



EMPIRICAL ANALYSIS OF TIME-VARYING CROSS-BORDER
CORRELATION AND SPILLOVER RISK

by

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Summary

This thesis consists of three papers analysing time-varying cross-border correlation and spillover risk. Existing literature has devoted significant resources to quantify these two types of risk within a variety of markets and asset classes. The implications of these studies have great importance in policy making, securities trading and in commercial banking activities. In the aftermath of the recent financial crisis dynamic risk related topics have gained a renewed interest. This thesis aims to bridge gaps in the currently available research.

"Dynamic Stock Market Covariances in the Eurozone" is a joint work with Professor Gregory Connor. This paper examines the short-term dynamics, macroeconomic sensitivities, and longer-term trends in the variances and covariances of national equity market index daily returns for eleven countries in the Euro currency zone. We modify Colacito, Engle and Ghysel's Mixed Data Sampling Dynamic Conditional Correlation GARCH (MIDAS-DCC GARCH) model to include a new scalar measure for the degree of correlatedness in time-varying correlation matrices. We also explore the robustness of the findings with a less model-dependent realized covariance estimator. We find a secular trend toward higher correlation during our sample period, and significant linkages between macroeconomic and market-wide variables and dynamic correlation. One notable finding is that average correlation between these markets is lower when their average GDP growth rate is lower or when more of them have negative GDP growth.

"Correlation Dynamics in the G7 Stock Markets" explores the changing magnitude of synchronised equity index return correlations within the G7 stock markets in response to dynamic variation in the economic environment and secular trends toward greater capital market integration. The full sample period is split into "pre-crisis" and "crisis" periods. The empirical results show that the G7 markets exhibit a significant positive trend toward higher cross-border correlations over the full sample period and that there is significant time-series autocorrelation in

the magnitude of cross-market return correlations. These findings are consistent for both periods. Correlation magnitude seems to behave differently during the "pre-crisis" and "crisis" periods in relation to the business-cycle-related effect and the turbulence of the financial markets. During the "crisis" period the average correlation between these financial markets is lower during quarters when more of them have negative GDP growth or when their average GDP growth is lower. The reverse holds for the "pre-crisis" period. Also, the positive relationship between the correlation magnitude and stock market variance is only present in the "crisis" period. We argue that during the crises periods, financial markets are strongly influenced by local factors.

"Directional Spillovers in Banks' Credit Default Risk and Related Variables" analyses the total and directional spillovers across carefully selected variables directly related to the credit risk of financial institutions: bank CDS spread, real estate market index, interest rate term spread, interbank liquidity spread and national stock market index, using daily data from 1st of January 2004 to 31st of December 2012. The spillover analysis is undertaken within five European Union countries: core countries France and Germany, periphery countries Spain and Italy, and a reference country, the UK. A multiple structural break estimation procedure is employed to detect sudden changes in shock transmission. The directional spillover framework reveals complex dynamics between the CDS spreads and credit risk related variables. The national stock markets show a clear leading role in shock transmission across selected variables; whereas the role of other variables in sample is reversed during the course of the crisis. The real estate index is found to be mostly affected by country specific events; and the shock transmission of the interest rate term spread and the interbank liquidity spread differs for the UK and the Eurozone countries.

List of Presentations and Publications

Publications:

Gregory Connor, Anita Suurlaht, Dynamic stock market covariances in the Eurozone, Journal of International Money and Finance, Volume 37, October 2013, Pages 353-370, ISSN 0261-5606, <http://dx.doi.org/10.1016/j.jimonfin.2013.06.008>

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Irish Society of New Economists Conference (ISNE) 2013, NUIM, Maynooth, " Directional Spillovers in Banks' Credit Default Risk", 5-6 September 2013

3rd International Conference of the Financial Engineering and Banking Society (FEBS) 2013, ESCP Europe Paris, "Correlation Dynamics in the G7 Stock Markets", 6 - 8 June 2013

Poster presentation at the Forecasting Structure and Time Varying Patterns in Economics and Finance, Econometrics Institute, Erasmus University Rotterdam, 24-25 of May 2013

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Irish Economic Association (IEA) Conference 2013, NUI Maynooth, "Correlation Dynamics in the G7 Stock Markets", 9-10 of May 2013

Money, Macro and Finance Conference 2012, TCD, Dublin, "Dynamic Stock Market Covariances in the Eurozone", 6 - 8 September 2012

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Irish Economic Association (IEA) Conference 2012, Institute of Bankers, Dublin, "Dynamic Stock Market Covariances in the Eurozone", 26 - 27 of April 2012

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I dedicate this thesis to my son Lennart whom we were so happy to welcome into this world on the 20th of September 2014.

Chapter 1 Dynamic Stock Market Covariances in the Eurozone

1.1 Introduction

This paper explores the changing magnitude of equity index return volatilities and correlations within the Eurozone, both in response to dynamic variation in the economic environment and in response to secular trends toward greater capital market integration. Although there are other regional economic co-operation agreements around the globe, the Eurozone is unique in the depth and breadth of its economic and financial integration, including the use of a common currency. This paper analyzes the equity market risk dynamics of this uniquely integrated regional capital market.

We use the Mixed Data Sampling GARCH (MIDAS-GARCH) model of Engle et al. (2008) to model the dynamic volatilities of the daily returns of eleven Eurozone stock market indices. As in Colacito et al. (2011), we combine the MIDAS-GARCH model with the Dynamic Conditional Correlation (DCC) model of Engle (2002) to model the dynamic correlation matrix of the returns. We modify the DCC model to include a new univariate measure of multivariate correlation magnitude. With this simplified DCC model, which is a special case of Engle's more general specification, we analyze the relationship between macroeconomic variables and the time-varying correlations between Eurozone markets.

As a robustness check, we also apply less model-dependent realized covariance estimators, together with the same univariate measure of correlation magnitude, and find reasonably consistent empirical results.

We find that there is a strong positive trend toward higher correlation magnitude across these Eurozone markets over our sample time period. We find some evidence for a "downside correlation" effect, so that, *ceteris paribus*, Eurozone markets seem to be more correlated when recent cumulative returns are on average lower within the region. Interestingly, correlation

magnitude varies positively with Eurozone GDP growth measures. In one specification of this effect, we find a negative link between Eurozone business downturns (the proportion of markets with negative quarterly GDP growth rates) and correlation magnitude. In an alternative, related, specification correlation magnitude is higher during quarters when the cross-country average quarterly GDP growth rate is higher.

We find evidence for a positive dynamic link between cross-market average variance and correlation magnitude within the region. This result holds using either a rolling-window-based sample variance or a forward-looking variance based on the Eurostoxx volatility index.

Our paper is related to several strands of the research literature. One topic of considerable interest concerns the level and secular trend in international capital market integration, e.g., Lessard (1974), Heston and Rouwenhorst (1994), Drummen and Zimmerman (1992), Beckers et al. (1996), Rouwenhorst (1999), Hopkins and Miller (2001) and Griffin and Karolyj (1998). Much of the work in this area has focussed upon European markets, reflecting the continent's six-decade experiment in politically-led regional economic integration.

Another relevant research strand examines international spillover effects in stock markets, e.g., King and Wadhvani (1990), Hamao et al. (1990), Baillie et al. (1993), Engle et al. (1994), Booth and Tse (1996), and Goetzmann et al. (2005). Related to this is the accumulated evidence that correlations between financial markets are significantly higher during periods of volatile markets, as in Ang and Bekaert (1999), Longin and Solnik (1995, 2001), and Capiello et al. (2006), and higher during "down" markets than during "up" markets, as found by Erb et al. (1994), Longin and Solnik (2001) and De Santis and Gerard (1997). Another related research area concerns empirical examination of the relationships between macroeconomic variables and stock market volatility, e.g., Officer (1973), Schwert (1989), Hamilton and Lin (1996) and Brandt and Kang (2004).

In terms of econometric technique, we utilize a covariance-stationary, two-component

GARCH-type model. The component specification distinguishes between short- and longer run sources of volatility. Engle and White (1999) proposed a GARCH model with a short and long run component. Various two-component volatility models have been proposed by Ding and Granger (1996), Chernov et al. (2003), and Adrian and Rosenberg (2006). The MIDAS-GARCH component model was inspired by two earlier contributions, Ghysels et al. (2005) on MIDAS filter and Engle and Rangel (2008) on spline-GARCH. Engle et al. (2008) formulate the MIDAS-GARCH component specification that we employ.

For correlation modeling we use a variant of the Dynamic Conditional Correlation (DCC) model. Bollerslev (1990) develops a multivariate time series model with time varying conditional variances and covariances, but constant conditional correlations. Building upon this, Engle (2002) proposed the DCC model, in which conditional correlation is also time varying. Colacito et al. (2011) utilized these specifications and proposed a new class of component correlation models, the DCC-MIDAS correlation models. Our paper extends the DCC model by imposing a one-dimensional structure on the multivariate dynamic correlations. We find that our model is numerically easy to estimate by maximum likelihood, at least in the case of a modest number of asset returns (there are eleven assets in our application to Eurozone equity market indices). This may be due in part to the simplified one-dimensional dynamic correlation measure which we introduce in this paper.

Section two describes our main econometric model and estimation technique. Section three describes an alternative, realized-covariance-based estimator, also based on our one-dimensional dynamic correlation measure but employing a simpler estimation methodology. Section four describes our data and presents all our empirical findings. Section five summarizes the paper.

1.2 A DCC-MIDAS-GARCH Specification with Univariate Correlation Dynamics

We adopt the Dynamic Conditional Correlation MIDAS-GARCH model but add to it a univariate measure of dynamic correlatedness. We do this by imposing a particular functional

form on the dynamics of the correlation matrix.

Assume that we observe an n -vector of returns r_t on n assets over the interval $t - 1$ to t . Further, we assume that the n -vector of returns r_t has a time-constant vector of means μ and time-varying nonsingular covariance matrix C_t :

$$r_t = \mu + C_t^{1/2} \eta_t \quad (1.1)$$

where η_t is an i.i.d. mean-zero n -vector time series process with covariance matrix equal to the identity matrix. We denote the vector of demeaned returns by \tilde{r}_t .

Let $s_t = (\sigma_{1t}, \dots, \sigma_{nt})$ denote the n -vector of individual asset return volatilities for time t returns based on time $t - 1$ information, and let $\Omega_t = \{Cov_{t-1}(r_{it}/\sigma_{it}, r_{jt}/\sigma_{jt}), i, j = 1, \dots, n\}$ denote the conditional correlation matrix of returns, conditional on time $t - 1$ information.

1.2.1 A Review of MIDAS-GARCH

The starting point in Engle's DCC approach is to model the individual return volatilities separately. For the components of s_t we use a model essentially identical to that in Colacito et al. (2011) and Engle et al. (2008): each individual return volatility follows a MIDAS-GARCH model. MIDAS-GARCH differs from standard GARCH in allowing time t "baseline" variance to vary slowly through time. This ameliorates a substantial flaw in standard GARCH when applied to long time samples, in particular, the empirically untenable assumption in standard GARCH that baseline variance is time-constant, see Taylor (1986).

Letting h_{it} denote baseline variance for asset i at time $t - 1$ for time t returns; we assume that it is a weighted linear combination of unconditional variance h_{0i} and lagged realized variances:

$$h_{it} = (1 - \theta_i)h_{0i} + \theta_i c(\omega_i) \sum_{k=1}^K \exp(-\omega_i k) RV_{i,t-nk}$$

with estimable parameters h_{0i} , θ_i , and ω_i , and where $RV_{i,t}$ denotes the J -period realized variance up to time t :

$$RV_{it} = \frac{1}{J} \sum_{j=1}^J \tilde{r}_{i,t-j}^2,$$

and $c(\omega_i) = \left(\sum_{k=1}^K \exp(-\omega_i k)\right)^{-1}$ ensures that the exponential weights sum to one. The model requires $h_{0i} > 0$ and $0 \leq \theta_i < 1$ to guarantee a covariance stationary process.

The slowly-changing variate h_{it} captures the low-frequency component of volatility but misses short-term GARCH effects. These are captured via a standard GARCH(1,1) model with unit unconditional variance:

$$g_{it} = (1 - \alpha_i - \beta_i) + \alpha_i g_{it-1} + \beta_i \frac{\tilde{r}_{i,t-1}^2}{h_{it-1}},$$

with $\alpha_i, \beta_i \geq 0$ and $\alpha_i + \beta_i < 1$. The product of baseline variance and the short-term GARCH effect gives time t variance:

$$\sigma_{it}^2 = h_{it} g_{it}. \quad (1.2)$$

1.2.2 A Modified DCC Model with Univariate Dynamics

We use $Diag[x]$ to denote an $n \times n$ diagonal matrix with the n -elements of the vector x on the diagonal, and $diag[X]$ to denote the diagonal matrix consisting of the diagonal elements of any square matrix X with all non-diagonal elements set to zero. By definition the covariance matrix is the quadratic product of the volatilities and correlation matrix:

$$C_t = Diag[s_t] \Omega_t Diag[s_t]. \quad (1.3)$$

Prior to Engle's work on the DCC model dynamic correlations have been estimated using simple univariate methods, such as rolling historical correlations, exponential smoothing method and multivariate GARCH models (see Engle (2009) for a comprehensive overview). A common goal of the literature in this field is the parameterization of the covariance matrix of a set of random variables conditional on a past information set. Building upon the constant conditional correlation model of Bollerslev (1990) (in which $\Omega_t = \Omega$, a time-constant matrix), Engle (2002) suggests modeling the correlation matrix separately from the volatilities and then combining them via (1.3) to produce a dynamic covariance matrix. Let X_{1t}, X_{2t} denote two symmetric, positive semi-definite $n \times n$ matrices at least one of which is strictly positive definite and let m_{1t}, m_{2t} denote two strictly positive scalars. (We are using the case of two explanatory variables

for notational convenience only; more or less are acceptable). Engle defines the quasi-correlation matrix Q_t as the linear combination:

$$Q_t = m_{1t}X_{1t} + m_{2t}X_{2t}. \quad (1.4)$$

The matrix Q_t is symmetric and positive definite but lacks one required property of a correlation matrix since the diagonal elements are not necessarily equal to one. Engle suggests a simple nonlinear transformation to impose this property while still maintaining symmetry and positive definiteness:

$$\Omega_t = \text{diag}[Q_t]^{-1/2}Q_t\text{diag}[Q_t]^{-1/2} \quad (1.5)$$

Equations (1.4) and (1.5) define Engle's dynamic conditional correlation (DCC) estimator. Together with models for the individual volatilities s_t , this gives a composite model of the dynamic covariance matrix.

Our model differs from standard DCC in the way we restrict the dynamics of the correlation matrix. Engle's DCC model is very clever, but is too high-dimensional for our application. The major objective of our paper is to explore the changing magnitude of correlation within the Eurozone, both in response to the dynamically varying economic environment and in response to European capital market integration trends. In place of the $\frac{1}{2}n(n-1)$ -dimensional correlation dynamics in (1.4) we want a univariate measure of time-varying correlation. This scalar measure of correlation magnitude should leave the pattern of correlation between individual markets essentially fixed. We now modify Engle's model to produce such a scalar measure.

We want to find a model for Ω_t with a simple one-dimensional state variable m_t capturing the time variation in Ω_t . When the univariate state variable m_t is high, the correlations between markets are relatively strong, when m_t is low, the correlations are relatively weak, and when m_t equals zero the correlations revert to their unconditional values. Except for this state variable the general "structure" of correlations is assumed invariant through time.

Let Ω_0 denote the time-constant unconditional correlation matrix:

$$(\Omega_0)_{ij} = cov_0\left[\frac{\tilde{r}_{it}}{\sigma_{it}}, \frac{\tilde{r}_{jt}}{\sigma_{jt}}\right]_{i,j=1,\dots,n} = E_0[\tilde{r}_t((Diag[s_t])^{-2})\tilde{r}_t'] \quad (1.6)$$

where the 0 subscript denotes the unconditional information set. Let U be the $n \times n$ matrix consisting entirely of ones. Our simple model for Ω_t is as follows:

$$\Omega_t = \Omega_0 + m_{t-1}(U - \Omega_0), \text{ for } -1 < m_{t-1} < 1 \quad (1.7)$$

The variable m_{t-1} is restricted to the interval $(-1, 1)$. We must show that (1.7) meets Engle's condition (1.4) that Ω_t is a positive linear combination of positive-semidefinite matrices.

Suppose that the following condition holds:

$$2\Omega_0 - U \text{ is strictly positive definite.} \quad (1.8)$$

Confirming that condition (1.8) holds is a straightforward empirical task, and is a condition easily met in our application to Eurozone equity markets.

Theorem 1: Given that condition (1.8) holds, then Ω_t defined by (1.6) and (1.7) is a symmetric, strictly positive definite matrix.

Proof: Note that (1.7) can be written as $\Omega_t = a_{t-1}(2\Omega_0 - U) + (1 + a_{t-1})U$ where $a_{t-1} = 2(m_{t-1} - \frac{1}{2})$. Since U is positive semi-definite and $0 < a_{t-1} < 1$ the matrix is a linear combination of a positive definite matrix and a positive semi-definite matrix, with strictly positive linear weights on both terms. Hence the matrix is strictly positive definite. The matrix is symmetric since it is a linear combination of symmetric matrices. **Q.E.D.**

Conveniently we do not need to use (1.5) since our construction always gives a matrix with units on the diagonal.

The model captures in a simple and intuitive way the notion that in some states of nature all correlations move higher, and in other states, lower. It can be easily seen from (1.7) that the dynamics in conditional correlation Ω_t are captured by the univariate measure m_t . When m_t is -1 the conditional correlation is low or negative, depending on the estimated unconditional correlation. Conditional correlation is at a higher level when m_t is positive and corresponds

to the unconditional sample correlation when $m_t = 0$. The model sacrifices the generality of Engle's original DCC (where all the correlations can move independently) in favour of greater simplicity and interpretability.

Our variant of the DCC model has some parallels to the Engle and Kelly (2012) Dynamic Equicorrelation (DECO) model. Our model, like the DECO model, is motivated by a desire for greater parsimony than the unrestricted DCC model. The DECO model does this by assuming that at each time point all correlations are equal; this produces a dynamic model of correlations which is truly univariate. In contrast, our model permits the unconditional correlation matrix to be unconstrained with full dimension, but imposes univariate dynamics on the movement of the conditional correlation matrix relative to its unconditional value. The difference in our approach relative to DECO reflects the difference in application: Engle and Kelly seek to model a very large cross-section of individual equities, whereas we want to examine the dynamics in a moderate number (eleven) of national equity indices.

As in Engle et al. (2008), we impose a linear structure on m_t based on a low-dimensional vector x_t of explanatory variables (such as macroeconomic variates and financial market stress indicators):

$$m_t = b'x_t \tag{1.9}$$

subject to $-1 < m_t < 1$. This mandates that the explanatory variables x_t have bounded support and imposes implicit restrictions on the parameters b (analogous to the positive-coefficient requirements of a GARCH model). It follows from (1.7) that the explanatory variables x_t must have unconditional expectations of zero.

Our model for Ω_t consists of (1.6), (1.7), (1.8) and (1.9) with estimable parameters a_0, b, Ω_0 . In our application, the endogenous variable m_t is daily but the explanatory variables are constant for all days within a quarterly frequency; this does not affect the econometric methodology.

Consider the average correlation at time t , found by averaging the off-diagonal elements of

the time- t correlation matrix:

$$avecorr_t = \frac{1}{n(n-1)} \sum_{i \neq j} [\Omega_t]_{ij} \quad (1.10)$$

Using Ω_0 in place of Ω_t in (1.10) gives $avecorr_0$. As we show next, the linear dynamic equation for the correlation matrix (1.9) implies a univariate linear model of $avecorr_t$. We define the correlation ratio as the deviation of time t average correlation from its long-term average, divided by one minus the long-term average:

$$ratio_t = \frac{avecorr_t - avecorr_0}{(1 - avecorr_0)}. \quad (1.11)$$

Theorem 2: Given $ratio_t$ as defined by (1.7), (1.10) and (1.11) then $ratio_t = m_t$ for all t .

Proof: Applying the matrix off-diagonal averaging transformation (1.10) to both sides of the dynamic correlation matrix equation (1.7) gives:

$$\frac{1}{n(n-1)} \sum_{i \neq j} [\Omega_t]_{ij} = (1 - m_t) \left(\frac{1}{n(n-1)} \sum_{i \neq j} [\Omega_0]_{ij} \right) + m_t, \quad (1.12)$$

using that the average of the off-diagonal components of U equals one since the matrix consists entirely of ones. Using the definitions of $avecorr_t$ and $avecorr_0$ and inserting in (1.12):

$$avecorr_t = (1 - m_t)avecorr_0 + m_t.$$

Subtracting $avecorr_0$ from both sides and the dividing both sides by $(1 - avecorr_0)$ gives the result. **Q.E.D.**

Inserting $ratio_t$ into (1.9) gives:

$$ratio_t = bx_t, \quad (1.13)$$

so that equation (1.9) in the dynamic system implies this linear model of time-varying average correlation.

1.2.3 A Maximum Likelihood Estimation Procedure

We follow Engle (2002) and Colacito et al. (2011) in applying two-component maximum likelihood to estimate the DCC-MIDAS-GARCH model. We begin by supposing that the innovation process η_t is i.i.d. multivariate normal; it is unit variance and uncorrelated

by definition; see (1.1). Weakening the assumption of normality gives rise to a quasi-maximum likelihood interpretation rather than true maximum likelihood. Recall that $C_t = \text{Diag}[s_t]\Omega_t\text{Diag}[s_t]$ where C_t is the time- t covariance matrix. Using a standard result, under i.i.d. multivariate normality of the innovations the data generating process for our sample return vector has log likelihood function:

$$\begin{aligned} L &= -\frac{1}{2}\left(\sum_{t=1}^T (n \log(2\pi) + \log(|C_t|) + \tilde{r}'_t C_t^{-1} \tilde{r}_t)\right) \\ &= -\frac{1}{2}\left(\sum_{t=1}^T (n \log(2\pi) + \log(|\text{Diag}[s_t]\Omega_t\text{Diag}[s_t]|) \right. \\ &\quad \left. + \tilde{r}'_t (\text{Diag}[s_t]\Omega_t\text{Diag}[s_t])^{-1} \tilde{r}_t)\right). \end{aligned} \quad (1.14)$$

Let $\Theta_1 = \{h_{0i}, \theta_i, \omega_i, \alpha_i, \beta_i\}_{i=1, \dots, n}$ denote the parameters of the MIDAS-GARCH model, and $\Theta_2 = (\Omega_0, a_0, b)$ the parameters of the dynamic correlation matrix model. Following Engle (2002) we use a two-component maximum likelihood approach. In the first step we use the individual time series of returns to estimate the MIDAS-GARCH parameters Θ_1 for each asset separately. Note that this is a collection of n unrelated individual-asset MIDAS-GARCH maximization likelihood estimation problems. Then in the second step we use these consistent, limited-information maximum likelihood values of Θ_1 to substitute $\text{Diag}[\hat{s}_t]$ for $\text{Diag}[s_t]$ in (1.14) to find the maximum likelihood estimate of Θ_2 .

The first-step estimation decomposes into a collection of individual GARCH-type model estimation problems with additively separable log likelihood maximization problems:

$$\begin{aligned} \hat{\Theta}_{1i} &= \arg \max_{\hat{\Theta}_{1i}} L_{1i} \text{ where} \\ L_{1i} &= \left\{ -\frac{1}{2} \left(\sum_{t=1}^T (\log(2\pi) + \log(h_{it}) + \frac{\tilde{r}_{it}^2}{h_{it}}) \right) \right\}. \end{aligned} \quad (1.15)$$

There are two commonly-used estimators for the covariance matrix of the parameters in (1.15). These are the inverse of the outer product of the score vector, and the inverse Hessian; under standard conditions either provides a consistent estimator:

$$E\left[\left(\frac{\partial L_{1i}}{\partial \hat{\Theta}_{1i}}\right)\left(\frac{\partial L_{1i}}{\partial \hat{\Theta}_{1i}}\right)'\right]^{-1} = \frac{1}{T} E\left[\frac{\partial^2 L_{1i}}{\partial^2 \hat{\Theta}_{1i}}\right]^{-1} = \frac{1}{T} \text{cov}[\hat{\Theta}_{1i}, \hat{\Theta}'_{1i}] \quad (1.16)$$

where $\stackrel{T}{=}$ denotes approximately equal for large T and relies on consistent estimates of $\widehat{\Theta}_{1i}$ (see, e.g., Greene (2008)). As discussed next, we use the outer product of the score vector.

In the second step, we use the first-step estimates from (1.15) to compute \widehat{s}_t and then substitute this for s_t in (1.14) giving a maximum likelihood problem in the parameters Θ_2 only. Engle (2002) notes that the standard errors of the coefficients in the second-step correlation matrix estimation are in general inconsistent due to the use of first-step estimated volatilities. Engle and Sheppard (2001) derive a consistent estimate of the covariance matrix of the estimated parameters in the second step by adjusting for the first-step estimation error:

$$\begin{aligned} cov[\widehat{\Theta}_2, \widehat{\Theta}'_2] &\stackrel{T}{=} E\left[\left(\frac{\partial L}{\partial \widehat{\Theta}_2}\right)\left(\frac{\partial L}{\partial \widehat{\Theta}_2}\right)'\right]^{-1} E[yy'] E\left[\left(\frac{\partial L}{\partial \widehat{\Theta}_2}\right)\left(\frac{\partial L}{\partial \widehat{\Theta}_2}\right)'\right]^{-1} \\ y &= \frac{\partial L}{\partial \widehat{\Theta}_2} - E\left[\frac{\partial^2 L}{\partial \Theta_1 \partial \Theta_2}\right] E\left[\frac{\partial^2 L_1}{\partial^2 \Theta_1}\right]^{-1} \frac{\partial L_1}{\partial \widehat{\Theta}_1}. \end{aligned} \quad (1.17)$$

Note that this is the matrix product of the standard outer-product-based estimator (the first term in (1.17) as in (1.16)) times an adjustment matrix (the second and third terms).

Consider the special case in which expectations of all the cross-partial derivatives of the log likelihood function equal zero, $E\left[\frac{\partial^2 L}{\partial \Theta_{1j} \partial \Theta_{2k}}\right] = 0$ for all j, k where j, k run over all the elements of the parameter vectors Θ_1 and Θ_2 , respectively. In this special case, the adjusted covariance matrix simplifies, and is equal to the unadjusted estimate using the outer product of the score vector:

$$cov[\widehat{\Theta}_2, \widehat{\Theta}'_2] = E\left[\left(\frac{\partial L}{\partial \widehat{\Theta}_2}\right)\left(\frac{\partial L}{\partial \widehat{\Theta}_2}\right)'\right]^{-1}$$

which is easy to see since if $E\left[\frac{\partial^2 L}{\partial \Theta_1 \partial \Theta_2}\right] = 0$ then $E[yy'] = E\left[\left(\frac{\partial L}{\partial \widehat{\Theta}_2}\right)\left(\frac{\partial L}{\partial \widehat{\Theta}_2}\right)'\right]$ and the adjustment matrix equals the identity matrix. This becomes relevant in our empirical application below.

1.3 A Robustness Check Using Realized Covariances

A drawback to the estimation approach of the last section is its reliance on numerical maximum likelihood and on the specific functional form of the DCC-MIDAS-GARCH model. In this section we provide a robustness check on the main empirical findings. We describe a stochastic-volatility variant of the model, treating the daily time interval as small and replacing

the DCC-MIDAS-GARCH specification with nonparametric, realized covariance estimators. This produces a model parallel to that of the previous sections, but which is simple to estimate, relying only on quarterly sample moments of daily returns and linear time series regression. It relies on the same one-dimensional dynamic measure of average correlation, using the implication of this model for the dynamic correlation ratio (1.11). This simple model is parallel to, rather than identical to, the model of the last two sections, but the empirical findings provide a robustness check on the main results from the more complex estimation methodology.

Let p_t denote a continuous-time n -vector stochastic process for the log prices of the stock indices, and suppose that this price vector follows a Brownian motion with time-constant drift and time-varying covariance matrix C_t

$$dp_t = \mu dt + C_t dz_t, \quad (1.18)$$

see Barndorff-Nielsen et al. (2011). Letting Δ denote a fixed-length, high-frequency return measurement interval define the return vector $r_{t,t+\Delta} = p_{t+\Delta} - p_t$. Using a fixed finite window Q define the integrated covariance matrix over the interval:

$$C_{t-Q,t} = \frac{1}{Q} \int_{t-Q}^t C_t dt$$

and the realized covariance estimator as the sample counterpart using high-frequency returns:

$$\hat{C}_{t-Q,t} = \frac{1}{(Q/\Delta)} \sum_{1 \leq j \leq \frac{Q}{\Delta}} r_{t-\Delta(j+1),t-\Delta j} r'_{t-\Delta(j+1),t-\Delta j}.$$

From Barndorff-Nielsen et al. (2011), letting $\Delta \rightarrow 0$, with Q fixed, and under appropriate regularity conditions, $\hat{C}_{t-Q,t}$ is a consistent and asymptotically normal (CAN) estimate of $C_{t-Q,t}$. The dynamic correlation ratio (1.11) of the discrete daily model in the last section has an obvious realized-covariance analogue in this continuous-time model:

$$ratio_{t-Q,t} = \frac{avecorr_{t-Q,t} - avecorr_0}{(1 - avecorr_0)}. \quad (1.19)$$

Note that the integrated correlation matrix, $\Omega_{t-Q,t} = Diag[C_{t-Q,t}]^{-\frac{1}{2}} (C_{t-Q,t}) Diag[C_{t-Q,t}]^{-\frac{1}{2}}$ and its average off-diagonal component are smooth transformations of $C_{t-Q,t}$. Hence, the

preservation of CAN under smooth transformations guarantees that the same functions applied to $\widehat{C}_{t-Q,t}$ provide consistent asymptotically normal estimates of $ratio_{t-Q,t}$. We estimate the linear relation between $ratio_{t-Q,t}$ and a set of zero-mean explanatory variables by time-series ordinary least squares regression at frequency Q . That is, we impose the data generating process:

$$ratio_{t-Q,t} = b^* x_{t-Q,t} + \varepsilon_t, \quad (1.20)$$

where $x_{t-Q,t}$ is a set of explanatory variables measured over the same frequency Q , and b^* is a vector of linear coefficients. These regression estimates provide alternative, less model dependent, parallels to the maximum-likelihood estimates of the dynamic model (1.9) described in the previous two subsections.

In our application, we use Δ equal to one day, and Q (the window length) equal to the number of days in one quarter of the year (approximately 65 trading days depending on the calendar). This matches the frequency of some of the independent variables in (1.13). There is not an exact match between the two models, but they capture related information over the same data history. We do not attempt to relate the simple regression specification (1.20) to the data generating process for individual returns (1.18). We view this regression model as a simpler alternative to the model described in the previous two sections, capturing some of the same empirical phenomena on the same data history.

1.4 Data and Empirical Findings

We use adjusted¹ daily closing prices from December 31st 1991 to December 31st 2010 for eleven European capitalization-weighted equity indices, Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain, obtained from Datastream. (Although the Euro currency formally came into existence on January 1st 1999, the Maastricht Treaty committing signatory states to join the currency was drafted in December 1991, and signed by delegates of the member states in February 1992.) We compute daily log returns. The

¹ Adjusted daily closing prices are the default data type for all equities and indices in Datastream. The closing price is adjusted for stock splits and other similar corporate actions.

Datastream database skips weekends and a few major holidays (Christmas and New Year's Day) but reproduces yesterday's closing price on other days on which a particular national exchange is closed. To partly correct for this, we ignore closing prices on days on which four or more of the eleven national exchanges are closed, and treat such a day the same as a weekend (the two-day return becomes a one-day return for the entire cross-section). This keeps the panel dataset balanced and seems to deal reasonably well with non-synchrony in the return computations (see below). There is a maximum two-hour time zone difference between the national markets in the sample; Ireland and Portugal are one hour behind the core European countries, and Greece is one hour ahead.

