Sectoral dynamics of financial contagion in Europe - The cases of the recent crises episodes

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Abstract

In this paper, we investigate the existence of financial contagion in the European Union during the recent Global Financial Crisis (GFC) of 2007-2009 and the European Sovereign Debt Crisis (ESDC) that started in 2009. Our sample includes sectorial equity indices for 15 countries from 2004 to 2014. We adopt an ADCC-GJR-GARCH model for the time-varying correlations and a Markov-Switching model to identify the lead/lag relationship in crisis transition dates across the countries and the sectors. We assess the patterns of financial contagion by sector and by country. Our results support the existence of financial contagion in all business sectors under the GFC and the ESDC. Financials and Telecommunications are the most affected, while the Industrials and the Consumer Goods the least in each crisis respectively. Stock markets in the Core EU are the most affected in both crises. We find evidence of a non-synchronised transition of all countries to the crisis regime, in both crises. We believe that our results may provide useful insights for investors and policy makers.

Keywords: Contagion • Global Financial Crisis • European Sovereign Debt Crisis • ADCC-GJR-GARCH • Economy sectors

JEL Classification: F36 • G15

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Introduction

The increasing globalization and integration of financial markets facilitates the functioning of a “Single Market” and has therefore been associated with prosperity and economic wellbeing. Nevertheless, at the same time financial integration may facilitate the spread of financial instability across countries and markets, as has been the case during both the Global Financial Crisis (GFC) of 2007-2009 and the European Sovereign Debt Crisis (ESDC), with adverse impact on the relations amongst the member countries of the European Union (EU).

Financial contagion, the phenomenon in which a financial crisis spreads across countries, has received a certain focus over the past two decades. Although no uniformly accepted definition exists for financial contagion, most of the empirical work typically follows the Forbes & Rigobon, (2002) and/or the Bekaert, Harvey, & Ng, (2005) seminal papers. One of the key distinctions in these two approaches is that the former, also dubbed as “shift-contagion”, examines for a significant increase in the cross-market correlation following a crisis event, where the latter emphasizes the role of (economic) fundamentals by attributing the characterisation of contagion only when correlations significantly increase over and above what fundamentals can explain.

In the field of empirical analysis, King & Wadhwani (1990) and Lee & Kim (1993) comprise some of the early work on the issue of financial contagion following the US stock market crash of October 1987. The East Asian crisis of 1997, the “dot.com” bubble of the early 2000s, the GFC of 2007 and the ESDC of 2009 have been used as a reference point to investigate contagion across a variety of countries (Cho and Parhizgari, 2008; Kenourgios, 2014; Naoui et al., 2010; Pappas et al., 2016; Yiu et al., 2010). Most of this research is focused on stock market indices (Chiang et al., 2007), however there are instances where exchange rates (Khalid and Rajaguru, 2007) or bond market data have been used (Coudert and Gex, 2010). Even rarer however are applications pertaining to sectorial equity data, with notable exceptions the studies of Baur (2012), Kenourgios & Dimitriou (2015) and Phylaktis & Xia (2009). All of these studies have some global focus as far as sectorial indices are concerned. For example, Kenourgios & Dimitriou (2015) use sectorial equity indices for six geographical regions (e.g., Developed Pacific, Emerging Asia). In terms of crisis focus, in the Phylaktis & Xia (2009) the data span covers most of the 1990s and early 2000s crises, from the 1992 ERM attacks up to the dot.com bubble. By contrast, Baur (2012) and Kenourgios & Dimitriou (2015) focus on the GFC and/or the ESDC crises.

The aim of this paper is to assess financial contagion across equity markets and business sectors in the EU following the GFC and the ESDC. For this purpose, we adopt a multivariate dynamic conditional correlation model. To identify lead/lag relationships in the crisis transition dates of the featured countries and business sectors we compare the estimated crisis transition dates from a Markov-Switching model to the official timeliness of the GFC and the ESDC.[1] To gauge the magnitude of financial contagion, we regress the conditional correlation estimates on a set of binary variables that identify different periods of the crisis in line with Kenourgios (2014) among others.

We contribute to the literature in two ways. First, we conduct a geographically focused analysis within the EU-15. Previous studies have often included a subset of EU countries and/or had a global focus. This may have been desirable for certain crises (e.g., the GFC) but the ESDC is largely Europe-specific. Furthermore, the ties between EU (and moreover Eurozone) members are much stronger than any non-

[1] Official timeliness of the crises are obtained from the Bank of International Settlements (BIS, 2009) and the Federal Reserve Board (Federal Reserve Board of St. Louis (2009).

EU sample of countries. In this respect, we expect that our statistical results will reveal more clearly the dynamics of a financial crisis. These results, may prove useful to the EU policy makers in terms of policies designed for future events and to investors wishing to ensure proper country and/or sectorial diversification for their portfolios.

Secondly, although other researchers have used sectorial equity indices, we are the first to the best of our knowledge to examine financial contagion in such a comprehensive manner. Specifically, we test for three distinct variants of financial contagion. Namely, within sector (across countries), within country (across sectors) and across country and sectors. The first allows us to examine if the existence, timing and magnitude of contagion differ by business sector. This variant assumes that the transmitter and the receiver of contagion is the same business sector and can classify them according to the resilience they offer to contagion transmission. The second examines how contagion spreads across the different business sectors within a country. Thus, it reveals similarities and differences in the resilience of each sector in each country. The third generalises even further by examining the magnitude of contagion where the transmitter and receiver may both be different countries and business sectors. Following the above analysis, we can derive valuable information for policy makers and investors since we can obtain very detailed dynamics dealing with the economic sectors and countries under investigation.

A preview of our results follows. We verify the existence of financial contagion for all business sectors under the GFC and the ESDC. Financials and Telecommunications sectors are the most affected, while the Industrials and Consumer Goods sectors are the least from the GFC and the ESDC respectively. In addition, all countries experienced financial contagion at varying magnitudes, with those in the Core EU being the most affected in both crises. The timing of the financial contagion differs between the two crises with the Core EU countries being affected first in the GFC crisis, but those of the PIIGS group being first in the ESDC. In both cases, we find evidence of a non-synchronised transition of all countries to the crisis regime.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the data while Section 4 presents the methodology we utilise. Section 5 presents and discusses the results analysis. A final section concludes.

2. Literature Review

Financial contagion may be perceived as the dark side of financial integration. Even though financial integration and contagion are found, to a larger or smaller extent, in a worldwide context, the European Union (EU) is regarded as the main workhorse for such investigations, in part owning to the long tradition of common institutions, rules and regulations and the existence of a monetary union. Financial integration in the EU has been perceived as an essential element for the effective implementation of European Central Bank (ECB) economic policies (ECB, 2010) with beneficial effects upon prosperity and economic wellbeing. By contrast, financial contagion is associated with uncertainty, market downturns and periods of economic, and often, political instability. The appeal and retraction of financial integration and contagion respectively may be evidenced by the expansion of the EU from 15 to 28 country members in the years prior to the GFC but also the increasing appreciation of a retrenchment to national borders policy in the years following the GFC and ESDC.[2]

[2] The popular representation of the hard-working North versus the lazy-South has also received much attention and highlights the lack of uniformity within the EU (Charlemagne, 2010). In June 2016, a referendum in the UK highlighted that continued membership in the EU (also dubbed as Brexit) may not be desirable.

Albeit there is an agreement in the literature about what financial contagion is about, no universally accepted definition of financial contagion exists. Instead, the definition of financial contagion seems to be customised to a handful of research methodologies that have been employed over the years, see Karolyi (2003) and Dungey, Fry, Gonzalez-Hermosillo, & Martin (2005) for some surveys on the topic. For example, contagion has been defined as a rise in the probability that a country experiences a crisis given that a crisis is developing in another country (Eichengreen and Rose, 1999). Alternative definitions suggest that contagion is identified by correlation levels beyond those that may be explained by economic fundamentals. As such, related approaches typically build on factor models where observable or latent fundamental factors and financial contagion tests are applied, see for example (Bekaert et al., 2014, 2005). Forbes & Rigobon (2002) provide yet another definition, that of an increase in cross-market linkages following an economic shock in one nation. This "shift-contagion" definition has the advantage of using correlation values that are intuitively straightforward to interpret and integrate well within the financial integration framework (Bekaert et al., 2009). Furthermore, this definition matches with investor perceptions about risk. When markets drop, investors reduce their exposure to risky assets by rebalancing their portfolios, hence placing more weight on easily available public information (i.e., herding behaviour), while often ignoring fundamentals (Bekaert et al., 2014; Kumar and Persaud, 2002).

The "shift-contagion" definition became quite popular following the innovation of multivariate GARCH models (e.g., ADCC-GARCH) that were capable of producing conditional correlation estimates, while handling a large number of assets, see for example Cappiello, Engle, & Sheppard (2006), Engle (2002), Tse & Tsui (2002). Much of the empirical literature investigates the existence of contagion following some crisis event. For example, Chiang et al., (2007) and Cho & Parhizgari (2008) look into East Asian stock market exchanges and find evidence of contagion after the 1997 Asian financial crisis. Yiu et al., (2010) and Naoui et al., (2010) focus on the 2000 dot.com and the GFC crisis and find evidence of contagion between the US and East Asia. Kenourgios (2014) compares the contagion experience of developed versus developing countries across a wide range of financial crises.

A large part of the literature has focused on financial crises, such as the GFC and ESDC, with several studies investigating contagion and financial linkages in multiple frameworks, such as cross-country (Alexakis et al., 2016; Dimitriou et al., 2017, 2013; Kalbaska and Gatkowski, 2012; Ludwig, 2014; Mollah et al., 2016; Neaime, 2016; Romero-Meza et al., 2015; Suh, 2015; Wang et al., 2017), cross-industry (Kenourgios and Dimitriou, 2015), cross-asset (Aloui et al., 2015; Leung et al., 2017; Tamakoshi and Hamori, 2014a) or some combination. A variety of asset classes has been examined including equity indices (Bhatti and Nguyen, 2012; Dimitriou et al., 2013; Kenourgios et al., 2016; Luchtenberg and Vu, 2015; Pappas et al., 2016; Romero-Meza et al., 2015; Wang et al., 2017; Yang and Hamori, 2013; Ye et al., 2017), CDS spreads (Broto and Pérez-Quirós, 2014; Kenourgios and Padhi, 2012; Tamakoshi and Hamori, 2016, 2014b, 2013a; Wang and Moore, 2012), bond markets (Claeys and Vašíček, 2014; Coudert and Gex, 2010), implied volatility markets (Kenourgios, 2014), exchange rates (Dimitriou and Kenourgios, 2013; Khalid and Rajaguru, 2007; Leung et al., 2017), individual stocks (Tamakoshi and Hamori, 2013b) and commodities (Aboura and Chevallier, 2015; Algieri and Leccadito, 2017; Gozgor et al., 2016) among others.

In our analysis, we focus on cross-country and cross-sector contagion during the GFC and the ESDC. Cross-sectorial contagion has largely been overlooked even though there has been empirical evidence that such factors can pose an important threat to an investor's portfolio during turbulent times (Baca et al., 2000; Baur, 2012; Cavaglia et al., 2000; Kenourgios and Dimitriou, 2015; Phylaktis and Xia, 2009).

Particularly in the EU context, geographical diversification may be of decreasing importance, while sectorial diversification may still be more effective (Eiling et al., 2012). Furthermore, the GFC has placed most of the attention on the financial sector, but contagion through non-financial sectors is also important, particularly during economic downturns (Akhtaruzzaman and Shamsuddin, 2016).

Our paper extends the previous literature by investigating cross-country and cross-sector financial contagion within the EU during the GFC and ESDC crises. In this respect, we adopt and extend Baur (2012) approach by investigating cross-sector contagion. Contrary to Kenourgios & Dimitriou (2015) we do not rely on aggregated geographically-focused sectorial indices but we analyse sectorial equity indices from each EU member country. Our extended sample may be better suited to capture the full magnitude of the ESDC for two reasons; first our sample ranges till 2014 – much later than either Baur (2012) and Kenourgios & Dimitriou (2015), second we include all EU-15 countries.[3]

3. Data and descriptive statistics

We use daily stock market sectorial indices from Dow Jones for 15 European countries covering the period from 1st January 2004 until 31st December 2014, giving a sample size of 2,870 observations. We opted to start from 2004 so as to eliminate any potential spin-off effect from the earlier "dot.com" crisis; hereby focusing exclusively on the Global Financial Crisis (GFC) and the Euro Sovereign Debt Crisis (ESDC). The sectors included are Financials, Consumer Goods, Telecommunications, Health Care and Industrials.

