSHALL ISLANDS	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.0%	0.0%
PHILIPPINES	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%
POLAND	0.1%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%
PORTUGAL	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%
CZECH REPUBLIC	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%
HUNGARY	0.1%	0.1%	0.1%	0.2%	0.1%	0.2%	0.1%	0.1%
TOTAL (USD bn)	3,995	2,748	5,253	4,329	3,318	2,560	2,079	1,613

Source: US Department of the Treasury

Figure B.1: Daily log returns of the 19 series.

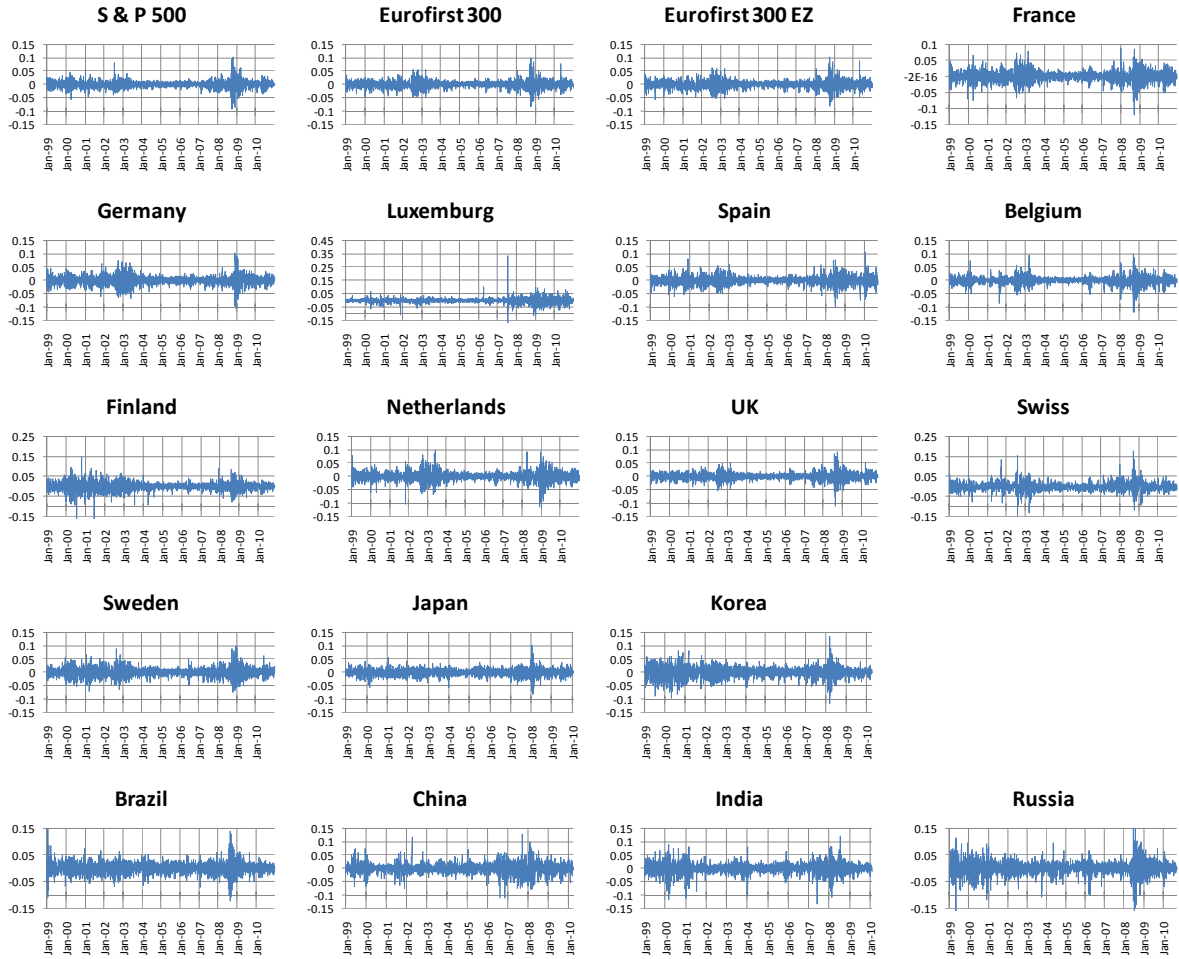
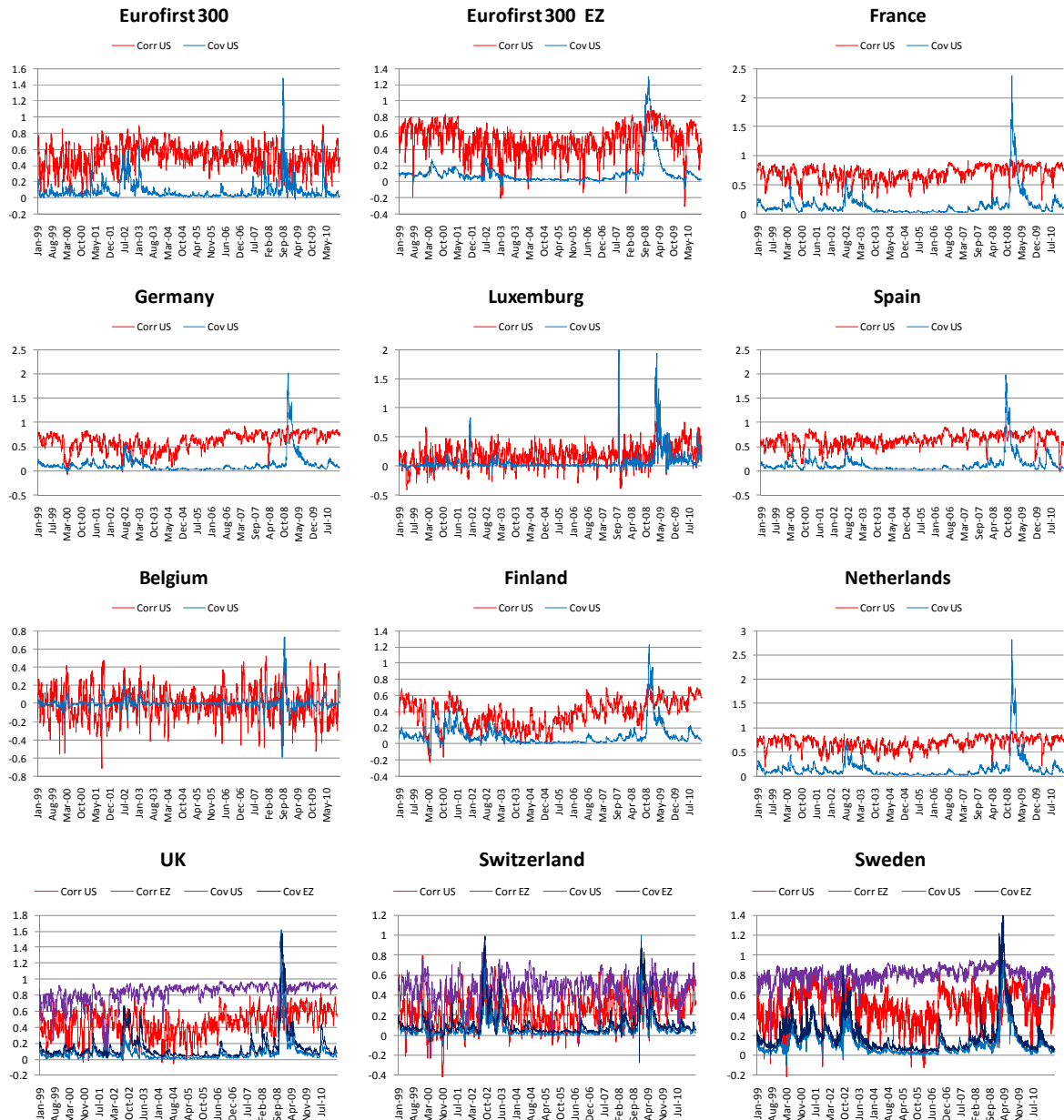
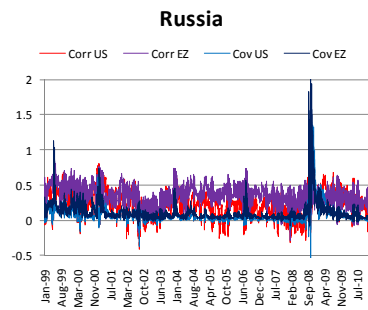
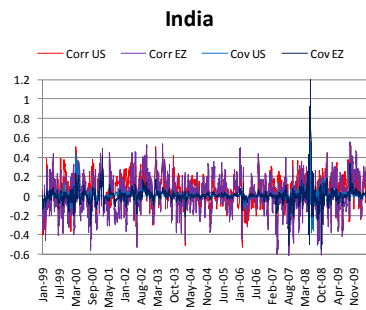
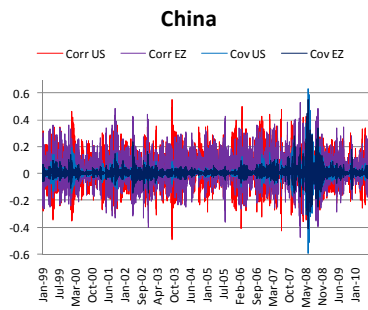
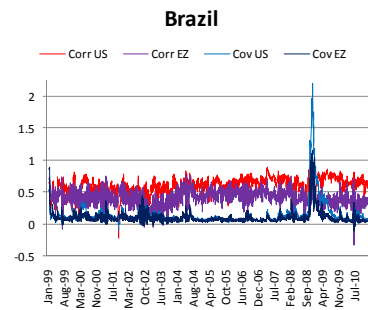
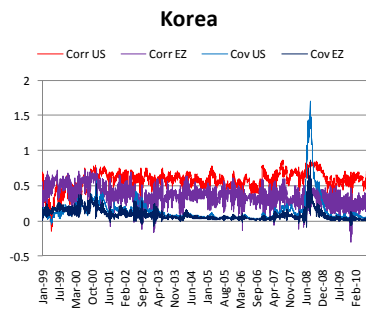
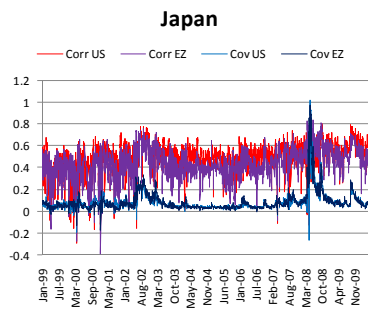


Figure B.2: Estimated conditional correlations and covariances: January 1999–December 2010.
(*Note:* For reporting purposes conditional covariances have been multiplied by 1000.)