Table 1.1 shows the annualized means and standard deviations, skewness, excess kurtosis, and first four autocorrelations for each of the eleven returns series. Two markets (Greece and Portugal) have fairly high first-order autocorrelations, indicating illiquid pricing or stale pricing of the daily index. Table 1.2 shows the sample correlation matrix, above the diagonal, and the first-order autocovariance and crosscovariance adjusted correlation matrix below the diagonal. The diagonal elements are autocorrelation-consistent estimates of the annualized standard deviations. To compute this table, an adjusted covariance matrix is found by adding the corresponding lagged and led cross-covariance matrices to the original sample cross-covariance matrix (see, e.g, Connor et al. (2010) section 2.5 for details of this adjustment). This adjustment allows for the possible impact of non-synchronous returns as found in correlation analysis of global equity markets, see Martens and Poon (2001). The adjusted standard errors and correlation matrix are then computed from this adjusted covariance matrix. There is little difference between the adjusted and unadjusted correlations or standard deviations (compare to Table 1.1). This reflects the limited cross-correlation of returns, as shown in Table 1.3. This shows that by skipping days on which four or more markets are closed, and restricting our panel to European markets (with their similarity of trading hours), we have mitigated the problem of

non-synchronous returns.

1.4.1 The MIDAS-GARCH Models of Individual Market Index Volatility

Table 1.4 columns one to three report the estimates for the GARCH(1,1). For all eleven markets, the estimated GARCH(1,1) coefficients are closer to or (in the case of Portugal) exceed the stationarity boundary $\alpha_i + \beta_i < 1$. Table 1.4 columns four to seven report the estimates for the MIDAS-GARCH model. For all countries the sum of the two MIDAS-GARCH coefficients α_i and β_i is well within the stationary boundary $\alpha_i + \beta_i < 1$. This shows one relative advantage of the MIDAS-GARCH model. The exponential weighting is not significantly different from 0 in most markets so that the optimal weighting is close to equal weighting of the four lagged fixed-window realized variances. The estimated decay coefficient θ_i is close to $1/2$ in most markets. The table shows that the covariance stationary, two-component MIDAS-GARCH volatility models with GARCH(1,1) short-term components and mean-reverting, exponentially-weighted medium-term components fit our daily equity index returns data sample reasonably well.

Figure 1.1 illustrates the trends in Euro-area volatility using two proxies: the square root of the cross-sectional average of the predicted variances from the MIDAS-GARCH models, and the square root of the cross-sectional average of the 65-day rolling window variances. Both proxies are annualized by multiplying by the square root of 261, the average number of trading days per year in our sample. The MIDAS-GARCH volatilities are noticeably more variable through time, but the two proxies follow each other closely in terms of lower-frequency components.

1.4.2 A Dynamic Model of Eurozone Equity Market Correlations

Recall that the DCC-MIDAS-GARCH maximum-likelihood estimation problem decomposes into MIDAS-GARCH and the separate estimation of the correlation matrix dynamics. In this subsection we discuss the second-step estimation of the correlation matrix using the dynamic volatilities from the last subsection to standardize returns.

For the dynamic correlation matrix model (1.9) we examine a variety of specifications. We consider seven potential explanatory variables: a time trend, the average cumulative returns to

the eleven indices using the previous 65 days of returns, the proportion of the eleven markets which had negative real GDP growth during the current quarter, the cross-sectional average of national GDP growth in the current quarter, the lagged correlation ratio (1.11) using the previous 65 days of daily returns, the lagged average sample variance using the previous 65 daily returns, and the current implied variance from the Eurostoxx options-based volatility index. All the explanatory variables are de-meanned. We use the 65 day rolling window to account for a quarter of the year based on a 260 day year.

Note that two of the proposed explanatory variables, the proportion of the eleven markets with negative quarterly GDP growth, and the cross-sectional average of national GDP growth in the current quarter, are similar measures of Eurozone business conditions. They have a correlation of $-.89$, so we use one or the other of these two explanatory variables, but not both simultaneously.

We also have two measures of market volatility. The first is the lagged average sample variance, taking a simple average of the rolling-window 65-day return variances of the eleven countries, lagged by one day. The second is an option-implied variance from the VSTOXX index, a volatility index based on Euro STOXX 50 realtime options prices; see Stoxx Strategy Index Guide (2012, section 6) for a description of the VSTOXX index. To transform it into daily variance units the VSTOXX index is divided by 100 and squared prior to including it in the analysis. These two variance measures have a correlation of 0.59, so we use one or the other but not both together. The STOXX data has a shorter data availability period (data beginning in 1999) so the model estimates relying on this measure are over a shorter sample period.

With these seven potential explanatory variables, there is an unmanageable number of possible specifications by adding or dropping variables. We impose discipline on our specification search as follows. We include the lagged daily correlation ratio and time trend in all specifications. Both of these have a fairly strong empirical/theoretical foundation. For the other

variables, the cumulative return measure, the business conditions variable (either negative GDP growth proportion or average GDP growth), and the volatility measure (either lagged average variance or STOXX volatility index-based variance), we try the combinations: none, each alone, and all three together. Taking account of the two alternative measures of business conditions and volatility, this gives nine specifications in total.

There are 55 estimable parameters in Ω_0 since it is a symmetric 11×11 matrix with unit diagonal. Additionally there are between two and five parameters in b depending upon the specification. We use the sample correlation matrix $\widehat{\Omega}_0$ as an initial (and consistent) estimate. Next, we estimate b consistently by limited information maximum likelihood applied to L (see (1.14)) with the value of $\widehat{\Omega}_0$ held fixed at this initial estimate. Finally we use these initial estimates of \widehat{b} and $\widehat{\Omega}_0$ and re-estimate all the parameters simultaneously by maximum likelihood. For all seven specifications, the maximum likelihood estimation problem converges quickly, and the b estimates are relatively unaffected by the simultaneous estimation of $\widehat{\Omega}_0$, that is, the initial and final estimates of b are quite similar. The initial estimates of b and Ω_0 are available in Connor and Suurlaht (2013b) along with other ancillary results and estimation code.

The results are presented in Table 1.5, using unadjusted one-step standard errors based on the outer product of the score vectors. (We will show in the next subsection that Engle's adjustment has negligible impact on the standard errors). Not surprisingly, there is an autocorrelation effect, captured in the positive coefficient on the lagged 65-day empirical correlation ratio. There is a strong positive trend in correlation magnitude over this time period within the Euro region. These are the two strongest findings. The "downside correlation" effect linking cumulative return negatively to correlation magnitude is only significant in the five-variable model including average GDP growth. When cumulative return is used without either of the GDP-based variables, the coefficient is significant with the "wrong" sign (this could be ascribed to a missing variable bias). There is a positive relationship between average variance and the

dynamic correlation measure.

There is also a business-cycle-related effect: correlations are lower when the proportion of markets with negative GDP growth is higher. The same finding holds when average GDP growth is used as a replacement variable (with the opposite sign, obviously). This shows that, for some reason for which we do not have a ready theory, there seems to be greater diversity in the national index returns when several Eurozone economies are in a business cycle downturn or their average GDP growth is lower. This finding differentiates our results from those of Erb et al. (1994) on the dynamic correlations of G7 equity markets. Erb, Harvey and Viskanta use the Center for International Business Cycle Research national business cycle peak/trough indicator to divide monthly return data pairs (each G7 market matched with each of the other G7 markets in pairs) into three subsamples: both national markets in a macroeconomic expansion phase, both in a macroeconomic contraction phase, and mixed (one in each phase). They find that the return correlations are lowest in the expansion-expansion subsamples and highest in the contraction-contraction subsamples. Treating our proportion of markets with negative GDP growth as a contraction/expansion indicator, our results for the Eurozone find an opposite effect. We attribute this difference to the different nature of the capital market and macroeconomic links within the tightly-integrated Eurozone versus the looser ties within the G7. However, we do not claim to have a satisfactory macroeconomic-financial theory to explain the findings.

Suurlaht (2013) applies exactly the same methodology as we use to G7 markets, and finds that a (somewhat weaker) positive integration trend is statistically significant for those markets, but the "downside correlation" effect and GDP-related effect are much weaker than for the Eurozone markets. Neither effect is statistically significant, or is only marginally significant, depending upon the specification.

Our empirical findings have practical implications for portfolio optimization and risk management for investors in European equity markets. The common dynamics in correlations

in the Eurozone impact on diversification strategies and portfolio risk levels. In this paper we do not attempt to integrate the findings explicitly into a portfolio optimization or portfolio risk forecasting model; we leave that for later research.

1.4.3 Adjusted Second-step Coefficient Standard Errors

In this subsection we implement the adjustment to the second-step parameter standard errors proposed by Engle (2002). Note that there are 44 parameters in the first-step parameter vector Θ_1 (4 parameters per national market index and 11 national market indices). Consider either model 6 or 7 in Table 1.5, in which there are 60 parameters in the second-step parameter set $\Theta_2 = (b, \Omega_0)$. In this case the matrix of expected cross-partial derivatives, $E[\frac{\partial^2 L(\Theta_1, \Theta_2)}{\partial \Theta_{1j} \partial \Theta_{2h}}]$, has dimension 60×44 . This matrix is numerically somewhat cumbersome to compute since it links the two steps of the component maximum likelihood procedure. The other elements of (1.17) are straightforward to compute; the score vectors of the likelihood function are created naturally as part of numerical maximum likelihood. Let d_{1j} denote a 44–vector with a one in element j and zeros elsewhere, d_{2h} denote a 60–vector with a one in element h and zeros elsewhere. For every combination j, h of first and second stage parameters we perturb each individual parameter positively and negatively away from its pre-estimated value, and re-estimate the second-stage expected log likelihood $E[L(\Theta_1^*, \Theta_2^*)]$ using the time-series average as a consistent estimate of the expectation. A linear combination of perturbed values of the expected log likelihood gives an approximation to the cross-partial derivative matrix:

$$\begin{aligned}
E\left[\frac{\partial^2 L(\Theta_1, \Theta_2)}{\partial \Theta_{1j} \partial \Theta_{2h}}\right] &= \lim_{\epsilon_j, \epsilon_h \rightarrow 0} \frac{1}{4\epsilon_j \epsilon_h} \{E[L(\Theta_1 + d_{1j}\epsilon_{1j}, \Theta_2 + d_{1h}\epsilon_{2h})] \\
&\quad - E[L(\Theta_1 + d_{1j}\epsilon_{1j}, \Theta_2 - d_{2h}\epsilon_{2h})] \\
&\quad - E[L(\Theta_1 - d_{1j}\epsilon_{1j}, \Theta_2 + d_{2h}\epsilon_{2h})] \\
&\quad + E[L(\Theta_1 - d_{1j}\epsilon_{1j}, \Theta_2 - d_{2h}\epsilon_{2h})]\}. \tag{1.21}
\end{aligned}$$

We use (1.21) to approximate the cross-partials numerically, using appropriately small values

for ϵ_j, ϵ_h . We compute the second-step likelihood time-series sample realizations for each of the $4 \times 60 \times 44 = 105600$ combinations of positive/negative parameter perturbations in (1.21) and take a time-series sample mean for each realized sample of log likelihood observations. The other terms of (1.17) are straightforward.

Table 1.6 compares the adjusted and unadjusted standard errors of the second-step coefficients for the two five-variable models (specifications 6 and 7) from Table 1.5. The adjustment has a negligible impact, which is unsurprising when the nature of the adjustment is traced. The perturbation of a first-step parameter has only a very modest and indirect impact on the likelihood scores of second-step parameters. A perturbation to one of the first-step parameters modestly influences \hat{s} and this, in turn, very modestly influences correlations via (1.3), which can theoretically at least influence the regression coefficients in (1.9). To summarize our findings in this regard, Engle's adjustment is theoretically appealing, but it is time-consuming and cumbersome to implement and has negligible impact in this application.

1.4.4 Alternative Estimates Using Realized Variances and Covariances

Table 1.7 parallels Table 1.5 but using the fixed-window variances and covariances and quarterly linear regression (1.20) in place of the DCC-MIDAS-GARCH. The dependent variable is the correlation ratio for each calendar quarter, based on the sample correlation matrix of daily returns during the quarter. The lagged correlation ratio among the explanatory variables is lagged by one full calendar quarter. The other explanatory variables are contemporaneous with the dependent variable over the same quarter. Although the model and methodology are different, the findings mostly parallel those with the DCC-MIDAS-GARCH model. The coefficients on the lagged correlation ratio and time trend are both positive and significant, as in the DCC-MIDAS-GARCH model. The coefficient on the proportion of markets with negative GDP growth is negative as in the DCC-MIDAS-GARCH model. The alternative variable choice, average-GDP growth, has a positive and significant sign in the five-variable model but is not

significant when used alone (in the DCC-MIDAS-GARCH model it was positive and significant in both cases). The "downside correlation" effect is significant and negative (the expected sign) when used alone and in one of the two five-variable models.

1.5 Conclusion

This paper uses a new variant of the Dynamic Conditional Correlation Mixed Data Sampling GARCH model (DCC-MIDAS-GARCH) to examine the dynamic volatilities and correlations of daily equity index returns for eleven countries in the Eurozone over the sample period January 2nd 1992 to December 30th 2010.

We develop a new variant of Engle's DCC model which simplifies the structure of that model by imposing a univariate measure of the dynamic changes in the correlation matrix. We use this new univariate measure of dynamic correlation magnitude to relate the dynamic variation in average correlation of equity markets in Europe to relevant macroeconomic variables.

We find that European markets show a significant positive trend toward higher inter-market correlations over the 1991-2010 time period. There is time-series autocorrelation in the magnitude of cross-market return correlations. Correlations are higher when cross-country average variances are higher. A "downside correlation" effect, negatively linking cumulative returns to dynamic correlations, is significant in some but not all of our chosen specifications. Also, there is a significant business-cycle effect: cross-market correlations tend to be lower when a larger proportion of the economies are in a negative-growth quarter. Alternatively (using a slightly different specification) correlations are higher when cross-market average GDP growth is higher. It is interesting to theorize as to why lower GDP growth, captured either by average growth or the proportion of countries with negative growth, is dynamically related to greater diversity of returns across national stock markets within the tightly-integrated Eurozone.

1.6 Tables and Figures

Table 1.1: Summary statistics

| Series | Annualized Mean Return | Annualized Std Deviation | Skewness | Excess Kurtosis | ρ_1 | ρ_2 | ρ_3 | ρ_4 |
|-------------|------------------------|--------------------------|----------|-----------------|----------|----------|----------|----------|
| Austria | 6.71 | 21.80 | -0.37 | 8.71 | 0.0745 | -0.0354 | -0.0064 | 0.0162 |
| Belgium | 4.81 | 19.08 | 0.04 | 7.20 | 0.0886 | -0.0097 | -0.0447 | 0.0230 |
| Finland | 13.25 | 30.08 | -0.36 | 6.76 | 0.0286 | -0.0209 | -0.0161 | 0.0335 |
| France | 4.35 | 23.16 | 0.01 | 4.78 | -0.0119 | -0.0414 | -0.0541 | 0.0373 |
| Germany | 8.40 | 23.86 | -0.11 | 4.83 | -0.0164 | -0.0329 | -0.0180 | 0.0418 |
| Greece | 2.91 | 27.15 | -0.12 | 3.89 | 0.1305 | -0.0159 | -0.0129 | 0.0278 |
| Ireland | 4.07 | 21.03 | -0.62 | 9.53 | 0.0665 | 0.0007 | 0.0018 | 0.0124 |
| Italy | 3.91 | 23.76 | -0.02 | 4.10 | 0.0270 | -0.0029 | -0.0233 | 0.0697 |
| Netherlands | 5.85 | 23.08 | -0.13 | 6.54 | -0.0036 | -0.0227 | -0.0570 | 0.0479 |
| Portugal | 8.40 | 16.30 | -0.33 | 12.86 | 0.1053 | 0.0184 | 0.0248 | 0.0438 |
| Spain | 7.52 | 22.98 | -0.02 | 5.75 | 0.0191 | -0.0394 | -0.0323 | 0.0202 |

Notes: Summary statistics including the first four autocorrelations for the eleven Eurozone stock market index daily log return series over the sample period from January 2, 1992 to December 30, 2010 (4788 observations).

Table 1.2: The sample correlation matrix and annualized standard deviations

| | R_{1t} | R_{2t} | R_{3t} | R_{4t} | R_{5t} | R_{6t} | R_{7t} | R_{8t} | R_{9t} | R_{10t} | R_{11t} |
|----------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-----------|-----------|
| R_{1t} | 0.226 | 0.585 | 0.448 | 0.572 | 0.570 | 0.361 | 0.561 | 0.531 | 0.585 | 0.540 | 0.570 |
| R_{2t} | 0.643 | 0.199 | 0.528 | 0.760 | 0.706 | 0.379 | 0.597 | 0.651 | 0.804 | 0.575 | 0.670 |
| R_{3t} | 0.446 | 0.532 | 0.305 | 0.649 | 0.618 | 0.315 | 0.487 | 0.555 | 0.655 | 0.525 | 0.601 |
| R_{4t} | 0.612 | 0.786 | 0.677 | 0.230 | 0.812 | 0.366 | 0.589 | 0.759 | 0.868 | 0.620 | 0.818 |
| R_{5t} | 0.613 | 0.764 | 0.668 | 0.866 | 0.237 | 0.344 | 0.540 | 0.696 | 0.818 | 0.579 | 0.736 |
| $Y_0 = R_{6t}$ | 0.451 | 0.467 | 0.376 | 0.465 | 0.472 | 0.289 | 0.379 | 0.323 | 0.382 | 0.389 | 0.368 |
| R_{7t} | 0.624 | 0.665 | 0.491 | 0.628 | 0.620 | 0.471 | 0.217 | 0.520 | 0.609 | 0.515 | 0.554 |
| R_{8t} | 0.575 | 0.678 | 0.575 | 0.757 | 0.730 | 0.414 | 0.560 | 0.241 | 0.739 | 0.573 | 0.738 |
| R_{9t} | 0.640 | 0.852 | 0.662 | 0.871 | 0.864 | 0.475 | 0.662 | 0.739 | 0.230 | 0.618 | 0.783 |
| R_{10t} | 0.552 | 0.579 | 0.519 | 0.616 | 0.611 | 0.484 | 0.533 | 0.572 | 0.609 | 0.171 | 0.650 |
| R_{11t} | 0.615 | 0.709 | 0.609 | 0.796 | 0.782 | 0.463 | 0.585 | 0.738 | 0.771 | 0.669 | 0.232 |

Notes: Sample correlation matrix for the eleven Eurozone stock market index return series (1. Austria 2. Belgium 3. Finland 4. France 5. Germany 6. Greece 7. Ireland 8. Italy 9. Netherlands 10. Portugal 11. Spain) over the sample period from January 2, 1992 to December 30, 2010. Sample correlations of national stock index returns are above the diagonal, and first-order autocovariance and cross-covariance adjusted correlations below the diagonal. The diagonal elements are first-order autocovariance-consistent estimates of the annualized standard deviations.

Table 1.3: Cross-correlation matrix

| | R_{1t-1} | R_{2t-1} | R_{3t-1} | R_{4t-1} | R_{5t-1} | R_{6t-1} | R_{7t-1} | R_{8t-1} | R_{9t-1} | R_{10t-1} | R_{11t-1} |
|------------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|-------------|-------------|
| R_{1t-1} | 0.075 | -0.004 | -0.020 | -0.050 | -0.040 | 0.709 | 0.043 | -0.020 | -0.022 | 0.007 | -0.034 |
| R_{2t-1} | 0.115 | 0.089 | 0.045 | 0.011 | 0.018 | 0.121 | 0.114 | 0.032 | 0.039 | 0.065 | 0.009 |
| R_{3t-1} | 0.040 | -0.011 | 0.029 | -0.015 | -0.017 | 0.079 | 0.052 | -0.001 | -0.016 | 0.023 | -0.019 |
| R_{4t-1} | 0.108 | 0.044 | 0.049 | -0.012 | 0.017 | 0.114 | 0.104 | 0.016 | 0.009 | 0.055 | -0.008 |
| R_{5t-1} | 0.099 | 0.066 | 0.071 | 0.025 | -0.016 | 0.138 | 0.126 | 0.031 | 0.043 | 0.079 | 0.023 |
| $Y_1 = R_{6t-1}$ | 0.065 | 0.018 | 0.011 | 0.012 | 0.016 | 0.131 | 0.055 | 0.025 | 0.009 | 0.052 | 0.010 |
| R_{7t-1} | 0.063 | 0.004 | -0.024 | -0.048 | -0.032 | 0.083 | 0.067 | -0.017 | -0.023 | 0.001 | -0.034 |
| R_{8t-1} | 0.093 | 0.034 | 0.037 | -0.012 | 0.007 | 0.099 | 0.083 | 0.027 | 0.009 | 0.055 | -0.003 |
| R_{9t-1} | 0.099 | 0.045 | 0.031 | -0.014 | -0.005 | 0.113 | 0.097 | 0.000 | -0.004 | 0.043 | -0.015 |
| R_{10t-1} | 0.055 | -0.005 | 0.005 | -0.032 | -0.021 | 0.101 | 0.063 | -0.019 | -0.021 | 0.105 | -0.027 |
| R_{11t-1} | 0.107 | 0.042 | 0.041 | -0.011 | 0.023 | 0.119 | 0.091 | 0.020 | 0.009 | 0.087 | 0.191 |

Notes: Cross-correlations for the eleven Eurozone stock market index return series (1. Austria 2.Belgium 3.Finland 4.France 5.Germany 6.Greece 7.Ireland 8.Italy 9.Netherlands 10.Portugal 11.Spain) over the sample period from January 2, 1992 to December 30, 2010. The diagonal elements are sample estimates of the first-order autocorrelations.

Table 1.4: GARCH(1,1) and MIDAS-GARCH coefficient estimates

| National Index | GARCH(1,1) | | | MIDAS-GARCH | | | |
|----------------|---------------------|----------------------|-----------------------|----------------------|-----------------------|-----------------------|--------------------|
| | c | α | β | α | β | θ | ω |
| Austria | 0.000*** (5.580) | 0.107*** (10.612) | 0.876*** (77.053) | 0.111*** (13.170) | 0.860*** (75.034) | 0.544*** (6.736) | -0.004 (-0.010) |
| Belgium | 0.000*** (5.631) | 0.114*** (11.654) | 0.873*** (83.805) | 0.133*** (16.925) | 0.843*** (82.0731) | 0.468*** (6.141) | 0.897** (1.846) |
| Finland | 0.000*** (3.599) | 0.063*** (9.003) | 0.935*** (134.704) | 0.075*** (20.647) | 0.903*** (145.817) | 0.819*** (14.802) | 0.421 (1.576) |
| France | 0.000*** (4.216) | 0.073*** (10.191) | 0.919*** (117.518) | 0.078*** (11.632) | 0.909*** (102.460) | 0.358*** (2.583) | 0.311 (0.557) |
| Germany | 0.000*** (5.531) | 0.093*** (10.901) | 0.897*** (102.600) | 0.094*** (13.875) | 0.887*** (98.616) | 0.480*** (4.466) | 0.411 (0.872) |
| Greece | 0.000*** (5.641) | 0.140*** (10.152) | 0.849*** (61.279) | 0.144*** (14.232) | 0.796*** (55.935) | 0.797*** (19.429) | 0.327 (1.493) |
| Ireland | 0.000*** (5.092) | 0.082*** (10.214) | 0.909*** (101.838) | 0.082*** (16.033) | 0.898*** (127.348) | 0.553*** (8.208) | -0.049 (-0.159) |
| Italy | 0.000*** (4.476) | 0.108*** (10.849) | 0.887*** (90.022) | 0.111*** (12.441) | 0.869*** (73.564) | 0.597*** (6.983) | 0.580 (1.443) |
| Netherlands | 0.000*** (4.982) | 0.099*** (12.143) | 0.895*** (109.758) | 0.107*** (14.183) | 0.876*** (92.624) | 0.578*** (6.685) | 0.640 (1.480) |
| Portugal | 0.000*** (5.811) | 0.175*** (12.186) | 0.831*** (67.683) | 0.166*** (25.599) | 0.804*** (96.889) | 0.584*** (10.0811) | 0.687** (2.135) |
| Spain | 0.000*** (5.414) | 0.103*** (10.343) | 0.885*** (81.999) | 0.104*** (13.231) | 0.871*** (79.515) | 0.520*** (6.858) | 0.965 (1.459) |

Notes: Columns 1-3: Individual GARCH(1,1) models are fitted to eleven Eurozone stock market indices using quasi-maximum likelihood estimation. The parameter space for each GARCH(1,1) model is $\Phi = \{c, \alpha, \beta\}$. The standard GARCH(1,1) model is defined as: $h_{it} = c + \alpha_i h_{i,t-1} + \beta_i \frac{\tilde{r}_{i,t-1}^2}{h_{i,t-1}}$ where h_{it} is the conditional variance. The t-statistics are reported in parentheses below the coefficient estimates. Columns 4-7: Individual MIDAS-GARCH models are fitted to eleven Eurozone stock market indices using quasi-maximum likelihood estimation. Each MIDAS-GARCH model is composed of several equations with a parameter space $\Theta = \{\alpha, \beta, \theta, \omega\}$. h_{it} denotes the baseline variance for asset i at time $t-1$ for time t returns capturing the low-frequency component of volatility: $h_{it} = (1 - \theta_i) h_{oi} + \theta_i c(\omega_i) \sum_{k=1}^4 \exp(-\omega_i k) RV_{i,t-nk}$, where RV_{it} denotes the 65-day realized variance up to day t : $RV_{it} = \sum_{j=0}^{65} \tilde{r}_{i,t-j}^2$. Short-term Garch effects are captured via a standard GARCH(1,1) model: $g_{it} = (1 - \alpha - \beta) + \alpha_i g_{i,t-1} + \beta_i \frac{\tilde{r}_{i,t-1}^2}{h_{i,t-1}}$. The t-statistics are reported in parentheses below the coefficient estimates. “***”, “**” indicates statistical significance at 1% and 5% level, respectively.

Table 1.5: Daily models of dynamic correlation magnitude

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8* | 9* | 10* |
|------------------------------|----------------------|----------------------|----------------------|-----------------------|----------------------|-----------------------|----------------------|----------------------|------------------------|----------------------|
| ratio_{t-1} | 0.518*** (20.892) | 0.533*** (20.529) | 0.509*** (19.631) | 0.507*** (19.668) | 0.575*** (22.422) | 0.496*** (18.765) | 0.548*** (20.479) | 0.558*** (8.881) | 0.537*** (11.827) | 0.510*** (8.473) |
| trend_t | 0.032*** (18.468) | 0.032*** (18.113) | 0.032*** (18.367) | 0.036*** (19.032) | 0.031*** (17.725) | 0.036*** (19.276) | 0.032*** (17.825) | 0.024*** (5.137) | 0.029*** (8.930) | 0.033*** (7.307) |
| cumret_t | | 0.002** (2.265) | | | | 0.000 (0.253) | -0.005** (-2.504) | 0.017*** (7.382) | | 0.004 (1.205) |
| negGDP_t | | | | -0.062*** (-4.948) | | -0.074*** (-3.871) | | | -0.225*** (-10.746) | |
| avegrowth_t | | | | | 0.003*** (5.886) | | 0.005*** (7.149) | | | 0.085*** (8.416) |
| avevar_t | | | 0.108 (1.412) | | | 0.242** (2.551) | 0.245** (2.609) | | | 0.217 (1.439) |
| vstoxx_t | | | | | | | | 0.737*** (11.419) | 0.754*** (12.734) | 0.826*** (12.607) |
| Nr of Obs | 4528 | 4528 | 4528 | 4528 | 4528 | 4528 | 4528 | 2779 | 2779 | 2779 |

Notes: The table reports estimated coefficients for the dynamic model of the correlation magnitudes using maximum likelihood. The sample period is January 2, 1992 to December 30, 2010. For the regressions marked with * the sample period is January 4, 1999 to December 30, 2010. The ten columns correspond to ten different specifications and differ only in the choice of the explanatory variables. Dependent variable is the dynamic correlation magnitude for all ten regressions. The seven macroeconomic variables are a lagged correlation ratio (using the previous 65 daily returns), a time trend, the average of the cumulative returns to the eleven indices over the previous 65 days, the contemporaneous proportion of the eleven markets which had negative real GDP growth during the quarter, the cross-sectional average of national GDP growth in the current quarter, the contemporaneous average sample variance (using the previous 65 daily returns) between the eleven markets, and the daily scaled and squared implied volatility index VSTOXX. The t-statistics are reported in parentheses below the coefficient estimates. “***”, “**”, “*” indicates statistical significance at 1%, 5% and 10% level, respectively.

Table 1.6: Effect of adjusting for the first-step estimation error

| Specification 6 | | | |
|------------------------|---------------------------------|-------------------------------|---------------------|
| | Unadjusted St Deviations | Adjusted St Deviations | % Difference |
| ratio _{t-1} | 0.0264 | 0.0264 | 0.016% |
| trend _t | 0.0019 | 0.0019 | -0.002% |
| cumret _{t-1} | 0.0019 | 0.0019 | 0.028% |
| avevar _{t-1} | 0.0949 | 0.0949 | 0.025% |
| negGDP _t | 0.0192 | 0.0192 | 0.024% |
| Specification 7 | | | |
| | Unadjusted St Deviations | Adjusted St Deviations | % Difference |
| ratio _{t-1} | 0.0268 | 0.0268 | 0.025% |
| trend _t | 0.0018 | 0.0018 | 0.008% |
| cumret _t | 0.0018 | 0.0018 | 0.017% |
| avevar _{t-1} | 0.0941 | 0.0941 | 0.053% |
| avegrowth _t | 0.0007 | 0.0007 | 0.013% |

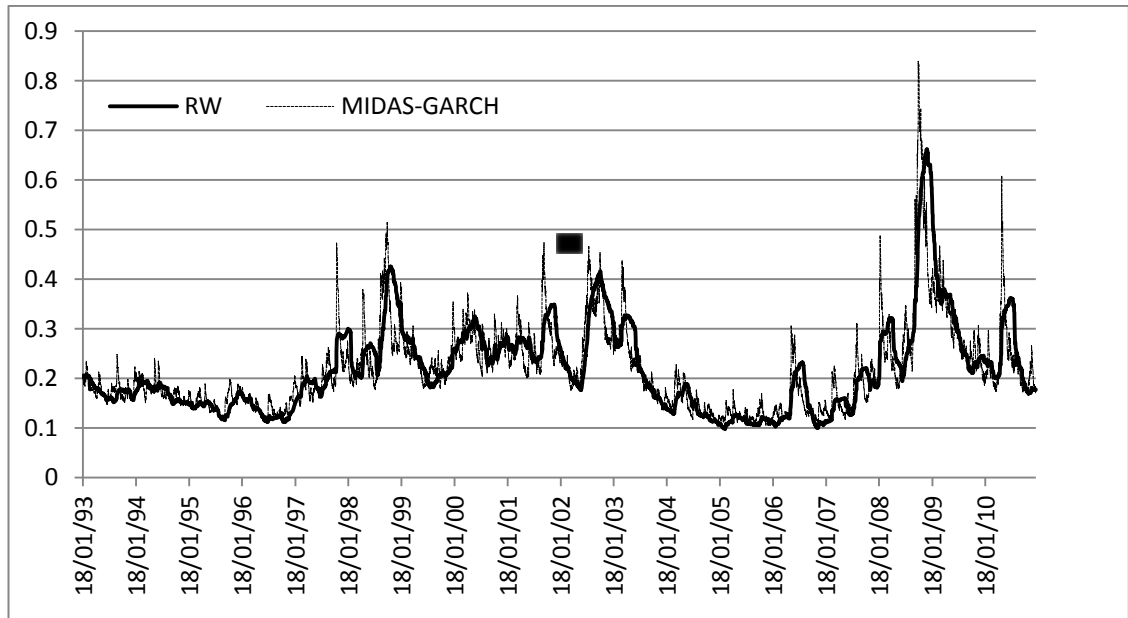
Notes: Table 1.6 compares the adjusted and unadjusted standard errors of the second-step coefficients for the dynamic correlation magnitude models 6 and 7 from Table 1.5. The standard errors of the coefficients in the second-step correlation matrix estimation are in general inconsistent due to the use of first-step estimated volatilities (Engle (2002)). To adjust for the first-step estimation error the standard outer product of the score vector (the chosen estimator for the covariance matrix of coefficients from the MIDAS-GARCH model) is multiplied by an adjustment matrix (see Equation (1.19)). The variables are the same as in Table 1.5.