The countries selected are the EU-15 group of countries that participated in the European Union until the 30th of April 2004.[4] These countries are Belgium (BE), Denmark (DK), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Luxembourg (LU), Netherlands (NL), Portugal (PT), Spain (ES), United Kingdom (UK), Austria (AT), Finland (FI) and Sweden (SE). In many databases Belgium and Luxembourg are reported together as one country, whereas no data were available for the Health Care index in Austria. For each Dow Jones stock index, the continuously compounded return is calculated as $r_t = \ln(p_t/p_{t-1}) \times 100$, where p_t is the closing price at day t. To facilitate discussion and to identify similarities across the EU countries we define the three following groups: Core EU (Austria, Belgium/Luxembourg, France, Germany, Netherlands and the UK), PIIGS (Portugal, Italy, Ireland, Greece and Spain) and the Scandinavian (Denmark, Finland and Sweden). The Scandinavian nations share a common history and significant trade linkages. Furthermore, Denmark and Sweden opted not to join the Eurozone. Finally, recent discussions relating to competitiveness, fiscal deficits and public debt problems underpin the PIIGS group of nations, see for example, Gebka & Karoglou (2013).

Table 1 (Panels A-E) presents key descriptive statistics for the Financial, Consumer Goods, Telecommunications and Health Care and Industrials indices for the respective countries. The stylised facts of non-normality of returns and excess kurtosis are verified for all sectors. However, the financial profile of the sectors shows increased heterogeneity in terms of mean return and annualised volatility.

[Table 1 around here]

[3] Baur (2012) and Bekaert et al., (2014) have 2009 as their last year of observations, while Kenourgios & Dimitriou (2015) extend this to 2010. Besides, Baur (2012) includes 25 countries but only 6 are from the EU.
[4] We would have liked to include the whole EU-28 but this was not possible due to data availability issues for some (or all) sectorial equity indices.

Figure 1 shows the evolution of the sectorial equity indices during the sample period. A high degree of alignment is observed across all countries and for all four sectorial indices. The alignment becomes more evident after the start of the financial turmoil (1st August 2007), intensifies further following the collapse of the Lehman Brothers on the 15th of September 2008 and eases of till the announcement of the Greek budget deficit (5th November 2009), where it intensifies again. Interestingly, the Health care sector seems the least affected from either crisis.

[Figure 1 around here]

4. Methodology

The multivariate DCC-GARCH framework, albeit common in financial contagion/linkages studies, is by no means the only approach that has been utilised. For example, Albulescu, Goyeau, & Tiwari (2015), Aloui et al., (2015), Bodart & Candelon (2009), Burzala (2016) use wavelet techniques and co-spectral analysis. In addition, BEKK models (Boamah, 2017; Jin & An, 2016; Koedijk, Kool, Schotman & van Dijk, 2002), cointegration relationships (Boubaker et al., 2016; Sander and Kleimeier, 2003), copulas (Bhatti and Nguyen, 2012; Horta et al., 2010; Kenourgios et al., 2011; Okimoto, 2008; Tamakoshi and Hamori, 2014b; Yang et al., 2015; Yang and Hamori, 2013) and Markov-Switching models (Guidolin and Pedio, 2017) have also been adopted among others. There is evidence from the literature that the DCC-GARCH and Copula approaches are similar in the context of financial contagion (Kenourgios et al., 2011). Wavelet techniques may allow for more complexity, but at the expense of ease of interpretation compared to the DCC approach. For these reasons, and also to make our study comparable to a large part of the literature we use a DCC-GARCH approach. In the following sections we outline the estimation techniques utilised in greater detail.

4.1 The Empirical Model

We consider an asymmetric dynamic conditional correlation (ADCC)-GARCH model, similar to Gjika & Horváth (2013). This model accounts for both the time varying nature and asymmetry of the cross-movement of volatilities. Dynamic Conditional Correlation (DCC)-GARCH models were introduced separately by Engle (2002) and Tse & Tsui (2002), with the two approaches differing in the parameterisation of the conditional correlation matrix. Subsequent extensions of DCC-GARCH models are of two kinds. The first is in the volatility modelling phase where the univariate GARCH has been superseded by models that account for asymmetries (EGARCH, GJR-GARCH), long-memory (FIGARCH) and regime changes (MS-GARCH) to name a few. The second relates to the DCC estimator itself, with the corrected DCC-GARCH model proposed by Aielli (2013) providing an alternative, asymptotically unbiased, estimator.[5] Further extensions include the asymmetric DCC (ADCC) model, which allows for asymmetric effects to impact the conditional correlations Cappiello et al., (2006).

In general, the estimation of an ADCC-GARCH type of model consists of three phases (Engle, 2002). In the first phase, univariate GARCH models are fitted to the asset returns. In the second phase, the unconditional correlation and covariance matrices of both standardised returns and negative standardised returns are estimated. The third phase consists of a quasi-maximum likelihood estimation procedure for the conditional correlation dynamics.

[5] Note though that the bias of the DCC-GARCH estimator is negligible even in large samples (Caporin and McAleer, 2014).

To outline the framework, consider a $T \times 1$ vector of asset returns in which, r_t is normally distributed with mean zero and variance h_t

$$r_t | \mathcal{F}_{t-1} \sim N(0, h_t) \tag{1}$$

$$h_t^2 = \omega + \sum_{i=1}^{p} \boldsymbol{A}_i u_{t-i}^2 + \sum_{j=1}^{q} \boldsymbol{B}_j r_{t-j}^2 + \sum_{k=1}^{r} \boldsymbol{\Gamma}_k u_{t-k}^2 I_{t-k} \tag{2}$$

where $\boldsymbol{\mathcal{F}}_{t-1}$ is the information set at time $t-1$, $I_t = 1$ if $u_t < 0$ and zero otherwise, and the variance process is characterised by a threshold GARCH process. In this case we opt for the widely adopted, see, GJR-GARCH(1,1,1) model of Glosten, Jagannathan, & Runkle (1993), in line with Kenourgios (2014), that allows asymmetrical effects on the conditional variance, and is given by:

$$r_t = \theta_0 + u_t, u_t \sim iid(0, h_t) \tag{3}$$

$$h_t^2 = \omega_0 + a_1 u_{t-1}^2 + \beta_1 h_{t-1}^2 + \gamma_1 u_{t-1}^2 I_{t-1} \tag{4}$$

For the $N \times T$ matrix of asset returns the time-varying covariance matrix $\boldsymbol{H}_t$ is defined as a product of time-varying standard deviations and time-varying correlations as follows:

$$\boldsymbol{H}_t = \boldsymbol{D'}_t \boldsymbol{R}_t \boldsymbol{D}_t \tag{5}$$

where

$$\boldsymbol{D}_t = diag\{h_{1t}^{1/2}, \dots, h_{Nt}^{1/2}\} \tag{6}$$

To incorporate asymmetries in the correlation dynamics Cappiello et al., (2006) modify the conditional correlation equation of Engle (2002) to the one given below:

$$\boldsymbol{Q}_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right) \overline{\boldsymbol{R}} - \sum_{k=1}^{K} g_k \overline{\boldsymbol{N}} + \sum_{m=1}^{M} a_m (\varepsilon_{t-m} \varepsilon'_{t-m}) + \sum_{k=1}^{K} g_k (n_{t-k} n'_{t-k}) + \sum_{n=1}^{N} b_n \boldsymbol{Q}_{t-n} \tag{7}$$

where n_t takes the value 1 when $\varepsilon_t < 0$, zero otherwise, representing therefore bad news. For the matrix $\boldsymbol{Q}_t$ to be positive definite, a set of restrictions is imposed. These restrictions require that: i) $a_m > 0$; ii) $b_n > 0$; iii) $\tau_k > 0$; iv) $\sum_{m=1}^{M} \alpha_m + \sum_{n=1}^{N} b_n + \eta \sum_{k=1}^{K} \tau_k < 1$ and $\eta =$ maximum eigenvalue$[\overline{\boldsymbol{R}}^{-1/2} \overline{\boldsymbol{N}} \overline{\boldsymbol{R}}^{-1/2}]$ is estimated from the data. A rescaling of $\mathbf{Q}_t$ ensures that the correlation matrix is well-defined with unitary values along the main diagonal and with each off-diagonal element ranging in absolute value between zero and one (Silvennoinen and Teräsvirta, 2008). The formula for the rescaling of correlations is:

$$\boldsymbol{R}_t = (\boldsymbol{I} \circ \boldsymbol{Q}_t)^{-1/2} \boldsymbol{Q}_t (\boldsymbol{I} \circ \boldsymbol{Q}_t)^{-1/2} \tag{8}$$

where $\boldsymbol{I}$ is the identity matrix and $\circ$ denotes the Hadamard product.

For the multivariate part of our setting (the univariate is described in the next section), we adopt an ADCC (1, 1, 1), following Gjika and Horváth (2013) among others. This is given by:

$$\boldsymbol{Q}_t = (1 - a - b)\overline{\boldsymbol{R}} - g\overline{\boldsymbol{N}} + a(\boldsymbol{\varepsilon}_{t-1} \boldsymbol{\varepsilon}'_{t-1}) + g(\boldsymbol{n}_{t-1} \boldsymbol{n}'_{t-1}) + b\boldsymbol{Q}_{t-1} \tag{9}$$

4.2 Statistical analysis of ADCC behaviour during the crises

To structure our hypotheses, we modify the testing framework of Baur (2012) and Kenourgios & Dimitriou (2015) to our aims and objectives. In particular, assuming that financial contagion can spread both across countries and business sectors, we define the following three variants. We dub these as cross-country, within-sector (Variant I), within-country, cross-sector (Variant II) and cross-country, cross-sector (Variant III). The first variant examines if financial contagion evidence varies by business sector. This would identify the business sectors that act as the best/worst conduits in transmitting financial contagion across countries. The second variant investigates how contagion spreads across business sectors, within the same country. As the business sectors across the EU countries may share different dynamics, this variant allows us to identify where cross-sector financial contagion resilience is greatest/lowest. As the first two variants restrict the analysis by holding *either* the sector *or* the country constant; the third variant generalises this by allowing *both* the country *and* the business sector to vary at the same time. Financial contagion between the Telecommunication equity indices of France and Italy would be an example of Variant I. The second variant examines contagion evidence from the Financials equity index of Italy to the Telecommunications equity index of Italy. The link between the Financials equity index of France and the Telecommunications equity index of Italy falls under Variant III.

Our testing approach is built on a regression framework where the dependent variable is the appropriate conditional correlation estimate from the ADCC-GJR-GARCH stage. The explanatory variables are seven dummy variables equal to one for each phase of the crises and zero otherwise according to the period identification explained in a previous section. Using these dummy variables allows identifying which of the phases, across the stable and turmoil periods, exhibit financial contagion for the indices examined. In all three variants of financial contagion our testable hypotheses relate to an increase in the dynamic conditional correlation estimates. Hence the statistical significance for the correlation across the identified periods boils down to t-test statistics where rejection of the null hypothesis (H_0) over the one-sided alternative (H_1) would give statistical evidence in favour of financial contagion. The following equation is estimated:

$$\rho_{ij,t} = c_0 + \varphi\rho_{ij,t-1} + \sum_{k=1}^{7} d_k dum_{k,t} + \varepsilon_{ij,t} \tag{10}$$

where $\rho_{ij,t}$ is the pairwise conditional correlation between different indices, the dummy variables $dum_{k,t}$ $\forall\, k = 1, \dots, 7$ correspond to the four phases of the GFC and the three phases of the ESDC, $\rho_{ij,t-1}$ is a first order autoregressive term and $\varepsilon_{ij,t}$ is the standard stochastic error term. The equation is estimated using maximum likelihood and Newey-West robust standard errors.

