Sovereign Credit Risk Co-movements in the Eurozone: Simple Interdependence or Contagion?*

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Abstract

Since the onset of the eurozone sovereign debt crisis, credit risk spreads in Europe have diverged. Despite this divergence, credit risk comoves strongly within certain country groups such as the eurozone periphery. We seek to answer what the determinants of the observed pattern of credit risk co-movements are and whether and during which periods sovereign debt markets have been subject to contagion. We proceed in three steps. First, we apply dynamic conditional correlations from a multivariate GARCH model to sovereign CDS spreads of 17 countries over the period 2008 to 2012. Second, we separate periods of simple interdependence from contagion. Third, we analyze the determinants behind credit risk co-movements and the role of contagion using regression analysis. Our results reveal a high degree of co-movements in sovereign credit risk, especially for eurozone countries during the sovereign debt crisis. We find strong evidence for both fundamentals and non-fundamentals based contagion. Similarities in economic fundamentals, cross-country linkages in banking and common market sentiment play a significant role.

Keywords: Sovereign debt crisis, financial contagion, banking market integration

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1 Motivation

Diverging sovereign credit risk in European countries received increasing attention in recent times. Credit risk spreads in periphery eurozone countries like Greece, Italy, or Spain are much higher than those in core eurozone countries like France or Germany. This divergence can be explained by worsened fiscal positions following government interventions in the banking sector during the financial crisis as well as fiscal stimulus packages. At the same time, a high degree of financial integration in eurozone countries due to cross-border activities of banks and the existence of a common currency gave rise to interdependencies. In how far these interdependencies translate into volatile market reactions across countries and cause co-movements in sovereign credit risk is, however, hardly understood.

Our objective is to take a closer look at the pattern of sovereign credit risk across European countries. To do so, we ask the following questions: First, does sovereign credit risk comove across countries? To answer this, we apply the dynamic conditional correlation (DCC) model developed by Engle (2002) to compute volatility adjusted correlations of sovereign credit risk spreads. The estimation sample covers 17 eurozone and non eurozone countries for the period 2008-2012.

Second, is there evidence for contagion in contrast to simple interdependence in sovereign credit risk markets? The DCC series are used to separate co-movements due to interdependencies existing in all states of the world from contagion. Contagion is defined as a significant increase in cross-market co-movements (Forbes and Rigobon, 2002).

Third, what are the determinants of sovereign credit risk co-movements and are there specific channels which cause contagion? To obtain an answer to this, we use a regression analysis to separate co-movements due to global factors or common fundamentals of country pairs. Furthermore, we test whether significant increases in co-movements, i.e. contagion, occurred due to direct bilateral linkages in trade or finance. This would provide evidence for fundamentals based contagion. Alternatively, they might be the outcome of pure changes in market sentiment and investors' risk perception which would provide evidence for non-fundamentals based contagion.

Given the increased relevance of the topic, the following strands of literature have emerged. A first strand of literature analyzes the determinants of government yield spreads. Besides common risk factors, weak fiscal fundamentals like deteriorating debt positions and high expected fiscal deficits gained in importance in explaining sovereign credit risk spreads during the sovereign debt crisis (Attinasi et al., 2009; Haugh et al., 2009; Beirne and Fratzscher, 2013). In contrast, we do not limit our analysis to the determinants of sovereign credit risk spreads in individual countries but focus on co-movements in sovereign credit risk spreads between financially integrated countries. In doing so, we can explicitly account for the role of bilateral links or similarities in economic fundamentals in determining common patterns regarding sovereign credit risk.

A second strand analyzes the transmission of distress in sovereign debt markets or the feedback between bank and sovereign credit risk. Accounting for effects that arise from strengthened interdependence between bank fragility and sovereign credit risk, these studies show that a larger or more distressed financial sector tends to increase sovereign credit risk (Acharya et al., 2011; Alter and Schüler, 2012; Dieckmann and Plank, 2012). This indicates that potential future bailout costs and credit losses are priced in by investors. On the theoretical side, one example is the paper by Bolton and Jeanne (2011). They show that international contagion in sovereign debt markets is facilitated by exposures of banks to foreign sovereign debt. However, empirical work on contagion in Eurozone sovereign debt markets and the feedback between bank and sovereign credit risk across national borders is scarce. We intend to fill this gap.

A third strand relates to the identification of contagion in financial markets. Forbes and Rigobon (2002) analyze contagion in stock markets during the Asian crisis in 1997. Significant changes in static correlations computed over a crisis and non-crisis sample provide evidence for contagion. This has the disadvantage that results might be driven by the choice of estimation windows. Forbes (2012) applies extreme value theory to measure contagion in stock markets and takes the results to identify channels of contagion. Gorea and Radev (2013) study the determinants of contagion in sovereign bond markets. They focus on tail events by computing the joint probability of default of eurozone countries. In contrast, we develop a data driven approach to detect contagion over time. Like this we do not have to specify periods related to tranquil and crisis times ex-ante. Using dynamic conditional correlations, we do not have to focus on extreme events or stop with the detection of contagion as e.g. Forbes and Rigobon (2002) or Caporin et al. (2013). Our approach allows separating the reasons behind interdependence in contrast to contagion. Especially for policymakers this is important to know. Interdependent patterns in sovereign credit risk due to common fundamentals like weak government finances would e.g. ask for structural reforms providing the ground for sustainable public budgets and increased competitiveness. Contagion arising from volatile market sentiment and uncertainty in sovereign debt markets might be mitigated by a reduction in uncertainty through the establishment of common fiscal backstops or ECB interventions.

Our main results are as follows. First, despite observing a divergence in sovereign risk spreads during the sovereign debt crisis, our analysis reveals that eurozone countries are still tied together. This is reflected by the fact that co-movements in sovereign risk spreads increase and remain at elevated levels. This finding holds for both eurozone countries with strong and those with weak fundamentals, pointing towards a "eurozone effect". Second, contagion cannot be attributed to one moment in time but shows a large variety both across time and countries. Third, we find strong evidence for both fundamentals and non-fundamentals based contagion. Similarities in economic fundamentals, cross-country linkages in banking and common market sentiment play a significant role. In this sense, our results have important policy implications: increased co-movements and contagion due to common weaknesses in economic fundamentals require adjustments at the national level. However, uncertainties arising from the currency union have to be dealt with at the supranational level, e.g. through the establishment of credible resolution schemes.

The paper is structured as follows. In Section 2, we discuss the concept of contagion. Section 3 describes the sample and properties of the CDS data used for the analysis. The following Section 4 outlines the empirical approach. We first give a brief description of the DCC model. Second, we explain how the DCC series are used to measure contagion and its determinants. Results are presented in Section 5 before we conclude in Section 6.

2 Contagion: Definition and Measurement

2.1 How to Define Contagion?

Contagion is a word commonly used by economist, policymakers and the media at least since the Russian and Asian crises. Yet, a common agreement on what actually constitutes contagion is lacking. For example, Forbes (2012) documents how different can be definitions of contagion in academic papers. Common to all of them is the idea that negative shocks are transmitted from one country or market to another in a non-standard way. Often this is referred to as "shift contagion", i.e. a change in cross-market correlations caused by a break in the transmission mechanism after a shock has occurred (see e.g. Forbes and Rigobon, 2002).[1]

In this paper, we define contagion as a significant increase in cross-market co-movements. This definition is not only in line with the related academic literature

[1] Further discussions on how to define contagion can be found in Dornbusch et al. (2000), Kaminsky et al. (2003) or Pericoli and Sbracia (2003).

(Forbes and Rigobon, 2002; Boyer et al., 2006; Caporin et al., 2013) but it has also various advantages.

First, we are able to separate co-movements due to linkages existing in all states of the world from significant increases in cross-market co-movements. This way, we do not restrict our analysis to "extreme events" but can separate periods of interdependence from contagion.

Second, this definition imposes no restrictions on the transmission channels of contagion. Hence, we can analyze the driving forces behind contagion considering both the possibility of non-fundamentals based contagion and structural changes in the underlying fundamental cross-country linkages that can cause contagion. We deliberately do not limit the concept of contagion to be non-fundamentals based as, for example, theoretical models show the occurrence of contagion due to direct links. A more detailed discussion of possible contagion channels is left to Section 4.3.

Third, despite being more restrictive compared to policymakers who tend to interpret the "normal" transmission of negative shocks due to existing linkages as contagion, our analysis still allows to draw a broad range of policy implications.

2.2 How to Measure Contagion?

The possibilities to measure contagion are as manifold as the number of existing definitions. For example, Forbes (2012) or Pericoli and Sbracia (2003) give excellent surveys of different methods like VAR models or probability analysis mentioning their particular strengths in measuring contagion but also inherent econometric problems.[2] Based on our definition of contagion, the most straightforward approach is to use correlation and volatility measures to analyze contagion. Among the first to use correlation analysis to measure contagion are King and Wadhwani (1990) who analyze the crash in world stock markets in October 1987 which took place despite countries differed in economic fundamentals.

We apply dynamic conditional correlations based on Engle (2002) to obtain volatility-adjusted correlations. Those are used to measure significant increases in co-movements of sovereign credit risk across countries which corresponds to our definition of contagion. This methodology has various advantages compared to alternative correlation measures.

[2] Papers that discuss empirical methods to measure contagion and their shortcomings in more detail are Corsetti et al. (2005), Dungey et al. (2005), Pesaran and Pick (2007) or Rigobon (2002).

First, as in Forbes and Rigobon (2002), the measure controls for heteroscedasticity and adjusts for changes in the underlying volatility. This is important as given in crisis times volatility increases, the correlation increases by statistical definition. This occurs even if fundamental cross-country linkages do not change. Only a significant change in volatility-adjusted correlations can thus be labeled as contagion.

Second, and in contrast to Forbes and Rigobon (2002) who rely on static correlations for the identification of contagion, our approach provides us with dynamic correlations. By obtaining time-varying correlation coefficients we can, for example, trace out the effects of changes in investors' behavior in response to market developments on cross-country co-movements.

Third, the approach is based on the full sample and does not require exogenous assumptions of crisis versus non-crisis periods. This avoids a selection bias arising from an arbitrary division into subsamples with a usually large non-crisis samples and small crisis sample. In a similar vein, and in order to circumvent this shortcoming, Caporale et al. (2005) select breakpoints endogenously to analyze contagion during the Asian crisis.

Fourth, as we obtain correlations for the whole period, this does not limit our analysis to extreme events as in Bae et al. (2003) or Forbes (2012) who uses extreme value analysis to find evidence for contagion in equity markets across 48 countries during the period 1980-mid 2012. Tough extreme value analysis is a very straightforward approach in analyzing contagion defined as the joint occurrence of negative extreme events, it has the shortcoming that the focus is on tail events and discrepancies in the transmission channels of shocks during tranquil and crisis times cannot be separated. In contrast, we can compare the determinants of significant increases in correlations with those causing cross-country correlations in "tranquil" times.

In sum, our approach allows us to make use of the time series of volatility-adjusted correlations to analyze when and why significant increases in cross-country correlations, i.e. contagion, took place without being forced to make assumptions on break points or facing restrictions by observation windows of different length.

3 Data Description

3.1 CDS Data Description

The analysis is based on credit default swap (CDS) spreads as a measure of credit risk in sovereign debt markets. The sample covers 17 countries of which eleven are eurozone member countries. We include non-eurozone countries mainly in order to get a clear picture of how co-movement patterns in the eurozone differ from those of non-eurozone countries. We use daily data on five year sovereign CDS spreads obtained from Datastream. A time to maturity of five years corresponds to a highly liquid type of contract. The type of the contract is chosen to be complete restructuring (CR) as this is available for all countries.

The sample period for estimating dynamic conditional correlations spans January 2008 to September 2012.[3] CDS spreads are a timely measure of (perceived) credit risk provided that markets exist and are active enough. Due to the fact that before 2007 the volume of CDS markets was relatively small and trading occurred infrequently, we conduct the estimations for the period starting in 2008. This has the advantage that we focus on a sample of crisis years. Figure 2 reveals that the volume of sovereign CDS has steadily increased over recent years reaching an amount outstanding of almost 3000 bn USD (around four percent of 2011 world nominal GDP) in 2012. This development provides evidence for a high degree of market activity such that CDS spreads can be assumed to contain relevant information about market participants' credit risk perceptions.[4]

When buying a CDS contract with a sovereign bond as reference obligation, an investor can insure against the credit risk of this particular sovereign. Along with the hedging motive, it can also be used for purely speculative as well as arbitrage purposes like any other financial derivative. If markets perceive a higher credit risk, i.e. a higher default probability or a lower recovery rate given default, the protection against credit risk is worth more and the spreads go up. The observed sovereign CDS spreads are thus a measure for sovereign credit risk as implied by market perceptions.

Compared to yield spreads on sovereign bonds, CDS data have the advantage that they already represent a risk premium and we do not have to have to omit e.g. Germany from the sample by computing yield spreads relative to German bund yields.

[3] Finland is the only country for which we do not obtain data before mid 2008. Data entries for Greek CDS spreads suddenly explode after February 2012 and remain constant. These observation points are excluded from the analysis.

[4] In addition, more activity in the market leads to more fluctuation in the data. This limits convergence problems in the following DCC estimations.

This would require the strong assumption that German bund yields represent a riskless benchmark. Also, as opposed to bond yields, CDS spreads lead price discovery in the market (Palladini and Portes, 2011) and no premia compensating for inflation or devaluation risk are included in the data as a CDS contract primarily insures against credit risk.

Datastream provides CDS data based on two sources. From CMA, CDS spreads can be obtained starting from 2004 but the series are no longer accessible after October 2010. The second source, Thomson Reuters, reports CDS data until recently but CDS series are for most countries only available from end of 2008 onwards. In order to obtain long time series, we append data from the two sources.[5]

The sovereign CDS contracts are denominated in US dollar for Austria, Belgium, Germany, Greece, Italy, Japan, Netherlands, Norway, Portugal, Spain and the United Kingdom. For Denmark, France, Ireland and Sweden, the contract is specified in Euro. For Finland and the United States, there is a switch in the underlying currency as CMA provides only CDS data based on a Euro (US dollar) contract while Thomson Reuters uses data for US dollar (Euro) denominated contracts.

Given the currency differences, the following considerations have to be taken. The change in currency for one and the same series can be problematic if CDS spreads vary depending on the underlying currency. The same concern emerges if we measure the correlation of e.g. CDS spreads for Belgium based on a US dollar denominated contract and CDS spreads for Denmark derived from a Euro denominated contract. The common argument for why currency differences can be ignored is that CDS data is measured in basis points, and that it is therefore free of units (see Ang and Longstaff, 2013; Longstaff et al., 2011). Additionally, comparing series for which data on both US dollar and Euro denominated contracts were available revealed that in general differences are small and the series strongly comove. As we are interested in co-movements rather than absolute differences among contracts denominated in different currencies, the discrepancies in underlying currencies remains a caveat but, given the objective of the analysis, the usage of both US dollar and Euro denominated contracts seems permissible.

Figure 3 shows that most of the series have an upward moving behavior in the second

[5] See the Datastream Extranet website for information on how to merge the two series: http://extranet.datastream.com/data/CDS/Index.htm; for the splice point we choose December 2008 (March 2009 for Austria) as before the coverage by Thomson Reuters is not complete for all countries. Mayordomo et al. (2013) find that CDS quotes from different providers moved, in general, into the same directions. This is confirmed by comparing CDS spreads from Thomson Reuters and CMA for the period for which we have data from both providers.

half of 2008. A further and more pronounced increase can be found for most countries at the beginning of 2010 when the sovereign debt crisis started. Since we are interested in co-movements, it has to be noted that time series of various countries show common patterns. This holds for, both, core eurozone countries, e.g. Germany and France or Austria and the Netherlands as well as periphery eurozone countries like Italy and Spain. There are, however, countries like Ireland which follow the common pattern up to a certain point but start to diverge afterwards. The CDS series show further discrepancies across countries. For example, the range of CDS prices varies widely across the different country groups. While non-eurozone countries' spreads tend to remain below 150 basis points, eurozone CDS spreads can lie above 200 basis points for core-eurozone countries and considerably higher for periphery states (up to a range from 1000 to 1500 basis points).

3.2 CDS Time Series Properties

Visual inspection (Figure 1) and augmented Dickey Fuller tests show that the data is clearly not stationary. We thus take the first difference of the natural log of the series. This data transformation is comparable to studies applying DCC models to financial asset returns and was also used in related work in which dynamic correlations for CDS spreads have been of interest (Chiang et al., 2007; Coudert and Gex, 2010). Augmented Dickey Fuller tests with lag length of up to ten reject the null of a unit root in the log differenced series. Summary statistics of the log differenced series are provided in Table 1. It is to note that the series are close to mean zero processes.