Table 1.7: Quarterly models of the dynamic correlation ratio

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8* | 9* | 10* |
|------------------------------|---------------------|-----------------------|---------------------|---------------------|---------------------|----------------------|-----------------------|----------------------|---------------------|---------------------|
| ratio_{t-1} | 0.309*** (2.750) | 0.375*** (3.576) | 0.215** (1.994) | 0.332*** (2.882) | 0.320*** (2.815) | 0.293*** (2.782) | 0.306*** (2.965) | -0.031 (-0.219) | -0.071 (-0.452) | 0.058 (0.381) |
| trend_t | 0.042*** (5.241) | 0.036*** (4.788) | 0.045*** (5.919) | 0.042*** (4.975) | 0.042*** (5.210) | 0.040*** (5.522) | 0.040*** (5.572) | 0.090*** (6.147) | 0.095*** (6.276) | 0.091*** (6.394) |
| cumret_t | | -6.341*** (-3.740) | | | | -4.210** (-2.323) | -4.770*** (-2.687) | -5.735** (-2.062) | | -5.338* (-1.804) |
| negGDP_t | | | | -0.050 (-0.558) | | -0.228** (-2.627) | | | -0.068 (-0.427) | |
| avegrowth_t | | | | | 0.026 (0.730) | | 0.109*** (3.185) | | | 0.120* (1.957) |
| avevar_t | | | 6.012*** (3.538) | | | 6.245*** (2.664) | 6.399*** (3.318) | | | 5.080* (1.754) |
| vstoxx_t | | | | | | | | 0.496 (1.542) | 0.883** (2.355) | 0.378 (1.053) |
| Adj. R2 | 0.774 | 0.809 | 0.805 | 0.762 | 0.662 | 0.828 | 0.753 | 0.728 | 0.701 | 0.745 |
| SSR | 2.484 | 2.076 | 2.116 | 2.372 | 2.219 | 1.811 | 1.567 | 1.405 | 1.544 | 1.253 |
| Nr of Obs | 75 | 75 | 75 | 75 | 75 | 75 | 75 | 46 | 46 | 46 |

Notes: Table 1.7 reports estimated coefficients for the time series quarterly regressions to explain the movement in cross-sectional average correlation, where the correlations are estimated using one quarter of daily returns. Each quarter consists of the trading days in a nonoverlapping three-month period, starting with January –March. The sample period is January 2, 1992 to December 30, 2010. For the regressions marked with * the sample period is January 4, 1999 to December 30, 2010. The ten columns correspond to ten different specifications and differ only in the choice of the explanatory variables. Dependent variable is the ratio $\frac{(qavecorr_t - avecorr_0)}{(1 - avecorr_0)}$, where $qavecorr_t$ is the cross-sectional average correlation for all ten regressions and $avecorr_0$ is the average cross-sample correlation. The seven independent variables are the lagged correlation ratio for each calendar quarter, a time trend, the average of the contemporaneous quarterly returns to the eleven indices, the contemporaneous proportion of the eleven markets which had negative real GDP growth during the quarter, the cross-sectional average of national GDP growth in the current quarter, the contemporaneous average sample variance (also using one quarter of daily returns) between the eleven markets, and the quarterly scaled and squared implied volatility index VSTOXX. The t-statistics are reported in parentheses below the coefficient estimates. The last two rows report the adjusted R² and the sum of squared residuals. “***”, “**”, “*” indicates statistical significance at 1%, 5% and 10% level, respectively.

Figure 1.1: MIDAS-GARCH and rolling window annualized return standard deviations



Notes: The figure shows the cross-sectional average of the annualized predicted return standard deviations from the MIDAS-GARCH models and the cross-sectional annualized average of the 65-day rolling window return standard deviations.

Chapter 2 Correlation Dynamics in the G7 Stock Markets

2.1 Introduction

Cross border correlation analysis has been widely used as a foundation for two strands of research: portfolio diversification benefits and dependence structure between financial markets. The latter has proven to provide useful insight into contagion and spillover effects during financial crises. Thus, understanding the causes behind changing correlation level across financial markets has great importance for both policy makers and practitioners. Earlier studies on the dynamic cross border connectedness relied on analysis of simple correlation coefficients and in time it became apparent that parameterized models were needed for structured analysis.

This paper uses the econometric method proposed in the first chapter of this dissertation to examine the dynamic equity index return comovement within the G7 equity markets. The aim is to explore the long term trend in the correlation level of the G7 financial markets and its response to the constantly changing economic environment. Empirical results in this paper show a positive trend toward higher correlation and significant time-series autocorrelation in the magnitude of cross-market return correlation within the G7 equity markets. Correlation level is higher when financial markets experience turbulent periods. Equity markets appear to be more correlated when the countries in the sample experience a GDP growth. When looking at the full sample period it appears that the G7 equity markets are more correlated when recent cumulative returns are higher; the sample is split into "pre-crisis" and "crisis" period and the results for both subsamples are consistent with the full sample period.

This paper draws on several strands of literature as the econometric framework applied allows addressing several distinct questions. There is a substantial amount of literature studying whether the equity markets connectedness has changed over time. Time variation of asset return correlation level is now recognised as a stylized fact. However, the empirical evidence on the

trend persistence is mixed at best and appears to be dependent on the chosen sample period. A collection of papers argues that the dependence between equity markets has increased over time. Baele and Inghelbrecht (2010) report increasing correlations over the period of 1970's to mid-2000's within the developed markets. Christoffersen et al. (2012) conclude that the cross border equity market copula correlations have increased markedly throughout the 1989 - 2009 period. Bekaert et al. (2009) study interdependence of the equity returns of 23 developed markets and find an upward trend in return correlations only among the subsample of the European markets. In contrast to these findings, King et al. (1994) study the correlation between the equity markets of 16 developed markets for 1970 - 1988 and argue that the dependence between equity markets has not increased, except around the 1987 market crash. Carrieri et al. (2007) study the correlation trend across emerging markets and conclude that there is no common pattern for the period from 1977 to 2000.

A related research area examines international spillover effects in equity markets, e.g., King and Wadhvani (1990), Hamao et al. (1990), Engle et al. (1994), Booth and Tse (1996), and Kohonen (2013). There is increasing evidence that the correlation between financial markets is significantly higher during periods of volatile markets, as in Karolyi and Stulz (1996), Ang and Bekaert (1999), Longin and Solnik (1995, 2001), and Capiello et al. (2006). This strand of research is closely related to the analysis of correlation asymmetries. Empirical evidence shows that the correlation between equity markets is higher during bear markets than during bull markets, as found by Erb et al. (1994), Longin and Solnik (2001) and Ang and Chen (2002). Another relevant research area concerns empirical examination of the relationships between macroeconomic variables and stock market volatility, e.g., Schwert (1989), Hamilton and Lin (1996), Paye (2012) and Christiansen et al. (2012). So far little is known on the relationship between the asset return correlation and macroeconomic variables.

Given that the G7 equity markets have different trading hours the use of daily closing

prices leads to an underestimation of the true correlations between stock markets (Martens and Poon (2001)). Engle (2009) suggests to use time aggregated data to find the correct unconditional correlations. However, the use of low frequency data significantly reduces the number of observations available, which is inefficient for multivariate modeling, particularly when dealing with time varying parameters. Scholes and Williams (1977), Lo and MacKinlay (1990), RiskmetricsTM (1996) and Audrino and Bühlmann (2003) discuss the issue and propose econometric approaches to the problem. This paper utilizes the VAR-based method of synchronising the non-synchronous returns before computing the correlations as in Burns et al. (1998).

Once the index returns have been "synchronised", this paper follows the method set out in Connor and Suurlaht (2013a). They utilize the existing models in the multivariate GARCH framework. Specifically, asset return volatilities and correlations are modeled separately, which has become popular since the introduction of the Dynamic Conditional Correlation (DCC) model of Engle (2002). For correlation modeling a variant of the DCC model is used. Bollerslev (1990) develops a multivariate time series model with time varying conditional variances and covariances, but constant conditional correlations. Building upon this, Engle (2002) proposed the DCC model in which conditional correlation is also time varying. Colacito et al. (2011) utilize these specifications and propose a new class of component correlation models, the DCC-MIDAS correlation models. Connor and Suurlaht (2013a) amend the Engle (2002) model by adding to it a univariate measure of dynamic correlatedness. They successfully apply the new model to a sample of 11 Eurozone national stock market index series. The model proposed proves to be numerically easy to estimate by maximum likelihood, at least in the case of a modest number of asset returns.

The remainder of the paper is organized as follows. Section two describes the econometric model and estimation technique applied in this study. Section three describes the data and

presents all the empirical findings. Section four concludes the chapter.

2.2 Econometric Framework

2.2.1 Adjusting for Non-synchronous Data

The national equity markets of the G7 group are located in various time zones; thus, the end of day closing prices of the indices are not measured synchronously. It is important to address this issue as the use of daily close-to-close prices leads to a likely bias in the estimation of the correlations between the stock markets. The problem can be illustrated using MSCI Germany and MSCI USA Index returns. The Frankfurt Stock Exchange in Germany closes at 5.35pm CEST which is 11.35am EDT; the prices used to calculate the MSCI Indices are the official exchange closing prices. The New York Stock Exchange (NYSE) continues to operate for a further four and a half hours; the news that arrive to the market during this time are not reflected in the MSCI Germany end of day price. See Table 2.1 for local stock exchange closing times, all data are synchronised to the NYSE closing time. See Figure 2.1 for graphical illustration of the problem. To overcome the non-synchronous data problem Burns et al. (1998) propose estimating the closing prices of markets that have closed conditional on information of markets that are open. The synchronised return on the German equity index can be defined as

$$\hat{r}_t = r_t - \varepsilon_{t-1} + \varepsilon_t \quad (2.1)$$

where r_t is the observed, unsynchronised return on the German index at t and ε_t is the return we would have observed from the closing time of the German index at t to the closing time of the US index at t . Following Burns et al. (1998) the unobserved component is estimated using the linear projection of the observed non-synchronous return on the full information set of all recorded prices at time t .

The synchronisation model can be formulated as a first-order moving average (VMA(1)) model:

$$\hat{r}_t = \varepsilon_t - M\varepsilon_{t-1} \quad (2.2)$$

where M is the moving average matrix and ε_t is the unpredictable part of returns from the perspective of time $t - 1$. Next, the unsynchronised returns are defined as the change in the log of unsynchronised prices, $r_t = \log(P_t) - \log(P_{t-1})$ and the synchronised returns are defined as the change in the log of synchronised prices, $\hat{r}_t = \log(\hat{P}_t) - \log(\hat{P}_{t-1})$. The expected price at $t + 1$ is also an unbiased estimator of the synchronised price at t , provided that further changes in synchronised prices are unpredictable, i.e. $\log(P_{t+1}) = E(\log(P_{t+1}) | I_t)$. Thus, the synchronised returns are given by

$$\begin{aligned} \hat{r}_t &= E_t(\log(P_{t+1})) - E_{t-1}(P_t) \\ &= E_t(r_{t+1}) - E_{t-1}(r_t) + \log(P_t) - \log(P_{t-1}) \\ &= M\varepsilon_t - M\varepsilon_{t-1} + r_t \\ &= \varepsilon_t - M\varepsilon_{t-1}. \end{aligned} \quad (2.3)$$

Galbraith et al. (2002) show that M can be estimated based on a vector autoregressive approximation of order p , VAR(p). Therefore, M is estimated as follows. The VMA(1) is represented as the following infinite order VAR process

$$r_t = \sum_{j=1}^{\infty} B_j r_{t-j} + \varepsilon_t, \quad (2.4)$$

where the coefficients of the matrices B_j are given by

$$\begin{aligned} B_1 &= M_1 \\ B_i &= -B_{i-1}M_1 \text{ for } j = 2, \dots \end{aligned} \quad (2.5)$$

By applying a VAR approximation, VMA coefficients from those of the VAR can be obtained.

The VAR(p) model with $p > 1$ is fitted by least squares. From the p estimated coefficient matrices of dimension $N \times N$ of the VAR representation $r_t = B_1 r_{t-1} + \dots + B_p r_{t-p} + \varepsilon_t$, $N \times N$ dimensional M is estimated by the relation $\hat{B}_1 = \hat{M}_1$ based on Equation (2.5).

2.2.2 A DCC-MIDAS-GARCH Specification with Univariate Correlation Dynamics

This paper adopts the DCC-MIDAS-GARCH model together with a univariate measure of dynamic correlatedness as set out in Connor and Surlaht (2013a). This is done by imposing a particular functional form on the dynamics of the correlation matrix.

Assume r_t is an n -vector of returns on n assets over the interval $t - 1$ to t with a vector of means μ and time-varying nonsingular covariance matrix C_t :

$$\hat{r}_t = \mu + C_t^{1/2} \eta_t \quad (2.6)$$

where η_t is an i.i.d. mean-zero n -vector time series process with covariance matrix equal to the identity matrix. \tilde{r}_t is the vector of demeaned returns.

Let $s_t = (\sigma_{1t}, \dots, \sigma_{nt})$ denote the n -vector of individual asset return volatilities for time t returns based on time $t - 1$ information, and let

$\Omega_t = \{Cov_{t-1}(r_{it}/\sigma_{it}, r_{jt}/\sigma_{jt}), i, j = 1, \dots, n\}$ denote the conditional correlation matrix of returns, conditional on time $t - 1$ information.

2.2.2.1 A Review of MIDAS-GARCH

The starting point in Engle's DCC approach is to model the individual return volatilities separately. For the components of s_t a model essentially identical to that in Colacito et al. (2011) and Engle et al. (2008) is applied: each individual return volatility follows a MIDAS-GARCH model. MIDAS-GARCH differs from standard GARCH in allowing time t "baseline" variance to vary slowly through time. This corrects for a substantial flaw in standard GARCH when applied to long time samples, in particular, the empirically untenable assumption in standard GARCH that baseline variance is time-constant, see Taylor (1986).

Letting h_{it} denote baseline variance for asset i at time $t - 1$ for time t returns; it is assumed

that it is a weighted linear combination of unconditional variance h_{0i} and lagged realized variances:

$$h_{it} = (1 - \theta_i)h_{0i} + \theta_i c(\omega_i) \sum_{k=1}^K \exp(-\omega_i k) RV_{i,t-k}$$

with estimable parameters h_{0i} , θ_i , and ω_i , and where $RV_{i,t}$ denotes the J -period realized variance up to time t :

$$RV_{it} = \frac{1}{J} \sum_{j=1}^J \hat{r}_{i,t-j}^2,$$

and $c(\omega_i) = (\sum_{k=1}^K \exp(-\omega_i k))^{-1}$ ensures that the exponential weights sum to one. The model requires $h_{0i} > 0$ and $0 \leq \theta_i < 1$ to guarantee a covariance stationary process.

The slowly-changing variate h_{it} captures the low-frequency component of volatility but misses short-term GARCH effects. These are captured via a standard GARCH(1,1) model with unit unconditional variance:

$$g_{it} = (1 - \alpha_i - \beta_i) + \alpha_i g_{it-1} + \beta_i \frac{\hat{r}_{i,t-1}^2}{h_{it-1}},$$

with $\alpha_i, \beta_i \geq 0$ and $\alpha_i + \beta_i < 1$. The product of baseline variance and the short-term GARCH effect gives time t variance:

$$\sigma_{it}^2 = h_{it} g_{it}. \quad (2.7)$$

2.2.2.2 A Modified DCC Model with Univariate Dynamics

Following notation in Connor and Suurlaht (2013a) $Diag[x]$ is used to denote an $n \times n$ diagonal matrix with the n -elements of the vector x on the diagonal, and $diag[X]$ to denote the diagonal matrix consisting of the diagonal elements of any square matrix X with all non-diagonal elements set to zero. By definition the covariance matrix is the quadratic product of the volatilities and correlation matrix:

$$C_t = Diag[s_t] \Omega_t Diag[s_t]. \quad (2.8)$$

Building upon the constant conditional correlation model of Bollerslev (1990) (in which $\Omega_t = \Omega$, a time-constant matrix), Engle (2002) suggests modeling the correlation matrix separately from the volatilities and then combining them via (2.8) to produce a dynamic covariance matrix. Let

X_{1t}, X_{2t} denote two symmetric, positive semi-definite $n \times n$ matrices with at least one of which is strictly positive definite and let m_{1t}, m_{2t} denote two strictly positive scalars. (The case of two explanatory variables is used for notational convenience only; more or less are acceptable). Engle defines the quasi-correlation matrix Q_t as the linear combination:

$$Q_t = m_{1t}X_{1t} + m_{2t}X_{2t}. \quad (2.9)$$

The matrix Q_t is symmetric and positive definite but lacks one required property of a correlation matrix since the diagonal elements are not necessarily equal to one. Engle suggests a simple nonlinear transformation to impose this property while still maintaining symmetry and positive definiteness:

$$\Omega_t = \text{diag}[Q_t]^{-1/2}Q_t\text{diag}[Q_t]^{-1/2} \quad (2.10)$$

Equations (2.9) and (2.10) define Engle's DCC estimator. Together with models for the individual volatilities s_t , this gives a composite model of the dynamic covariance matrix.

The model applied in Connor and Suurlaht (2013a) differs from standard DCC in the way they restrict the dynamics of the correlation matrix. In place of the $\frac{1}{2}n(n-1)$ -dimensional correlation dynamics in Equation (2.9) Connor and Suurlaht (2013a) propose a univariate measure of time-varying correlation. This scalar measure of correlation magnitude should leave the pattern of correlation between individual markets essentially fixed. The model for Ω_t is formulated with a simple one-dimensional state variable m_t capturing the time variation in Ω_t . When the univariate state variable m_t is high, the correlations between markets are relatively strong, when m_t is low, the correlations are relatively weak, and when m_t equals zero the correlations are average. Except for this state variable the general "structure" of correlations is assumed invariant through time.

Let Ω_0 denote the time-constant unconditional correlation matrix:

$$(\Omega_0)_{ij} = \text{cov}_0\left[\frac{\tilde{r}_{it}}{\sigma_{it}}, \frac{\tilde{r}_{jt}}{\sigma_{jt}}\right]_{i,j=1,\dots,n} = E_0[\tilde{r}_t((\text{Diag}[s_t])^{-2})\tilde{r}_t'] \quad (2.11)$$

where the 0 subscript denotes the unconditional information set. Let U be the $n \times n$ matrix

consisting entirely of ones. The model for Ω_t is as follows:

$$\Omega_t = \Omega_0 + m_{t-1}(U - \Omega_0), \text{ for } -1 < m_{t-1} < 1. \quad (2.12)$$

The variable m_{t-1} is restricted to the interval $(-1, 1)$. It must be shown that (2.12) meets Engle's condition (2.9) that Ω_t is a positive linear combination of positive-semidefinite matrices. Suppose that the following condition holds:

$$2\Omega_0 - U \text{ is strictly positive definite.} \quad (2.13)$$

A necessary condition for this to hold is that all the off-diagonal elements of Ω_0 are positive; in the case that they are all equal this is also a sufficient condition. Confirming that condition (2.13) holds is a straightforward empirical task, and is a condition easily met in the current application. Note that (2.12) can be written as $\Omega_t = a_{t-1}(2\Omega_0 - U) + (1 + a_{t-1})U$ where $a_{t-1} = 2(m_{t-1} - \frac{1}{2})$. Since U is positive semi-definite and $0 < a_{t-1} < 1$ the system (2.12) meets the positive definiteness criterion. Using (2.10) then becomes redundant since the construction of the model always gives a matrix with units on the diagonal.

The model captures in a simple and intuitive way the notion that in some states of nature all correlations move higher, and in other states, lower. It provides a univariate measure of this dynamic correlation. The model sacrifices the generality of Engle's original DCC (where all the correlations can move independently) in favour of greater simplicity and interpretability. As in Engle et al. (2008), a linear structure is imposed on m_t based on a low-dimensional vector x_t of explanatory variables (such as macroeconomic variates and financial market stress indicators):

$$m_t = b'x_t \quad (2.14)$$

subject to $-1 < m_t < 1$. This mandates that the explanatory variables x_t have bounded support and imposes implicit restrictions on the parameters b (analogous to the positive-coefficient requirements of a GARCH model). It follows from (2.12) that the explanatory variables x_t must have unconditional expectations of zero.

The model for Ω_t consists of (2.11), (2.12), (2.13) and (2.14) with estimable parameters

a_0, b, Ω_0 . In the application considered, the endogenous variable m_t is daily but the explanatory variables are constant for all days within a quarterly frequency; this does not affect the econometric methodology.

Consider the average correlation at time t , found by averaging the off-diagonal elements of the time- t correlation matrix:

$$avecorr_t = \frac{1}{n(n-1)} \sum_{i \neq j} [\Omega_t]_{ij}. \quad (2.15)$$

Connor and Suurlaht (2013a) show that the linear dynamic equation for the correlation matrix (2.14) implies a univariate linear model of $avecorr_t$. Applying the matrix off-diagonal averaging transformation (2.15) to both sides of the dynamic correlation matrix equation (2.12) and rearranging, gives a variable that Connor and Suurlaht (2013a) call the correlation ratio; it is the deviation of time t average correlation from its long-term average, divided by one minus the long-term average:

$$ratio_t = \frac{avecorr_t - avecorr_0}{(1 - avecorr_0)} = m_t. \quad (2.16)$$

Inserting $ratio_t$ into (2.14) gives:

$$ratio_t = bx_t, \quad (2.17)$$

so that equation (2.14) in the dynamic system implies this linear model of time-varying average correlation.

2.2.3 A Maximum Likelihood Estimation Procedure

Following Engle (2002) and Colacito et al. (2011) the DCC-MIDAS-GARCH model is estimated by applying two-component maximum likelihood. Suppose that the innovation process η_t is i.i.d. multivariate normal; it is unit variance and uncorrelated by definition; see (2.6). Weakening the assumption of normality gives rise to a quasi-maximum likelihood interpretation rather than true maximum likelihood. Recall that $C_t = Diag[s_t]\Omega_t Diag[s_t]$ where C_t is the time- t covariance matrix. Using a standard result, under i.i.d. multivariate normality of the innovations the data generating process for the sample return vector has log

likelihood function:

$$\begin{aligned}
L &= -\frac{1}{2} \left(\sum_{t=1}^T (n \log(2\pi) + \log(|C_t|) + \tilde{r}_t' C_t^{-1} \tilde{r}_t) \right) \\
&= -\frac{1}{2} \left(\sum_{t=1}^T (n \log(2\pi) + \log(|\text{Diag}[s_t] \Omega_t \text{Diag}[s_t]|)) \right) \\
&\quad + \tilde{r}_t' (\text{Diag}[s_t] \Omega_t \text{Diag}[s_t])^{-1} \tilde{r}_t.
\end{aligned} \tag{2.18}$$

Let $\Theta_1 = \{h_{0i}, \theta_i, \omega_i, \alpha_i, \beta_i\}_{i=1, \dots, n}$ denote the parameters of the GARCH-MIDAS model, and $\Theta_2 = (\Omega_0, a_0, b)$ the parameters of the dynamic correlation matrix model. Following Engle (2002) a two-component maximum likelihood approach is utilized. In the first step the individual time series of returns are used to estimate the MIDAS-GARCH parameters Θ_1 for each asset separately. Note that this is a collection of n unrelated individual-asset MIDAS-GARCH maximization likelihood estimation problems. Then in the second step these consistent, limited-information maximum likelihood values of Θ_1 are used to substitute $\text{Diag}[\hat{s}_t]$ for $\text{Diag}[s_t]$ in (2.18) to find the maximum likelihood estimate of Θ_2 .

The first-step estimation decomposes into a collection of individual GARCH-type model estimation problems with additively separable log likelihood maximization problems:

$$\hat{\Theta}_{1i} = \arg \max_{\Theta_{1i}} L_{1i} \text{ where} \tag{2.19}$$

$$L_{1i} = \left\{ -\frac{1}{2} \left(\sum_{t=1}^T (\log(2\pi) + \log(h_{it}) + \frac{\tilde{r}_{it}^2}{h_{it}}) \right) \right\}. \tag{2.20}$$

In the second step, the first-step estimates from (2.19) are used to compute \hat{s}_t and then substitute this for s_t in (2.18) giving a maximum likelihood problem in the parameters Θ_2 only. Engle (2002) notes that the standard errors of the coefficients in the second-step correlation matrix estimation are in general inconsistent due to the use of first-step estimated volatilities. Connor and Suurlaht (2013a) implement the adjustment to the second-step parameter standard errors proposed by Engle (2002) and conclude that the adjustment has a negligible impact in their application. Therefore, this adjustment is excluded from the current analysis.

2.3 Data and Empirical Findings

The dataset consists of daily adjusted closing prices for Morgan Stanley Capital International (MSCI) national equity indices for the G7 stock markets, namely, France, Germany, Italy, UK, Japan, United States and Canada. The sample period spans twenty years, from 31st December 1990 to 31st December 2011 and includes 5427 observations. The entire dataset is obtained from Datastream at the daily frequency and subsequently daily log returns are computed. All equity index returns are denominated in US dollars. Common currency denomination alleviates the problem of the exchange rate movement effect. The Datastream database skips weekends and a few major holidays (Christmas and New Year's Day) but reproduces yesterday's closing price on other days on which a particular national exchange is closed. To partly correct for this, closing prices on days on which three or more of the seven national exchanges are closed are ignored, and such a day is treated the same as a weekend (the two-day return becomes a one-day return for the entire cross-section). Table 2.2 shows the annualized means and standard deviations, skewness, excess kurtosis, and first four autocorrelations for each of the seven return series.

2.3.1 Synchronised Daily Returns

Given that the G7 equity markets have different trading hours the use of daily closing prices leads to an underestimation of the true correlations between stock markets. Table 2.3 shows the daily sample correlations of the G7 equity index returns over the period January 2, 1991 to December 30, 2011. Of course, the true correlations are unknown, but it is reasonable to assume that due to the non-synchronous closing prices the sample correlations are underestimated. Engle (2009) suggests to use time aggregated data to find the correct unconditional correlations. Table 2.4 shows the sample correlations of the G7 equity returns series calculated using weekly data. Following Burns et al. (1998), the week is defined as five trading days and, thus, the daily log returns are aggregated over five consecutive days. The differences between daily and weekly correlations are not significant for the markets trading in the same time zone. In most cases the

weekly correlations are substantially higher for markets trading in different time zones. For example, correlation between MSCI France and US jumps from daily value of .474 to .711 for weekly correlation. MSCI Japan still appears to be least correlated with all other indices in G7.

If the differences arise from the non-synchronous data, lag effects should also reflect the underestimation of true correlations in the original data. Table 2.5 shows the lagged daily cross correlations for the G7 equity market index return series. The largest values are in the last two rows of the table, which implies that US and Canadian index returns predict markets that close earlier. As Japan is a full day behind all the other markets, it appears that it reacts to the news from other markets with a full lag. As a consequence, all markets predict the Japanese index.

Although using weekly data ameliorates the non-synchronicity problem, the use of low frequency data significantly reduces the number of observations available, which is inefficient for multivariate modeling, particularly when dealing with time varying parameters. Instead, we utilize the VAR-based method of synchronising the non-synchronous returns before computing the correlations as in Burns et al. (1998). Prior to estimating Equation (2.2), MSCI index return series are checked for non-stationarity using conventional tests. Both Augmented Dickey-Fuller test for unit root and Kwiatkowski–Phillips–Schmidt–Shin test for stationarity indicate that all seven log return series are stationary. The results of the tests are not reported in this paper.

Table 2.6 shows the daily correlations of the synchronised G7 equity index returns. As expected, the correlations for the markets trading in the same time zone are largely similar. Correlations between the synchronised US and other equity market indices are much closer to the weekly values than daily values. The only noticeable exception is the Japan equity index - when synchronised, it appears to be less correlated with all other markets. This finding lends support to view of low spillover transmission mechanism between Japanese and other G7 equity markets (e.g. Andrikopoulos et al. (2014), Tsai (2014)). The possible reason behind decreasing correlation of Japanese equity market and other markets when calculated using synchronised

returns is that weekly data may miss daily dynamics that contribute to the lower correlation.

2.3.2 The MIDAS-GARCH Models of Individual Market Index Volatility: G7 Equity Markets

Table 2.7 reports the estimates for the MIDAS-GARCH model. For all countries the sum of the two MIDAS-GARCH coefficients α_i and β_i is well within the stationary boundary $\alpha_i + \beta_i < 1$ for most countries in the sample, with the exception of Italy. The exponential weighting is close to 0 in most markets so that the optimal weighting is close to equal weighting of the four lagged fixed-window realized variances. The estimated decay coefficient θ_i varies from -.129 to 1.442 for the markets in the sample. The table shows that the covariance stationary, two-component MIDAS-GARCH volatility models with GARCH(1,1) short-term components and mean-reverting, exponentially-weighted medium-term components fit the daily equity index returns data sample reasonably well.

2.3.3 A Dynamic Model of G7 Stock Market Correlations

For the dynamic correlation matrix model (see Equation (2.14)) 7 different specifications are examined. The six explanatory variables are a time trend, the average cumulative return to the seven indices using the previous 65 days of returns, the proportion of the seven markets which had negative real GDP growth during the current quarter, the lagged correlation ratio (Equation (2.16)) using the previous 65 days of daily returns, the cross-sectional average GDP growth, and the contemporaneous average sample variance using the previous 65 daily returns. As an alternative specification, cross-sectional average of national GDP growth in the current quarter is used. This has a correlation of $-.84$ with the negative-growth-proportion variable, so one or the other of these two explanatory variables is used but not both simultaneously. All the explanatory variables are de-meanned.

Table 2.8 shows the estimation results for the full sample. Six potential explanatory variables allow specification of a large number of various regression models. The seven specifications in Tables 2.8 and 2.9 were chosen as follows. The lagged daily correlation ratio and time trend have

a strong empirical/theoretical foundation, therefore, both are included in all specifications. For the other variables, the cumulative return measure, negative GDP growth proportion or average GDP growth, and lagged average variance, combinations are tried: none, each alone, and all three together. Although not reported, the results presented in Table 2.8 are replicated using the weekly data that is free from the non-synchronous problem. The results using weekly data are very similar to when the synchronised daily data is used.

The sample is subsequently divided into "pre-crisis" and "crisis" periods and results for the two periods are compared. Table 2.9 presents the estimation results when the sample is split in two: January 2, 1991 to November 30, 2007 and December 01, 2007 to December 30, 2011. No formal testing procedure was performed to detect the break date as the G7 countries entered recessionary period at different times. It would be impossible to detect a simultaneous break for all countries in the sample and there is no official date for the start of the global financial crisis. Therefore, the break was chosen based on the observation of the historical events at the start of the crisis: the first signs of the turbulence moving across border from the US could be observed in early December 2007 (ECB Press Release, December 2007).

When considering the full sample, an autocorrelation effect is observed, captured by the positive coefficient on the lagged 65-day empirical correlation ratio. There is a strong positive trend in correlation level over this time period within the G7 financial markets. Similar result can be observed in the two subsamples (Table 2.9 (a),(b)). Although the autocorrelation and the increasing trend effects appear to be slightly weaker for the "crisis" period, it can be concluded that this finding is not dependent on the state of the financial markets.

