EUROPEAN EQUITY MARKET RETURN, VOLATILITY AND LIQUIDITY SPILLOVER DYNAMICS DURING THE EUROZONE DEBT CRISIS

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Abstract

We investigate the interdependence among European Union equity markets during the Eurozone debt crisis by studying spillovers in returns, volatility and liquidity using the Diebold-Yilmaz (2009, 2011) Spillover Index. We identify the EU-wide shocks that are likely to have had the highest impact on these markets before and during the crisis episode. We then analyze the economic events that triggered the shocks and study how their unfolding might have caused spillovers from developed to emerging equity markets. We conclude that negative economic events have had in general disproportionate effects on member states, with the higher burden falling on those countries with less developed capital markets.

Keywords: contagion, spillover index, market liquidity, financial crisis

JEL Classification: C32, C53, G12, G15

1. Introduction

The literature on contagion and spillovers in financial markets has grown in the 1990s and early 2000s, a period marked by frequent financial crises whose negative effects tended to extend beyond the market or country of origin. Following a period of relative calm, the US subprime mortgage crisis and the subsequent Eurozone debt crisis have revived the interest of the academic community in this research area and have led to important contributions, especially related to the development of econometric techniques for identifying and measuring spillovers and contagion.

Contagion can be defined as an increase of common movements in a set of financial asset markets during a crisis period compared to those existing in a benchmark, non-crisis period (Forbes and Rigobon, 2002). A more comprehensive definition, by Allan and Gale (2012), interprets contagion as a consequence of excess

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spillovers. Spillovers result from the transmission of an unexpected but identified shock from one variable to receiving or responding variables in the system (Alter and Beyer, 2014). Under both definitions, contagion is the component that is unexplained and unexpected.

The new models of contagion typically rely on advanced econometric techniques in order to take into account the interdependencies and common factors among markets, such as trade linkages, systematic capital flows and banking linkages, before measuring the contagion component. In contrast, some models of spillovers can be constructed using only basic econometric techniques and still provide valuable information about contagion episodes.

In this paper we examine and interpret a simple measure of spillovers based on the VAR variance-decomposition Spillover Index developed by Diebold and Yilmaz (2009, 2011), using data for equity markets from all 28 EU member states. We study the exact spillover effects to and from every market in the European Union in relation to all other markets, while excluding global influences coming from outside the EU.

In addition to deriving the time-series of spillover indices of market returns and volatilities, we also derive spillovers in market illiquidity. In interpreting the variation of the spillover indices over time, we focus on the events that marked the Eurozone debt crisis of 2010-2011. This approach allows us to draw conclusions regarding the similarity of that period to more recent periods of market turmoil.

The paper is structured as follows: in Section 1 we discuss important contributions made to the literature of spillover and contagion modeling in recent years; in Section 2 we present the data and methodology employed for data transformation; in Section 3 we describe the Spillover Indices framework; in Section 4 we interpret the results and in Section 5 we conclude.

2. Literature review

Connectedness, or interdependence, is a central concept to modern risk measurement and management, having applications in market risk, credit risk, counterparty risk and grid-lock risk, as well as systemic risk (Diebold and Yilmaz, 2014). The most popular method of modeling connectedness is through correlation-based measures, which are based on linear Gaussian methods. Models that rely less on linear Gaussian methods have been recently proposed in the literature, including the CoVaR approach of Adrian and Brunnermeier (2009) or the marginal expected shortfall of Acharya et al. (2010).

One appealing way of modeling connectedness has been introduced by Diebold and Yilmaz (2009). They propose a measure of interdependence called the Spillover Index, based on variance decompositions associated with an *N*-variable VAR. The method is appealing because it does not require the definition of "contagion episodes"; instead, the framework allows the identification of such episodes in the dynamics of spillovers, which appear to be sensitive to economic shocks. However, being based on VAR variance-decomposition, the index is sensitive to variable ordering, which means that the correct interpretation of results requires a preliminary step that consists of ordering the VAR based on a-priori, model-free, judgment. In their article, Diebold and Yilmaz (2009) study spillovers in returns and volatility of global equity market indices and are able to identify and associate with meaningful economic events the episodes when the value of the indices, especially that of the volatility spillover index, abruptly rises or falls.

Diebold and Yilmaz (2012) build on their previous work to create spillover measures in volatility that are independent of the ordering used for forecast variance decomposition. Analyzing volatility spillovers from four asset classes in the United States, – stocks, bonds, foreign exchange and commodities, – they find that spillovers among markets may have been an important component of the global financial crisis of 2007. Their results indicate that bond and stock markets have been the most volatile, with FX and commondities less so. Moreover, volatility dynamics appear to be highly persistent and to exhibit high jumps.

More recently, Diebold and Yilmaz (2014) combine VAR variance-decomposition theory and network topology theory to propose measures of connectedness at all levels – from system-wise to pair-wise. They analyze the dynamics of these new measures over time, and then turn their attention to the financial crisis, starting from 2007 to the end of 2008.

Alter and Beyer (2014) extend the framework of Diebold and Yilmaz (2011) to quantify spillovers between sovereign credit markets and banks in the euro area during the Eurozone debt crisis. Their methodology assesses the systemic effect of an unexpected shock to the creditworthiness of a particular sovereign or country-specific bank index to other sovereign or bank CDS, between October 2009 and July 2012. Their results show clearly that during that period the interdependencies between banks and sovereigns had been growing, an indication of rising systemic risk. They also show that several policy interventions had mitigating impact on spillover risks.

Bubák et al. (2011) study volatility transmission in emerging European foreign exchange markets using a dynamic version of the Diebold-Yilmaz spillover index, and find that the magnitude of the volatility spillovers increases significantly during periods of market uncertainty. Their approach relies on model-free, non-parametric measures of ex-post volatility based on high-frequency data. One interesting finding of this study is that in the medium-term volatility increases for those countries with under-developed financial sectors.

Most of the literature concentrated either on different markets within one country, or on one market across different countries. One exception is the study by Ehrmann et al. (2011), who analyze the degree of financial transmission between money, bond and equity markets and exchange rates between the United States and the Euro area. Their results show that asset prices react strongest to other domestic asset prices, but also indicate a significant difference between the United States and the euro area in how financial markets react to domestic financial shocks. One explanation given by the authors is that the United States and the Euro zone have different economic structures, degrees of openness, as well as different policy objectives.

Two studies on Asian equity markets employ different methodologies to identify contagion episodes. Gallo and Otranto (2008) propose a Markow-Switching approach to characterize the transmission mechanism of volatility between markets. In their model, the state of one variable feeds into the transition probability of the state of the other. Forbes and Rigobon (2002) also use a Markov-Swiching model to the same effect, but base their analysis only on the behavior of correlation coefficients, and on a significant increase changing from a state of low to another of high volatility.

Baur and Fry (2009) propose a multivariate test based on the cross-sectional and time-series dimension of the data that controls for interdependencies and systematic risk through regional and global equity market indices. In their framework, contagion is analyzed through the significance of fixed time effects. The methodology of Baur and Fry (2009) controls for interdependencies arising through relationships with nearby countries, as well as from global financial crisis. Their test of contagion is applied to the equity markets of eleven countries during the Asian financial crisis of 1997-1998. They find that contagion in common volatility arising during a crisis period affects interdependencies rather than contagion, and that contagion had both negative and positive effects in all asset markets simultaneously.

In the context of the literature, our study uses the same methodology as Diebold and Yilmaz (2011), but focuses only on European Union equity markets. By excluding global markets from the analysis, we focus strictly on how shocks are transmitted among EU member states. Moreover, we contribute to the understanding of the relationship between market volatility and liquidity, by studying simultaneously volatility and liquidity spillovers.