Another noteworthy feature is that the data is found to have a negative skewness and high values for the kurtosis. This suggests that the series do not follow a normal distribution but show extreme events, which is supported by the Jarque-Bera test statistic. An analysis of the squared series reveals for most countries significant first-order autocorrelation both by visual inspection of the (non-reported) autocorrelation functions and based on the Portmanteau (or Q) test statistic with up to 10 lags. For the residuals of the mean equation, non-reported ARCH-LM tests broadly reject the null of no autocorrelation. This, together with signs of persistence in the log differenced time series depicted in Figure 4, gives evidence for volatility clustering. In sum, the daily log differenced CDS data show signs for non-normality, autocorrelation and volatility clustering. This supports the computation of conditional correlations based on a GARCH model which accounts for these data properties.

Simple pairwise correlations are given in Table 2. To get a better picture of the ongoing dynamics in co-movements in sovereign credit risk, we investigate separately correlation coefficients during the financial crisis and before the sovereign debt crisis as well as after the start of the sovereign debt crisis. For the latter, we choose as a starting date the Greek announcement of the fiscal deficit being twice as large as expected in November 2009. Comparing correlation coefficients across sovereign CDS markets for the different time periods shows that correlations increase for eurozone countries and in particular for the periphery (excluding Greece) during the sovereign debt crisis. However, it is to note that this still does not provide any evidence for contagion as an increase in these unconditional correlation coefficients might simply be driven by an increase in volatility during crisis times (Forbes and Rigobon, 2002).

Nevertheless, the correlation matrices reveal interesting patterns for different country pairs. Within the group of eurozone countries, there is strong evidence for common patterns as correlation coefficients tend to be higher than 0.5 from 2007 on. Interestingly, this also holds for periphery-core country pairs, e.g. Germany and Portugal. Not surprisingly, co-movements are more pronounced if both countries belong to the periphery crisis countries, e.g. Ireland or Greece. For the sovereign debt crisis period, the correlations reveal strong interdependencies for Italy, Portugal and Spain while Greek CDS spreads seem to follow a more distinct pattern. The non-eurozone countries, in particular Japan and the United States, show small correlations with the remaining countries across all periods. This provides first evidence that the developments in eurozone sovereign debt markets are a regional phenomenon and affected by the membership in the currency union. Whether this result continues to hold for volatility-adjusted conditional correlation is part of the following analysis.

4 Empirical Methodology

The empirical estimation strategy consists of three steps. First, we apply dynamic conditional correlations from a multivariate GARCH model to sovereign CDS spreads of 17 countries over the period 2008 to 2012. Second, we separate periods of simple interdependence from contagion. Third, we analyze the determinants behind interdependent credit risk co-movements and the role of contagion using a regression analysis.

4.1 Correlation Analysis

We estimate dynamic conditional correlations (DCC) to get an indicator for the time-varying pattern of co-movements in sovereign credit risk spreads. The DCC series are obtained from a bivariate GARCH model as proposed by Engle (2002) and have been applied by e.g. Chiang et al. (2007) to study contagion in stock markets during the Asian crisis.[6]

Like in Engle (2002) or Chiang et al. (2007), the estimation of the DCC model evolves in two steps. First, univariate GARCH models are estimated for each de-meaned time series of returns (or in our case risk spreads). Thereby, time-varying standard deviations $\sqrt{h_{i,t}}$ are obtained. Second, these standard deviations are used to adjust the residuals $\xi_{i,t}$ corresponding to the time series under consideration, i.e. $v_{i,t} = \frac{\xi_{i,t}}{\sqrt{h_{i,t}}}$. From the standardized residuals, one can derive the conditional correlations. The DCC model is estimated by maximum likelihood in a two stage procedure (see Engle, 2002). In contrast to Chiang et al. (2007), we do not specify a source country but estimate bivariate DCC GARCH models to obtain conditional correlations for each possible country pair separately. This accounts for heterogeneity in the parameters characterizing the underlying correlation process. A detailed description of the model can be found in the appendix.

The dynamic conditional correlation framework provides us with estimates of volatility-adjusted co-movements of credit risk spreads between countries. Based on Forbes and Rigobon (2002), we interpret a significant increase in estimated correlations between two countries' credit risk spreads as an indicator for contagion. The underlying definition of contagion implies that a necessary condition to find evidence of contagion is the rejection of a constant conditional correlation model. If this is the case, the next

[6] Coudert and Gex (2010) apply the GARCH DCC approach to study contagion among firms in the CDS market during the GM and Ford crisis. Wang and Moore (2012) use a DCC model to study co-movements in the sovereign CDS market during the subprime crisis. Missio and Watzka (2011) find evidence for contagion during the sovereign debt crisis based on conditional correlations but focus on yield spreads for the period 2008-2010 and rating announcements as main determinant of contagious effects.

step requires the measurement of significant increases in conditional correlations. Once contagious episodes have been found, the results can be used to analyze the determinants of credit risk co-movements in sovereign debt markets and their role in causing contagion. The empirical implementation to achieve this is presented in the following two sections.

4.2 Measurement of Contagion

We interpret an episode as contagious only if we find a significant increase in volatility-adjusted correlations. The literature uses different methods to label a period as contagious: if a threshold is exceeded, i.e. if the correlation falls outside of a certain confidence interval, if mean difference tests between stable and turmoil times deliver significant results, or if time dummies capturing periods of (suspected) structural changes e.g. crisis versus non-crisis times, have a significant impact on co-movements (Chiang et al., 2007; Caporale et al., 2005). Based on the third method, we take the weekly average of the dynamic conditional correlation ρ_{ijt} and test for contagion as follows:

$$\rho_{ijw} = d_0 + \sum_{k=1}^{K} d_k \rho_{ijw-k} + q_w dummy_w + \epsilon_{ijw}, \tag{1}$$

where ρ_{ijw} is the weekly average of the dynamic conditional correlation of country pair ij and $dummy_w$ is an indicator variable taking a value of one for a given week w and zero otherwise. If q_w shows a positive sign and is significantly different from zero at conventional significance levels, we interpret the episode corresponding to the dummy variable $dummy_w$ as contagious. The regressions are conducted for each country pair separately and in a sequential way.

It is important to note that we deviate from previous studies in various ways. First, we do not specify periods related to tranquil and crisis times ex-ante as in Forbes and Rigobon (2002) or Chiang et al. (2007) in order to test whether correlations behave differently across periods. The reasons is that the definition of crisis versus non-crisis periods remains to a large extent arbitrary or has to rely on a narrative approach. Instead, we take a very agnostic approach in that we aggregate the data to weekly frequency, construct dummies for each week of the estimation period and test their significance sequentially. Aggregating to a lower frequency serves to eliminate possible short-run (over-)reactions in investors' perceptions. Constructing weekly dummies instead of separating the sample into specific periods has the advantage that we do not impose strong assumptions about cut-off points or certain time spans suspected to coincide with contagious episodes. In contrast, the data tells us when significant changes in cross-country correlations of sovereign credit risk occur.[7]

Second, we do not specify a source crisis country but conduct the regression to measure contagion for each country pair in our sample separately. This allows obtaining contagion indicators that vary across two dimensions, (i) over time and (ii) across country pairs. This can be exploited in the subsequent regression analysis and delivers a refined measure of contagion.[8]

Third, in contrast to e.g. Caporin et al. (2013), we do not limit the analysis to the detection of contagion but want to find out through which channels it affects credit risk co-movement. Similarly to the literature on the determinants of sovereign credit risk (Attinasi et al., 2009; Haugh et al., 2009), we are interested in the reasons behind the observed pattern in sovereign markets. However, our focus is not on the determinants of individual country's credit risk but on the driving forces behind increased co-movements among countries.

4.3 Regression Analysis

The determinants of sovereign credit risk co-movements. Based on the previous steps we can analyze which economic variables explain the observed pattern of sovereign credit risk co-movements or interdependence in sovereign credit risk markets. The dynamic conditional correlation framework outlined in section 4.1 provides us with estimates of daily credit risk co-movements (ρ_{ijt}), which we aggregate to monthly averages denoted by ρ_{ijm} for the following analysis. Monthly data seems appropriate as it still captures short-run variation in co-movements but smoothes out high-frequency noise. This approach is also in line with data availability as most of the explanatory variables, which are listed in Table 3, are available at monthly or even lower frequency. In order to investigate the determinants, we use the credit risk co-movements as dependent variable in the following regression model (**specification (I)**):[9]

$$\rho_{ijm} = \mathbf{x}'_{ijm}\boldsymbol{\beta}_I + u_{ijm}, \tag{2}$$

[7] Applying multiple tests for contagion per period might involve the risk of rejecting the null of no contagion too often. Nevertheless, we prefer this approach to imposing a limited set of time dummies and our results show reasonable evidence of contagion during key crisis events.

[8] As the regression analysis is based on monthly data, the country pair specific contagion indicator is aggregated to monthly frequency and takes on a value of one if at least one of the weekly dummies showed evidence for contagion and zero otherwise.

[9] Flavin et al. (2002) and Beine and Candelon (2011) use similar regression models applied to stock market correlations.

where $\mathbf{x}_{ijm}$ denotes a vector containing the elements for all K explanatory variables ("determinants") for a certain country pair (ij) and time period (m), β_I is a vector containing the parameters, and u_{ijm} is the error term.

To control for unobservables, a regression model which involves fixed effects can be chosen (**specification (II)**):

$$\rho_{ijm} = \boldsymbol{\phi}'_{ijm}\boldsymbol{\beta}_{II} + \lambda_{ij} + \gamma_m + v_{ijm}, \tag{3}$$

where $\boldsymbol{\phi}_{ijm}$ is a subset of $\mathbf{x}_{ijm}$ which contains the explanatory variables that vary across time and country pairs, λ_{ij} denotes constant country pair specific effects and γ_m time fixed effects.[10]

The channels of contagion. The contagion indicator described in section 4.2 allows labeling a certain period in time for a certain country pair as contagious episode. Based on our definition of contagion, contagion means that shocks are transmitted differently in crisis than in tranquil times leading to a significant increase in co-movements. Consequently, we call the channels through which this state-dependent shock transmission occurs *channels of contagion.* These channels of contagion might be linkages which also exist in tranquil times but abruptly change either their strength or their role (or both) in crisis times. Furthermore, they might be new channels which exclusively emerge in times of crisis and can be related to shifts in market sentiment. We refer to the first phenomenon as fundamentals based contagion and to the latter as non-fundamentals based contagion. We can empirically separate channels of contagion by adding interaction terms of the explanatory variables and the contagion indicator to the right-hand side of the regression (**specification (III)**):

$$\rho_{ijm} = \mathbf{x}'_{ijm}\boldsymbol{\beta}_{III} + \tilde{\mathbf{x}}'_{ijm}\boldsymbol{\delta}_{III} \times CI_{ijm} + u_{ijm} \tag{4}$$

An explanatory variable constitutes a channel of contagion only if it affects the pattern of co-movements differently conditional on the occurrence of contagion. In the estimated regression, this would turn out as significant effect of the interaction term which exceeds the impact of the variable alone. The equivalent specification with fixed-effects is straightforward (**specification (IV)**):

$$\rho_{ijm} = \boldsymbol{\phi}'_{ijm}\boldsymbol{\beta}_{IV} + \tilde{\boldsymbol{\phi}}'_{ijm}\boldsymbol{\delta}_{IV} \times CI_{ijm} + \lambda_{ij} + \gamma_m + v_{ijm} \tag{5}$$

Choice of explanatory variables. We divide the explanatory variables into three

[10] Interpretation of marginal effects is thus always with respect to a certain reference country pair and a certain reference month.

groups based on their economic interpretation and theoretical considerations: (i) global controls, (ii) similarity in economic fundamentals, and (iii) direct and indirect linkages between countries.[11]

(i) Global controls: Common macroeconomic shocks which affect all countries at the same time, such as changes in risk aversion or liquidity, are likely to affect the structure of credit risk co-movements in sovereign debt markets. We control for this global factors by including the VDAX implied volatility index and the Euribor-Eonia spread in specifications (I) and (III). We expect increases in risk aversion and decreases in liquidity to lead to stronger credit risk co-movements. Macro shocks of any kind are implicitly controlled for by the time-fixed effects in specifications (II) and (IV).

(ii) Similarity in economic fundamentals: As the creditworthiness of a sovereign is connected to economic fundamentals, two countries with similar economic fundamentals should exhibit a higher degree of credit risk co-movements. This justifies the inclusion of similarity measures based on GDP growth, public debt, and foreign reserves. We also include similarities in banks' total assets and common portfolio exposure, where the latter is proxied by the correlation of bank equity prices. The rationale behind the inclusion of these banking sector related variables is to capture the interdependence between sovereign and bank credit risk as an important feature of the eurozone debt crisis (Acharya et al., 2011). We expect sovereign credit risk to comove more strongly for two countries that are more similar to each other in specifications (I) and (II). By interacting the similarity measures with the contagion indicator in specifications (II) and (III), we can test the occurrence of "wake-up call" contagion, which might arise if weak fundamentals in one country make investors aware of (similar) structural problems in other countries. In such a case, similarities in economic fundamentals constitute a channel of contagion.

(iii) Direct and indirect linkages: Variables related to direct linkages between countries account for simple interdependence in specifications (I) and (II). They comprise linkages associated with the real and financial sectors. The real linkage is captured by bilateral trade flows. As banks hold sovereign debt on their balance sheets, they are likely to play a critical role in the transmission of shocks related to sovereign debt markets. We thus compute the financial linkage using bilateral data on banks' foreign claims from the Bank for International Settlements. In tranquil times, the financial linkage is assumed to improve international risk sharing and thus to reduce co-movements in sovereign credit risk (see e.g. Kalemli-Ozcan et al., 2013). However, direct real and financial linkages might constitute channels of contagion in two re-

[11] Table 3 shows the list of explanatory variables and their classification.

spects. First, the *strength* of the linkages will most certainly fluctuate as trade flows might collapse, banks might rebalance their portfolios via asset sales, international interbank markets might freeze and bailouts might take place. Second, the *role* of the linkages might change completely: For instance from serving risk sharing and stabilization purposes to being a transmission channel of contagion risk. In both cases we would expect an increase in credit risk co-movements. Bolton and Jeanne (2011) provide a theoretical framework for this state-dependent role of financial (or banking sector) integration in the transmission of shocks in sovereign debt markets.[12] By interacting both linkages with the contagion indicator in specifications (III) and (IV), we can test this channel of contagion, which we call *fundamentals based contagion.* In addition to direct linkages, sovereign debt markets might also be connected via more indirect or non-fundamental linkages. These linkages do not exist in tranquil times as they only emerge in crisis times. From a theoretical point of view, they can be related to concepts such as herding behavior, changes in market sentiment and the occurrence of “bad equilibria” or “risk panics” (De Grauwe and Ji, 2012; Bacchetta et al., 2012). Even though non-fundamentals are generally not observable, there exist proxies. We choose the GDP weighted stock market volatility as a measure of common market sentiment for a given country pair. We do not expect the non-fundamental linkage to have an impact on credit risk co-movement in tranquil times. A significant impact of this variables when interacted with the contagion indicator in specifications (III) and (IV), however, would be a strong indication that sovereign debt markets have been subject to *non-fundamentals based contagion.*

5 Estimation Results

5.1 Dynamic Conditional Correlations

For all country pairs, we conduct bivariate DCC estimations with standard errors robust to non-normality. The DCC estimations deliver parameter estimates for the mean, conditional variance and correlation equation for $17 \times 16/2$ country pairs. These are reported in Table 6.[13] The AR(1) term in the mean equation is mostly positive and significant. This can be explained by, for example, delayed adjustments in CDS prices (Duffie, 2011). The conditional variance equation shows in general significant coeffi-

[12] The relation between the degree of market integration in general and the vulnerability to transmission of shocks and/or contagion is addressed in many papers and usually found to be non-monotonic. While a comprehensive literature review is out of scope of this paper, we refer to Allen and Gale (2000) as the seminal paper in this strand of literature.

[13] For some country pairs, we do not obtain DCC estimates due to convergence problems in the maximum likelihood estimations. Given the initial values caused convergence problems, we used a later starting date than data would have been available.

cients both for the lagged variance and the squared error term. This justifies the use of a time-varying volatility model. As the coefficients a and b of the conditional variance equation almost sum up to one, this points towards a high persistence in volatility. The coefficients α and β which characterize the time-varying correlation process are for most country pairs highly significant.