The "downside correlation" known from previous literature is not observed in either full (Table 2.8) or subsamples (Table 2.9 (a),(b)). However, this should not be interpreted as a contradiction to the past empirical literature. The variable used in this analysis is average cumulative return to the seven indices using the previous 65 days of returns. It is well known that

the G7 equity markets go through up and down phases at different time periods and by averaging cumulative returns we may not be able to capture the overall state of the G7 financial markets.

There is a business-cycle-related effect present in the full sample (Table 2.8): correlation level is lower when the proportion of markets with negative GDP growth is higher. The same finding holds when average GDP growth is used as an alternative variable (with the opposite sign, obviously). This shows that there seems to be greater diversity in the national index returns when several G7 economies are in a business cycle downturn or their average GDP growth is lower. Connor and Suurlaht (2013a) apply the econometric framework described above to the Eurozone markets and find a very similar result. Splitting the full sample into two subsamples (Table 2.9 (a), (b)) reveals a notable finding: the full sample result is driven by the "crisis" period. During the "pre-crisis" period correlation level is higher when the proportion of markets with negative GDP growth is higher (same holds when looking at the average GDP growth variable). The results for the "crisis" period are consistent with the full sample. The business-cycle-related effect is dependent on the state of the financial markets.

Table 2.8 reports that there is a positive relationship between the average variance across the G7 equity index returns and the dynamic correlation measure. This is consistent with previous literature that consistently find higher correlation between markets when they are experiencing volatile periods. Table 2.9 shows, however, that this finding is also largely driven by the state of the financial markets: the average variance variable is statistically significant only for the "crisis" period subsample.

2.4 Conclusion

Although globalisation has significantly changed the dynamics of correlation levels of international financial markets, the recent crisis has shown that financial markets react strongly to local factors. This paper explores the long term trend in the correlation magnitude of the G7 financial markets and its response to the constantly changing economic environment. The full

sample period is 31 December 1990 to 31 December 2011, which is divided into "pre-crisis" and "crisis" periods.

To measure the level of correlation across the G7 equity markets we use the econometric method proposed in Connor and Suurlaht (2013a), who propose adding a univariate measure of dynamic correlatedness to the DCC model of Engle (2002). The empirical results show that for the full sample, G7 markets exhibit a significant positive trend toward higher cross-border correlations over the sample period and there is significant time-series autocorrelation in the magnitude of cross-market return correlations. This finding is also consistent for both subsamples.

Correlation magnitude seems to behave differently during the "pre-crisis" and "crisis" periods in relation to the business-cycle-related effect and the turbulence of the financial markets. During the "crisis" period the average correlation between these financial markets is lower when more of them have negative GDP growth or when their average GDP growth is lower. The reverse holds for the "pre-crisis" period. Also, the positive relationship between the correlation magnitude and stock market variance is only present in the "crisis" period.

2.5 Tables and Figures

Table 2.1: Market closing times

| MSCI Index | France | Germany | Italy | UK | Japan | USA | Canada |
|--------------------|--------|---------|--------|--------|-------|-----|--------|
| Closing Local Time | 5.35pm | 5.35pm | 5.40pm | 4.35pm | 3pm | 4pm | 4pm |
| 4pm New York Time | 10pm | 10pm | 10pm | 9pm | 6am | 4pm | 4pm |

Notes: First row of the table reports the official exchange local closing times. The second row reports the local time for each market when it is 4pm in New York.

Table 2.2: Summary statistics

| Series | Obs | Annualized Mean Return | Annualized Std Deviation | Skewness | Excess Kurtosis | ρ_1 | ρ_2 | ρ_3 | ρ_4 |
|---------|------|------------------------|--------------------------|----------|-----------------|----------|----------|----------|----------|
| France | 5427 | 4.73 | 24.12 | -0.09 | 6.51 | 0.0059 | -0.0441 | -0.0585 | 0.0368 |
| Germany | 5427 | 4.48 | 25.20 | -0.22 | 5.79 | 0.0007 | -0.0281 | -0.0308 | 0.0305 |
| Italy | 5427 | 0.65 | 26.19 | -0.14 | 5.49 | 0.0436 | -0.0279 | -0.0414 | 0.0509 |
| UK | 5427 | 3.59 | 20.96 | -0.12 | 8.84 | -0.0016 | -0.0459 | -0.0739 | 0.0402 |
| Japan | 5427 | -1.12 | 23.84 | 0.11 | 4.20 | -0.0145 | -0.0562 | -0.0186 | 0.0127 |
| Canada | 5427 | 6.74 | 19.05 | -0.25 | 8.82 | -0.0617 | -0.0337 | -0.0049 | -0.0025 |
| US | 5427 | 7.55 | 21.55 | -0.81 | 10.86 | 0.0656 | -0.0574 | 0.0380 | 0.0292 |

Notes: Summary statistics including the first four autocorrelations for the G7 stock market index daily log return series over the sample period from January 2, 1991 to December 30, 2011 (5427 observations).

Table 2.3: Daily correlations of G7 equity index returns

| | fra_t | ger_t | ita_t | uk_t | jap_t | us_t | can_t |
|---------|---------|---------|---------|--------|---------|--------|---------|
| fra_t | 1.000 | 0.840 | 0.786 | 0.825 | 0.227 | 0.473 | 0.557 |
| ger_t | 0.840 | 1.000 | 0.733 | 0.751 | 0.221 | 0.491 | 0.541 |
| ita_t | 0.786 | 0.733 | 1.000 | 0.706 | 0.189 | 0.402 | 0.487 |
| uk_t | 0.825 | 0.751 | 0.706 | 1.000 | 0.227 | 0.458 | 0.556 |
| jap_t | 0.227 | 0.221 | 0.189 | 0.227 | 1.000 | 0.048 | 0.172 |
| us_t | 0.473 | 0.491 | 0.402 | 0.458 | 0.048 | 1.000 | 0.670 |
| can_t | 0.557 | 0.541 | 0.487 | 0.556 | 0.172 | 0.670 | 1.000 |

Notes: Daily sample correlation matrix for the G7 stock market index log return series (France, Germany, Italy, UK, Japan, US and Canada) over the sample period from January 2, 1991 to December 30, 2011.

Table 2.4: Weekly correlations of G7 equity index returns

| | fra _t | ger _t | ita _t | uk _t | jap _t | us _t | can _t |
|------------------|------------------|------------------|------------------|-----------------|------------------|-----------------|------------------|
| fra _t | 1.000 | 0.884 | 0.776 | 0.824 | 0.420 | 0.711 | 0.681 |
| ger _t | 0.884 | 1.000 | 0.742 | 0.775 | 0.408 | 0.706 | 0.654 |
| ita _t | 0.776 | 0.742 | 1.000 | 0.688 | 0.330 | 0.588 | 0.580 |
| uk _t | 0.824 | 0.775 | 0.688 | 1.000 | 0.429 | 0.694 | 0.681 |
| jap _t | 0.420 | 0.408 | 0.330 | 0.429 | 1.000 | 0.360 | 0.413 |
| us _t | 0.711 | 0.706 | 0.588 | 0.694 | 0.360 | 1.000 | 0.752 |
| can _t | 0.681 | 0.654 | 0.580 | 0.681 | 0.413 | 0.752 | 1.000 |

Notes: Weekly sample correlation matrix for the G7 stock market index log return series (France, Germany, Italy, UK, Japan, US and Canada) over the sample period from January 2, 1991 to December 30, 2011.

Table 2.5: Lagged cross correlations of G7 equity index returns

| | fra _t | ger _t | ita _t | uk _t | jap _t | us _t | can _t |
|--------------------|------------------|------------------|------------------|-----------------|------------------|-----------------|------------------|
| fra _{t-1} | 0.006 | 0.024 | 0.025 | 0.001 | 0.298 | -0.017 | 0.064 |
| ger _{t-1} | 0.043 | 0.001 | 0.037 | 0.033 | 0.277 | -0.011 | 0.071 |
| ita _{t-1} | 0.007 | 0.015 | 0.044 | -0.006 | 0.245 | -0.006 | 0.061 |
| uk _{t-1} | 0.010 | 0.011 | 0.020 | -0.002 | 0.296 | -0.022 | 0.059 |
| jap _{t-1} | -0.037 | -0.031 | -0.027 | -0.041 | -0.014 | -0.035 | -0.015 |
| us _{t-1} | 0.269 | 0.232 | 0.212 | 0.283 | 0.347 | -0.062 | 0.153 |
| can _{t-1} | 0.137 | 0.112 | 0.113 | 0.144 | 0.305 | -0.085 | 0.066 |

Notes: Lagged cross correlations for the G7 stock market index return series (France, Germany, Italy, UK, Japan, US and Canada) over the sample period from January 2, 1991 to December 30, 2011. The diagonal elements are sample estimates of the first-order autocorrelations.

Table 2.6: Daily correlations of synchronised G7 equity index returns

| | fra _t | ger _t | ita _t | uk _t | jap _t | us _t | can _t |
|------------------|------------------|------------------|------------------|-----------------|------------------|-----------------|------------------|
| fra _t | 1.000 | 0.838 | 0.719 | 0.612 | 0.205 | 0.875 | 0.501 |
| ger _t | 0.838 | 1.000 | 0.705 | 0.555 | 0.078 | 0.873 | 0.498 |
| ita _t | 0.719 | 0.705 | 1.000 | 0.479 | 0.046 | 0.807 | 0.447 |
| uk _t | 0.612 | 0.555 | 0.479 | 1.000 | 0.260 | 0.697 | 0.452 |
| jap _t | 0.205 | 0.078 | 0.046 | 0.260 | 1.000 | 0.177 | 0.148 |
| us _t | 0.875 | 0.873 | 0.807 | 0.697 | 0.177 | 1.000 | 0.690 |
| can _t | 0.501 | 0.498 | 0.447 | 0.452 | 0.148 | 0.690 | 1.000 |

Notes: Daily sample correlation matrix for the synchronised G7 stock market log index return series (France, Germany, Italy, UK, Japan, US and Canada) over the sample period from January 2, 1991 to December 30, 2011.

Table 2.7: MIDAS-GARCH coefficient estimates

| | α | β | θ | ω |
|---------|----------|-----------|----------|----------|
| France | 0.070*** | 0.918*** | 0.341** | 0.572 |
| | (11.921) | (108.631) | (2.207) | (1.051) |
| Germany | 0.094*** | 0.887*** | 0.480*** | 0.411 |
| | (13.875) | (98.616) | (4.466) | (0.872) |
| Italy | 0.081*** | 0.923*** | 0.016*** | 1.442 |
| | (11.487) | (140.286) | (0.118) | (0.148) |
| UK | 0.072*** | 0.905*** | 0.523*** | 0.716* |
| | (12.276) | (95.243) | (4.842) | (1.705) |
| Japan | 0.099*** | 0.863*** | 0.384*** | 0.465 |
| | (16.794) | (101.165) | (3.585) | (1.146) |
| US | 0.088*** | 0.895*** | 0.639*** | 0.373 |
| | (14.175) | (104.268) | (6.821) | (0.956) |
| Canada | 0.077*** | 0.905*** | 0.596*** | -0.129 |
| | (11.583) | (90.934) | (8.151) | (-0.382) |

Notes: Individual MIDAS-GARCH models are fitted to G7 stock market indices using quasi-maximum likelihood estimation. Each MIDAS-GARCH model is composed of several equations with a parameter space $\Theta = \{\alpha, \beta, \theta, \omega\}$. h_{it} denotes the baseline variance for asset i at time $t-1$ for time t returns capturing the low-frequency component of volatility: $\mathbf{h}_{it} = (\mathbf{1} - \boldsymbol{\theta}_i)\mathbf{h}_{oi} + \boldsymbol{\theta}_i\mathbf{c}(\boldsymbol{\omega}_i) \sum_{k=1}^4 \exp(-\boldsymbol{\omega}_i\mathbf{k})\mathbf{RV}_{i,t-nk}$,

where RV_{it} denotes the 65-day realized variance up to day t : $\mathbf{RV}_{it} = \sum_{j=0}^{65} \hat{r}_{i,t-j}^2$. Short-term GARCH

effects are captured via a standard GARCH(1,1) model: $\mathbf{g}_{it} = (\mathbf{1} - \boldsymbol{\alpha} - \boldsymbol{\beta}) + \boldsymbol{\alpha}_i\mathbf{g}_{i,t-1} + \boldsymbol{\beta}_i \frac{\hat{r}_{i,t-1}^2}{h_{i,t-1}}$. The t -statistics are reported in parentheses below the coefficient estimates. “***”, “**”, “*” indicates statistical significance at 1%, 5% and 10% level, respectively.

Table 2.8: Daily models of dynamic correlation magnitude: Full sample

| Full Sample | | | | | | | |
|------------------------------|----------------------|----------------------|----------------------|-----------------------|----------------------|----------------------|----------------------|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ratio_{t-1} | 0.663*** (19.343) | 0.670*** (19.348) | 0.622*** (17.704) | 0.688*** (19.736) | 0.676*** (19.330) | 0.646*** (18.032) | 0.632*** (17.733) |
| trend_t | 0.028*** (21.254) | 0.027*** (21.246) | 0.027*** (20.264) | 0.027*** (20.793) | 0.028*** (21.328) | 0.025*** (19.336) | 0.026*** (19.569) |
| cumret_t | | 0.005* (1.846) | | | | 0.013*** (3.175) | 0.017*** (3.804) |
| negGDP_t | | | | -0.055*** (-3.256) | | -0.047** (-2.091) | |
| avegrowth_t | | | | | 0.002** (2.228) | | 0.001 (0.588) |
| avevar_t | | | 0.408*** (6.885) | | | 0.638*** (9.178) | 0.652*** (9.153) |

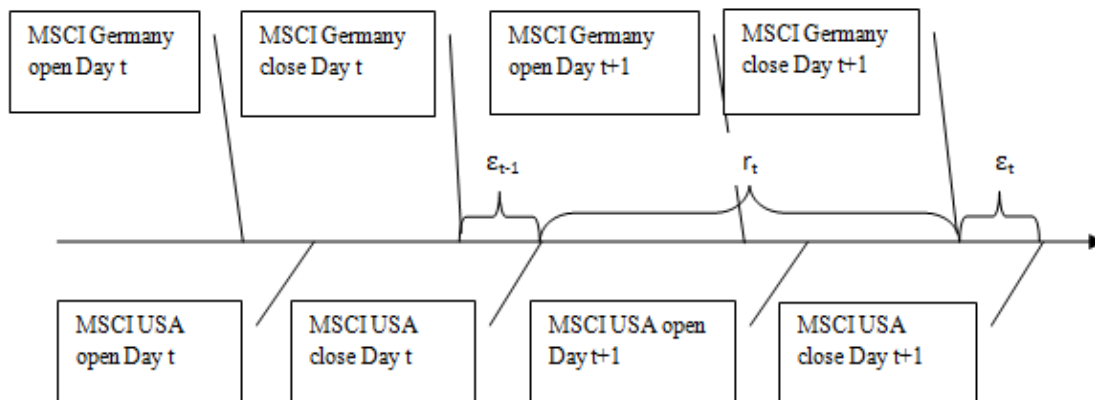
Notes: The table reports estimated coefficients for the dynamic model of the correlation magnitudes using maximum likelihood. The sample period is January 2, 1991 to December 30, 2011. The seven columns correspond to seven different specifications and differ only in the choice of the explanatory variables. The dependent variable is the dynamic correlation magnitude for all seven regressions. The six macroeconomic variables are a lagged correlation ratio (using the previous 65 daily returns), a time trend, the average of the cumulative returns to the G7 indices over the previous 65 days, the contemporaneous proportion of the seven markets which had negative real GDP growth during the quarter, the cross-sectional average of national GDP growth in the current quarter and the contemporaneous average sample variance (using the previous 65 daily returns) between the seven markets. The t-statistics are reported in parentheses below the coefficient estimates. “***”, “**”, “*” indicates statistical significance at 1%, 5% and 10% level, respectively.

Table 2.9: Daily models of dynamic correlation magnitude: Split sample

| a) January 1991 - November 2007 | | | | | | | |
|---|----------------------|----------------------|----------------------|-----------------------|-----------------------|----------------------|-----------------------|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ratio_{t-1} | 0.703*** (16.890) | 0.704*** (16.886) | 0.695*** (16.440) | 0.676*** (15.835) | 0.663*** (15.625) | 0.659*** (15.054) | 0.633*** (14.438) |
| trend_t | 0.031*** (14.471) | 0.031*** (14.573) | 0.032*** (14.180) | 0.033*** (14.862) | 0.034*** (15.523) | 0.034*** (14.502) | 0.035*** (14.624) |
| cumret_t | | 0.003 (0.4780) | | | | 0.013** (1.991) | 0.024*** (3.272) |
| negGDP_t | | | | 0.083** (2.203) | | 0.115*** (2.699) | |
| avegrowth_t | | | | | -0.014*** (-4.478) | | -0.020*** (-5.226) |
| avevar_t | | | 0.214 (0.833) | | | 0.311 (1.044) | 0.596** (1.877) |
| b) December 2007 - December 2011 | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| ratio_{t-1} | 1.297*** (11.854) | 1.832*** (10.521) | 0.403 (1.363) | 1.747*** (11.674) | 1.856*** (13.246) | 0.433 (1.230) | 0.541 (1.665) |
| trend_t | 0.025*** (6.985) | 0.012** (2.159) | 0.045*** (7.787) | 0.008 (1.374) | 0.007* (1.754) | 0.028*** (3.682) | 0.028*** (3.913) |
| cumret_t | | 0.017*** (4.114) | | | | 0.004 (0.601) | 0.003 (0.439) |
| negGDP_t | | | | -0.129*** (-4.975) | | -0.096** (-2.283) | |
| avegrowth_t | | | | | 0.007*** (6.335) | | 0.005 (2.357) |
| avevar_t | | | 0.976*** (5.775) | | | 0.899*** (4.770) | 0.845*** (4.737) |

Notes: The table reports estimated coefficients for the dynamic model of the correlation magnitudes using maximum likelihood. The sample period January 2, 1991 to December 30, 2011 is split in two: January 2, 1991 to November 30, 2007 and December 01, 2007 to December 30, 2011 to detect a structural break. The seven columns correspond to seven different specifications and differ only in the choice of the explanatory variables. Dependent variable is the dynamic correlation magnitude for all seven regressions. The six macroeconomic variables are a lagged correlation ratio (using the previous 65 daily returns), a time trend, the average of the cumulative returns to the G7 indices over the previous 65 days, the contemporaneous proportion of the seven markets which had negative real GDP growth during the quarter, the cross-sectional average of national GDP growth in the current quarter and the contemporaneous average sample variance (using the previous 65 daily returns) between the seven markets. The t-statistics are reported in parentheses below the coefficient estimates. “***”, “**”, “*” indicates statistical significance at 1%, 5% and 10% level, respectively.

Figure 2.1: Graphical illustration of the non-synchronous data problem



Notes: This figure illustrates the problem of non-synchronous data. Two indices are considered: MSCI Germany and MSCI USA. Time t lies on the horizontal axis, MSCI Germany closes at 5.35pm CEST which is 11.35am EDT. ε_t is the unobserved component of the synchronised closing price $\hat{r}_t = r_t - \varepsilon_{t-1} + \varepsilon_t$ (see also Burns et al., 1998)

Chapter 3 Directional Spillovers in Banks' Credit Default Risk and Related Variables

3.1 Introduction

In the aftermath of the recent financial crisis existing literature has devoted significant resources to establishing key determinants of the credit risk of various entities. Pinpointing the exact drivers of credit risk for financial and non-financial institutions alike has proven to be a Sisyphean task. It has been shown that not only do variables that follow from structural credit risk models have limited explanatory power in credit risk spreads (Eom et al. 2004, Ericsson et al. 2009), but the relative importance of the different credit risk factors changes substantially over time (González-Hermosillo, 2008; Annaert et al. 2013). Moreover, the explanatory power of credit risk variables depends on the type of the entity studied. For example, Raunig (2011) finds that the financial markets distinguish between the banks and other firms when pricing the default risk and Grammatikos and Vermeulen (2012) show that the relationships between certain credit risk variables are important for financial but not for non-financial firms. These issues show that the dynamics behind the credit risk is of a highly complex nature and call for a flexible framework.

The recent financial crisis has highlighted the importance of the banking system to the functioning of the economy as a whole in most countries affected by the turmoil. This paper analyses the directional spillovers within carefully selected variables directly related to the credit risk of financial institutions ("banks" for short) over the period from 1st of January 2004 to 31st of December 2012. The spillover analysis is undertaken within five European Union countries: core countries France and Germany, periphery countries Spain and Italy, and a reference country UK. The contribution of this paper to the existing literature is threefold. First, following the methodology proposed in Diebold and Yilmaz (2012) the dynamic spillover effects between the banks' credit risk spreads and related variables are studied. The aim is to allow for the

direction of the spillover effects to change over time while avoiding imposing any particular structural model. Second, it introduces a significant variable into the analysis that has not been widely studied in this context before - the real estate market risk. Third, Bai and Perron (2003) procedure is applied to test for multiple structural breaks in net spillovers of credit risk variables. This allows detecting the exact dates when relationships between the credit risk variables changed.

There are different measures of the credit risk itself, two being the most popular ones: corporate bond and bank credit default swap (CDS) spreads. It has been shown that under a set of restrictive assumptions CDS spreads and bond spreads are closely related (Duffie, 1999; Hull et al. 2004). This paper uses the CDS spreads to measure the banks' credit risk for several reasons. CDS spreads can be easily observed, while bond spreads have to be derived using a risk free benchmark rate and it can be notoriously difficult to choose an appropriate rate for calculations (Houweling and Vorst, 2005). Hull et al. (2004) and Blanco et al. (2005) show that CDS spreads react faster to information related to the credit quality of the underlying reference entity compared to bond spreads. Credit default swaps (CDS) can best be thought of as a simple insurance product, providing insurance against corporate default. Periodic payments are exchanged against a lump sum payment contingent on default.

The real estate sector is an important constituent of bank portfolios in countries with highly developed financial systems. Goodhart and Hofmann (2008) find that due to the banks' role as mortgage lenders and the frequent use of real estate as collateral, sustained imbalances in real estate markets can threaten the stability of the financial sector. However, the relationship between the real estate sector and bank stability is multidirectional. On the one hand, increase in the real estate prices may raise the economic value of bank's real estate portfolio, which in turn may increase the value of loans collateralized by real estate, decrease perceived risk of real estate lending and further increase the price of real estate. On the other hand, reverse process

applies. A decline in the real estate prices can have a negative effect on bank's capital to the extent banks own real estate. As a result, banks are vulnerable to a decline in the real estate prices and may face default if greatly exposed to real estate lending. Herring and Wachter (1999) analyse how real estate cycles and banking crises are related and show that even in very different institutional settings real estate booms often end in banking busts. Martins et al. (2012) and Mei and Saunders (1995) show that there is a positive relation between bank stock returns and real estate returns after controlling for general market conditions and interest rates in US and Euro area, respectively. Koetter and Poghosyan (2010) find that house price deviations from their fundamental value contribute to bank instability.

This paper adopts the econometric method proposed in Diebold and Yilmaz (2012) to measure dynamic spillovers between the CDS spreads and other credit risk determinants. This is of particular interest since measuring and revealing spillover trends could help monitoring the early signs of difficulties in the banking system.

Diebold and Yilmaz (2009) provide a simple and intuitive measure of interdependence using variance decompositions of traditional vector autoregression (VAR) model. Variance decompositions allow splitting the forecast error variances of each VAR model variable into parts attributable to the various system shocks. Diebold and Yilmaz (2012) show that this method can be further improved by applying the generalized VAR framework originally proposed in Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998). Generalized VAR framework circumvents the issue of dependence on variable ordering present in the traditional VAR model. Thus, it allows measuring not only total spillovers within variables included in the VAR framework, but also directional spillovers and net pairwise spillovers within variables in the system. The Diebold-Yilmaz method proves to be even more useful when estimated on a moving window basis as it then allows to see how spillover trends vary over time.

Despite of the numerous advantages and useful insights provided by the Diebold and Yilmaz

(2012) framework there are some downsides to using this method. First, the framework does not imply any causality. It is up to the reader to interpret the changes in the spillover index. Second, it is unknown whether the change in spillover index is caused by a favourable or unfavourable event. Intuitively one may associate the increase in the spillover index with negative shocks based on existing findings in the financial research field. However, the Diebold and Yilmaz (2012) framework does not make assumptions about asymmetry of negative or positive shocks to the system. Third, when applying the Diebold-Yilmaz framework on a rolling window basis, the method potentially introduces serial autocorrelation in the resulting time series.

In order to give structure to the analysis of net spillover indices it is important to find significant turning points in the series resulting from the Diebold-Yilmaz framework. Bai and Perron (1998, 2003) propose a procedure that allows estimating a model with an unknown number of structural breaks that occur at unspecified dates. Since this paper analyses five variables in five countries that are affected by both country specific and cross border events, the dynamics of spillovers can differ significantly for each country. The Bai-Perron method proves to be a flexible data-driven method that does not require imposing break dates or the number of breaks a priori.

The paper is organised as follows. Section two describes the methodological approach. Section three describes the data used for empirical analysis. Section four presents the empirical findings of the paper. Section five concludes.

3.2 Methodology

3.2.1 Measurement of Directional Spillovers

This paper adopts the framework developed in Diebold and Yilmaz (2012) to measure total and directional spillovers within a group of variables. As in Diebold and Yilmaz (2012) spillovers are measured from/to each time series i , to/from all other times series, added across i .

Consider a covariance stationary N -variable vector autoregressive (VAR) model of order p ,

$$x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t, \text{ where } \varepsilon \sim iid(0, \Sigma). \quad (3.1)$$

Equation (3.1) can be rewritten as the infinite moving average (MA) representation,

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \quad (3.2)$$

where the $N \times N$ coefficient matrices A_i can be obtained using the following recursion:

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}, \quad (3.3)$$

with $A_0 = I_N$ and $A_i = 0$ for $i < 0$. The dynamics in the system is captured by these moving average coefficients. Diebold and Yilmaz (2012) proceed by using the forecast error variance decompositions to uncover the interrelationships among the variables in the system. Specifically, they use the variance decompositions to measure the fraction of the H -step ahead error variance in forecasting x_i that is due to shocks to x_j , for each $i, \forall j \neq i$. Whereas the "standard" way to carry out the analysis of variance decompositions is using the orthogonal innovations, methods such as Cholesky factorization is not invariant to ordering of the variables in the VAR. Pesaran and Shin (1998), building on Koop et al. (1996), propose a method to avoid this issue, which they call generalized VAR. The generalized approach allows for correlated innovations using the historically observed distribution of the innovations.

Diebold and Yilmaz (2012) define own variance shares as the fractions of the H -step ahead forecast error variances of x_i that are due to shocks in x_i , for $i = 1, 2, \dots, N$, and cross variance shares, or spillovers, as the fractures of the H -step ahead forecast error variances of x_i that are due to shocks in x_j , for $i, j = 1, 2, \dots, N \mid i \neq j$.

Following the notation in Pesaran and Shin (1998), the forecast error variance decompositions for $H = 1, 2, \dots$, are denoted by $\theta_{ij}^g(H)$:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} e_i' A_h \Sigma A_h' e_i}, \quad i, j = 1, \dots, m \quad (3.4)$$

where Σ is the variance matrix for the vector of innovations ε , σ_{jj} is the standard deviation of the error term for the j th equation, and e_i is the selection vector, with one as the i th element and zeros otherwise.

Note that as the innovations to each variable are not orthogonalized, the sum of the contributions to the variance of the forecast error is not necessarily one: $\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$. Each entry of the variance decomposition matrix is then normalized by the row sum in order to use the information contained in the variance decomposition matrix to express the spillover index:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}, \quad (3.5)$$

by construction, $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$.

Spillover measures, by construction, are divided into total spillovers, directional spillovers and net pairwise spillovers. The total spillover index measures the contribution of spillovers of shocks across the five time series to the total forecast error variance. Using the return contributions from the variance decompositions, the total spillover index can be constructed as:

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} * 100 = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{N} * 100. \quad (3.6)$$

Directional spillovers are calculated using the normalized elements of the generalized variance decomposition matrix. Directional spillovers to time series i from all other time series j is measured as:

$$S_{i \leftarrow \circ}^g(H) = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} * 100 = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{N} * 100, \quad (3.7)$$

and, directional spillovers from time series i to all other time series j is measured as:

$$S_{\circ \leftarrow i}^g(H) = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ji}^g(H)} * 100 = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ji}^g(H)}{N} * 100. \quad (3.8)$$

The net spillover from time series i to all other time series j is calculated as the difference between the gross volatility shocks transmitted to and those received from all other series:

$$S_i^g(H) = S_{\circ \leftarrow i}^g(H) - S_{i \leftarrow \circ}^g(H) \quad (3.9)$$

Finally, the net pairwise spillovers are measured as:

$$S_{ij}^g(H) = \left(\frac{\tilde{\theta}_{ji}^g(H)}{\sum_{i,k=1}^N \tilde{\theta}_{ik}^g(H)} - \frac{\tilde{\theta}_{ij}^g(H)}{\sum_{j,k=1}^N \tilde{\theta}_{jk}^g(H)} \right) * 100 = \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \right) * 100. \quad (3.10)$$

Although both total and directional spillover indices reveal a lot of useful information, they do not take into consideration the time-varying nature of the events that potentially may drive the changes in spillover levels. To account for this, all spillover indices described above are estimated based on a 260-day rolling window for each individual country. The resulting spillover index series are then analysed graphically.

3.2.2 The Bai-Perron Test for Multiple Structural Changes

Bai and Perron (1998, 2003) propose a procedure that allows estimating a model with an unknown number of structural breaks that occur at unspecified dates. In the specified procedure the number of breaks and their timing are estimated simultaneously with the autoregressive coefficients. The model considered is an AR(1) process with m breaks, or, equivalently, $m + 1$ regimes:

$$x_t = \alpha_j + \beta_j x_{t-1} + \varepsilon_t, j = 1, \dots, m + 1. \quad (3.11)$$

Equation (3.11) allows for m breaks, where the coefficients shift from one stable autoregressive relationship to a different one. The first break occurs at t_1 , so the duration of the first regime is from $t = 1$ to $t = t_1$, the duration of the second regime is from $t_1 + 1$ to t_2

and so forth until the m th break that lasts from $t_m + 1$ until the end of the dataset. The goal of the analysis is to determine the number and location of the breakpoints T_j , $j = 1, \dots, m$. The computation of the coefficient estimates and the breakpoints can be done by applying OLS segment by segment without constraints among them. The resulting minimal residual sum of squares is given by

$$RSS(i, j) = \sum_{i=1}^j r_{ss}(i, j), \quad (3.12)$$

where $r_{ss}(i, j)$ is the minimal residual sum of squares at time j obtained using the sample that starts at date i . Bai and Perron present the following recursive relation (proposed in Brown, et al, 1975):

$$RSS(i, j) = RSS(i, j - 1) + r_{ss}(i, j)^2. \quad (3.13)$$

All the relevant information is contained in the values of the triangular matrix $SSR(i, j)$ for the relevant combinations (i, j) . The number of matrix inversions needed is of order $O(T)$.

Bai and Perron (2003) propose applying a version of the dynamic programming algorithm for pure and structural change models. The optimal segmentation satisfies the recursion

$$RSS(\{T_{m,T}\}) = \min_{mh \leq j \leq T-h} [RSS(\{T_{m-1,j}\}) + RSS(j + 1, T)]. \quad (3.14)$$

See Bai and Perron (2003) for details on this dynamic algorithm and Bai and Perron (2003) for discussion of assumptions underlying the methodology applied.