4.3 Turmoil period identification

Turmoil period identification typically follows either an economic approach which is based on major economic and financial events (Forbes and Rigobon, 2002) or a statistical approach where endogenously identified structural breaks on the series of interest would give evidence of a transition to a crisis period (Boyer et al., 2006; Rodriguez, 2007; Tamakoshi and Hamori, 2014c). Each comes with advantages and disadvantages. For example, with the economic approach it may be unrealistic to assume that one event is equally applicable to all examined countries at the same point in time. Similarly, there is an abundance of statistical methods that can identify regimes in a financial times series that include but are not limited to smooth transition autoregressive models (SETAR) (Teräsvirta, 1994), Markov-Switching models (Hamilton, 1994) and structural break-point tests (Bai and Perron, 2003).[6] Therefore some researchers opt to do a combination of an economic and a statistical approach (Kenourgios and Dimitriou, 2015; Pappas et al., 2016). In this study we mainly rely on an economic identification but we use a Markov-Switching model to compare and contrast the differences between the economically defined crisis transition dates and those estimated from the Markov model across the countries and the sectorial indices, following Pappas et al., (2016).

According to the Bank for International Settlements (BIS, 2009) and the (Federal Reserve Board of St. Louis (2009) the GFC is separated into four phases. Phase 1 starts on the 1st of August 2007 and ends on the 15th of September 2008, termed the "initial financial turmoil". Phase 2 spanning from 16th September 2008 until 31st December 2008 is a period of "sharp financial market deterioration". Phase 3 is termed as "macroeconomic deterioration" (1st January 2009-31st March 2009) and phase 4 as "stabilization and tentative signs of recovery" from 1st April 2009 onwards. The ESDC is identified based on timelines from the European Central Bank (ECB) and Reuters and summarized by Kenourgios (2014). Phase 1 dates from 5th November 2009 until 22nd April 2010 including the Greek budget deficit announcement and the sharp increase of European sovereign risk. Phase 2 (23rd April 2010-14th July 2011) begins before the Greek bailout in May 2010 when the country requested bailout funds from the Eurozone and the IMF. Phase 3 (15 July 2011 onwards) initiated when European authorities published the banking stress tests and other European countries (i.e., Italy) announced austerity measures.

Markov-switching models, introduced by Hamilton (1994), permit the endogenous estimation of crisis dates, while determining the prevalence of one of two regimes[7]; a tranquil, relatively stable regime of the economy and a turbulent one that intuitively corresponds to a crisis regime. Mandilaras & Bird (2010) use a Markov-switching in a VAR setting to detect contagion effects in the Exchange Rate Mechanism (ERM) for 9 countries over the period 1978 - 1993. Baele (2005) finds that volatility spillovers to 13 European stock markets - from within the EU and the USA over the period 1980-2001 - have been intensified during the crisis regimes, which are identified via a Markov-switching model.

A Markov-Switching set-up allows transition probabilities to be estimated, from one state of the economy to another.[8] Markov-Switching models rely on the data to identify the timing of the shift.[9] Typically a latent state variable (s_t) is used to denote which of the M states the economy is in period t with $s_t = m\,;\ m = 1, \dots, M$. In our case the Markov-Switching model assumes the existence of two regimes ("calm" and "turmoil") based on the conditional volatility series; see equation (4). Upon the identification of the two regimes, we compute the synchronisation variable (Sync), in line with Pappas et al., (2016) as follows:

$$Sync_{i,m} = T_{C_{i,m}} - T_{C_{bench}} \tag{11}$$

[6] Several studies have suggested alternative techniques to tackle effectively the same problem. For example, Olbrys & Majewska (2014) divide market states into "up" and "down" markets in an attempt to assess the timing of crisis periods for the Central and Eastern Europe stock markets. Dividing the volatility series according to the timing of structural breaks prior to testing for financial contagion is followed in Blatt, Candelon, & Manner (2014).
[7] Markov-switching models can be estimated for more than two regimes. However, as the number of regimes increases the computational burden gets more pronounced without a clear benefit in terms of interpretation.
[8] The Markov-Switching model of Hamilton (1994) belongs to the family of non-linear models which includes SETAR (Tong, 1995) and LSTAR models (Teräsvirta, 1994). For a broader discussion of these models the reader is directed to (Tsay, 2010).
[9] Strictly speaking, a Markov-switching model employs a state variable which is governed by a first-order Markov chain; thus leaving no room for explanatory variables. The more generic time-varying transition probability models may include explanatory variables to determine the regime of the economy at the cost, however, of greater complication (Filardo, 1994).

where i denotes the nation, m denotes the business sector, T_{C_i} denotes the crisis transition date for each nation and $T_{C_{bench}}$ corresponds to the crisis benchmark date. Positive (negative) values indicate a lag (lead) in the transition, relative to the benchmark date for the particular country/business sector.

5. Results and discussion

5.1 ADCC-GJR-GARCH results

Table 2 reports the estimated coefficients, standard errors, goodness-of-fit statistics for the univariate parts of the ADCC-GJR-GARCH model estimated for each country. Panel A reports the statistics for the Financials equity indices, while Panels B-E repeat for the sectors of Telecommunications, Health Care, Consumer Goods and Industrials respectively. The volatility of most of the indices (Panels A-E) displays a high persistence since the sum of the estimated ARCH and GARCH (α_1+β_1) coefficients in each variance equation is close to unity. The leverage terms γ_1 are positive and statistically significant, suggesting that the volatility of all equity indices exhibits asymmetric responses to good and bad news. Moreover, the impact of the bad news ($\alpha_1 + \gamma_1$) is greater in magnitude compared to the good news (α_1), for the Health Care, Telecommunications, Industrials and, particularly, the Financials sectors. Interestingly, the volatility of the Consumer Goods sector appears more sensitive to positive shocks; a potentially interesting finding for portfolio managers. The parameters for the ADCC model are statistically significant and non-negative, which justifies the appropriateness of the ADCC-GJR-GARCH model.[10]

[Table 2 around here]

5.2 Financial contagion

5.2.1 Variant I: Cross-country within-sector financial contagion

Table 3, Panels A-E, present the estimated coefficients and standard errors for equation (10) associated with cross-country within-sector financial contagion across the phases of the GFC and the ESDC. The table also reports a battery of statistical significance tests that assess the overall statistical significance of the dummy variables and two key subsets of them, one related to the GFC and another to the ESDC. Whether the shift in the conditional correlation at the peak of the GFC and the ESDC crises is significantly different is assessed via a t-test. The logarithmic change between the corresponding coefficients is also reported with positive values indicating that the ESDC has been the most pronounced. Panel A, focuses on the contagion effects between the Financials equity indices, while Consumer Goods, Telecommunications, Health Care and Industrials are reported in Panels B-E respectively.

[Table 3 around here]

[Figure 2 around here]

The results (see also Figure 3) verify that financial contagion is evidenced at varying intensities, if at all, across the five examined business sectors. On average, financial contagion during phase 2 of the GFC is the strongest in Financials (1.21% increase), followed by Consumer Goods (0.90% increase), Telecommunications (0.78% increase), Health Care (0.23% increase) and Industrials (0.18% increase).

[10] These results are omitted for brevity but they are available on request.

The financial contagion associated with the ESDC (phase 2) both stronger in magnitude and impacts the business sectors in a different manner compared to the GFC. In particular, Telecommunications are the most affected (2.28% increase), followed by Financials (2.01% increase), Health Care (1.69% increase), Industrials (1.27% increase) and Consumer Goods (0.45% increase). Nevertheless, in both cases the Financials and Telecommunications sectors proved to be the most affected. This is not an unanticipated result. Financial sector is expected to be strongly affected by financial crisis since it is highly exposed as it is linked with all other industries through the financial business of lending. Thus, it receives quickly the negative effects of a financial crisis because of the nature of its business, which is further aggravated by the derivative operations. On the other hand, Telecommunications is the most heavily leveraged industry (see also Table 4) and it is well known that leverage may aggravate financial losses. In addition, financing costs exceed the income generated by the leveraged asset, due to the volatile demand and the rapid technology changes. In particular, the Telecommunications sector is characterized by large investments in assets which, however, become quickly obsolete due to rapid technology changes. Consequently, investors in this hi-tech sector are mainly drawn by short-term return prospects, with little emphasis on longer-term prospects, which may contribute, in part, to the observed significant contagion effect. The above leverage effect in combination with the size of the Telecommunications sector, as seen again in Table 4, may result to the estimated sensitivity of this sector to the financial crisis.

[Table 4 around here]

Certain country group pairs are more affected by financial contagion of specific business sectors. For example, financial contagion between the PIIGS / Core EU country groups is manifested for four out of the five sectors, in the case of the GFC, and all sectors in the ESDC case, at varying intensities. In particular, during phase 2 of the GFC the correlation between these two groups increases by 1.47% for the Financials sector, with the other sectors showing more muted evidence as highlighted by the increases of 1.18%, 0.94% and 0.48% for the Consumer Goods, Telecommunications and Health Care respectively. The same country pair during phase 2 of the ESDC records correlation gains of 2.42%, 2.15%, 1.39%, 1.34% and 0.60% for the Financials, Telecommunications, Industrials, Health Care and Consumer Goods sectors respectively. The Consumer Goods and Industrials sector, in line with expectations are the least affected sectors during either crisis (Heaton, 2010).

The remaining two country group pairs, namely Core EU-Scandinavian and Scandinavian-PIIGS broadly confirm these conclusions apart from the lack of contagion evidence for the Health care sectors between either Core EU / Scandinavian or Scandinavian / PIIGS groups during the GFC crisis, indicating the relevant robustness of this sector to financial crises. This may be related to the counter cyclical response of health expenditure to the GFC, where health expenditure was maintained in spite of the GFC’s severity (Keegan et al., 2013). Many countries however cut back on health related expenditure during the ESDC, see for example Ó Cinnéide & Considine (2010) for a case study of Ireland and Keegan et al., (2013) for Europe.

Overall, our results verify that Financials and Telecommunications are the most affected business sectors during the GFC and ESDC respectively. Investments in the Industrials are relatively safe from financial contagion owing to financial crises, but not recessions; in the latter the Consumer Goods sectors appears to be the least affected. However, no business sector is immune to financial contagion from any type of crisis.

5.2.2 Variant II: Within-country cross-sector financial contagion

Table 5, Panels A-C, present the estimated coefficients and standard errors for equation (10) associated with within-country cross-sector financial contagion across the phases of the GFC and the ESDC. The table also reports a battery of statistical significance tests that assess the overall statistical significance of the dummy variables and two key subsets, one related to the GFC and another to the ESDC. Whether the shift in the conditional correlation at the peak of the GFC and the ESDC crises is significantly different is assessed via a t-test. The logarithmic change between the corresponding coefficients is also reported with positive values indicating that the ESDC has been the most pronounced. Panel A, focuses on the contagion effects between the Financials and each of the Consumer Goods, Health Care, Telecommunications and Industrials sectors for the Core EU, with Panels B and C repeating for PIIGS and Scandinavian respectively.[11]

[Table 5 around here]

[Figure 3 around here]

The results (see also Figure 4) support the existence of financial contagion for all three country groups. This is verified for both the GFC and the ESDC crises, albeit during the latter with a higher magnitude. In particular, the average correlation increases by 0.45% and by 1.20% for the GFC and ESDC respectively. The Core EU country group was the most severely affected by financial contagion during both crises, with an average correlation increase of 0.66% and 1.40% for GFC and ESDC respectively. By contrast, the PIIGS and the Scandinavian have been those the least affected by the GFC and the ESDC respectively.

Cross sector differences reveal that the Industrials are generally the least affected in the Core EU and the Scandinavian but not in the PIIGS, a finding verified for both crises. More evidence for sectorial heterogeneity across the country groups is evident during the ESDC. Specifically, the Health Care in the Core EU is about six times more affected compared to the Scandinavian group.

Overall, the results from the second variant of financial contagion show that all country groups were affected by financial contagion in both the GFC and ESDC crises. Albeit it may be expected that some sectors would be more affected than others, the patterns we unveil do not conform to some standard, which poses additional difficulties for market participants.