Based on the coefficients of the correlation equation, we test if our assumption of a dynamic instead of a static model is reasonable. Except for three out of 126 cases, we reject the null of static correlations at a significance level of 5%. This is a necessary pre-condition to not rule out the possibility of contagion, i.e. significant increases in volatility-adjusted correlations. To see whether our model fits the data in an acceptable way, we test the estimated standardized residuals for remaining ARCH effects. Following ARCH-LM tests, we cannot reject the null of no second order autocorrelation for the majority of cases. This lowers concerns of model misspecification and is in line with the common finding that it is often hard to improve on a GARCH(1,1) model.[14]

Pair wise dynamic conditional correlations averaged across country pairs belonging to the same or different country groups are shown in Figure 5. Countries are classified into four groups: eurozone core countries, eurozone periphery (GIIPS) countries, countries belonging to the EU but not the eurozone, countries outside the EU (see also Table 4). From Figure 5 it becomes obvious that, across all combinations of country groups, co-movements in sovereign CDS spreads increase after September 2008. The increase is highest for country pairs with both countries belonging to the eurozone periphery and points towards the importance of weak economic fundamentals and common structural problems. Not surprisingly, the averaged dynamic conditional correlation series for this country group remains at high levels in the time following.

Nevertheless, crucial events leave their mark. E.g. after the announcement of the twice as large as expected Greek deficit in November 2009, the correlations for the periphery countries go up to 0.8. The following decline can be associated with the announcement of rescue packages in April 2010. Another peak takes place during October 2011 which refers to a month with a lot of uncertainty stemming from the failure of Dexia and negotiations about private sector involvement regarding Greek sovereign bonds. Co-movements reach again a lower level ranging around 0.6 in November 2011 - probably in response to ECB interventions in sovereign debt markets. In sharp contrast, correlation series referring to countries belonging to the EU and non EU countries

[14] For brevity, results of post estimation tests are not reported but can be obtained from the authors on request. In addition, it has to be noted that test statistics for ARCH-LM tests have to be taken with caution as tests are applied after estimating a GARCH model such that the actual asymptotic distribution of the test statistics is unknown.

tend to persist at low levels.

For the remaining three groups of country pairs, sovereign CDS spreads show similar co-movement patterns. This can be seen by comparung combinations with both countries in the core eurozone group or country pairs with one core and one periphery eurozone country. The importance of being a member in the eurozone is reflected in the fact that risk spreads of eurozone country pairs show on average stronger co-movements than correlation series for combinations of eurozone and EU countries outside the eurozone.[15] Series among eurozone and EU/non eurozone countries decline with the start of the sovereign debt crisis but show again a peak at the end of 2011. Comparing EU/non eurozone and eurozone country pairs with core and periphery country pairs subject to the common currency, we see that for the eurozone country pairs the decline in co-movements during the sovereign debt crisis does not take place. With the start of the financial crisis core eurozone country pairs behave very similar to eurozone and EU/non-eurozone pairs but correlation patterns diverge during the sovereign debt crisis. Like in the case of core periphery pairs, correlations stay around 0.5 with a temporary increase in October 2011. In this regard, the sovereign debt crisis seems to keep common dynamics at a higher level within eurozone countries whereas rescue packages lower predominantly co-movements between GIIPS countries as well as among EU countries in and outside the eurozone.

Summary statistics of the DCC series averaged per country group and for different sub-periods confirm the findings above (Table 5). Correlations are highest and on average close to 0.60 for country pairs belonging to the eurozone periphery. Except for country pairs belonging to the GIIPS countries, correlations are relatively low before the collapse of Lehman Brothers in September 2008, e.g. on average 0.36 for core eurozone country pairs. With the onset of the financial crisis, CDS spreads comove stronger and the mean correlation for this group goes up to 0.53. For the period of the sovereign debt crisis starting in November 2009, there is a tendency for reduced correlations. Interestingly, this holds above all for country pairs with one country belonging to the eurozone and one non-eurozone country being member in the EU. Co-movements among EU and non EU country pairs seem to be unaffected by the sovereign debt crisis in the eurozone.

[15] Similarly, using a multifactor model, Ang and Longstaff (2013) find high levels of systemic risk among eurozone sovereigns compared to US states whereby the latter share not only a common currency but also a political union.

5.2 Measurement of Contagion

As outlined above, the regression model to measure contagion as a significant increases in DCC series is given by:

$$\rho_{ijw} = d_0 + d_1\rho_{ijw-1} + d_2\rho_{ijw-2} + q_w dummy_w + \epsilon_{ijw}, \tag{6}$$

where ρ_{ijw} is the dynamic correlation of country pair ij and $dummy_w$ is an indicator variable taking a value of one for a given week w and zero otherwise. We choose an AR(2) model following the general tendency suggested by conventional model selection criteria. Further specification tests revealed for most correlation series no evidence for non-stationarity as well as first order serial correlation and remaining ARCH effects in the residuals of the estimation equation could be ruled out.

The number of measured contagious episodes, i.e. the number of q_w being positive and significant, summed up across country pairs for each week of the estimation period is shown in Figure 6. Both the total number as well as the number of contagious episodes per country group can be seen and the result confirms our strategy to test for contagion by country pair and across time. Without doubt, there are common patterns across country groups like, for example, a high number of significant increases in correlations after the failure of Lehman brothers. However, the figure shows that there are also discrepancies. For example, looking at the period in between the announcement of the unexpectedly high Greek deficit in November 2009 and the Greek bailout combined with ECB interventions in securities markets in May 2010, it becomes obvious that contagion occurs much more frequently in periphery eurozone countries than in core eurozone countries. This indicates that uncertainty about the sustainability of Greek government finances affected in particular countries assumed to have similar economic fundamentals and structural problems like Greece. Trying to measure contagion by imposing a single dummy variable for e.g. a crisis period which is in continuation held constant across all country pairs would miss this variation.

5.3 Regression Analysis: Estimation Results

The estimation results of the regression analysis are shown in Table 7. The column numbers correspond to the numbers of the empirical specifications presented in section 4.3. Accordingly, columns (I) and (II) show which economic variables explain sovereign credit risk co-movements. Columns (III) and (IV) show through which channels contagion occurs.

The determinants of sovereign credit risk co-movements. The estimation results given in columns (I) and (II) – the latter based on the specification with fixed effects – shed light on the factors which explain the general pattern of sovereign credit risk co-movements. The VDAX volatility index and the Euribor-Eonia spread were chosen as global controls which measure the degree of risk aversion and overall liquidity, respectively. Results suggest that higher risk aversion and lower liquidity in financial markets are associated with higher credit risk co-movements. These results are in line with findings by the literature on the determinants of sovereign bond yield spreads such as Manganelli and Wolswijk (2009). Furthermore, sovereign credit risk comoves more strongly for two countries that are more similar with respect to GDP growth as well as total assets in the banking system and common portfolio exposures of banks proxied by the correlation in bank equity prices. The significant impact of the two banking sector related variables indicates the interconnection between the financial and the public sector as described, for instance, in Acharya et al. (2011). In contrast, neither similarities in foreign reserves (only weakly significant in (II)) nor in public debt seem to play a role for sovereign credit risk co-movements. The results for the variables capturing cross-country linkages suggest that stronger financial linkages, as measured by banks' foreign claims, tend to reduce co-movements (in (I) only), while the real linkage, as measured by bilateral trade flows, does not seem to have an effect. Adverse shifts in common market sentiment, as measured by an increase in GDP weighted stock market volatilities, are associated with higher co-movements.

Channels of contagion. Columns (III) and (IV) show the estimation results of the two corresponding specifications which include interaction terms of selected explanatory variables and the contagion indicator to separate the different channels of contagion. As outlined in section 4.3, the idea behind is that an explanatory variable constitutes a channel of contagion if it affects the pattern of co-movements differently conditional on the occurrence of contagion. The results in the upper parts of the table show that for all three groups of variables, the direct impact (without interaction) does not change much as compared to the previous two columns. This confirms the role of these variables as determinants of sovereign credit risk co-movements in tranquil times which constitute the underlying interdependence structure. The picture changes, however, as soon as not only simple interdependence but also episodes labeled as contagious are accounted for. This is done in the lower part of the table where the effects of the interaction terms on the pattern of sovereign credit risk co-movements can be attributed to either "wake-up call", fundamentals based or non-fundamentals based contagion.

"Wake-up call" contagion. Conditional on the occurrence of contagion, the effect of similarity in public debt on sovereign credit risk co-movements is positive and statistically significant. This is evidence for "wake-up call" contagion related to the re-

assessment of public sector debt as an important determinant of credit risk by investors. In contrast, we do not find such a significant state-dependent re-assessment regarding banks' common portfolio exposures proxied by the correlation in bank equity prices.

Fundamentals based contagion. In tranquil times, sovereign credit risk in two countries that are more financially integrated in terms of their banks' foreign claims seems to be unaffected (column (IV)) or if anything tends to comove less (column (III)). This supports the notion that this kind of financial linkage enhances risk diversification, a result also found in Kalemli-Ozcan et al. (2013). Conditional on the occurrence of contagion, however, a stronger linkage is associated with stronger co-movement in sovereign credit risk (column (IV) only). The financial linkage changes its role from a tool for risk diversification to a channel of contagion. The result provides strong evidence for the state dependent role of banking sector integration as outlined in Bolton and Jeanne (2011) and thus what we call fundamentals based contagion. The real linkage seems to increase co-movements in tranquil times but decreases credit risk co-movements during contagious episodes. An interpretation for the latter result might be that during the observed period, risk diversification via bilateral trade was still possible.

Non-fundamentals based contagion. We find a positive and significant relationship between adverse shifts in common market sentiment, i.e. higher GDP weighted stock market volatility, and credit risk co-movements. Consequently, part of the pattern of credit risk co-movements can be attributed to non-fundamentals based contagion. Based on a different methodology, Beirne and Fratzscher (2013) find evidence for "herding contagion" in sovereign debt markets which corresponds closely to our definition of non-fundamentals based contagion. Against this background, our result also supports the usefulness of our proxy for common market sentiment. It allows to analyze the impact of non-fundamentals more directly without having to refer to the "unexplained part" of the regression and thus mitigates a potential omitted variables problem.

5.4 Regression Analysis: Robustness

Table 8 shows that the estimation results presented in section 5.3 are robust to a number of alternative specifications.[16] Results in column (A-I) are based on a specification in which the Fisher z-transformation is applied to the sovereign credit risk co-movements as dependent variable. The Fisher z-transformation mitigates a potentially skewed distribution in correlation coefficients which could lead to incorrect inference. While the point estimates differ in size due to the transformation, there are no major changes with

[16] All results take specification (IV) in section 4.3 as a starting point and thus control for fixed effects and include the interaction terms.

respect to their statistical significance. Columns (A-II) and (A-III) show that the main results also stay unaltered if the contagion indicator is based on a lower significance level (1% and 5%, respectively). This does not hold true for "wake-up call" contagion, however, as the interaction term with public debt now turns insignificant. Column (A-IV) demonstrates that the results with respect to fundamentals and non-fundamentals based contagion cannot be confirmed if only the time span starting from the onset of the sovereign debt crisis (November 2009) is considered: Both the interactions with the financial linkage and the proxy for common market sentiment are not significant any more.

Eurozone only. Table 9 gives the results of estimations performed on the subsample of eurozone countries. Column (B-I) and (B-II) are equivalent to specifications (III) and (IV) and confirm the results regarding "wake-up call" and fundamentals based contagion found for the full sample of countries in section 5.3. However, the finding of non-fundamentals based contagion is not robust to the smaller sample of eurozone countries. Specification (B-III) additionally includes the euro exchange rate (EUR/USD) as global control which turns out to have a large and significant effect on credit risk co-movements. Interestingly, including the euro exchange rate renders the impact of global risk aversion insignificant. While risk aversion was found to be a key driver of sovereign bond yield spreads (see e.g. Haugh et al., 2009), it seems to be dominated by a common regional factor as it comes to eurozone countries. This suggests that eurozone countries are tied together and it is by no means only national factors that play a role in shaping the pattern of credit risk co-movements. This strong eurozone effect points towards the need for eurozone-wide policy measures to mitigate contagion in sovereign debt markets.

6 Concluding Remarks

The start of the eurozone sovereign debt crisis tends to be defined as the sharp widening in Greek sovereign risk spreads during the second half of 2010. This development quickly spilled over to other periphery eurozone countries like Spain or Italy. However, despite diverging credit risk spreads, eurozone countries still show a considerable degree of co-movement. This can be observed irrespective of whether countries belong to core or periphery eurozone member states. While diverging credit risk spreads might be explained by a deterioration in fiscal sustainability in periphery countries, credit risk co-movements among countries with different economic fundamentals seem surprising.

In this sense and in contrast to the vast literature analyzing the divergence in sovereign credit risk, our objective is to take a closer look at co-movements in sovereign markets. To do so, we apply, in a first step, a DCC GARCH model to sovereign CDS spreads of 17 countries. In this way, we obtain time-varying correlations for each country pair. Our sample includes both eurozone countries and countries outside the currency union. This offers the opportunity to identify the effect of sharing a common currency on sovereign credit risk co-movements. In a second step, we use the correlation series between countries' CDS spreads to separate contagion from simple interdependence structures and finally to analyze the driving forces behind. Following Forbes and Rigobon (2002), we define contagion as a significant increase in cross-country co-movements which we measure by volatility-adjusted correlations.

Thereby, our estimation strategy allows separating simple interdependence structures from contagion on a country pair basis. This gives us a bilateral indicator for contagion which varies across countries and over time. Successively, we exploit this to investigate the determinants of credit risk co-movements in sovereign debt markets in general and to explain the channels through which contagion takes place in particular. For the latter, we consider contagion due to direct bilateral linkages and non-fundamentals based contagion going back to market perceptions. From a policy perspective, separating the channels behind contagion is crucial. E.g. bail-outs and financial support might reduce the risk of non-fundamentals based contagion by calming down investors and reducing overpriced risk spreads. However, given the reaction of markets is based on weak fundamentals and direct linkages between countries, financial assistance is at best a short-term solution delaying necessary adjustments and structural reforms.

Our main results are as follows. First, the correlation analysis shows that sovereign markets in the eurozone are strongly interconnected. This holds for both countries belonging to the core and the periphery of the eurozone and is in contrast to the vastly documented divergence in individual country's credit risk. Hence, membership in the currency union ties country movements together.

Second, we document that contagion cannot be attributed to one moment in time but shows a large variety both across time and countries. This, in turn, asks for flexible and timely intervention measures and a thorough understanding of the driving forces behind contagion.

Third, our results suggest that both common country fundamentals, direct linkages between countries' banking systems or common market sentiment, and risk perceptions are likely to increase co-movements in credit risk. This implies that one-sided policy interventions will not be sufficient to stop contagion. Both measures that target an improvement in country-specific fundamentals and credible mechanisms like common fiscal backstops and resolution schemes in the eurozone are necessary.

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Appendix

GARCH DCC Model

The estimation of a GARCH DCC model requires time series with mean zero Engle and Sheppard (2001). Thus, to start with, we have to apply a demeaning process to the credit risk spreads in order to obtain appropriate residual series. The mean equation for each 2×1 vector of daily CDS spreads $y_t = (y_{1,t}, y_{2,t})'$ is specified as

$$y_t = \gamma_0 + \gamma_1 y_{t-1} + \xi_t \tag{7}$$

where $y_{i,t}$ is the log first difference of the CDS spreads, i.e. $log(CDS_{i,t}) - log(CDS_{i,t-1})$, and $\xi_t = (\xi_{1,t}, \xi_{2,t})'$ is a 2×1 vector of residual terms. Conditional on time $t-1$ information Ω_{t-1}, the residuals are assumed to be multivariate normally distributed with mean zero and variance-covariance matrix H_t such that $\xi_t|\Omega_{t-1} \sim N(0, H_t)$. The method exploits the fact that the variance-covariance matrix can be written as

$$H_t = D_t R_t D_t \tag{8}$$

where R_t is a 2×2 matrix of time-varying conditional correlations and D_t is a 2×2 diagonal matrix of time-varying standard deviations with $\sqrt{h_{i,t}}$ on the $i-$th diagonal. The elements of D_t are assumed to follow a univariate GARCH (1,1) process given by:

$$h_{i,t} = \omega_i + a_i \xi_{i,t-1}^2 + b_i h_{i,t-1} \tag{9}$$

with a constant ω_i and the parameters a_i and b_i accounting for the effect of past innovations, respectively capturing the persistence in volatility.[17] In the first stage of the estimation procedure, univariate GARCH models for $h_{i,t}$ are estimated and the obtained estimates for the standard deviations $\sqrt{h_{i,t}}$ are used to standardize the residuals, i.e. $v_{i,t} = \frac{\xi_{i,t}}{\sqrt{h_{i,t}}}$.

