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

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August 2013

Abstract

Until the eurozone sovereign debt crisis, movements in sovereign debt markets had been highly synchronized across countries. However, with the onset of the eurozone sovereign debt crisis, credit risk spreads have diverged, and distress in one country seems to be transmitted to financially interconnected countries with similar characteristics: Credit risk comoves strongly within certain country groups such as the eurozone periphery. We seek to answer what the determinants of this 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, this allows disentangling periods of simple interdependence from contagion. Third, we analyze the determinants behind credit risk co-movements and the role of contagion using gravity-type regressions. Our results reveal a high degree of co-movements in sovereign credit risk, especially for eurozone countries during the sovereign debt crisis, and we find strong evidence for contagion.

Keywords: Sovereign debt crisis, financial contagion, banking integration
JEL Classification: F30, F65, G01, G15

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* We are grateful to Claudia Buch and Elena Carletti for continuous advice and encouragement. Furthermore, we would like to thank Martin Biewen, Elena Dumitrescu, Peter Hansen, Massimiliano Marcellino, Esteban Prieto and Saverio Simonelli for many helpful comments as well as the Bank for International Settlements for kindly providing data. The paper has also benefited from comments by seminar participants at the Frankfurt School of Finance & Management, the Università Politecnica delle Marche, and the European University Institute. All errors and inaccuracies are solely in our own responsibility.

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1 Motivation

Sovereign credit risk in European countries receives increased attention in recent times and changes in sovereign credit risk spreads, such as sovereign bond yield and/or sovereign CDS spreads, are considered worth a headline in many newspapers. On the one hand, this can be explained by worsened fiscal positions following government interventions in the banking sector during the financial crisis as well as fiscal stimulus packages. High debt positions can be found especially in countries like Greece, Italy, or Spain, and concerns of investors about the sustainability of government finances are reflected in high sovereign yield and CDS spreads. On the other hand, 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. Thereby, uncertainty about the consequences of deteriorating fiscal positions and increased credit risk in one country for other nations is high and translates into volatile market reactions across countries. It is, however, hardly understood in how far and for what reasons developments in sovereign debt markets are tied together and cause feedback effects.

Given the relevance of the topic, there is a growing literature on the determinants of sovereign yield or CDS spreads during crisis times. For example, Attinasi et al. (2009) or Haugh et al. (2009) analyze government yield spreads and find that, with the onset of the financial crisis, 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.[1] A second strand of literature extends the analysis and takes into account 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 indicating that potential future bailout costs and credit losses are priced in by investors (Acharya et al., 2011; Dieckmann and Plank, 2012).

In contrast, few papers analyze the transmission of distress in sovereign debt markets or the feedback between bank and sovereign credit risk across national borders. On the theoretical side, one recent exception 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. The relative scarcity of not only theoretical models but also of empirical studies seems surprising as looking at a graph showing,

[1] This result is supported by Beirne and Fratzscher (2013) who identify a deterioration in fundamentals as main drivers behind risk spreads during the sovereign debt crisis. Papers that analyze the determinants of sovereign credit risk spreads before the crisis are, for example, Beber et al. (2009) who find that spreads are explained to a high degree by differences in credit quality, Manganelli and Wolswijk (2009) or Favero et al. (2010) showing the importance of an aggregate risk factor in determining sovereign bond yield spreads.

for example, sovereign bond yield or CDS spreads of European countries gives rise to many questions (see Figure 1): Why do all countries show a similar pattern before the

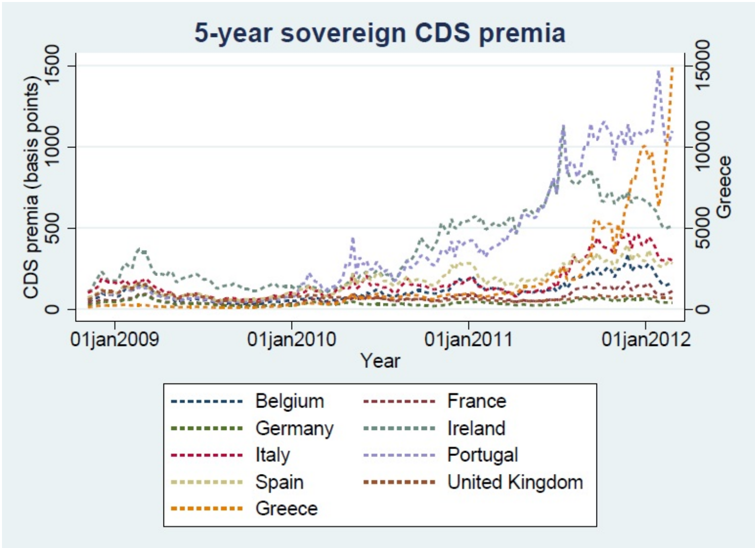

Figure 1: 5-year sovereign CDS premia

start of the Greek sovereign debt crisis whereas the periphery countries seem to move together but differently from the core eurozone countries later on? Are these patterns just related to standard co-movements and if yes, what caused the break in the time series behavior? Or is it the outcome of contagion and if this is the case, why has contagion occurred?

Our objective is to take a closer look at the pattern of sovereign credit risk across European countries. In a first step, we compute correlations of sovereign credit risk spreads based on CDS data and applying the dynamic conditional correlation (DCC) model developed by Engle (2002). In a second step, these correlations are used to detect changes in co-movements and separate stronger correlations that originate from a general increase in the underlying volatility from contagion, i.e. unexpected shocks that propagate in a more intense way than in tranquil times resulting in a significant increase in co-movements (Forbes and Rigobon, 2002).[2] Finally, we examine which are the determinants of co-movements in sovereign credit risk. Using a gravity-type model allows disentangling co-movements going back to global factors or common fundamentals of country pairs. Furthermore, we can test whether significant shifts in volatility-adjusted correlations, i.e. contagion, occurred due to direct bilateral links in trade respectively finance, or if they are the outcome of pure changes in market sentiments and investors' risk perception which would provide evidence for non-fundamentals based contagion. In a similar vein, Forbes (2012) applies extreme value theory to measure contagion in

[2] For recent discussions on how to measure contagion in sovereign debt or stock markets see Caporin et al. (2013) or Forbes (2012).

stock markets and takes the results to identify channels of contagion. Gorea and Radev (2012) study the determinants of contagion in sovereign bond markets but focus on tail events by computing the joint probability of default of eurozone countries.

We contribute to the existing literature in two main points. First, we do not limit our analysis to the determinants of sovereign credit risk spreads in individual countries (see e.g. Attinasi et al., 2009; Haugh et al., 2009) 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. Additionally, our analysis enables to study the feedback between bank and sovereign credit risk as shown, for example, by Acharya et al. (2011) or Alter and Schüler (2012). Second, our objective is to separate simple interdependence structures from contagion and, more importantly, explain why we observe partially strong co-movements in perceived risk patterns and which channels cause contagion. Thus, we do not only focus on extreme events like Forbes (2012) or Gorea and Radev (2012) and do not stop with the detection of contagion as e.g. Forbes and Rigobon (2002) or Caporin et al. (2013) but want to disentangle the reasons behind. Especially for policymakers this is important to know as interdependent patterns in sovereign credit risk due to common fundamentals like weak government finances would require different policy measures than contagion arising from volatile market sentiments and uncertainty in sovereign debt markets. While the former would e.g. ask for structural reforms providing the ground for sustainable public budgets and increased competitiveness, the latter might be mitigated by a reduction in uncertainty through the establishment of common fiscal backstops or ECB interventions.