Appendix C

Table C.1: Nonlinear functions of estimated coefficients for 4-variable Asymmetric BEKK-GARCH(1,1).

	$h_{1,t}$	$h_{12,t} = h_{21,t}$	$h_{13,t} = h_{31,t}$	$h_{14,t} = h_{41,t}$	$h_{2,t}$	$h_{23,t} = h_{32,t}$
<i>Constant</i>	c_{11}^2	$c_{11}c_{21}$	$c_{11}c_{31}$	$c_{11}c_{41}$	$c_{21}^2 + c_{22}^2$	$c_{21}c_{31} + c_{22}c_{32}$
ε_1^2	a_{11}^2	$a_{12}a_{11}$	$a_{13}a_{11}$	$a_{14}a_{11}$	a_{12}^2	$a_{13}a_{12}$
$\varepsilon_1\varepsilon_2$	$2a_{11}a_{21}$	$a_{12}a_{21} + a_{22}a_{11}$	$a_{13}a_{21} + a_{23}a_{11}$	$a_{24}a_{11} + a_{14}a_{21}$	$2a_{12}a_{22}$	$a_{23}a_{12} + a_{13}a_{22}$
$\varepsilon_1\varepsilon_3$	$2a_{11}a_{31}$	$a_{12}a_{31} + a_{32}a_{11}$	$a_{33}a_{11} + a_{13}a_{31}$	$a_{14}a_{31} + a_{34}a_{11}$	$2a_{12}a_{32}$	$a_{33}a_{12} + a_{13}a_{32}$
$\varepsilon_1\varepsilon_4$	$2a_{11}a_{41}$	$a_{42}a_{11} + a_{12}a_{41}$	$a_{43}a_{11} + a_{13}a_{41}$	$a_{44}a_{11} + a_{14}a_{41}$	$2a_{12}a_{42}$	$a_{43}a_{12} + a_{13}a_{42}$
ε_2^2	a_{21}^2	$a_{22}a_{21}$	$a_{23}a_{21}$	$a_{24}a_{21}$	a_{22}^2	$a_{23}a_{22}$
$\varepsilon_2\varepsilon_3$	$2a_{21}a_{31}$	$a_{22}a_{31} + a_{32}a_{21}$	$a_{23}a_{31} + a_{33}a_{21}$	$a_{24}a_{31} + a_{34}a_{21}$	$2a_{22}a_{32}$	$a_{33}a_{22} + a_{23}a_{32}$
$\varepsilon_2\varepsilon_4$	$2a_{21}a_{41}$	$a_{42}a_{21} + a_{22}a_{41}$	$a_{43}a_{21} + a_{23}a_{41}$	$a_{24}a_{41} + a_{44}a_{21}$	$2a_{22}a_{42}$	$a_{23}a_{42} + a_{43}a_{22}$
ε_3^2	a_{31}^2	$a_{32}a_{31}$	$a_{33}a_{31}$	$a_{34}a_{31}$	a_{32}^2	$a_{33}a_{32}$
$\varepsilon_3\varepsilon_4$	$2a_{31}a_{41}$	$a_{32}a_{41} + a_{42}a_{31}$	$a_{33}a_{41} + a_{43}a_{31}$	$a_{34}a_{41} + a_{44}a_{31}$	$2a_{32}a_{42}$	$a_{33}a_{42} + a_{43}a_{32}$
ε_4^2	a_{41}^2	$a_{42}a_{41}$	$a_{43}a_{41}$	$a_{44}a_{41}$	a_{42}^2	$a_{43}a_{42}$
h_1	b_{11}^2	$b_{12}b_{11}$	$b_{13}b_{11}$	$b_{14}b_{11}$	b_{12}^2	$b_{13}b_{12}$
h_{12}	$2b_{21}b_{11}$	$b_{12}b_{21} + b_{22}b_{11}$	$b_{21}b_{13} + b_{23}b_{11}$	$b_{24}b_{11} + b_{21}b_{14}$	$2b_{22}b_{12}$	$b_{22}b_{13} + b_{23}b_{12}$
h_{13}	$2b_{31}b_{11}$	$b_{12}b_{31} + b_{32}b_{11}$	$b_{31}b_{13} + b_{33}b_{11}$	$b_{31}b_{14} + b_{34}b_{11}$	$2b_{32}b_{12}$	$b_{32}b_{13} + b_{33}b_{12}$
h_{14}	$2b_{41}b_{11}$	$b_{42}b_{11} + b_{12}b_{41}$	$b_{41}b_{13} + b_{43}b_{11}$	$b_{44}b_{11} + b_{41}b_{14}$	$2b_{42}b_{12}$	$b_{42}b_{13} + b_{43}b_{12}$
h_2	b_{21}^2	$b_{22}b_{21}$	$b_{23}b_{21}$	$b_{24}b_{21}$	b_{22}^2	$b_{23}b_{22}$
h_{23}	$2b_{31}b_{21}$	$b_{32}b_{21} + b_{22}b_{31}$	$b_{33}b_{21} + b_{31}b_{23}$	$b_{34}b_{21} + b_{31}b_{24}$	$2b_{32}b_{22}$	$b_{33}b_{22} + b_{32}b_{23}$
h_{24}	$2b_{41}b_{21}$	$b_{42}b_{21} + b_{22}b_{41}$	$b_{41}b_{23} + b_{43}b_{21}$	$b_{41}b_{24} + b_{44}b_{21}$	$2b_{42}b_{22}$	$b_{42}b_{23} + b_{43}b_{22}$
h_3	b_{31}^2	$b_{32}b_{31}$	$b_{33}b_{31}$	$b_{34}b_{31}$	b_{32}^2	$b_{33}b_{32}$
h_{34}	$2b_{41}b_{31}$	$b_{42}b_{31} + b_{32}b_{41}$	$b_{41}b_{33} + b_{43}b_{31}$	$b_{41}b_{34} + b_{44}b_{31}$	$2b_{42}b_{32}$	$b_{42}b_{33} + b_{43}b_{32}$
h_4	b_{41}^2	$b_{42}b_{41}$	$b_{43}b_{41}$	$b_{44}b_{41}$	b_{42}^2	$b_{43}b_{42}$
ϵ_1^2	d_{11}^2	$d_{12}d_{11}$	$d_{13}d_{11}$	$d_{14}d_{11}$	d_{12}^2	$d_{13}d_{12}$
$\epsilon_1\epsilon_2$	$2d_{11}d_{21}$	$d_{12}d_{21} + d_{22}d_{11}$	$d_{13}d_{21} + d_{23}d_{11}$	$d_{24}d_{11} + d_{14}d_{21}$	$2d_{12}d_{22}$	$d_{23}d_{12} + d_{13}d_{22}$
$\epsilon_1\epsilon_3$	$2d_{11}d_{31}$	$d_{12}d_{31} + d_{32}d_{11}$	$d_{33}d_{11} + d_{13}d_{31}$	$d_{14}d_{31} + d_{34}d_{11}$	$2d_{12}d_{32}$	$d_{33}d_{12} + d_{13}d_{32}$
$\epsilon_1\epsilon_4$	$2d_{11}d_{41}$	$d_{12}d_{41} + d_{42}d_{11}$	$d_{43}d_{11} + d_{13}d_{41}$	$d_{44}d_{11} + d_{14}d_{41}$	$2d_{12}d_{42}$	$d_{43}d_{12} + d_{13}d_{42}$
ϵ_2^2	d_{21}^2	$d_{22}d_{21}$	$d_{23}d_{21}$	$d_{24}d_{21}$	d_{22}^2	$d_{23}d_{22}$
$\epsilon_2\epsilon_3$	$2d_{21}d_{31}$	$d_{22}d_{31} + d_{32}d_{21}$	$d_{23}d_{31} + d_{33}d_{21}$	$d_{24}d_{31} + d_{34}d_{21}$	$2d_{22}d_{32}$	$d_{33}d_{22} + d_{23}d_{32}$
$\epsilon_2\epsilon_4$	$2d_{21}d_{41}$	$d_{42}d_{21} + d_{22}d_{41}$	$d_{43}d_{21} + d_{23}d_{41}$	$d_{24}d_{41} + d_{44}d_{21}$	$2d_{22}d_{42}$	$d_{23}d_{42} + d_{43}d_{22}$
ϵ_3^2	d_{31}^2	$d_{32}d_{31}$	$d_{33}d_{31}$	$d_{34}d_{31}$	d_{32}^2	$d_{33}d_{32}$
$\epsilon_3\epsilon_4$	$2d_{31}d_{41}$	$d_{42}d_{31} + d_{32}d_{41}$	$d_{33}d_{41} + d_{43}d_{31}$	$d_{34}d_{41} + d_{44}d_{31}$	$2d_{32}d_{42}$	$d_{33}d_{42} + d_{43}d_{32}$
ϵ_4^2	d_{41}^2	$d_{42}d_{41}$	$d_{43}d_{41}$	$d_{44}d_{41}$	d_{42}^2	$d_{43}d_{42}$

