Working Paper Series | 8 | 2015

European Government Bond Dynamics and Stability Policies: Taming Contagion Risks

This paper analyses bond yields of euro area sovereign bonds and finds that the distance between core and periphery has narrowed since the EFSF/ESM was established.

Peter Schwendner
Zurich University of Applied Sciences
Martin Schuele
Zurich University of Applied Sciences
Thomas Ott
Zurich University of Applied Sciences
Martin Hillebrand
European Stability Mechanism

European Stability Mechanism
esm

European Government Bond Dynamics and Stability Policies: Taming Contagion Risks

Peter Schwendner[1] Zurich University of Applied Sciences
Martin Schuele[2] Zurich University of Applied Sciences
Thomas Ott[2] Zurich University of Applied Sciences
Martin Hillebrand[3] European Stability Mechanism

Abstract

From 2004 to 2015, the market perception of the sovereign risks of the euro area government bonds experienced several different phases, reflected in a clear time structure of the correlation matrix between the yield changes. "Core" and "peripheral" bonds cluster in a bloc-like structure, but the correlations between the blocs are time-dependent and even become negative in periods of stress. Using noise-filtered partial correlation influences, this time dependency can be evaluated and visualized using network graphs. Our results support the view that market-implied spillover risks have decreased since the European rescue and stability mechanisms came into force in 2011. EFSF bond issues have been trading as part of the "core" bloc since 2011. In 2015, spillover risks reappeared during the Eurogroup's negotiations with Greece, although the periphery yields did not show risk spreads that were as large as those in 2012.

Key words

Contagion risk; correlation networks; euro area; sovereign bonds; European Stability Mechanism; financial stability

JEL codes

C14, G01, G11, G12, G15, D85

[1]Institute for Wealth and Asset Management, Zurich University of Applied Sciences, Switzerland; E.mail: scwp@zhaw.ch.
[2]Institute for Applied Simulation, Zurich University of Applied Sciences, Switzerland; E.mail: scli@zhaw.ch, ottt@zhaw.ch.
[3]European Stability Mechanism, Luxembourg; E.mail: M.Hillebrand@esm.europa.eu.

ISSN 2443-5503
ISBN 978-92-95085-14-5

doi:10.2852/672368
EU catalog number DW-AB-15-009-EN-N

1 Introduction

Over the last two decades, the European sovereign bond market has been driven not only by the converging forces of the common currency but also by the centrifugal forces of investment and trade imbalances and unequal sovereign credit capacity. As the American "subprime" crisis burst a credit bubble in the European banking system, privately held debt was transferred to public balance sheets to prevent a chain reaction of defaults. This risk transfer and a repricing of perceived sovereign risk led to increased spreads of "peripheral" versus "central" government bonds within the Euro area (Beirne and Fratscher (2013); Tola and Waelti (2015)). According to D'Agostino and Ehrmann (2014), the increase and variability of the observed spreads overestimated the change in fundamentals and point to a structural change in risk perception before and during the crisis. Erce (2015) models the transmission channels between bank and sovereign risk in terms of CDS spreads and warns of a feedback loop, in particular from banking to sovereign risk. Shoesmith (2014) observes the cointegration of Euro area core countries in different periods of the crisis and finds CDS spreads driving bond yields. Glover and Richards-Shubik (2014) compare the linkages between countries' credit holdings and the comovement of their yields; they find little relationship. Broner et al. (2013) conclude that capital transfer from private to public sectors via sovereign bond purchases in crisis can lead to a "crowding-out" effect that reduces domestic growth.

In the current literature, European Central Bank (ECB) actions and communication since 2012 have been credited with maintaining the Euro area's cohesion. Recently, Gerlach-Kristen (2015) employed a regression setup to analyse the impact of ECB crisis measures on CDS spreads of Euro area banks and sovereigns. The author finds that the ECB's open-market operations decreased CDS spreads. She also warns, however, that the market couls misinterpret some of the central bank's crisis mitigation actions as a crisis warning, causing them to backfire. Blasques et al. (2014) also confirm the effectiveness of the ECB measures on sovereign credit.

The non-bailout clause of the Maastricht treaty was supplemented by a rescue and stability mechanism based on mutual guarantees and commitments in the form of the European Financial Stability Facility (EFSF) and the European Stability Mechanism (ESM). As the capital requirements of programme countries are served via bond placements on the private capital market, the bond yields in the secondary market are a valuable observable to monitor the market perception not only of sovereign but also of the new supranational, credit quality. With exceptions, the market activity of the supranational issuer and the ECB commitments successfully lowered the bond yields of all European sovereigns.

Private credit demand did not fully recover, however, prompting increasing political activity in the EU. Currently, the ECB's massive "quantitative easing" programme at already low yields coupled with the unwillingness of institutional investors to sell their high-quality sovereign bond holdings raise concerns that the decay in observed yields may overshoot the anticipated effect of the traded volumes. Hence, absolute yield levels may increasingly be dominated by liquidity shortages. On the other hand, the influence of ECB's monetary policy related activities on relative yield changes between sovereigns is limited. Therefore, analyses explaining the collective dynamics of European sovereign and supranational bonds are currently in demand.

From a ratings perspective, EFSF depends exclusively on the guarantee structure, which would imply a strong correlation with the bond yields of the AAA and AA rated countries of the Euro area core. This analysis can explain whether the market perceives EFSF creditworthiness as dependent on the guarantee structure or instead on asset quality, which would imply a strong correlation between EFSF bond yields and those issued directly by the periphery. This dichotomy can also be viewed as the perception that the EFSF/ESM have the risk profile of sovereigns (derived from the sovereign guarantees) or of typical supranational agencies (dependent on asset quality).

A well-established methodology to model financial data dynamics is the network framework. Networks are very flexible as they are able to capture complex structures as well as bring out the dominant forces behind these structures. Many approaches exist to model the collective dynamics of financial data in terms of networks.

In a seminal paper, Diebold and Yilmaz (2011) have calculated volatility interdependency of stock returns in a VAR-model framework by decomposing forecast error variance h-steps ahead into contributions of single stock return shocks. Interpreting these contributions, also called spillovers, as a directed weighted-dependency network then makes it possible to bring in network theory and tools. Alter and Beyer (2013) extend the model with exogenous variables and apply it to European sovereign and bank CDS spreads. Furthermore, they introduce a contagion index, an average of spillover effects, as a measure of potential contagion. Among other findings, they recognize different spillover effects on core and peripheral countries. Gross and Kok (2013) analyze spillover effects and contagion in an even more general model framework by using a global vector autoregressive model with a mixed cross-section framework (MCS-GVAR) to calculate spillover potential of sovereign and bank CDS markets.

Our analysis uses a different model framework based on two very elementary economic features that we observe in our data of interest, the Euro area sovereign bond yields. First, we notice that correlations of yield changes are more sensitive to changes in short-term market sentiment than absolute yield levels which are currently dominated by central bank activities. Second, we observe that the price-building process is very fast, in particular price reactions to any kind of external "shock" such that instantaneous cross-correlations are stronger than autocorrelations. As a consequence, we do not incorporate any time lag into our model, focusing on the contemporaneous reaction of the market to external news.

We decide to base our analysis on the correlations of the yield returns. This allows us, in contrast to other approaches such as Diebold and Yilmaz (2011) or a mutual-information-based network approach like Kaya (2015), to distinguish between positive and negative interdependencies. Instead of identifying time-lag-implying spillover effects as a source of contagion, we are measuring (simultaneous) connectedness in terms of correlation. A strong co-movement of bond yields can then be both adverse or in the same direction. This distinction is an important feature in the data and allows for a nuanced economic interpretation.

Even without basing the applied method on a classical regression model, it still seems to have some predictive power. The hedge example in the concluding section offers evidence of this: the method filters not only strong but also stable dependencies at a point in time which show some persistence in the following time steps.

This article shows that the correlations display patterns that can clearly be explained by risk-related events during the crisis. In particular, these patterns reflect the market view that the Euro area was segmented into core and periphery countries; that investors gained confidence in the EFSF's guarantee structure from the start, recognizing the EFSF as a "core" issuer; and the stabilizing effect of the rescue programmes helped reconnect the peripheral countries with the core.

An in-depth understanding of the dependency structure of the Euro area sovereign yields is also of significant importance for investors: stable statistical dependencies allow for stable risk-reducing cross-hedging of a Euro area bond portfolio, including EFSF bonds. In contrast to the other countries in a financial assistance programme, Greece decoupled not only in macroeconomic terms, but also from a correlation viewpoint. The negative correlations between Greece and core Euro area countries could be strong enough for cross-hedging of Greek (illiquid) bond positions with long positions in Bund futures.