The second stage makes use of the standardized residuals in order to estimate the time-varying correlation of the DCC (1,1) process which can be expressed as follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha v_{t-1} v_{t-1}' + \beta Q_{t-1} \tag{10}$$

where $\bar{Q}$ is the 2×2 unconditional time-invariant covariance matrix while Q_t with elements $q_{ij,t}$ is the 2×2 time-varying variance-covariance matrix of the standardized

[17] To improve on the fit of the specification, selection criteria can be applied to determine the GARCH(p, q)-order.

residuals v_t. The parameters α and β are non-negative and restricted to $\alpha + \beta < 1$. The final correlation matrix R_t is then given by

$$R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2}. \tag{11}$$

The scaling of Q_t ensures to obtain a correlation matrix with ones on the diagonal and elements $\in [-1, 1]$ otherwise. Individual off-diagonal elements of R_t provide information on the correlation between CDS spreads in country i and j and can be written as $\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}$ for $i \neq j$.

Following Engle (2002), the GARCH DCC model is estimated by maximum likelihood in two steps. The log likelihood function is given below:

$$\ell = -1/2 \sum_{t=1}^{T} (2log(2\pi) + log|H_t| + \xi_t' H_t^{-1} \xi_t) \tag{12}$$

and can be decomposed in a volatility part being the sum of the individual GARCH likelihoods and a correlation component such that we can write

$$\ell(\theta, \phi) = \ell_v(\theta) + \ell_c(\theta, \phi) \tag{13}$$

where

$$\ell_v(\theta) = -1/2 \sum_{t=1}^{T} (2log(2\pi) + 2log|D_t| + \xi_t' D_t^{-1} D_t^{-1} \xi_t)$$

and

$$\ell_c(\theta, \phi) = -1/2 \sum_{t=1}^{T} (log|R_t| + v_t' R_t v_t - v_t' v_t).$$

Thereby, $\theta = (\omega_i, a_i, b_i)$ denotes the parameters belonging to D_t and $\phi = (\alpha, \beta)$ contains the remaining parameters in R_t. In a first step, the log likelihood $\ell_v(\theta)$ is maximized yielding estimates for θ. The following estimation step conditions on these estimates $\hat{\theta}$ and maximizes $\ell_c(\hat{\theta}, \phi)$ with respect to the correlation coefficients in ϕ. Under a set of regularity conditions the parameter estimates are consistent and asymptotically normal (see Engle and Sheppard, 2001).

Figures and Tables

Figure 1: **Credit risk in sovereign debt markets (CDS, basis points)**
This graph plots sovereign CDS premia in basis points for six selected eurozone countries (France, Germany, Ireland, Italy, Portugal and Spain) and the period from January 2008 to September 2012. Source: Datastream.

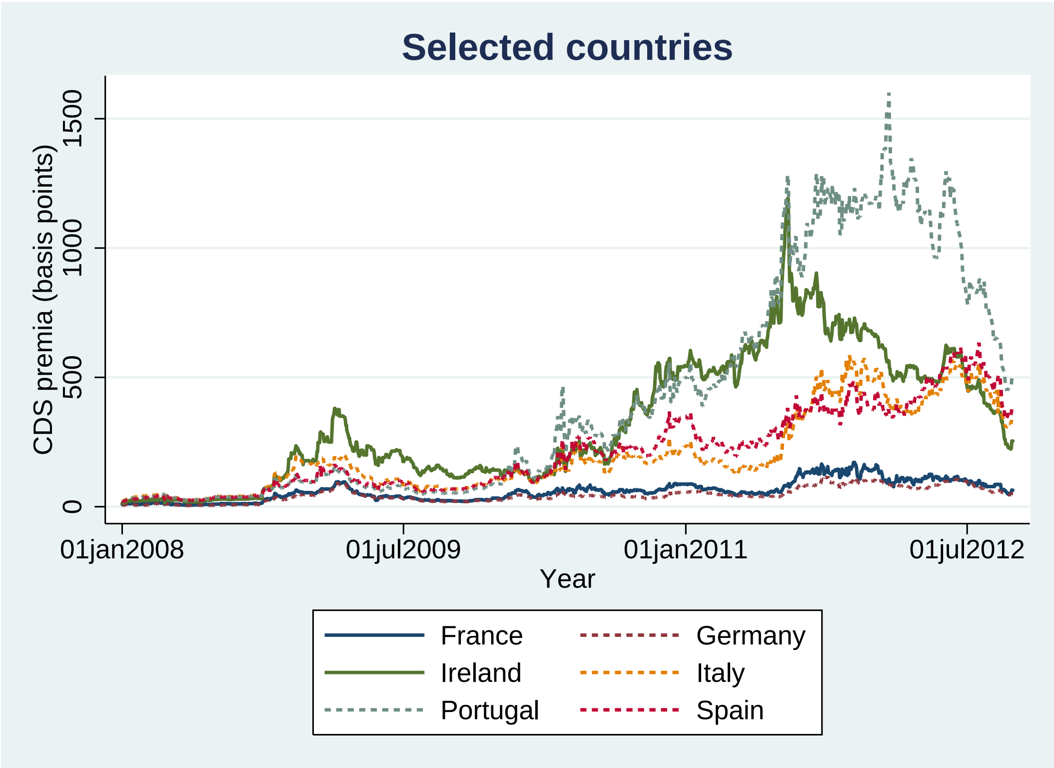

Figure 2: **Sovereign CDS market**
This graph describes developments in sovereign CDS markets. The vertical bars indicate the notional amount outstanding of sovereign CDS single-name instruments in billion USD. The solid line shows the share of sovereign CDS contracts in total CDS contracts. Source: Bank for International Settlements.

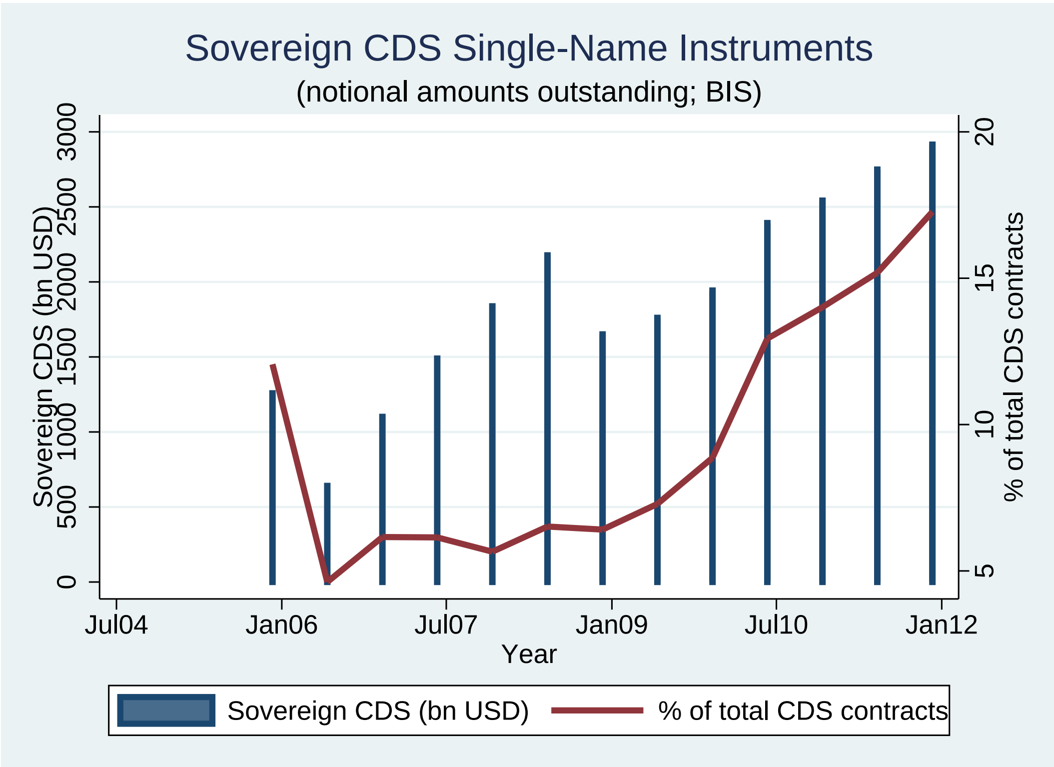

Figure 3: **Credit risk in sovereign debt markets (CDS, basis points)**
This graph plots sovereign CDS premia in basis points the period from January 2008 to September 2012. The series for six selected eurozone countries (France, Germany, Ireland, Italy, Portugal and Spain) are depicted in the upper left. The series for the group of periphery eurozone countries (Ireland, Italy, Portugal, Spain and Greece) are shown in the upper right. The lower left refers to the core eurozone countries (Austria, Belgium, Finland, France, Germany and the Netherlands) and the lower right to the non-eurozone countries (Denmark, Japan, Norway, Sweden, United Kingdom and United States).Source: Datastream.

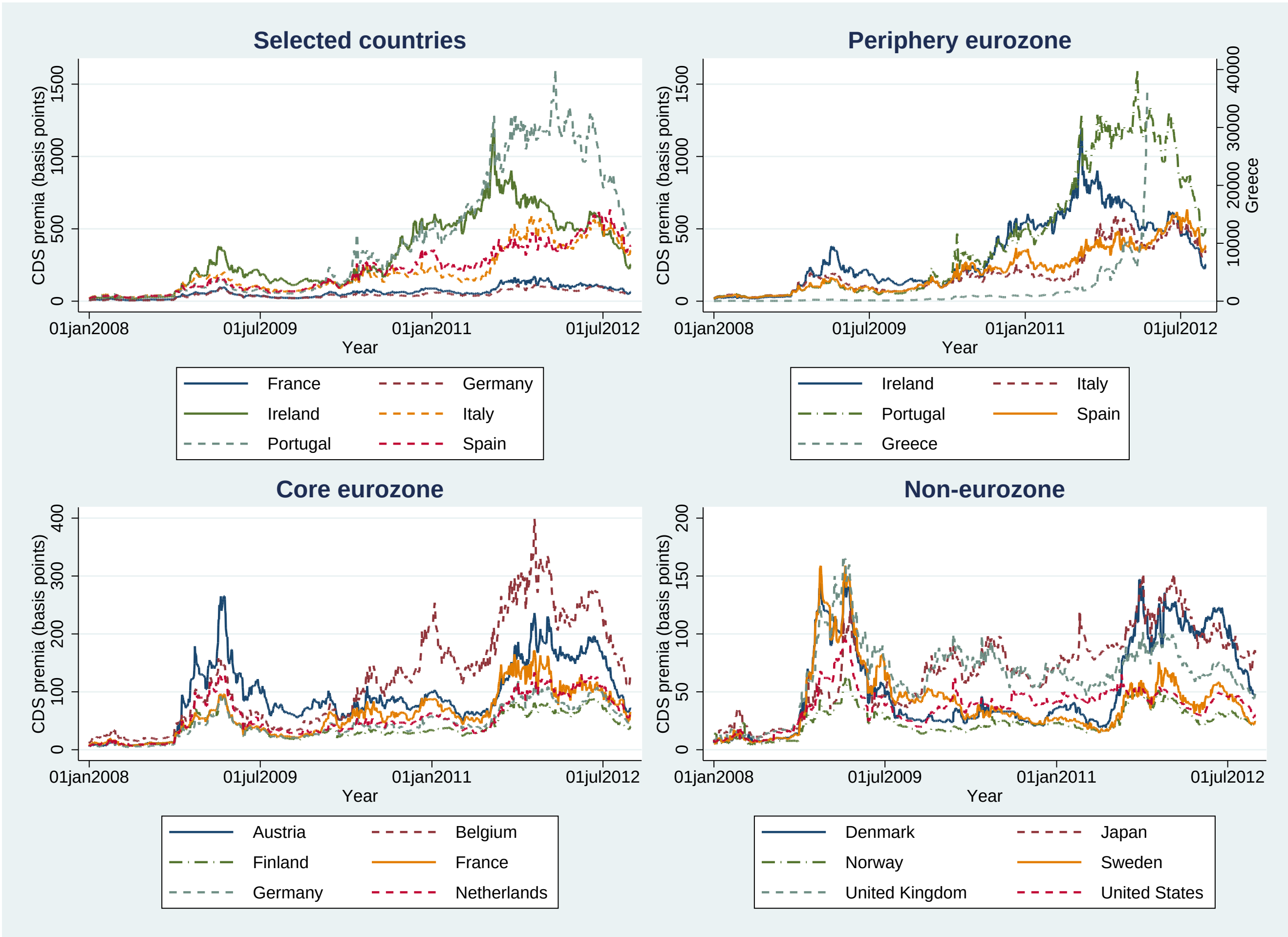

Figure 4: **Credit risk in sovereign debt markets (CDS, log difference)**
This graph plots the log differenced series of sovereign CDS premia for the 17 countries in the sample over the period from January 2008 to September 2012. Source: Datastream, own calculations.

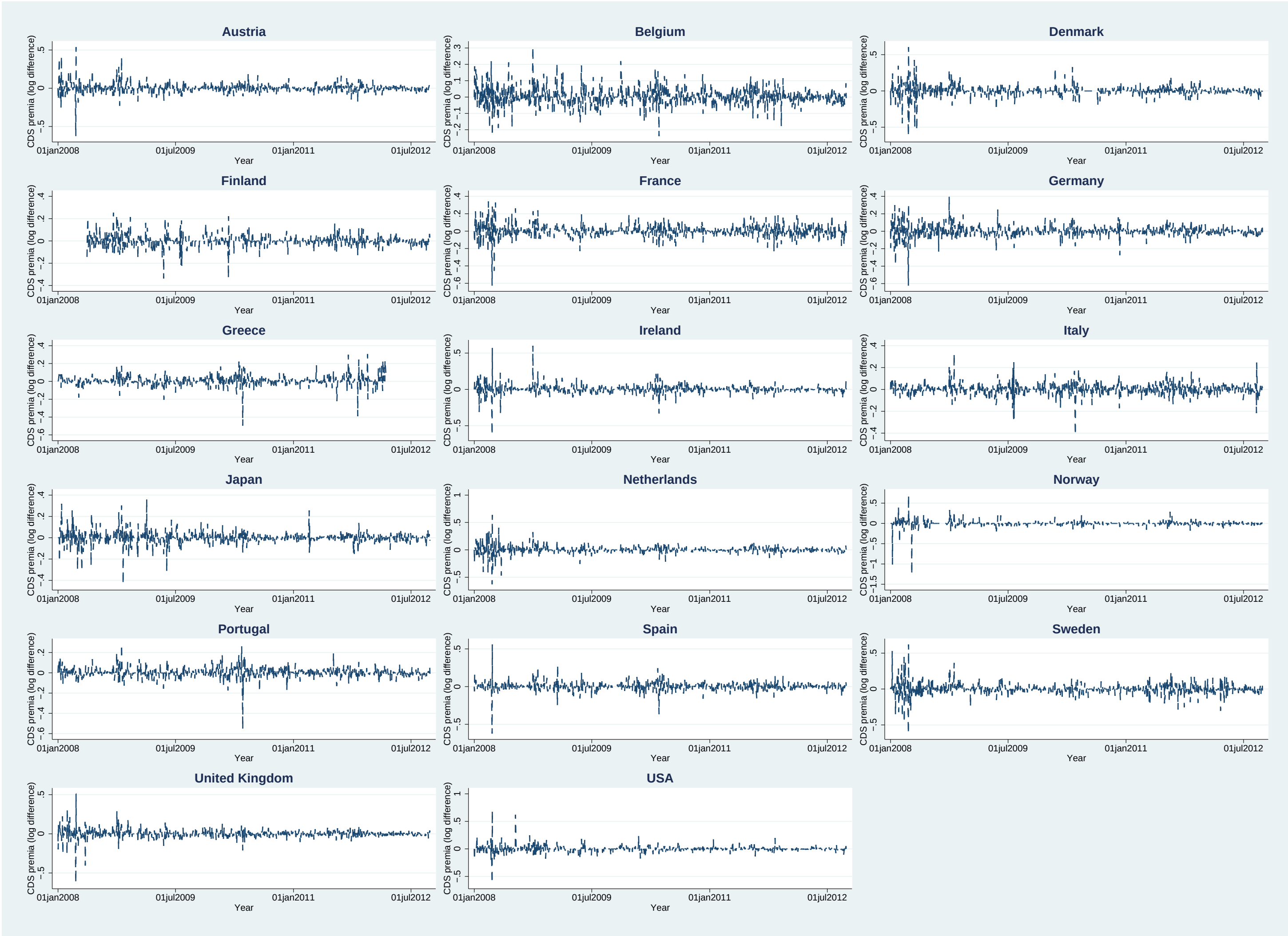

Figure 5: **Dynamic conditional correlations by country group**

This graph shows dynamic conditional correlations by country groups for the estimation period from January 2008 to September 2012. The individual series are averaged across countries belonging to one country group. All series are depicted in the upper left panel followed by the averaged series across the core eurozone country pairs (EZ: Core-core), the periphery eurozone country pairs (EZ: Periphery-periphery), the core and periphery eurozone country pairs (EZ: Core-periphery), the eurozone and non eurozone country pairs belonging to the EU (EU: EZ-non EZ), the EU and non EU country pairs (Other: EU-non EU). Key events are marked by a vertical line, e.g. 1 corresponds to the failure of Lehman Brothers in September 2008. Source: Own calculations.