Our analysis reveals that despite observing a divergence in sovereign risk spreads during the sovereign debt crisis, 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. Interestingly, this finding holds for both countries with strong fundamentals and eurozone sovereigns with weak fiscal positions. In this sense, our results have important policy implications. While increased co-movements and contagion due to common weaknesses in economic fundamentals require adjustments at the national level, 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. While economists want to explain contagion, policymakers fear contagion and the media likes contagion for providing headlines and despite the common interest in contagion, 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 - in the broadest sense - 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 linkages taking place after a shock has occurred (see e.g. Forbes and Rigobon, 2002).[3]

As soon as one looks at contagion and its transmission channels in more detail, diversity in definitions and opinions enters. Global shocks are just one example. Many economists would argue that increased co-movement across countries due to a common shock that hits countries in the same way does not qualify as contagion. However, the failure of Lehman Brothers was a shock affecting countries and banking systems around the globe. Hence, would one qualify the resulting repercussions not a result of contagion? And can a global shock be considered in isolation to existing fundamental links between countries? E.g. banking systems of many countries had exposures to US subprime loans and among themselves which facilitated global spillovers. But does the transmission of shocks trough fundamental links like trade flows or cross-border loans constitute contagion or can only non-fundamentals be blamed for causing contagion? Again here, there is lots of disagreement and some economists argue that the concept of contagion relates only to spillovers which are not due to fundamentals. Risk panics leading investors to sell assets in an (ir)rational way would be an example.[4] However, this is a restrictive definition, not easy to reconcile with a large part of the theoret-

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

[4] Masson (1998) was one of the first to distinguish between monsoonal effects or common shocks, spillovers due to fundamental linkages and jumps between multiple equilibria due to non-fundamental factors. Other examples for non-fundamentals based contagion are Karolyi (2003) or Bekaert et al. (2011).

ical literature where contagion arises due to fundamental links. Just to mention the literature starting with Allen and Gale (2000) who show how interbank linkages can cause contagion. In addition, difficulties quickly emerge in the practical implementation as the objective is to explain contagion from non-observables. But even if a broader definition is used allowing contagion to take place through fundamental links, the discussion does not become less controversial. For example, does the "normal" transmission of a negative shock through cross-market linkages that exist in all states of the world qualify as contagion? Or is it necessary that there is a significant change in cross-market linkages that cause a different propagation after the realization of (large) negative shocks? In the literature the first is often referred to as "interdependence" while only the latter is named contagion (Forbes and Rigobon, 2002).

Importantly, the concrete interpretation of contagion has consequences for the choice of both policy measures to mitigate contagion and econometric techniques to identify contagion. On the one hand, policymakers come under pressure to act as soon as negative events in one country affect another country. This holds irrespective of whether shocks transmit in a non-standard way or simply due to existing fundamental links in all states of the world. On the other hand, economists understanding contagion as anything that goes above and beyond fundamentals might choose an approach to analyze residual effects which would be of limited use for economists who consider fundamental links as a possible source of contagion.

In this paper, we define contagion as a significant increase in cross-market linkages, i.e. co-movements or volatility-adjusted correlations. This definition is not only in line with the related academic literature (Forbes and Rigobon, 2002; Boyer et al., 2006; Caporin et al., 2013) but has also various advantages. First, we are able to separate co-movements due to unchanged linkages existing in all states of the world from significant increases in cross-market correlations. This way, we do not restrict our analysis to "extreme events" but can disentangle periods of interdependence from contagion. Second, it 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 links that can cause contagion.[5] Third, despite being more restrictive compared to policymakers who tend to interpret the transmission of negative shocks being proportional to the transmission of positive shocks due to existing links as contagion, our analysis still allows to draw a broad range of policy implications.

[5] A more detailed discussion of possible contagion channels is left to Section 4.

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.[6] Based on our definition of contagion, the most straightforward approach is to use correlation and volatility measures to analyze contagion.

In the related literature different methods have been used. Among the first to use correlation analysis to measure contagion are King and Wadhwani (1990). They analyze the crash in world stock markets in October 1987 which took place despite countries differed in economic fundamentals. Contagion is explained by the attempt of rational market participants to extract information on price changes from other markets. This causes that misleading information in one market is transferred to another resulting in increased volatility. Empirically, they show that correlations increased after the crash suggesting contagious effects. While the authors discuss the impact of volatility on correlation measures, they still do not adjust for changes in the volatility.

Forbes and Rigobon (2002) move further into this direction and raise the issue that higher correlations might only go back to more volatile markets. If in crisis times volatility increases, this causes that - by statistical definition - the correlation increases even if fundamental cross-country linkages do not change. Only a significant change in volatility-adjusted co-movements can thus be labeled as contagion. Anything else is just due to interdependence. Applying this concept to the Asian crisis in 1997 and calculating volatility-adjusted correlations using stock market data, Forbes and Rigobon (2002) do not find evidence for contagion. High correlations between markets are according to their results the outcome of interdependence arising due to cross-market linkages which exist in all states of the world.

While Forbes and Rigobon (2002) achieve to correct for changes in the underlying volatility, their identification of contagion is based on static correlations. Significant changes in these static correlations computed over a crisis and a non-crisis subsample are then interpreted as evidence for contagion. This implies that the outcome depends crucially on the chosen break point and results might be driven by different estimation windows for the usually large non-crisis sample and small crisis sample. In order to circumvent this shortcoming, Caporale et al. (2005) follow Forbes and Rigobon (2002) but base their estimation on the full sample in order to analyze contagion during the

[6] 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).

Asian crisis. This is achieved by selecting the breakpoints endogenously.

Another method to measure contagion which also avoids the disadvantage of having to choose exogenous breakpoints is the assessment of joint occurrence of extreme events across markets or countries. For example, Bae et al. (2003) analyze the propagation of large return shocks by counting coincidences of extreme returns across emerging markets during the 1990s. In a similar vein, Forbes (2012) uses extreme value analysis to find evidence for contagion in equity markets across 48 countries during the period 1980-mid 2012. Her results show, for example, that euro area countries are more likely to face joint coincidence of extreme events during the last decade. Tough this approach is very straightforward 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 disentangled.