The paper is structured as follows: First, we explain and motivate influence networks as a tool to monitor the time dynamics of relationships between sovereign bond yield changes. To address concerns about noise and non-stationarity in the time series of yield changes, we suggest a bootstrap scheme to carve out the most relevant characteristics of the observed collective yield changes. Then, we apply these methods on a dataset of 10-year Euro area sovereign bond yields and show the intermediate steps from the basic correlation matrices calculated in sequential time slices to the resulting filtered influence networks. We interpret the numerical results in the light of the recent political developments. The last section concludes.

2 Methods

As motivated in the introduction, we want to discuss the yield dynamics as close to the market data as possible. Therefore, we are not aiming to construct a parametric model and to fit the parameters to the market data but are instead choosing a model-free approach driven by the data themselves.

Correlation and Partial Correlation Analysis As a starting point, we employ the Pearson correlation coefficient C_{ij} as an estimator of the correlations of the return time series r_i and r_j,

$$C_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sigma_i \sigma_j} \tag{1}$$

where the averages $\langle ... \rangle$ of the return time series r_i and r_j are taken over a given time horizon T and σ_i and σ_j are their respective standard deviations. The values of the correlation coefficient range between $+1$ (perfect positive correlation) and -1 (perfect negative correlation) indicating how similar the change in returns of a given pair of bonds over a period of time T is. Calculating the pairwise coefficients of N return time series results in the correlation matrix C_{ij} of size $N \times N$. It should be noted that the Pearson correlation coefficient measures the strength of an assumed linear relationship and can give spurious results if applied to non-stationary time series data, as e.g. discussed in Johansen (2007). For this reason, we employ a noise analysis of the correlation matrices, as addressed below.

The daily returns time series is approximated as

$$r_i^t = -D_i(y_i^t - y_i^{t-1}), \tag{2}$$

where y_i^t is the yield of bond i with duration D_i at time t. As the yields refer to the 10-year reference bonds, the durations D_i are assumed to be constant in a rather short time window and thus are not supposed to influence the resulting correlation.

To analyse the dynamics of the correlation structure of returns, we then calculate the moving-window correlation matrices $C_{ij}(T_n)$ for non-overlapping periods T_n. The results are shown in the next section.

The correlation coefficients do not, however. tell us whether a correlation is due to the influence of one variable on the other, or vice versa or mutually, or due to the influence of some third variable. The partial correlation measure is one approach to detect direct influences between variables. It is defined by

$$\rho_{ij:k} = \frac{C_{ij} - C_{ik}C_{kj}}{\sqrt{1 - C_{ik}^2}\sqrt{1 - C_{kj}^2}}, \tag{3}$$

where C_{ij}, C_{ik}, etc are the correlations between return series r_i and r_j, r_i and r_k, etc. A small absolute value of $\rho_{ij:k}$ indicates that r_k strongly affects the correlation between r_i and r_j. Conversely, a large absolute value indicates that r_k does not contribute much to the correlation between r_i and r_j, implying that either r_i and r_j strongly influence each other directly or that the correlation stems from some other factor.

A strong correlation between r_i and r_j is due to the potent influence of r_k if the absolute value of C_{ij} is large and the absolute value of $\rho_{ij:k}$ is small and both values have the same sign. For this reason, Kenett et al. (2010) introduced the measure

$$d_{i,j:k} = C_{ij} - \rho_{ij:k} \tag{4}$$

to quantify the "influence" of time series r_k on the series r_i and r_j. If the absolute value of this quantity is large, a significant fraction of the correlation between the series r_i and r_j is explained in terms of r_k. If the quantity is positive, r_k has a positive, converging influence on the correlation between the series r_i and r_j; if the quantity is negative, r_k has a negative, diverging influence on the correlation between the series r_i and r_j.

Partial Correlation Networks To further analyse and visualize the influences of specific bonds on the correlation structure of the system, we construct partial correlation networks (PCNs). There are various methods to construct PCNs. We first follow the method presented by Kenett et al. (2010) who define the average influence $d_{i:k}$ of the series r_k on the correlation between the series r_i and all the other time series as

$$d_{i:k} = \langle d_{i,j:k} \rangle_{j \neq i,k} \,. \tag{5}$$

In general, $d_{i:k} \neq d_{k:i}$. Therefore, (5) allows us to set a directed link $r_k \rightarrow r_i$, indicating an influence of node k on node i with weight or strength $d_{i:k}$.

Now, to filter out the most relevant and statistically robust information contained in the average influence matrix $d_{i:k}$ we need a measure of statistical robustness: if the values $d_{i:k}$ fluctuate too much the purported influence is too unstable to be counted an effective influence. We argue that the bootstrap approach detailed below gives us such a measure. Accordingly, we retain a directed link $r_k \rightarrow r_i$ if and only if

$$|d_{i:k}| > Q \times \sigma_{bootstrap}(d_{i:k}), \tag{6}$$

where $\sigma_{bootstrap}(d_{i:k})$ is the standard deviation calculated by bootstrapping the measure $d_{i:k}$. For our application, we set the fluctuation threshold to $Q = 3$ standard deviations as higher values lead to a "pruning" of the resulting influence networks. The threshold parameter Q directly limits the allowed statistical noise. Given a small number of nodes, we do not need a further topological constraint like a planarity condition.

Bootstrapping correlations To evaluate the quality of the calculated correlations and to quantify the variability of the correlations within the chosen time window, we employ a correlation bootstrap scheme (Efron (1979)), with similar applications in Fengler and Schwendner (2004) and Morales et al. (2014). In our application, we draw time blocks of daily return vectors across all markets with replacement to compute samples of artificial pseudo-time series. For each of these samples b, we compute a correlation matrix $C_{ij}(T_n, b)$. The standard deviation of the correlation matrix entries for each pair of markets across all samples b is a measure for the variability of correlation in this time window. We can interpret this measure as the minimum uncertainty the correlation output bears due to its calculation method and due to the underlying market mechanism. The standard deviation shows the degree of "blur" in the correlation estimator. The block length is drawn from a uniform distribution in the range [1; 10] to account for serial dependence, as per Politis and Romano (1992). This time window is motivated by an ACF analysis of the yield change timeseries.

As a filter criterion for the influence networks, we compute $\sigma_{bootstrap}(d_{i:k})$ as the standard deviation of the $d_{i:k}(b)$ distances across all samples b. The bootstrap scheme can easily be parallelised, Sloan et al. (2014). Recently, Kenett et al. (2015) also employed a resampling validation scheme for correlation influences, but via a direct noise analysis of the independent time series instead of a synchronous bootstrap.

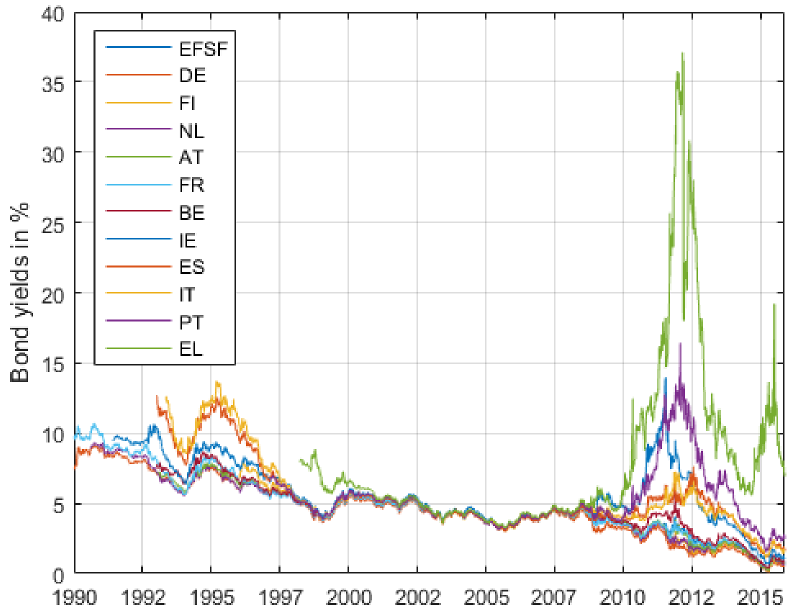

Figure 1: Euro area sovereign bond yield time series.

3 Results

We analyse the system of daily returns time series of the most important 10-year government reference bonds of the Euro area from January 2004 - October 2015. The bonds are issued by the European Financial Stability Facility (EFSF), Germany (DE), Finland (FI), the Netherlands (NL), Austria (AT), France (FR), Belgium (BE), Ireland (IE), Spain (ES), Italy (IT), Portugal (PT) and Greece (EL). For the EFSF yields, we use a yield time series composed of the single bond issues EFSF 3.375 07/05/21, EFSF 3 1/2 02/22, EFSF 2.25 09/22, EFSF 1.875 05/23, EFSF 2.125 02/24, EFSF 1.75 06/24 and EFSF 0.2 04/25. We exchange the bond tickers as soon as the new issue becomes available. For the sovereign bond yield time series, we use the generic 10-year yields from Bloomberg (GDBR10, GFIN10YR, GNTH10YR, GAGB10YR, GFRN10, GBGB10YR, GIGB10YR, GSPG10YR, GBTPGR10, GSPT10YR and GGGB10YR). For Austria, Ireland and Portugal, we replace stale data with Reuters data in the period 2005-2007.