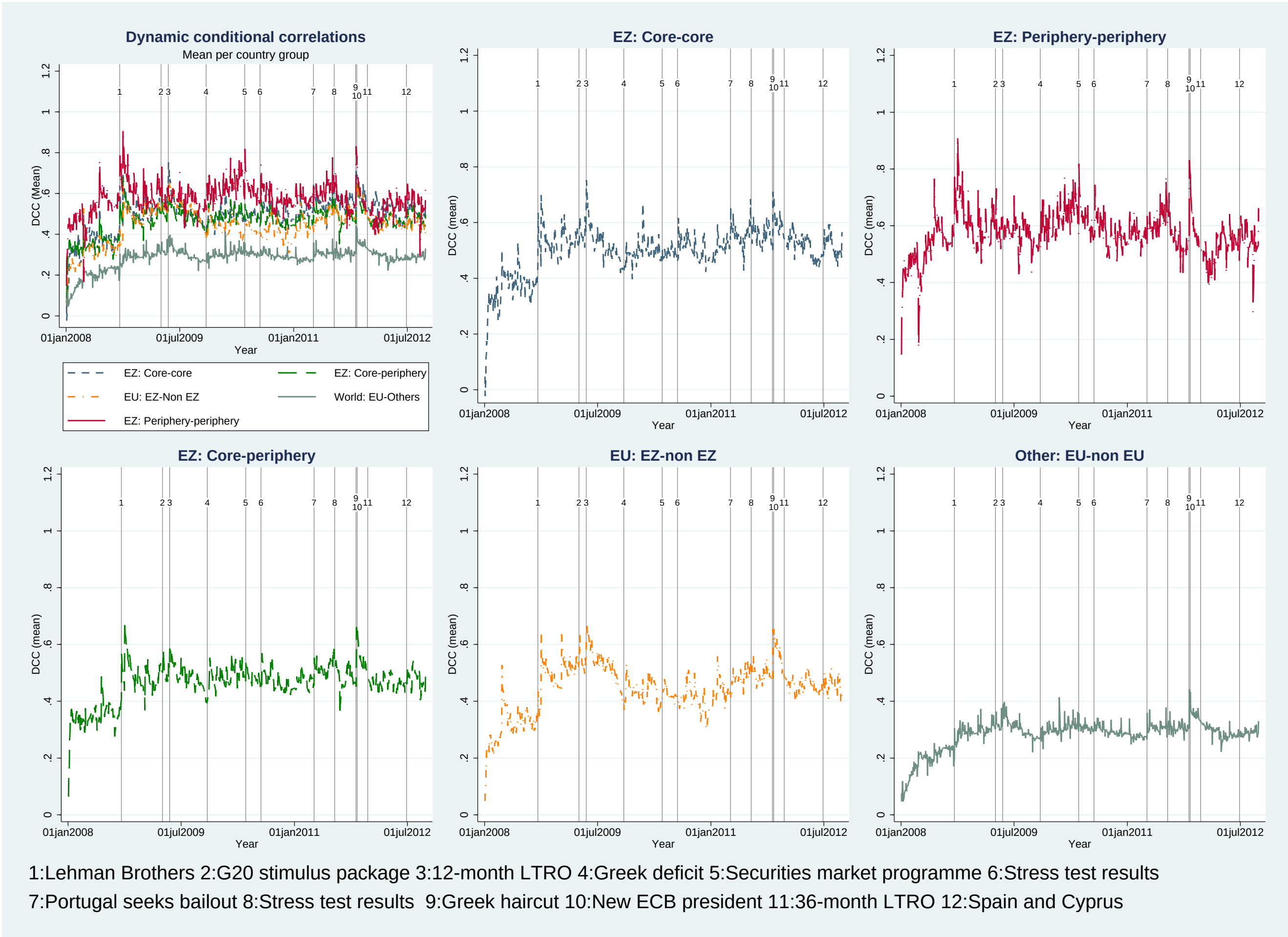

Figure 6: **Contagious episodes**

This graph shows the number of measured contagious episodes, i.e. the number of q_w being positive and significant, summed up across country pairs for each week of the estimation period from January 2008 to September 2012. The total sum across all country pairs is depicted in the upper left panel followed by the partial sums over the core eurozone country pairs (EZ: Core-core), the periphery eurozone country pairs (EZ: Periphery-periphery), the core and periphery eurozone country pairs (EZ: Core-periphery), the eurozone and non eurozone country pairs belonging to the EU (EU: EZ-non EZ), the EU and non EU country pairs (Other: EU-non EU). Key events are marked by a vertical line, e.g. 1 corresponds to the failure of Lehman Brothers in September 2008. Source: Own calculations.

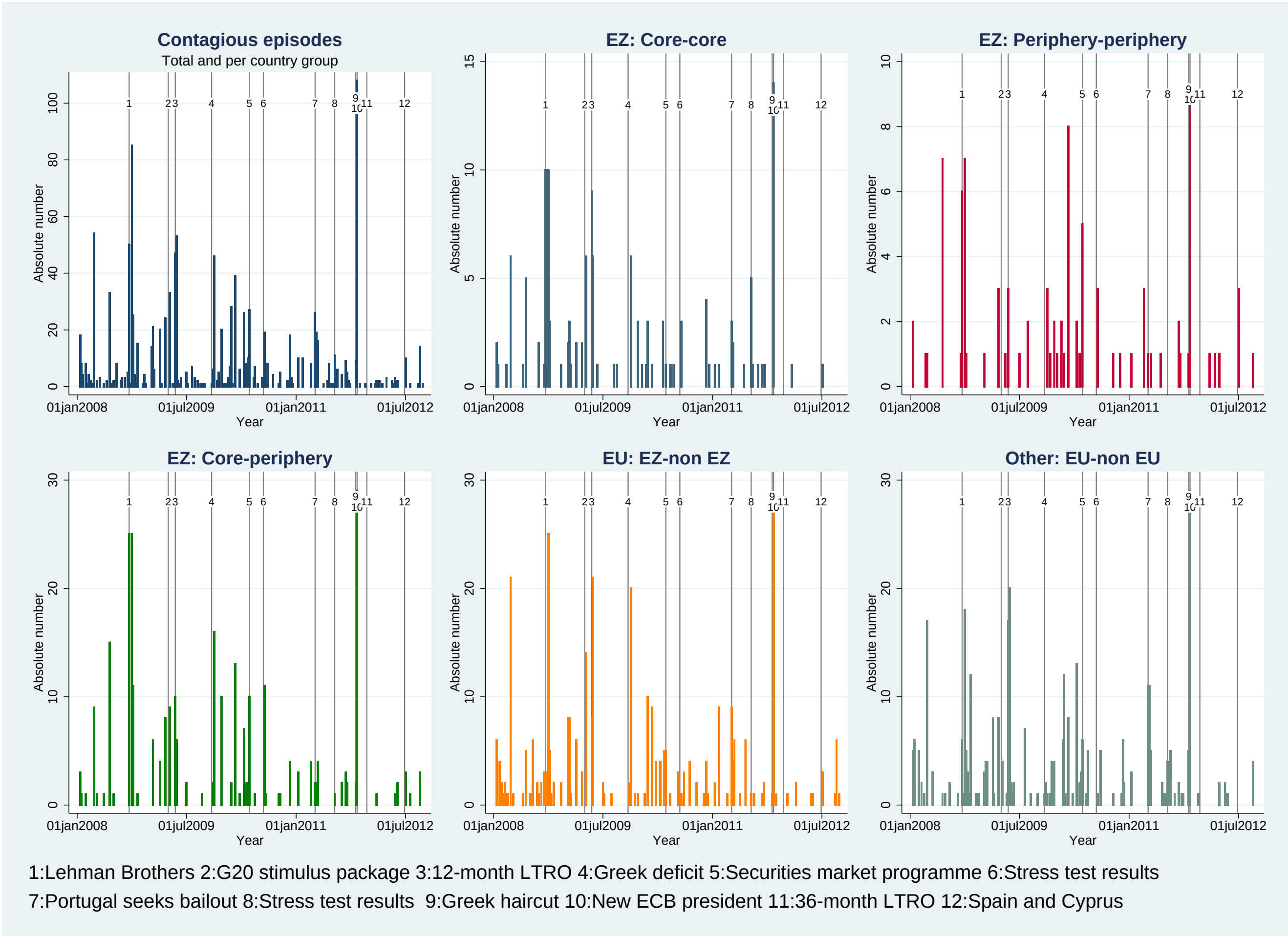

Table 1: Summary statistics: daily 5-year CDS premia (log difference) (2008-2012)

Country	Min	Max	Mean	Std.Dev.	Skewness	Kurtosis	ADF lag(10)	Jarque-Bera	Q-statistic lag (10)
Austria	-0.627	0.539	0.002	0.058	0.69	26.43	-9.71	28000	191
Belgium	-0.239	0.306	0.002	0.050	0.45	7.28	-10.93	986	100
Denmark	-0.624	0.606	0.002	0.069	-0.54	24.86	-10.26	25000	302
Finland	-0.337	0.255	0.002	0.048	-0.03	11.75	-10.14	3638	190
France	-0.626	0.343	0.002	0.065	-0.50	14.56	-10.96	6942	268
Germany	-0.622	0.398	0.002	0.060	-0.59	18.73	-11.06	13000	115
Greece	-0.497	0.307	0.007	0.052	-0.53	18.15	-8.32	10000	54
Ireland	-0.626	0.601	0.002	0.057	0.61	35.56	-11.33	55000	120
Italy	-0.416	0.331	0.002	0.049	-0.28	12.82	-11.69	4993	164
Japan	-0.437	0.363	0.002	0.053	-0.10	16.35	-10.00	9191	97
Netherlands	-0.628	0.640	0.002	0.065	-0.10	26.42	-11.22	28000	320
Norway	-1.259	0.699	0.000	0.071	-5.77	125.30	-13.07	780000	1
Portugal	-0.560	0.280	0.003	0.048	-0.88	21.91	-10.90	19000	122
Spain	-0.624	0.559	0.003	0.053	-0.34	31.07	-11.92	41000	220
Sweden	-0.621	0.621	0.001	0.072	0.26	19.77	-11.13	15000	265
United Kingdom	-0.628	0.511	0.001	0.051	-0.84	37.07	-10.69	60000	195
United States	-0.620	0.699	0.001	0.054	1.88	53.87	-9.89	130000	158

The table shows summary statistics for the daily series of 5-year sovereign CDS premia in log differences. The period starts in January 2008 and ends in September 2012. For all 17 countries in the sample, the table gives the minimum, maximum, mean, standard deviation, skewness, kurtosis, the augmented Dickey Fuller tests with lag order 10 to test for a unit root, the Jarque Bera test statistic to test for normality, and the Q-statistic with lag order 10 to test for serial correlation in the squared series.

Table 2: Correlation matrix: daily 5-year CDS premia (log difference)

	January 2008 - October 2009																
	AU	BE	DK	FI	FR	DE	GR	IE	IT	JP	NL	NO	PT	ES	SE	UK	USA
Austria	1.00																
Belgium	0.66	1.00															
Denmark	0.63	0.62	1.00														
Finland	0.51	0.52	0.59	1.00													
France	0.64	0.64	0.60	0.52	1.00												
Germany	0.51	0.53	0.50	0.50	0.63	1.00											
Greece	0.69	0.61	0.65	0.51	0.62	0.53	1.00										
Ireland	0.65	0.63	0.54	0.41	0.61	0.55	0.67	1.00									
Italy	0.65	0.57	0.53	0.44	0.56	0.53	0.69	0.57	1.00								
Japan	0.35	0.28	0.26	0.20	0.25	0.17	0.19	0.25	0.28	1.00							
Netherlands	0.68	0.62	0.61	0.58	0.62	0.63	0.58	0.56	0.54	0.22	1.00						
Norway	0.55	0.53	0.46	0.40	0.51	0.45	0.50	0.50	0.47	0.15	0.49	1.00					
Portugal	0.72	0.62	0.55	0.47	0.61	0.51	0.66	0.68	0.69	0.31	0.59	0.50	1.00				
Spain	0.70	0.64	0.59	0.53	0.66	0.53	0.69	0.63	0.65	0.28	0.58	0.49	0.73	1.00			
Sweden	0.60	0.52	0.60	0.51	0.58	0.50	0.63	0.53	0.53	0.26	0.57	0.47	0.57	0.57	1.00		
United Kingdom	0.55	0.59	0.55	0.48	0.62	0.44	0.56	0.46	0.50	0.18	0.52	0.43	0.53	0.60	0.50	1.00	
United States	0.29	0.33	0.33	0.31	0.47	0.36	0.34	0.26	0.36	0.13	0.36	0.24	0.32	0.36	0.24	0.46	1.00
	November 2009 - September 2012																
	AU	BE	DK	FI	FR	DE	GR	IE	IT	JP	NL	NO	PT	ES	SE	UK	USA
Austria	1.00																
Belgium	0.70	1.00															
Denmark	0.50	0.48	1.00														
Finland	0.54	0.47	0.43	1.00													
France	0.64	0.66	0.43	0.46	1.00												
Germany	0.64	0.64	0.53	0.45	0.66	1.00											
Greece	0.41	0.50	0.31	0.32	0.44	0.41	1.00										
Ireland	0.53	0.63	0.41	0.39	0.54	0.52	0.52	1.00									
Italy	0.64	0.78	0.48	0.47	0.65	0.62	0.54	0.69	1.00								
Japan	0.21	0.21	0.20	0.21	0.22	0.24	0.18	0.20	0.23	1.00							
Netherlands	0.68	0.65	0.52	0.52	0.59	0.66	0.36	0.46	0.59	0.22	1.00						
Norway	0.60	0.50	0.44	0.51	0.48	0.56	0.34	0.42	0.46	0.18	0.56	1.00					
Portugal	0.55	0.66	0.39	0.39	0.55	0.60	0.57	0.74	0.76	0.18	0.46	0.43	1.00				
Spain	0.62	0.76	0.50	0.44	0.65	0.63	0.56	0.72	0.88	0.17	0.54	0.46	0.80	1.00			
Sweden	0.44	0.39	0.39	0.42	0.36	0.41	0.30	0.30	0.37	0.12	0.46	0.42	0.30	0.37	1.00		
United Kingdom	0.65	0.68	0.43	0.45	0.62	0.65	0.44	0.59	0.71	0.21	0.58	0.48	0.62	0.68	0.38	1.00	
United States	0.44	0.48	0.32	0.38	0.40	0.44	0.30	0.36	0.48	0.20	0.40	0.38	0.43	0.44	0.25	0.51	1.00

The table shows the correlation matrix for the daily series of 5-year sovereign CDS premia in log differences. The upper part is based on the period January 2008 to October 2009. The lower part is based on the period November 2009 to September 2012.

Table 3: Explanatory variables descriptions and sources: Regression analysis

Classification	Variable	Description	Frequency	Source
Global controls (m)	%ΔVDAX volatility	pct. change of DAX implied volatility	monthly	Datastream
	%ΔEuribor - Eonia	pct. change in spread	monthly	Datastream
	%ΔEUR/USD	pct. change in exchange rate (Euro/USD)	monthly	Datastream
Similarity in economic fundamentals (ij)	ΔGDP	Q/Q change in sum of log GDP (times 100)	quarterly	Datastream
	Public debt	$-\lvert X_i - X_j\rvert \times 100$ with $X_i = \frac{\text{Public debt}_i}{\text{GDP}_i}$ (percent)	quarterly	BIS
	Foreign reserves	$-\lvert X_i - X_j\rvert \times 100$ with $X_i = \frac{\text{Foreign reserves}_i}{\text{GDP}_i}$ (percent)	monthly	Datastream
	Bank assets	$-\lvert X_i - X_j\rvert \times 100$ with $X_i = \frac{\text{Bank assets}_i}{\text{GDP}_i}$ (percent)	monthly	ECB
	Bank equity	monthly correlation of bank stock price index (percent)	monthly	Datastream
linkages (ij)	Banks' foreign claims	sum of bilateral claims over sum of GDP (percent)*	monthly	BIS Consolidated Banking Statistics
	Trade	sum of exports over sum of GDP (percent)	monthly	IMF DOTS
	Stock market volatility	GDP weighted average of countries' stock market volatilities	monthly	Datastream

* Bilateral claims are banks' total foreign claims reported on *ultimate risk basis* (URB). If data on URB was not available, data reported on *intermediate borrower basis* (IBB) was used instead.