As mentioned earlier, when applying the Diebold-Yilmaz framework on a rolling window basis, the method introduces serial autocorrelation in the resulting spillover time series. This may further lead to a bias in the Bai-Perron estimation procedure. To reduce this bias, the Bai-Perron procedure has been applied to quarterly net spillover series, which has been obtained by selecting every 65th rolling window estimate of each net spillover series. Thus, the results in

Table 3.4 are also presented on a quarterly basis.

3.3 Data

The framework for measuring spillovers is applied to five variables closely related to the banks' credit risk: bank CDS spreads, real estate market index, term spread, interbank liquidity spread and national stock market index. The data frequency of all series is daily and covers the period from 1st of January 2004 to 31st of December 2012, with a total of (balanced) 2348 observations for each series. The data covers five countries: France, Germany, Italy, Spain and UK. These five countries were selected as they have continuous series of the five variables starting from 2004.

All original series exhibited non-stationarity and data transformations were computed (see below) to achieve stationarity of the series prior to applying the econometric framework of Diebold and Yilmaz (2012). Augmented Dickey-Fuller and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were applied to ensure that the transformed series are stationary, results of this analysis are reported in Table 3.5.

Bank CDS spreads: CDS spreads of individual banks are obtained from Datastream and a country specific index is calculated by taking an arithmetic mean of all CDS spreads relating to each country. CMA data are available from January 2004 until September 2010. Starting from October 2010 until March 2013 Datastream provides CDS quotes obtained from Thomson Reuters. A total of 73 financial institutions are included in the sample, the list of the index components is presented in Table 3.6. Since the banks in the sample are all large listed banks we did not feel that adjusting for the bank size would add to the analysis. The 5-year CDS contract quotes on senior debt were chosen as these are the most actively traded contracts on the market (Meng and Ap Gwilym, 2008). In order to avoid issues related to non-stationarity first differences of the daily series are computed. Figure 3.1 illustrates the time series of CDS spreads: prior to the crisis period the CDS spreads were close to zero for all countries. This

reflects low perception of bank credit risk in the EU countries by the financial markets. There is a significant change in the behaviour of the CDS spreads from mid-2007. By Q3 2008 the banks' CDS spreads rose to 2.1% (on average among the countries in the sample) from the starting point of 0.3%. The most dramatic increase can be observed in the UK, when the CDS spread average across domestic banks reached a peak over 10% in March 2009.

Real estate market index: The FTSE/European Public Real Estate Association (EPRA, for short) country specific price indices were obtained from Datastream. These are stock market index series jointly managed by FTSE and EPRA and are composed of property company constituents. The indices are designed to represent general trends in eligible real estate equities. FTSE defines relevant real estate activities as the ownership, sales and development of income-producing real estate. Daily percent changes are computed in order to make the original series stationary. It has become a general practice to use listed real estate as a proxy for direct real estate. The indices for direct real estate markets are compiled at a monthly frequency at best (most often quarterly) because they are based on the valuations of individual properties; whereas listed real estate is available daily. Concern that the performance of listed real estate is primarily driven by stock markets is valid, particularly in the short term. However, numerous authors show that the medium to long-term performance of listed real estate correlates significantly with the development of direct real estate markets (e.g. Sebastian and Schätz, 2009; Pavlov and Wachter, 2011).

Interest rate term spread: Term spread, otherwise known as yield spread or the slope of the yield curve, is computed as the difference between 10-year government bond yield and 3-month Treasury bill yield. Country specific debt security yield series for both maturities are obtained from Datastream. The term spread is extensively used as a predictor of real economic activity and is known to contain information of future interest rate and inflation levels. It has been widely accepted for a long time that the term spread increases in times of economic contractions

(Fama, 1990; Estrella and Mishkin, 1995; Estrella, 2005). However, decreasing term spreads for all five countries in the sample starting in Q2 2007 tell the opposite story. This makes it hard to predict the relationship between the CDS spreads and term spread. Notwithstanding, this variable has been shown to be a significant determinant of the CDS spreads and bond spreads (Collin-Dufresne et al., 2001, Otker-Robe and Podpiera, 2010; Annaert et al., 2013; Galil et al., 2014; Benbouzid and Mallick, 2013). First differences of the daily series are used in the analysis to avoid non-stationarity issues.

Interbank liquidity spread: Interbank liquidity spread, otherwise known as TED spread, is computed as the difference between 3-month Euro Interbank Offered Rate (EURIBOR) (London Interbank Offered Rate (LIBOR) in case of UK) and 3-month German Treasury bill yield (UK Treasury bill in the case of UK). Both series are obtained from Datastream. Liquidity spread is commonly used as an indicator to measure funding liquidity in the general market. A rising liquidity spread indicates a downturn in the national stock market, as it indicates that interbank liquidity is being withdrawn (Michaud and Upper, 2008; Angelini et al., 2011; Eisenschmidt and Tapking, 2009). It is more common to use the spread between a short-term government debt yield and EURIBOR rate with the same maturity; however, during the recent crisis the country specific spread is very likely to reflect the local events. As the intention behind using this variable is capturing the interbank market liquidity rather than individual sovereign credit risk, German liquidity spread was used in the case of France, Spain and Italy. Again, first differences of the series are used in the analysis to make the series stationary.

National stock market index: MSCI country specific stock indices are used as proxies for the overall state of the local economies (following Annaert et al., 2013; Collin-Dufresne et al., 2001; Ericsson et al., 2009; Galil et al., 2014; Benbouzid and Mallick, 2013). MSCI stock market indices were obtained from Bloomberg. Daily percentage change transformation is applied in order to avoid the non-stationarity issues.

Both Bloomberg and Datastream databases skip weekends and a few major holidays (Christmas and New Year's Day) but reproduce yesterday's closing price on other days on which a particular national exchange is closed. To keep the panel dataset balanced, closing prices on days on which three or more of the five series included do not trade are ignored, and such a day is treated the same as a weekend.

Table 3.1 reports the means, standard deviations and the minimum and maximum values for each of the five country specific series: banks' CDS spreads, real estate market index, term spread, liquidity spread and national stock index. All values are reported in percentage; real estate and stock market indices report summary statistics on daily percentage changes rather than the original price indices. Columns 1-4 in the upper section of the table report the main statistics of the banks' CDS spreads of each individual country. The CDS spread ranges are wide for all countries reflecting a significant shift in the credit risk of banks; the widest range can be observed for the UK from .18% to 10.09% and Spain from .08% to 8.47%. Summary statistics for real estate index (columns 5-8, upper section) reflect the nature of the real estate market for the sample period. Minimum and maximum values show a significant fall and rise of the real estate markets, attributable to the crisis and no-crisis period, respectively. Stock market index summary statistics (columns 9-12, upper section) show a similar picture in financial markets. Summary statistics for term spread series (columns 1-4, lower section) reflect the difference in sovereign credit risk between the periphery and core countries of the EU: average term spread is highest for Italy and Spain and the minimum and maximum values suggest the same (ranging from .5% to 6.44% for Italy and from .15% to 6.43% for Spain in comparison to Germany: -.28% to 4.11%). Columns 5-8 (lower section) report the summary statistics for the liquidity spread variable.

Table 3.2 shows the sample correlation matrices of original series for each individual country. The sample correlation coefficients reveal a general pattern among the variables: highest

pairwise correlation levels can be observed between CDS spreads and real estate indices, CDS spreads and stock market indices, and real estate and stock market indices.

3.4 Empirical Findings

3.4.1 Total Spillover Index: Full-sample and 260-day Rolling Window Estimation

Table 3.3 reports the full-sample total spillovers within the variables. This is a static analysis where the ij th entry is the estimated contribution to the forecast error variance of market i coming from innovations to market j . The off-diagonal row sums (labeled contributions *from* others) and column sums (labeled contributions *to* others) are the “*from*” and “*to*” directional spillovers, and the “*from* minus *to*” differences are the net volatility spillovers. The diagonal elements (own connectednesses) tend to be the highest individual elements of the table. This table is informative about how shocks to one variable within a country spread to other variables.

The “directional *to* others” row and “directional *from* others” column show that for all five countries the stock index seems to be the most significant transmitter and receiver of shocks (the spillover index is largest for most countries in the sample, with the exception of “directional *from* others” for Spain). Real estate index comes second for all countries except Spain. A closer look at the tables reveals that this trend is dominated by a high connectedness of the two variables. CDS spread variable is also one of the most sensitive variables in the sample for both directions and is mostly affected by shocks to the stock index and real estate index variables.

The total spillover index appears in the lower right corner of the spillover table. It is approximately the total off-diagonal row sum relative to the total row sum including diagonals, expressed as a percentage. The total spillovers index shows what percentage of the total forecast error variance in all five variables comes from spillovers. It is lowest for Spain at 9.9% suggesting a low connectedness level within the variables, and it is highest for France at 29.6%. For Germany, Italy and UK it ranges from 23.4% to 24.9%. In summary of Table 3.3, both the total and directional spillovers over the full sample period were rather low. The full-sample spillover index analysis provides a good overall picture of the connectedness between the

variables. However, it is likely to miss the rich dynamics in the banking sector during the sample period of January 2004 to December 2012.

As a next step, the spillover index is estimated using the 260-day rolling samples which are reported in Figure 3.2. In the pre-crisis period the spillover index ranged from below 10% to 30% for all countries. After the onset of the financial crisis, however, the spillovers suddenly jump to 40% and fluctuate strongly in the region 12% to 55% over the remaining sample period. Four distinctive waves can be observed in the total spillover index. First, June 2007 to November 2007 coincides with the onset of the financial crisis in the EU. Q3 2007 witnessed liquidity shortages worldwide and slowdown in the interbank lending, which is reflected by the first steep rise in the total spillover index. Financial markets became increasingly vulnerable in response to the subprime crisis that hit the US. In December 2007 the Bank of England and the ECB announced measures to address elevated pressures in short-term funding markets (ECB, December 2007), these measures seemed to offer some relief as the spillover index decreased from 41% to 30% for the UK and from 35% to 22% for Germany. The sudden spike in the spillover index on the 10th of October 2008 reflects the sudden downturn of financial markets after an initial positive response to the ECB's Governing Council lowering its rates (ECB, October 2008). The next jump in the total spillover index corresponds to the agreement between the Euro area leaders and IMF to offer financial support to Greece (ECB, March 2010) at the end of March 2010. The ongoing uncertainty and carrying out of the bailout programmes result in the spillovers remaining high for the twelve months. Summer of 2011 was an important time in the EU as a succession of decisions were made by the ECB on the refinancing operation within the EU (ECB, August 2011). It is interesting to observe that the spillover index for Spain falls significantly (from 40% to 19%) after February 2011 remains between 15% and 29% for the remaining of the sample period. This coincides with Spain becoming a prime concern for the EU after the interest rates on its long-term bonds increased to 7%.

3.4.2 Net Spillover Indices, Pairwise Spillovers and Structural Breaks

Figures 3.3 to 3.7 reports net spillovers for CDS spreads, real estate, term spread, liquidity spread and stock index variables within the five countries, respectively. In order to understand the dynamics of the spillover series and the relationship between the variables at a deeper level, the net spillover indices need to be analysed in conjunction with the relevant pairwise spillovers (Figures 3.9 to 3.12) and the break dates estimated using the Bai-Perron procedure (Table 3.4). As a reminder to the reader, the net spillover *from* time series i to all other time series j is calculated as the difference between the gross volatility shocks transmitted *to* and those received *from* all other series. As the most useful information for the analysis can be inferred from dynamics of the net spillover and net pairwise spillover indices the directional spillover index series (corresponds to "contributions *from* others" and "contributions *to* others" columns in the total spillover table - Table 3.3) are presented in Figures 3.8 ((a)-(e)) and 3.14 ((a)-(e)).

Following notation in Diebold and Yilmaz (2012), when the index is negative the variable is called net receiver of shocks and when positive it is called net transmitter of shocks. In practice, when a particular variable is a net transmitter of shocks its estimated contribution *to* the forecast error variance of all other variables is larger than the estimated contribution *from* all other variables. Hence, it can be concluded that the effects of shocks to variable i affect other variables more than the effects of shocks to other variables affect variable i .

3.4.2.1 CDS Spread

Figure 3.3 shows that until the beginning of 2007 the net CDS spillover series have been broadly unchanging. Both *to* and *from* directional spillovers (not reported here) were at a similar low level for all countries in the sample. Overall, CDS variable became a net receiver of shocks during the period from mid 2007 to end of 2010. The net pairwise spillover series presented in Figure 3.10 show that this relationship is mostly caused by shock transmissions from the real estate index (Figure 3.3 (a)) and stock market index (Figure 3.3 (d)).

A closer look at the individual countries reveals that the sensitivity of the CDS variable was most pronounced for France, Germany and Italy as the fluctuations of the index is the strongest for these countries. Table 3.4 reports that the Bai-Perron multiple break estimation procedure places the first structural break in the net CDS spillover series in Q3 2006 in Germany and Q4 2007 in France and Italy. Figure 3.1 shows that this corresponds to time point when the CDS spread for all countries started rising for the first time after being close to zero since CDS contracts began actively trading in 2004.

The first structural break in the CDS net spillover index for Germany is detected in Q3 2006 when the index fell from -0.35% to -1.28% . The net pairwise spillover indices in Figure 3.10 indicate that this change was driven mostly by changes in the CDS spread - real estate index (Figure 3.10 (a)) and CDS spread - stock market index relationships (Figure 3.10 (d)).

The first structural break in the net spillover index of CDS for Italy is estimated to be in Q3 2007 when the net CDS variable decreased by 1.65% during the quarter. For France it was Q4 2007 and the CDS net spillover index fell by 2.14% . The timing of the structural break coincides with a halt in the Italian and French real estate market, respectively. As for the case of Germany, Figure 3.10 indicates that the changes for both of these countries are driven by the shocks to the real estate variable (Figure 3.10 (a)).

Figure 3.3 shows that the next major change in CDS variable occurs in Q1 2010; the Bai-Perron procedure estimates the structural break for this time point for Germany, France and Spain (see Table 3.4). In Italy, a turning point is not detected until Q2 2010. The CDS net spillover index changed from being net receiver to net transmitter of shocks. Figure 3.10 shows that the driver for this change was the relationship of the CDS variable with all other variables except liquidity spread - a sudden increase in the transmission of shocks from the CDS spread variable to real estate (Figure 3.10 (a)), term spread (Figure 3.10 (b)) and stock market index (Figure 3.10 (d)) can be observed. Hence, the source of shocks to these variables appears to be

an increase in banks' credit risk. The timing of this turning point coincides with the disclosure of severe irregularities in Greek accounting procedures (European Commission, January 2010), and thus, the negotiations on the first sovereign bailout in the European Union. A strong link between banking sector and sovereign credit risk has been reported in previous literature. See, for example, Acharya et al., 2012; De Bruyckere et al., 2013; Alter and Schuler, 2012; and Avino and Cotter, 2014.

The Bai-Perron procedure estimates the next structural break in the CDS net spillovers in Q1 2011 for France, Germany and Spain (see Table 3.4). The CDS variable changed from being net transmitter to net receiver of shocks. Figure 3.10 indicates that this change was mostly driven by the relationship between the CDS spread and stock market index (Figure 3.10 (d)). Q1 2011 saw numerous changes within the Eurozone government structure. Some of the key events were the increase and reorganisation of the European bail-out fund, which was renamed European Stability Mechanism (previously known as European Financial Stability Facility) (European Council, January 2011), revealing a new set of rules and guidelines for the upcoming EU-wide bank stress testing by the European Banking Authority (European Banking Authority, March 2011). This is an indication that the uncertainty in the financial markets affected the credit risk of banks rather than vice versa.

In Italy, Q3 2011 witnesses a gradual increase in the CDS net spillover index and this is picked up by the Bai-Perron structural breaks estimation procedure (see Table 3.4). This coincides with Italy passing a 54bn-euro austerity budget after long negotiations in parliament (The Guardian, September 2011). September 2011 also saw Italy's debt rating cut by Standard & Poor's, to A from A+ (Bloomberg, September 2011).

The Bai-Perron procedure detects a structural break for the UK in Q3 2011 (see Table 3.4) and Figure 3.3 shows that the CDS net spillover index had an unprecedented surge during this time. This seems to be driven by the CDS relationship with the term spread (Figure 3.10 (b))

and stock market index (Figure 3.10 (d)). This is indicative of the bank credit risk being affected purely by the investor uncertainty.

3.4.2.2 Real Estate Index

Figure 3.4 illustrates the net real estate spillover index series for five countries (France, Germany, Italy, Spain and UK) over the sample period 5th of January 2005 to 21st of December 2012. The directional spillovers were cancelling each other out until mid-2007, but started to increase noticeably since then. Overall, the net real estate spillover index seems to be a net transmitter of shocks, but fluctuations of the country specific series move quite independently of each other. The net real estate spillover for Spain fluctuates around zero largely throughout the whole sample period. Net pairwise spillovers in Figure 3.11 show that the dynamics of the net spillover index is driven by the real estate relationship with CDS spread (Figure 3.11 (a)) and term spread (Figure 3.11 (b)) variables.

The Bai-Perron procedure detects a structural break in Germany in Q1 2006. This coincides with the turmoil in the German Open-End Real Estate Funds (GOEREFs). Open-end real estate funds work like mutual funds except that they buy property—mostly European office and retail complexes—instead of stock. In Q1 2006 these funds faced a liquidity drain on an unprecedented scale due to a devaluation of one of the largest funds, Grundbezits Invest (Banner et al., 2008; Fecht and Wedow, 2014).

The structural break in the net real estate spillover index for France is detected in Q3 2006 (see Table 3.4). France experienced the biggest downturn in its real estate markets in the beginning of 2008, but the timing of first signs of deteriorating house prices coincide with the structural break as detected by the Bai-Perron procedure (Ferrera and Vigna, 2009).

The Bai-Perron procedure detects three structural breaks in Italy: Q2 2007 (a sudden increase in net spillover index), Q3 2008 (net spillover index dropped dramatically) and Q1 2010 (another sudden rise in net spillover index). Figure 3.11 ((a) - (d)) shows that the shocks to the real estate

variable has driven shocks in all variables, with an exception of the Q3 2008 to Q2 2010 period. During this period the shocks to CDS spread, term spread and stock market index variables affected real estate variable more than vice versa. Consistent with the CDS series, it indicates that during this period the real estate variable is driven by events taking place in the financial markets. In October 2008, the Italian government adopted a series of measures to protect the financial sector. The measures included guarantees of bank liabilities, increase of retail deposit guarantees and assistance programme by Banca d'Italia (Banca d'Italia, 2008).

Figure 3.4 reports the net real estate spillover index for Spain. Spain, like many other countries in the EU, experienced a major property bubble that burst around Q1 2007, but it does not seem to be reflected as strongly in the net real estate spillovers as for other countries in the sample. Figure 3.11 shows that the shocks to the real estate variable have affected all other variables except liquidity (Fig 3.11 (c)) mostly at the start of the financial crisis period. After that, shocks to the CDS spread (Figure 3.11 (a)) and stock index (Fig 3.11 (d)) were transmitted to the real estate index. This indicates that the bank credit risk and uncertainty in financial markets affected shocks to the real estate index more than vice versa. The Bai-Perron procedure does not detect any structural breaks in the net real estate spillover index for Spain.

Net real estate spillover index for UK has mostly been a net transmitter of shocks. This effect has been especially pronounced during the crisis period Q3 2007 up to Q3 2008 and when the real estate market in UK picked up again in 2009. Figure 3.11 ((a) - (c)) shows that the shocks to the real estate variable have transmitted to CDS spread and term spread more than vice versa over the entire sample period, and to stock market index from Q3 2010. The Bai-Perron procedure detects a structural break in the index in Q2 2010; this coincides with the stabilisation and growth of real estate prices in UK after a sharp fall from the peak of August 2007.

3.4.2.3 Term Spread

Figure 3.5 reports the net term spread spillovers series for the five countries in the sample. The

net spillover series move closely together until the beginning of 2010 for four countries: France, Germany, Italy and Spain. Net term spread spillover index for UK follows an independent path and since the beginning of 2010 the series for all five countries become less correlated. The Bai-Perron procedure detects one structural break for each country (see Table 3.4). It is detected in Q3 2005 for France, Germany, Italy and Spain, and two quarters later (Q1, 2006) for the UK. In the strongly co-moving series of four countries the net term spread spillover index decreases significantly around the time of the structural break. For example, the year on year (September 2005 to September 2006) decrease of the index was 11% for Germany. Although the term spread variable has largely continued transmitting more shocks to other variables than it has received, its effect on the other credit risk variables has decreased significantly. Figure 3.12 reveals that this dynamics was driven by the relationship between the term spread and all other variables except liquidity spread (Figure 3.12 (b)). It is worth noting the sharp rise in the net pairwise spillovers from term spread to all other variables (Fig 3.12 (a)-(d)) in Italy. This coincides with the timing of bank guarantees undertaken by Banca d'Italia (see previous Section 4.2.2).

In the UK, however, the net term spread spillover index increased by 3.5% from April 2006 to July 2006. There is no ready theory or specific event to explain this difference in regional dynamics. It helps to look at the general differences in the monetary policy responses of European Central Bank and Bank of England. There are numerous papers outlining the differences in the central banks' responses to the crisis (see, for example, de la Dehesa, 2012; Lenza et al., 2010). There are several structural differences that directly affect the interest rate policies of the two central banks, but the three key differences are the following. First, the monetary transmission mechanisms (MTM) of the two central banks are different. In the case of the BoE the majority of the MTM is mainly done through financial markets and in the case of the ECB it is mainly done through banks. Second, the BoE has more than one primary objective for monetary policy, while the ECB has only one primary objective: price stability.

Third, decision making at the ECB is much more complex and difficult than that of the BoE. As a result, the ECB has been much more conservative at reducing interest rates and decisions have been undertaken at a slower rate. Thus, financial markets have been more sensitive to the interest rates policies undertaken by the BoE, whereas in the case of the Eurozone financial markets seem to be driving the changes in the term spread.

3.4.2.4 Interbank Liquidity Spread

Figure 3.6 reports the net liquidity spread spillover index over the sample period. The variable is mostly a net receiver of shocks from other variables. The dynamics of the index is quite similar between all the Eurozone countries and moves somewhat independently for the UK. From the pairwise spillovers presented in Figure 3.13 ((a)-(d)) it can be seen that the net spillover indices are receivers of shocks from all other variables. The Bai-Perron places a structural break test for the Eurozone countries very early in the sample, between Q3 and Q4 2005 and in Q3 2007 for the UK. This coincides with the first fluctuations in the liquidity spread for these countries after a very stable period.

Liquidity spread is commonly used as an indicator to measure funding liquidity in the general financial market (Michaud and Upper, 2008; Angelini et al., 2011; Eisenschmidt and Tapking, 2009). The empirical findings in this paper imply that the liquidity spread reflects turmoil in bank credit risk and financial markets in general and not vice versa. However, it has to be noted that the liquidity spread variable as used in the current analysis may not be an accurate reflection of the state of interbank lending market, on the grounds that it is being skewed by the ECB's monetary policies.

3.4.2.5 National Stock Market Index

Figure 3.7 reports the net stock index spillovers. In Q2 2007 the spillover index increases significantly for all countries in the sample. It remains a net transmitter of shock for the remaining sample period and Figure 3.14 ((a)-(d)) reports that this effect can be observed between all pairwise variables. The Bai-Perron procedure detects a structural break test for

all countries simultaneously in Q2 2007. This coincides with a sudden fall in all the national stock market indices in response to the market uncertainty across borders. This indicates that the shocks to the stock markets in all sample countries strongly influence shocks to all other variables.

3.5 Conclusion

This paper analyses the total and directional spillovers across carefully selected variables directly related to the credit risk of financial institutions: bank CDS spread, real estate market index, interest rate term spread, interbank liquidity spread and national stock market index, using daily data from January 2004 to December 2012. The spillover analysis is undertaken within five European Union countries: core countries France and Germany, periphery countries Spain and Italy, and a reference country UK. Multiple structural break estimation procedure is employed to detect sudden changes in shock transmission. A number of salient implications can be drawn from the econometric results reported in this study.

The net spillover indices for all variables are highly time-varying and exhibit strong country specific features. Overall, the national stock market indices appear to lead the shock transmission across the five variables. The role of the bank credit risk, measured by the CDS spread, and the real estate index changes over the course of the crisis. At the start of the crisis the real estate index is a shock transmitter to all other variables and as the crisis progresses it becomes a shock receiver and the exact opposite applies to the CDS spread. This lends support to the view that the real estate plays a significant role in bank stability and initial shocks to the real estate sector eventually have a strong influence on bank performance. The net term spread and liquidity spread spillover series also move in opposite directions over the course of the sample period. This, and the pairwise spillover indices (shocks to term spread appear to transmit to liquidity spread rather than vice versa) suggest that interest rate changes lead the changes in interbank liquidity.

As for the country specific dynamics, the most obvious outlier appears to be the UK; the variation from other countries is most pronounced when looking at the term spread variable. The explanation for this seems to be the general differences in the monetary policy responses of European Central Bank and Bank of England. Financial markets have been more sensitive to the interest rates policies undertaken by the BoE, whereas in the case of the Eurozone financial markets seem to be driving the changes in the term spread. The net real estate index spillovers exhibit strongest country specific dynamics. This is a reasonable observation as every country experienced downturn in real estate prices at different times. The national stock markets are most globalised across the variables in the sample as the net stock market spillovers are strongly co-moving for all countries.

The Bai-Perron multiple structural break estimation procedure seems to detect sudden changes in shock transmission only for original shocks, but not for later shocks of the same nature. For example, a structural break is detected in the net CDS spread spillovers in Q1 2010, around the first sovereign bailout within the Eurozone of Greece, but not for the subsequent bailouts of Ireland, Portugal, Cyprus or the second Greek bailout. These results are in line with findings in earlier literature. Conefrey and Cronin (2013) show that the spillover effect in Euro area bond markets decrease significantly after the first bailout of Greece. Alter and Beyer (2014) find evidence that, when analysing the sovereign-bank credit risk spillovers, the systemic contributions of Euro zone periphery to core countries decrease after the implementation of the IMF/EU programs.

As pointed out in Bai and Perron (2003), the multiple structural break estimation methodology is highly dependent on the specification of the testing procedure. The methodology can have a low statistical power leading to rejection of structural breaks even when they are ‘true’ breaks. The statistical power of the test is dependent on the dynamics of the underlying series; the Bai-Perron procedure may “reject” the null of no breaks and identify as a “true” break a certain

shift in one series and “fail to reject” a break of the exact same magnitude in another series that is more volatile. Therefore, when analysing the spillover index series, it is important to take into account the full dynamics of the series and not only the structural breaks detected. The spillover index methodology can then provide useful information to those tasked with monitoring the developments in bank credit risk.

3.6 Tables and Figures

Table 3.1: Summary statistics

| | Banks' CDS spread 5-yr | | | | Real Estate Price Index | | | | Equity Market Price Index | | | |
|----------------|------------------------|---------|-------|-------|-------------------------|---------|--------|-------|---------------------------|---------|-------|-------|
| | Mean | Std Dev | Min | Max | Mean | Std Dev | Min | Max | Mean | Std Dev | Min | Max |
| France | 1.32 | 1.13 | 0.11 | 4.48 | 0.03 | 1.20 | -6.08 | 6.12 | 0.01 | 1.43 | -8.89 | 10.92 |
| Germany | 0.94 | 0.74 | 0.09 | 2.71 | 0.00 | 1.13 | -7.10 | 6.76 | 0.03 | 1.41 | -7.12 | 11.77 |
| Italy | 1.36 | 1.43 | 0.09 | 5.97 | -0.02 | 1.96 | -10.77 | 26.80 | -0.01 | 1.52 | -8.27 | 11.61 |
| Spain | 1.99 | 2.16 | 0.08 | 8.47 | -0.05 | 2.47 | -14.14 | 61.66 | 0.01 | 1.58 | -9.61 | 15.63 |
| UK | 1.49 | 1.50 | 0.18 | 10.09 | 0.01 | 1.64 | -9.29 | 9.29 | 0.01 | 1.32 | -8.95 | 9.98 |
| | Term Spread | | | | Liquidity Spread | | | | | | | |
| | Mean | Std Dev | Min | Max | Mean | Std Dev | Min | Max | | | | |
| France | 2.47 | 1.21 | 0.38 | 4.19 | - | - | - | - | | | | |
| Germany | 2.07 | 1.09 | -0.28 | 4.11 | 1.49 | 0.88 | -0.34 | 3.16 | | | | |
| Italy | 3.36 | 1.66 | 0.50 | 6.44 | - | - | - | - | | | | |
| Spain | 2.96 | 1.75 | 0.15 | 6.43 | - | - | - | - | | | | |
| UK | 1.33 | 1.82 | -1.38 | 3.89 | 1.08 | 1.48 | -1.05 | 3.78 | | | | |

Notes: This table reports the mean, standard deviation, minimum and maximum value of banks' CDS spreads, real estate index, national stock market index, term spread and liquidity spread. All numbers are in percentages; real estate and stock market index report summary statistics on daily percentage changes rather than the original price indices. All data is daily and covers the period 1st of January 2004 to 31st of December 2012.

Table 3.2: Sample correlation matrices

| France | | | | | | Spain | | | | | |
|------------------|------------|------------|----------------|---------------|------------------|------------------|------------|------------|----------------|---------------|------------------|
| | CDS | RLE | Term Sp | Liq Sp | Stock Ind | | CDS | RLE | Term Sp | Liq Sp | Stock Ind |
| CDS | 1.00 | -0.35 | 0.59 | 0.33 | -0.68 | CDS | 1.00 | -0.75 | 0.75 | 0.35 | -0.56 |
| RLE | -0.35 | 1.00 | -0.66 | -0.62 | 0.88 | RLE | -0.75 | 1.00 | -0.86 | -0.73 | 0.77 |
| Term Sp | 0.59 | -0.66 | 1.00 | 0.92 | -0.82 | Term Sp | 0.75 | -0.86 | 1.00 | 0.78 | -0.66 |
| Liq Sp | 0.33 | -0.62 | 0.92 | 1.00 | -0.69 | Liq Sp | 0.35 | -0.73 | 0.78 | 1.00 | -0.54 |
| Stock Ind | -0.68 | 0.88 | -0.82 | -0.69 | 1.00 | Stock Ind | -0.56 | 0.77 | -0.66 | -0.54 | 1.00 |
| | | | | | | | | | | | |
| Germany | | | | | | UK | | | | | |
| | CDS | RLE | Term Sp | Liq Sp | Stock Ind | | CDS | RLE | Term Sp | Liq Sp | Stock Ind |
| CDS | 1.00 | -0.83 | 0.37 | 0.42 | -0.25 | CDS | 1.00 | -0.64 | 0.53 | 0.60 | -0.74 |
| RLE | -0.83 | 1.00 | -0.63 | -0.65 | 0.55 | RLE | -0.64 | 1.00 | -0.82 | -0.80 | 0.90 |
| Term Sp | 0.37 | -0.63 | 1.00 | 0.96 | -0.64 | Term Sp | 0.53 | -0.82 | 1.00 | 0.95 | -0.68 |
| Liq Sp | 0.42 | -0.65 | 0.96 | 1.00 | -0.63 | Liq Sp | 0.60 | -0.80 | 0.95 | 1.00 | -0.75 |
| Stock Ind | -0.25 | 0.55 | -0.64 | -0.63 | 1.00 | Stock Ind | -0.74 | 0.90 | -0.68 | -0.75 | 1.00 |
| | | | | | | | | | | | |
| Italy | | | | | | | | | | | |
| | CDS | RLE | Term Sp | Liq Sp | Stock Ind | | | | | | |
| CDS | 1.00 | -0.75 | 0.68 | 0.24 | -0.81 | | | | | | |
| RLE | -0.75 | 1.00 | -0.83 | -0.60 | 0.96 | | | | | | |
| Term Sp | 0.68 | -0.83 | 1.00 | 0.84 | -0.90 | | | | | | |
| Liq Sp | 0.24 | -0.60 | 0.84 | 1.00 | -0.65 | | | | | | |
| Stock Ind | -0.81 | 0.96 | -0.90 | -0.65 | 1.00 | | | | | | |

Notes: This table reports the sample correlation matrices for the five original (before transformation due to non-stationarity) series of credit risk determinants (banks' CDS spreads, real estate index, term spread, liquidity spread, and national stock market index) for each individual country: France, Germany, Italy, Spain and UK. All data is daily and covers the period 1st of January 2004 to 31st of December 2012.