The resulting yield time series are shown in Figure 1. We first calculate the correlation matrices C_{ij}, i.e., the correlations between daily returns r_i and r_j in non-overlapping yearly time windows. We do not calculate the correlations between the yields but instead the correlations between the daily changes of yields. Therefore, high correlations between two countries do not imply that their credit risks are similar. Instead, we understand high correlations between the daily yield changes of two sovereign bonds as a similar reaction to the same external influence. In a situation of market stress, a high positive correlation is interpreted as a convergent behaviour of two markets. On the other hand, a high negative correlation is interpreted as a divergent behaviour of two markets, given external stress. We point out that a positive day-to-day correlation should not be confused with a common longer-term trend, as explained by Lhabitant (2012).

To analyse the dynamics of the correlation structure of returns, we calculate the moving-window correlation matrices $C_{ij}(T_n)$ for non-overlapping periods of one calendar year. The number of trading days per year is significantly larger than the rank of the matrix, which is the number of government bond markets $N = 12$. For a discussion about the implications of too small time windows in relation to the dimension of a correlation matrix, we refer to Laloux et al. (1999) and Plerou et al. (2002). The introduced noise filter makes it possible to limit the tolerated noise in the correlation influence estimator and thus in the resulting network with a statistical motivation.

In Figure 2, we can see that the dynamics of the correlation structure exhibit different phases, e.g. of low correlations, high correlations and phases where correlation clusters emerge. After the introduction of the Euro, the bonds were seen to differ only by a liquidity spread. This is reflected in the correlation heatmaps from 2004 to 2008, with very high correlations across all countries, forming a monolithic bloc. At the beginning of the financial crisis, the "subprime" credit problem led to an increase in Irish yields. In 2009, the strong euro-area-wide correlations decreased. In 2010, the centre stage of the financial crisis moved to Europe. A two-tier bloc structure of the correlations emerged that persisted through 2012: a "core" bloc with Germany, Finland, the Netherlands, Austria and France; and a "periphery" bloc with Ireland, Italy, Spain, Portugal and Greece. In 2012, within the "core" bloc, another sub-bloc of Austria, Belgium and France emerged after a rating downgrade.

This core-periphery correlation bloc structure motivates to represent the dataset in the format of the yield timeseries for all markets rather than in the format of yield spreads relative to Germany. Although Germany shows the lowest yields across the whole timespan, it does not play a distinct role in the correlation matrices, but is located within the core bloc. Treating it not as the benchmark yield, but as a separate market also allows to study the correlation influences originating from and targeting Germany.

The first EFSF 10-year bond, issued in June 2011, developed a correlation pattern like the core countries. In 2013 and 2014, the rescue and stability architecture led to a dissolution of the negative correlations between the two blocs.

How can correlations be interpreted from the viewpoint of risk contagion? A significant negative correlation between the daily changes of bond yields of two sovereigns signals that the market anticipates that the two sovereigns' risks would decouple at rising volatilities. Therefore, a positively correlated bloc reflects a bloc of sovereigns with converging credit risk, while negative correlations suggest diverging credit risks between two

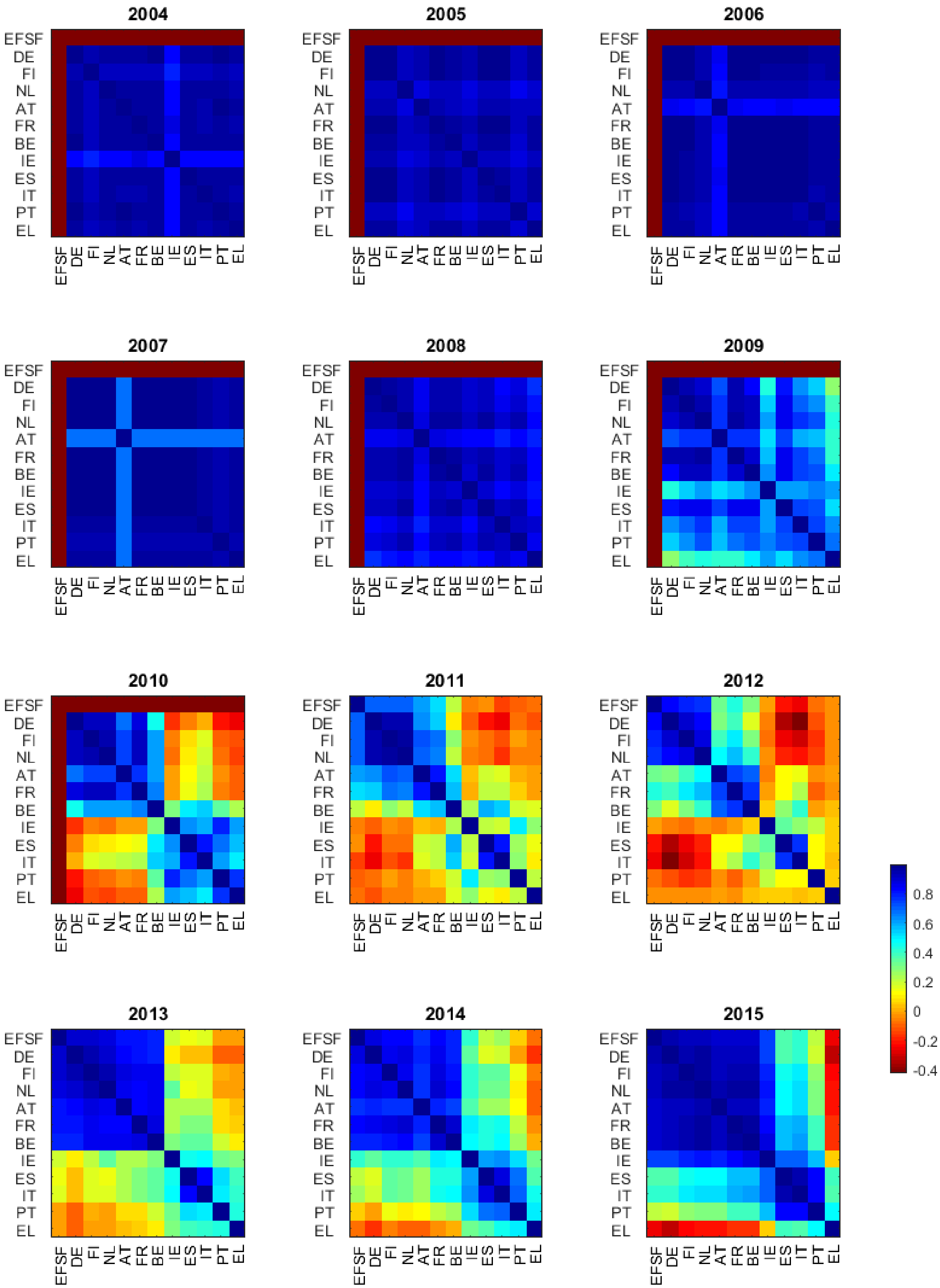

Figure 2: Visualization of correlation matrices of daily return time series of 10-year government bonds at different times in the period 2004-2015. Each heatmap shows the correlations in a one-year time window.

blocs.

In a stress situation, this divergence between core and peripheral bonds could lead to a transfer of capital from weaker to stronger countries. This could happen both at the long end of the yield curve, where it could affect sovereign funding, and at the short end, where it might lead to a transfer of bank deposits, affecting the stability of the national banking systems. On the other hand, insignificant and fluctuating correlations between the yield changes of all assets would point to a market far less focused on systemic risk than is currently the case.

Applied to the Euro area bond market, this means that, with significant negative correlations appearing in 2012 and dissolving in 2013/14, contagion risk and "fragility" decreased in this period.

Figure 3 shows the standard deviations of the density of correlation matrices calculated for 10,000 bootstrap samples. The standard deviations are not necessarily large during the peak of the crisis and low otherwise. In fact, in 2008 and 2009, the standard deviations are especially low. In 2010, they assume the largest values, as a structural break from positive to negative correlations between the "core" and "periphery" blocs occurs. The first EFSF issues appear on the scene in 2011 and display a very low correlation uncertainty immediately thereafter to all other markets.

In 2012, the bloc structure contains only low noise in the correlations. In 2013, a second structural break is visible between the core and periphery, as the negative correlations almost disappear.