Table 4: Sample countries: Classification into country groups

Core eurozone	Periphery eurozone	EU, non-eurozone	Non EU
AU: Austria	GR: Greece	DK: Denmark	JP: Japan
BE: Belgium	IE: Ireland	SE: Sweden	NO: Norway
FI: Finland	IT: Italy	UK: United Kingdom	USA: United States
FR: France	PT: Portugal		
DE: Germany	ES: Spain		
NL: Netherlands			

The table shows the 17 sample countries classified into country groups: Core eurozone; periphery eurozone; EU but non eurozone; non EU countries.

Table 5: Summary statistics: DCC time series

Country group	Min	Max	Mean	Std.Dev.
(2008-2012)				
EZ: Core-core	-0.38	0.91	0.50	0.12
EZ: Periphery-periphery	-0.48	0.98	0.57	0.14
EZ: Core-periphery	-0.24	0.92	0.47	0.14
EU: EZ-non EZ	-0.51	0.95	0.44	0.16
Other: EU-non EU	-0.67	0.93	0.29	0.13
Total	-0.67	0.98	0.42	0.17
(January 2008-mid September 2008)				
EZ: Core-core	-0.38	0.91	0.36	0.17
EZ: Periphery-periphery	-0.37	0.97	0.51	0.16
EZ: Core-periphery	-0.24	0.92	0.34	0.17
EU: EZ-non EZ	-0.38	0.95	0.31	0.17
Other: EU-non EU	-0.67	0.93	0.19	0.14
Total	-0.67	0.97	0.30	0.19
(mid September 2008-October 2009)				
EZ: Core-core	-0.02	0.91	0.53	0.10
EZ: Periphery-periphery	-0.20	0.98	0.59	0.13
EZ: Core-periphery	-0.12	0.88	0.49	0.12
EU: EZ-non EZ	-0.24	0.93	0.51	0.12
Other: EU-non EU	-0.32	0.87	0.30	0.12
Total	-0.32	0.98	0.46	0.15
(November 2009-September 2012)				
EZ: Core-core	-0.01	0.89	0.52	0.09
EZ: Periphery-periphery	-0.48	0.97	0.58	0.14
EZ: Core-periphery	-0.15	0.91	0.48	0.12
EU: EZ-non EZ	-0.51	0.86	0.45	0.14
Other: EU-non EU	-0.30	0.91	0.30	0.12
Total	-0.51	0.97	0.43	0.15

The table shows summary statistics (minimum, maximum, mean and standard deviation) for the estimated dynamic conditional correlation (DCC) series. The statistics are reported for different time periods (January 2008-September 2012; January 2008-mid September 2008; mid September 2008-October 2009; November 2009-September 2012) and for different groups of country pairs (core eurozone country pairs (EZ: Core-core), periphery eurozone country pairs (EZ: Periphery-periphery), core and periphery eurozone country pairs (EZ: Core-periphery), eurozone and non eurozone country pairs belonging to the EU (EU: EZ-non EZ), the EU and non EU country pairs (Other: EU-non EU).

Table 6: DCC GARCH model: Estimation results

Country pair ij		Mean equation								Variance equation												Covariance equation			
i	j	γ_{0i}	SE	γ_{1i}	SE	γ_{0j}	SE	γ_{1j}	SE	ω_{0i}	SE	a_i	SE	b_i	SE	ω_{0j}	SE	a_j	SE	b_j	SE	α	SE	β	SE
1) AU	Belgium	-0.001	0.001	0.124 ***	0.027	0.000	0.001	0.090 ***	0.028	0.000 ***	0.000	0.072 ***	0.008	0.932 ***	0.006	0.000 ***	0.000	0.116 ***	0.019	0.865 ***	0.023	0.076 ***	0.011	0.859 ***	0.015
	Denmark	-0.001	0.001	0.099 ***	0.028	0.000	0.001	0.072 **	0.030	0.000 ***	0.000	0.053 ***	0.007	0.943 ***	0.006	0.000 ***	0.000	0.061 ***	0.009	0.911 ***	0.013	0.149 ***	0.026	0.463 ***	0.092
	Finland	-0.001	0.001	0.110 ***	0.029	0.000	0.001	0.078 **	0.035	0.000 ***	0.000	0.067 ***	0.010	0.923 ***	0.010	0.000 ***	0.000	0.185 ***	0.030	0.722 ***	0.043	0.003	0.002	0.991 ***	0.002
	France	-0.001	0.001	0.064 **	0.028	0.000	0.001	0.021	0.029	0.000 ***	0.000	0.058 ***	0.007	0.941 ***	0.005	0.000 ***	0.000	0.102 ***	0.018	0.882 ***	0.019	0.026 ***	0.006	0.958 ***	0.009
	Germany	-0.001	0.001	0.083 ***	0.028	0.000	0.001	0.033	0.030	0.000 **	0.000	0.070 ***	0.008	0.935 ***	0.006	0.000 ***	0.000	0.099 ***	0.014	0.898 ***	0.013	0.042 ***	0.008	0.900 ***	0.022
	Greece	-0.001	0.001	0.138 ***	0.029	0.002 **	0.001	0.114 ***	0.032	0.000 **	0.000	0.057 ***	0.007	0.943 ***	0.006	0.000 ***	0.000	0.074 ***	0.008	0.929 ***	0.006	0.053 ***	0.011	0.878 ***	0.020
	Ireland	-0.002	0.001	0.147 ***	0.028	0.000	0.001	0.194 ***	0.030	0.000 ***	0.000	0.063 ***	0.009	0.934 ***	0.006	0.000 ***	0.000	0.176 ***	0.020	0.863 ***	0.010	0.028	0.017	0.272	0.189
	Italy	-0.002	0.001	0.133 ***	0.027	0.000	0.001	0.088 ***	0.029	0.000 **	0.000	0.059 ***	0.007	0.942 ***	0.005	0.000 ***	0.000	0.168 ***	0.021	0.793 ***	0.024	0.064 ***	0.014	0.845 ***	0.027
	Japan	-0.002	0.001	0.141 ***	0.032	0.000	0.001	0.064 *	0.033	0.000 **	0.000	0.061 ***	0.008	0.939 ***	0.006	0.000 ***	0.000	0.089 ***	0.011	0.908 ***	0.009	0.006	0.006	0.958 ***	0.025
	Netherlands	-0.001	0.001	0.101 ***	0.027	-0.001	0.001	0.082 ***	0.028	0.000 **	0.000	0.057 ***	0.007	0.945 ***	0.005	0.000 ***	0.000	0.081 ***	0.013	0.917 ***	0.012	0.007 *	0.004	0.972 ***	0.007
	Norway	-0.002	0.001	0.133 ***	0.029	-0.002 *	0.001	0.054	0.034	0.000 **	0.000	0.052 ***	0.007	0.948 ***	0.005	0.000 ***	0.000	0.050 ***	0.007	0.943 ***	0.007	0.012 **	0.005	0.968 ***	0.005
	Portugal	-0.001	0.001	0.158 ***	0.028	0.001	0.001	0.153 ***	0.029	0.000 ***	0.000	0.059 ***	0.007	0.941 ***	0.005	0.000 ***	0.000	0.104 ***	0.016	0.863 ***	0.021	0.066 ***	0.012	0.868 ***	0.015
	Spain	-0.002	0.001	0.122 ***	0.027	0.001	0.001	0.029	0.030	0.000 ***	0.000	0.081 ***	0.010	0.921 ***	0.007	0.000 ***	0.000	0.132 ***	0.018	0.854 ***	0.017	0.031 ***	0.012	0.869 ***	0.050
	Sweden	-0.001	0.001	0.085 ***	0.029	-0.003 **	0.001	-0.053 *	0.030	0.000 ***	0.000	0.060 ***	0.008	0.940 ***	0.006	0.000 ***	0.000	0.061 ***	0.007	0.930 ***	0.008	0.050 ***	0.010	0.894 ***	0.023
	UK	-0.002	0.001	0.110 ***	0.027	-0.001	0.001	0.016	0.027	0.000 ***	0.000	0.066 ***	0.008	0.936 ***	0.006	0.000 ***	0.000	0.057 ***	0.009	0.940 ***	0.008	0.084 ***	0.013	0.810 ***	0.023
	USA	-0.002 **	0.001	0.151 ***	0.029	-0.002 *	0.001	0.023	0.040	0.000 ***	0.000	0.058 ***	0.008	0.942 ***	0.006	0.000 ***	0.000	0.305 ***	0.044	0.705 ***	0.033	0.002	0.004	0.992 ***	0.003
2) BE	Denmark	0.001	0.001	0.078 **	0.035	0.001	0.001	0.084 **	0.039	0.000	0.000	0.071 **	0.034	0.905 ***	0.057	0.000	0.000	0.063 **	0.026	0.920 ***	0.040	0.025 ***	0.008	0.974 ***	0.007
	Finland	0.001	0.001	0.118 ***	0.038	0.000	0.001	0.104 **	0.042	0.000	0.000	0.088 ***	0.029	0.872 ***	0.059	0.000 *	0.000	0.185 **	0.078	0.725 ***	0.109	0.044 *	0.026	0.777 ***	0.066
	France	0.001	0.001	0.061	0.038	0.000	0.001	0.087 **	0.037	0.000	0.000	0.078 **	0.031	0.891 ***	0.057	0.000	0.000	0.108 ***	0.036	0.879 ***	0.040	0.103 ***	0.034	0.697 ***	0.083
	Greece	0.001	0.001	0.100 ***	0.034	0.003 **	0.001	0.126 ***	0.037	0.000	0.000	0.071 *	0.041	0.881 ***	0.087	0.000	0.000	0.074 ***	0.021	0.929 ***	0.021	0.017 ***	0.005	0.974 ***	0.004
	Ireland	0.000	0.001	0.105 ***	0.038	0.000	0.001	0.213 ***	0.075	0.000	0.000	0.053	0.036	0.932 ***	0.053	0.000	0.000	0.165 *	0.087	0.876 ***	0.041	0.076 ***	0.025	0.683 ***	0.124
	Italy	0.000	0.001	0.124 ***	0.036	0.000	0.001	0.079 **	0.036	0.000	0.000	0.093 ***	0.029	0.893 ***	0.040	0.000 **	0.000	0.146 ***	0.029	0.823 ***	0.039	0.059	0.079	0.906 ***	0.160
	Netherlands	0.000	0.001	0.055	0.038	0.000	0.001	0.104 ***	0.035	0.000	0.000	0.072 **	0.031	0.914 ***	0.044	0.000 *	0.000	0.105 ***	0.031	0.896 ***	0.028	0.053 ***	0.014	0.874 ***	0.017
	Norway	0.000	0.001	0.120 ***	0.041	-0.002	0.001	0.082	0.050	0.000	0.000	0.075 **	0.036	0.896 ***	0.060	0.000	0.000	0.055 *	0.032	0.939 ***	0.028	0.003	0.002	0.972 ***	0.009
	Portugal	0.001	0.001	0.114 ***	0.033	0.002	0.001	0.168 ***	0.033	0.000	0.000	0.065 **	0.032	0.902 ***	0.059	0.000 **	0.000	0.105 ***	0.026	0.854 ***	0.033	0.054	0.034	0.774 ***	0.112
	Spain	0.000	0.001	0.119 ***	0.034	0.002 *	0.001	0.087 **	0.037	0.000	0.000	0.094 ***	0.032	0.887 ***	0.043	0.000 **	0.000	0.156 ***	0.040	0.834 ***	0.025	0.114 ***	0.025	0.850 ***	0.019
	Sweden	0.000	0.001	0.086 **	0.035	-0.003 *	0.002	-0.033	0.039	0.000	0.000	0.094 **	0.045	0.871 ***	0.080	0.000 *	0.000	0.067 ***	0.019	0.927 ***	0.020	0.050 **	0.021	0.886 ***	0.030
	UK	0.000	0.001	0.097 ***	0.037	-0.001	0.001	0.038	0.037	0.000	0.000	0.073 **	0.031	0.913 ***	0.042	0.000	0.000	0.063 ***	0.018	0.939 ***	0.019	0.019 ***	0.007	0.971 ***	0.005
	USA	0.000	0.001	0.147 ***	0.039	-0.002	0.001	0.083 *	0.048	0.000	0.000	0.100 **	0.046	0.869 ***	0.073	0.000 *	0.000	0.272	0.195	0.729 ***	0.124	0.164 **	0.079	0.019	0.016
3) DK	Finland	0.001	0.001	0.057	0.039	0.000	0.001	0.041	0.041	0.000	0.000	0.035 **	0.017	0.937 ***	0.049	0.000 **	0.000	0.169 ***	0.058	0.730 ***	0.083	0.019 ***	0.004	0.979 ***	0.004
	France	0.001	0.002	0.028	0.051	0.001	0.002	0.074 **	0.032	0.000	0.000	0.102	0.115	0.860 ***	0.162	0.000	0.000	0.100 *	0.051	0.879 ***	0.066	0.138 **	0.065	0.663 ***	0.102
	Germany	0.000	0.002	0.066 *	0.037	0.001	0.001	0.044	0.033	0.000	0.000	0.077 *	0.041	0.900 ***	0.056	0.000 *	0.000	0.092 ***	0.024	0.902 ***	0.026	0.044 **	0.019	0.926 ***	0.025
	Greece	0.001	0.002	0.086 **	0.042	0.003 ***	0.001	0.131 ***	0.036	0.000	0.000	0.066 **	0.032	0.899 ***	0.048	0.000	0.000	0.075 ***	0.022	0.928 ***	0.022	0.034 ***	0.006	0.960 ***	0.005
	Ireland	0.000	0.002	0.099 **	0.039	0.000	0.001	0.200 ***	0.073	0.000	0.000	0.070 **	0.033	0.898 ***	0.048	0.000 *	0.000	0.153 *	0.084	0.876 ***	0.040	0.017 **	0.008	0.979 ***	0.010
	Italy	0.000	0.002	0.094 **	0.040	0.000	0.001	0.093 **	0.036	0.000	0.000	0.065 *	0.033	0.906 ***	0.051	0.000 **	0.000	0.153 ***	0.035	0.797 ***	0.051	0.064 ***	0.017	0.862 ***	0.027
	Japan	0.000	0.001	0.095 **	0.043	0.000	0.001	0.065	0.041	0.000	0.000	0.063 **	0.031	0.910 ***	0.047	0.000	0.000	0.091 ***	0.031	0.907 ***	0.028	0.003	0.004	0.995 ***	0.001
	Netherlands	0.000	0.002	0.050	0.039	-0.001	0.001	0.063 *	0.034	0.000	0.000	0.074 **	0.035	0.901 ***	0.053	0.000 **	0.000	0.068 ***	0.017	0.925 ***	0.018	0.099 ***	0.025	0.801 ***	0.055
	Norway	0.000	0.001	0.085 **	0.041	-0.002	0.001	0.044	0.052	0.000	0.000	0.055 **	0.026	0.917 ***	0.042	0.000	0.000	0.050	0.032	0.942 ***	0.030	0.004	0.004	0.991 ***	0.001
	Portugal	0.000	0.002	0.114 ***	0.040	0.001	0.001	0.160 ***	0.034	0.000	0.000	0.067 *	0.036	0.903 ***	0.056	0.000 **	0.000	0.111 ***	0.031	0.852 ***	0.037	0.052	0.034	0.858 ***	0.087
	Spain	0.001	0.002	0.136 ***	0.037	0.002	0.001	0.090 **	0.042	0.000	0.000	0.083 **	0.039	0.884 ***	0.053	0.000 **	0.000	0.140 ***	0.040	0.836 ***	0.026	0.081 ***	0.030	0.756 ***	0.057
	Sweden	0.001	0.002	0.037	0.039	-0.002	0.002	-0.058	0.035	0.000	0.000	0.076 **	0.036	0.891 ***	0.053	0.000 **	0.000	0.064 ***	0.018	0.921 ***	0.022	0.149 ***	0.044	0.300 **	0.121
	UK	0.000	0.002	0.060	0.038	-0.001	0.001	-0.002	0.035	0.000	0.000	0.060 **	0.027	0.915 ***	0.039	0.000	0.000	0.056 ***	0.017	0.941 ***	0.018	0.027 ***	0.005	0.972 ***	0.003
	USA	-0.001	0.002	0.103 **	0.042	-0.002	0.001	0.014	0.045	0.000	0.000	0.060 **	0.025	0.916 ***	0.041	0.000 *	0.000	0.314	0.232	0.687 ***	0.142	0.008	0.006	0.990 ***	0.002
4) FI	France	0.000	0.001	0.080 **	0.041	0.001	0.001	0.081 **	0.034	0.000 **	0.000	0.164 ***	0.060	0.741 ***	0.087	0.000	0.000	0.110 ***	0.037	0.857 ***	0.053	0.077 **	0.033	0.304	0.266
	Germany	0.001	0.001	0.048	0.042	0.001	0.001	0.061 *	0.036	0.000	0.000	0.215 **	0.108	0.704 ***	0.131	0.000	0.000	0.104 **	0.050	0.872 ***	0.079	0.043 ***	0.016	0.890 ***	0.025
	Greece	0.001	0.001	0.124 ***	0.047	0.003 **	0.001	0.139 ***	0.038	0.000 *	0.000	0.176 ***	0.068	0.738 ***	0.089	0.000	0.000	0.072 ***	0.019	0.933 ***	0.019	0.014	0.013	0.914 ***	0.019
	Ireland	0.000	0.001	0.128 **	0.054	0.000	0.001	0.207 ***	0.067	0.000	0.000	0.222 **	0.111	0.670 ***	0.155	0.000 **	0.000	0.223 *	0.122	0.815 ***	0.049	0.002	0.001	0.992 ***	0.001
	Italy	0.000	0.001	0.115 ***	0.043	0.000	0.001	0.075 **	0.037	0.000 *	0.000	0.188 ***	0.073	0.725 ***	0.095	0.000 **	0.000	0.196 ***	0.043	0.765 ***	0.051	0.004	0.004	0.989 ***	0.002
	Netherlands	0.000	0.001	0.062	0.040	0.000	0.001	0.111 ***	0.035	0.000 *	0.000	0.187 ***	0.071	0.727 ***	0.096	0.000	0.000	0.109 **	0.048	0.871 ***	0.060	0.105 ***	0.038	0.674 ***	0.134
	Norway	0.000	0.001	0.074	0.048	-0.001	0.001	0.021	0.038	0.000 **	0.000	0.187 **	0.076	0.724 ***	0.094	0.000 *	0.000	0.106 **	0.046	0.833 ***	0.068	0.082	0.051	0.650 ***	0.075
	Portugal	0.000	0.001	0.140 ***	0.046	0.002	0.001	0.172 ***	0.035	0.000 **	0.000	0.171 ***	0.059	0.752 ***	0.068	0.000 **	0.000	0.126 ***	0.032	0.844 ***	0.031	0.007	0.009	0.987 ***	0.006
	Spain	0.000	0.001	0.145 ***	0.044	0.002	0.001	0.073 **	0.033	0.000 *	0.000	0.183 **	0.073	0.720 ***	0.103	0.000 *	0.000	0.135 ***	0.035	0.833 ***	0.047	0.002	0.002	0.992 ***	0.002
	Sweden	0.000	0.001	0.049	0.042	-0.002	0.002	-0.039	0.036	0.000 **	0.000	0.165 ***	0.060	0.746 ***	0.082	0.000	0.000	0.071 **	0.030	0.913 ***	0.044	0.027	0.020	0.802 ***	0.118
	UK	0.000	0.001	0.081 *	0.047	-0.001	0.001	-0.003	0.040	0.000 *	0.000	0.197 **	0.083	0.710 ***	0.113	0.000 ***	0.000	0.195 ***	0.071	0.653 ***	0.089	0.023 ***	0.008	0.972 ***	0.008
5) FR	Germany	0.000	0.001	0.046	0.032	0.000	0.001	-0.009	0.033	0.000 **	0.000	0.121 ***	0.032	0.870 ***	0.034	0.000 **	0.000	0.091 ***	0.022	0.903 ***	0.023	0.110 ***	0.027	0.670 ***	0.066
	Greece	0.001	0.001	0.142 ***	0.036	0.003 **	0.001	0.093 **	0.038	0.000 *	0.000	0.143 ***	0.049	0.850 ***	0.049	0.000	0.000	0.073 ***	0.020	0.928 ***	0.020	0.039 ***	0.014	0.887 ***	0.028
	Ireland	0.000	0.001	0.150 ***	0.042	0.000	0.001	0.177 **	0.083	0.000 **	0.000	0.144 ***	0.047	0.835 ***	0.052	0.000	0.000	0.166 *	0.086	0.872 ***	0.039	0.065 *	0.038	0.692 ***	0.069
	Italy	0.000	0.001	0.077 **	0.031	0.000	0.001	0.061 *	0.032	0.000 *	0.000	0.126 ***	0.044	0.850 ***	0.054	0.000 **	0.000	0.149 ***	0.032	0.804 ***	0.041	0.054 ***	0.014	0.862 ***	0.015
	Japan	0.000	0.001	0.106 ***	0.034	0.000	0.001	0.058	0.040	0.000 *	0.000	0.117 ***	0.039	0.860 ***	0.047	0.000	0.000	0.093 ***	0.033	0.904 ***	0.030	0.004 **	0.002	0.996 ***	0.001
	Netherlands	0.000	0.001	0.048	0.031	0.000	0.001	0.050	0.033	0.000	0.000	0.111 ***	0.037	0.876 ***	0.044	0.000 **	0.000	0.085 ***	0.020	0.910 ***	0.019	0.034 ***	0.009	0.940 ***	0.009
	Norway	0.000	0.001	0.105 ***	0.038	-0.002	0.001	0.032	0.048	0.000	0.000	0.119 **	0.047	0.862 ***	0.053	0.000	0.000	0.049	0.037	0.943 ***	0.037	0.016 *	0.008	0.965 ***	0.007
	Portugal	0.000	0.001	0.113 ***	0.034	0.002	0.001	0.126 ***	0.033	0.000 *	0.000	0.132 ***	0.043	0.855 ***	0.048	0.000 **	0.000	0.109 ***	0.029	0.864 ***	0.036	0.023 ***	0.007	0.956 ***	0.008
	Spain	0.001	0.001	0.115 ***	0.035	0.002 *	0.001	0.037	0.043	0.000 **	0.000	0.124 ***	0.035	0.861 ***	0.037	0.000 **	0.000	0.165 ***	0.044	0.828 ***	0.026	0.100 ***	0.036	0.714 ***	0.077
	Sweden	0.000	0.001	0.077 **	0.034	-0.003 *	0.002	-0.057	0.038	0.000 *	0.000	0.127 ***	0.045	0.855 ***	0.051	0.000 *	0.000	0.062 ***	0.016	0.930 ***	0.018	0.030 ***	0.009	0.956 ***	0.017
	UK	0.000	0.001	0.062 **	0.030	-0.001	0.001	-0.002	0.033	0.000	0.000	0.089 ***	0.031	0.900 ***	0.036	0.000	0.000	0.064 ***	0.017	0.937 ***	0.017	0.041 ***	0.013	0.936 ***	0.019
	USA	0.000	0.001	0.095 ***	0.033	-0.002	0.001	0.027	0.041	0.000 *	0.000	0.132 ***	0.042	0.846 ***	0.048	0.000 **	0.000	0.341	0.210	0.662 ***	0.127	0.019 **	0.009	0.967 ***	0.009