$h_{24,t} = h_{42,t}$	$h_{3,t}$	$h_{34,t} = h_{43,t}$	$h_{4,t}$
$c_{22}c_{42} + c_{21}c_{41}$	$c_{31}^2 + c_{33}^2 + c_{32}^2$	$c_{32}c_{42} + c_{31}c_{41} + c_{33}c_{43}$	$c_{43}^2 + c_{44}^2 + c_{41}^2 + c_{42}^2$
$a_{14}a_{12}$	a_{13}^2	$a_{14}a_{13}$	a_{14}^2
$a_{24}a_{12} + a_{14}a_{22}$	$2a_{13}a_{23}$	$a_{14}a_{23} + a_{24}a_{13}$	$2a_{14}a_{24}$
$a_{34}a_{12} + a_{14}a_{32}$	$2a_{13}a_{33}$	$a_{34}a_{13} + a_{14}a_{33}$	$2a_{14}a_{34}$
$a_{44}a_{12} + a_{14}a_{42}$	$2a_{13}a_{43}$	$a_{14}a_{43} + a_{44}a_{13}$	$2a_{14}a_{44}$
$a_{24}a_{22}$	a_{23}^2	$a_{24}a_{23}$	a_{24}^2
$a_{34}a_{22} + a_{24}a_{32}$	$2a_{23}a_{33}$	$a_{24}a_{33} + a_{34}a_{23}$	$2a_{24}a_{34}$
$a_{24}a_{42} + a_{44}a_{22}$	$2a_{23}a_{43}$	$a_{24}a_{43} + a_{44}a_{23}$	$2a_{24}a_{44}$
$a_{34}a_{32}$	a_{33}^2	$a_{34}a_{33}$	a_{34}^2
$a_{44}a_{32} + a_{34}a_{42}$	$2a_{33}a_{43}$	$a_{44}a_{33} + a_{34}a_{43}$	$2a_{34}a_{44}$
$a_{44}a_{42}$	a_{43}^2	$a_{44}a_{43}$	a_{44}^2
$b_{14}b_{12}$	b_{13}^2	$b_{14}b_{13}$	b_{14}^2
$b_{24}b_{12} + b_{22}b_{14}$	$2b_{23}b_{13}$	$b_{23}b_{14} + b_{24}b_{13}$	$2b_{24}b_{14}$
$b_{34}b_{12} + b_{32}b_{14}$	$2b_{33}b_{13}$	$b_{33}b_{14} + b_{34}b_{13}$	$2b_{34}b_{14}$
$b_{44}b_{12} + b_{42}b_{14}$	$2b_{43}b_{13}$	$b_{44}b_{13} + b_{43}b_{14}$	$2b_{44}b_{14}$
$b_{24}b_{22}$	b_{23}^2	$b_{24}b_{23}$	b_{24}^2
$b_{32}b_{24} + b_{34}b_{22}$	$2b_{33}b_{23}$	$b_{34}b_{23} + b_{33}b_{24}$	$2b_{34}b_{24}$
$b_{44}b_{22} + b_{42}b_{24}$	$2b_{43}b_{23}$	$b_{44}b_{23} + b_{43}b_{24}$	$2b_{44}b_{24}$
$b_{34}b_{32}$	b_{33}^2	$b_{34}b_{33}$	b_{34}^2
$b_{44}b_{32} + b_{42}b_{34}$	$2b_{43}b_{33}$	$b_{43}b_{34} + b_{44}b_{33}$	$2b_{44}b_{34}$
$b_{44}b_{42}$	b_{43}^2	$b_{44}b_{43}$	b_{44}^2
$d_{14}d_{12}$	d_{13}^2	$d_{14}d_{13}$	d_{14}^2
$d_{24}d_{12} + d_{14}d_{22}$	$2d_{13}d_{23}$	$d_{14}d_{23} + d_{24}d_{13}$	$2d_{14}d_{24}$
$d_{34}d_{12} + d_{14}d_{32}$	$2d_{13}d_{33}$	$d_{34}d_{13} + d_{14}d_{33}$	$2d_{14}d_{34}$
$d_{44}d_{12} + d_{14}d_{42}$	$2d_{13}d_{43}$	$d_{14}d_{43} + d_{44}d_{13}$	$2d_{14}d_{44}$
$d_{24}d_{22}$	d_{23}^2	$d_{24}d_{23}$	d_{24}^2
$d_{34}d_{22} + d_{24}d_{32}$	$2d_{23}d_{33}$	$d_{24}d_{33} + d_{34}d_{23}$	$2d_{24}d_{34}$
$d_{24}d_{42} + d_{44}d_{22}$	$2d_{23}d_{43}$	$d_{24}d_{43} + d_{44}d_{23}$	$2d_{24}d_{44}$
$d_{34}d_{32}$	d_{33}^2	$d_{34}d_{33}$	d_{34}^2
$d_{44}d_{32} + d_{34}d_{42}$	$2d_{33}d_{43}$	$d_{44}d_{33} + d_{34}d_{43}$	$2d_{34}d_{44}$
$d_{44}d_{42}$	d_{43}^2	$d_{44}d_{43}$	d_{44}^2

Table C.2: Conditional covariances of “old members” with German stock market. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	Neth	SWIS	IT	AUT	FIN	SWD
	coeff	coeff	coeff	coeff	coeff	coeff
ε_1^2	0.279	-0.85	0.709	0.079	0.124	0.198
$\varepsilon_1\varepsilon_2$	1.888**	3.263	-3.529	0.161	-0.32	0.694
$\varepsilon_1\varepsilon_3$	-1.358**	-1.876	2.401	-0.799	-0.441	-0.393
$\varepsilon_1\varepsilon_4$	3.956***	0.652	-5.171	-0.907	-1.966***	1.563
ε_2^2	0.733	1.377	4.266	-0.079	0.206	0.204
$\varepsilon_2\varepsilon_4$	-1.076	-3.686	-5.922	-0.091	0.598	0.044
$\varepsilon_2\varepsilon_3$	2.197	-1.601	14.477	-1.279	2.675**	0.876
ε_3^2	0.394	1.909	2.026	1.21*	0.094	-0.137
$\varepsilon_3\varepsilon_4$	-1.627	1.002	-9.076	5.394***	0.581	0.138
ε_4^2	1.305	-0.119	4.14	2.427	0.67*	0.936
h_1	-15.881	-6.719	88.697*	-4.041	9.08*	27.354*
h_{12}	8.844	17.363	13.543	-10.73	-16.319	115.201***
h_{13}	12.929	-24.257*	-164.217**	-23.779**	-13.666**	17.228*
h_{14}	-51.316	-56.244	-221.151***	14.926	-66.099***	-52.396**
h_2	-1.116	-7.869*	0.438	6.041**	-2.475	-8.592
h_{23}	-3.154	12.732*	-11.827	22.799***	17.212**	0.37
h_{24}	21.943	20.363	-21.789	27.715***	124.806***	8.05
h_3	-2.2	3.965	74.415	21.158***	4.522**	0.231
h_{34}	35.717**	43.837	226.724*	60.229***	33.3***	-0.136
h_4	85.909***	86.585***	61.905	-12.599***	11.249*	-1.884
ε_1^2	2.462	2.905	1.536	0.233	-0.068	-3.961
$\varepsilon_1\varepsilon_2$	8.68**	4.157	2.817	-0.511	0.43	6.361
$\varepsilon_1\varepsilon_3$	-9.429	-3.484	-6.457	-0.325	0.144	6.214**
$\varepsilon_1\varepsilon_4$	-9.948*	8.282**	16.711**	6.632***	1.005	2.987
ε_2^2	2.988	1.284	1.156	-0.248	-0.317	5.429
$\varepsilon_2\varepsilon_3$	-10.411*	-2.229	-4.77	0.088	1.282	0.858
$\varepsilon_2\varepsilon_4$	-8.833*	7.621**	10.598	2.721	-0.926	-0.681
ε_3^2	6.959**	0.959	4.352	0.08	2.023	-1.367
$\varepsilon_3\varepsilon_4$	13.252***	-6.066*	-15.137	-2.095	4.347**	-1.714
ε_4^2	5.987**	2.371	4.414	-0.052	-0.213	-0.471

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported.

*, ** and *** denote significance at 10, 5 and 1% respectively.