Figure 4 contains the unfiltered average influences $d_{i:k}$ as defined in equation (5). These matrices are not symmetric. The rows represent the index k that denotes the "source" of the influence, and the columns represent the index i, denoting the "target" of the influences. The numerical range of the influences is [-0.24; +0.85] within the time window 2004-2015. The scaling of the influences to the colormap was capped at a maximum value of +0.55 to get a better visual discrimination around the zero level.

In the heatmaps, patterns are visible across the columns of specific rows, but less so across the rows of specific columns. The reason is that the influence measure $d_{i:k}$ averages across "outgoing" influences, hence the measure is more stable horizontally. The strongest average influences appear from the markets in the middle of the rows and point to the upper and lower rows. Before the financial crisis, the average influences are higher than afterwards. From the beginning of 2010, influences with negative signs appear in the matrix.

We point out that entries with negative signs in the $d_{i:k}$ matrix must not be misinterpreted politically as some countries influencing other countries in a "negative" way. They could instead simply be seen as a statistical measure for the mutually reinforcing or shearing influences of correlations between bond yield changes that happen at the same time. The negative signs appear between the core and peripheral blocs. The absolute values in the direction from the core to the periphery are stronger, consistent with the findings of Karaflos (2015). From 2013 on, the positive signs dominate the influence matrix again.

Figure 5 displays the uncertainties of the average influence matrices, also computed as standard deviations of the bootstrapped average influences according to equation (6). The influence uncertainty shows different

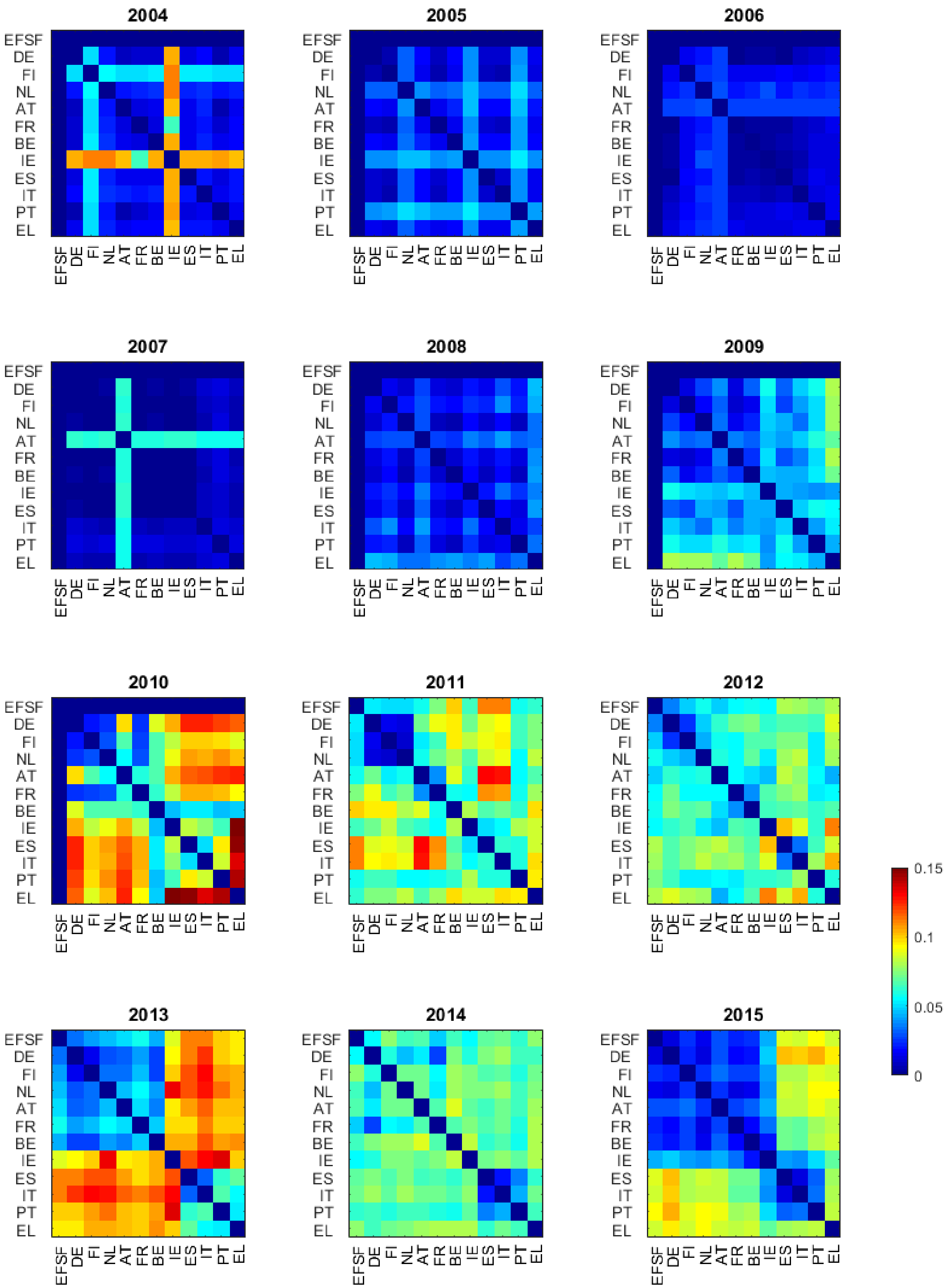

Figure 3: Standard deviation of correlation matrix bootstrap samples. Each heatmap shows the standard deviation of a bootstrap with 10,000 draws in a one-year time window.

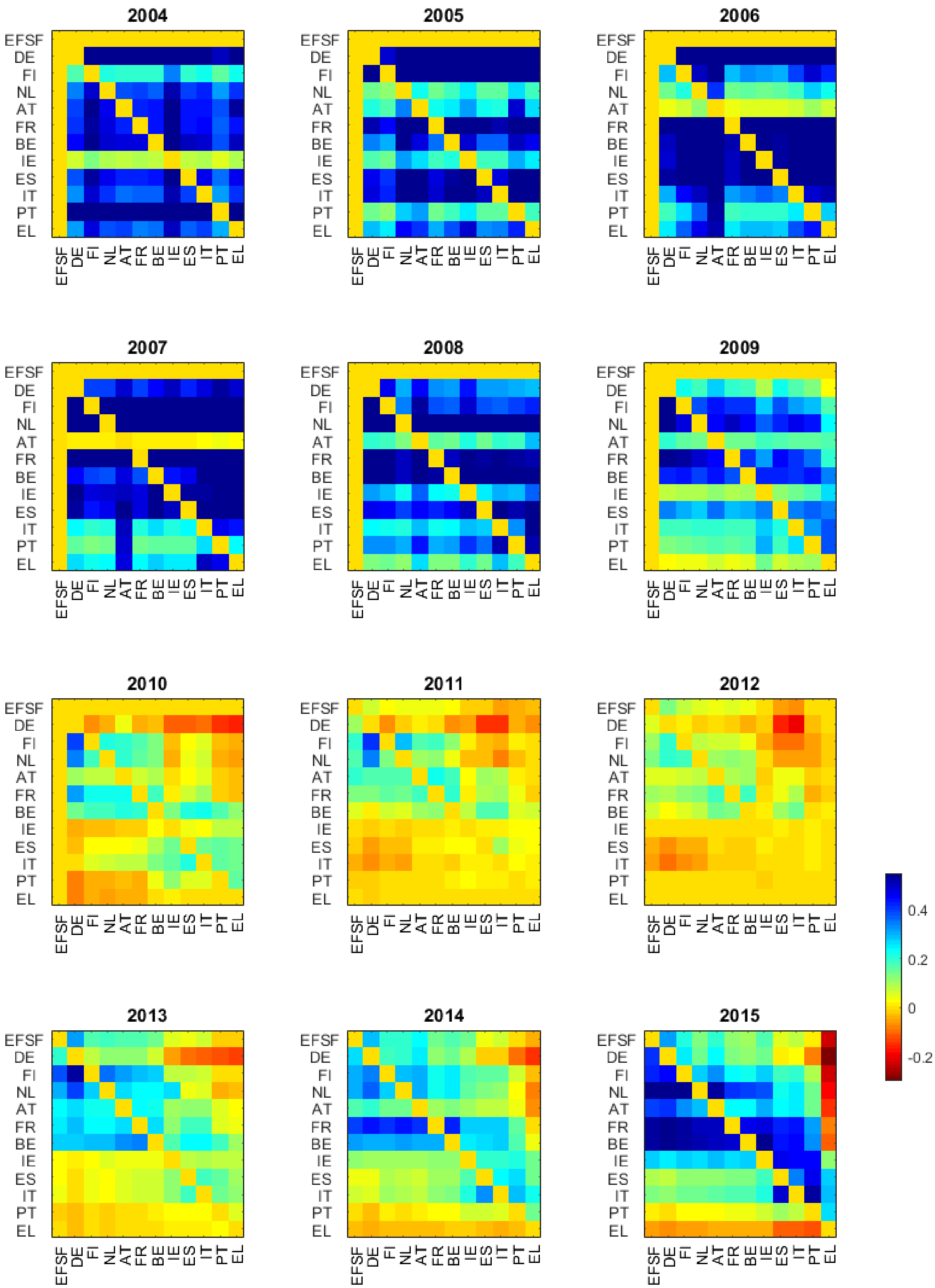

Figure 4: Unfiltered average influence matrix $d_{i:k}$ as defined in equation 5. The rows denote the index k (the "source" of the influence), the columns denote the index i (the "target" of the influence).