We apply dynamic conditional correlations based on Engle (2002) to obtain volatility-adjusted correlations or co-movements of sovereign credit risk across countries. This methodology has various advantages compared to alternative correlation measures. First, as in Forbes and Rigobon (2002), the measure controls for heteroscedasticity and adjusts for changes in the underlying volatility. Second and in contrast to Forbes and Rigobon (2002), it 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. In addition, as we obtain correlations for the whole period, this does not limit our analysis to extreme events and we can compare the determinants of significant increases in correlations with driving forces behind 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 The Market for Credit Default Swaps

The analysis is based on credit default swap (CDS) spreads as measure of credit risk in sovereign debt markets. This section gives a brief description of the sovereign CDS markets which is helpful to understand to what extent CDS spreads can be taken as an appropriate measure of sovereign credit risk. The concrete data used in the analysis is described in the following section. A credit default swap constitutes a credit derivative transaction in which a protection buyer and a protection seller enter a contract linked to a specified reference obligation. Within this contract, the protection buyer pays a fixed quarterly premium, the CDS spread denoted in basis points, to the protection seller for a specified period. A time to maturity of five years corresponds thereby to a highly liquid type of contract. If no credit event occurs, the payment of the CDS spread constitutes the only cash flow. If a credit event related to the specified reference obligation - e.g. a sovereign bond - takes place, the contract terminates and the protection seller has to compensate the protection buyer for the loss. This can happen in two ways. Under physical settlement, the protection buyer delivers the defaulted bond to the protection seller in exchange for the face value of the bond. Deliverable obligations can be any set of bonds with maturity at least equal to that of the reference obligation specified in the contract. Under cash settlement, no actual bond trade occurs but the protection buyer receives the difference between the face value and the recovery price of the bond which is set in an auction procedure.[7]

Credit events are defined by the International Swaps and Derivative Association (ISDA). The most relevant ones include bankruptcy, failure to pay interest or various kinds of debt restructuring likely to cause negative effects for the creditor. Thereby, the restructuring type of the contract defines the credit events that trigger a CDS. Complete restructuring (CR) implies that any restructuring event triggers the credit event and there is no limitation with respect to the maturity of the underlying bond. Modified restructuring (MR) limits the maturity of a deliverable bond to less than 30 months after a restructuring, modified modified restructuring (MMR) relates to a maturity of up to 60 months and a contract of type no restructuring (NR) excludes all restructuring events. 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,

[7] For more details on CDS contractual agreements see Duffie (1999) or Pan and Singleton (2008).

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.

CDS spreads are a timely measure of credit risk provided that markets exist and are active enough. Figure 2 shows that the market volume of single-name CDS instruments was relatively low in 2004 but has steadily increased and reached its peak in the first half of 2008. The data obtained from the Bank for International Settlements (BIS) can be disaggregated by type of reference obligation. Figure 3 reveals that the volume of sovereign CDS also declined in the second half of 2008 but in contrary to the total CDS market, it increased again reaching an amount outstanding of almost 3000 bn USD (around four percent of 2011 world nominal GDP). This results in an increasing share of sovereign CDS in the total CDS market volume. Data on individual entities including sovereign reference obligations is available by the Trade Information Warehouse of the Depository Trust & Clearing Corporation (DTCC) from 2008 onwards. Throwing a closer look at the OTC market for sovereign reference obligations tells that not only gross notional amounts outstanding but also the number of open contracts continued to increase in recent times (see Figure 4). 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.

3.2 CDS Data Description

The measure of co-movements in sovereign credit risk is calculated using daily data on five year sovereign CDS spreads obtained from Thomson Reuters Datastream for a sample of 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. The sample period for estimating dynamic conditional correlations spans January 2008 to August 2012.[8] 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 series are available for all countries except Finland and, as Figure 4 has shown, the market volume and the number of contracts are constantly high and increasing. Given there is active trading in sovereign CDS markets, CDS spreads can be taken as a reliable and timely measure of (perceived) credit risk.[9]

[8] 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.

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

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. Also, as opposed to bond yields, no premia compensating for inflation or liquidity risk are included in the data as a CDS contract solely 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.[10] [11] As CDS contracts are traded over the counter, CMA respectively Thomson Reuters collect information on prices, maturities and restructuring type from market contributors like asset managers, banks or hedge funds. The type of the contract is chosen to be complete restructuring (CR) as this is available for all countries. The sovereign CDS contracts are denominated in US dollar for Austria, Belgium, Germany, Greece, Italy, Japan, Netherlands, Norway, Portugal, Spain and the United Kingdom.[12] 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, 2011; Longstaff et al., 2011). Additionally, comparing series for which data on both US dollar and Euro denominated contracts were available revealed that

[10] 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.

[11] Mayordomo et al. (2012) find that CDS quotes from different providers moved, in general, into the same directions while deviations are higher in crisis times, for low trading frequency or small entities. As we focus on sovereign entities that trade frequently, data from different providers should not show major discrepancies. This is confirmed by comparing CDS spreads from Thomson Reuters and CMA for the period for which we have data from both providers.

[12] Specifying CDS contracts for European sovereign bonds in US dollar can be a way for investors to avoid losses due to currency depreciation in case of a default that triggers the protection payment (see also Fontana and Scheicher, 2010).

in general differences are small and the series strongly co-move.[13] 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 5 shows that most of the series have an upward moving behavior in the second half of 2008. A second and more pronounced increase can be found for most countries at the beginning of 2010 which can be explained by the sovereign debt crisis. 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).

3.3 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. The difference in the minimum and the maximum indicates to what extent the series fluctuate over time.

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-

[13] One exception is Germany with higher CDS spreads for US dollar denominated contracts. This might reflect an increased value of the CDS contract in US dollar given in a state of default the contract pays out in US dollar and not in a, most likely, depreciating Euro and suggests that default and currency risk are not necessarily independent.

order autocorrelation both by visual inspection of the (non-reported) autocorrelation functions and based on the Portmanteau (or Q) test statistic with up to 20 lags. Also 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 6, 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 separately investigate 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, this allows disentangling periods of simple interdependence from contagion. Third, we analyze the determinants behind interdependent credit risk co-movements and the role of contagion using gravity-type regressions.

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.[14] 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 allows for heterogeneity in the parameters characterizing the underlying correlation process.

The estimation of a GARCH DCC model requires time series with mean zero (see 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

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

where $y_{i,t}$ is the log first difference of the CDS spreads, i.e. $log(CDS_{i,t}) - log(CDS_{i,t-1})$,

[14] 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.

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

$$H_t = D_t R_t D_t \tag{2}$$

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:

$$h_{i,t} = \omega_i + a_i \xi^2_{i,t-1} + b_i h_{i,t-1} \tag{3}$$

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.[15] 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:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha v_{t-1} v'_{t-1} + \beta Q_{t-1} \tag{4}$$

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 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

$$R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2}. \tag{5}$$

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 likeli-

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

hood in two steps. The log likelihood function is given below:

$$\ell = -1/2 \sum_{t=1}^{T} (2log(2\pi) + log|H_t| + \xi_t' H_t^{-1} \xi_t) \tag{6}$$

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

$$\ell(\theta, \phi) = \ell_v(\theta) + \ell_c(\theta, \phi) \tag{7}$$

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).