Table C.3: Conditional covariances of “old members” with UK stock market. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	Neth	SWIS	IT	AUT	FIN	SWD
	coeff	coeff	coeff	coeff	coeff	coeff
ε_1^2	-0.003	0.205	-0.02	-0.193	-0.012	-0.012
$\varepsilon_1\varepsilon_2$	0.308	-0.976	-1.286	-0.355	0.047	0.618
$\varepsilon_1\varepsilon_3$	0.07	0.586	1.241	0.479	-0.09	0.009
$\varepsilon_1\varepsilon_4$	-0.03	-0.135	-0.436	1.142	0.184	-0.135
ε_2^2	2.092**	0.467	2.747	0.177	-0.04	2.083
$\varepsilon_2\varepsilon_4$	-1.154	-0.238	-4.768	0.753*	0.049	-1.552
$\varepsilon_2\varepsilon_4$	4.667***	0.347	9.619	3.283	-0.506	4.579*
ε_3^2	-0.248	-0.063	2.046	-0.226	0.431	0.039
$\varepsilon_3\varepsilon_4$	0.676	-0.215	-9.016	-0.394	1.996***	-0.006
ε_4^2	0.236	0.022	3.582	1.97	-0.037	-0.371
h_1	3.81	-0.039	50.323*	-29.251***	-5.901*	-5.228
h_{12}	17.033	7.811	-37.187	-2.656	-7.981**	-11.08
h_{13}	-2.181	-1.152	-75.039	42.848***	5.664	2.634
h_{14}	14.606	0.059	-119.614*	65.908***	42.579***	22.942**
h_2	-3.436	-15.449	-1.836	7.93**	-1.006	48.505**
h_{23}	-4.06	31.131	29.655	3.555	7.206	32.061*
h_{24}	79.483***	74.118**	85.368	41.573***	50.907***	32.522
h_3	0.305	-3.781	27.867	-15.61***	0.323	3.607
h_{34}	-5.031**	-8.081	84.618	-44.386***	1.602	-3.57
h_4	-10.396**	4.262	22.401	9.449***	-4.618***	-24.861***
ε_1^2	0.381	0.704	0.166	0.011	-0.04	0.322
$\varepsilon_1\varepsilon_2$	0.744	3.095	1.542	0.123	-0.114	-1.514
$\varepsilon_1\varepsilon_3$	-1.89	-0.715	-0.778	0.075	0.285	-2.67
$\varepsilon_1\varepsilon_4$	-1.627	2.369	2.079	0.312	0.562	-0.665
ε_2^2	-1.416	1.252	1.629	-0.395	1.788*	1.776
$\varepsilon_2\varepsilon_3$	-1.27	-1.375	-4.777	-0.39	2.041**	6.044
$\varepsilon_2\varepsilon_4$	0.332	7.287***	14.62	4.327*	4.831***	1.523
ε_3^2	2.297	0.177	0.747	-0.094	-0.156	2.935
$\varepsilon_3\varepsilon_4$	3.726	-1.298	-3.448	2.469	-0.264	1.837
ε_4^2	1.219	1.491	3.435	-0.001	0.173	0.262

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported.

*, ** and *** denote significance at 10, 5 and 1% respectively.

Table C.4: Conditional covariances of “old members” with French stock market. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	Neth	SWIS	IT	AUT	FIN	SWD
	coeff	coeff	coeff	coeff	coeff	coeff
ε_1^2	0.011	0.233	-0.251	-0.438*	-0.119	-0.128
$\varepsilon_1\varepsilon_2$	0.168	-1.304	-1.094	0.039	0.101	-0.317
$\varepsilon_1\varepsilon_3$	0.159	0.355	1.508	1.084**	0.53	0.743
$\varepsilon_1\varepsilon_4$	0.261	0.276	0.788	2.798	1.791***	-0.835
ε_2^2	0.639	1.36	3.34	0.057	0.054	0.289
$\varepsilon_2\varepsilon_4$	0.855*	0.457	-6.552	0.148	-0.012	1.223
$\varepsilon_2\varepsilon_4$	2.12**	-1.362	11.96	1.193	0.767	0.952
ε_3^2	-0.942***	-0.991*	3.074	-0.506	-0.438	-1.029*
$\varepsilon_3\varepsilon_4$	2.339**	1.121	-13.489	-1.242	-1.824***	3.047**
ε_4^2	1.586	-0.102	5.166	2.985*	0.99***	0.67
h_1	-1.069	0.353	64.179	-4.247	-2.735	18.273
h_{12}	0.462	5.115	8.01	-47.609***	-20.118**	104.232***
h_{13}	19.124	-5.108	-139.156***	13.85***	13.392**	-12.757
h_{14}	-4.729	11.552	-152.895*	12.809	16.666	-26.368
h_2	-0.049	-11.629**	0.234	23.688***	-2.775	111.138***
h_{23}	-3.709	34.783**	-8.085	33.949***	21.5*	-86.918***
h_{24}	1.132	40.209	-11.548	117.281***	139.828***	-10.847
h_3	-4.569	-24.245*	69.942	-8.255***	-10.766**	-14.796**
h_{34}	83.897***	-31.809	202.576***	-27.206***	-72.651***	52.563***
h_4	0.108	78.846***	29.322	-6.363***	19.659***	-18.098***
ε_1^2	0.82	1.818	0.443	0.044	0.102	-0.883
$\varepsilon_1\varepsilon_2$	3.556	2.958	1.498	-0.085	-0.606	0.534
$\varepsilon_1\varepsilon_3$	-4.094	-2.064	-1.436	0.108	-1.007	-0.841
$\varepsilon_1\varepsilon_4$	-3.521	6.222	4.97	1.27	-1.49*	0.578
ε_2^2	3.089	0.964	1.166	-0.077	0.29	3.176
$\varepsilon_2\varepsilon_3$	-8.355*	-1.495	-3.162	-0.438	2.178**	6.294
$\varepsilon_2\varepsilon_4$	-5.805	6.139	10.512	0.808	0.857	0.512
ε_3^2	5.023**	0.55	-0.178	-0.169	2.217**	2.6
$\varepsilon_3\varepsilon_4$	8.165**	-3.947	-0.35	4.431***	4.973***	0.912
ε_4^2	2.687	4.113	2.874	0.387	0.226	-0.059

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported.

*, ** and *** denote significance at 10, 5 and 1% respectively.

Table C.5: Conditional covariances of “new members” with Hungarian stock market. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	SLN	EST	LIT	LAT	ROM	BUL	TUR	CRO
	coeff	coeff	coeff		coeff	coeff	coeff	coeff
ϵ_1^2	1.265*	-0.227	1.253	0.072	1.356	0.613	4.02**	0.952
$\epsilon_1\epsilon_2$	-0.948	0.132	-1.272	-0.094	0.576	-2.127**	2.941*	-1.685*
$\epsilon_1\epsilon_3$	-0.84	0.661	0.137	-0.422	-0.55	0.37	-0.356	1.311
$\epsilon_1\epsilon_4$	9.102***	5.506**	6.285	-0.682	8.991**	-5.846***	5.188***	-2.045
ϵ_2^2	-0.398	0.027	-0.73	-0.523	-0.115	1.179	0.534	0.708
$\epsilon_2\epsilon_4$	-0.248	0.214	0.118	0.117	0.352	-0.364	-0.137	-1.114
$\epsilon_2\epsilon_3$	2.61	0.826	1.861	3.068	-1.396	4.24**	2.049**	1.31
ϵ_3^2	0.002	0.41	-0.005	0.609	-0.256	0.027	0.005	0.437
$\epsilon_3\epsilon_4$	-0.082	2.615	-0.106	2.386	2.57	-0.534	-0.093	-1.095
ϵ_4^2	0.637	-1.656	1.822	-1.478	-0.586	0.863	0.223	-0.584
h_1	-0.427	1.597	4.068	-2.858	1.623	0.175	51.455***	2.518
h_{12}	1.544	1.771	15.527	2.099	-0.784	0.61	81.041***	-2.583
h_{13}	-0.039	-8.298	6.827	0.024	0.504	-1.203	23.811***	0.158
h_{14}	82.752***	81.901***	-78.118***	80.737***	77.283***	89.743***	-76.266***	90.66***
h_2	-0.017	-0.133	0.057	0.096	0.011	-0.027	-4.289	0.084
h_{23}	-0.004	0.926	-0.202	0.033	0.006	0.07	-2.433*	-0.019
h_{24}	-0.907	-5.701	-0.6	3.507	-1.175	-3.945	11.943**	-3.044
h_3	0	-1.462	-0.101	0.001	-0.01	-0.034	-0.345	0.001
h_{34}	-0.227	13.623	1.005	1.1	-1.439	2.538	3.422*	0.503
h_4	-0.977	3.226*	1.576	0.686	2.916	-0.746*	-7.544**	0.445
ϵ_1^2	-0.307	-0.597	-0.305	1.279	-3.409	-0.584	0.084	-2.629
$\epsilon_1\epsilon_2$	0.244	2.11	-3.459	-2.996	3.627	-0.523	1.477	-0.069
$\epsilon_1\epsilon_3$	2.399**	5.315*	0.717	2.775	4.716	0.935	-0.262	3.289
$\epsilon_1\epsilon_4$	-7.089**	-5.49	-2.939	6.411**	-7.02	2.246*	-0.301	3.563
ϵ_2^2	0.015	0.438	4.646	-0.466	0.647	-0.106	-1.834	0.772
$\epsilon_2\epsilon_3$	0.136	0.711	3.051	1.209	0.847	0.544	0.069	1.619
$\epsilon_2\epsilon_4$	-0.391	-1.324	1.281	0.216	-0.156	1.348	1.886*	2.884**
ϵ_3^2	0.015	-0.746	-0.403	-0.734	0.115	-0.037	0.035	-0.226
$\epsilon_3\epsilon_4$	0.002	0.249	2.823	-0.802	0.806	0.046	-0.176	0.664
ϵ_4^2	-0.131	0.577	-1.509	1.316*	-1.266	0.36	-0.347	1.397

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported. *, ** and *** denote significance at 10, 5 and 1% respectively.