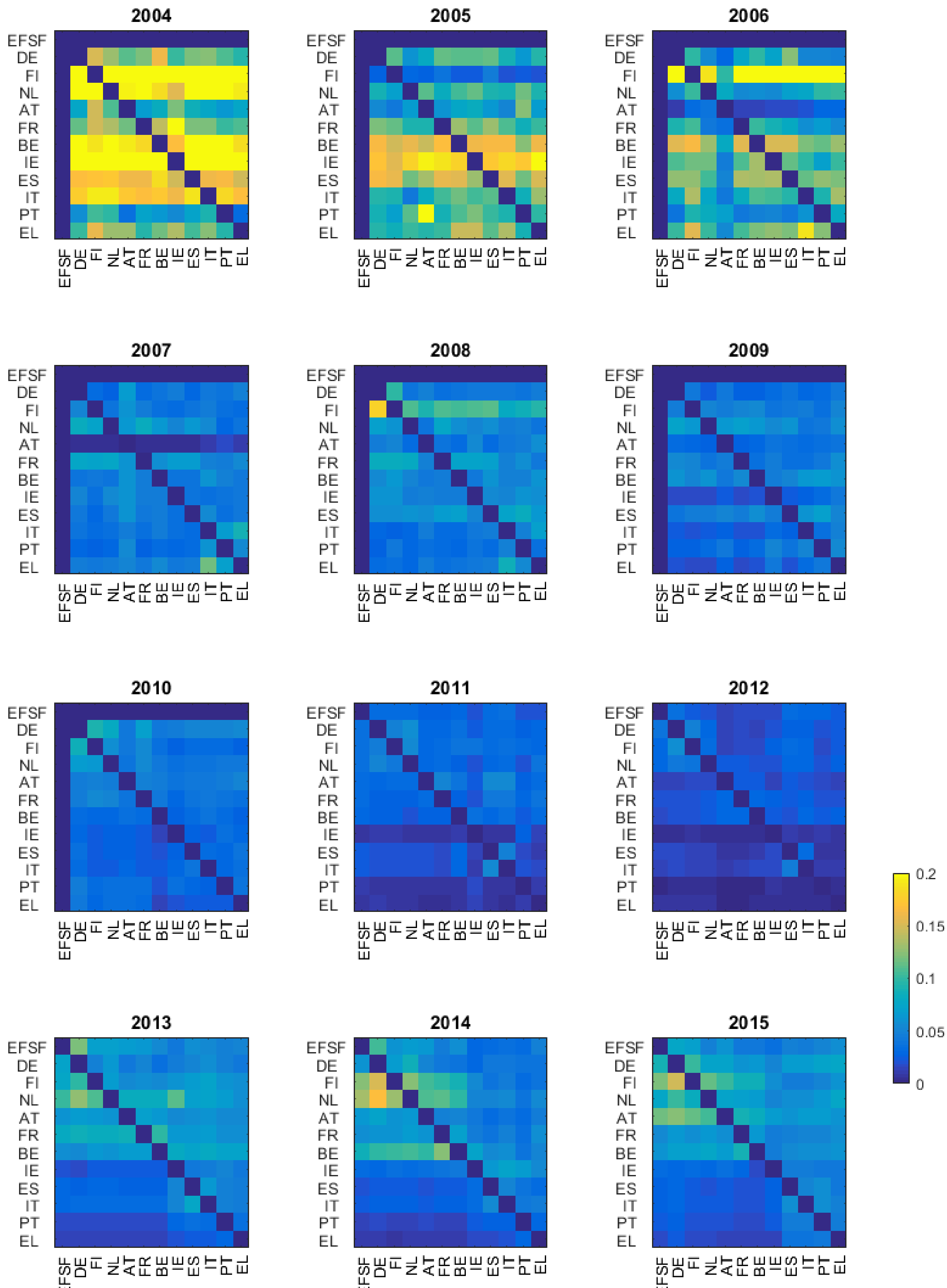

Figure 5: Bootstrap of average influence matrix $\sigma_{bootstrap}(d_{i:k})$ according to equation 6. Each heatmap shows the standard deviation of a bootstrap with 10,000 draws in a one-year time window. The rows denote the index k, the columns denote the index i.

patterns in time compared to the correlation uncertainty: the influences show high noise before the crisis and very low noise between 2009 and 2012. From 2013 on, influence uncertainty increases again, especially for the direction pointing from the core to the periphery. We use these uncertainties as a noise filter in our construction of network graphs, as detailed in the methods section. Figure 6 at last shows[1] filtered directed networks based on the noise-filtered average influences (Figure 4), i.e., the influences found to be three times stronger than the noise depicted in Figure 5. The arrows always end at the geographical locations of the respective capitals of the countries. The colors of the arrows are drawn according to the same colormap as those used for Figure 4.

The networks correspond to the same yearly time windows as the correlation heatmaps in Figure 2. From 2004 to 2009, we observe strong positive correlation influences across the Euro area with decreasing noise in the correlation influence estimator. In 2009, the influences within the core remain strong, but weaken from the core to the periphery. The 2010 network reflects the period in which the financial crisis - which at that time was thought to be a crisis of the U.S. banking system due to an over-expansion of mortgage credit - found a new focus in the sovereign credit market of peripheral European countries. Greece entered a 110 bn EUR financial assistance programme.

The two-tier structure of the graph reflects the clustering into core and peripheral countries visible in the correlation matrices. High correlations within these clusters show up as su-bnetworks of the network with reinforcing within each bloc. The peripheral countries build a second correlated bloc that is visible in the correlation matrix, but with higher correlation fluctuations than in the core bloc.

The 2011 time window was characterized by a deterioration of sovereign credit that led to a downgrade of the U.S. in August, followed by a selloff in equities, but remarkably a rally in the downgraded U.S. treasuries and in the USD. The Swiss national bank (SNB) announced that it planned to keep the EURCHF rate above CHF1.20 to prevent further upvaluation of the CHF. In Europe, further political steps were taken to reduce spillover risk between the smaller countries Portugal, Ireland and Greece and the larger states Spain and Italy. Portugal and Ireland agreed to financial assistance programmes. The markets did not immediately acknowledge these efforts, as the influence networks show: while strong influences within the core bloc remain, there appear to be some significant negative entries in the influence matrix, i.e., their absolute values pass the noise filter. Shearing forces (red arrows) are visible between Germany, Spain and Italy. The peripheral countries Ireland, Portugal and Greece are not part of the network in this year due to the noise filter.

In 2012, political changes took place in many European countries, as their economics deteriorated. The negative correlations between core and periphery become especially pronounced (Figure 2). The fluctuations of the correlation matrix decrease and the fluctuations in the influence matrix remain very low, giving a clear influence graph representing significant contagion risk between periphery and core. Greece entered a second

[1] the network graphs are FNA screenshots (www.fna.fi)