Note: The table reports estimation results of bivariate DCC-GARCH models. The return equation is given by: $y_t = \gamma_0 + \gamma_1 y_{t-1} + \xi_t$. The variance equations is: $h_{i,t} = \omega_i + a_i \xi^2_{i,t-1} + b_i h_{i,t-1}$. The coefficients of the correlation process are given by: α and β. *,**,*** denotes statistical significance at the 10%, 5% and 1% level, respectively. Standard errors (SE) are robust to non-normality.

Table 6 *Continued*

Country pair ij		Mean equation								Variance equation												Covariance equation			
i	j	γ_{0i}	SE	γ_{1i}	SE	γ_{0j}	SE	γ_{1j}	SE	ω_{0i}	SE	a_i	SE	b_i	SE	ω_{0j}	SE	a_j	SE	b_j	SE	α	SE	β	SE
6) DE	Greece	0.000	0.001	0.080 **	0.037	0.003 **	0.001	0.105 ***	0.038	0.000	0.000	0.102 ***	0.034	0.888 ***	0.038	0.000	0.000	0.075 ***	0.020	0.929 ***	0.020	0.032 **	0.014	0.870 ***	0.032
	Ireland	0.000	0.001	0.138 ***	0.034	-0.001	0.001	0.165 **	0.066	0.000 **	0.000	0.131 ***	0.041	0.861 ***	0.040	0.000 *	0.000	0.159 **	0.078	0.877 ***	0.035	0.036 ***	0.010	0.843 ***	0.031
	Italy	0.000	0.001	0.080 **	0.032	0.001	0.001	0.061 *	0.035	0.000 *	0.000	0.102 ***	0.027	0.895 ***	0.027	0.000 **	0.000	0.147 ***	0.030	0.818 ***	0.039	0.066 ***	0.022	0.820 ***	0.047
	Netherlands	0.000	0.001	0.037	0.030	-0.001	0.001	0.068 **	0.032	0.000 *	0.000	0.086 ***	0.019	0.910 ***	0.020	0.000 *	0.000	0.090 ***	0.025	0.909 ***	0.024	0.066 ***	0.023	0.798 ***	0.095
	Norway	0.000	0.001	0.077 *	0.043	-0.002	0.001	0.031	0.050	0.000 *	0.000	0.086 ***	0.027	0.907 ***	0.028	0.000	0.000	0.052	0.035	0.942 ***	0.033	0.003	0.004	0.977 ***	0.008
	Portugal	0.000	0.001	0.114 ***	0.034	0.002	0.001	0.144 ***	0.033	0.000	0.000	0.111 ***	0.031	0.887 ***	0.031	0.000 **	0.000	0.128 ***	0.034	0.838 ***	0.037	0.008	0.005	0.984 ***	0.004
	Spain	0.001	0.001	0.125 ***	0.033	0.002 *	0.001	0.066	0.042	0.000 **	0.000	0.107 ***	0.028	0.884 ***	0.028	0.000 **	0.000	0.175 ***	0.043	0.824 ***	0.029	0.073 ***	0.019	0.790 ***	0.043
	Sweden	0.000	0.001	0.032	0.033	-0.003 *	0.002	-0.061	0.039	0.000 *	0.000	0.087 ***	0.027	0.901 ***	0.029	0.000 *	0.000	0.061 ***	0.018	0.930 ***	0.020	0.064 **	0.029	0.253	0.183
	UK	0.000	0.001	0.022	0.033	-0.001	0.001	-0.010	0.034	0.000 **	0.000	0.081 ***	0.023	0.910 ***	0.024	0.000	0.000	0.062 ***	0.017	0.938 ***	0.018	0.036 ***	0.007	0.951 ***	0.008
	USA	-0.001	0.001	0.077 **	0.032	-0.002	0.001	0.034	0.043	0.000 *	0.000	0.093 ***	0.027	0.896 ***	0.030	0.000 **	0.000	0.302	0.186	0.698 ***	0.114	0.125 ***	0.047	0.171	0.154
7) GR	Ireland	0.002	0.001	0.154 ***	0.049	0.000	0.001	0.208 **	0.084	0.000	0.000	0.079 ***	0.021	0.930 ***	0.020	0.000	0.000	0.148 *	0.079	0.885 ***	0.037	0.193 **	0.077	0.408	0.285
	Italy	0.002 *	0.001	0.115 ***	0.036	0.000	0.001	0.152 ***	0.034	0.000	0.000	0.072 ***	0.021	0.928 ***	0.023	0.000 **	0.000	0.145 ***	0.026	0.836 ***	0.031	0.029 ***	0.011	0.939 ***	0.016
	Netherlands	0.002 **	0.001	0.112 ***	0.038	-0.001	0.001	0.125 ***	0.037	0.000	0.000	0.074 ***	0.021	0.930 ***	0.021	0.000	0.000	0.090 ***	0.033	0.908 ***	0.030	0.013 *	0.007	0.961 ***	0.014
	Norway	0.002 **	0.001	0.168 ***	0.041	-0.002	0.001	0.111 **	0.055	0.000	0.000	0.071 ***	0.020	0.930 ***	0.020	0.000	0.000	0.052	0.037	0.941 ***	0.035	0.017	0.031	0.914 ***	0.061
	Portugal	0.003 **	0.001	0.088 **	0.036	0.002 **	0.001	0.123 ***	0.034	0.000	0.000	0.075 ***	0.020	0.926 ***	0.023	0.000	0.000	0.111 ***	0.029	0.875 ***	0.035	0.068 ***	0.015	0.892 ***	0.016
	Spain	0.003 **	0.001	0.122 ***	0.037	0.001	0.001	0.094 *	0.049	0.000	0.000	0.081 ***	0.024	0.926 ***	0.021	0.000	0.000	0.183 ***	0.063	0.824 ***	0.028	0.088 **	0.035	0.822 ***	0.038
	Sweden	0.002 *	0.001	0.090 **	0.037	-0.002	0.002	-0.005	0.041	0.000	0.000	0.073 ***	0.020	0.930 ***	0.021	0.000	0.000	0.058 ***	0.014	0.937 ***	0.015	0.044	0.033	0.941 ***	0.059
	UK	0.003 **	0.001	0.105 ***	0.040	-0.001	0.001	0.070 *	0.039	0.000	0.000	0.071 ***	0.019	0.932 ***	0.021	0.000	0.000	0.061 ***	0.017	0.941 ***	0.019	0.026 ***	0.007	0.969 ***	0.005
	USA	0.002 *	0.001	0.147 ***	0.038	-0.002	0.002	0.056	0.047	0.000	0.000	0.071 ***	0.020	0.932 ***	0.020	0.000	0.000	0.326	0.293	0.666 ***	0.204	0.012	0.010	0.973 ***	0.007
8) IE	Italy	-0.001	0.001	0.211 ***	0.077	0.000	0.001	0.157 ***	0.048	0.000	0.000	0.151 *	0.080	0.881 ***	0.041	0.000 **	0.000	0.209 ***	0.040	0.763 ***	0.042	0.063	0.058	0.788 ***	0.246
	Japan	-0.001	0.001	0.231 ***	0.083	0.000	0.001	0.066	0.040	0.000	0.000	0.167 *	0.092	0.874 ***	0.042	0.000	0.000	0.091 ***	0.032	0.907 ***	0.029	0.000	0.000	0.990 ***	0.011
	Netherlands	-0.001	0.001	0.194 **	0.076	-0.001	0.001	0.149 ***	0.038	0.000 *	0.000	0.151 *	0.080	0.879 ***	0.039	0.000	0.000	0.111 **	0.049	0.881 ***	0.048	0.064 **	0.027	0.732 ***	0.083
	Norway	-0.001	0.001	0.218 ***	0.080	-0.002 *	0.001	0.077	0.053	0.000	0.000	0.154 *	0.088	0.881 ***	0.042	0.000	0.000	0.053 *	0.032	0.940 ***	0.029	0.006	0.007	0.976 ***	0.005
	Portugal	-0.001	0.001	0.181 **	0.077	0.001	0.001	0.190 ***	0.052	0.000	0.000	0.157 **	0.078	0.880 ***	0.037	0.000 **	0.000	0.184 ***	0.055	0.794 ***	0.051	0.081	0.064	0.752 ***	0.286
	Spain	0.000	0.001	0.170 **	0.079	0.001	0.001	0.084 *	0.048	0.000 **	0.000	0.220 **	0.102	0.829 ***	0.039	0.000 **	0.000	0.192 ***	0.045	0.807 ***	0.040	0.077 ***	0.028	0.574 ***	0.117
	Sweden	-0.001	0.001	0.187 **	0.078	-0.003 *	0.001	-0.031	0.040	0.000	0.000	0.171 *	0.096	0.872 ***	0.043	0.000 *	0.000	0.059 ***	0.016	0.933 ***	0.018	0.020 ***	0.006	0.970 ***	0.004
	UK	-0.001	0.001	0.163 **	0.078	-0.002	0.001	0.045	0.037	0.000 *	0.000	0.159 *	0.087	0.876 ***	0.037	0.000	0.000	0.076 ***	0.022	0.926 ***	0.020	0.063 ***	0.015	0.884 ***	0.028
	USA	-0.001	0.001	0.223 ***	0.082	-0.002	0.001	0.065	0.046	0.000	0.000	0.171 *	0.098	0.871 ***	0.043	0.000 *	0.000	0.309	0.223	0.694 ***	0.135	0.004	0.003	0.990 ***	0.002
9) IT	Netherlands	0.000	0.001	0.073 **	0.034	-0.001	0.001	0.123 ***	0.035	0.000 **	0.000	0.179 ***	0.037	0.783 ***	0.044	0.000 *	0.000	0.125 **	0.051	0.875 ***	0.044	0.057 ***	0.018	0.864 ***	0.018
	Norway	0.000	0.001	0.140 ***	0.045	-0.002 *	0.001	0.070	0.049	0.000 **	0.000	0.186 ***	0.041	0.766 ***	0.049	0.000	0.000	0.049	0.037	0.943 ***	0.036	0.004	0.004	0.973 ***	0.007
	Portugal	0.000	0.001	0.119 ***	0.029	0.001	0.001	0.142 ***	0.031	0.000 **	0.000	0.137 ***	0.024	0.809 ***	0.041	0.000 **	0.000	0.115 ***	0.026	0.829 ***	0.036	0.019 **	0.009	0.970 ***	0.020
	Spain	-0.003	0.003	0.170 *	0.089	-0.001	0.002	0.111	0.085	0.000 *	0.000	0.176 ***	0.055	0.747 ***	0.075	0.000 *	0.000	0.170 ***	0.047	0.790 ***	0.038	0.349	0.226	0.307 ***	0.098
	Sweden	0.000	0.001	0.101 ***	0.035	-0.003 **	0.001	-0.028	0.038	0.000 **	0.000	0.184 ***	0.038	0.764 ***	0.047	0.000 *	0.000	0.064 ***	0.017	0.929 ***	0.019	0.066 ***	0.015	0.870 ***	0.019
	UK	0.000	0.001	0.076 **	0.036	-0.001	0.001	0.035	0.038	0.000 **	0.000	0.139 ***	0.029	0.817 ***	0.044	0.000	0.000	0.057 ***	0.017	0.944 ***	0.018	0.044 ***	0.015	0.896 ***	0.027
	USA	0.000	0.001	0.143 ***	0.036	-0.002	0.001	0.068	0.048	0.000 **	0.000	0.167 ***	0.036	0.781 ***	0.048	0.000 *	0.000	0.296	0.192	0.711 ***	0.116	0.110 *	0.061	0.325	0.395
10) JP	Norway	0.000	0.001	0.087 **	0.042	-0.002	0.001	0.065	0.044	0.000	0.000	0.085 **	0.033	0.913 ***	0.029	0.000	0.000	0.066 ***	0.021	0.931 ***	0.016	0.000	0.001	0.995 ***	0.002
	Portugal	0.000	0.001	0.069 *	0.040	0.001	0.001	0.199 ***	0.035	0.000	0.000	0.087 ***	0.032	0.908 ***	0.030	0.000 **	0.000	0.114 ***	0.032	0.846 ***	0.036	0.007	0.010	0.900 ***	0.054
	Spain	0.000	0.001	0.072 *	0.040	0.001	0.001	0.167 **	0.071	0.000	0.000	0.087 ***	0.031	0.908 ***	0.029	0.000	0.000	0.185 ***	0.064	0.809 ***	0.031	0.010	0.013	0.772 ***	0.111
11) NL	Norway	-0.001	0.001	0.128 ***	0.045	-0.002 *	0.001	0.040	0.048	0.000 *	0.000	0.069 ***	0.022	0.924 ***	0.022	0.000	0.000	0.047	0.037	0.945 ***	0.038	0.004	0.006	0.974 ***	0.007
	Portugal	-0.001	0.001	0.142 ***	0.035	0.001	0.001	0.150 ***	0.032	0.000 *	0.000	0.123 **	0.050	0.874 ***	0.044	0.000 **	0.000	0.125 ***	0.035	0.838 ***	0.041	0.026	0.022	0.899 ***	0.042
	Spain	0.000	0.001	0.147 ***	0.033	0.002	0.001	0.064	0.040	0.000 *	0.000	0.099 ***	0.032	0.898 ***	0.031	0.000 **	0.000	0.167 ***	0.042	0.826 ***	0.026	0.086 ***	0.025	0.795 ***	0.053
	Sweden	-0.001	0.001	0.084 **	0.034	-0.003 *	0.002	-0.051	0.038	0.000 *	0.000	0.081 ***	0.025	0.912 ***	0.025	0.000 *	0.000	0.061 ***	0.018	0.931 ***	0.020	0.053 **	0.022	0.855 ***	0.102
	UK	-0.001	0.001	0.093 ***	0.034	-0.001	0.001	0.016	0.033	0.000 *	0.000	0.078 ***	0.019	0.919 ***	0.018	0.000	0.000	0.056 ***	0.016	0.943 ***	0.016	0.034 ***	0.009	0.945 ***	0.010
	USA	-0.001	0.001	0.153 ***	0.036	-0.002	0.001	0.055	0.044	0.000 *	0.000	0.091 ***	0.029	0.903 ***	0.028	0.000 *	0.000	0.271	0.194	0.723 ***	0.125	0.132 *	0.071	0.104	0.247
12) NO	Portugal	-0.002	0.001	0.095 **	0.042	0.001	0.001	0.188 ***	0.033	0.000 **	0.000	0.098 ***	0.028	0.905 ***	0.021	0.000 **	0.000	0.115 ***	0.036	0.851 ***	0.038	0.012	0.011	0.970 ***	0.004
	Spain	0.001	0.002	0.044	0.034	0.002 *	0.001	0.093 **	0.037	0.009 ***	0.003	0.003 **	0.001	-0.954 ***	0.020	0.000 **	0.000	0.207 ***	0.067	0.799 ***	0.029	0.005	0.003	0.976 ***	0.004
	Sweden	-0.002	0.001	0.014	0.046	-0.003 *	0.002	-0.031	0.040	0.000	0.000	0.047	0.029	0.943 ***	0.028	0.000 *	0.000	0.057 ***	0.016	0.931 ***	0.019	0.052 ***	0.019	0.255	0.226
	UK	-0.002 *	0.001	0.045	0.053	-0.002 *	0.001	0.038	0.049	0.000	0.000	0.052	0.035	0.941 ***	0.033	0.000	0.000	0.058 ***	0.019	0.942 ***	0.019	0.017	0.011	0.966 ***	0.007
	USA	-0.002 *	0.001	0.055	0.050	-0.002	0.001	0.040	0.050	0.000	0.000	0.051	0.035	0.941 ***	0.033	0.000 *	0.000	0.303	0.216	0.700 ***	0.133	0.002	0.004	0.990 ***	0.004
13) PT	Spain	0.001	0.001	0.198 ***	0.061	0.001	0.001	0.100	0.075	0.000 **	0.000	0.136 ***	0.035	0.808 ***	0.042	0.000	0.000	0.152 ***	0.058	0.817 ***	0.029	0.172	0.117	0.263 ***	0.095
	UK	0.001	0.001	0.137 ***	0.035	-0.002 *	0.001	0.063 *	0.038	0.000 *	0.000	0.105 ***	0.029	0.868 ***	0.036	0.000	0.000	0.064 ***	0.018	0.938 ***	0.019	0.022 ***	0.008	0.963 ***	0.008
	USA	0.001	0.001	0.171 ***	0.035	-0.002	0.001	0.075	0.047	0.000 **	0.000	0.122 ***	0.034	0.837 ***	0.039	0.000 **	0.000	0.307	0.203	0.705 ***	0.118	0.160 *	0.084	0.022	0.032
14) ES	Sweden	0.001	0.001	0.084 *	0.048	-0.002	0.002	-0.012	0.039	0.000 *	0.000	0.168 ***	0.052	0.820 ***	0.027	0.000 *	0.000	0.062 ***	0.019	0.927 ***	0.022	0.053 ***	0.014	0.865 ***	0.019
	UK	0.001	0.001	0.034	0.036	-0.001	0.001	0.043	0.030	0.000 **	0.000	0.117 ***	0.031	0.860 ***	0.026	0.000 *	0.000	0.074 ***	0.023	0.919 ***	0.024	0.057 **	0.022	0.840 ***	0.091
	USA	0.001	0.001	0.128 **	0.053	-0.002	0.001	0.074	0.048	0.000 *	0.000	0.170 ***	0.054	0.825 ***	0.024	0.000	0.000	0.241	0.192	0.747 ***	0.130	0.053 ***	0.017	0.906 ***	0.021
15) SE	UK	-0.003 **	0.002	-0.053	0.039	-0.002	0.001	0.012	0.036	0.000 *	0.000	0.061 ***	0.017	0.930 ***	0.019	0.000	0.000	0.063 ***	0.020	0.938 ***	0.020	0.039 **	0.016	0.866 ***	0.051
	USA	-0.004 **	0.002	-0.045	0.041	-0.002	0.001	0.027	0.046	0.000 *	0.000	0.063 ***	0.018	0.928 ***	0.021	0.000 *	0.000	0.286	0.194	0.710 ***	0.120	0.029 ***	0.011	0.917 ***	0.024
16) UK	USA	-0.002 *	0.001	0.041	0.038	-0.002	0.001	0.057	0.045	0.000	0.000	0.077 ***	0.025	0.923 ***	0.025	0.000	0.000	0.218	0.170	0.761 ***	0.124	0.180 ***	0.067	0.273	0.265