5.2.3 Variant III: Cross-country cross-sector financial contagion

Table 6, Panels A-D, present the estimated coefficients and standard errors for equation (10) associated with cross-country cross-sector financial contagion across the phases of the GFC and the ESDC. The table also reports a battery of statistical significance tests that assess the overall statistical significance of the dummy variables and two key subsets, one related to the GFC and another to the ESDC. Whether the shift in the conditional correlation at the peak of the GFC and the ESDC crises is significantly different is assessed via a t-test. The logarithmic change between the corresponding coefficients is also reported with positive values indicating that the ESDC has been the most pronounced. Panel A, focuses on the contagion effects between the Financials and the Consumer Goods sectors, with Panels B, C and D focusing on the contagion between Financials and Health Care, Telecommunication and Industrials sectors respectively.[12]

[11] One sector in these bivariate measures is the Financials as it has received prominent attention due to the Global Financial Crisis.

[12] Each panel examines contagion in a two-way manner; that is contagion from Financials to Consumer Goods and Consumer Goods to Financials. For brevity, we have analysed those equity indices pairs where one sector is the Financials.

[Table 6 around here]

[Figure 4 around here]

Visual inspection of Figure 5 shows how financial contagion affected different sectors and countries, while allowing an easy comparison between the GFC and ESDC. The convention we follow in this figure is that in each country pair, the first country group is represented by the Financials sector, while the second varies between Consumer Goods (C), Health Care (H), Telecommunications (T) and Industrials (I). The figure itself is split into four quadrants, with the top-right being the Consumer Goods (according to the second country group in a pair), then moving clockwise with Health Care, Telecommunications and Industrials. The two crises are represented as different lines. A convex line in a quadrant would imply sectorial homogeneity across the country groups.

For example, financial contagion in the Telecommunications quadrant during the ESDC has a more pronounced effect across the country groups than during the GFC. By contrast, the impact of the GFC on the Telecommunications has had a more uniform effect across the country groups than in Health Care.

5.3 Synchronisation of the crisis phases

Table 7 presents the estimated crisis transition dates and the lead/lag relationship (Sync) of the respective phases of the two crises as the latter have been identified in the timeline of Federal Reserve Board of St. Louis (2009) and BIS (2009) and analysed in an earlier section.[13] As evidenced from the previous section where most transitions to a crisis regime were associated with the 2nd phase of the GFC and the 2nd and 3rd phases of the ESDC, we compare the Markov-estimated transitions dates to these three guideline dates. The Sync variable is in line with Pappas et al., (2016) and gauges the synchronicity of the transition into a crisis regime of the countries. Synchronicity of transition in/out of crisis is an important feature for policy makers and investors, as highlighted in (Tamakoshi and Hamori, 2014c).

[Table 7 around here]

In the GFC case most of the countries of the Core EU and Scandinavian groups show a synchronised transition into a crisis regime, approximately 5 days after the collapse of Lehman Brothers. Only exception is Germany which follows around 13 days later, possibly due to the country's stronger economic position. By contrast, the PIIGS are neither synchronised nor they follow suit. The larger economies within the PIIGS group, Italy and Spain appear more synchronised with their Core EU partners as indicated by the 5-day lag. However, Portugal and Greece are affected at a 20 and a 28-day lag respectively; a fact that could be associated with the lower trading activity in their stock markets and/or relative size of these economies.

By contrast, during the ESDC crisis, the PIIGS are the countries that are affected the earliest, yet not fully in synchronisation due to the different nature of the problems that were brought to surface. For example, Ireland appears to be off-sync compared to the other PIIGS members possibly due to the banking nature of the problems it faced. A period of rapid economic growth reliant on a property bubble and fuelled both by the foreign direct investments and the abundance of credit by local banks has been

[13] The $Sync_{i,m}$ metric is computed for all five business sectors and average values are reported in Table 7 and discussed in this section.

the main driver behind Ireland's financial crisis experience (Whelan et al., 2016). By contrast, in countries like Portugal, Greece, Italy and Spain fiscal deficit, soaring public debt and decreasing competitiveness have been the main drivers.

In the first phase of the ESDC, investor sentiment is largely unaffected as evident by the timing of the first estimated crisis transition date during the ESDC period that does not occur till the 29th of April 2010 (which is well into the 2nd phase of the ESDC), with Portugal being the first to be affected, followed by Greece and Spain on the 5th of May. Around six months elapsed since the announcement - on the 20/10/2009 - that the Greek budget deficit was more than four times than that permitted till Greece officially asked for the EU/ECB/IMF (Troika) rescue mechanism on the 23/4/2010. During this period the severity of the upcoming debt crisis was largely underestimated or it was largely believed that the problems would be contained within Greece. It quickly turned out that the rest of the south-EU countries were in a similar situation with worsening fiscal deficits. The tip point was on the 2nd of May 2010, when the $110 billion loan package at preferential interest rates was entered into; thus being the first time that a monetary value had been assigned to the ESDC. Amidst these developments, stock markets in the PIIGS enter into a crisis regime. The Core EU and Scandinavian countries were affected a week later when the $750 billion European Financial Stability Facility (EFSF) was deemed necessary to prevent contagion to other European countries by the unveiling sovereign debt crisis to which Greece, Portugal, Italy and Spain were the "weakest links". Ireland has been relatively unaffected by the bulk of these developments due to the banking nature of its problems up until 21st of November 2010 when it officially asked for support from the EFSF mechanism as the costs of bank restructuring had turned out to be much larger than anticipated, and consequently enters the crisis regime with a significant lag relative to the rest of the PIIGS.

The start of the third phase of the ESDC is governed by the second bailout deal for Greece of an extra $109 billion and discussions for a significant contribution from private sector bondholders. Financial markets are sceptical about the successful completion of the private sector involvement and whether that would be sufficient to put Greece back on track. However, the variability in the Sync variable during the third phase of the ESDC shows that synchronised crisis transitions in the EU are no longer the case. This could be attributed to further developments at the south-EU states where Portugal, Spain and Italy realise that there is limited scope for a generalised solution[14] to the European Sovereign Debt / Low Competitiveness problem; hence each of these troubled countries should rely on their own means and biparty negotiations with European and international institutions (e.g., EFSF, IMF). At the same time the violent reactions to the austerity measures in Greece coupled with negative EU sentiment and/or the occasional break down of negotiations between Greek authorities and the Troika increased in frequency; thus distancing Greece further from either the rest of the PIIGS or the remaining EU countries. The latter, namely the Core EU and Scandinavian countries do not react in a uniform manner, in line with the disparity of political approaches about a solution to the ESDC crisis. The financially stronger economies of Germany and Netherlands are affected with a larger delay compared to France, whose debt-to-GDP ratio is worryingly increasing (Voss, 2011). By contrast, the UK that is not part of the Eurozone does not show any reaction to any of the ESDC phases.

6. Conclusion and Policy Implications

[14] Within the US and the UK, there are inter-regional permanent fiscal transfers that are non-existent within the Eurozone. The European Financial Stability Facility (EFSF) and the European Stability Mechanism (ESM), two institutions that would allow the transfer of funds between EU nations for the short and long-term stability respectively came into force in 2013.

Financial contagion is an important aspect within the financial literature that typically examines the international cross-market linkages following a crisis event. In this paper we investigate the impact of the most recent Global Financial Crisis (GFC) and European Sovereign Debt Crisis (ESDC) on the stock markets of the EU-15. We use sectorial equity indices over the 2004-2014 that represent the Financials, Consumer Goods, Telecommunications, Health Care and Industrials sectors. Our methodology utilises a multivariate ADCC-GJR-GARCH models to estimate dynamic conditional correlations, while a Markov-Switching model is used to identify the crisis transition dates for each market in each crisis. With regards to the financial contagion specification, we follow Forbes & Rigobon (2002) but we adjust our framework to cater for the sectorial data. In particular, we allow for three variants of financial contagion. The first looks at each business sector in isolation, but across countries. The second, focuses on specific countries, but across sectors. A third relaxes the former restrictions by looking at financial contagion cross-country and cross-sector at the same time.

Our results show that the timing of the financial contagion differs between the GFC and the ESDC crises. The Core EU countries are affected first in the GFC crisis, but those of the PIIGS group are affected first in the case of the ESDC. In both cases, we find evidence of a non-synchronised transition of all countries to the crisis regime. With regards to financial contagion, our results confirm its presence for all business sectors under the GFC and the ESDC. Financials and Telecommunications are the most affected, while the Industrials and Consumer Goods sectors are the least affected during the GFC and ESDC respectively. In addition, all countries experienced financial contagion at varying magnitudes, with those in the Core EU being the most affected in both crises.

The results of our study will be of a certain interest to investors and policy makers. Financial contagion has a damaging impact on portfolio diversification. According to our contagion results, although it is expected that some sectors would be more affected than others, the patterns we unveil neither conform to some pre-set standard nor are identical across the two crises. This may pose additional difficulties for market participants that wish to diversify geographically and/or by sector. Both the timing and the nature of the crisis are important to investors wishing to utilise the safest countries/sectors in their portfolios. “Thematic” portfolios which focus on specific countries and/or sectors might turn out to be particularly risky. In terms of policy implications, we believe that it is important for policy makers to ensure that the financial system is in line with economic sustainability. This is the essence of the Final Report by the EU High-Level Expert Group on Sustainable Finance, which suggests that the European Supervisory Authorities (ESAs) must promote sustainable finance, while ensuring financial stability (European Commision, 2018). Hence, policy makers need to work together with the investment community and promote long-term investment strategies, particularly for sectors (besides Financials) that are known to be particularly sensitive to financial contagion, such as Telecommunications.