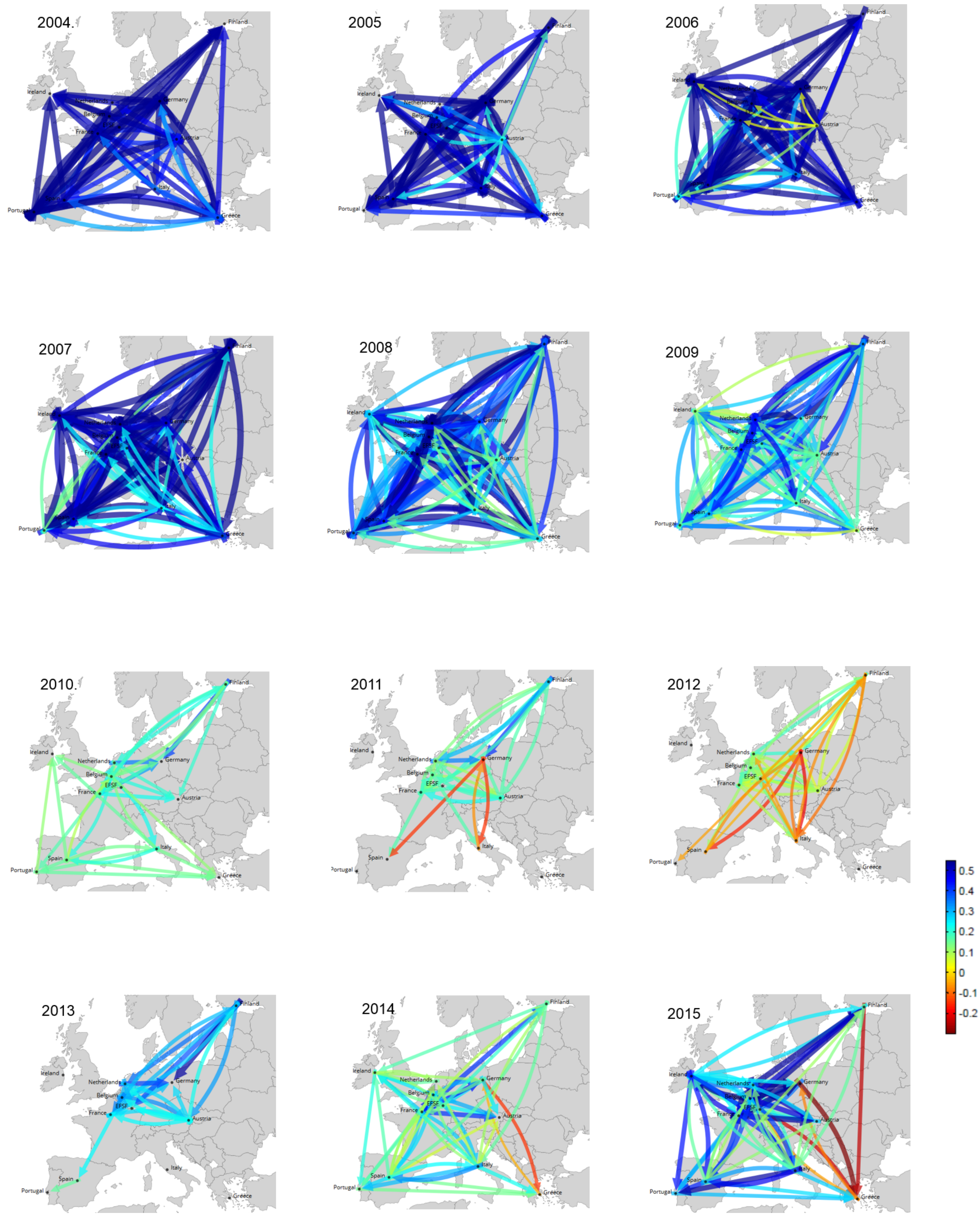

Figure 6: Visualization of filtered influence networks corresponding to the correlation matrices of Figure 2. Blue colors denote reinforcing influences in the same direction, red denotes shearing forces. The thickness of each arrow is proportional to the absolute level of the corresponding distance $d_{k:i}$.

financial assistance programme. Spain agreed to a financial assistance programme for its banking system. The EFSF clearly established itself as an issuer in the core bloc of the sovereigns. Draghi's "whatever it takes" comment and the establishing of the OMT programme came later the year and hence could not dominante the 2012 influences.

During 2013, correlations between periphery and center improve massively. A two-tier structure of the correlation matrix translates into a similar structure of reinforcing influences in the network graph, with even stronger influences within the core bloc, a partial reconnection of the peripheral bloc and reinforcing influences from the core to the periphery.

In autumn 2014, political uncertainty in Greece heightened, leading to a weak negative correlation between the bond yields of Greece and other countries, especially Germany. This is reflected in a shearing force between the Greek and German bond yields in the 2014 network graph. An example for the transmission mechanism could be the Bund future, the most liquid hedging instrument for 10-year euro sovereign rates. When traders buy Bund futures to hedge long positions of illiquid Greek bonds, this could both make use of such a negative correlation and contribute to it. In 2014, the influence network keeps its general structure but is growing, in particular with an increasing number of influences between core and periphery. This clearly reflects the recognition of the progressive stabilization of the peripheral countries, where structural reforms lead to economic growth above the euro area average.

For 2015, the influence uncertainty declines from what it was in 2014. The connections within the core and between the core and the periphery strengthen. Greece continues to be an exception: using daily yield time series, it is the only market exposed to negative influences. As frequent political twists in Greece dominated the headlines through August 2015, we use a second dataset with hourly yields for the time window October 2014 - November 2015 (see Figure 9). In October 2014, Greek yields started to rise. After the Syriza election victory in January 2015, a possible contagion scenario of a "Grexit" to other Euro area states or even a "meltdown" of the Euro area was discussed in the media, and was also used as a negotiation leverage from Greece towards the Eurogroup. The yield top was in July 2015 shortly before a third programme was negotiated on July 12th. After that, Greek yields decreased again. The bonds of all other countries showed a bullish trend until April 2015. Then, inflation expectations increased and bond yields also rose until July. During July, the focus of the news shifted from Greece to China. After a yuan devaluation and equity corrections, bond yields decreased slightly again. If we compare Figure 9 to Figure 1, the striking difference of the 2015 dynamics relative to the 2010-2012 yield movements is that in 2015 the levels of all other markets beyond Greece did move way less than in 2012. Obviously a broad "contagion" did not materialize.

Figure 7 depicts the situation from the week before the Greek elections (25.1.) to a week after the commitment to honor the extension agreement (Eurogroup 20.2. in Brussels). The upper six heatmaps depict the correlations, the lower six maps show the corresponding filtered correlation influences. As the political decisions were often made at the weekends, weekly time slices seem to be adequate. Within these six weeks

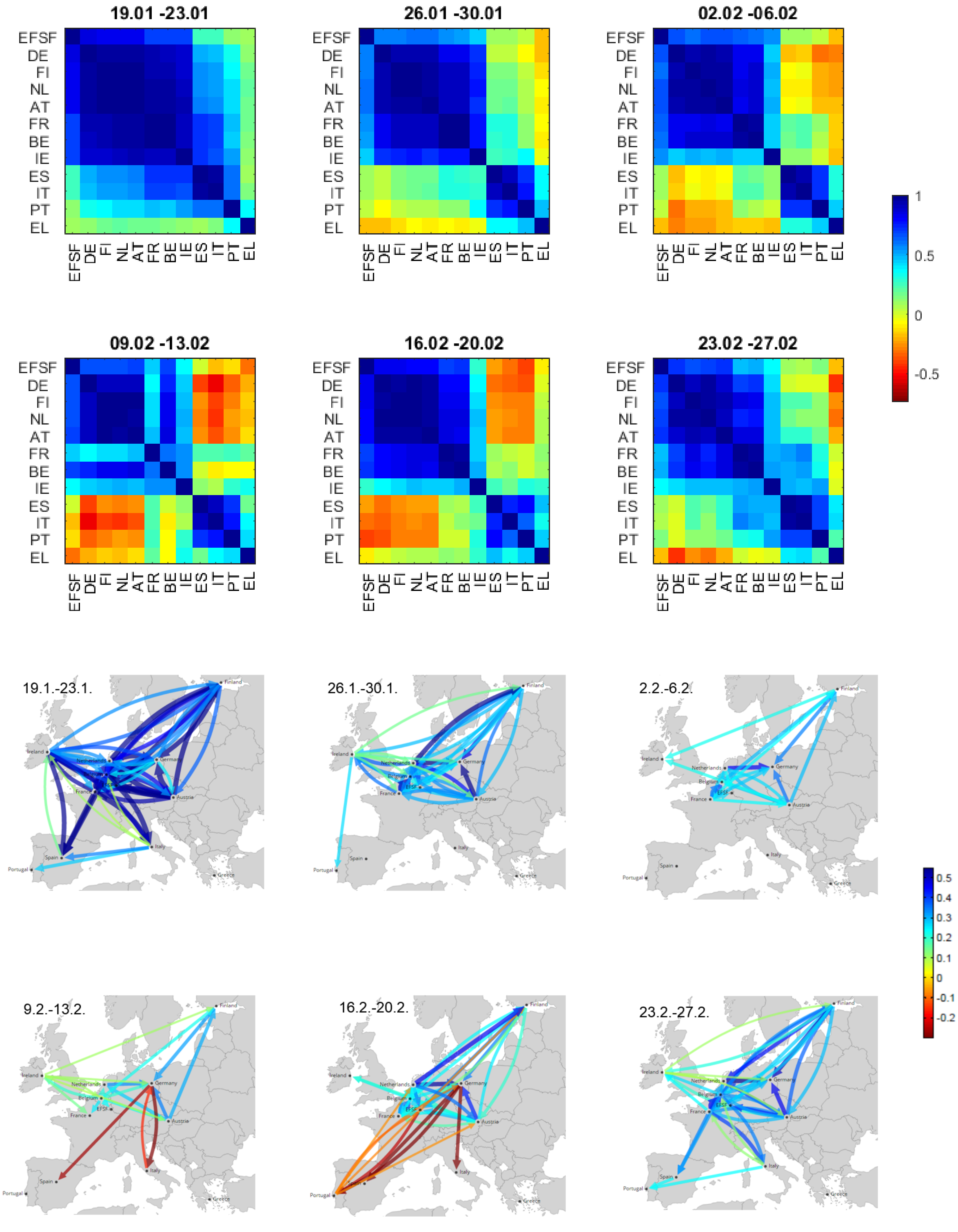

Figure 7: Weekly correlation heatmaps and influence maps using hourly data around the first Greek elections in 2015 (January 19th to February 27th, 2015).