3. Data

Data consists of equity market return indices band traded volumes of 28 European Union countries, downloaded from Thomson Reuters Datastream. We use 10-year daily series, from 4 April 2005 to 6 April 2015.

3.1. Returns

We first generate the stationary series[1] of daily returns by taking the logarithms of the ratio between the return index values measured on consecutive days. Then, we derive the weekly series by summing the five return values of each week. Descriptive statistics of weekly returns are provided in Table 1.

3.2. Volatility

The spillover analysis requires the derivation of measures of volatility and liquidity from the raw return index and volume series[2].

Volatility can be estimated using parametric or non-parametric methods. For example, Diebold and Yilmaz (2009) use in their study a non-parametric method that generates weekly volatility series based on high, low and close prices recorded every week.

We choose to estimate conditional daily and weekly volatility using a parametric model of the GARCH family. The model, proposed by Glosten et al. (1993), has been shown to perform well on equity data. The GJR(P,Q) model has *P* GARCH coefficients associated with lagged variances, *Q* ARCH coefficients associated with lagged squared innovations, and *Q* leverage coefficients associated with the square of negative lagged innovation. The specification of the model is given by:

$$y_t = \mu + \varepsilon_t$$

where $\varepsilon_t = \sigma_t z_t$ and

$$\sigma_t^2 = \kappa + \sum_{i=1}^{P} \gamma_i \sigma_{t-i}^2 + \sum_{j=1}^{Q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{Q} \xi_j I[\varepsilon_{t-j} < 0] \varepsilon_{t-j}^2$$

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[1] *Return series are usually stationary. We check our series by performing standard ADF stationarity tests.*

[2] *Both volatility and liquidity can be measured in various ways, ranging from very simple (such as the standard deviation of returns for a given period for volatility, or value turnover for liquidity) to the very complex. Since our interest is in measuring and interpreting spillovers in liquidity and volatility, we avoid using highly sophisticated methods and instead rely on measures that have been shown to capture well the main features of these variables while being relatively straightforward to derive.*

The indicator function $I[\varepsilon_{t-j} < 0]\varepsilon_{t-j}^2$ equals 1 if $\varepsilon_{t-j} < 0$ and 0 otherwise. Thus, the leverage coefficients are applied to negative innovations, giving negative changes additional weight.

Although we use weekly data in our spillover analysis, it is useful first to analyze the evolution of daily conditional volatility over the entire sample. We therefore estimate a GJR-GARCH(1,1) model for each country in the sample and then plot all the conditional daily volatility series resulting from the model on the same chart using a data visualization technique called heat-map, as illustrated in the Figure 1.

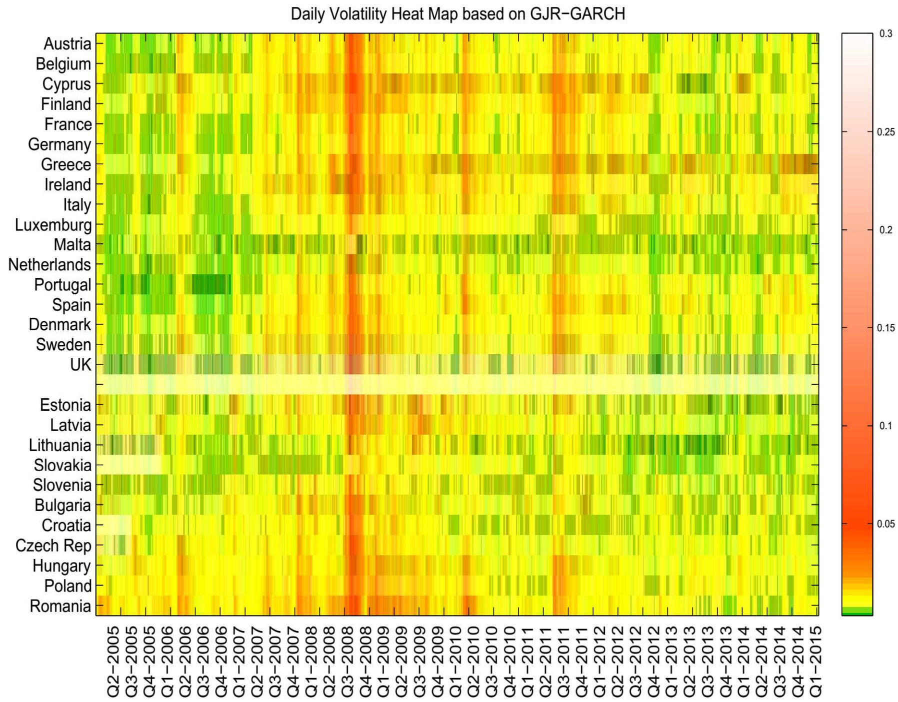
The volatility heat map provides interesting insights into the behavior of cross-country volatility over the previous ten years.

The financial crisis of 2008-2009 is marked on the chart by the red pattern that stretches vertically at the dates corresponding to the third quarter of 2008. This period is the first reference point on the chart. We see that the financial crisis affected all equity markets simultaneously. Another interesting fact revealed by the heat map is that, prior to the crisis, volatility regimes of developed and emerging markets in Europe were markedly different. While developed markets volatility was indicative of a low-risk regime (predominantly green pattern), emerging markets volatility was indicative of a moderate-risk regime (predominantly yellow pattern). Furthermore, the effects of the financial crisis on volatility persisted more in emerging countries, such as Romania, Poland and Hungary (red pattern stretching to the right for these countries), but faded relatively quickly in other countries.

The second relevant episode is the Eurozone debt crisis. This is shown by another red pattern stretching vertically through the chart. This time, the high-volatility regime has been less intense and can be observed in fewer countries. We notice that volatility in the equity markets of Latvia, Lithuania, Slovakia, Slovenia, Bulgaria, Croatia and the Czech Republic has been only moderate during that crisis episode, while Hungary, Poland and Romania appeared again to be more vulnerable.

Figure 1

Heat-map of daily volatility estimated using GJR-GARCH(1,1) models



The spillover analysis in the next section is performed on weekly series. We estimate again the GJR-GARCH models on the weekly return series and provide descriptive statistics of weekly volatility in Table 2.

3.3. Liquidity

Equity market liquidity is an important feature of capital markets. A market is often said to be liquid when the prevailing structure of transactions provides a prompt and secure link between the demand and supply of assets, thus delivering low costs of transaction (Gabrielsen et al, 2011). The characteristics of liquid markets are tightness, immediacy, depth, breadth, and resiliency (Sarr and Lybek, 2002). Because market liquidity has different dimensions, no single measure will be sufficient to capture all its characteristics. Gabrielsen et al. (2011) offer a recent survey of liquidity measures.

Since we use price and volume data aggregated at market level, an appropriate measure of market liquidity (or illiquidity, in this case) is the Amihud (2002) illiquidity indicator. This indicator falls into the category of volume-based liquidity measures and provides an understanding of the link between volume and price change, representing a rough measure of price impact.