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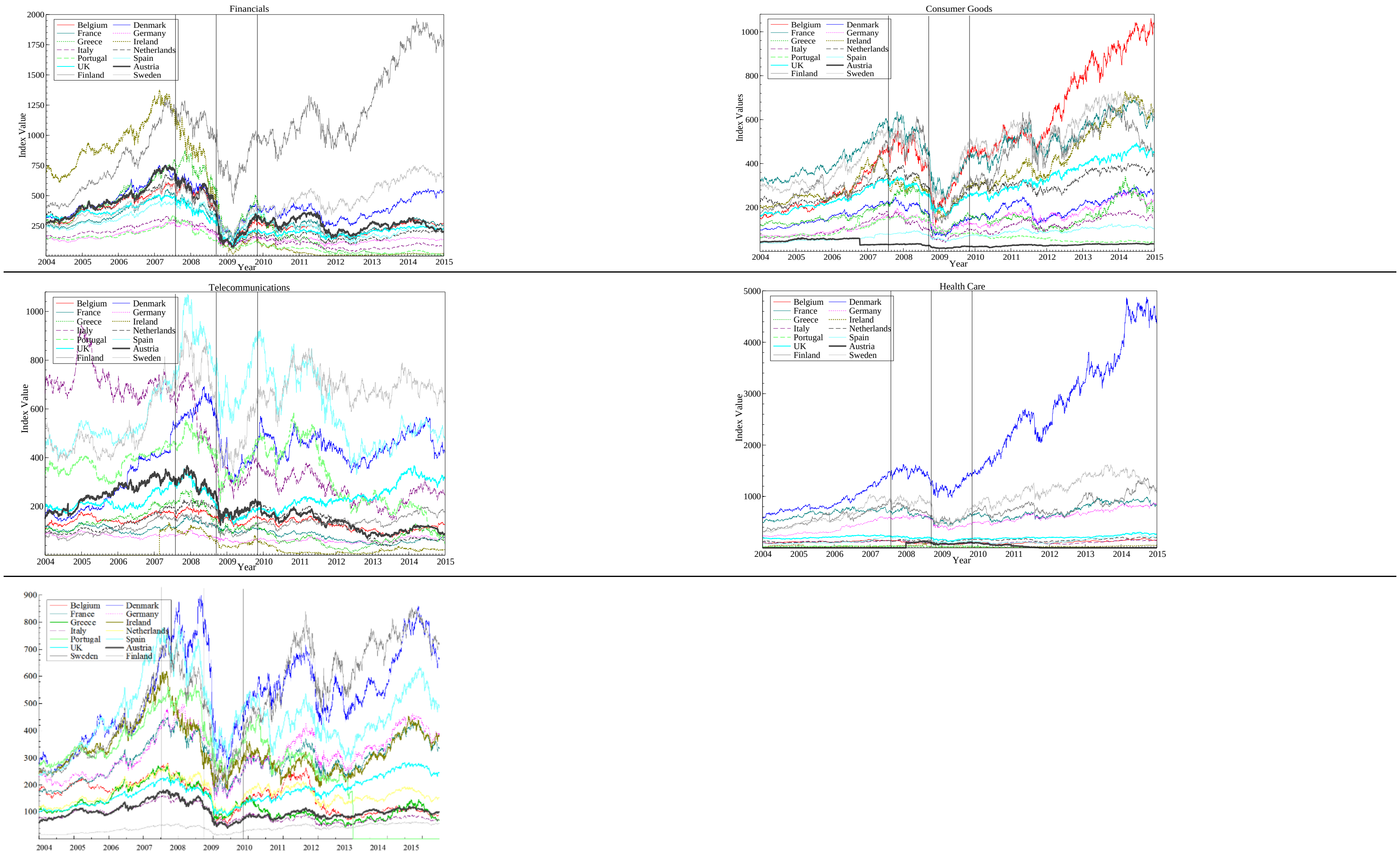
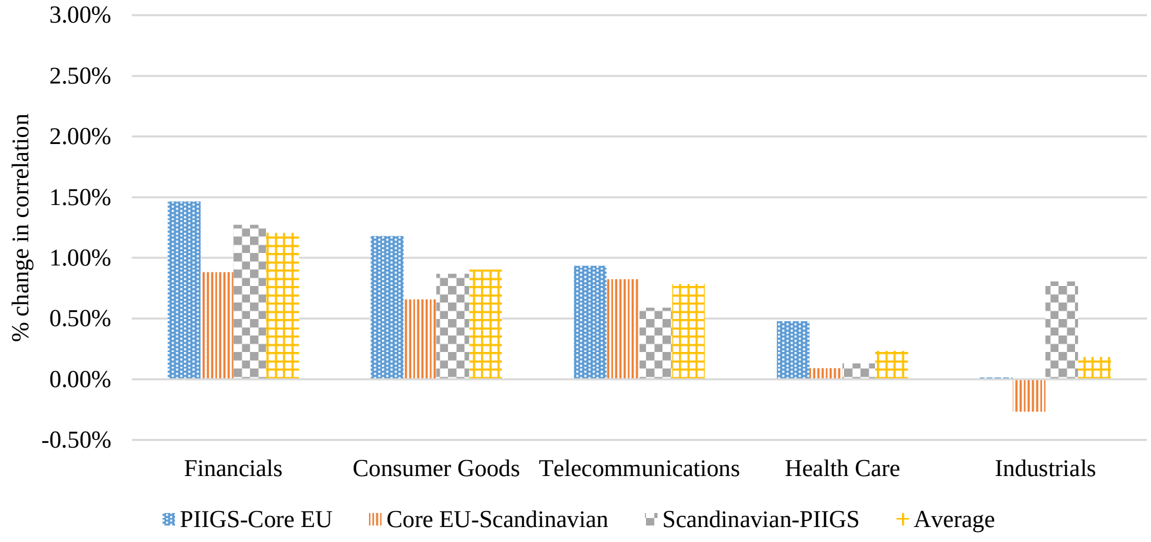
Figure 1. Evolution of sectorial equity indices across time.



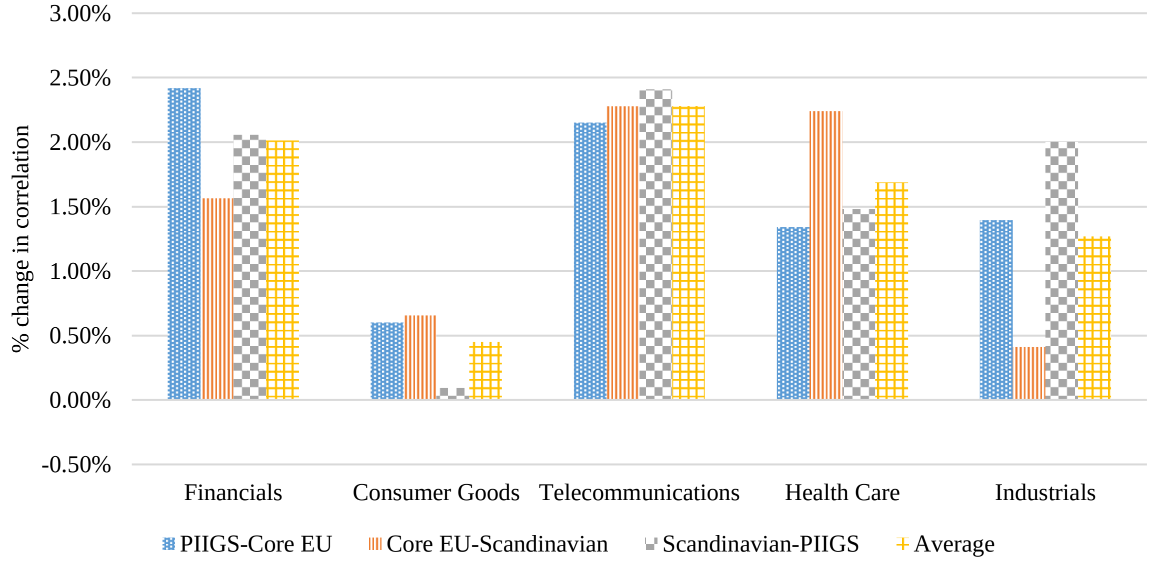
Notes: The black vertical lines correspond to the onset of the Global Financial Crisis (1/8/2007), the collapse of the Lehman Brothers (15/9/2008) and the announcement of the Greek budget deficits (5/11/2009) respectively.

Figure 2. Cross-country, within-sector financial contagion

Panel A: GFC (2nd phase)



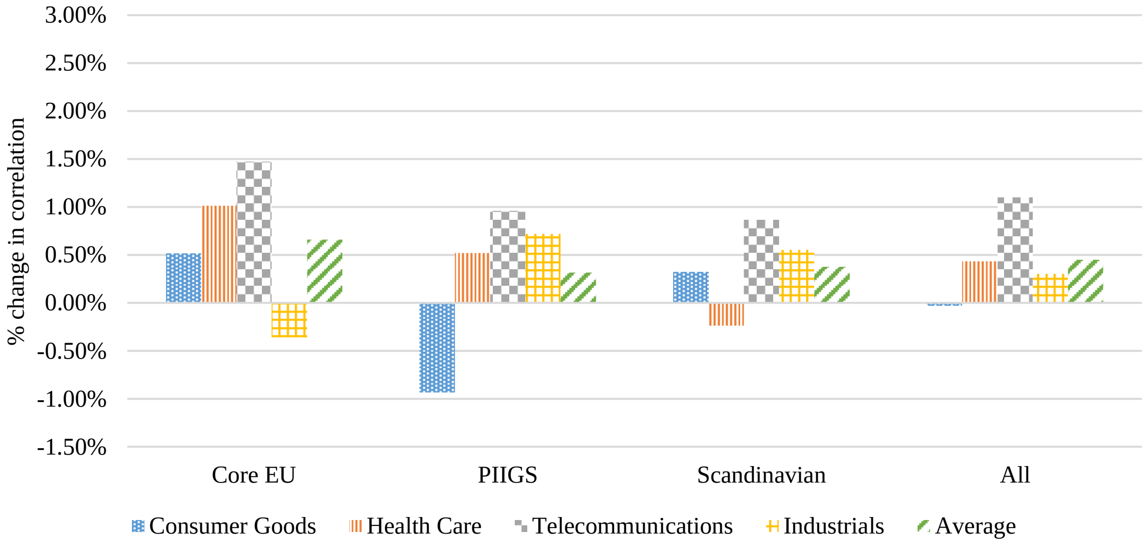
Panel B: ESDC (2nd phase)



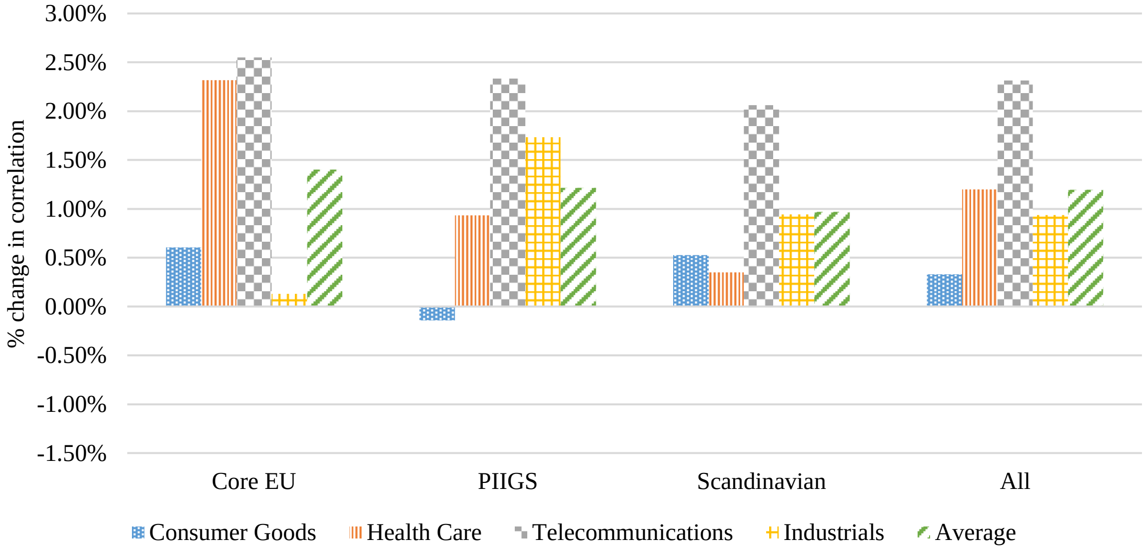
Notes: The charts show the increase in conditional correlations (as estimated from Eq.10) for the five business sectors of our sample for the GFC (Panel A) and ESDC (Panel B) cases; see also Table 3.

Figure 3. Within-country, cross-sector financial contagion

Panel A: GFC (2nd phase)

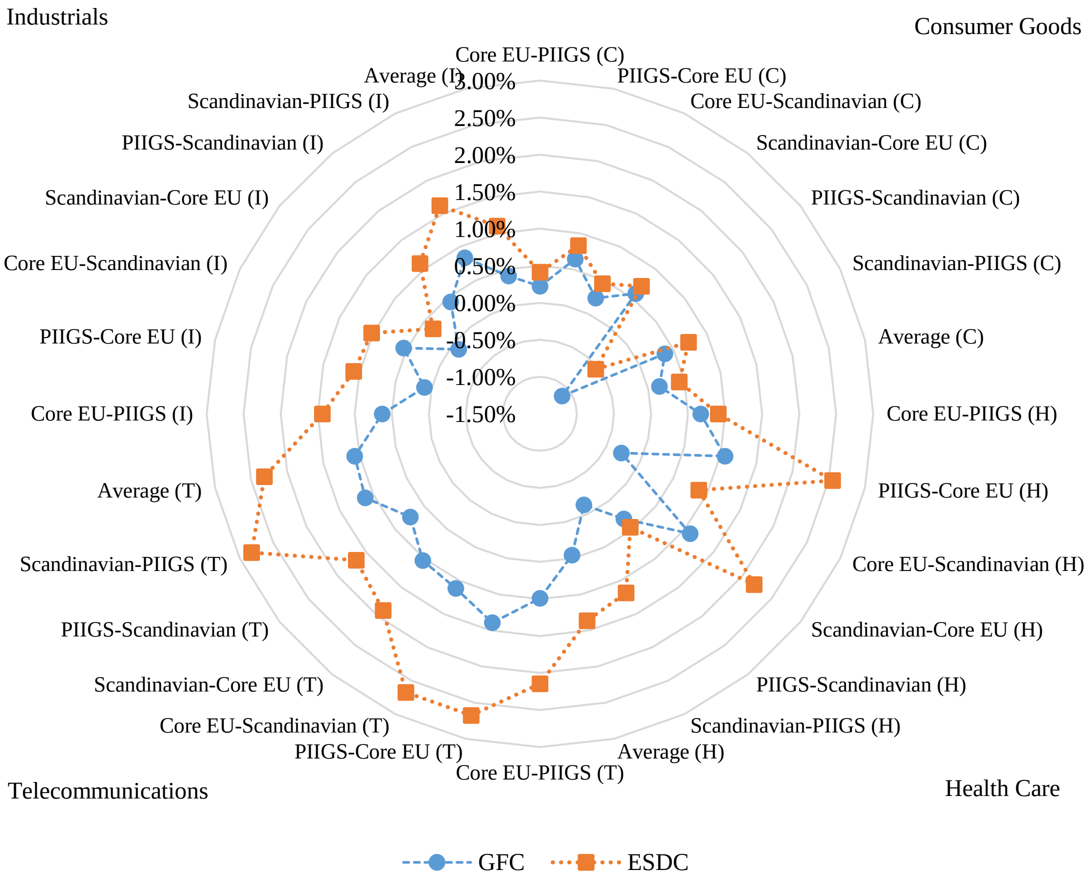


Panel B: ESDC (2nd phase)



Notes: The charts show the increase in conditional correlations (as estimated from Eq.10) for the three country groups of our sample for the GFC (Panel A) and ESDC (Panel B) cases; see also Table 5.