Table C.6: Conditional covariances of “new members” with Czech stock market. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	SLN	LIT	EST	LAT	ROM	BUL	TUR	CRO
	coeff	coeff	coeff		coeff	coeff	coeff	coeff
ϵ_1^2	-0.096	-0.073	0.154	-0.513	0.242	0.521	0.066	0.494
$\epsilon_1\epsilon_2$	1.285**	-0.247	-0.789	-0.767	1.452	-1.985**	3.871***	-0.347
$\epsilon_1\epsilon_3$	0.102	0.231	1.058	1.321	-0.213	0.473	0.185	0.719
$\epsilon_1\epsilon_4$	-0.585	1.772*	1.345	5.832**	1.954	-4.939**	-0.134	-1.116
ϵ_2^2	-1.243**	0.224	0.812	0.681	0.753	1.492**	1.288	-0.203
$\epsilon_2\epsilon_4$	-0.824	1.051	-1.553	-0.777	-0.924	-0.839	-0.216	-0.192
$\epsilon_2\epsilon_3$	8.336***	7.204***	-3.571	-3.588	8.991***	5.162**	4.724***	-0.526
ϵ_3^2	-0.026	0.07	0.141	-0.046	0.033	0.105	-0.014	0.258
$\epsilon_3\epsilon_4$	0.209	0.416	4.963***	-0.264	-0.553	-1.917	0.252	-0.707
ϵ_4^2	0.715	-0.494	2.931	-0.257	2.244**	0.412	-0.27*	-0.168
h_1	-0.005	-0.028	-0.048	0.174	0.011	-0.005	-1.381	-0.058
h_{12}	-0.403	1.648	3.774	-3.167	1.646	0.151	49.506***	2.54
h_{13}	-0.001	0.204	0.038	0.022	-0.01	0.044	-1.262*	-0.027
h_{14}	0.982	-1.414	0.843	-4.896***	0.463	-2.725	6.571***	-2.018
h_2	1.517	1.984	15.084	2.357	-0.773	0.599	84.163***	-2.465
h_{23}	-0.039	-8.96	7.151	0.046	0.55	-1.148	23.694***	0.165
h_{24}	81.552***	86.187***	-76.162***	85.64***	78.549***	87.083***	-74.377***	89.331***
h_3	0	-0.288	0.202	-0.001	-0.004	-0.048	-0.288	-0.001
h_{34}	0.028	2.631	-2.41	-0.739	-0.643	3.571	3.046**	-0.852
h_4	0.238	1.141	1.409	-0.377	-1.927	-0.516	-6.923***	2.321
ϵ_1^2	0.043	0.109	-0.404	0.325	0.938	0.176	-0.011	0.135
$\epsilon_1\epsilon_2$	-0.463	-0.964	-4.299	0.628	-4.013	-0.843	0.009	-4.542*
$\epsilon_1\epsilon_3$	-0.305	-0.998	0.627	0.89	-2.565	-0.523	0.05	-0.779
$\epsilon_1\epsilon_4$	0.978	0.966	-3.714	1.773	1.71	-0.866	0.052	0.167
ϵ_2^2	0.363	2.072	9.728	-3.576	3.498	-0.275	4.006	2.364
$\epsilon_2\epsilon_3$	3.312**	5.009***	-0.402	3.191	5.555*	1.323	-0.302	5.594**
$\epsilon_2\epsilon_4$	-9.838***	-4.969**	6.541	6.362**	-5.292	3.537*	-0.907	7.269**
ϵ_3^2	-0.227	0.343	-0.078	0.26	1.752	0.389	-0.053	0.731
$\epsilon_3\epsilon_4$	0.729	0.091	0.56	1.034	-2.266	1.252*	-0.089	0.574
ϵ_4^2	-0.171	-0.483	-0.364	1.027	-0.063	0.655	-0.013	-0.657

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported. *, ** and *** denote significance at 10, 5 and 1% respectively.

Table C.7: Conditional covariances of “new members” with Polish stock market. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	SLN	LIT	EST	LAT	ROM	BUL	TUR	CRO
	coeff	coeff	coeff		coeff	coeff	coeff	coeff
ϵ_1^2	0.317	-0.197	0.966	-0.074	0.473	0.39	0.136	1.215
$\epsilon_1\epsilon_2$	-0.484	0.044	-1.475	-0.366	0.109	-1.188*	0.733	-1.394
$\epsilon_1\epsilon_3$	0.856**	0.791	-0.661	0.501	0.725	-0.194	2.34***	0.07
$\epsilon_1\epsilon_4$	2.254**	4.709***	4.833**	0.838	3.191*	-3.727***	0.337	-3.018**
ϵ_2^2	0.159	0.076	0.143	-0.444	-0.093	0.289	0.23	0.086
$\epsilon_2\epsilon_4$	-1.018*	0.268	1.115	1.196	0.711	1.048**	0.737	0.928*
$\epsilon_2\epsilon_3$	-1.071	2.464*	-0.881	2.368*	-1.075	1.158	0.913**	0.296
ϵ_3^2	-0.705	-0.389	-0.108	-0.796	-0.715	-0.206	-0.17	-0.745
$\epsilon_3\epsilon_4$	7.597***	-2.657	-3.691	-3.55*	7.001**	3.689***	2.916***	2.124*
ϵ_4^2	-0.039	0.383	1.353	-0.001	0.143	0.611	0.209	0.235
h_1	0.005	1.157	-0.019	0.155	-0.023	-0.003	-0.636	-0.025
h_{12}	-0.014	2.343	-0.204	-0.214	-0.02	-0.012	-2.094	-0.022
h_{13}	-0.442	-7.919	4.185	-3.042	1.713	0.204	56.036***	2.588
h_{14}	-0.921	59.421***	0.385	-4.357***	-1.098	-1.53	1.535	-0.909
h_2	-0.013	1.155	-0.501	0.072	0.014	-0.005	-1.723	0.047
h_{23}	1.593	-7.274	15.859	2.365	-0.816	0.656	91.117***	-2.574
h_{24}	-0.699	50.347*	2.591	2.605**	-1.472	-0.725	2.536	-1.71
h_3	-0.041	9.191	7.14	0.066	0.567	-1.265	26.863***	0.148
h_{34}	85.627***	-88.598***	-80.872***	85.855***	81.843***	93.992***	-88.496***	93.253***
h_4	-0.039	8.051	-0.346	-0.904	0.555	-0.601	-0.84	0.175
ϵ_1^2	0.01	-0.065	-0.147	0.146	0.281	0.009	0.109	0.355
$\epsilon_1\epsilon_2$	-0.109	0.086	-1.578	-0.302	-1.328	-0.197	2.132	-1.485
$\epsilon_1\epsilon_3$	-0.239	0.384	0.47	1.367	-1.779	-0.396	-0.482	-2.773
$\epsilon_1\epsilon_4$	0.246	-0.677	-1.385	0.843	0.043	-0.051	-0.458	-0.464
ϵ_2^2	0.085	0.589	3.368	-0.149	1.202	-0.061	1.64	0.686
$\epsilon_2\epsilon_3$	0.92	2.089	2.909	-2.385	3.074	0.194	-3.224*	2.775**
$\epsilon_2\epsilon_4$	-2.325*	-1.213	1.839	-0.074	-1.248	0.793	0.229	2.102*
ϵ_3^2	1.245**	1.657	-0.371	2.448	1.947	0.595	0.471	2.775*
$\epsilon_3\epsilon_4$	-3.765**	-1.16	2.449	5.228**	-1.897	1.548	0.612	3.787
ϵ_4^2	0.271	-0.636	-0.434	0.698	-0.892	0.057	-0.149	-0.217

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported.
*, ** and *** denote significance at 10, 5 and 1% respectively.