The index is calculated using the following formula:

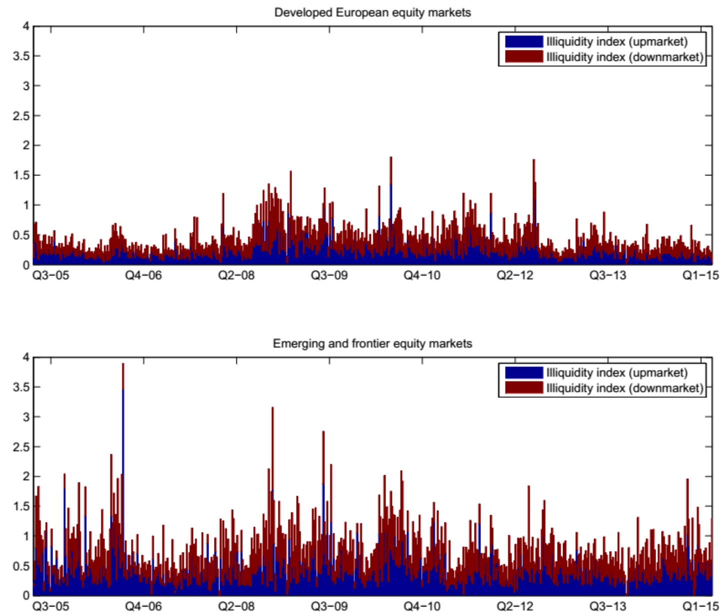
$$ILLIQ_T^i = \frac{1}{D_T}\sum_{t=1}^{D_T} \frac{|R_{t,T}^i|}{V_{t,T}^i}$$

where D_T is the number of days for which data are available (in our case, $D_T = 5$), $R_{t,T}^i$ is the return of the equity index *i* on day *t* of week *T*, and $V_{t,T}^i$ is the daily volume. We also compute upmarket *ILLIQ*, based only on $R_{t,T}^i > 0$ and down-market *ILLIQ,* based only on $R_{t,T}^i < 0$.

In Figure 2 we illustrate the evolution of the weekly Amihud illiquidity index calculated for the 10-year data sample. In the upper section of the figure we plot the evolution of the average index of developed EU markets, while in the lower section we plot the average index of emerging EU markets. In the figure, higher values of the index indicate less liquidity. Comparing with the volatility heat-map in Figure 1, we see that the aggregate behavior of the illiquidity index is not as easy to interpret. On the one hand, illiquidity tends to be higher in more volatile periods, but on the other hand, it displays a much more irregular pattern. The peaks of market illiquidity, especially in emerging markets, need more careful consideration before any conclusion can be drawn. What is obvious nonetheless from Figure 2 is that, on average, emerging markets are less liquid and are experiencing more liquidity volatility, as evidenced also by descriptive statistics in Table 3.

Figure 2

Variation of weekly up-market and down-market price-impact (Amihud) market illiquidity measure, EU developed markets [upper plot] vs. EU emerging markets [lower plot]. Higher value indicates less liquid markets



4. Methodology

The method used in this paper to analyze spillovers among EU equity markets has been introduced by Diebold and Yilmaz (2009), hereafter DY2009, and refined by Diebold and Yilmaz (2011), hereafter DY2011. DY2009 focus on total spillovers in a simple VAR frameworks (with potentially order-dependent results driven by Cholesky factor-orthogonalization). DY2011 address the order-dependency shortcoming by developing a measure of directional spillovers in a generalized auto-regressive framework in which forecast-error variance decompositions are invariant to variable ordering. We describe below how spillover indices are computed by DY2011.

We start from a covariance stationary *N*-variable VAR(p):

$$VAR(p), x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$$

where $\varepsilon_t\,(0,\Sigma)$ is a vector of independently and identically distributed disturbances.

The moving average representation of the *VAR(p)* is:

$$x_t = \sum_{i=0}^{\infty} \mathrm{A}_i \varepsilon_{t-i}$$

where the *NxN* coefficient matrices A_i can be written as:

$$A_i = \sum_{t=1}^{p} \Phi_i \mathrm{A}_{i-t}$$

with A_0 an *NxN* identity matrix and $\mathrm{A}_i = 0$ for *i<0*.

The moving average coefficients are used to derive the variance decompositions, which allow the description of the forecast error variances of each variable into parts attributable to the various system shocks.

DY2011 rely on the generalized VAR framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), which produces variance decompositions invariant to ordering.

Define own variance shares to be of the *H*-step-ahead error variances in forecasting the variables of interest x_i due to shocks in their own realizations, and cross variance shares, or spillovers, to be the fractions of the *H*-step ahead error variances in forecasting the variable of interest x_i due to shocks to other variables in the system.

We follow DY2011 in denoting the H-step-ahead forecast error variance decompositions by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e'_i \mathrm{A}_h e_j)^2}{\sum_{h=0}^{H-1} (e'_i \mathrm{A}_h \Sigma A'_h e_i)}$$

Σ – variance matrix for the error vector ε

σ_{ii} – standard deviation of the error term for the *i*th equation

e_i – selection vector with one as the *i*th element and zeros otherwise

The sum of the elements of each row of the variance decomposition table is not equal to one.

Each entry of the variance decomposition matrix is normalized by the row sum:

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

The total volatility spillover index is defined then as:

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

The total spillover index measures the contribution of spillovers to volatility shocks across all markets to the total forecast error variance.

The directional spillover index is calculated using the normalized elements of the generalized variance decomposition matrix.

Directional volatility spillovers received by market *I* from all other markets *j* is:

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

Directional volatility spillovers transmitted by market *I* to all other markets *j* is:

$$S^{g}_{ji}(H)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}^{g}_{ji}(H)}{\sum_{j=1}^{N}\tilde{\theta}^{g}_{ji}(H)}\cdot 100$$

5. Results

5.1. Spillover Tables

The full-sample analysis of the European equity return, volatility and illiquidity spillover indices, based on DY2011 methodology, is summarized in Tables 4, 5, 6, respectively.

The results are based on the full 10 year sample of data, including thus the financial crisis of 2007-2008 and the Eurozone debt crisis of 2010-2011.

The tables are structured as follows: the *ij*th entry in the table is the estimated contribution to the forecast error variance coming from innovations in country *j*. The off-diagonal column sums or row sums, when totaled across countries, give the numerator of the Spillover Index. The column sums or row sums, including diagonals, when totaled across countries, give the denominator of the Spillover Index.

We first remark by analyzing the Tables 4 to 6 that the European equity markets are quite interdependent, as the contribution from others to all countries (last column of the tables) is relatively high (close to 90% in the case of return and volatility spillovers). Moreover, we observe that the innovations in each country returns or volatilities are responsible in general for a modest percentage of error variations in forecasting the returns of other countries. In this respect, the analysis on European markets, which excludes global influences coming from outside the European Union, is different from an analysis at the global level, where possibly spillovers would mostly be caused by a predominant market such as the US.

The last cell of Tables 4 to 6 is the Spillover Index. The values of 85% for returns, 83% for volatilities indicate that the forecast error variance comes from spillovers among member states. We find, as DY2009, that return and volatility spillovers are of the same magnitude, but the values that we observe for the Spillover Indices are more than twice as high than those obtained by DY2009.

Dividing the country sample into developed and emerging markets, we note that, as we expect regarding return and volatility spillovers, the contribution to others from emerging markets is much lower than the contribution to others from developed markets. So, in other words, although in most cases the forecast error variance of all markets comes from innovations in other markets, emerging markets contribute less to others.

The illiquidity spillovers are different, in the sense that the contribution from others is significantly higher, on average, for developed markets than for emerging markets. Also, emerging markets contribute less to the illiquidity of other markets, including other emerging markets.

5.2. Spillover plots

Spillover plots in Figure 3 are based on the DY2009 methodology, using a 200 estimation window VAR and forecast horizons of 2 weeks and 10 weeks.