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 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 only interpret an episode as contagious 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:

$$\rho_{ijw} = d_0 + \sum_{k=1}^{K} d_k \rho_{ijw-k} + q_w dummy_w + \epsilon_{ijw}, \tag{8}$$

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 if correlations behave differently across periods as the definition of crisis versus non-crisis periods remains somehow arbitrary. 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.[16]

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 us to obtain contagion indicators that vary across two dimensions, (i) over time and (ii) across country pairs. This can be exploited in the subsequent gravity-type estimation and delivers a refined measure of contagion.[17]

[16] 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.

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

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 Gravity-type Model

Based on the previous steps, we are able to investigate the determinants of sovereign credit risk co-movements and the channels through which contagion occurs. The dynamic conditional correlation (DCC) matrices give us bilateral measures of sovereign credit risk co-movements ρ_{ijt} between countries i and j. The DCC matrices are symmetric such that $\rho_{ijt} = \rho_{jit}$. For the following analysis, we aggregate the daily co-movements to monthly averages denoted by ρ_{ijm}. 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 of co-movements in sovereign credit risk, we use this bilateral measure as dependent variable in the following regression model:

$$\rho_{ijm} = \mathbf{x}'_{ijm}\,\boldsymbol{\beta} + u_{ijm}, \tag{9}$$

where $\mathbf{x}_{ijm}$ denotes a vector containing the elements for all K explanatory variables for a certain country pair (ij) and time period (m), β is a vector containing the parameters, and u_{ijm} is the error term. The explanatory variables which enter equation (9) do not necessarily have to vary in all three dimensions (i.e., i, j and m). They can be either country pair specific and as such time-varying (ijm-variables) respectively constant (ij-variables) or common to all country pairs and time-varying (m-variables). There might be several unobservables involved. For this reason, a regression model which involves fixed effects can be chosen:

$$\rho_{ijm} = \boldsymbol{\phi}'_{ijm}\,\tilde{\boldsymbol{\beta}} + \lambda_{ij} + \gamma_m + v_{ijm}, \tag{10}$$

where λ_{ij} denotes constant country pair specific effects and γ_m time fixed effects.[18] The cost of estimating a fixed effects regression model is that only the impact of variables which vary across all three dimensions, i.e. the ϕ_{ijm}, can be assessed. In order to check the robustness of our results, we run regressions with and without fixed effects.

The regression models (9) and (10) resemble the gravity equation widely used in the empirical trade literature on the determinants of international trade flows. Gravity equations have also been adopted in other fields where bilateral flows (or stocks) are involved such as bilateral trade in financial assets (see, e.g., Buch, 2003; Portes and Rey, 2005). Of special interest in this literature are the bilateral terms (ij- and ijm-variables) which capture barriers to trade such as transportation (goods trade) or information costs (financial assets trade) depending on the theoretical underpinning. The bilateral terms are proxied by observable variables, among them distance, common language, and common border, or captured by fixed effects.

As we consider bilateral co-movements and not bilateral flow or stock variables, we refer to the applied methodology as gravity-type (as opposed to solely "gravity") regressions. Applications of gravity-type models to stock market correlations can be found in Flavin et al. (2002) and Beine and Candelon (2011). From a theoretical point of view, there is no reason why one should ex ante expect variables that perform well in the empirical trade literature to do the same in the present application. Thus, we divide the explanatory variables into three classes based on their economic interpretation as well as theoretical considerations: Variables that are related to (i) common (macroeconomic) shocks and similarities in economic fundamentals, (ii) direct linkages between countries accounting for interdependence and fundamentals based contagion, and (iii) indirect linkages like herding behavior or market sentiments leading to non-fundamentals based contagion.[19]

(i) Common (macroeconomic) shocks and similarities in economic fundamentals: Common macroeconomic shocks which affect all countries at the same time, such as changes in risk aversion (measured by e.g. the VDAX implied volatility index) or liquidity, are likely to affect the structure of credit risk co-movements in sovereign debt markets. As the creditworthiness of a sovereign is always 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, public debt, and foreign reserves. However, these variables might not only cause interdependence but also lead to fundamentals based contagion due to

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

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

"wake-up calls". This might happen if weak fundamentals in one country make investors aware of structural problems in another country. Financial sector variables are of special interest as one feature of the eurozone sovereign debt crisis is the interdependence between sovereign and bank credit risk (Acharya et al., 2011). For this reason we include similarity measures based on banks' total assets and common portfolio exposures which we approximate by the correlation of bank equity prices.

(ii) Direct linkages: Variables related to direct linkages between countries account for simple interdependence as well as fundamentals based contagion. They comprise linkages associated with the financial and real economy. The financial linkage can be captured by banks' foreign claims. The real linkage can be captured by bilateral trade. Including the banking sector related financial linkage is of great importance due to the strong interdependence between the banking sector and the sovereign and related feedback effects (Bolton and Jeanne, 2011). The intensification of one or more of these linkages between two countries is usually associated with a higher degree of interdependence, which in normal times improves international risk sharing and causes "simple" cross-country interdependence. However, in crisis times stronger linkages also provide channels through which large shocks in one country can be more easily transmitted to another country. In this case, they might thus cause contagion reflected by a significant increase in co-movements.[20]

Contagion through direct linkages can arise in times of crisis in two respects. First, the *strength* of 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. Already the seminal setting presented by Allen and Gale (2000), where countries' banking systems are connected via international interbank deposits, can be seen from this perspective: in normal times, when liquidity shocks are negatively correlated across regions, interlinkages between banks serve risk sharing purposes. These linkages change their role, however, as soon as an unexpected liquidity shock hits one region. The transmission of this shock to other regions might lead to complete default of all banking systems. This has implications for the pattern of credit risk co-movements. Changes in co-movements might be observed, even though sovereign debt markets are not subject to non-fundamentals based contagion like risk panics but simply because existing linkages change their role.

[20] The relation between the degree of market integration 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.

Crucially, using a time-varying co-movement measure allows disentangling simple interdependence from fundamentals based contagion. By interacting our contagion indicator as developed in Section 4.2 with the variables capturing common fundamentals (e.g. similarities in public debt) or direct linkages (e.g. bilateral financial links) which cause simple cross-country interdependence in tranquil times, we are able to account for their (state-dependent) changing role in times of crisis and thus for what we call fundamentals based contagion:

$$\tilde{\rho}_{ijm} = \mathbf{x}'_{ijm}\boldsymbol{\beta} + \mathbf{x}'_{ijm}\boldsymbol{\delta} * CI_{ijm} + u_{ijm} \tag{11}$$

In the regression, this would turn out in a significant effect of the interaction term exceeding the direct impact of the variable alone. As soon as we have controlled for fundamentals based contagion, the remaining part would consequently fall on non-fundamentals based contagion.