Figure 4. Cross-country, cross-sector financial contagion



Notes: The charts show the increase in conditional correlations (as estimated from Eq.10) for the five business sectors and the three country groups in our sample for the GFC (blue line) and ESDC (orange line), see also Table 6.

Table 1. Descriptive statistics for the equity indices.

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	United Kingdom	Austria	Finland	Sweden
Panel A: Financials														
Mean (%)	0.001	0.018	0.002	-0.002	-0.132	-0.125	-0.024	-0.019	-0.085	-0.005	-0.012	-0.009	0.052	0.031
Volatility (%)	28.917	29.742	36.964	32.968	59.482	67.594	35.891	42.487	40.137	34.627	30.904	38.3	29.138	33.738
Min	-13.141	-15.433	-13.711	-14.577	-27.921	-68.824	-12.366	-20.119	-23.934	-13.034	-14.168	-18.689	-14.225	-11.711
Max	13.66	12.01	18.394	18.696	26.259	25.452	16.712	20.727	20.943	20.585	17.68	16.747	13.013	15.752
JB	5900***	4224***	6581***	11921***	5756***	111990***	2846***	12438***	7484***	6588***	15477***	9861***	5298***	5474***
Panel B: Consumer Goods														
Mean (%)	0.067	0.036	0.023	0.040	0.016	0.039	0.03	0.017	-0.012	0.036	0.036	-0.007	0.033	0.026
Volatility (%)	32.033	28.16	24.494	34.014	37.123	24.047	28.849	22.204	30.45	21.086	19.243	30.225	35.721	27.249
Min	-19.671	-14.016	-10.932	-32.731	-19.202	-11.912	-10.244	-9.126	-26.929	-11.493	-9.321	-69.122	-14.926	-9.415
Max	16.358	10.337	11.332	40.541	10.491	11.222	12.585	9.613	21.824	13.895	10.628	8.376	16.681	13.316
JB	19550***	6656***	4211***	1135800***	2402***	3428***	1786***	3193***	209660***	7562***	9815***	43944000***	3522***	3984***
Panel C: Telecommunications														
Mean (%)	0.004	0.034	-0.016	-0.004	-0.007	-0.052	-0.035	-0.013	-0.067	0.004	0.017	-0.018	0.031	0.007
Volatility (%)	23.58	26.406	28.049	27.253	43.32	122.489	33.716	29.782	33.583	27.291	26.014	33.398	30.781	29.02
Min	-9.633	-18.148	-8.817	-14.985	-18.646	-79.816	-14.229	-17.483	-13.625	-11.386	-11.763	-21.331	-13.568	-9.55
Max	9.012	15.135	12.073	16.959	17.072	82.236	13.013	15.304	18.642	13.191	11.822	16.597	17.864	11.222
JB	1419***	26468***	1755***	14125***	2618***	153990***	2097***	15074***	9286***	4545***	5238***	19603***	9113***	2139***
Panel D: Health Care														
Mean (%)	0.02	0.07	0.018	0.046	-0.088	0.042	0.01	0.019	-0.054	0.034	0.011	—	0.043	0.046
Volatility (%)	27.552	23.194	24.933	19.902	55.213	71.372	25.136	27.393	122.111	27.501	20.496	—	28.423	28.674
Min	-12.445	-11.5	-9.986	-9.267	-30.068	-115.28	-8.728	-13.622	-110.96	-13.741	-9.27	—	-15.178	-10.588
Max	16.437	9.951	14.282	9.454	138.58	23.786	9.189	10.69	119.96	10.602	10.102	—	13.49	11.86
JB	11841***	4630***	4058***	4979***	93849000***	5043600***	1198***	2160***	336610***	2259***	4908***	—	8052***	2329***
Panel E: Industrials														
Mean (%)	-0.025	0.03	0.023	0.018	-0.016	0.016	-0.003	0.009	-0.033	0.025	0.032	0.018	0.044	0.037
Volatility (%)	31.674	32.054	29.639	30.517	37.33	34.068	27.244	28.35	28.446	26.62	22.558	27.35	30.884	34.237
Min	-12.771	-15.354	-12.573	-13.494	-15.461	-13.68	-10.287	-11.352	-19.437	-10.233	-8.789	-9.497	-12.415	-10.77
Max	11.997	14.787	14.258	18.678	13.229	13.11	8.858	12.391	11.904	10.426	8.763	10.116	11.628	14.812
JB	1236***	2089***	3556***	7357***	1533***	1184***	1176***	2217***	19245***	1329***	2123***	913***	1240***	1366***

Notes: The table presents descriptive statistics of the returns during the full sample (2004-2014) and the crisis period (August 2007 - December 2014) for the 15 EU countries. Volatility denotes the annualised volatility. JB denotes the Jarque-Bera statistic for the normality of the distribution test. ***, **, * denote statistical significance at the 1, 5, and 10% respectively.

Table 2. Univariate GJR-GARCH models estimation results.

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	United Kingdom	Austria	Finland	Sweden
Panel A: Financials														
θ_0	0.0004*	0.0006**	0.0001	0.0005*	0.0006	0.0005	0.0003	0.0003	0.0005**	0.0001	0.0001	0.0004	0.0007***	0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
ω_0	0.0238***	0.0256***	0.0243***	0.0315***	0.0245**	0.0089	0.0117***	0.0255***	0.0129*	0.0253***	0.0132***	0.0429***	0.0297***	0.0288***
	(0.0088)	(0.0096)	(0.0076)	(0.0115)	(0.0110)	(0.0064)	(0.0040)	(0.0086)	(0.0068)	(0.0091)	(0.0048)	(0.0133)	(0.0107)	(0.0098)
α_1	0.0303**	0.0583***	0.0085	0.0494***	0.0544***	0.0495***	0.0216**	0.0190	0.0576***	0.0046	0.0215**	0.0231**	0.0169	0.0175*
	(0.0132)	(0.0171)	(0.0076)	(0.0134)	(0.0111)	(0.0186)	(0.0090)	(0.0140)	(0.0192)	(0.0081)	(0.0101)	(0.0116)	(0.0108)	(0.0089)
β_1	0.9218***	0.9123***	0.9304***	0.9043***	0.9203***	0.9298***	0.9353***	0.9146***	0.9181***	0.9312***	0.9309***	0.9183***	0.9378***	0.9275***
	(0.0177)	(0.0182)	(0.0122)	(0.0175)	(0.0130)	(0.0200)	(0.0103)	(0.0201)	(0.0206)	(0.0156)	(0.0136)	(0.0152)	(0.0151)	(0.0149)
γ_1	0.0747***	0.0439***	0.1134***	0.0757***	0.0553***	0.0542**	0.0802***	0.1230***	0.0558***	0.1158***	0.0847***	0.0958***	0.0682***	0.0931***
	(0.0182)	(0.0167)	(0.0203)	(0.0261)	(0.0197)	(0.0251)	(0.0174)	(0.0234)	(0.0193)	(0.0226)	(0.0174)	(0.0199)	(0.0174)	(0.0198)
AIC	-5.655	-5.553	-5.248	-5.482	-4.343	-4.367	-5.284	-5.205	-5.016	-5.311	-5.744	-5.195	-5.512	-5.389
BIC	-5.642	-5.544	-5.235	-5.470	-4.331	-4.355	-5.271	-5.193	-5.004	-5.299	-5.731	-5.183	-5.500	-5.376
Observations	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869
Panel B: Consumer Goods														
θ_0	0.0006**	0.0006**	0.0003	0.0005*	0.0004	0.0004**	0.0006**	0.0001	0.0002	0.0004*	0.0004**	-0.0016**	0.0006*	0.0001
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0007)	(0.0003)	(0.0002)
ω_0	0.0401**	0.0191***	0.0208***	0.0315***	0.0945	0.0066*	0.0358***	0.0174***	0.0402	0.0279**	0.0247***	1.5174***	0.0631*	0.0261**
	(0.0190)	(0.0072)	(0.0068)	(0.0115)	(0.0730)	(0.0037)	(0.0128)	(0.0056)	(0.0434)	(0.0136)	(0.0075)	(0.5004)	(0.0336)	(0.0104)
α_1	0.0002	0.0214*	0.0198**	0.0494***	0.0459*	0.0105	0.0356***	0.0121	0.0468***	0.0310	-0.0055	5.1594	0.0241**	0.0138*
	(0.0087)	(0.0118)	(0.0095)	(0.0134)	(0.0254)	(0.0069)	(0.0103)	(0.0083)	(0.0174)	(0.0245)	(0.0093)	(9.1205)	(0.0110)	(0.0072)
β_1	0.9494***	0.9429***	0.9245***	0.9043***	0.9037***	0.9702***	0.9195***	0.9388***	0.9667***	0.9318***	0.9201***	0.0102	0.9326***	0.9368***
	(0.0180)	(0.0134)	(0.0128)	(0.0175)	(0.0473)	(0.0091)	(0.0165)	(0.0120)	(0.0209)	(0.0187)	(0.0184)	(0.0144)	(0.0208)	(0.0148)
γ_1	0.0729***	0.0541***	0.0922***	0.0757***	0.0739*	0.0321***	0.0642***	0.0765***	-0.0421***	0.0482*	0.1278***	-4.6801	0.0585**	0.0770***
	(0.0188)	(0.0142)	(0.0211)	(0.0261)	(0.0396)	(0.0104)	(0.0207)	(0.0152)	(0.0161)	(0.0268)	(0.0248)	(9.0010)	(0.0243)	(0.0207)
AIC	-5.372	-5.665	-5.860	-5.535	-4.851	-5.781	-5.477	-6.008	-5.210	-5.929	-6.336	-5.096	-5.037	-5.646
BIC	-5.362	-5.655	-5.849	-5.525	-4.841	-5.770	-5.466	-5.997	-5.200	-5.919	-6.325	-5.085	-5.027	-5.635
Observations	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869

Notes: The table presents estimated coefficients and robust standard errors in parenthesis of the univariate GJR-GARCH models of equation (3 & 4). AIC and BIC denote the Akaike and Schwartz Information Criteria respectively. ***, **, * denote statistical significance at the 1, 5, and 10% respectively.

Table 2. Univariate GJR-GARCH models estimation results (cont'd).