In Table 4 we see that the Eurozone debt crisis started unfolding on May 25, 2010, when the EU first offered support to Greece. However, by examining the spillover plots, we see that a structural break in the indices took place only the year after, starting around April 6, 2011, when Portugal requested the activation of the aid mechanism. After that date, there was an obvious increase in all the Spillover Indices, with the illiquidity index making the first jump after the return and volatility indices had already moved to a different regime. We see that the crisis was fully over after the EU summit of June 28, 2012, when the spillover indices swiftly started to trend downward.

It is interesting to point out that the turmoil in financial markets caused by the negotiations between Greece and its creditors taking place after the new Greek government came to power at the beginning of 2015 is showing again in the spillover indices, which seem to display a very similar behavior to that observed during the Eurozone debt crisis. Most strikingly, although the return and volatility spillover indices are still at lower levels than before, the illiquidity index is already higher than the previous peak. This suggests that the illiquidity spillover index could be this time a leading indicator for the other two. Further research is needed to confirm this finding and to understand the economic forces that cause liquidity to behave differently from the last crisis episode.

Figure 3

DY2009 Spillover indices at 10-week and 2-week forecast horizon, based on 200-week VAR estimation windows

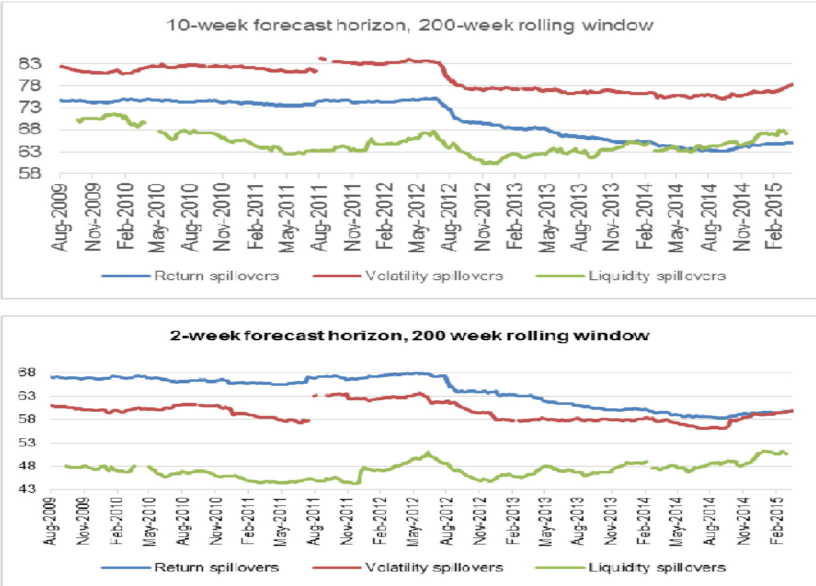


Table 4

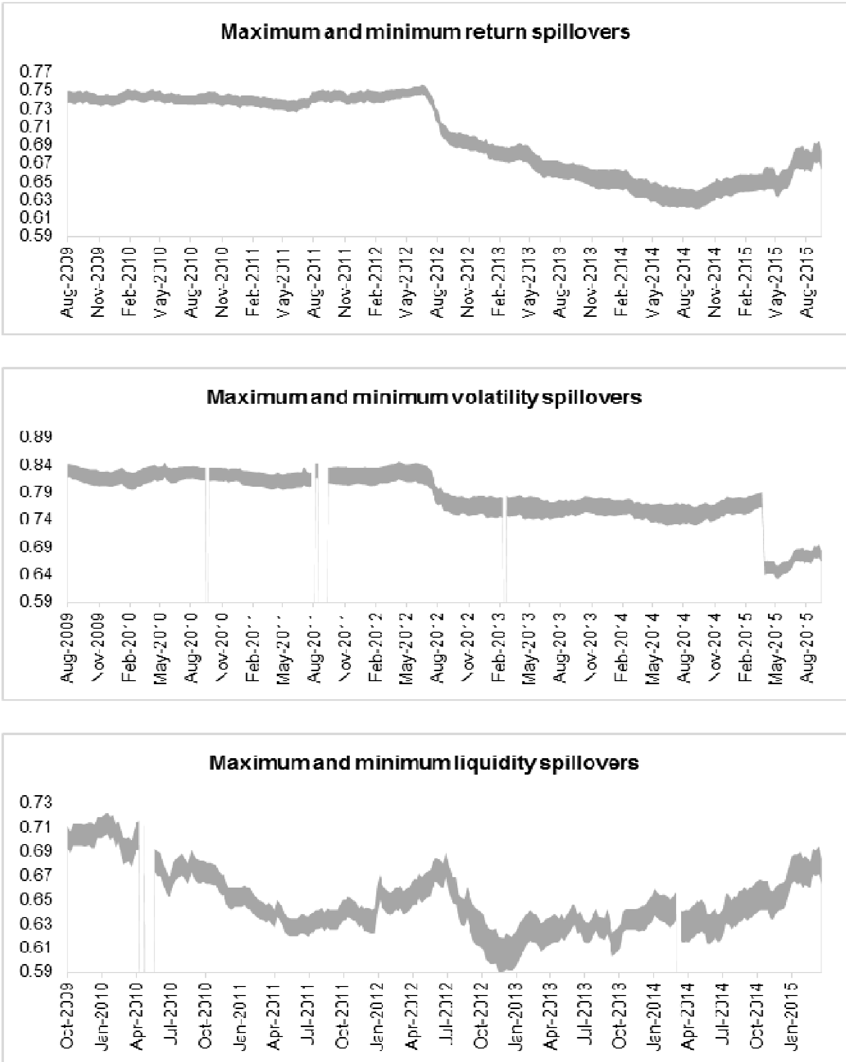
Significant events during 2010-2012

Date	Event
25-Mar-2010	EU offers support to Greece
10-May-2010	EU sets up the EFSF; ECB starts SMP
22-Nov-2010	Ireland seeks financial support
06-Apr-2011	Portugal requests activation of the aid mechanism
15-Jul-2011	EBA bank stress test results are published
06-Oct-2011	ECB announces second covered bond purchase programme
08-Dec-2011	ECB lowers interest rates by 25bps
22-Dec-2011	LTRO I
01-Mar-2012	LTRO II
10-May-2012	Spain seizes control of Bankia
18-Jun-2012	G20 summit
28-Jun-2012	EU summit

Source: Alter and Beyer (2014)

Figure 4

DY2009 minimum and maximum spillovers based on randomly rotated orderings, forecast horizon 10 weeks



5.3. Robustness

The spillover indices in Figure 3 are computed using the DY2009 methodology, which is based on a simple VAR variance-decomposition that depends on the ordering of variables in the VAR. We therefore check whether the results are robust to variations with respect to the ordering of the VAR and the forecast horizon.

We fix the estimation window width at 200 because, on the one hand, the VAR becomes unstable at small widths (has explosive roots) and on the other, any larger window would smooth out most interesting variations in spillovers.

In Figure 4 we illustrate the maximum and minimum volatility spillovers across a variety of alternative VAR orderings, using the fixed window size of 200 weeks and a forecast horizon of 10 weeks. The procedure checks for fifty randomly-chosen orderings. As expected, the results show that all spillover indices are robust to order variation.

6. Conclusions

The Eurozone debt crisis of 2010-2012 has been an important episode in the recent history of European financial markets, with consequences that extended to all European Union member states and beyond. The purpose of this paper has been to analyze the spillovers in equity markets caused by the Eurozone debt crisis and to draw conclusions regarding the nature of these spillovers between emerging and developed markets.