Table C.8: Conditional covariances of “new members” with UK stock market. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	HUN	CZ	POL	SLK	SLN	EST	LIT	LAT	ROM	BUL	TUR	CRO
	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff
ε_1^2	-0.238	0.085	0.08	0.078	0.301	0.099	0.056	0.05	-1.016	0.844	0.748	0.19
$\varepsilon_1\varepsilon_2$	0.05	0.033	0.052	0.087	-0.5	-2.027	-0.569	-0.601	-0.878	2.322	2.012	-0.726
$\varepsilon_1\varepsilon_3$	0.813	0.079	0.063	0.088	0.24	1.453	0.278	0.423	2.01	-3.358	-1.409	0.54
$\varepsilon_1\varepsilon_4$	-0.906	2.217*	-0.51	-2.373**	2.324	-3.704*	-0.78	-0.694	4.829***	-1.818	1.27	-0.872
ε_2^2	0.274	-0.002	-0.499	-0.188	0.1	1.685	-0.657	1.791	0.107	1.572	-2.559*	-0.125
$\varepsilon_2\varepsilon_4$	0.037	0.032	0.747	0.06	0.094	-0.445	1.305	-2.505	0.732	-4.456	-1.118	0.383
$\varepsilon_2\varepsilon_3$	1.755	0.941	0.988	2.592	-3.42	2.955	6.873	4.293	4.75*	-2.144	4.224***	3.078
ε_3^2	-0.681	0.004	-0.247	0.025	-0.152	-0.659	-0.533	0.849	-0.978	3.073	0.625	-0.228
$\varepsilon_3\varepsilon_4$	1.913	0.16	-1.027	-1.441	2.949*	1.847	-3.812	-3.501	-5.389*	2.453	-1.446**	-2.462
ε_4^2	1.634**	1.144*	0.158*	-0.05	-0.634	-0.522	1.727*	0.19	0.244	-0.279	0.135	0.39
h_1	-0.573	-0.044	0.106	-0.658	-3.609	0.085	-6.56	-1.47	0.678	5.528	0.959	0.867
h_{12}	-5.395	1.988**	4.385	-6.268	-3.831	-1.267	14.052	6.112	1.906	-7.08	-5.796	-6.044
h_{13}	2.048	0.007	-0.45	1.79	0.296	-0.101	12.88	0.179	-4.735	-12.056	-4.96	-3.253
h_{14}	9.897	-2.032**	2.341	10.591	27.386*	-6.03	-32.485	-36.941	-43.37*	-51.469	-9.446	-10.052
h_2	-1.25	-1.029	1.082	-2.532	4.709	3.235	2.025	-6.265	-4.309	-3.15	-17.848	-8.37
h_{23}	9.652	-0.541	-5.703	7.176	2.412	-1.355	-13.858	0.206	1.757	8.573	19.593	13.21
h_{24}	90.736***	90.797***	96.732*	96.577***	49.489*	70.26***	73.752***	85.685*	64.241***	83.861***	79.078***	82.395
h_3	-1.83	0.001	0.405	-1.182	0.216	-0.717	-6.322	0.967	5.136	6.539	6.212	3.004
h_{34}	-17.664	-0.236	-6.938	-16.945	5.762	21.475	31.76	32.249	58.235***	52.114	20.044	16.506
h_4	-0.189	-0.284	-0.311	0.15	1.407	0.242	-0.48	-0.634	-0.095	0.216	-0.747*	-0.537
ε_1^2	-0.182	-1.225	-1.258	-0.309	-0.069	-0.255	0.6	0.008	-0.307	-0.271	0.828	-0.145
$\varepsilon_1\varepsilon_2$	0.501	-2.553	-4.168	-1.211	-0.636	-3.166	1.953	-0.586	-1.191	-5.276	-7.838	-11.849
$\varepsilon_1\varepsilon_3$	-0.672	0.994	1.965	0.629	0.196	0.62	0.985	0.017	2.33	-1.569	-2.527	-0.105
$\varepsilon_1\varepsilon_4$	1.02	1.17	1.787	-0.664	1.075	0.377	1.177	-0.178	-2.547	-0.563	-0.517	0.161
ε_2^2	5.603**	4.082**	3.188	4.353	-0.347	1.225	-8.652	5.001	9.499	5.826	5.764	2.001
$\varepsilon_2\varepsilon_3$	-1.55	-0.06	3.836	-0.496	0.899	3.326	4.495	-2.956	-10.037	2.918	8.71**	12.139
$\varepsilon_2\varepsilon_4$	4.69	5.427**	6.952*	-5.989**	9.138**	6.809	5.711	8.781**	11.057*	4.149***	2.049	8.478*
ε_3^2	-0.363	-0.146	-0.755	-0.185	-0.139	-0.371	0.201	-0.223	0.55	0.355	1.722	0.258
$\varepsilon_3\varepsilon_4$	0.616	-0.901	-1.22	1.407	-1.52	-0.562	0.432	0.248	-1.259	1.15	0.739	0.123
ε_4^2	0.132	0.538	-0.034	0.636	-0.169	0.315	0.227	0.794*	0.72	0.443*	0.078	-0.041

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported.

*, ** and *** denote significance at 10, 5 and 1% respectively.

Table C.9: Conditional covariances of “new members” with French stock market. The indices 1, 2 and 3 represent Germany, UK and France stock markets respectively. The index i represents the own conditional variance/covariance in period $t - 1$.

	HUN	CZ	POL	SLK	SLN	EST	LIT	LAT	ROM	BUL	TUR	CRO
	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff	coeff
ϵ_1^2	0.908	0.164	0.156	0.084	0.436	0.16	0.015	0.035	-0.785	0.95	0.097	0.12
$\epsilon_1\epsilon_2$	1.875**	0.006	-0.147	0.007	0.175	-3.364	0.015	-0.88	0.955	3.079	0.315	-1.954
$\epsilon_1\epsilon_3$	-2.438*	0.125	0.367	0.203	-0.474	2.438**	-0.12	0.729	0.031	-3.98	2.144	1.809
$\epsilon_1\epsilon_4$	5.05*	4.228**	-0.985	-2.559**	3.392	-6.017**	-0.348	-0.473	3.691	-2.307	0.178	-0.689
ϵ_2^2	0.965	-0.001	-1.682	-0.393	-0.064	4.408	0	3.891	-0.094	2.489	-0.383	-0.325
$\epsilon_2\epsilon_4$	-2.531**	0.013	2.502	0.256	-0.047	-3.74	-0.103	-5.764	-0.682	-6.509	-2.375*	1.041
$\epsilon_2\epsilon_4$	5.468*	0.343	3.46	5.429**	2.227	8.5	-0.19	9.125	-4.17	-3.882	0.621	8.036***
ϵ_3^2	1.622**	-0.016	-0.826	0.083	0.122	0.263	0.145	2.032	0.559	3.964	-1.582	-0.692
$\epsilon_3\epsilon_4$	-6.228***	-0.429	-3.494	-4.818***	-2.301	-0.696	1.372	-8.251	3.173	3.877	3.489**	-7.503**
ϵ_4^2	1.961**	1.278*	0.25	-0.091	-0.747	0.108	2.058	-0.052	0.368	0.282	0.038	0.806
h_1	-5.376	-0.075*	4.262	-5.996	-3.884	0.071	-3.725	-1.483	1.584	3.274	-7.424	-7.109
h_{12}	-4.7	0.034	4.901	-4.915	-16.403	-2.562	-1.507	9.824	4.729	1.986	-26.675	-15.002
h_{13}	13.658	2.002**	-9.333	9.556	11.79	1.124	23.499	-3.312	-9.6	-17.229	30.188	20.405
h_{14}	92.617***	-3.443***	94.634	96.633***	29.427*	-5.102	-18.641	-37.226	-101.383***	-30.424	73.487*	82.847**
h_2	-0.813	0.003	0.954	-1.006	14.018	7.619	-0.136	-13.043	-8.887	0.294	-22.467	-7.797
h_{23}	7.082	-1.036	-5.911	3.865	-2.216	-8.648	3.675	9.377	8.84	-5.668	47.518	20.3
h_{24}	59.007**	-0.226	85.307	38.355*	147.093***	165.629***	-4.981	178.298***	132.399***	-7.817	98.872	76.765
h_3	-7.226	-0.548	4.946	-3.166	-3.083	2.266	-19.543*	-1.653	3.735	15.66	-23.141	-11.432
h_{34}	-69.433***	91.53***	-85.108	-45.37**	-81.417***	-68.022***	98.137*	-55.146	42.457**	124.692**	-74.902***	-63.299
h_4	2.426	-0.089	1.061	0.783	1.823	3.978	-1.242	-0.178	1.13	-0.373	2.026	-0.637
ϵ_1^2	-0.45	-2.004*	-3.186**	-0.886	-0.13	0.043	0.966	-0.121	0.223	-0.968	-2.671	-3.083
$\epsilon_1\epsilon_2$	3.238	1.075	-0.16	0.774	-0.502	-2.122	0.12	0.804	3.282	-1.228	-2.099	-4.528
$\epsilon_1\epsilon_3$	-1.961*	-1.172	2.507	0.784	0.143	-1.294	2.237	-0.796	-2.507	-4.298	1.24	-0.071
$\epsilon_1\epsilon_4$	2.528	2.307	4.609	-2.26	1.944	-0.408	1.738	1.912	1.969	-0.299	0.512	1.241
ϵ_2^2	-0.319	1.112	1.411	2.821	-0.248	0.791	-6.361	3.822	12.048	2.349	3.412	0.851
$\epsilon_2\epsilon_3$	4.348**	1.855*	2.134	-0.619	0.578	2.701	1.363	-2.423	-18.028	5.214	5.564	5.684
$\epsilon_2\epsilon_4$	0.105	1.663	2.991	-4.186**	6.498	4.479	4.312	7.014*	13.663*	2.297	1.193	3.771
ϵ_3^2	-1.803	0.301	0.266	-0.167	0.058	1.323	1.237	-0.063	5.988	0.983	1.541	3.272
$\epsilon_3\epsilon_4$	3.247*	2.074	0.294	1.238	0.706	2.921	1.608	-0.282	-7.036	2.94	0.539	3.276
ϵ_4^2	0.293	0.372	-0.204	0.796	0.791	0.659	0.087	1.109*	0.518	0.541*	0.04	0.688

Note: For reporting purposes coefficients are multiplied by 100. Estimated coefficient of the constant term is not reported.