Note: *Same footnote as above applies.*

Table 7: Regression analysis: Estimation results

			(I) No FE	(II) $ij + m$ FE	(III) No FE	(IV) $ij + m$ FE
Global controls		%ΔVDAX volatility	0.0165***		0.0150***	
			(0.0048)		(0.0047)	
		%ΔEuribor-Eonia	0.0044***		0.0043***	
			(0.0008)		(0.0008)	
Similarity in economic fundamentals		ΔGDP	0.1152***	0.1748***	0.1109***	0.1647***
			(0.0139)	(0.0413)	(0.0137)	(0.0396)
		Public debt	-0.0058	-0.0128	-0.0088	-0.0156*
			(0.0068)	(0.0081)	(0.0070)	(0.0082)
		Foreign reserves	-0.0220	-0.0312*	-0.0235	-0.0309
			(0.0164)	(0.0186)	(0.0169)	(0.0189)
		Bank assets	0.0002***	0.0001*	0.0002***	0.0001
			(0.0000)	(0.0001)	(0.0000)	(0.0001)
		Bank equity	0.0051**	0.0113***	0.0083**	0.0132***
			(0.0026)	(0.0031)	(0.0032)	(0.0034)
Linkages	financial	Banks' foreign claims	-0.0918**	-0.0526	-0.0922*	-0.0711
			(0.0463)	(0.0496)	(0.0517)	(0.0509)
	real	Trade	-0.0132	0.0284	-0.0018	0.0444*
			(0.0126)	(0.0253)	(0.0133)	(0.0265)
	non-fundamental	Stock market volatility	0.0459***	0.0204**	0.0178*	-0.0044
			(0.0087)	(0.0099)	(0.0091)	(0.0093)
Interaction (× CI)		Public debt			0.0209**	0.0189**
					(0.0095)	(0.0084)
		Bank equity			-0.0156	-0.0135
					(0.0117)	(0.0089)
		Banks' foreign claims			-0.0589	0.1671**
					(0.0666)	(0.0757)
		Trade			-0.1395***	-0.0722***
					(0.0268)	(0.0247)
		Stock market volatility			0.0944***	0.0929***
					(0.0149)	(0.0191)
Observations			5,677	5,677	5,677	5,677
Country pairs			107	107	107	107
R-squared			0.05	0.27	0.05	0.28

The dependent variable is the measure for sovereign credit risk co-movements adjusted for volatility (ρ_{ijm}) in percent. The estimation period runs from January 2008 to March 2012 on a monthly basis. Quarterly data is (linearly) interpolated to monthly frequency. Specifications (II) and (IV) report the estimated coefficients of the panel data model including country pair as well as time fixed effects. Specifications (III) and (IV) include interaction terms of the (0/1)-contagion indicator (CI) with public debt, bank equity, the financial linkage (banks' foreign claims), the real linkage (trade), and the proxy for common market sentiment (GDP weighted stock market volatilities). Continuous variables entering the interaction terms are centered around their mean to facilitate interpretation. Standard errors are clustered by country pair. The reported R-squared is the R-squared within. P-values: * < 0.1, ** < 0.05, *** < 0.01.

Table 8: Regression analysis: Robustness A

			(A-I) Fisher Z	(A-II) CI (1%)	(A-III) CI (5%)	(A-IV) Debt Crisis
Similarity in economic fundamentals		ΔGDP	0.4358***	0.1698***	0.1648***	0.1355***
			(0.1086)	(0.0401)	(0.0397)	(0.0408)
		Public debt	-0.0368*	-0.0130	-0.0146*	-0.0277***
			(0.0208)	(0.0083)	(0.0083)	(0.0092)
		Foreign reserves	-0.0731	-0.0308*	-0.0299	-0.012
			(0.0487)	(0.0186)	(0.0188)	(0.0238)
		Bank assets	0.0003	0.0001*	0.0001	0.0001***
			(0.0002)	(0.0001)	(0.0001)	(0.0000)
		Bank equity	0.0317***	0.0111***	0.0129***	0.0149***
			(0.0082)	(0.0030)	(0.0032)	(0.0038)
Linkages	financial	Banks' foreign claims	-0.2062*	-0.0604	-0.0721	0.1767**
			(0.1208)	(0.0501)	(0.0498)	(0.0780)
	real	Trade	0.1180*	0.0296	0.0419	0.0764***
			(0.0671)	(0.0253)	(0.0274)	(0.0270)
	non-fundamental	Stock market volatility	-0.0160	0.0167	0.0049	0.0005
			(0.0251)	(0.0116)	(0.0126)	(0.0124)
Interaction (× CI)		Public debt	0.0453**	0.0040	0.0150	0.0300***
			(0.0223)	(0.0119)	(0.0095)	(0.0109)
		Bank equity	-0.0327	0.0016	-0.0176*	-0.0190*
			(0.0230)	(0.0156)	(0.0104)	(0.0100)
		Banks' foreign claims	0.4340**	0.2245*	0.3043***	-0.0266
			(0.2072)	(0.1183)	(0.1060)	(0.0757)
		Trade	-0.2277***	-0.0227	-0.0891**	-0.0854*
			(0.0682)	(0.0458)	(0.0356)	(0.0505)
		Stock market volatility	0.2406***	0.0303	0.0798***	-0.0629
			(0.0507)	(0.0223)	(0.0223)	(0.0461)
Observations			5,677	5,677	5,677	3,551
Country pairs			107	107	107	107
R-squared			0.27	0.27	0.27	0.18

The table presents various robustness checks based on the preferred specification (IV) of Table 7. Specification (A-I) applies the Fisher z-transformation to the measure for sovereign credit risk co-movements in percent ($\tilde{\rho}_{ijm} = \log(1 + \rho_{ijm})/(1 - \rho_{ijm})$). The transformed variable is used as dependent variable to mitigate the potentially skewed distribution of correlation coefficients. In specifications (A-II) and (A-III), computation of the contagion indicator (CI) is based on lower significance levels of 1% and 5%, respectively. Specification (A-IV) is based on a sample split considering only observations from November 2009 capturing the onset of the sovereign debt crisis in the eurozone. Standard errors are clustered by country pair. The reported R-squared is the R-squared within. P-values: * $<$ 0.1, ** $<$ 0.05, *** $<$ 0.01.

Table 9: Regression analysis: Robustness B (eurozone only)

			(B-I) EZ	(B-II) EZ	(B-III) EZ
Global controls		%ΔVDAX volatility	0.0140*		-0.0034
			(0.0078)		(0.0065)
		%ΔEuribor-Eonia	0.0053***		0.0064***
			(0.0010)		(0.0010)
		%ΔEUR/USD			-24.3742***
					(3.4238)
Similarity in economic fundamentals		ΔGDP	0.0848***	0.3016*	0.0568***
			(0.0146)	(0.1725)	(0.0123)
		Public debt	-0.0136	-0.0392***	-0.0156
			(0.0105)	(0.0140)	(0.0108)
		Foreign reserves	-0.2922**	-0.1197	-0.0656
			(0.1329)	(0.0847)	(0.1350)
		Bank assets	0.0047***	0.0016	0.0031**
			(0.0014)	(0.0011)	(0.0013)
		Bank equity	-0.0022	0.0048	0.0026
			(0.0054)	(0.0050)	(0.0049)
Linkages	financial	Banks' foreign claims	-0.2441***	-0.1163**	-0.1998***
			(0.0475)	(0.0467)	(0.0420)
	real	Trade	0.0285*	0.0568	0.0413*
			(0.0172)	(0.0369)	(0.0240)
	non-fundamental	Stock market volatility	0.1034***	0.0683*	0.1061***
			(0.0329)	(0.0383)	(0.0322)
Interaction (× CI)		Public debt	0.0335**	0.0285*	0.0385**
			(0.0153)	(0.0155)	(0.0154)
		Bank equity	0.0119	0.0065	0.0054
			(0.0214)	(0.0161)	(0.0201)
		Banks' foreign claims	0.0310	0.2005*	0.0157
			(0.0647)	(0.1031)	(0.0694)
		Trade	-0.1596***	-0.1302***	-0.1530***
			(0.0284)	(0.0381)	(0.0269)
		Stock market volatility	0.0216	0.0497	0.0389
			(0.0321)	(0.0356)	(0.0305)
Observations			2,311	2,311	2,311
Country pairs			44	44	44
R-squared			0.08	0.39	0.13

The table presents robustness checks excluding non-eurozone countries. Based on the smaller sample of eurozone countries, specifications (B-I) and (B-II) are equivalent to specifications (III) and (IV) of Table 7. Specification (B-III) additionally includes the exchange rate (EUR/USD). Standard errors are clustered by country pair. The reported R-squared is the R-squared within. P-values: * < 0.1, ** < 0.05, *** < 0.01.