Table 3.3: Total spillover table: full sample estimation

| France | | | | | | | Spain | | | | | | |
|---------------------------|------|------|-------------|------------------|-------------|-------------------------|---------------------------|------|------|-------------|------------------|-------------|-------------------------|
| | CDS | RLE | Term Spread | Liquidity Spread | Stock Index | Directional FROM others | | CDS | RLE | Term Spread | Liquidity Spread | Stock Index | Directional FROM others |
| CDS | 65.4 | 13.9 | 1.2 | 0 | 19.5 | 35 | CDS | 82.3 | 3.3 | 0.3 | 0 | 14.1 | 18 |
| RLE | 10.7 | 57.1 | 1 | 0.3 | 30.9 | 43 | RLE | 1.4 | 93.2 | 0.1 | 0 | 5.2 | 7 |
| Term Spread | 1.2 | 2.2 | 89.9 | 3.3 | 3.4 | 10 | Term Spread | 0.1 | 0.1 | 98.4 | 0.2 | 1.2 | 2 |
| Liquidity Spread | 2 | 2.2 | 6.5 | 84.4 | 4.8 | 16 | Liquidity Spread | 1.3 | 0.2 | 0.6 | 93.2 | 4.6 | 7 |
| Stock Index | 13.8 | 29.4 | 1.5 | 0.1 | 55.2 | 45 | Stock Index | 10.9 | 4.4 | 1.2 | 0.1 | 83.4 | 17 |
| Directional TO others | 28 | 48 | 10 | 4 | 59 | 148 | Directional TO others | 14 | 8 | 2 | 0 | 25 | 50 |
| Directional including own | 93 | 105 | 100 | 88 | 114 | 29.60% | Directional including own | 96 | 101 | 101 | 94 | 109 | 9.90% |
| Germany | | | | | | | UK | | | | | | |
| | CDS | RLE | Term Spread | Liquidity Spread | Stock Index | Directional FROM others | | CDS | RLE | Term Spread | Liquidity Spread | Stock Index | Directional FROM others |
| CDS | 78.3 | 6.2 | 4.2 | 0.4 | 11 | 22 | CDS | 79.3 | 9.1 | 0.3 | 0.6 | 10.7 | 21 |
| RLE | 3.9 | 68.2 | 2.9 | 0.2 | 24.8 | 32 | RLE | 7.6 | 64.2 | 0.1 | 0.3 | 27.7 | 36 |
| Term Spread | 2.9 | 3.6 | 86.1 | 0 | 7.4 | 14 | Term Spread | 0.4 | 0.1 | 94.3 | 4.7 | 0.5 | 6 |
| Liquidity Spread | 1.3 | 1.2 | 14.3 | 78.4 | 4.7 | 22 | Liquidity Spread | 2.4 | 3.5 | 4.6 | 81.1 | 8.4 | 19 |
| Stock Index | 6.3 | 23.1 | 5.5 | 0.4 | 64.7 | 35 | Stock Index | 7.9 | 27.5 | 0.4 | 0.3 | 64 | 36 |
| Directional TO others | 14 | 34 | 27 | 1 | 48 | 124 | Directional TO others | 18 | 40 | 5 | 6 | 47 | 117 |
| Directional including own | 93 | 102 | 113 | 79 | 113 | 24.90% | Directional including own | 98 | 104 | 100 | 87 | 111 | 23.40% |
| Italy | | | | | | | | | | | | | |
| | CDS | RLE | Term Spread | Liquidity Spread | Stock Index | Directional FROM others | | CDS | RLE | Term Spread | Liquidity Spread | Stock Index | Directional FROM others |
| CDS | 66.3 | 10.1 | 1.9 | 0.1 | 21.5 | 34 | | | | | | | |
| RLE | 9.3 | 65.4 | 1 | 0.4 | 24 | 35 | | | | | | | |
| Term Spread | 2.9 | 0.5 | 94.3 | 0.3 | 2 | 6 | | | | | | | |
| Liquidity Spread | 3.3 | 1.2 | 1.2 | 89.6 | 4.7 | 10 | | | | | | | |
| Stock Index | 16.7 | 21.4 | 1.5 | 0.2 | 60.2 | 40 | | | | | | | |
| Directional TO others | 32 | 33 | 6 | 1 | 52 | 124 | | | | | | | |
| Directional including own | 99 | 99 | 100 | 91 | 112 | 24.80% | | | | | | | |

Notes: This table reports the full-sample total spillovers within the five transformed variables (banks' CDS spreads, real estate index, term spread, liquidity spread, and national stock market index) for each individual country: France, Germany, Italy, Spain and UK. All data is daily and covers the period 1st of January 2004 to 31st of December 2012. See Eq (3.6) for calculation of the total spillovers index.

Table 3.4: The Bai-Perron estimation procedure results

| CDS | | | | | RLE | | | | |
|---------------------|----------------|--------------|--------------|-----------|---------------------|----------------|--------------|--------------|-----------|
| France | Germany | Italy | Spain | UK | France | Germany | Italy | Spain | UK |
| Q4 2007 | Q3 2006 | Q3 2007 | Q1 2010 | Q3 2011 | Q3 2006 | Q1 2006 | Q2 2007 | - | Q2 2010 |
| Q1 2010 | Q1 2010 | Q2 2010 | Q1 2011 | | | | Q3 2008 | | |
| Q1 2011 | Q1 2011 | Q3 2011 | | | | | Q1 2010 | | |
| Term Sp | | | | | Liquidity Sp | | | | |
| France | Germany | Italy | Spain | UK | France | Germany | Italy | Spain | UK |
| Q3 2005 | Q3 2005 | Q3 2005 | Q3 2005 | Q1 2006 | Q4 2005 | Q3 2005 | Q3 2005 | Q3 2005 | Q3 2007 |
| Equity Index | | | | | | | | | |
| France | Germany | Italy | Spain | UK | | | | | |
| Q2 2007 | Q2 2007 | Q2 2007 | Q2 2007 | Q2 2007 | | | | | |

Notes: This table reports the Bai-Perron estimation procedure results for the quarterly net spillover series of the five credit risk determinants in the sample (banks' CDS spreads, real estate index, term spread, liquidity spread, and national stock market index) for each individual country: France, Germany, Italy, Spain and UK. The sample period is 1st of January 2004 to 31st of December 2012.

Table 3.5: Adjusted Dickey-Fuller and KPSS test results

| a) Adjusted Dickey-Fuller and KPSS test results for original data series | | | | | | | | | | | | | | |
|--|--------------------|-------------|------------------|--------------------|-------------|------------------|--------------------|-------------|------------------|--------------------|-------------|------------------|--------------------|-------------|
| France | | | Germany | | | Italy | | | Spain | | | The UK | | |
| | Adjusted DF | KPSS | | Adjusted DF | KPSS | | Adjusted DF | KPSS | | Adjusted DF | KPSS | | Adjusted DF | KPSS |
| CDS | -1.155 | 34.353*** | CDS | -1.122 | 38.974*** | CDS | -0.74 | 33.345*** | CDS | -0.219 | 39.776*** | CDS | -1.407 | 15.899*** |
| RLE | -1.786 | 12.711*** | RLE | -1.185 | 11.689*** | RLE | -2.113 | 13.419*** | RLE | -1.809 | 17.584*** | RLE | -1.774 | 13.407*** |
| Term Spread | -1.299 | 19.562*** | Term Spread | -1.461 | 10.529*** | Term Spread | -1.229 | 27.583*** | Term Spread | -1.301 | 26.731*** | Term Spread | -0.937 | 32.879*** |
| Liquidity Spread | - | - | Liquidity Spread | -2.114 | 11.086*** | Liquidity Spread | - | - | Liquidity Spread | - | - | Liquidity Spread | -0.993 | 27.353*** |
| Stock Index | -1.724 | 12.788*** | Stock Index | -1.85 | 4.938*** | Stock Index | -0.544 | 31.424*** | Stock Index | -1.607 | 10.668*** | Stock Index | -1.607 | 12.462*** |
| b) Adjusted Dickey-Fuller and KPSS test results after data transformation | | | | | | | | | | | | | | |
| France | | | Germany | | | Italy | | | Spain | | | The UK | | |
| | Adjusted DF | KPSS | | Adjusted DF | KPSS | | Adjusted DF | KPSS | | Adjusted DF | KPSS | | Adjusted DF | KPSS |
| CDS | -42.236*** | 0.074 | CDS | -43.974*** | 0.075 | CDS | -38.492*** | 0.077 | CDS | -38.909*** | 0.118 | CDS | -38.936*** | 0.101 |
| RLE | -31.7*** | 0.146 | RLE | -32.38*** | 0.219 | RLE | -31.561*** | 0.121 | RLE | -31.601*** | 0.23 | RLE | -33.444*** | 0.172 |
| Term Spread | -46.178*** | 0.227 | Term Spread | -43.571*** | 0.186 | Term Spread | -46.895*** | 0.134 | Term Spread | -45.52*** | 0.123 | Term Spread | -51.771*** | 0.203 |
| Liquidity Spread | - | - | Liquidity Spread | -60.99*** | 0.142 | Liquidity Spread | - | - | Liquidity Spread | - | - | Liquidity Spread | -48.316*** | 0.238 |
| Stock Index | -50.517*** | 0.098 | Stock Index | -48.274*** | 0.079 | Stock Index | -48.5*** | 0.152 | Stock Index | -47.776*** | 0.16 | Stock Index | -50.367*** | 0.098 |

Notes: This table reports the Adjusted Dickey-Fuller test results for unit root present in time series and the KPSS test results for stationarity of the time series. Part a) reports the test results before the data transformations and part b) report the results after the data transformations. Data transformations are applied as follows. For variables CDS spreads, term spread and liquidity spread the first differences were calculated. For variables real estate index and stock index percentage change has been calculated. The statistically significant test statistic for the ADF test indicates that the presence of a unit root in the time series is rejected. The statistically significant test statistic for the KPSS test indicates that the non-stationarity of the time series is rejected. The *** indicates that the test statistic is significant at 1% significance level.

Table 3.6: List of financial institutions included in the calculation of the country specific banks' CDS index

| France | |
|----------------|--|
| 1 | AXA France |
| 2 | Banque Fédérative du Crédit Mutuel |
| 3 | BNP Paribas |
| 4 | Credit Agricole |
| 5 | Natixis |
| 6 | Scor |
| 7 | Societe Generale |
| 8 | Wendel |
| 9 | Dexia Crédit Local |
| Germany | |
| 10 | Allianz |
| 11 | Deutsche Bank |
| 12 | Bayerische Landesbank |
| 13 | Commerzbank |
| 14 | UniCredit Bank (formerly Bayerische Hypo- und Vereinsbank) |
| 15 | Landesbank Hessen-Thüringen |
| 16 | Landesbank Baden-Württemberg |
| 17 | HSH Nordbank |
| 18 | IKB Deutsche Industriebank |
| 19 | DZ Bank |
| 20 | WestLB |
| 21 | Munich Re Group |
| 22 | Landesbank Saar |
| 23 | Bremer Landesbank |
| 24 | Deutsche Postbank |
| 25 | KfW (formerly KfW Bankengruppe) |
| 26 | Landesbank Berlin |
| 27 | Norddeutsche Landesbank |
| 28 | UniCredit Bank Germany |
| Italy | |
| 29 | Assicurazioni Generali |
| 30 | Mediobanca |
| 31 | Banca Italease |
| 32 | Banca Popolare Italiana |
| 33 | Banca Popolare di Milano |
| 34 | Unicredito Italiano |
| 35 | Unione di Banche Italiane |
| 36 | Banca Monte dei Paschi di Siena |
| 37 | Unipol Gruppo Finanziario |
| 38 | Banca Nazionale del Lavoro |

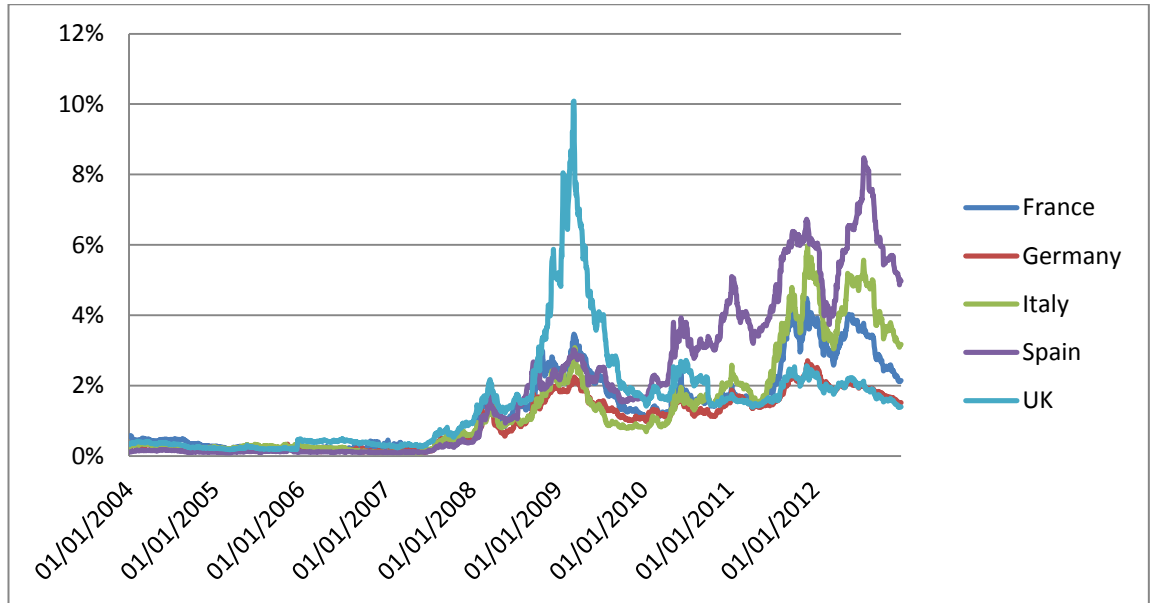
Spain

- 39 Bankinter
- 40 Banco Sabadell
- 41 Banco Bilbao Vizcaya Argentaria
- 42 Banco de Galicia
- 43 Banco Popular Español
- 44 Caja de Ahorros del Mediterráneo
- 45 La Caixa
- 46 Banco Santander Central Hispano
- 47 Ibercaja
- 48 CatalunyaCaixa
- 49 Fundació Bancaixa
- 50 Caja Madrid

The UK

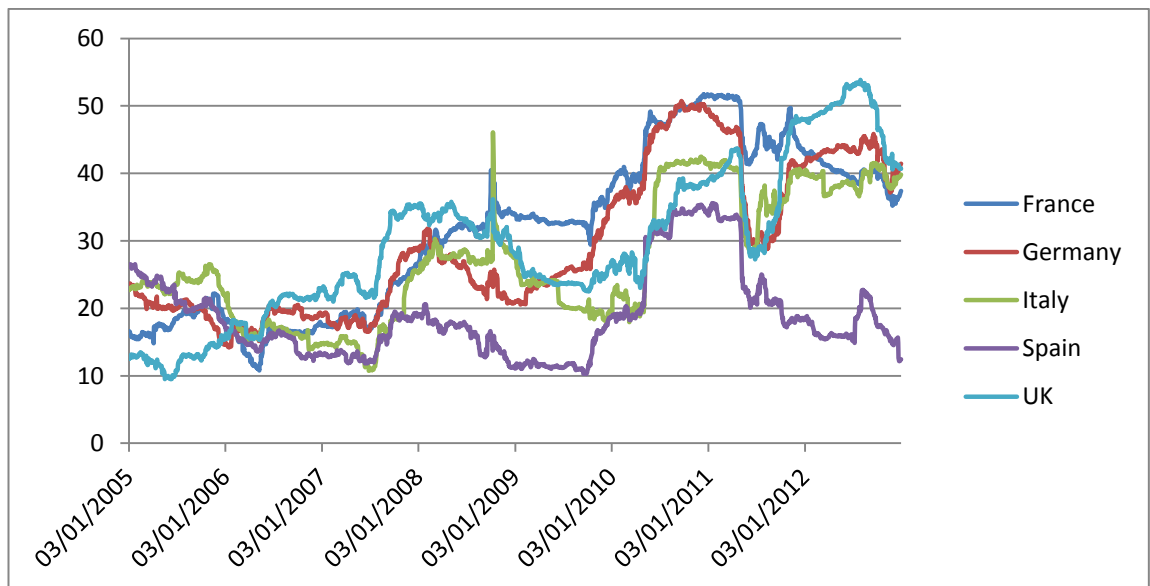
- 51 Santander UK
- 52 3i Group
- 53 Barclays Bank
- 54 Northern Rock
- 55 Alliance & Leicester
- 56 Aviva
- 57 The Royal Bank of Scotland
- 58 Standard Chartered Bank UK
- 59 HBOS
- 60 HSBC Bank
- 61 Man Group
- 62 Old Mutual
- 63 Prudential
- 64 Lloyds TSB
- 65 Legal & General Group
- 66 RSA Insurance Group
- 67 The Yorkshire Building Society
- 68 Standard Life Funding BV
- 69 The Skipton Building Society
- 70 Ono Finance
- 71 Piraeus Bank Group
- 72 FCE Bank
- 73 Nationwide Building Society

Figure 3.1: Bank CDS spreads



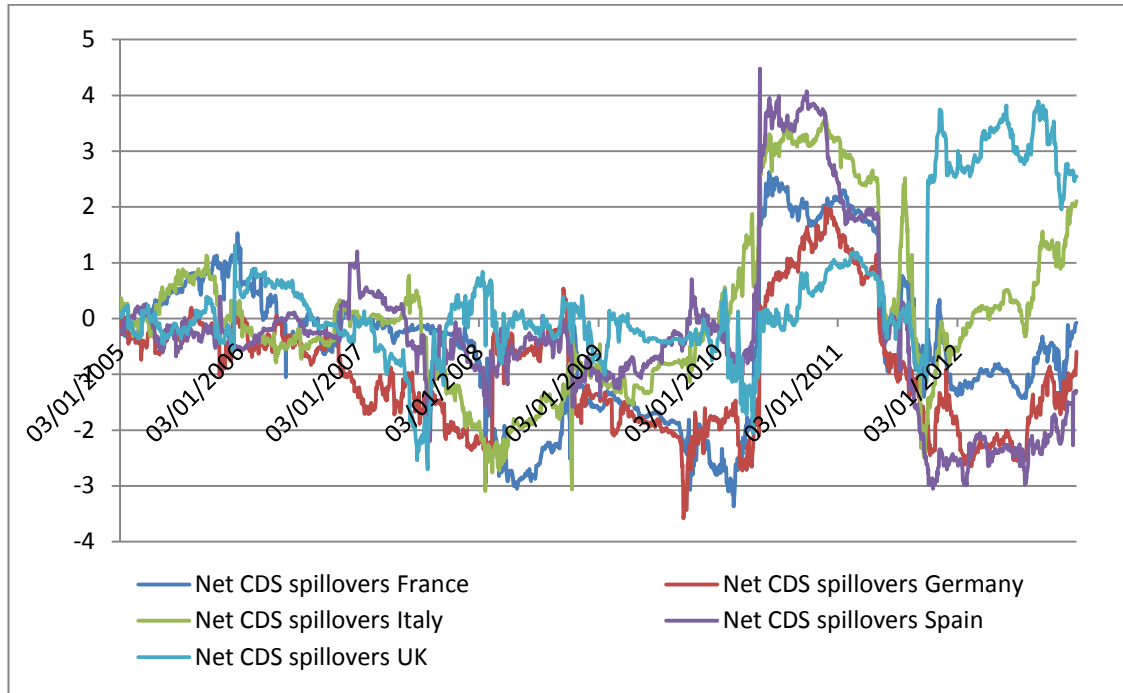
Notes: This figure illustrates bank CDS spread series over the sample period 1st of January 2004 to 31st of December 2012 for France, Germany, Italy, Spain and UK.

Figure 3.2: Total spillover index: 260-day rolling window estimation



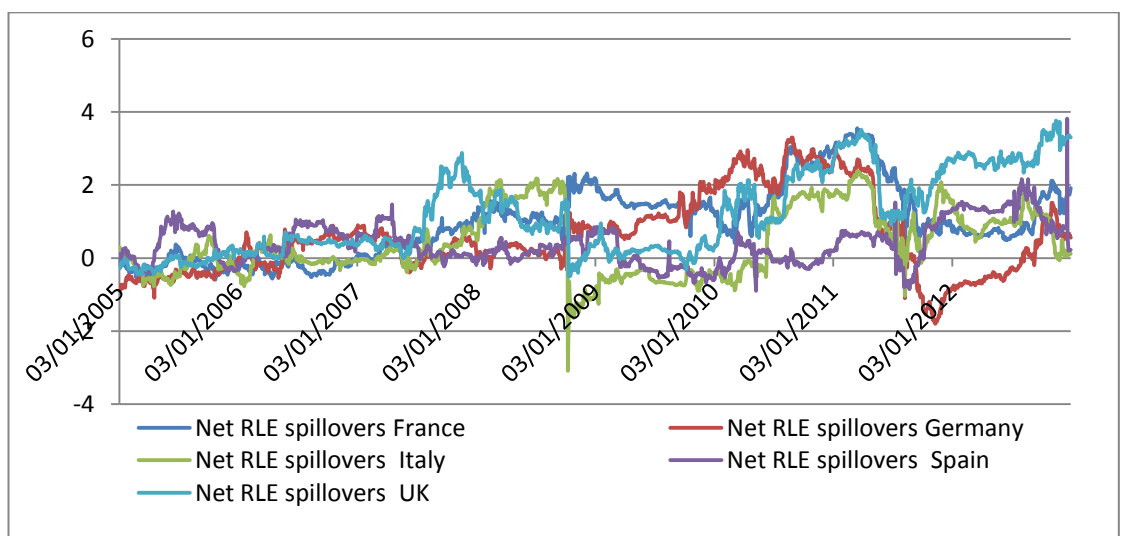
Notes: This figure illustrates the total spillover index time series from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.6) for calculation of the total spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.3: Net CDS spread spillover index: 260-day rolling window estimation



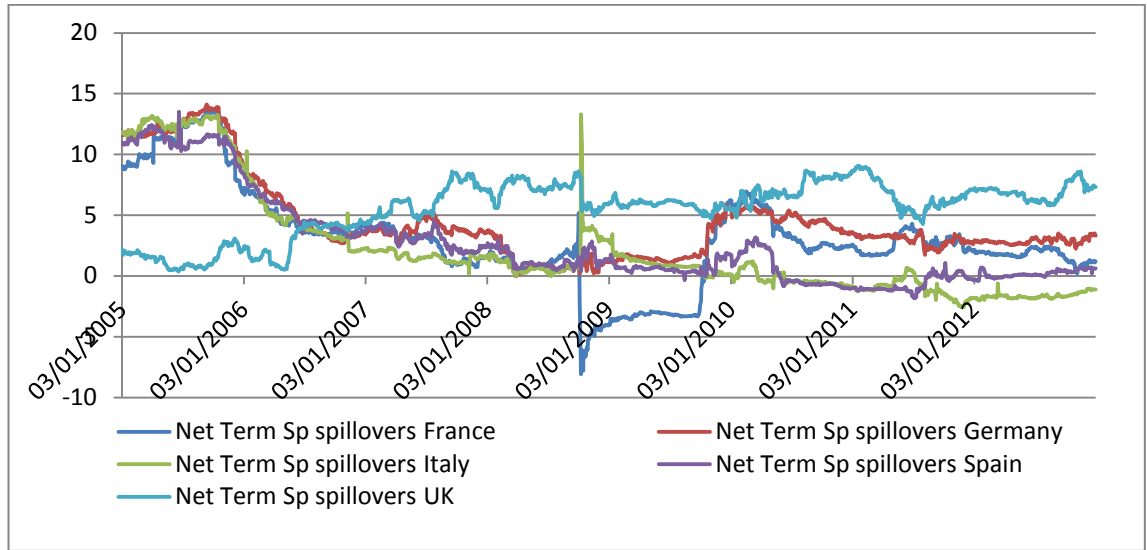
Notes: This figure illustrates the net CDS spread spillover index time series from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.9) for calculation of the net spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.4: Net real estate index spillover series: 260-day rolling window estimation



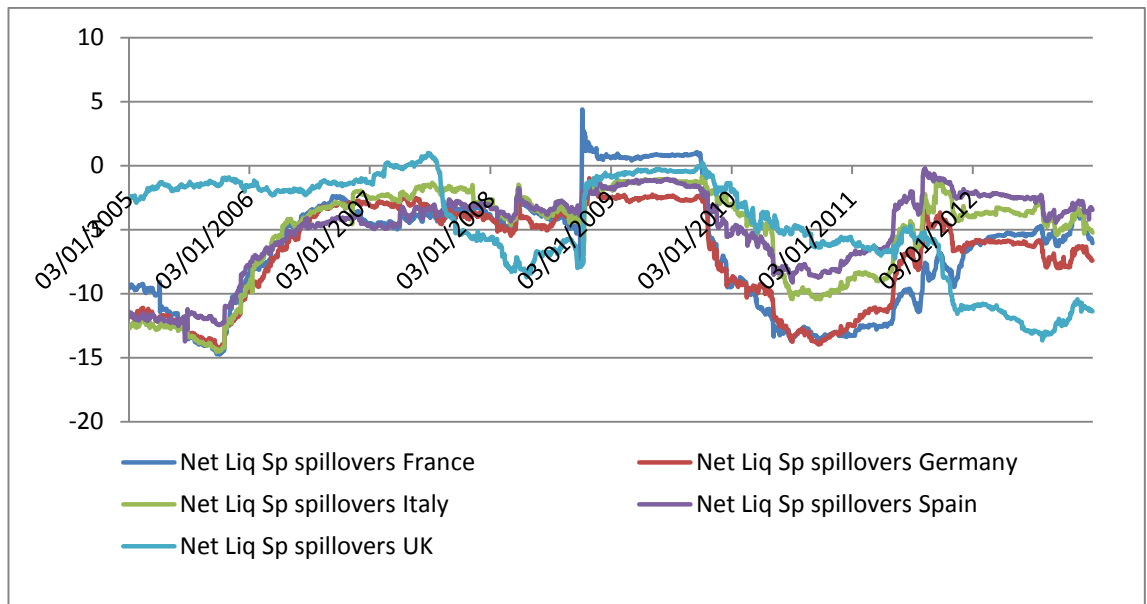
Notes: This figure illustrates the net real estate index spillover time series from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.9) for calculation of the net spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.5: Net term spread spillover index: 260-day rolling window estimation



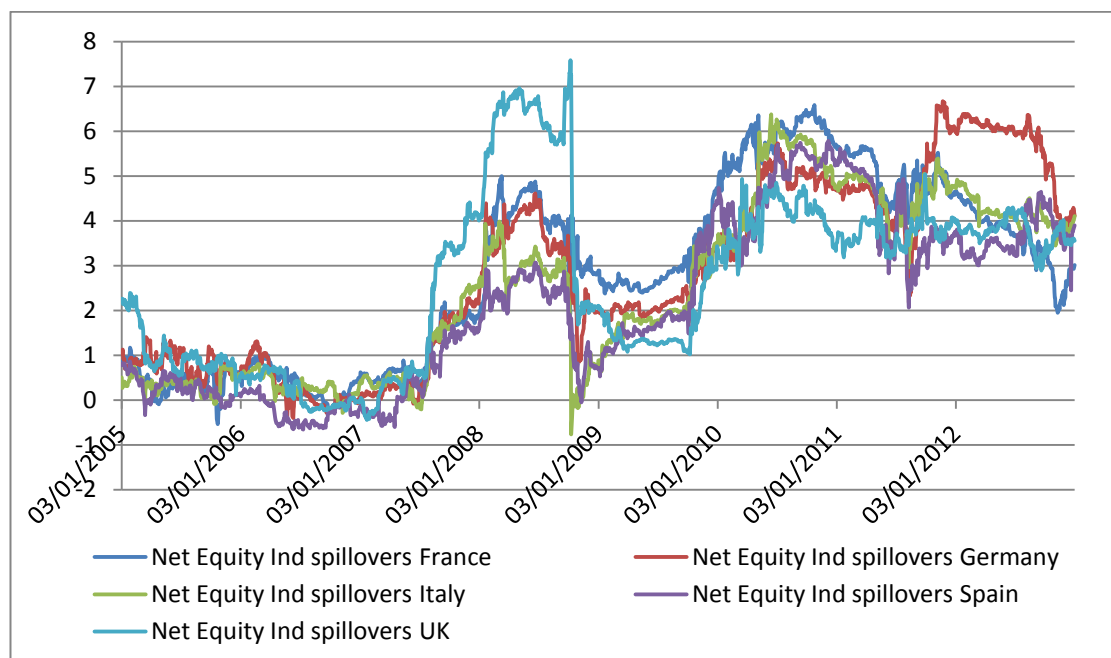
Notes: This figure illustrates the net term spread spillover index time series from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.9) for calculation of the net spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.6: Net liquidity spread spillover index: 260-day rolling window estimation



Notes: This figure illustrates the net liquidity spread spillover index time series from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.9) for calculation of the net spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

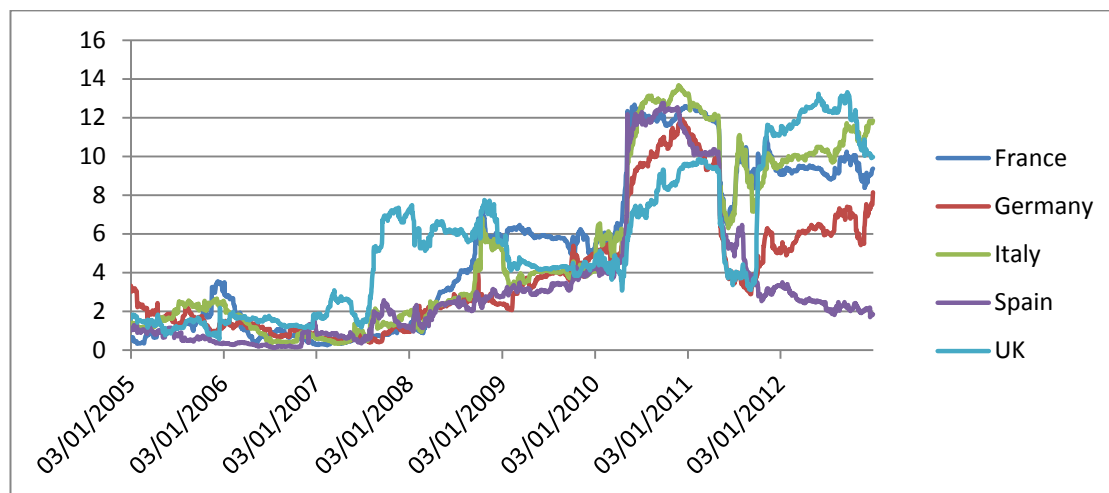
Figure 3.7: Net stock index spillover series: 260-day rolling window estimation



Notes: This figure illustrates the net stock index spillover time series from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.9) for calculation of the net spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