*, ** and *** denote significance at 10, 5 and 1% respectively.

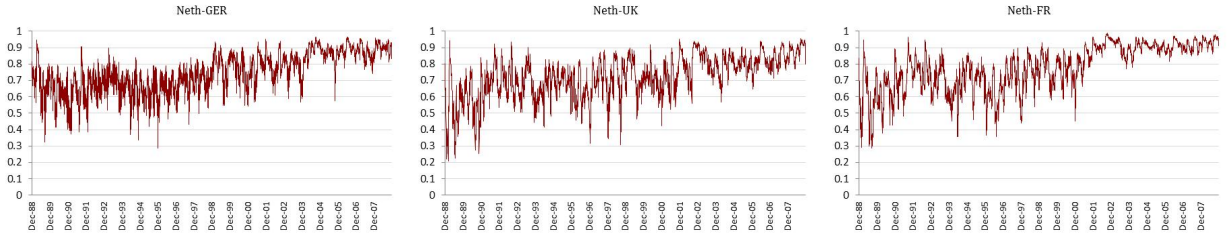


Figure C.1: Conditional correlations for the Netherlands.

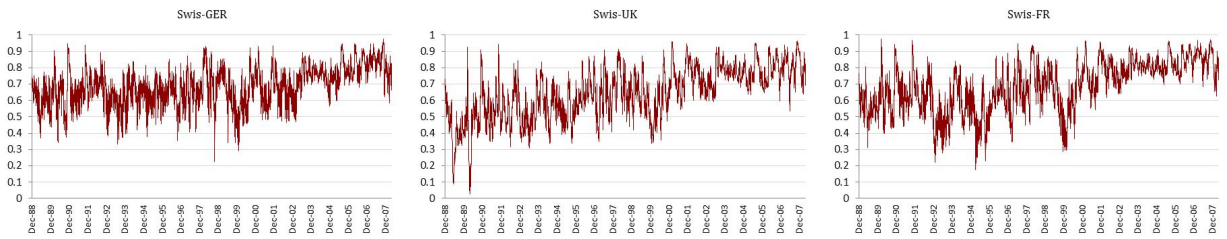


Figure C.2: Conditional correlations for Switzerland.

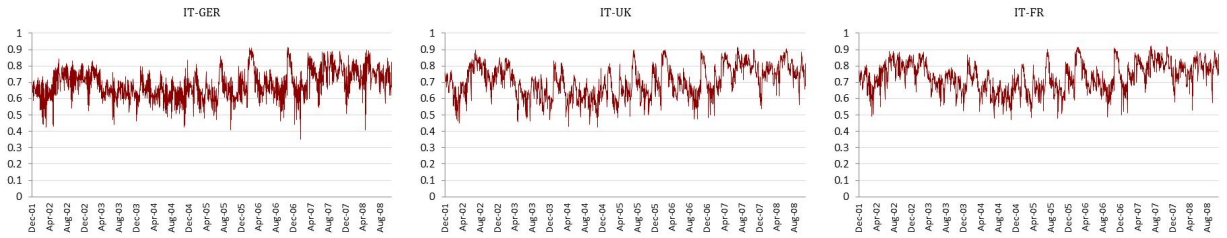


Figure C.3: Conditional correlations for Italy.

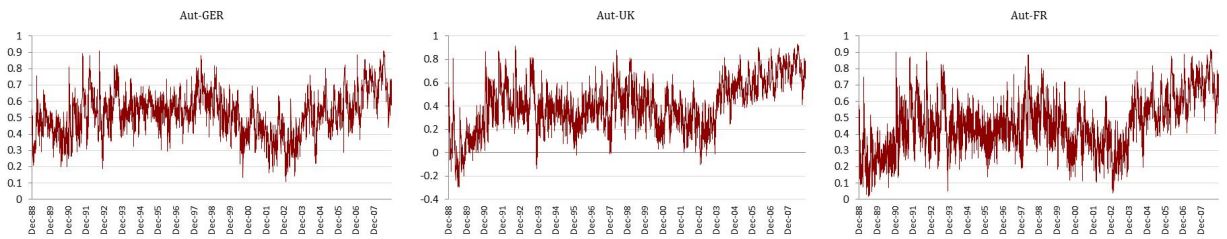


Figure C.4: Conditional correlations for Austria.

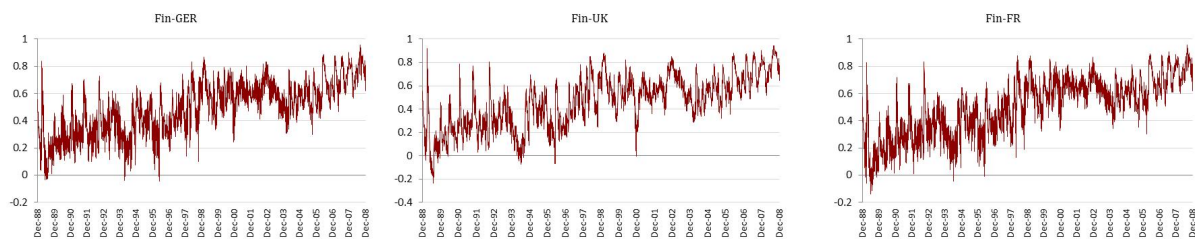


Figure C.5: Conditional correlations for Finland.

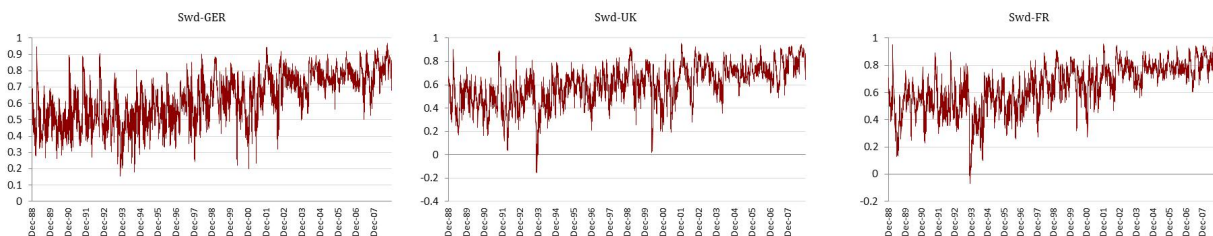


Figure C.6: Conditional correlations for Sweden.

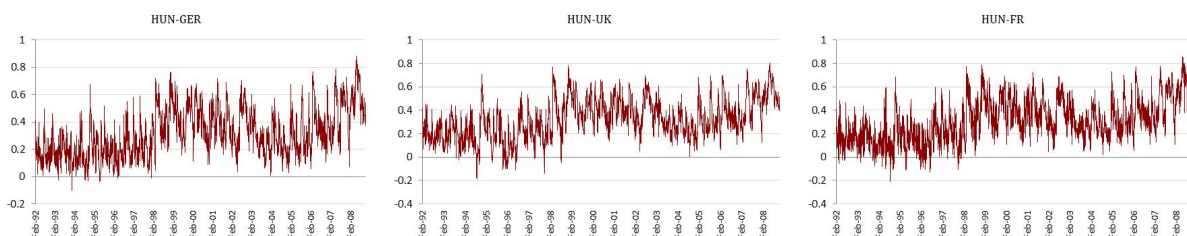


Figure C.7: Conditional correlations for Hungary.

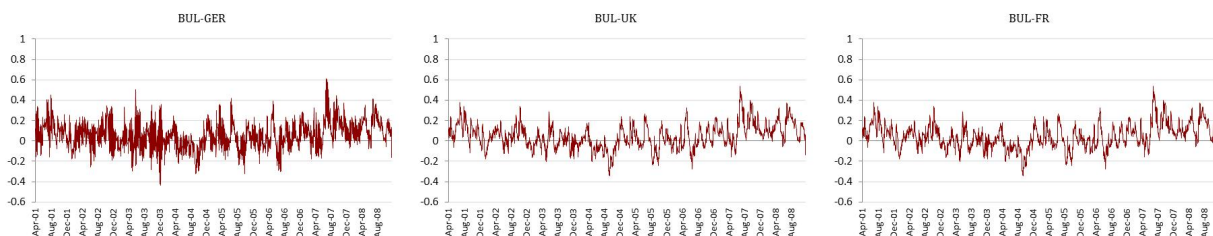


Figure C.8: Conditional correlations for Bulgaria.

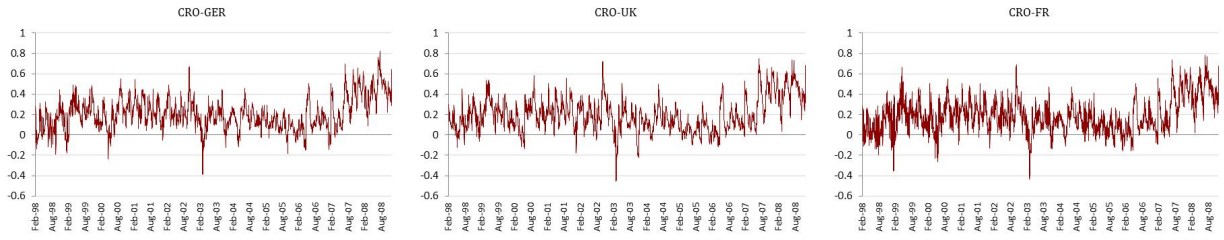


Figure C.9: Conditional correlations for Croatia.