Our analysis is based on the methodology of Diebold and Yilmaz (2009) and Diebold and Yilmaz (2011), but differs from theirs in important respects. We model nominal returns instead of real returns, use local currencies instead of a fixed currency, estimate weekly volatility based on a GARCH approach, and, most importantly, we measure spillovers in illiquidity in addition to spillovers in volatility and returns.

The analysis revealed that, while emerging equity markets are reasonably well integrated in the European financial system, they are more likely spillover takers than givers, especially in what regards illiquidity, which makes them vulnerable to shocks originating in the more advanced economies. Given the Greek debt crisis that has grown in intensity from the beginning of 2015, it is important to understand the likelihood and the consequences of another crisis episode. Our results indicate that, when combined with a volatility spillover index, an illiquidity spillover index could help identify more precisely such episodes.

7. Acknowledgement

This work was financially supported through the project "Routes of academic excellence in doctoral and post-doctoral research - READ" co-financed through the European Social Fund, by Sectorial Operational Programme Human Resources Development 2007-2013, contract no POSDRU/159/1.5/S/137926.

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Table 1. Descriptive statistics of weekly nominal returns of the full 10-year sample (period 04 Apr 2005 – 06 Apr 2015).

	Austria	Belgium	Cyprus	Estonia	Finland	France	Germany	Greece	Ireland	Italy	Lithuania	Luxemburg	Malta
Mean	0.0%	0.1%	-0.3%	0.0%	0.1%	0.1%	0.1%	-0.3%	0.0%	0.0%	0.1%	0.2%	0.1%
Min.	-17.4%	-14.7%	-23.7%	-19.7%	-16.5%	-13.9%	-16.8%	-22.4%	-18.0%	-13.3%	-15.0%	-7.8%	-7.5%
Max.	15.3%	15.9%	17.0%	15.7%	13.7%	13.6%	11.6%	15.4%	16.1%	12.3%	14.2%	6.6%	10.8%
Skewness	-1.02	-0.94	-0.57	-0.69	-0.44	-0.47	-0.85	-0.42	-0.81	-0.39	-0.82	-0.36	0.34
Kurtosis	8.69	9.72	5.67	8.26	5.80	6.07	7.36	4.66	7.83	5.04	11.13	4.54	7.57
St. dev	3.2%	2.9%	4.8%	3.4%	3.3%	2.8%	2.7%	4.6%	3.4%	3.1%	2.6%	1.9%	1.9%

	Netherlands	Portugal	Slovenia	Spain	Bulgaria	Croatia	Czech Republic	Denmark	Hungary	Poland	Romania	Sweden	UK
Mean	0.1%	0.0%	0.0%	0.1%	-0.1%	0.1%	0.1%	0.2%	0.0%	0.1%	0.1%	0.2%	0.1%
Min.	-14.9%	-14.9%	-12.9%	-17.8%	-18.1%	-17.9%	-21.3%	-21.6%	-18.8%	-13.0%	-34.4%	-15.3%	-13.5%
Max.	13.3%	11.7%	9.6%	13.1%	12.4%	11.4%	12.4%	16.7%	27.6%	12.7%	19.0%	15.5%	14.2%
Skewness	-0.82	-0.84	-0.93	-0.49	-0.85	-0.98	-1.12	-1.31	0.29	-0.55	-1.13	-0.27	-0.42
Kurtosis	7.26	6.37	8.14	5.89	8.00	10.44	10.91	12.21	11.70	5.51	14.27	7.10	7.50
St. dev	2.9%	2.9%	2.4%	3.1%	3.4%	2.7%	2.9%	3.0%	3.6%	3.0%	4.3%	3.1%	2.6%

Table 2. Descriptive statistics of conditional standard deviation (volatility) of weekly nominal returns (period 04 Apr 2005 – 06 Apr 2015), estimated using GJR-GARCH models.

	Austria	Belgium	Cyprus	Estonia	Finland	France	Germany	Greece	Ireland	Italy	Lithuania	Luxemburg	Malta
Mean	2.8%	2.5%	4.6%	3.2%	3.2%	2.6%	2.5%	4.3%	2.9%	2.8%	2.4%	2.0%	1.8%
Min.	1.4%	1.3%	1.0%	1.2%	1.7%	1.2%	1.3%	2.0%	1.6%	1.4%	1.0%	1.0%	1.1%
Max.	10.9%	10.5%	14.0%	7.6%	7.8%	7.0%	7.8%	8.1%	9.1%	7.2%	7.1%	5.0%	4.5%
Skewness	2.70	2.88	0.81	0.58	1.39	1.41	2.01	0.22	1.99	1.34	2.06	1.71	1.69
Kurtosis	13.11	14.17	4.24	2.94	4.58	5.19	8.58	2.64	7.73	5.53	8.24	7.08	6.88
St. dev	1.3%	1.2%	2.1%	1.4%	1.2%	1.0%	0.9%	1.3%	1.3%	0.9%	1.0%	0.6%	0.6%

	Netherlands	Portugal	Slovenia	Spain	Bulgaria	Croatia	Czech Republic	Denmark	Hungary	Poland	Romania	Sweden	UK
Mean	2.6%	2.6%	2.2%	2.8%	3.4%	2.4%	2.7%	2.6%	3.2%	2.8%	4.1%	2.8%	2.3%
Min.	1.2%	1.3%	1.2%	1.6%	1.4%	0.8%	1.9%	1.6%	2.0%	1.8%	1.7%	1.3%	1.0%
Max.	9.7%	8.0%	5.5%	6.5%	9.7%	9.7%	9.5%	11.0%	10.6%	7.0%	16.7%	8.0%	7.0%
Skewness	2.41	1.67	2.14	0.95	1.42	2.10	3.40	3.04	3.07	1.57	2.54	1.52	1.77
Kurtosis	10.64	7.17	8.75	4.10	6.14	8.70	21.95	16.36	17.68	6.39	13.53	5.36	6.89
St. dev	1.2%	0.9%	0.6%	0.8%	1.3%	1.4%	0.8%	1.1%	1.0%	0.8%	1.9%	1.1%	0.9%

Table 3. Descriptive statistics of weekly Amihud illiquidity measure (period 04 Apr 2005 – 06 Apr 2015)

	Austria	Belgium	Cyprus	Estonia	Finland	France	Germany	Greece	Ireland	Italy	Lithuania	Luxemburg	Malta
Mean	0.07	0.09	0.58	0.37	0.26	0.05	0.11	0.59	0.48	0.07	0.38	5.66	0.59
Min.	0.01	0.02	0.03	0.03	0.04	0.01	0.01	0.05	0.05	0.01	0.05	0.14	0.03
Max.	0.28	0.29	2.80	5.68	1.40	0.41	0.36	2.49	2.63	0.48	1.68	47.64	11.86
Skewness	1.52	1.28	1.39	5.26	1.69	4.08	1.22	1.30	1.90	2.65	1.66	3.22	6.37
Kurtosis	6.54	5.13	5.18	39.58	9.23	43.62	4.47	5.37	7.98	15.12	6.39	16.42	63.01
St. dev	0.04	0.05	0.47	0.52	0.15	0.03	0.07	0.37	0.39	0.05	0.27	6.45	0.91