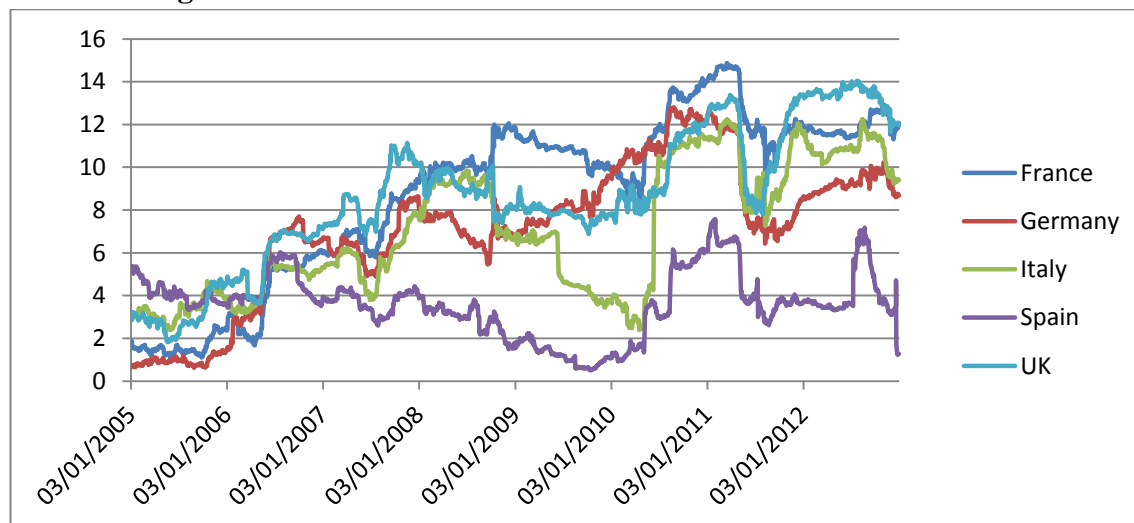
Figure 3.8 Directional spillovers from one variable to all other variables: 260-day rolling window estimation

a) Directional spillovers from CDS spread to all other variables: 260-day rolling window estimation



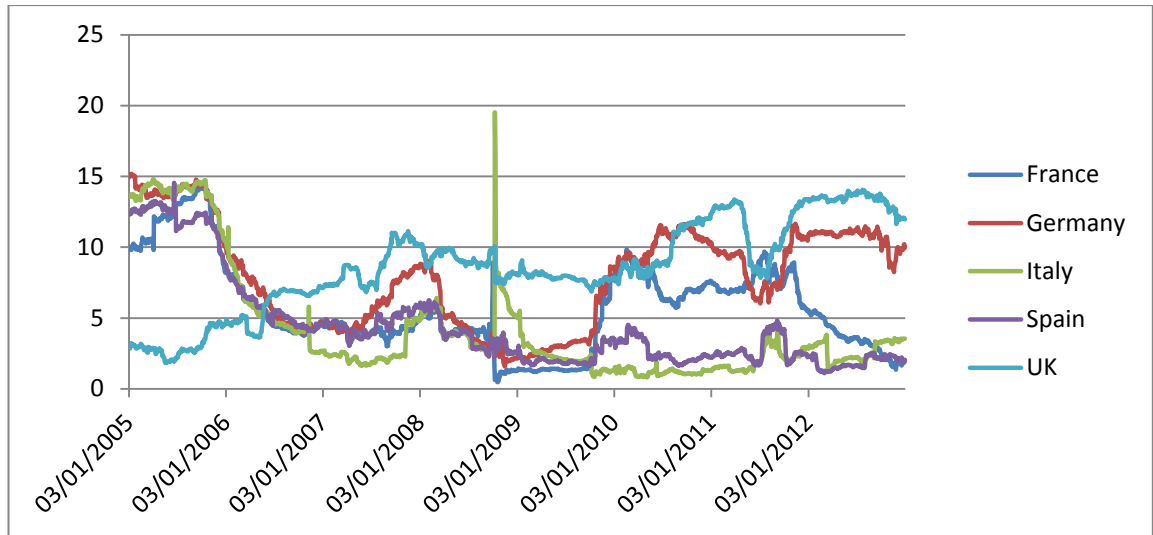
Notes: This figure illustrates the time series of the directional spillovers from the CDS spreads to all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.8) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

b) Directional spillovers from real estate index to all other variables: 260-day rolling window estimation



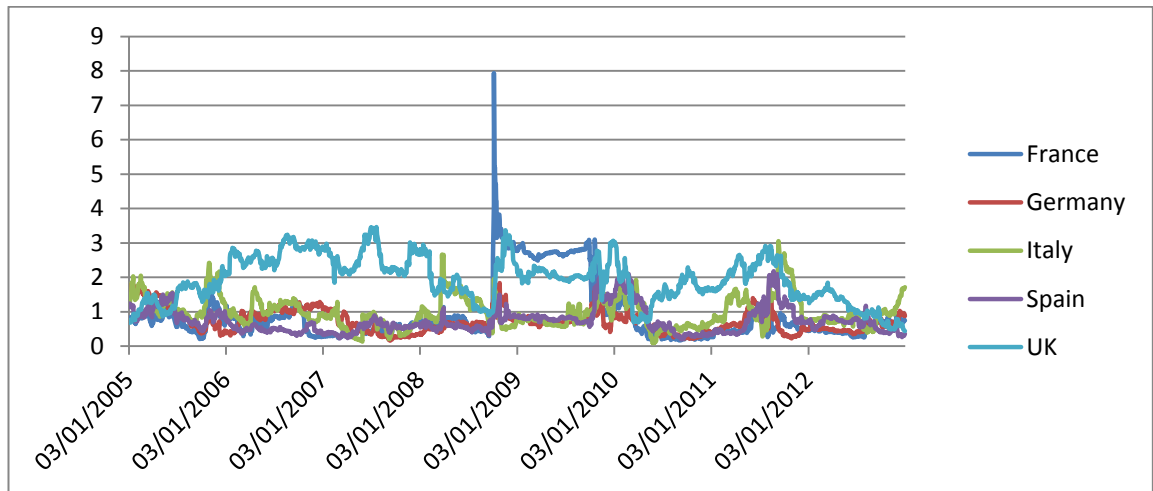
Notes: This figure illustrates the time series of the directional spillovers from the real estate index to all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.8) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

c) Directional spillovers from term spread to all other variables: 260-day rolling window estimation



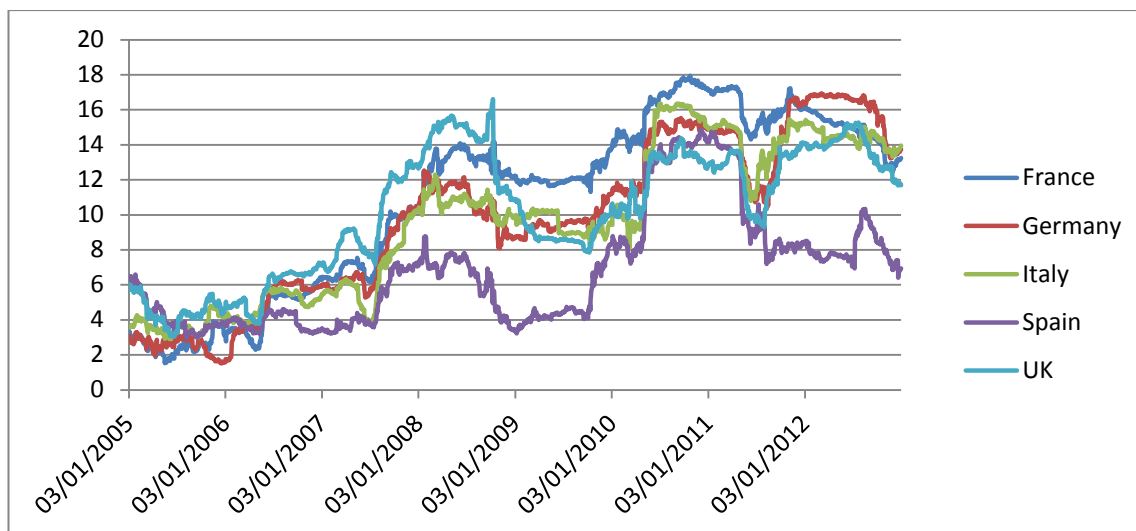
Notes: This figure illustrates the time series of the directional spillovers from the term spread to all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.8) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

d) Directional spillovers from liquidity spread to all other variables: 260-day rolling window estimation



Notes: This figure illustrates the time series of the directional spillovers from the liquidity spread to all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.8) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

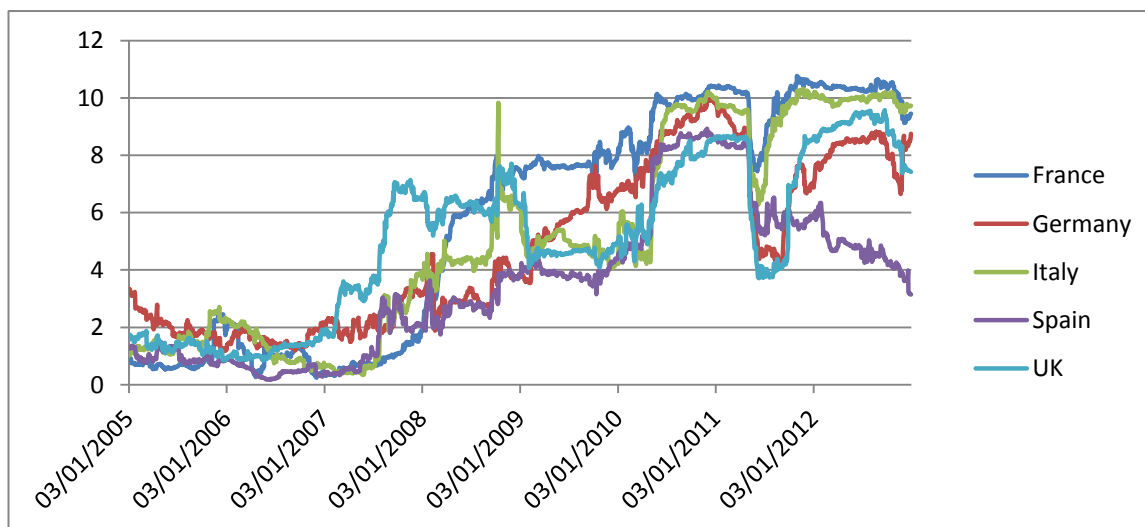
e) Directional spillovers from stock index to all other variables: 260-day rolling window estimation



Notes: This figure illustrates the time series of the directional spillovers from the stock index to all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.8) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

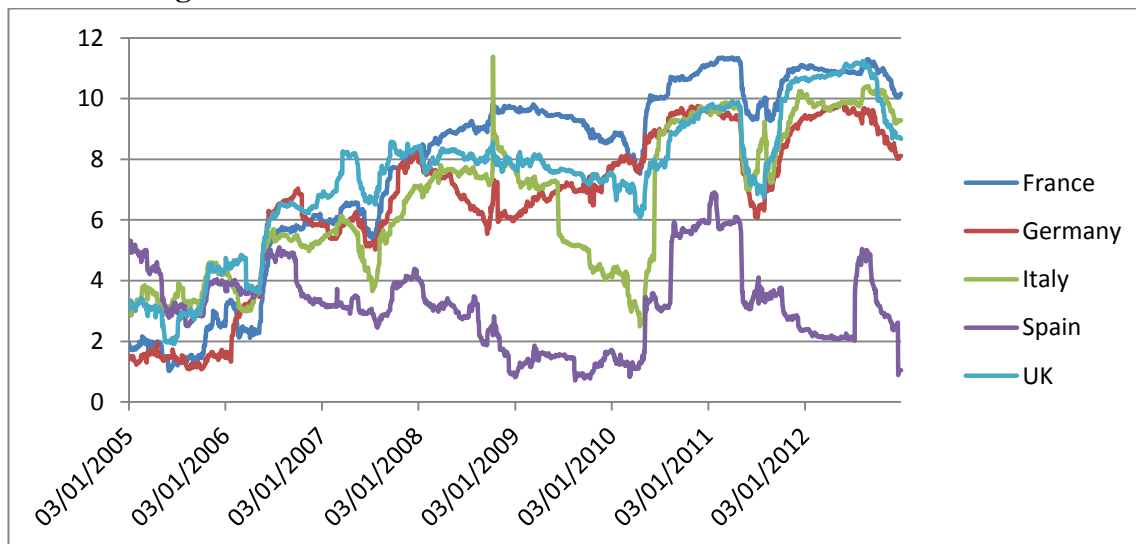
Figure 3.9 Directional spillovers to one variable from all other variables: 260-day rolling window estimation

a) Directional spillovers to CDS spread from all other variables: 260-day rolling window estimation



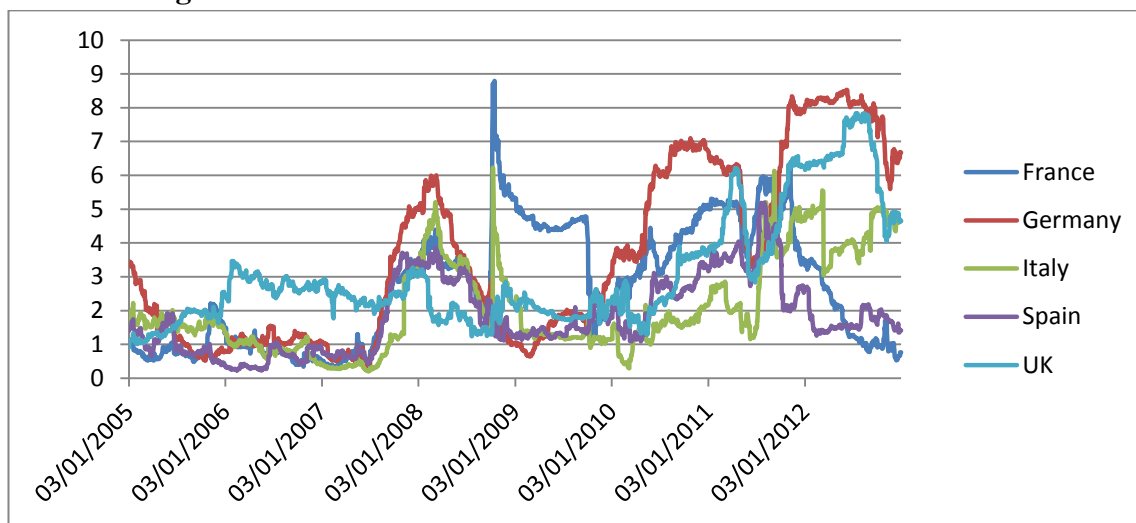
Notes: This figure illustrates the time series of the directional spillovers to the stock index from all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.7) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

b) Directional spillovers to real estate index from all other variables: 260-day rolling window estimation



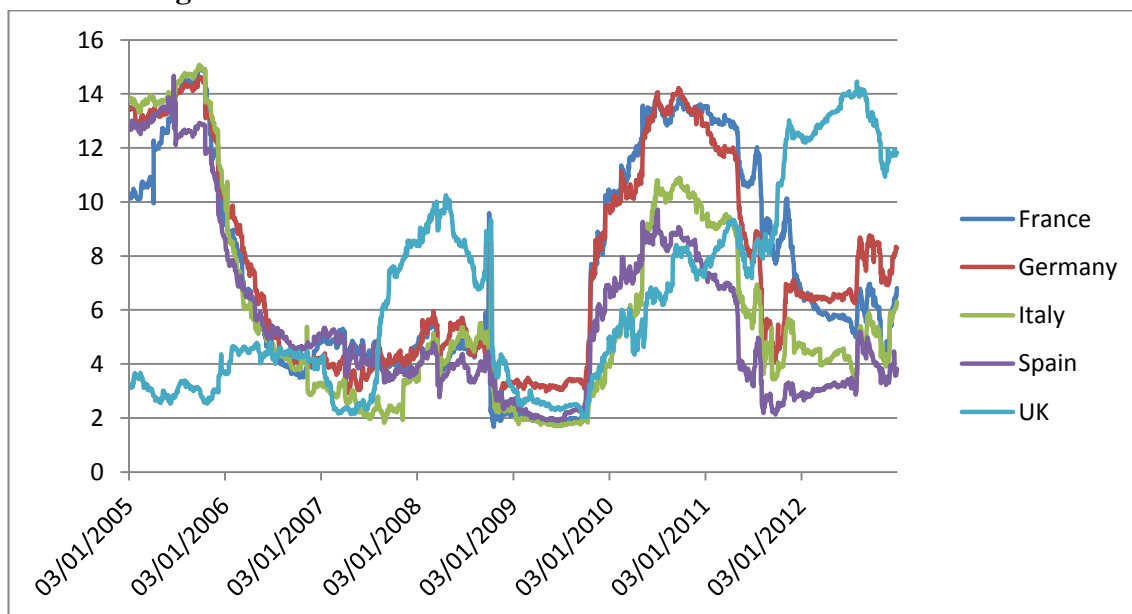
Notes: This figure illustrates the time series of the directional spillovers to the real estate index from all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.7) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

c) Directional spillovers to term spread from all other variables: 260-day rolling window estimation



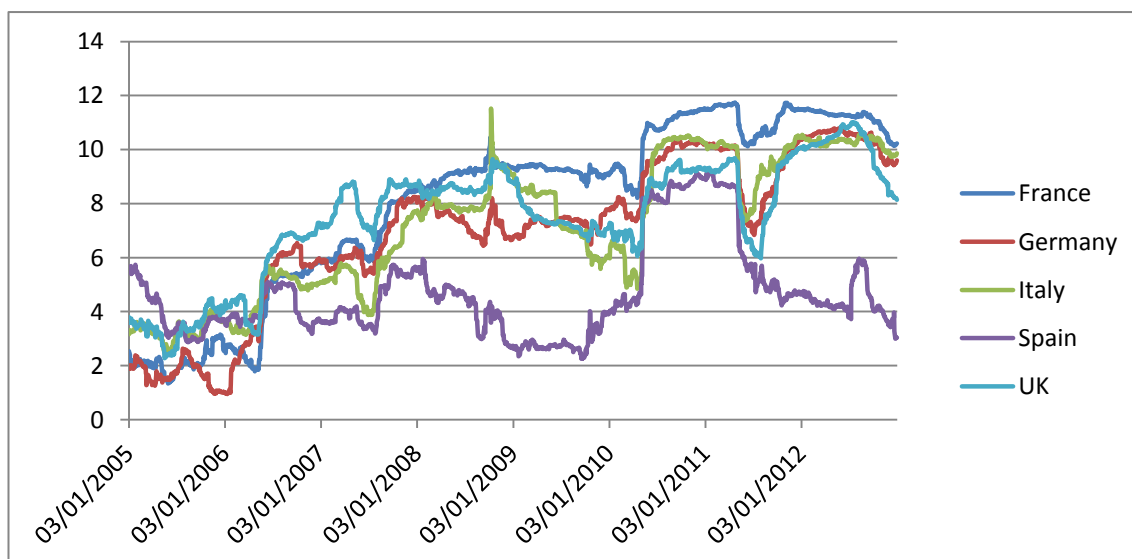
Notes: This figure illustrates the time series of the directional spillovers to the term spread from all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.7) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

d) Directional spillovers to liquidity spread from all other variables: 260-day rolling window estimation



Notes: This figure illustrates the time series of the directional spillovers to the liquidity spread from all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.7) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

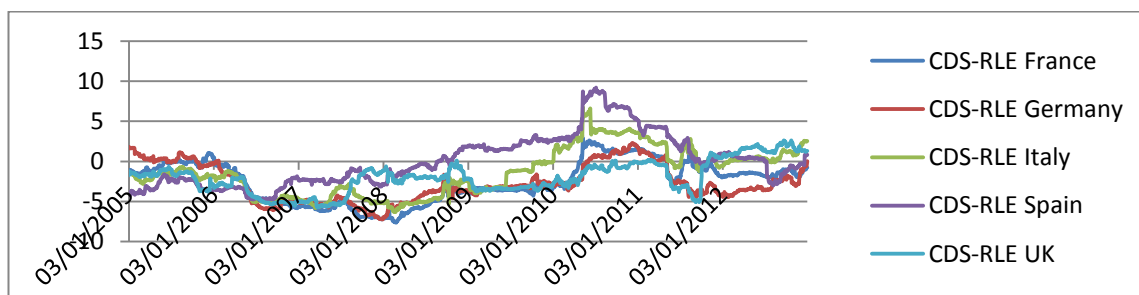
e) Directional spillovers to stock index from all other variables: 260-day rolling window estimation



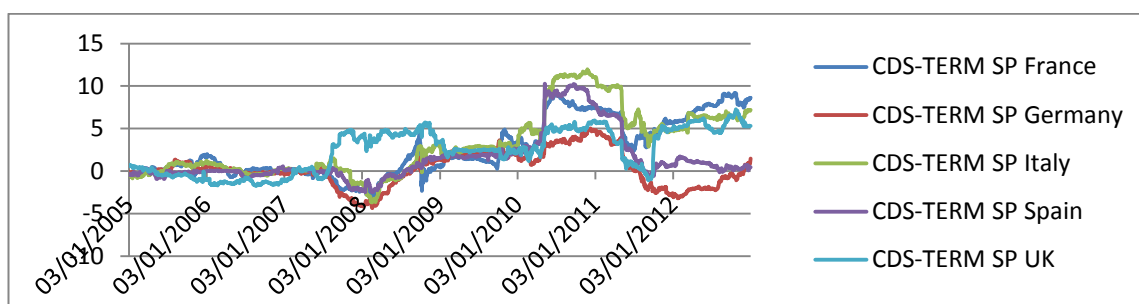
Notes: This figure illustrates the time series of the directional spillovers to the stock index from all other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.7) for calculation of this directional spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.10: Net pairwise spillovers: CDS spread to other variables, 260-day rolling window estimation

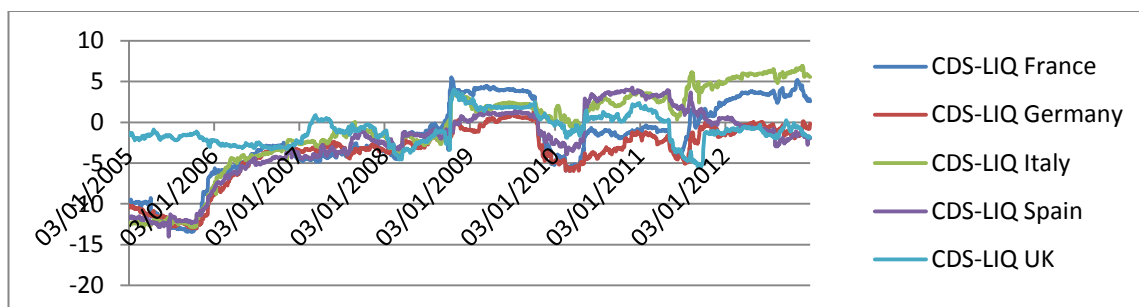
(a) Net pairwise spillovers: CDS spread to real estate index



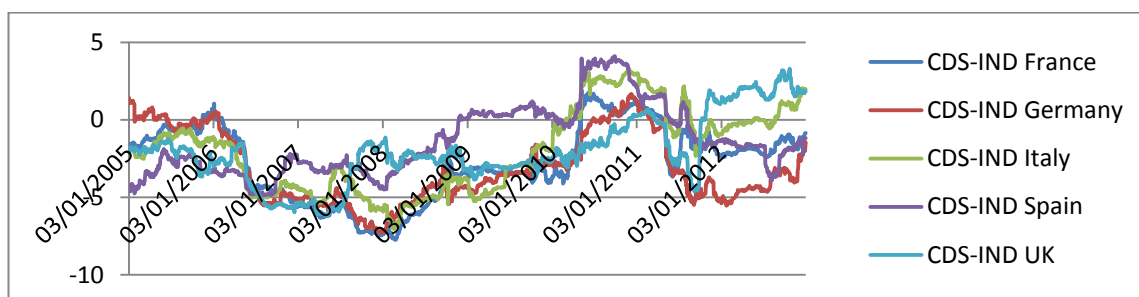
(b) Net pairwise spillovers: CDS spread to term spread



(c) Net pairwise spillovers: CDS spread to liquidity spread



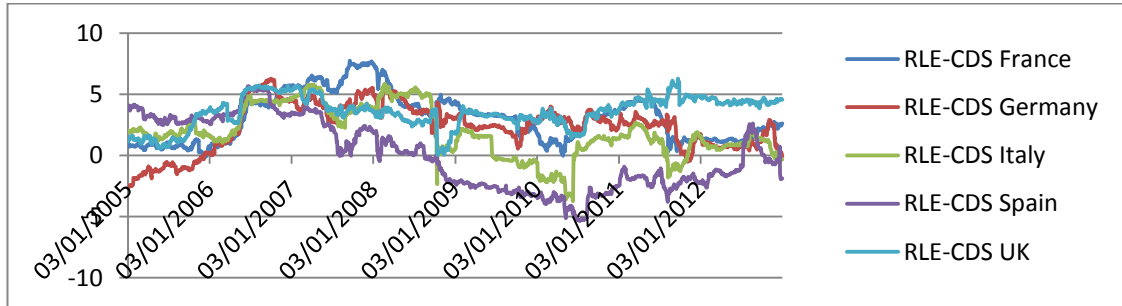
(d) Net pairwise spillovers: CDS spread to stock index



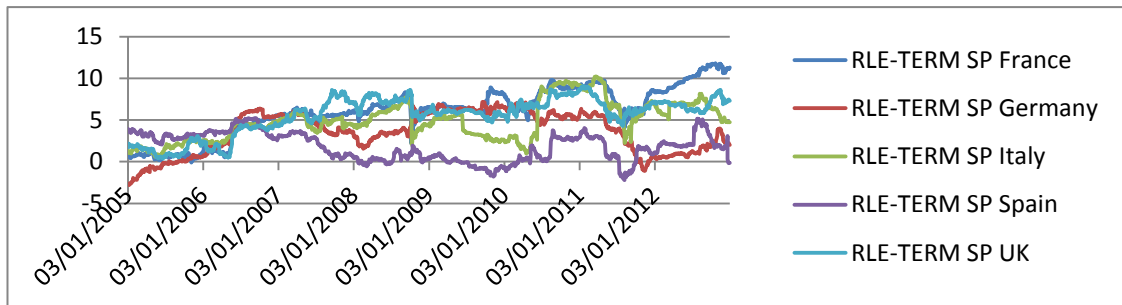
Notes: This figure illustrates the net pairwise spillover time series from CDS to other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.10) for calculation of the net pairwise spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.11: Net pairwise spillovers: Real estate index to other variables, 260-day rolling window estimation

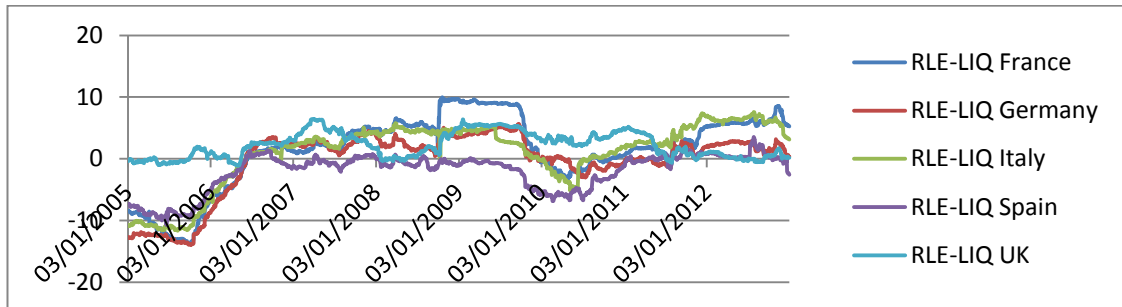
(a) Net pairwise spillovers: real estate index to CDS spread



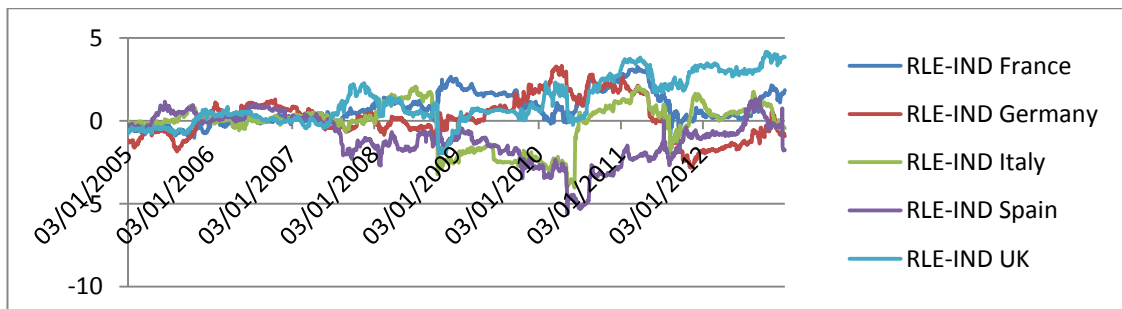
(b) Net pairwise spillovers: real estate index to term spread



(c) Net pairwise spillovers: real estate index to liquidity spread



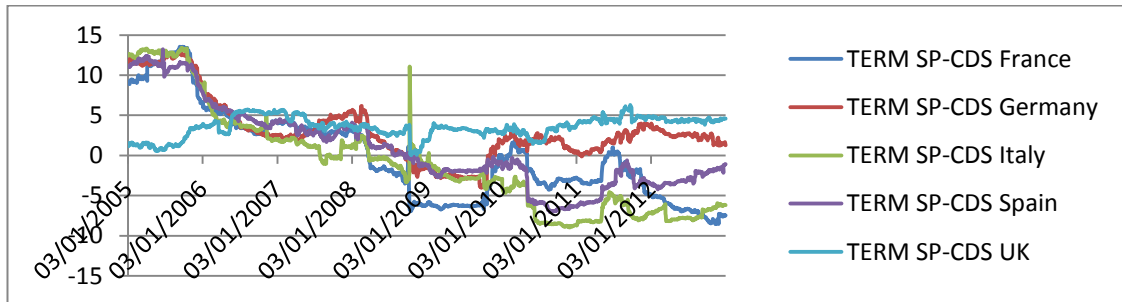
(d) Net pairwise spillovers: real estate index to stock index



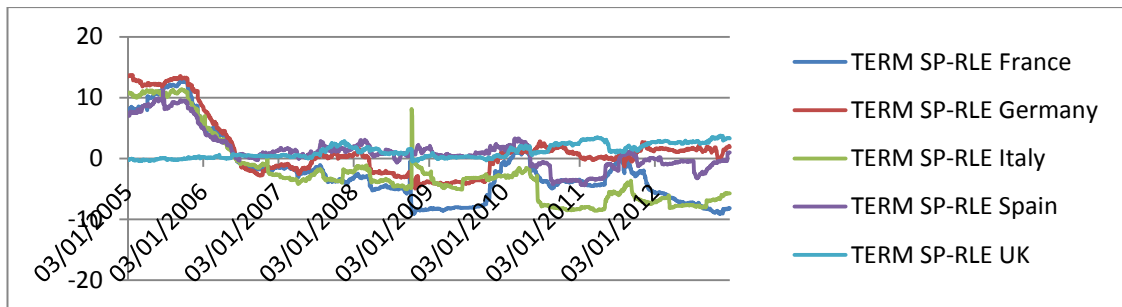
Notes: This figure illustrates the net pairwise spillover time series from real estate index to other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.10) for calculation of the net pairwise spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.12: Net pairwise spillovers: Term spread to other variables, 260-day rolling window estimation

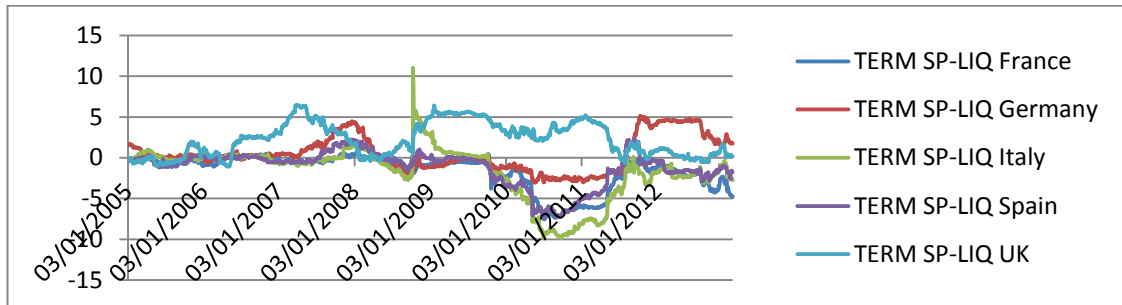
(a) Net pairwise spillovers: term spread to CDS spread