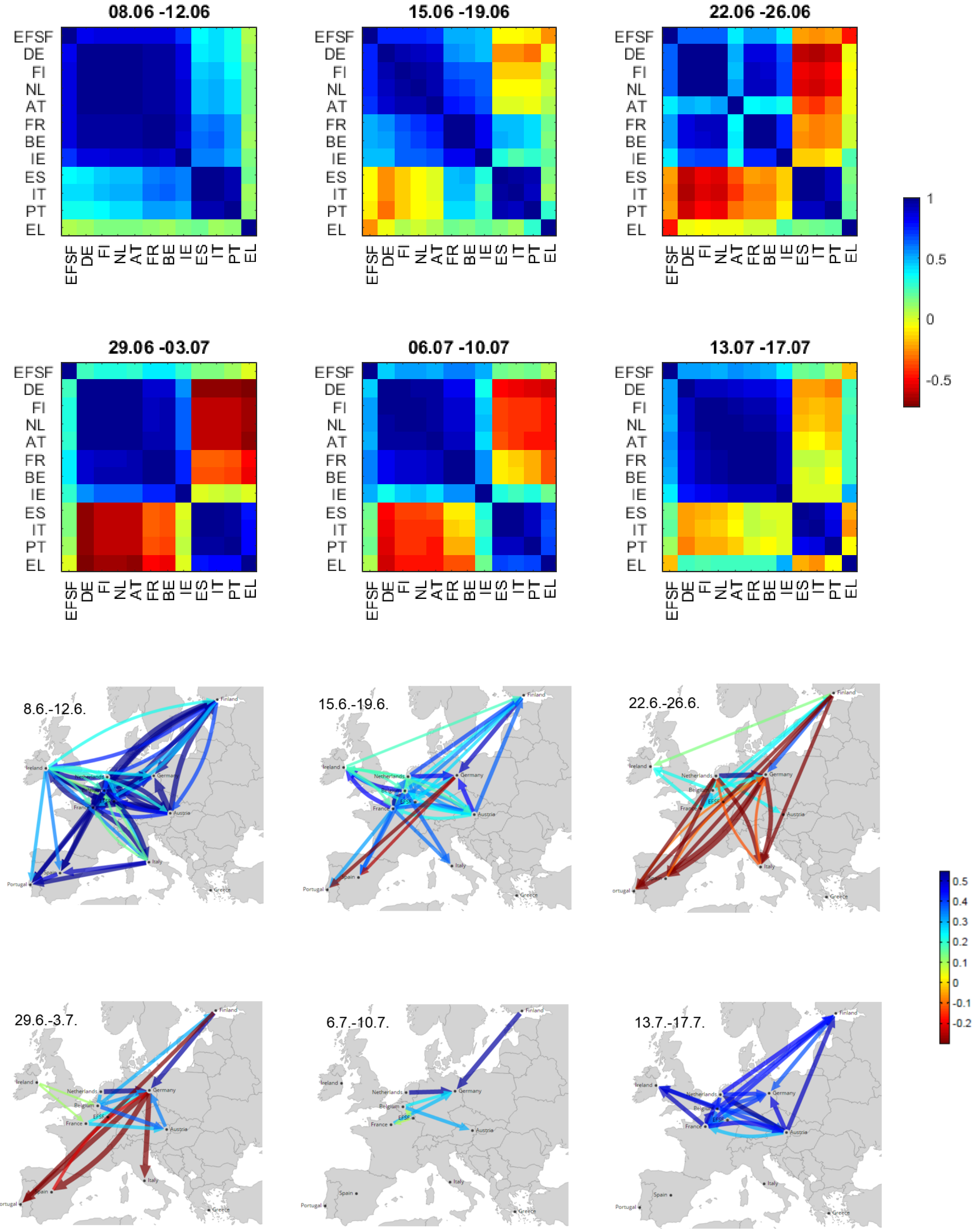

Figure 8: Weekly correlation heatmaps and influence maps using hourly data around the end of the negotiations concerning the third Greek financial assistance programme (June 8th to July 17th, 2015).

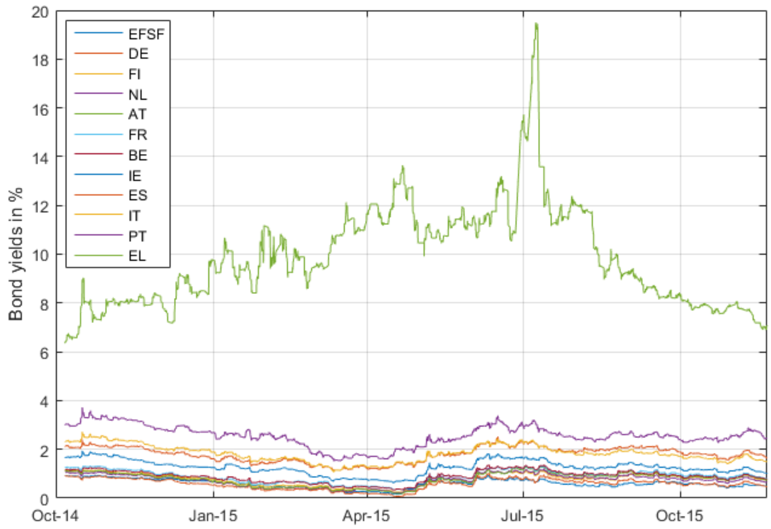

Figure 9: Euro area sovereign bond yield time series from October 2014 to November 2015.

the correlations change drastically. They transition in a similar fashion to 2009-2014, but they do so much faster. To assess the statistical validity, we again calculate correlation influences and use the noise filter. The resulting networks confirm the appearance of significant negative influences after the new Greek government confirmed at the beginning of February its election promises to end the financial assistance schemes. During the first week of this series, the ECB announced a 1.1 trillion EUR quantitative easing plan (on January 22nd), which strengthened the yield correlations across the Euro area. The week before (on January 15th), the Swiss national bank (SNB) dropped its EURCHF floor which caused a massive upvaluation of the CHF. In the two weeks after the Syriza election victory (26.1.-6.2.), Euro area bond correlations weakened as the new Greek government tried to convince other European governments to support its hard-line negotiation policies for a prolongation of the financial assistance programme. From February 2nd on, as in 2011, the influence network showed increasing shearing forces between the Euro area core and periphery. After Greece committed to the financial assistance extension at February 20th, the network quickly normalized. We point out that Greece is not part of the network in any of these six weeks as the correlation influences between its bonds and the rest of the Euro area do not pass the noise filter. Thus, it is not the Greek bond market that "influences" the other bond markets, but the news about Greece.

A second transition sequence from the second week of June to mid-July is shown in Figure 8. In the week of June 15th, Greek Prime Minister

Alexis Tsipras met Russian president Putin in St. Petersburg, demonstrating his commitment to look for sources of funding and political liaison beyond the Euro area. In this week, the shearing forces reappeared and intensified in the next week (June 22th) as many Eurogroup meetings took place without agreement. As the Greek government announced a referendum with a recommendation against a financial assistance programme at the end of June, the negative influences dominated the network. As the ECB then decided not to further raise the Emergency Liquidity Assistance (ELA), Greece had to implement capital controls. A week later (July 5th), the Greek voters followed government's recommendation and Greek bond yields spiked. The network shows significant influences in the Euro area core in the week of July 6th as the fluctuations increased. After a further exhausting negotiation weekend and a Greek commitment to a third financial assistance programme on July 12th, the correlations started to normalize again. The fact that the absolute yield levels of the periphery bonds beyond Greece did not increase in this phase as they did between 2010-2012 confirms the respect of market participants towards the rescue and stability architecture, but the correlations reveal a similar risk potential as in 2010-2012.