	Netherlands	Portugal	Slovenia	Spain	Bulgaria	Croatia	Czech Republic	Denmark	Hungary	Poland	Romania	Sweden	UK
Mean	0.15	0.47	48.21	0.05	4.89	0.53	0.18	0.08	0.16	0.10	1.31	0.19	0.03
Min.	0.03	0.04	3.03	0.01	0.19	0.03	0.02	0.01	0.02	0.01	0.14	0.02	0.00
Max.	0.59	2.44	327.59	0.28	63.16	2.39	0.86	0.28	0.49	0.49	6.15	0.66	0.11
Skewness	1.53	1.64	2.39	2.17	3.82	1.48	1.50	1.31	0.96	1.75	1.66	0.97	1.00
Kurtosis	5.92	6.49	14.34	12.23	33.26	6.32	5.61	5.06	4.27	7.20	6.09	3.83	4.10
St. dev	0.09	0.39	33.38	0.03	5.26	0.36	0.13	0.05	0.08	0.07	1.00	0.12	0.02

Table 5. DY2011 Spillover table, weekly Amihud index, period 04 Apr 2005 – 06 Apr 2015

	OE	BG	CP	ET	FN	FR	BD	GR	IR	IT	LN	LX	MT	NL	PT	SJ	ES	BL	CT	CZ	DK	HN	PO	RM	SD	UK	From Others
OE	23.9	4	1.2	1.2	3.7	5.4	3.6	2.7	0.6	5.3	1.2	0.3	0.7	6.9	4.8	3.3	7.9	0.3	0.3	0.9	2.4	3.1	1.7	0.3	7.5	6.9	76
BG	4.7	23	0.1	0.9	3.6	8.8	10.5	2.2	2.4	6.3	0.2	1.1	0.2	5.1	1.6	2.9	6.2	0.2	0.2	0.9	4.4	2.1	2.3	0.6	4.6	4.8	77
CP	1.7	0.2	66.3	0.3	1.1	2.2	2.3	6.7	0.9	0.6	0.3	0.4	0.1	1.3	5.5	0.8	1.8	0.6	0.6	0.3	0.4	0.3	0.2	1.4	0.6	3.1	34
ET	1.7	1.5	0.2	69.5	0.3	0.7	0.8	1.2	0.8	1.9	0.5	1.7	0.3	1.4	0.5	1.1	1.1	0.6	3.3	0.2	0.6	3	5.6	0.5	0.2	0.9	31
FN	3.3	3.3	1	0.1	21.7	10.1	4.5	1.2	2.9	5.6	0.2	0.2	0.4	11.1	4.6	2.1	4.9	0.1	0.1	0.4	4.6	1	1.2	0.5	7.3	7.4	78
FR	4	5.2	1	0.1	7.2	13.9	6.3	2.1	3.8	7.7	0.2	0.4	0.5	10	4	2.1	7.7	0.2	0.3	0.2	4.4	1.5	1.5	0.7	6.9	7.9	86
BD	3.1	9.1	1	0.3	5.2	9.4	22.7	1.5	2.9	6.2	0.2	0.8	0.3	7.3	2.2	2.5	5.2	0.3	0.2	0.7	3.2	1.6	2.5	1.2	4.8	5.6	77
GR	2.4	2.8	3.1	0.6	3	5.4	2.8	29.3	3.6	4	0.5	1.1	2.6	4.1	6.2	3.5	6	1.3	0.8	0.4	2.4	2.6	1.4	2.3	4.4	3.3	71
IR	1.1	2.6	1.2	0.4	5.4	7.6	4	4.3	25.2	3.9	0.1	2.7	1.1	6.6	5.3	2.9	3.9	0.3	0.7	0.4	8.3	0.4	1	1.7	5.9	3.1	75
IT	4	4.4	0.6	0.5	4.8	9.7	6.5	2	3.2	16.1	0.2	0.3	0.4	10.3	4.4	2.3	6.7	0.1	0.2	0.4	3.9	1.6	3.2	0.5	7.8	5.7	84
LN	3.4	1.8	0.6	0.7	3.6	4.8	2.8	0.5	1.7	3.7	47.3	0.2	0.2	6.5	1.3	2.1	5.3	0.4	0.5	0.2	2	1.1	0.4	0.6	3.9	4.2	53
LX	1.1	4.4	0.1	1.2	2.6	3.6	3.8	2.5	9	1.3	0.1	43.5	0.8	1.2	2.2	3.9	2.5	0.4	0.9	0.1	6.6	0.9	0.2	1.9	3.1	2.1	56
MT	1.4	0.9	0.1	2.6	0.6	1.1	0.7	1.3	0.8	0.7	0.2	0.7	68.9	2	4.5	0.4	5.1	0.2	0.7	0.1	1.1	1.5	0.3	0.1	3.4	0.6	31
NL	4.4	3.4	1.1	0.2	7.5	10	5.4	2.2	3.7	6.5	0.2	0.3	0.7	17.8	5.6	2.7	5.3	0.2	0.2	0.3	4.6	1.1	2	1	7	6.7	82
PT	4.5	1.8	2.3	0.3	5	5	3	4.8	3.7	3.6	0.4	0.1	1.4	8.7	26.9	4.3	4.9	0.4	0.2	0.4	4.5	1.3	1.2	1.4	4	5.9	73
SJ	4	1.1	0.7	0.5	4.9	3.5	2.4	2.2	3.6	1.4	0.8	1	0.8	4.7	6	44.8	1.8	0.8	0.3	0.3	3.6	1.8	0.6	2.2	3.3	3	55
ES	6.3	4.4	0.7	0.7	4.2	8.7	4.4	4	2.5	6.5	0.5	0.7	1.4	6.8	5.9	1.9	19.9	0.1	0.2	0.1	3.4	2.4	1.6	0.7	6	5.8	80
BL	0.3	0.9	0.8	0.2	5.2	7.1	1.9	1.3	1.9	7.3	0.5	0.1	0.1	6.8	0.5	1.3	3	47.6	1.7	0.2	2	2.5	1	1	3.2	1.4	52
CT	1.1	1	0.5	3	0.5	1	1.2	1.1	0.6	1.2	1.4	0.9	0.4	0.6	0.6	0.8	0.4	2.2	75.7	0.3	0.3	0.4	3.1	0.6	0.3	0.7	24
CZ	2.6	1.3	2.9	0.9	1.9	2.6	6.2	0.4	0.8	3.9	3.1	0.2	0.1	2.6	0.8	0.6	3.6	0.6	0.6	51.1	0.6	2.3	0.9	0.3	4.3	5.1	49
DK	4.1	4.6	1.2	0.3	6	7.3	4	2.8	5.1	3.7	0.5	1	0.4	8.5	7.3	3.8	4.2	0.2	0.4	0.2	17.8	0.5	2.5	2.3	5.4	5.8	82
HN	3.9	4.8	1.5	1.4	2.5	5.6	5.3	3.3	2.1	5.1	0.8	1	1.2	5.1	2.1	2.3	5.4	0.1	0.6	0.6	2.1	31	2.1	0.2	5.7	4.2	69
PO	3.6	4.8	0.4	2.3	1.9	4.9	6	2.5	2.1	7.7	1.6	0.7	0.2	6.7	1.4	1.7	2.5	0.8	1.5	0.4	2.5	1.5	37.3	0.9	2.4	1.4	63
RM	0.9	0.9	3.3	1.6	1.3	2.9	1.5	4.7	6.9	1.3	0.1	1	0.7	2.7	4.2	1.5	2	0.8	1	0.3	3	0.3	0.7	52.1	1.1	2.8	48
SD	4.7	3.5	2.4	0.1	5.5	7.4	5	2.2	3.3	6.3	0.7	0.8	2.3	7.9	4.3	2	8.1	0.1	0.3	0.6	4.5	1.6	1.1	0.3	17.1	7.9	83
UK	5.6	4	2.7	0.2	5.7	8.4	4.8	2.2	2.7	4.3	0.7	0.5	0.6	8.2	6.2	3.5	5.7	0.1	0.3	0.3	4.1	1.2	1.1	0.9	7.7	18.7	81
Contribution to others	78	77	31	21	93	143	100	62	72	106	15	18	18	143	92	57	111	11	16	9	80	37	39	24	111	106	1671
Contribution incl. own	102	100	97	90	115	157	122	91	97	122	63	62	87	161	119	101	131	59	91	60	97	68	77	76	128	125	64.30%