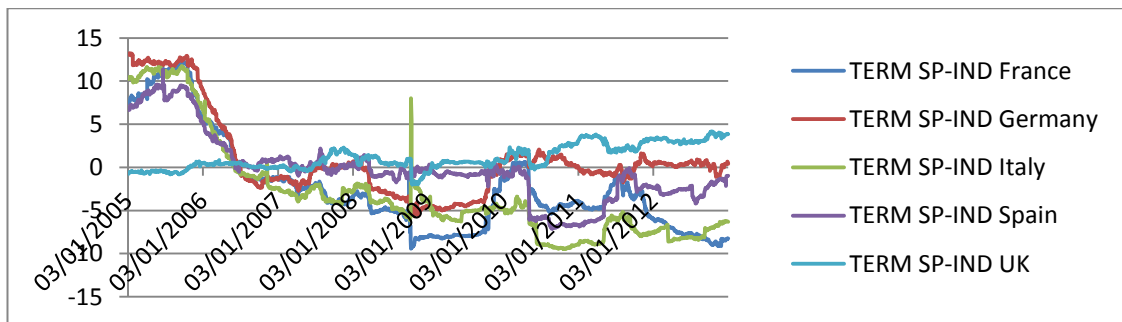
(b) Net pairwise spillovers: term spread to real estate index



(c) Net pairwise spillovers: term spread to liquidity spread



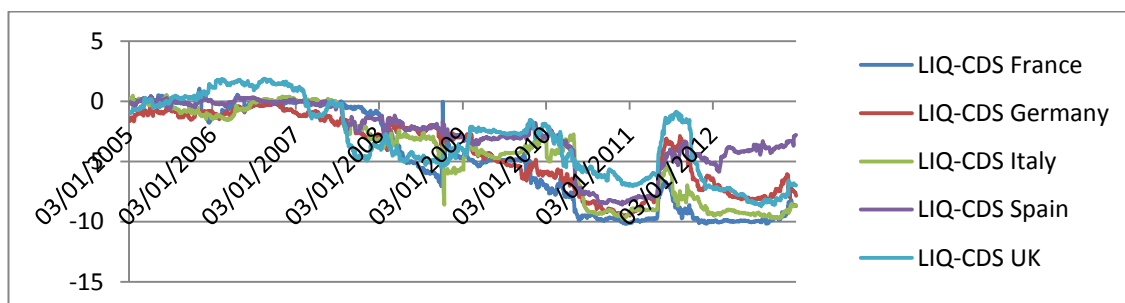
(d) Net pairwise spillovers: term spread to stock index



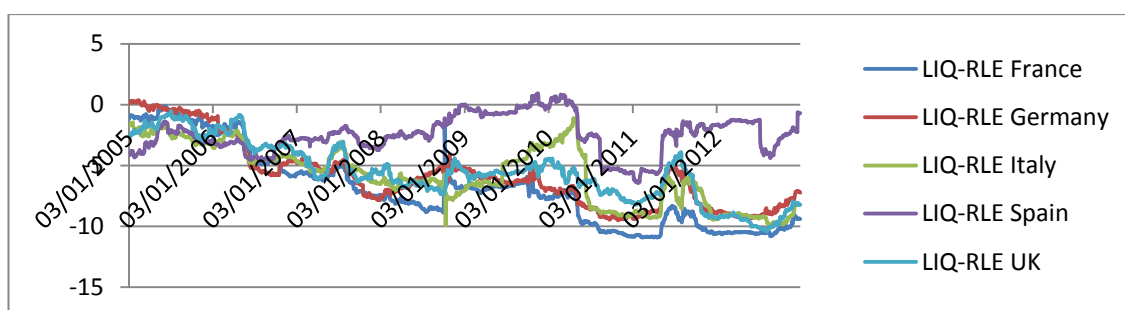
Notes: This figure illustrates the net pairwise spillover time series from term spread to other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.10) for calculation of the net pairwise spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.13: Net pairwise spillovers: Liquidity spread to other variables, 260-day rolling window estimation

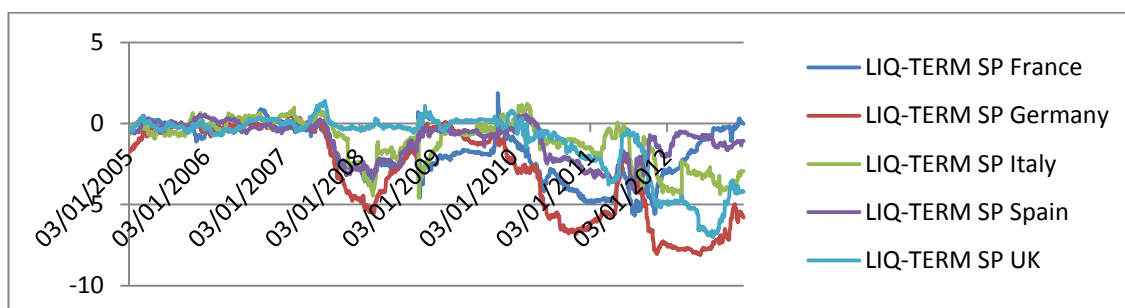
(a) Net pairwise spillovers: liquidity spread to CDS spread



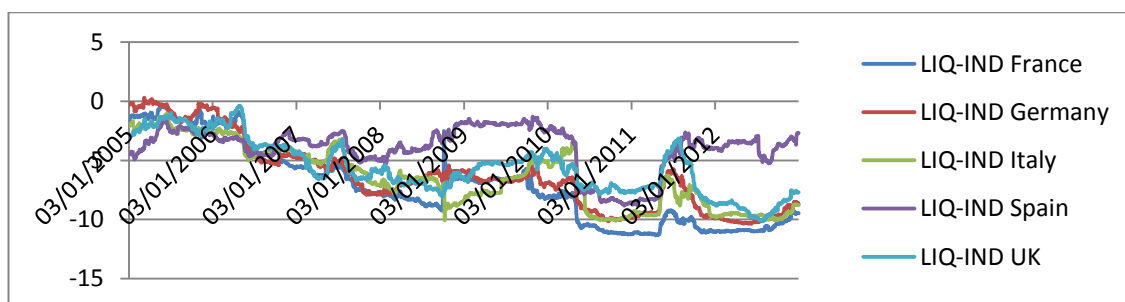
(b) Net pairwise spillovers: liquidity spread to real estate index



(c) Net pairwise spillovers: liquidity spread to term spread



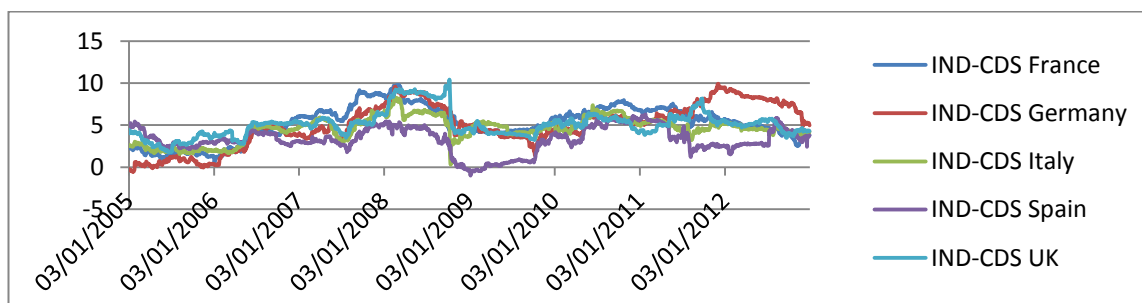
(d) Net pairwise spillovers: liquidity spread to stock index



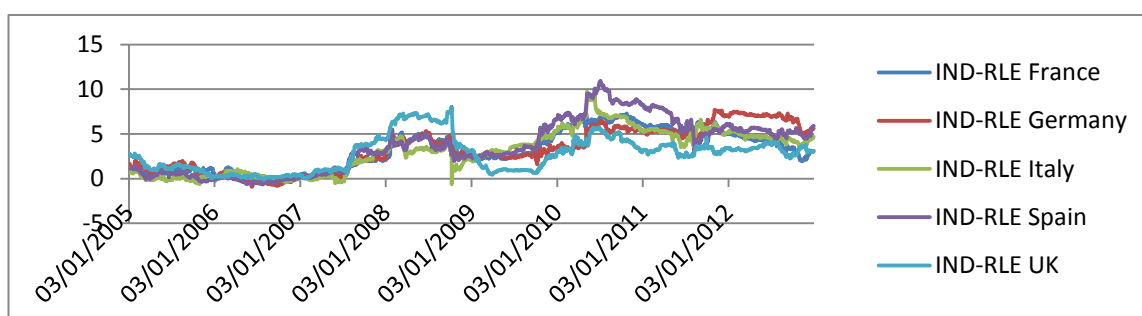
Notes: This figure illustrates the net pairwise spillover time series from liquidity spread to other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.10) for calculation of the net pairwise spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

Figure 3.14: Net pairwise spillovers: National stock index to other variables, 260-day rolling window estimation

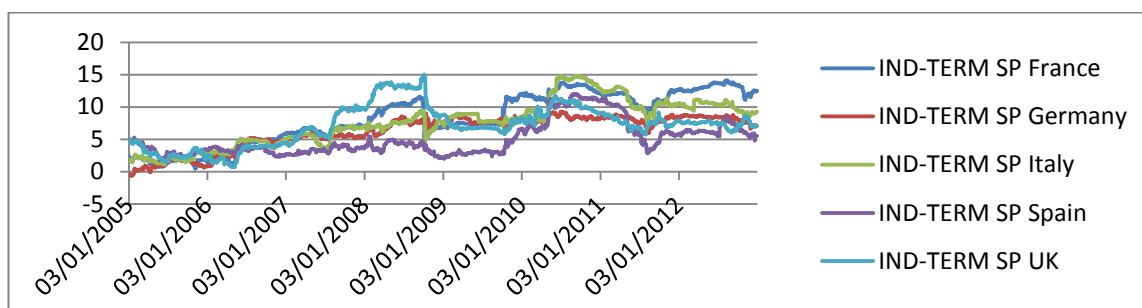
(a) Net pairwise spillovers: stock index to CDS spread



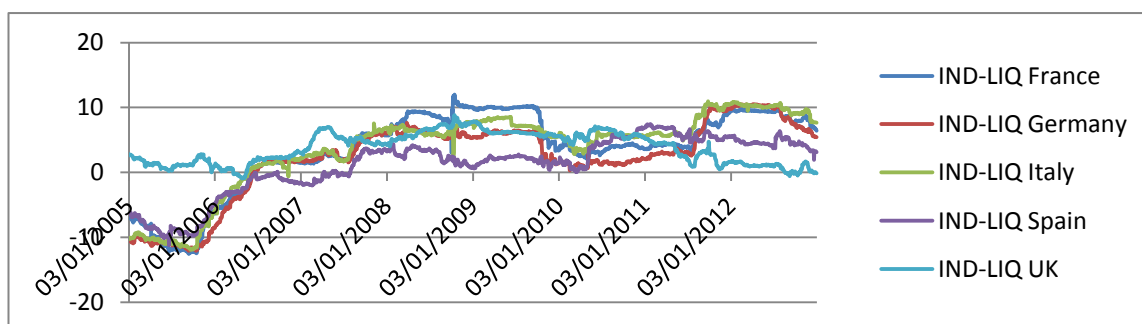
(b) Net pairwise spillovers: stock index to real estate index



(c) Net pairwise spillovers: stock index to term spread



(d) Net pairwise spillovers: stock index to liquidity spread



Notes: This figure illustrates the net pairwise spillover time series from stock index to other variables from the DY (2012) estimation procedure based on 260-day rolling window sample. Total number of observations is 2085, as the rolling sample estimation uses 260 observations. All numbers are in percentages. See Eq (3.10) for calculation of the net pairwise spillovers index. The series covers the period 3rd of January 2004 to 31st of December 2012.

References

- [1] Acharya, V.V., Drechsler, I., Schnabl, P., 2012. A tale of two overhangs: the nexus of financial sector and sovereign credit risks. *Financial Stability Review* No 16
- [2] Adrian, T., Rosenberg, J., 2006. Stock returns and volatility: Pricing the short-run and long-run components of market risk. Federal Reserve Bank of New York, New York
- [3] Alter, A., Beyer, A., 2014. The dynamics of spillover effects during the European sovereign debt turmoil. *Journal of Banking & Finance* 42, 134-153
- [4] Alter, A., Schüler, Y.S., 2012. Credit spread interdependencies of European states and banks during the financial crisis. *Journal of Banking & Finance* 36, 3444-3468
- [5] Andrikopoulos, A., Angelidis, T., Skintzi, V., 2014. Illiquidity, return and risk in G7 stock markets: Interdependencies and spillovers. In Press, Upcoming in *International Review of Financial Analysis*
- [6] Ang, A., Bekaert, G., 1999. International asset allocation with time-varying correlations. In: NBER working paper series no w7056. National Bureau of Economic Research, Cambridge, Mass.
- [7] Ang, A., Chen, J., 2002. Asymmetric correlations of equity portfolios. *Journal of Financial Economics* 63, 443-494
- [8] Angelini, P., Nobili, A., Picillo, C., 2011. The interbank market after August 2007: what has changed, and why? *Journal of Money, Credit, and Banking* 43, 923-958

- [9] Annaert, J., De Ceuster, M., Van Roy, P., Vespro, C., 2013. What determines Euro area bank CDS spreads? *Journal of International Money and Finance* 32, 444-461
- [10] Audrino, F., Buhlmann, P., 2003. Synchronizing multivariate financial time series. *Journal of Risk* 6, 81-106
- [11] Avino, D., Cotter, J., 2014. Sovereign and bank CDS spreads: two sides of the same coin? *Journal of International Financial Markets, Institutions and Money* 32, 72-85
- [12] Baele, L., Inghelbrecht, K., 2010. Time-varying integration, interdependence and contagion. *Journal of International Money and Finance* 29, 791-818
- [13] Bai, J., Perron, P., 1998. Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica* 66, 47-78
- [14] Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. *Journal of Applied Econometrics* 18, 1-22
- [15] Baillie, R.T., Bollerslev, T., Redfearn, M.R., 1993. Bear squeezes, volatility spillovers and speculative attacks in the hyperinflation 1920s foreign exchange. *Journal of International Money and Finance* 12, 511-521
- [16] Banca d'Italia, 2008. Economic Bulletin. Number 50 October 2008. Available at: http://www.bancaditalia.it/pubblicazioni/econo/bollec/2008/bolls54/ecbull50/ecbull_50.pdf
- [17] European Central Bank, 2007. Press Release. 12 December 2007 Available at <https://www.ecb.europa.eu/press/pr/date/2007/html/pr071212.en.html>

- [18] Banner, C.E., Fecht, F., Tyrell, M., 2008. Open-end real estate funds in Germany - genesis and crisis. *Kredit und Kapital* 41, 9-36
- [19] Barndorff-Nielsen, O.E., Hansen, P.R., Lunde, A., Shephard, N., 2011. Multivariate realised kernels: Consistent positive semi-definite estimators of the covariation of equity prices with noise and non-synchronous trading. *Journal of Econometrics* 162, 149-169
- [20] Beckers, S., Connor, G., Curds, R., 1996. National versus global influences on equity returns. *Financial Analysts Journal* 52, 31-39
- [21] Bekaert, G., Hodrick, R.J., Zhang, X., 2009. International stock return comovements. *The Journal of Finance* 64, 2591-2626
- [22] Benbouzid, N., Mallick, S., 2013. Determinants of bank credit default swap spreads: The role of the housing sector. *The North American Journal of Economics and Finance* 24, 243-259
- [23] Blanco, R., Simon, B., Marsh, I.W., 2005. An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps. *The Journal of Finance* 60, 2255-2281
- [24] Bloomberg News Report, 2011. Italy's Rating Cut One Level by S&P as Greek Crisis Fans Contagion Concern. 20 September 2011. Available at: <http://www.bloomberg.com/news/2011-09-19/italy-s-credit-rating-cut-one-level-to-a-by-s-p-as-government-debt-mounts.html>
- [25] Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *The Review of Economics and Statistics* 72, 498-505

- [26] Booth, G.G., Tse, Y., 1996. Common volatility and volatility spillovers between U.S. and Eurodollar interest rates: Evidence from the futures market. *Journal of Economics and Business* 48, 299-312
- [27] Brandt, M.W., Kang, Q., 2004. On the relationship between the conditional mean and volatility of stock returns: A latent VAR approach. *Journal of Financial Economics* 72, 217-257
- [28] Brown, R. L., Durbin, J., Evans, J.M., 1975. Techniques for Testing the Constancy of Regression Relationships over Time. *Journal of the Royal Statistical Society. Series B (Methodological)* 37, 149-192
- [29] Burns, P., Engle, R., Mezrich, J., 1998. Correlations and volatilities of asynchronous data. *The Journal of Derivatives* 5, 7-18
- [30] Cappiello, L., Engle, R.F., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics* 4, 537-572
- [31] Carrieri, F., Errunza, V., Hogan, K., 2007. Characterizing world market integration through time. *Journal of Financial and Quantitative Analysis* 42, 915-940
- [32] Chernov, M., Gallant, R.A., Ghysels, E., Tauchen, G., 2003. Alternative models for stock price dynamics. *Journal of Econometrics* 116, 225-257
- [33] Christiansen, C., Schmeling, M., Schrimpf, A., 2012. A comprehensive look at financial volatility prediction by economic variables. *Journal of Applied Econometrics* 27, 956-977
- [34] Christoffersen, P., Errunza, V., Jacobs, K., Langlois, H., 2012. Is the potential for inter-

national diversification disappearing? A dynamic copula approach. *Review of Financial Studies* 25, 3711-3751

[35] Colacito, R., Engle, R.F., Ghysels, E., 2011. A component model for dynamic correlations. *Journal of Econometrics* 164, 45-59

[36] Collin-Dufresne, P., Goldstein, R.S., Martin, J.S., 2001. The determinants of credit spread changes. *Journal of Finance* 56, 2177-2207

[37] Conefrey, T., Cronin, D., 2013. Spillover in Euro area sovereign bond markets. Central Bank of Ireland Research technical paper no 05/RT/13

[38] Connor, G., Goldberg, L.R., Korajczyk, R.A., 2010. *Portfolio Risk Analysis*. Princeton University Press.

[39] Connor, G., Suurlaht, A., 2013a. Dynamic Stock Market Covariances in the Eurozone. *Journal of International Money and Finance* 37, 353-370

[40] Connor, G., Suurlaht, A., 2013b. Ancillary Results and Estimation Code for Dynamic Stock Market Covariances in the Eurozone, NUIM Economics and Finance Department Working Paper Series

[41] Corò, F., Dufour, A., Varotto, S., 2013. Credit and liquidity components of corporate CDS spreads. *Journal of Banking & Finance* 37, 5511-5525

[42] De Bruyckere, V., Gerhardt, M., Schepens, G., Vander Vennet, R., 2013. Bank/sovereign risk spillovers in the European debt crisis. *Journal of Banking & Finance* 37, 4793-4809

- [43] de la Dehesa, G., 2012. Monetary policy responses to the crisis by ECB, FED and BoE European Parliament Policy Dept A: Economic and scientific policy Working paper no IP/A/ECON/NT/2012-04
- [44] De Santis, G., Gerard, B., 1997. International asset pricing and portfolio diversification with time-varying risk. *The Journal of Finance* 52, 1881-1912
- [45] Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association* 74, 427-431
- [46] Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal* 119, 158-171
- [47] Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28, 57-66
- [48] Ding, Z., Granger, C.W.J., 1996. Modeling volatility persistence of speculative returns: A new approach. *Journal of Econometrics* 73, 185-215
- [49] Drummen, M., Zimmermann, H., 1992. The structure of european stock returns. *Financial Analysts Journal* 48, 15-26
- [50] Duffie, D., 1999. Credit swap valuation. *Financial Analysts Journal* 55, 73-87
- [51] Eisenschmidt, J., Tapking, J., 2009. Liquidity risk premia in unsecured interbank money markets. European Central Bank Working paper no 1025
- [52] Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the

variance of United Kingdom inflation. *Econometrica* 50, 987-1007

[53] Engle, R.F., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics* 20, 339-350

[54] Engle, R.F., 2009. *Anticipating correlations: A new paradigm for risk management*. Princeton University Press.

[55] Engle, R.F., Kelly, B., 2012. Dynamic equicorrelation. *Journal of Business & Economic Statistics* 30, 212-228

[56] Engle, R.F., Ghysels, E., Sohn, B., 2008. On the economic sources of stock market volatility. In: *American Finance Association 2008 New Orleans Meetings*. American Finance Association, New Orleans

[57] Engle, R.F., Ito, T., Lin, W.-L., 1994. Do Bulls and bears move across borders? International transmission of stock returns and volatility. *The Review of Financial Studies* 7, 507-538

[58] Engle, R.F., Rangel, J.G., 2008. The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *The Review of Financial Studies* 21, 1187-1222

[59] Engle, R.F., Sheppard, K., 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. National Bureau of Economic Research Working Paper Series No. 8554

[60] Engle, R.F., White, H., 1999. A permanent and transitory component model of stock

return volatility. In: Engle RF, Granger CWJ & White H (eds.) Cointegration, causality, and forecasting: a festschrift in honour of Clive W.J. Granger. Oxford University Press, pp. 475-497.

[61] Eom, Y.H., Helwege, J., Huang, J.-Z., 2004. Structural models of corporate bond pricing: An empirical analysis. *Review of Financial Studies* 17, 499-544

[62] Erb, C.B., Harvey, C.R., Viskanta, T.E., 1994. Forecasting international equity correlations. *Financial Analysts Journal* 50, 32-45

[63] Ericsson, J., Jacobs, K., Oviedo, R., 2009. The determinants of credit default swap premia. *Journal of Financial and Quantitative Analysis* 44, 109-132

[64] Estrella, A., 2005. Why does the yield curve predict output and inflation? *Economic Journal* 115, 722-744

[65] Estrella, A., Mishkin, F.S., 1995. The term structure of interest rates and its role in monetary policy for the European Central Bank. National Bureau of Economic Research Working Paper Series No 5279

[66] European Banking Authority, 2011. Overview of the EBA 2011 banking EU-wide stress test. Available at: <http://www.eba.europa.eu/documents/10180/15932/EBA-ST-2011-003-Overview-of-2011-EBA-EU-wide-stress-test.pdf>

[67] European Central Bank Press Release, 2007. Measures designed to address elevated pressures in short-term funding markets. 12 December 2011. Available at: <https://www.ecb.europa.eu/press/pr/date/2007/html/pr071212.en.html>

- [68] European Central Bank Press Release, 2008. Monetary policy decisions. 8 October 2008. Available at: <https://www.ecb.europa.eu/press/pr/date/2008/html/pr081008.en.html>
- [69] European Central Bank Press Release, 2010. Statement by the heads of state and government of the Euro area. 25 March 2010. Available at: http://www.consilium.europa.eu/uedocs/cms_data/docs/pressdata/en/ec/113563.pdf
- [70] European Central Bank Press Release, 2011. ECB announces details of refinancing operations with settlement in the period from 12 October 2011 to 17 January 2012. 4 August 2011. Available at: https://www.ecb.europa.eu/press/pr/date/2011/html/pr110804_1.en.html
- [71] European Commission, 2010. Report on Greek Government Deficit and Debt Statistics. Brussels, January 2010
- [72] European Council, 2011. Conclusions of the European Council Meeting (16-17 December 2010). Brussels, January 2011
- [73] Fama, E.F., 1990. Term-structure forecasts of interest rates, inflation, and real returns. *Journal of Monetary Economics* 25, 59-76
- [74] Fama, E.F., French, K.R., 1989. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25, 23-49
- [75] Fecht, F., Wedow, M., 2014. The dark and the bright side of liquidity risks: Evidence from open-end real estate funds in Germany. *Journal of Financial Intermediation* 23, 376-399
- [76] Ferrara, L., Vigna, O., 2009. Evidence of relationships between macroeconomics and

housing market in France Banque de France Working Paper, 9 November 2009

[77] Ferson, W.E., Harvey, C.R., 1991. The variation of economic risk premiums. *Journal of Political Economy* 99, 385-415

[78] Galbraith, J.W., Ullah, A., Zinde-Walsh, V., 2002. Estimation of the vector moving average model by vector autoregression. *Econometric Reviews* 21, 205-219

[79] Galil, K., Shapir, O.M., Amiram, D., Ben-Zion, U., 2014. The determinants of CDS spreads. *Journal of Banking & Finance* 41, 271-282

[80] Ghysels, E., Santa-Clara, P., Valkanov, R., 2005. There is a risk-return trade-off after all. *Journal of Financial Economics* 76, 509-548

[81] Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance* 48, 1779-1801

[82] Goetzmann, William N., Li, L., Rouwenhorst, K.G., 2005. Long-term global market correlations. *The Journal of Business* 78, 1-38

[83] Gomez-Biscarri, J., 2009. The predictive power of the term spread revisited: A change in the sign of the predictive relationship. *Applied Financial Economics* 19, 1131-1142

[84] González-Hermosillo, B., 2008. Investors' risk appetite and global financial market conditions. *International Monetary Fund Working Paper* no WP/08/85

[85] Goodhart, C., Hofmann, B., 2008. House prices, money, credit and the macroeconomy.

- [86] Grammatikos, T., Vermeulen, R., 2012. Transmission of the financial and sovereign debt crises to the EMU: Stock prices, CDS spreads and exchange rates. *Journal of International Money and Finance* 31, 517-533
- [87] Greene, W.H., 2008. *Econometric analysis*. Pearson, Upper Saddle River, N.J.
- [88] Griffin, J.M., Karolyi, A.G., 1998. Another look at the role of the industrial structure of markets for international diversification strategies. *Journal of Financial Economics* 50, 351-373
- [89] Hafner, C.M., Herwartz, H., 2006. Volatility impulse responses for multivariate GARCH models: An exchange rate illustration. *Journal of International Money and Finance* 25, 719-740
- [90] Hamao, Y., Masulis, R.W., Ng, V., 1990. Correlations in price changes and volatility across international stock markets. *Review of Financial Studies* 3, 281-307
- [91] Hamilton, J.D., Lin, G., 1996. Stock market volatility and the business cycle. *Journal of Applied Econometrics* 11, 573-93
- [92] Herring, R.J., Wachter, S.M., 1999. Real estate booms and banking busts - an international perspective. Group of Thirty, Washington, DC.
- [93] Heston, S.L., Rouwenhorst, K.G., 1994. Does industrial structure explain the benefits of international diversification? *Journal of Financial Economics* 36, 3-27
- [94] Hopkins, P.J.B., Miller, C.H., 2001. Country, sector, and company factors in global

equity portfolios. Research Foundation of AIMR.

[95] Houweling, P., Vorst, T., 2005. Pricing default swaps: Empirical evidence. *Journal of International Money and Finance* 24, 1200-1225

[96] Hull, J., Predescu, M., White, A., 2004. The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of Banking & Finance* 28, 2789-2811

[97] Karolyi, G.A., Stulz, R.M., 1996. Why do markets move together? An investigation of U.S.-Japan stock return comovements. *The Journal of Finance* 51, 951-986

[98] King, M., Sentana, E., Wadhvani, S., 1994. Volatility and links between national stock markets. *Econometrica* 62, 901-33

[99] King, M.A., Wadhvani, S., 1989. Transmission of volatility between stock markets. National Bureau of Economic Research Working Paper Series No. 2910

[100] King, M.A., Wadhvani, S., 1990. Transmission of volatility between stock markets. *The Review of Financial Studies* 3, 5-33

[101] Koetter, M., Poghosyan, T., 2010. Real estate prices and bank stability. *Journal of Banking & Finance* 34, 1129-1138

[102] Kohonen, A., 2013. On detection of volatility spillovers in overlapping stock markets. *Journal of Empirical Finance* 22, 140-158

[103] Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear

multivariate models. *Journal of Econometrics* 74, 119-147

[104] Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics* 54, 159-178

[105] Lenza, M., Pill, H., Reichlin, L., 2010. Monetary policy in exceptional times. *Economic Policy*, 295

[106] Lessard, D.R., 1974. World, national, and industry factors in equity returns. *Journal of Finance* 29, 379-91

[107] Lo, A.W., MacKinlay, C.A., 1990. An econometric analysis of nonsynchronous trading. *Journal of Econometrics* 45, 181-211

[108] Longin, F., Solnik, B., 1995. Is the correlation in international equity returns constant: 1960-1990? *Journal of International Money and Finance* 14, 3-26

[109] Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. *The Journal of Finance* 56, 649-676

[110] Martens, M., Poon, S.-H., 2001. Returns synchronization and daily correlation dynamics between international stock markets. *Journal of Banking and Finance* 25, 1805-1827

[111] Martins, A.M., Serra, A.P., 2012. Real estate market risk in bank stock returns: evidence for 15 European countries. Universidade do Porto, Faculdade de Economia do Porto CEF.UP Working Papers no 2012-03

- [112] Mei, J., Saunders, A., 1995. Bank risk and real estate: an asset pricing perspective. *Journal of Real Estate Finance and Economics* 10, 199-224
- [113] Meng, L., ap Gwilym, O., 2008. The determinants of CDS bid-ask spreads. *Journal of Derivatives* 16, 70-80
- [114] Michaud, F.-L., Upper, C., 2008. What drives interbank rates? Evidence from the Libor panel. *Bank of International Settlements Quarterly Review* March 2008
- [115] Officer, R.R., 1973. The variability of the market factor of the New York Stock Exchange. *The Journal of Business* 46
- [116] Pavlov, A.D., Wachter, S.M., 2011. REITs and underlying real estate markets: is there a link? U of Penn, Inst for Law & Econ Research Paper No. 11-20
- [117] Paye, B.S., 2012. 'Déjà vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics* 106, 527-546
- [118] Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58, 17-29
- [119] Raunig, B., 2011. The credit risk of banks and non-banks during the crisis: Evidence from the CDS market. *Austrian National Bank*
- [120] RiskmetricsTM, 1996. Technical document. J.P. Morgan fourth ed.
- [121] Rouwenhorst, K.G., 1999. European equity markets and the EMU. *Financial Analysts Journal* 55, 57-64

- [122] Scholes, M., Williams, J., 1977. Estimating betas from nonsynchronous data. *Journal of Financial Economics* 5, 309-327
- [123] Schwert, G.W., 1989. Why does stock market volatility change over time? *Journal of Finance* 44, 1115-53
- [124] Sebastian, S., Schätz, A., 2009. Real estate equities - real estate or equities? *European Public Real Estate Association*
- [125] Suurlaht, A., 2012. Correlation dynamics in the G7 stock markets. National University of Ireland, Maynooth, Working Paper.
- [126] Taylor, S., 1986. *Modelling financial time series*. John Wiley & Sons, New York.
- [127] The Guardian Business Blog Report, 2011. EU debt crisis: Italy approves €54bn austerity package - as it happened. 14 September 2011. Available at: <http://www.theguardian.com/business/blog/2011/sep/14/french-banks-downgraded-europe-debt-crisis>
- [128] Tsai, I.C., 2014. Spillover of fear: Evidence from the stock markets of five developed countries. *International Review of Financial Analysis* 33, 281-288
- [129] Ötoker-Robe, N., Podpiera, J., 2010. The fundamental determinants of credit default risk for European large complex financial institutions International Monetary Fund Working paper no WP/10/153