(iii) Indirect linkages: From a theoretical point of view, non-fundamentals based contagion is related to concepts such as herding behavior, changes in market sentiments and the occurrence of "bad equilibria" (De Grauwe and Ji, 2012). E.g. Bacchetta et al. (2012) show that risk panics which become apparent given high volatilities of asset prices do not necessarily have to be due to fundamentals but can be self-fulfilling. In a country with weak fundamentals, there might exist a high volatility equilibrium for asset prices. If the jump to the high volatility equilibrium in one country also increases the probability of a jump in another country, this could consequently be understood as non-fundamentals based contagion. Even though these variables are generally not observable, there exist proxies such as countries' stock market volatilities or sentiment indicators. A significant impact of these variables 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.[21] The AR(1) term in the mean equation is mostly positive and

[21] 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

significant. This can be explained by, for example, delayed adjustments in CDS prices (Duffie, 2011). The conditional variance equation shows in general significant coefficients 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.[22]

Pair wise dynamic conditional correlations averaged across country pairs belonging to the same or different country groups are shown in Figure 7. 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 7 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 pattern in the series. 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

a later starting date than data would have been available.

[22] 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.

to ECB interventions in sovereign debt markets. In sharp contrast, correlation series referring to countries belonging to the EU and non EU countries tend to persist at low levels.

For the remaining three groups of country pairs, i.e. combinations with both countries in the core eurozone group, one core and one periphery eurozone country, one eurozone country and a country belonging to the EU but not the eurozone, sovereign CDS spreads show similar co-movement patterns. 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.[23] 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 co-move 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.

[23] Similarly, using a multifactor model, Ang and Longstaff (2011) 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, i.e. significant increases in DCC series, is given by:

$$\rho_{ijw} = d_0 + d_1\rho_{ijw-1} + d_2\rho_{ijw-2} + q_w dummy_w + \epsilon_{ijw}, \tag{12}$$

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 8. 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 Gravity-type Model: Estimation Results

The estimation results of the gravity-type regressions are shown in Table 7. The estimation results of specifications (I) and (II) – the latter including fixed effects – shed light on factors determining the general pattern of sovereign credit risk co-movements. Results for the *global controls* in specification (I) show that higher risk aversion and illiquidity in financial markets are associated with higher credit risk co-movements: the estimated effect of the volatility index and the Euribor-Eonia spread are both positive and significant. As expected, two countries with *similar economic fundamentals* seem to exhibit a higher degree of co-movements based on the significant and positive impact of similarity in GDP. Similarity in foreign reserves and public debt show less evidence for significance. In contrast, the variables associated with similarities of the two countries' banking systems (bank assets and equity prices) have a significant impact on co-movements. This gives a first indication of the strong interconnection between the financial and the public sector which could be observed during the sovereign debt crisis. Results on the impact of *linkages* are mixed. The non-fundamental link measured by the GDP weighted average of countries' stock market volatilities is associated with higher credit risk co-movements. The financial link measured by banks' foreign claims seems to decrease credit risk co-movements. The result is not robust with respect to the inclusion of fixed effects in specification (II) tough. The trade link does not seem to have any impact.

Specifications (III) and (IV) include the interaction terms with the contagion indicator. Including the interaction terms allows investigating the reassessment of economic fundamentals ("wake-up call") and disentangling the role of links during contagious and "normal" episodes. While in normal times, credit risk of two countries which are similar with respect to the amount of public debt co-moves less, this picture changes in times of contagion: Similarity in the amount of public debt leads to higher credit risk co-movements. This provides evidence for the occurrence of wake-up call contagion and the re-assessment of public sector debt as an important determinant of credit risk in crisis times. In contrast, we do not find significant changes regarding the role of common portfolio exposures, proxied by the correlation in bank equity prices, in contagious as opposed to normal times.

Stock market volatility, i.e. our proxy for non-fundamental links, does not seem to have an effect on co-movements during normal times. It increases co-movements significantly when interacted with the contagion indicator tough. This supports the existence of non-fundamentals based contagion. While the variable can only be an (imperfect) proxy, it seems to capture non-fundamentals related to market sentiments and investors' perception.

Evidence for the risk diversification effect of the financial link is weak at this stage of analysis. The financial link is associated with lower co-movements during normal episodes. Its significance is however limited to specifications which do not include fixed effects. As specifications (II) and (IV) also control for arbitrary common global shocks and country-pair specific heterogeneity, we judge these results to be more reliable. Importantly, the overall effect of more intense financial links is positive as indicated by summing up the coefficients on the financial link and the corresponding interaction variable in column (IV). During contagious episodes, the effect of financial links on co-movements thus goes in the other direction. This provides evidence for fundamentals based contagion as the role of linkages appears to change as soon as contagion occurs. Conditionally on contagion, the benefits of risk diversification do not outweigh the cost of shocks being transmitted more easily from one country to the other. Using the values of the point estimates, we can also get an insight into the magnitude of the effect and thus its economic relevance. The overall effect of a one percentage point increase in the financial link on the co-movements appears to be rather small (in specification (IV) the increase is roughly 0.1 percentage point for financial links not being too far away from the average). However, an increase by one standard deviation of the financial link (about 19%) would imply a considerable increase in co-movements by more than 1.9 percentage points. Given that financial links are very likely to change considerably in size precisely during contagious episodes, one can conclude that fundamentals based contagion via financial links matters also in economic terms. The trade link seems to increase co-movements in normal times but decreases credit risk co-movements during contagious episodes. An interpretation for the latter result might be that while risk diversification via financial markets is not possible any longer in crisis times, it might still be possible via bilateral trade.

5.4 Gravity-type Model: Robustness

Table 8 shows that the results of the empirical estimations are robust to the transformation of the dependent variable or changes in the threshold for determining if a contagious episode occurred.[24] Specification (I) applies the Fisher z-transformation on the measure for credit risk co-movements. This mitigates a potentially skewed distribution in correlation coefficients. While the size of the point estimates differs due to the transformation, the picture remains the same with respect to the statistical significance of the estimates. Specifications (II) and (III) show that the main results stay unaltered when computing the contagion indicator based on a lower significance level (1% and 5%, respectively). One exception is wake-up call contagion as the interaction term with public debt now turns insignificant. Results on non-fundamentals and fundamentals based contagion are less robust when the estimation is based on observations after the onset of the sovereign debt crisis (November 2009) as in specification (IV). The interactions with the financial link and stock market volatility are not significant any more. Yet similarities in the amount of public debt conditional on a contagious episode taking place gain in significance compared to the result in Table 7. This result

[24] All specifications are equivalent to specification (IV) of Table 7 as they include fixed effects and the interaction terms.

supports the idea of wake-up call contagion, i.e. investors becoming aware of unsound public finances in similar countries during the debt crisis.

Table 9 only considers a subsample of eurozone countries and presents estimations without and with fixed effects (specifications (I) and (II)). The exchange rate (Euro/USD) is considered as an additional global control variable in specification (III). It is included to control for developments common to all eurozone countries. The results present a more detailed picture of what determines the pattern of credit risk co-movements within the eurozone. Interestingly, the exchange rate is highly significant and a strong euro is associated with lower credit risk co-movements. The main results on fundamentals based variables stay more or less the same. Yet specification (II) does not show any impact of banking sector related variables any more. The changing role of the financial link during normal and crisis times is strongly supported by the results in column (II). Within the eurozone, financial links indeed serve risk diversification purposes in normal times. They increase credit risk co-movements in crisis times tough. This provides strong evidence for fundamentals based contagion as well as feedback effects between the banking and public sector through international links. Furthermore, the results regarding similarities in public debt indicate that wake-up call contagion has taken place within the eurozone.