Table 6. DY2011 Spillover table, weekly nominal returns, period 04 Apr 2005 – 06 Apr 2015

	OE	BG	CP	ET	FN	FR	BD	GR	IR	IT	LN	LX	MT	NL	PT	SJ	ES	BL	CT	CZ	DK	HN	PO	RM	SD	UK	From Others
OE	8.3	5.3	2	2	5	6	5.6	2.7	4.6	5.5	1.7	2.5	0.1	6.2	4.1	1.6	4.8	0.9	1.4	2.7	4.6	3.7	4.1	3.5	5.3	5.8	92
BG	5.7	9	1.9	2.1	4.4	6.2	5.6	2.3	5.3	5.2	1.5	2.5	0.2	6.8	4	1.6	4.9	0.6	1.6	2.3	5.4	3.3	3.2	3	5.4	5.9	91
CP	4.5	3.9	18	1.3	3.6	4.6	3.7	6.1	3.4	4.5	1.6	1.4	0.3	4.5	3.5	2.4	4.6	1.2	1.7	3	3.3	3.1	4.2	3.4	3.8	4.1	82
ET	5.4	4.6	1.6	16.3	4.4	4.3	3.9	1.4	3.7	3.4	6.5	2.7	0.4	4.8	2.4	2.6	3.3	1.4	1.9	2.5	4.6	3.3	3	3.3	3.6	4.5	84
FN	5.6	4.6	1.8	1.9	9.1	6.8	6.4	2.4	4.2	5.8	1.3	2.3	0.3	6.3	4.1	1.3	4.9	1	1.3	2.4	5.1	2.8	3.1	2.4	6.2	6.4	91
FR	5.5	5.3	1.9	1.6	5.6	7.7	6.5	2.4	4.5	6.4	1.1	2.4	0.2	6.6	4.5	1.3	5.7	0.7	1.3	2.3	4.8	3.1	3.6	2.7	5.9	6.4	92
BD	5.6	5.1	1.7	1.6	5.7	7.1	8.3	2.3	4.5	5.9	1.1	2.6	0.3	6.8	4.2	1.3	5	0.6	1.3	2.2	4.9	3.1	3.7	2.4	6.3	6.4	92
GR	5.2	4.1	5.4	1.2	4.2	5.1	4.3	15.6	3.5	5.9	1.3	1.4	0.1	4.7	5.3	1.5	5.3	0.5	0.9	2.7	3.7	2.9	4.1	2.7	3.9	4.5	84
IR	5.7	6.3	1.8	1.5	4.7	6.2	5.7	2.3	10.4	5	1.1	3.1	0.1	6.7	3.8	1.3	4.5	0.6	1.3	2	5.2	3.1	3	2.8	5.5	6.2	90
IT	5.6	5	2.1	1.5	5.3	7.1	6.1	3.2	4.1	8.6	0.9	2.3	0.2	6.4	5.1	1.3	6.5	0.7	1.1	2.1	4.4	3.1	3.4	2.6	5.3	6	91
LN	5.7	3.9	2.3	8.4	4.2	3.7	3.1	2.2	3.5	2.7	20.7	2.6	0	4.2	2.2	1.9	2.6	1.9	1.8	2.5	3.5	2.9	3.4	3.2	2.9	3.8	79
LX	5.2	4.9	1.3	1.7	4.5	5.7	5.3	1.5	5.5	4.6	1.3	17.8	0.1	6	3.6	1	3.5	1.3	0.9	1.3	4	3.1	3.2	2.6	5	5.1	82
MT	2.2	1.3	1.1	1.5	1	1.4	1.9	0.4	2	1.9	0.9	1.5	65	1.9	1.6	0.8	1.5	0.8	0.7	1.7	2	1.3	1.1	1.8	1.3	1.7	35
NL	5.8	5.9	1.9	1.7	5.3	6.7	6.3	2.3	5	5.8	1.1	2.8	0.3	7.7	3.8	1.5	4.9	0.7	1.5	2.3	4.8	3.3	3.6	2.7	5.8	6.4	92
PT	5.4	4.8	2.2	1.5	4.9	6.4	5.5	3.8	4	6.6	1.1	2.4	0.1	5.5	11.2	1.4	6.6	0.9	1	2	4.8	2.7	2.9	2.3	4.7	5.4	89
SJ	4.7	3.7	3	3.1	3.4	3.7	3.4	2.3	3.3	3.4	2	1.6	0.3	4.4	2.8	21.3	2.9	2	4.6	3	4.9	2.5	3.1	4.2	2.7	3.7	79
ES	5.4	5.1	2.4	1.7	4.9	6.9	5.7	3.1	4	7.1	1	1.8	0.1	5.9	5.6	1.3	9.4	0.6	1.3	2.4	4.2	3.2	3.3	2.8	5	5.6	91
BL	4.4	2.3	2.9	1.9	3.7	3.3	2.7	1.7	2.5	2.8	2.2	2.8	0.2	3.8	3.6	3.2	2.3	30.3	1.6	2.9	4	2.1	3	2.6	2.9	4.1	70
CT	4.2	4.3	2.4	2.8	3.7	4.1	3.5	1.6	3.5	3.2	1.9	1.4	0.5	4.8	2.2	4.7	3.2	1.6	22.1	3.1	4.1	3	2.5	3.6	3.5	4.6	78
CZ	5.2	3.9	2.5	1.7	3.9	4.6	4.2	2.8	3.1	3.8	1.4	1.6	0.2	4.5	2.8	2.2	4	1.2	1.8	15.6	5	4.9	5.7	4.7	4.1	4.6	84
DK	5.3	5.7	1.8	2.4	5.1	5.9	5.6	2.1	4.8	4.9	1.5	2.3	0.3	5.9	4.1	2.3	4.2	1.1	1.7	3.1	9.8	2.8	2.9	2.8	5.7	5.8	90
HN	5.7	4.8	2.1	1.7	4	5.3	4.8	2.4	3.9	4.8	1.2	2.3	0.3	5.5	3.2	1.2	4.5	0.6	1.3	4.1	4	13.1	5.6	3.8	4.7	5.2	87
PO	5.8	4.3	2.7	1.3	4	5.6	5.3	3.1	3.4	4.7	1.5	2.2	0.3	5.4	3.1	1.5	4.2	0.9	1.2	4.4	3.6	5.3	11.8	3.5	5.3	5.6	88
RM	6	4.6	2.5	2.2	3.5	4.8	4	2.5	3.7	4.3	1.9	2.7	0.2	4.8	2.9	2.7	3.9	1.3	2	4.1	3.9	4.8	4.4	13.5	4	4.8	87
SD	5.5	5.3	1.8	1.6	5.7	6.7	6.6	2.1	4.5	5.4	1	2.6	0.2	6.5	3.7	1.2	4.7	0.7	1.5	2.4	5.3	3.2	3.9	2.6	8.9	6.5	91
UK	5.6	5.3	1.8	1.8	5.5	6.7	6.2	2.3	4.7	5.7	1.2	2.3	0.2	6.6	4	1.4	4.9	0.9	1.6	2.4	4.9	3.2	3.8	2.9	6	8	92
Contribution to others	131	114	55	52	110	135	122	61	99	119	40	56	5	136	90	45	107	25	38	66	109	80	88	75	115	129	2203
Contribution incl. own	139	123	73	68	119	143	130	77	110	128	60	74	70	143	101	66	117	55	61	82	119	93	100	88	124	137	84.70%