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	United Kingdom	Austria	Finland	Sweden
							Panel C: Telecommunications							
θ_0	0.0001	0.0006**	-0.0001	0.0001	0.0003	-0.0031**	-0.0002	0.0001	0.0001	0.0002	0.0004	0.0001	0.0007**	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0013)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
ω_0	0.0471**	0.0648	0.0470	0.0682	0.0172**	-0.0110	0.0240**	0.0255*	0.0119	0.0463***	0.0516**	0.0974	0.4053	0.0485*
	(0.0231)	(0.0565)	(0.0302)	(0.0556)	(0.0073)	(0.0537)	(0.0111)	(0.0133)	(0.0083)	(0.0159)	(0.0235)	(0.0657)	(0.4024)	(0.0281)
α_1	0.0147	0.0106	0.0108	0.0262	0.0123*	0.0048	0.0164*	0.0051	-0.0052*	0.0413***	0.0461***	0.0828	0.0609	0.0208
	(0.0116)	(0.0191)	(0.0096)	(0.0283)	(0.0070)	(0.0088)	(0.0089)	(0.0130)	(0.0031)	(0.0107)	(0.0150)	(0.0583)	(0.0517)	(0.0131)
β_1	0.9422***	0.9578***	0.9551***	0.9225***	0.9612***	0.9793***	0.9554***	0.9642***	0.9724***	0.9045***	0.8978***	0.8744***	0.7503***	0.9393***
	(0.0215)	(0.0321)	(0.0201)	(0.0514)	(0.0092)	(0.0078)	(0.0109)	(0.0153)	(0.0092)	(0.0193)	(0.0286)	(0.0589)	(0.1984)	(0.0244)
γ_1	0.0401***	0.0146	0.0358***	0.0491	0.0488***	0.0412***	0.0450***	0.0444***	0.0610***	0.0717***	0.0704**	0.0548	0.1680	0.0453**
	(0.0149)	(0.0157)	(0.0138)	(0.0332)	(0.0115)	(0.0110)	(0.0147)	(0.0136)	(0.0168)	(0.0246)	(0.0325)	(0.0379)	(0.1274)	(0.0176)
AIC	-5.661	-5.419	-5.335	-5.514	-4.699	-2.318	-5.109	-5.330	-5.187	-5.599	-5.660	-5.150	-5.204	-5.386
BIC	-5.651	-5.408	-5.325	-5.504	-4.688	-2.305	-5.099	-5.320	-5.177	-5.589	-5.650	-5.139	-5.194	-5.376
Observations	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869
							Panel D: Health Care							
θ_0	0.0002	0.0007***	0.0002	0.0006***	-0.0002	0.0016***	0.0004	0.0002	-0.0017	0.0004	0.0001	—	0.0008**	0.0006**
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0013)	(0.0006)	(0.0003)	(0.0003)	(0.0017)	(0.0003)	(0.0002)	—	(0.0003)	(0.0003)
ω_0	0.0292	0.1059**	0.0524*	0.0676***	0.0008***	0.7783	0.0686**	0.0342**	2.3656	0.1094***	0.0497*	—	0.5350**	0.0440**
	(0.0223)	(0.0511)	(0.0285)	(0.0262)	(0.0000)	(1.6376)	(0.0281)	(0.0155)	(1.9484)	(0.0332)	(0.0292)	—	(0.2465)	(0.0214)
α_1	0.0165	0.0365	0.0309**	0.0677	0.1162***	0.0094	0.0276*	0.0133	0.0278	0.0476**	0.0238	—	0.0760**	0.0172*
	(0.0212)	(0.0252)	(0.0135)	(0.0538)	(0.0376)	(0.0279)	(0.0168)	(0.0135)	(0.0262)	(0.0204)	(0.0154)	—	(0.0351)	(0.0104)
β_1	0.9466***	0.8812***	0.9175***	0.8644***	0.8385***	0.8358***	0.9133***	0.9512***	0.9273***	0.8897***	0.9093***	—	0.7300***	0.9428***
	(0.0331)	(0.0424)	(0.0278)	(0.0475)	(0.0751)	(0.1418)	(0.0269)	(0.0169)	(0.0315)	(0.0247)	(0.0399)	—	(0.0924)	(0.0193)
γ_1	0.0539***	0.0627*	0.0563**	0.0456	-0.6225***	0.4636	0.0552***	0.0467***	0.0108	0.0556***	0.0651**	—	0.0557	0.0489**
	(0.0175)	(0.0336)	(0.0253)	(0.0400)	(0.0897)	(1.5694)	(0.0191)	(0.0123)	(0.0299)	(0.0193)	(0.0274)	—	(0.0526)	(0.0198)
AIC	-5.505	-5.733	-5.652	-6.091	-3.967	-3.578	-5.603	-5.411	-2.401	-5.384	-6.064	—	-5.272	-5.391
BIC	-5.495	-5.723	-5.641	-6.080	-3.962	-3.568	-5.593	-5.401	-2.391	-5.373	-6.054	—	-5.261	-5.381
Observations	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	—	2,869	2,869

Notes: The table presents estimated coefficients and robust standard errors in parenthesis of the univariate GJR-GARCH models of equation (3 & 4). AIC and BIC denote the Akaike and Schwartz Information Criteria respectively. ***, **, * denote statistical significance at the 1, 5, and 10% respectively.

Table 2. Univariate GJR-GARCH models estimation results (cont'd).

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	United Kingdom	Austria	Finland	Sweden
							Panel E: Industrials							
θ_0	0.0001	0.0006**	0.0004*	0.0003	0.0003	0.0005*	0.0003	0.0004	0.0003	0.0006***	0.0004**	0.0005*	0.0007***	0.0004
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
ω_0	0.0514*	0.0370**	0.0305***	0.0333***	0.0234**	0.0186**	0.0199***	0.0205	0.0264*	0.0248***	0.0260***	0.0293***	0.0227***	0.0208**
	(0.0279)	(0.0151)	(0.0093)	(0.0105)	(0.0099)	(0.0076)	(0.0076)	(0.0138)	(0.0142)	(0.0068)	(0.0093)	(0.0110)	(0.0081)	(0.0084)
α_1	0.0285*	0.0153	0.0084	0.0123	0.0290***	0.0217	0.0112	0.0115	0.0216	0.0036	0.0066	0.0178*	0.0222***	0.0151*
	(0.0164)	(0.0107)	(0.0083)	(0.0080)	(0.0095)	(0.0150)	(0.0092)	(0.0113)	(0.0182)	(0.0083)	(0.0090)	(0.0092)	(0.0084)	(0.0090)
β_1	0.9242***	0.9411***	0.9191***	0.9278***	0.9426***	0.9500***	0.9440***	0.9465***	0.9207***	0.9424***	0.9199***	0.9419***	0.9350***	0.9412***
	(0.0286)	(0.0173)	(0.0150)	(0.0116)	(0.0120)	(0.0139)	(0.0144)	(0.0245)	(0.0317)	(0.0095)	(0.0187)	(0.0134)	(0.0128)	(0.0125)
γ_1	0.0611***	0.0622***	0.1215***	0.0939***	0.0509***	0.0460***	0.0696***	0.0658**	0.1057**	0.0804***	0.1119***	0.0549***	0.0703***	0.0762***
	(0.0228)	(0.0166)	(0.0257)	(0.0224)	(0.0154)	(0.0152)	(0.0174)	(0.0274)	(0.0506)	(0.0157)	(0.0275)	(0.0159)	(0.0171)	(0.0166)
AIC	-5.324	-5.302	-5.596	-5.515	-4.916	-5.210	-5.626	-5.589	-5.613	-5.653	-6.032	-5.537	-5.446	-5.271
BIC	-5.313	-5.292	-5.586	-5.505	-4.905	-5.200	-5.615	-5.579	-5.600	-5.642	-6.021	-5.527	-5.435	-5.261
Observations	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869

Notes: The table presents estimated coefficients and robust standard errors in parenthesis of the univariate GJR-GARCH models of equation (3 & 4). AIC and BIC denote the Akaike and Schwartz Information Criteria respectively. ***, **, * denote statistical significance at the 1, 5, and 10% respectively.

Table 3. Estimation results for cross-country, within-sector financial contagion.

		Panel A: Financials			Panel B: Consumer Goods		
		PIIGS-Core EU	Core EU – Scandinavian	Scandinavian – PIIGS	PIIGS-Core EU	Core EU – Scandinavian	Scandinavian – PIIGS
	d_1	0.0073***	0.0089***	0.0099***	0.0161***	0.0023***	0.0121***
		(0.0005)	(0.0007)	(0.0005)	(0.0008)	(0.0008)	(0.0007)
GFC	d_2	0.0147***	0.0088***	0.0127***	0.0118***	0.0066***	0.0087***
		(0.0011)	(0.0010)	(0.0011)	(0.0012)	(0.0014)	(0.0011)
	d_3	0.0133***	0.0087***	0.0121***	0.0112***	0.0075***	0.0077***
		(0.0016)	(0.0013)	(0.0017)	(0.0016)	(0.0017)	(0.0015)
	d_4	0.0155***	0.0102***	0.0141***	0.0102***	0.0072***	0.0045***
		(0.0021)	(0.0017)	(0.0023)	(0.0020)	(0.0020)	(0.0020)
	d_5	0.0193***	0.0115***	0.0160***	0.0076***	0.0049**	0.0052***
		(0.0026)	(0.0021)	(0.0028)	(0.0024)	(0.0024)	(0.0024)
ESDC	d_6	0.0242***	0.0156***	0.0206***	0.0060**	0.0065**	0.0009
		(0.0031)	(0.0025)	(0.0033)	(0.0028)	(0.0027)	(0.0029)
	d_7	0.0231***	0.0151***	0.0192***	0.0077**	0.0046	0.0022
		(0.0034)	(0.0028)	(0.0037)	(0.0031)	(0.0030)	(0.0033)
	φ	0.9949***	0.9961***	0.9954***	0.9948***	0.9952***	0.9948***
		(0.0018)	(0.0016)	(0.0018)	(0.0020)	(0.0018)	(0.0020)
	c_0	0.6228***	0.6783***	0.5490***	0.3944***	0.5083***	0.3887***
		(0.0156)	(0.0207)	(0.0201)	(0.0142)	(0.0168)	(0.0155)
LM(2) statistic		1.089	0.644	1.112	1.381	0.240	1.112
$\mathrm{F-statistic}_{\mathrm{GFC\ \&\ ESDC}}$		27.35***	37.27***	8.97***	14.51***	12.31***	132.45***
$\mathrm{F-statistic}_{\mathrm{GFC}}$		43.85***	23.21***	7.11***	11.09***	6.85***	37.65***
$\mathrm{F-statistic}_{\mathrm{ESDC}}$		17.62***	74.37***	18.10***	18.81***	20.18***	43.68***
$\Delta(\mathrm{GFC-ESDC})$		0.502	0.572	0.480	-0.677	-0.006	-2.251
$\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$		4.066***	4.110***	3.127***	3.023***	0.020	3.723***
Observations		2,869	2,869	2,869	2,869	2,869	2,869
		Panel C: Telecommunications			Panel D: Health Care		
	d_1	0.0030***	0.0044***	0.0023***	0.0010	-0.0013	0.0003
		(0.0001)	(0.0001)	(0.0001)	(0.0010)	(0.0018)	(0.0006)
GFC	d_2	0.0094***	0.0083***	0.0059***	0.0048***	0.0009	0.0013
		(0.0001)	(0.0003)	(0.0002)	(0.0014)	(0.0026)	(0.0009)
	d_3	0.0095***	0.0088***	0.0067***	0.0042**	0.0009	0.0009
		(0.0002)	(0.0003)	(0.0004)	(0.0017)	(0.0032)	(0.0014)
	d_4	0.0143***	0.0145***	0.0140***	0.0041*	-0.0055	-0.0023
		(0.0003)	(0.0005)	(0.0005)	(0.0022)	(0.0039)	(0.0019)
	d_5	0.0179***	0.0182***	0.0179***	0.0086***	0.0060	0.0025
		(0.0004)	(0.0006)	(0.0006)	(0.0026)	(0.0047)	(0.0023)
ESDC	d_6	0.0215***	0.0228***	0.0241***	0.0134***	0.0224***	0.0148***
		(0.0005)	(0.0007)	(0.0007)	(0.0031)	(0.0054)	(0.0027)