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, it is to note that - 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 compared to core eurozone 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. Thereby, 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 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 both consider contagion due to direct bilateral links and non-fundamentals based contagion going back to market perceptions. From a policy perspective, disentangling 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 links 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. Second, our results suggest that both common country fundamentals, direct links between countries' banking systems or the membership in the currency union 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. Third, 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.

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Appendix: Figures and Tables

Figure 2: OTC derivatives market - CDS

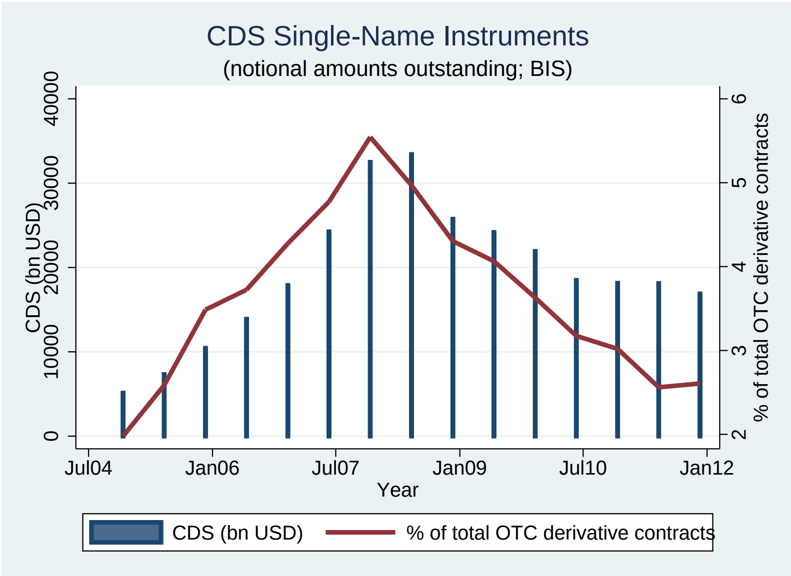

Figure 3: Sovereign CDS market - BIS data

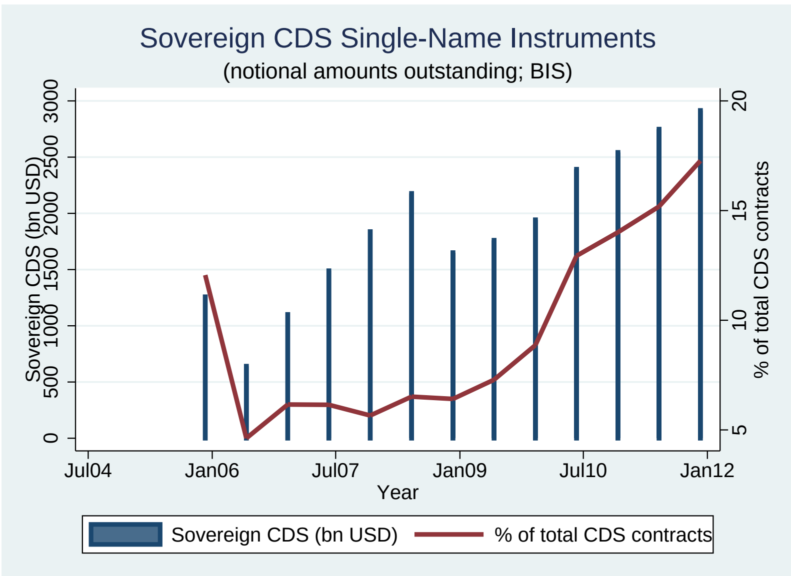

Figure 4: Sovereign CDS market - DTCC data

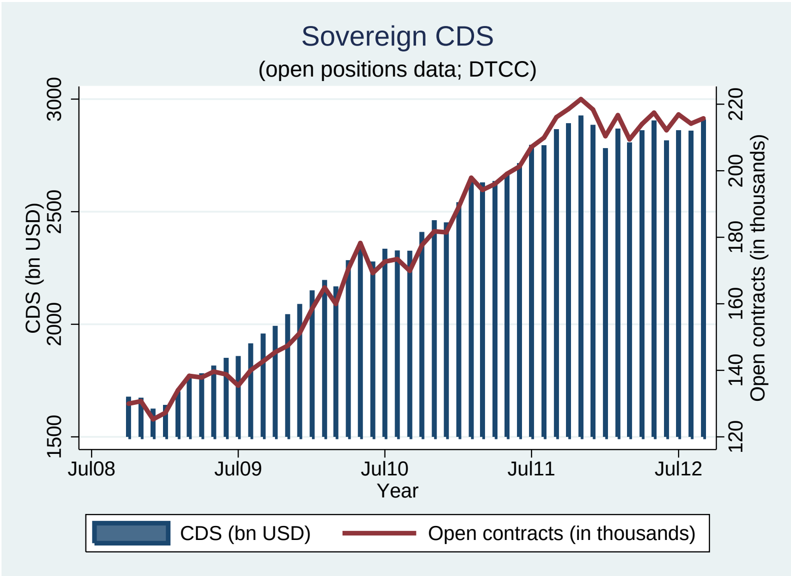

Figure 5: Credit risk in sovereign debt markets (CDS, basis points)

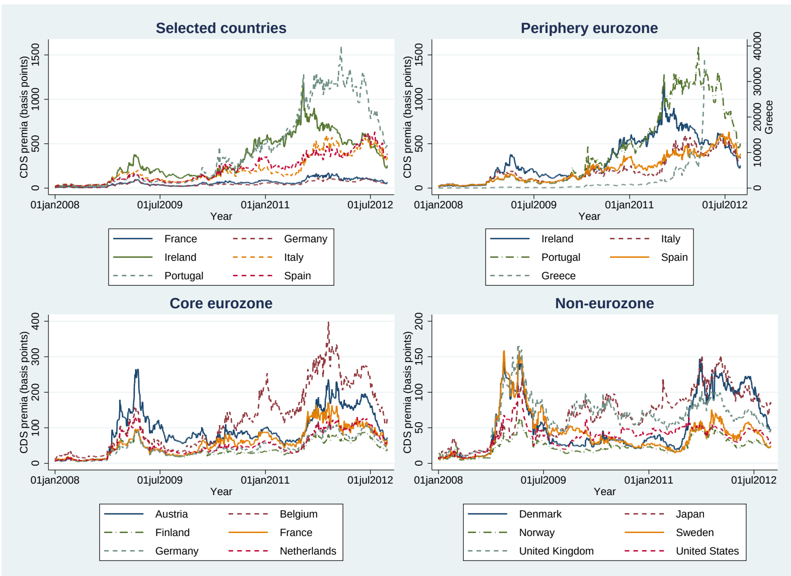

Figure 6: Credit risk in sovereign debt markets (CDS, log difference)