Table 7. DY2011 Spillover table, weekly conditional volatility, period 04 Apr 2005 – 06 Apr 2015

	OE	BG	CP	ET	FN	FR	BD	GR	IR	IT	LN	LX	MT	NL	PT	SJ	ES	BL	CT	CZ	DK	HN	PO	RM	SD	UK	From Others
OE	9.3	5.7	0.3	1.8	6.4	6.2	6.1	2.5	6.4	5.2	1.4	4.1	0	7.8	4.4	0.9	3.7	0	0.2	3	5.2	2.1	3.5	0.5	6.1	7	91
BG	6.5	9.5	0	1.8	5.4	6.8	6	2.3	6.3	5	1.6	3.5	0.1	8.6	4.3	1.7	4.6	0.1	0.4	3	5.1	1.8	3.2	0.2	5.4	7	91
CP	8	3.8	29	3	8.1	2.9	3.3	0.7	4.6	2.1	4.3	0.5	0.4	6.3	2.3	0.2	1.3	0.2	0.2	1.7	4.7	0.5	1.5	2.7	3.9	4.4	71
ET	7	5	0.4	14	4.3	4.3	4.9	0.9	7.2	3.1	6.5	6.4	0.3	6.3	3.1	0.9	2.6	0.6	0.7	2.4	4.6	1	3.1	0.7	4.1	5.6	86
FN	6.5	4.5	0.3	1	11	7.3	7.2	1.9	5.5	6.3	1	2.9	0	8	3.8	0.5	5.1	0	0.3	2.6	5.1	1.4	2.5	0.6	7.4	7.6	89
FR	6.1	5.9	0	1.2	6.7	8.9	7.6	2.4	5.2	6.8	0.7	2.1	0	8.3	4.8	0.7	6	0	0.3	2.4	4.7	1.8	2.5	0.4	6.7	7.7	91
BD	6.7	5.6	0.2	1.5	7	7.6	9	2.1	5.3	6	1.2	2.6	0	8	4.4	0.6	4.7	0	0.3	2.4	5	1.8	3.1	0.7	6.9	7.4	91
GR	6.8	4.9	0	1.1	5.5	5.4	4.8	14	5.2	6	1.2	3.7	0	6.6	6.8	1	4.8	0	0.2	2	5.5	2.1	2.3	0.1	3.6	6	86
IR	6.1	6.3	0.5	1.9	5.5	6.4	5.3	1.5	14	4.6	1.2	5.9	0.3	7.7	4.3	1.5	3.4	0.1	0.2	2	5.2	1.3	2	0.1	5.5	6.9	86
IT	5.6	5.2	0	1	6.9	8.2	7.2	3	5.3	9.5	0.6	2.2	0	8.4	5.1	0.7	7	0.1	0.3	2.4	4.8	1.7	1.9	0.4	5.6	7.1	90
LN	6.5	3.3	0.7	7.9	3.6	1.7	4.1	0.7	6.1	1.5	26	10	0.2	4.6	2.3	1.4	0.6	1.4	1.6	2.4	4.9	0.4	1.8	0.5	2.8	3.2	74
LX	6.1	4	0.1	1.2	5.8	5.7	6.3	1.2	8.4	5.6	0.6	19	0	6.5	4.1	1.5	4	0.1	0.3	2.1	4.8	1.3	1.7	0.2	3.9	5.4	81
MT	0.8	0.7	0.2	0.9	0	0.2	0.5	1.1	0	0.4	0.2	3.4	80	0.5	0.4	0.1	0.2	2	0.4	0.3	2.3	2.4	0.6	0.9	0.8	0.4	20
NL	6.5	6.6	0.1	1.5	6.6	7.4	6.8	2.2	6.6	5.8	1.2	3.5	0	9.5	3.9	0.9	4.7	0	0.2	2.7	5.1	1.6	2.7	0.4	5.9	7.6	91
PT	5.9	6.1	0	1.3	4.8	7.2	5.5	4.4	3.9	7	1.2	2.2	0	7.2	13	1.1	6.2	0.1	0.6	2.5	4.7	1.6	2.9	0.4	4.4	5.9	87
SJ	5.8	5.1	0.6	1.7	4.8	3.8	3.7	0.9	7.4	2.9	2.2	2.5	0	5.7	3.1	19	2.4	0.2	3.9	5	6.9	1.1	3.9	0.1	2.9	4.3	81
ES	5	5.5	0	1.6	6.2	8.6	6.5	3.1	3.8	8.2	0.6	1.9	0.1	8	6	0.9	12	0	0.3	2.1	4.3	1.8	1.7	0.4	5	6.8	88
BL	3.9	2.5	0.4	2.3	3.6	2.1	1.2	0.4	6.1	0.8	5.9	4.9	1.3	2.9	0.9	2.4	0.4	43	3.4	2.7	2.5	0.2	1.2	0.7	1.7	3.1	57
CT	4	3.7	0.1	1.8	4.3	3.6	3	0.8	5.6	2.7	1.8	3	1.1	4.9	2.7	6.7	2.7	1.4	19	4.6	6.2	2.6	6.7	0.1	2.4	4.5	81
CZ	6.8	5.3	0.1	1.7	4.9	5.1	5.1	1.8	6	4.3	1.2	5.2	0.1	6.4	2.2	1.7	3	0	0.5	12	5.7	3.7	5.3	0.3	5.6	5.9	88
DK	6.5	5.7	0.2	2	6.4	6.2	6.3	2.2	6.4	5.7	1.5	3.3	0	8	4	1.3	4.3	0	0.7	3.3	8.5	1.6	2.8	0.4	5.7	7	92
HN	7.5	4.5	0.1	1.5	5.6	5.8	5.4	2.3	6.3	4.5	0.7	4.4	0.2	7.3	2.7	0.6	3.3	0	0.2	4.4	4	12	4.4	0.4	5.5	6.8	88
PO	7.6	5.9	0.1	1.7	5.5	5.8	6.2	1.9	5.4	4.1	1.3	4.9	0	6.7	3.2	0.8	3	0	0.4	4.7	4.4	2.8	9.5	0.2	6.9	6.8	91
RM	6.1	4.7	1.3	2.7	5.1	4.6	4.5	1.5	5.1	4.4	1.6	4	0.2	6.8	3.8	1.6	4.1	0.2	0.5	4.6	5.5	2.6	3.7	11	4.4	5.5	89
SD	7.4	5.6	0.2	1.4	7.1	7.1	7	1.5	6.3	5.5	1	3.6	0.1	7.9	3.9	0.4	4	0	0.2	2.5	5.1	1.6	2.7	0.6	9.9	7.6	90
UK	6.5	5.7	0.1	1.6	7.1	7.6	7.1	2.4	6.1	5.6	1	2.7	0	8.1	4	0.7	4.8	0	0.4	2.6	5.2	1.7	2.9	0.5	6.8	8.8	91
Contribution to others	152	122	6	47	137	138	132	46	140	114	42	93	5	167	91	31	91	7	17	70	122	43	70	13	120	147	2161
Contribution incl. own	162	131	35	61	148	147	141	60	155	124	67	112	85	177	104	50	103	49	36	82	130	54	80	23	130	156	83.10%