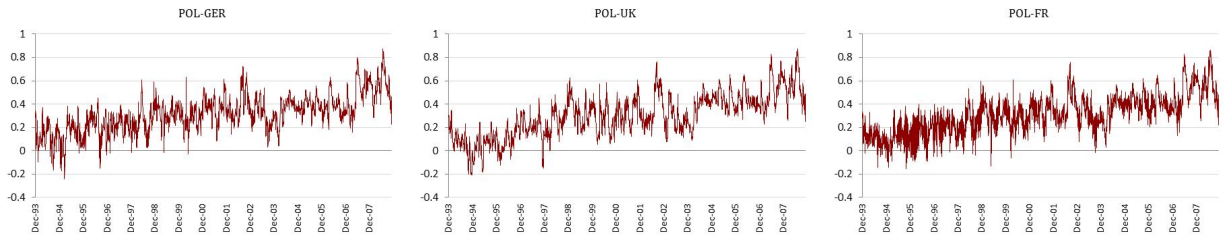


Figure C.10: Conditional correlations for Poland.

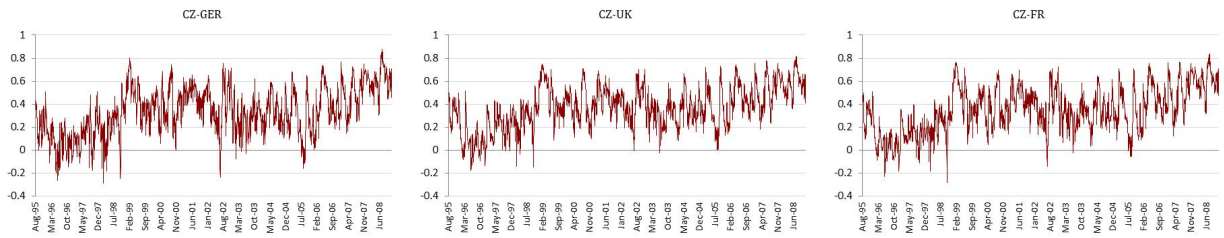


Figure C.11: Conditional correlations for the Czech Republic.

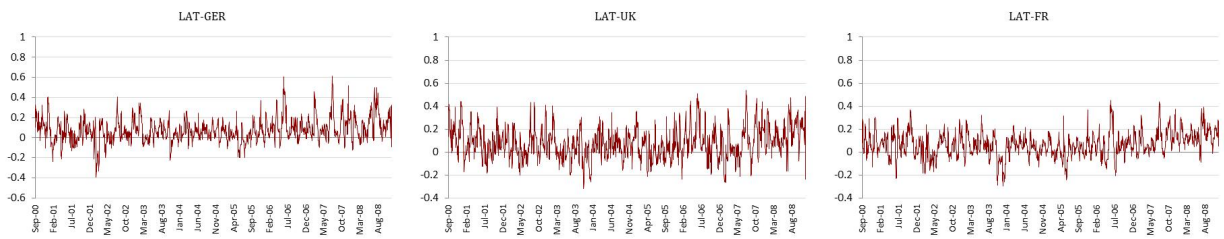


Figure C.12: Conditional correlations for Latvia.

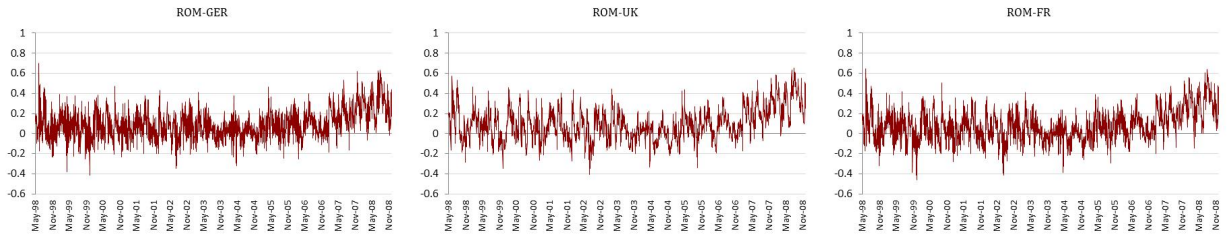


Figure C.13: Conditional correlations for Romania.

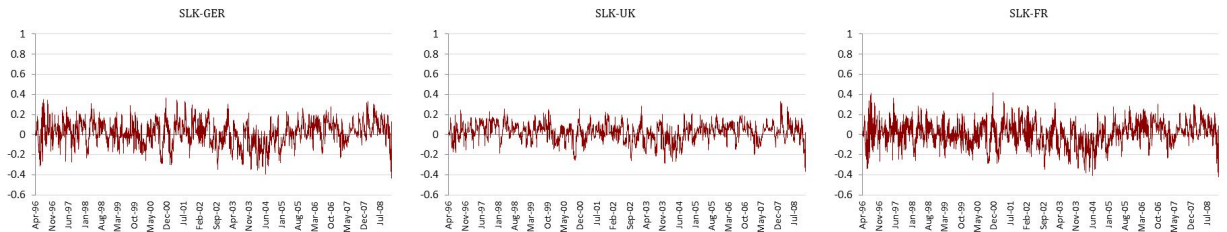


Figure C.14: Conditional correlations for Slovakia.

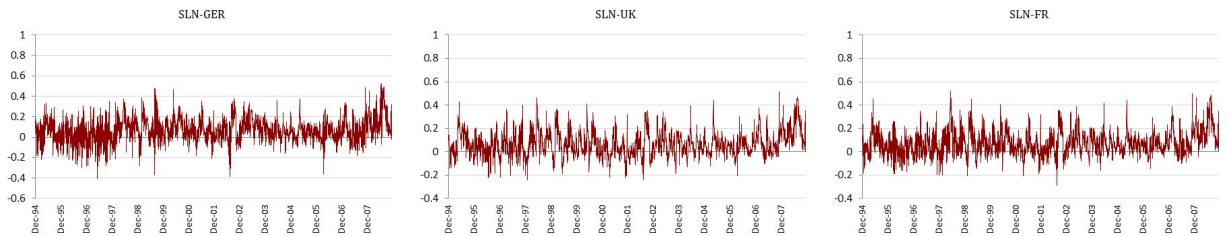


Figure C.15: Conditional correlations for Slovenia.

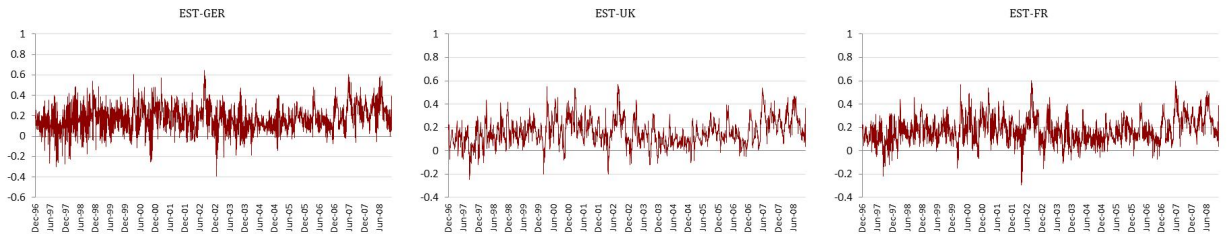


Figure C.16: Conditional correlations for Estonia.

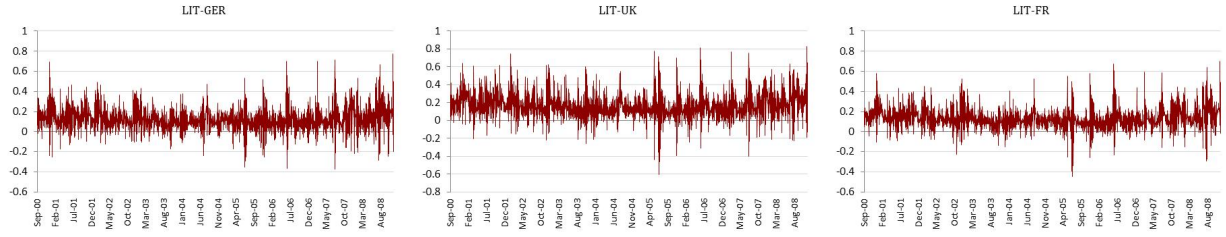


Figure C.17: Conditional correlations for Lithuania.

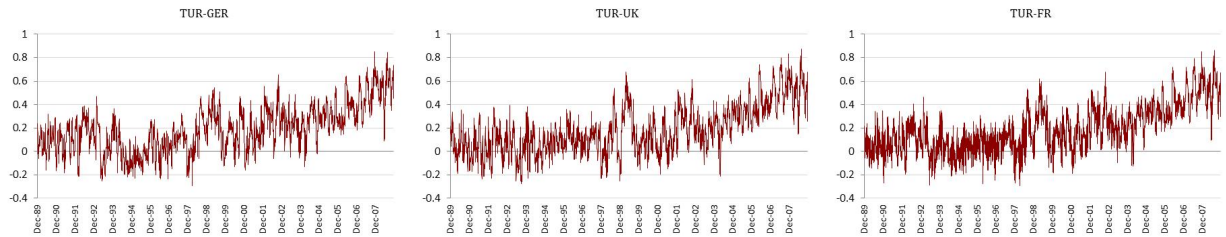


Figure C.18: Conditional correlations for Turkey.