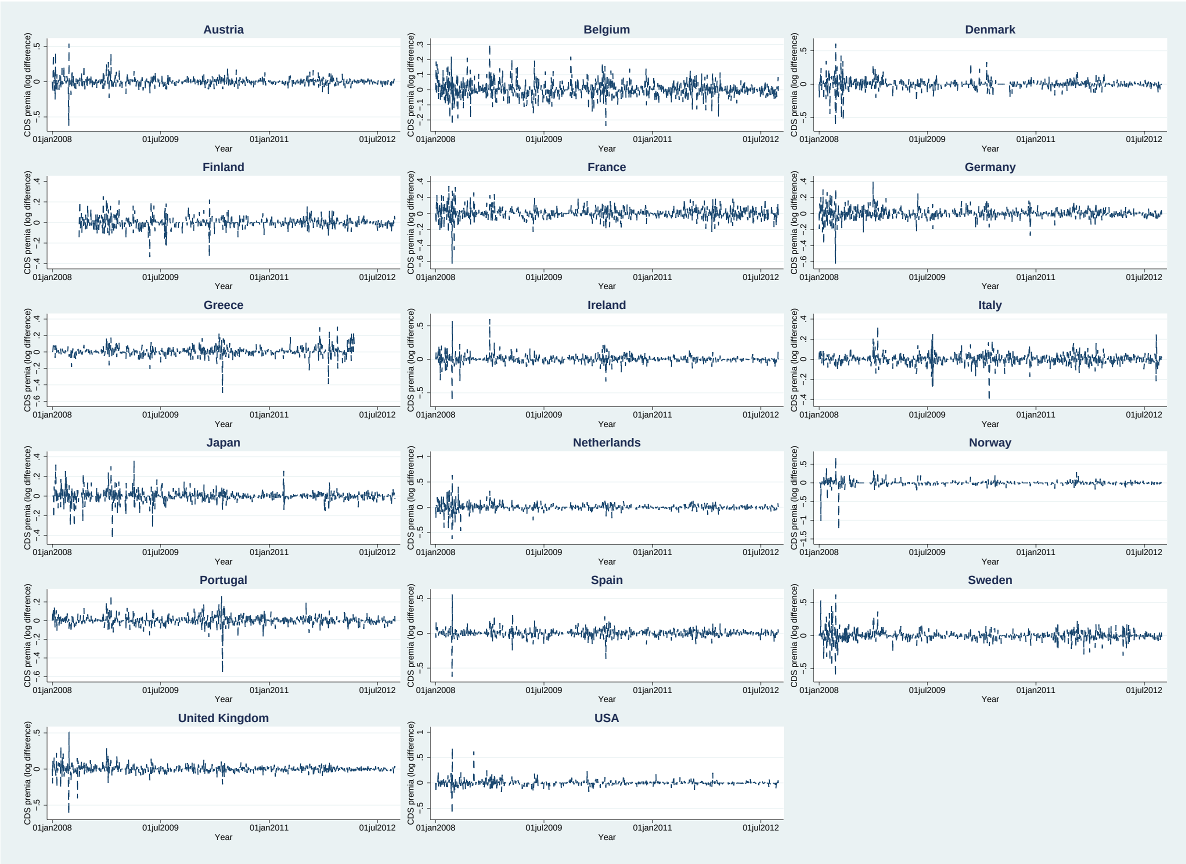

Figure 7: Dynamic conditional correlations by country group

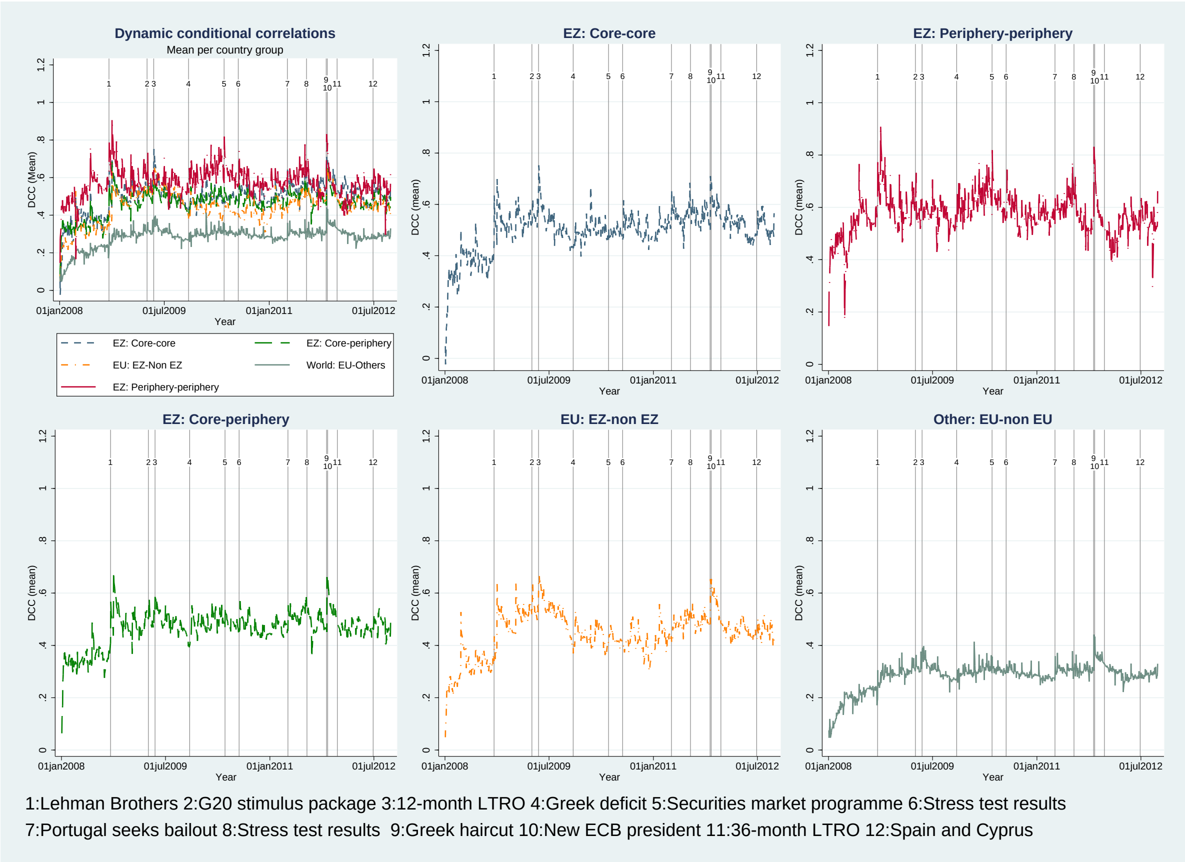

Table 1: Summary statistics: daily 5-year CDS premia (log difference) (2008-2012)