4 Conclusion and Outlook

We constructed noise-filtered influence networks to better understand the collective yield dynamics of the Euro area sovereign bonds. We implemented a noise filter with a bootstrap scheme to have a statistical motivation and a single threshold parameter, the number of standard deviations Q that limits the allowed statistical noise. Our method is a generic approach to analyse the structure of collective time series dynamics and may be applied to other similar cases.

The influence network graphs were mapped on a geographic map of the Euro area as the standard network visualizations often lead to an abstract "ball of wool" with fluctuating locations of the nodes as time passes. The graphs show both reinforcing and shearing influences as the Euro area sovereign crisis develops. We regard negative correlation influences between core and periphery bonds during crisis as an early warning indicator, signalling "flight to quality".

Our correlation analysis suggests that the EFSF bond issues were priced as part of the "core" bloc of the Euro area sovereigns, thus reflecting the quality of the guarantee structure and confirming the efficiency of the funding on the private capital market. In periods of market stress, the EFSF bond yields move in the same direction as those of the guarantor countries and withstand contagion risk from adverse movements of the bond markets of the periphery.

After 2012, the financial situation of the peripheral euro area countries improved substantially. In 2013 and 2014, the financial assistance programmes proved to be effective. The negative correlations between the compliant programme countries and the core countries disappeared and the positive, reinforcing influences prevailed.

In 2015, negative correlation influence reappeared during the negotia-

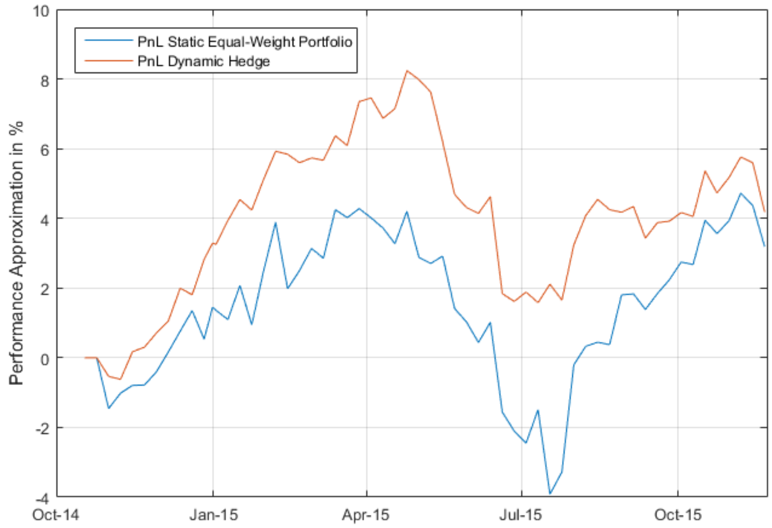

Figure 10: Hedging backtest from October2014 to November 2015: markets experiencing significant negative correlation influences are hedged in the following week.

tions between Greece and the Eurogroup. But in contrast to 2010-2012, the absolute levels of the periphery yields beyond Greece did not move much. Our interpretation of this observation is that the negative short-term correlations come from market makers already positioning themselves for potential shocks that have yet to occur.

Future analysis may use the influence networks for the selection of macroeconomic explanatory variables for a joint euro area yields model: macroeconomic variables of countries found to have a strong influence in the networks presented may also help explain other euro area yields.

A further interesting follow-up is to investigate how the observed structures in the yield correlations are visible in secondary market trading: while the observed influences in the yield changes are of statistical nature, secondary market flows could show the mechanisms behind these changes.

Finally, influence networks could also be of interest for the market timing of hedging instruments for a bond portfolio from an investor's viewpoint, and as an early warning tool to detect developing crises. Figure 10 compares the performance of two portfolios in the timeframe from October 2014 to November 2015: a static equal-weighted portfolio consisting of all 12 Euro area bonds of the dataset, and a dynamically hedged portfolio that allocates only to those markets that do not experience negative correlation influences after the noise filter on a weekly basis. In April and May 2015, inflation expectations increased, leading to a drawdown of all bonds. The hedged portfolio shows a lower volatility than the static portfolio, although there was no default in the respective period. The computation only used a duration approximation and the running carry component without transaction cost to approximate the performance and therefore does not show an investable performance, but motivates further studies.

Acknowledgments We thank Veni Arakelian, Antonello D'Agostino, Aitor Erce, Eugene Neduv, Jochen Papenbrock, Martín Saldías, Veni

Arakelian and Petra Gerlach-Kristen for valuable discussions. We are also grateful for valuable comments received from participants of the "Financial Risk and Network Theory" conference at Judge Business School (Cambridge, 2015) and the "European Seminar on Bayesian Econometrics" (Gerzensee, 2015).

References

Alter, A. and Beyer, A. (2013). The dynamics of spillover effects during the european sovereign debt turmoil. *ECB Working Paper Series*, (1558).

Beirne, J. and Fratscher, M. (2013). The pricing of sovereign risk and contagion during the european sovereign debt crisis. *ECB Working Paper No. 1625.*

Blasques, F., Koopman, S. J., Lucas, A., and Schaumburg, J. (2014). Spillover dynamics for systemic risk measurement using spatial financial time series models. *Tinbergen Institute Discussion Paper*, (14/107/III).

Broner, F., Erce, A., Martin, A., and Ventura, J. (2013). Sovereign debt markets in turbulent times: Creditor discrimination and crowding-out. *IMF Working Paper*, WP/13/270.

D'Agostino, A. and Ehrmann, M. (2014). The pricing of G7 sovereign bond spreads - the times, they are a-changin. *Journal of Banking and Finance*, 47:155–176.

Diebold, F. X. and Yilmaz, K. (2011). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *PIER Working Paper*, (11-031).

Efron, B. (1979). Bootstrap methods: Another look at the jackknife. *Annals of Statistics*, 7.

Erce, A. (2015). Bank and sovereign risk feedback loops. *ESM Working Paper*, 1.

Fengler, M. and Schwendner, P. (2004). Quoting multiasset equity options in the presence of errors from estimating correlations. *Journal of Derivatives*, 11(4).

Gerlach-Kristen, P. (2015). The impact of ecb crisis measures on euro-area CDs spreads. *Financial Markets and Portfolio Management*, 29.

Glover, B. and Richards-Shubik, S. (2014). Contagion in the european sovereign debt crisis. *NBER Working Paper No. 20567.*

Gross, M. and Kok, C. (2013). Measuring contagion potential among sovereigns and banks using a mixed-cross-section gvar. *ECB Working Paper Series*, (1570).

Johansen, S. (2007). Correlation, regression, and cointegration of nonstationary economic time series. *Discussion paper, Department of Economics, University of Copenhagen*.

Karaflos, D. (2015). The implied volatility of greek options and the political risk in eurozone. *SSRN Working Paper*, (http://ssrn.com/abstract=2589162).

Kaya, H. (2015). Eccentricity in asset management. *Journal of Network Theory in Finance*, 1.

Kenett, D. Y., Huang, X., Vodenska, I., Havlin, S., and Stanley, H. E. (2015). Partial correlation analysis: applications for financial markets. *Quantitative Finance*, 15.

Kenett, D. Y., Tumminello, M., Madi, A., Gur-Gershgoren, G., Mantegna, R. N., and Ben-Jacob, E. (2010). Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market. *PloS one*, 5(12):e15032.

Laloux, L., Cizeau, P., Bouchaud, J.-P., and Potters, M. (1999). Noise dressing of financial correlation matrices. *Physical Review Letters*, 83(1467).

Lhabitant, F.-S. (2012). Correlation vs. trends in portfolio management: A common misinterpretation. *The Journal of Wealth Management*, 15(3).

Morales, R., T., D. M., and Aste, T. (2014). Dependency structure and scaling properties of financial time series are related. *Scientific Reports*, 4(4589).

Plerou, V., Gopikrishnan, V., Rosenow, B., Amaral, L., Guhr, T., and Stanley, H. (2002). Random matrix approach to cross correlations in financial data. *Physical Review E*, 65(6).

Politis, D. and Romano, J. (1992). A circular block-resampling procedure for stationary data. In LePage, R. and Billard, L., editors, *Exploring the Limits of Bootstrap*, pages 263–270. John Wiley.

Shoesmith, G. L. (2014). A time-series postmortem on eurozone financial integration and the debt crisis: Modeling and policy implications. *International Journal of Business*, 19(2).

Sloan, T. M., Piotrowski, M., Forster, T., and Ghazal, P. (2014). Parallel optimisation of bootstrapping in r. *http://arxiv.org/abs/1401.6389*.

Tola, A. and Waelti, S. (2015). Deciphering financial contagion in the euro area during the crisis. *The Quarterly Review of Economics and Finance*, 55.

European Stability Mechanism

6a Circuit de la Foire Internationale
L-1347 Luxembourg

Tel: +352 260 292 0

www.esm.europa.eu

info@esm.europa.eu