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

Figure 8: Contagious episodes

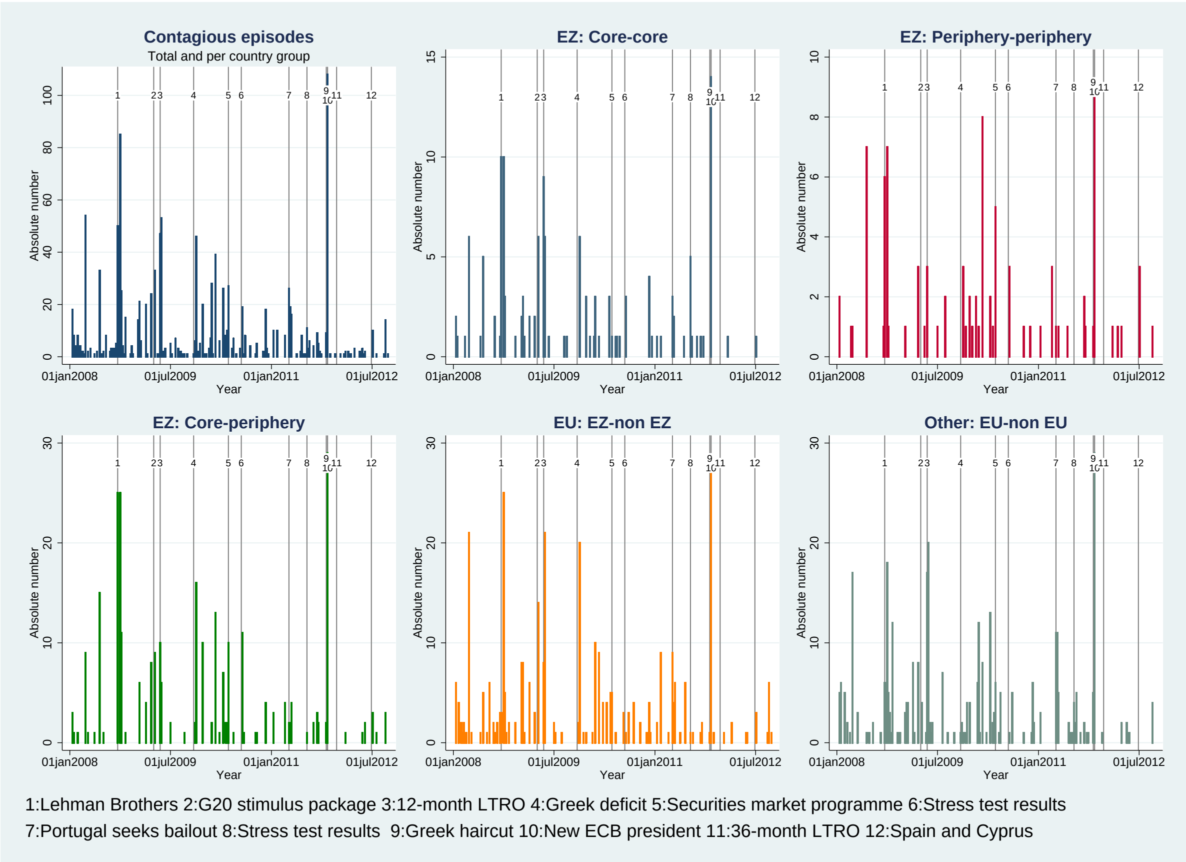

Table 2: Correlation matrix: daily 5-year CDS premia (log difference)

	AU	BE	DK	FI	FR	DE	GR	IE	IT	JP	NL	NO	PT	ES	SE	UK	USA
January 2008 - October 2009																	
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

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			

Table 3: Explanatory variables descriptions and sources: Gravity-type regressions

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	change in sum of log GDP (times 100)	quarterly	Datastream
	Public debt	$-\|X_i - X_j\| \times 100$ with $X_i = \frac{\text{Public debt}_i}{\text{GDP}_i}$ (percent)	quarterly	BIS
	Foreign reserves	$-\|X_i - X_j\| \times 100$ with $X_i = \frac{\text{Foreign reserves}_i}{\text{GDP}_i}$ (percent)	monthly	Datastream
	Bank assets	$-\|X_i - X_j\| \times 100$ 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
Links (ij)	Stock market volatility	GDP weighted average of countries' stock market volatilities	monthly	Datastream
	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

* 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 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
World: EU-Others	-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
World: EU-Others	-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
World: EU-Others	-0.32	0.87	0.30	0.12
Total	-0.32	0.98	0.46	0.15
(from November 2009)				
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
World: EU-Others	-0.30	0.91	0.30	0.12
Total	-0.51	0.97	0.43	0.15

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: Gravity-type regressions: Estimation results

			(I)	(II)	(III)	(IV)
			No FE	$ij + m$ FE	No FE	$ij + m$ 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)
Links	non-fundamental	Stock market volatility	0.0459***	0.0204**	0.0178*	-0.0044
			(0.0087)	(0.0099)	(0.0091)	(0.0093)
	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)
Interaction (× CI)		Public debt			0.0209**	0.0189**
					(0.0095)	(0.0084)
		Bank equity			-0.0156	-0.0135
					(0.0117)	(0.0089)
		Stock market volatility			0.0944***	0.0929***
					(0.0149)	(0.0191)
		Banks' foreign claims			-0.0589	0.1671**
					(0.0666)	(0.0757)
		Trade			-0.1395***	-0.0722***
					(0.0268)	(0.0247)
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}). 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 proxy for non-fundamental links (stock market volatility), the financial link (banks' foreign claims), and the real link (trade). Standard errors are clustered by country pairs. The reported R-squared is the R-squared within. P-values: * < 0.1, ** < 0.05, *** < 0.01.

Table 8: Gravity-type regressions: Robustness I

			(I) Fisher Z	(II) CI (1%)	(III) CI (5%)	(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)
Links	non-fundamental	Stock market volatility	-0.0160	0.0167	0.0049	0.0005
			(0.0251)	(0.0116)	(0.0126)	(0.0124)
	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)
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)
		Stock market volatility	0.2406***	0.0303	0.0798***	-0.0629
			(0.0507)	(0.0223)	(0.0223)	(0.0461)
		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)
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 (I) applies the Fisher z-transformation to the measure for sovereign credit risk co-movements ($\tilde{\rho}_{ijm} = \log(1+\rho_{ijm})/(1-\rho_{ijm})$). The transformed variable is used as dependent variable to mitigate the potentially skewed distribution of correlation coefficients. In specifications (II) and (III), computation of the contagion indicator (CI) is based on lower significance levels of 1% and 5%, respectively. Specification (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 pairs. The reported R-squared is the R-squared within. P-values: * < 0.1, ** < 0.05, *** < 0.01.

Table 9: Gravity-type regressions: Robustness II (eurozone only)

			(I)	(II)	(III)
			EZ	EZ	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)
Links	non-fundamental	Stock market volatility	0.1034***	0.0683*	0.1061***
			(0.0329)	(0.0383)	(0.0322)
	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)
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)
		Stock market volatility	0.0216	0.0497	0.0389
			(0.0321)	(0.0356)	(0.0305)
		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)
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 (I) and (II) are equivalent to specifications (III) and (IV) of Table 7. Specification (III) additionally includes the exchange rate (EUR/USD). Standard errors are clustered by country pairs. The reported R-squared is the R-squared within. P-values: * < 0.1, ** < 0.05, *** < 0.01.