	d_7	0.0201^{***}	0.0212^{***}	0.0230^{***}	0.0124^{***}	0.0217^{***}	0.0133^{***}
		(0.0006)	(0.0008)	(0.0009)	(0.0034)	(0.0060)	(0.0030)
	φ	0.9988^{***}	0.9981^{***}	0.9977^{***}	0.9907^{***}	0.9903^{***}	0.9923^{***}
		(0.0012)	(0.0014)	(0.0015)	(0.0027)	(0.0024)	(0.0025)
	c_0	0.3361^{***}	0.3962^{***}	0.2975^{***}	0.2091^{***}	0.4084^{***}	0.2056^{***}
		(0.0464)	(0.0366)	(0.0259)	(0.0066)	(0.0099)	(0.0074)
LM(2) statistic		0.364	0.380	0.074	0.790	1.915	1.145
$\mathrm{F-statistic}_{\mathrm{GFC\ \&\ ESDC}}$		2415.40^{***}	1950.71^{***}	1331.38^{***}	41.59^{***}	97.08^{***}	158.13^{***}
$\mathrm{F-statistic}_{\mathrm{GFC}}$		3996.44^{***}	3452.48^{***}	1897.12^{***}	9.09^{***}	17.19^{***}	17.80^{***}
$\mathrm{F-statistic}_{\mathrm{ESDC}}$		1296.54^{***}	1063.46^{***}	1319.29^{***}	39.71^{***}	119.01^{***}	260.08^{***}
$\Delta(\mathrm{GFC-ESDC})$		0.833	1.015	1.406	1.027	3.192	2.423
$\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$		31.668^{***}	29.360^{***}	30.604^{***}	3.761^{***}	5.490^{***}	6.499^{***}
Observations		2,869	2,869	2,869	2,869	2,869	2,869
		Panel E: Industrials					
GFC	d_1	-0.0056^{***}	-0.0062^{***}	0.0012			
		(0.0011)	(0.0004)	(0.0013)			
	d_2	0.0002	-0.0027^{***}	0.0081^{***}			
		(0.0015)	(0.0006)	(0.0018)			
	d_3	0.0004	-0.0026^{***}	0.0089^{***}			
		(0.0017)	(0.0007)	(0.0021)			
	d_4	0.0039^{*}	-0.0021^{**}	0.0106^{***}			
		(0.0020)	(0.0008)	(0.0025)			
ESDC	d_5	0.0111^{***}	0.0024^{**}	0.0178^{***}			
		(0.0023)	(0.0010)	(0.0028)			
	d_6	0.0139^{***}	0.0041^{***}	0.0200^{***}			
		(0.0027)	(0.0011)	(0.0032)			
	d_7	0.0133^{***}	0.0043^{***}	0.0192^{***}			
		(0.0028)	(0.0012)	(0.0033)			
	φ	0.9948^{***}	0.9977^{***}	0.9946^{***}			
		(0.0021)	(0.0016)	(0.0023)			
	c_0	0.6293^{***}	0.7239^{***}	0.6082^{***}			
		(0.0192)	(0.0394)	(0.0204)			
LM(2) statistic		2.205	1.312	2.211			
$\mathrm{F-statistic}_{\mathrm{GFC\ \&\ ESDC}}$		65.26^{***}	97.09^{***}	40.47^{***}			
$\mathrm{F-statistic}_{\mathrm{GFC}}$		25.60^{***}	40.82^{***}	14.81^{***}			
$\mathrm{F-statistic}_{\mathrm{ESDC}}$		21.33^{***}	16.32^{***}	7.95^{***}			
$\Delta(\mathrm{GFC-ESDC})$		4.513	2.530	0.910			
$\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$		7.899^{***}	8.845^{***}	5.679^{***}			
Observations		2,869	2,869	2,869			

Notes: The table reports estimated coefficients and standard errors in brackets for equation (10) in the text. LM(2) denotes the Breusch-Godfrey LM test statistic for autocorrelation allowing for up to two lags. $\mathrm{F-statistic}_{\mathrm{GFC\ \&\ ESDC}}$, $\mathrm{F-statistic}_{\mathrm{GFC}}$ and $\mathrm{F-statistic}_{\mathrm{ESDC}}$ test the joint significance of those dummy variables that correspond to both the GFC and the ESDC, only the GFC, only the ESDC respectively. The $\Delta(\mathrm{GFC-ESDC})$ reports the logarithmic change between the estimated coefficients that correspond to peak (i.e., the second phase) of each crisis and a positive value indicates that the impact of the ESDC has been more pronounced. The $\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$ tests the equality of the coefficients that correspond to peak of each crisis. $^{***},^{**},^{*}$: denote statistical significance at the 1, 5 and 10% significance level.

Table 4. Sectorial Financial Characteristics.

Sectors	Debt/Equity	Debt/Capital	Mcap (bil USD)
Consumer Goods	97.33	42.31	42.00
Financials	71.78	30.33	9.49
Health Care	102.70	34.98	48.00
Industrials	199.99	40.76	25.90
Telecommunications	202.84	64.83	108.00

Source: Thomson Reuters Eikon and authors' calculations.

Table 5. Estimation results for within-country, cross-sector financial contagion.

Group	Financials	Panel A: Core EU Consumer Goods	Panel A: Core EU Health Care	Panel A: Core EU Telecom/ns	Panel A: Core EU Industrials	Panel B: PIIGS Consumer Goods	Panel B: PIIGS Health Care	Panel B: PIIGS Telecom/ns	Panel B: PIIGS Industrials	Panel C: Scandinavian Consumer Goods	Panel C: Scandinavian Health Care	Panel C: Scandinavian Telecom/ns	Panel C: Scandinavian Industrials
	d_1	0.0024***	0.0072***	0.0053***	-0.0048***	-0.0119***	0.0001***	0.0034***	0.0008***	0.0016***	-0.0023***	0.0059***	0.0031***
		(0.0003)	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0008)	(0.0003)	(0.0005)	(0.0005)	(0.0003)
GFC	d_2	0.0052***	0.0101***	0.0147***	-0.0036***	-0.0093***	0.0052***	0.0096***	0.0072***	0.0032***	-0.0024***	0.0087***	0.0055***
		(0.0005)	(0.0008)	(0.0005)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0011)	(0.0005)	(0.0007)	(0.0010)	(0.0005)
	d_3	0.0053***	0.0095***	0.0142***	-0.0039***	-0.0092***	0.0048***	0.0095***	0.0072***	0.0037***	-0.0018*	0.0098***	0.0061***
		(0.0006)	(0.0012)	(0.0009)	(0.0004)	(0.0005)	(0.0006)	(0.0008)	(0.0015)	(0.0006)	(0.0010)	(0.0013)	(0.0006)
	d_4	0.0050***	0.0128***	0.0170***	-0.0023***	-0.0065***	0.0049***	0.0146***	0.0094***	0.0048***	-0.0049***	0.0139***	0.0070***
		(0.0008)	(0.0016)	(0.0013)	(0.0005)	(0.0007)	(0.0008)	(0.0011)	(0.0020)	(0.0008)	(0.0013)	(0.0016)	(0.0007)
	d_5	0.0064***	0.0175***	0.0215***	-0.0002	-0.0040***	0.0073***	0.0190***	0.0139***	0.0028***	-0.0022	0.0158***	0.0072***
		(0.0010)	(0.0020)	(0.0016)	(0.0006)	(0.0008)	(0.0011)	(0.0014)	(0.0024)	(0.0009)	(0.0016)	(0.0020)	(0.0008)
ESDC	d_6	0.0061***	0.0232***	0.0255***	0.0013**	-0.0014	0.0093***	0.0233***	0.0173***	0.0053***	0.0035*	0.0206***	0.0094***
		(0.0011)	(0.0024)	(0.0020)	(0.0006)	(0.0010)	(0.0013)	(0.0017)	(0.0028)	(0.0011)	(0.0019)	(0.0024)	(0.0009)
	d_7	0.0052***	0.0229***	0.0247***	0.0013*	-0.0019*	0.0089***	0.0215***	0.0167***	0.0053***	0.0033	0.0180***	0.0097***
		(0.0013)	(0.0027)	(0.0024)	(0.0007)	(0.0011)	(0.0014)	(0.0020)	(0.0031)	(0.0012)	(0.0022)	(0.0026)	(0.0009)
	φ	0.9966***	0.9945***	0.9936***	0.9979***	0.9975***	0.9958***	0.9939***	0.9913***	0.9970***	0.9962***	0.9933***	0.9974***
		(0.0016)	(0.0019)	(0.0024)	(0.0015)	(0.0015)	(0.0016)	(0.0024)	(0.0028)	(0.0013)	(0.0016)	(0.0022)	(0.0016)
	c_0	0.5760***	0.4947***	0.4984***	0.7225***	0.3724***	0.2141***	0.3587***	0.5564***	0.5778***	0.4896***	0.4907***	0.6829***
		(0.0128)	(0.0114)	(0.0117)	(0.0249)	(0.0184)	(0.0092)	(0.0098)	(0.0079)	(0.0164)	(0.0175)	(0.0118)	(0.0232)
LM(2) statistic		0.276	2.349*	0.125	2.765	1.550	1.096	0.625	1.375	0.254	3.480**	0.663	3.306**
$\mathrm{F-statistic}_{\mathrm{GFC\,\&\,ESDC}}$		35.11***	133.86***	285.91***	61.08***	59.96***	144.95***	83.92***	90.49***	634.16***	569.47***	25.56***	17.88***
$\mathrm{F-statistic}_{\mathrm{GFC}}$		42.75***	176.02***	533.50***	58.50***	90.68***	271.51***	148.93***	156.71***	20.52***	537.61***	17.25***	20.30***
$\mathrm{F-statistic}_{\mathrm{ESDC}}$		8.65***	130.17***	66.94***	62.11***	55.77***	21.12***	38.46***	18.39***	102.88***	142.08***	45.97***	29.60***
$\Delta(\mathrm{GFC-ESDC})$		0.160	0.827	0.548	1.360	-1.883	0.588	0.889	0.879	0.494	2.468	0.868	0.538
$\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$		1.111	7.585***	6.542***	10.760***	10.101***	4.157***	9.280***	5.129***	2.761***	4.399***	1.869**	5.992***
Observations		2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869	2,869

Notes: The table reports estimated coefficients and standard errors in brackets for equation (10) in the text. LM(2) denotes the Breusch-Godfrey LM test statistic for autocorrelation allowing for up to two lags. $\mathrm{F-statistic}_{\mathrm{GFC\,\&\,ESDC}}$, $\mathrm{F-statistic}_{\mathrm{GFC}}$ and $\mathrm{F-statistic}_{\mathrm{ESDC}}$ test the joint significance of those dummy variables that correspond to both the GFC and the ESDC, only the GFC, only the ESDC respectively. The $\Delta(\mathrm{GFC-ESDC})$ reports the logarithmic change between the estimated coefficients that correspond to peak (i.e., the second phase) of each crisis and a positive value indicates that the impact of the ESDC has been more pronounced. The $\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$ tests the equality of the coefficients that correspond to peak of each crisis. ***,**,*: denote statistical significance at the 1, 5 and 10% significance level.

Table 6: – Panel A. Estimation results for cross-country, cross-sector financial contagion.

	Financials	Core EU	PIIGS	Core EU	Scandinavian	Scandinavian	PIIGS
	Consumer Goods	PIIGS	Core EU	Scandinavian	Core EU	PIIGS	Scandinavian
GFC	d_1	0.0013***	0.0030***	0.0012***	0.0034***	-0.0129***	0.0015***
		(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
	d_2	0.0022***	0.0064***	0.0023***	0.0058***	-0.0112***	0.0037***
		(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
	d_3	0.0022***	0.0062***	0.0023***	0.0060***	-0.0106***	0.0035***
		(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0004)	(0.0005)
ESDC	d_4	0.0033***	0.0064***	0.0035***	0.0057***	-0.0090***	0.0051***
		(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0006)	(0.0008)
	d_5	0.0016	0.0082***	0.0018*	0.0064***	-0.0077***	0.0042***
		(0.0010)	(0.0010)	(0.0010)	(0.0008)	(0.0007)	(0.0010)
	d_6	0.0041***	0.0083***	0.0045***	0.0070***	-0.0053***	0.0073***
		(0.0013)	(0.0012)	(0.0012)	(0.0010)	(0.0009)	(0.0011)
	d_7	0.0041***	0.0076***	0.0044***	0.0057***	-0.0060***	0.0070***
		(0.0014)	(0.0013)	(0.0013)	(0.0011)	(0.0010)	(0.0013)
	φ	0.9968***	0.9967***	0.9971***	0.9972***	0.9976***	0.9976***
		(0.0015)	(0.0017)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
	c_0	0.5713***	0.4493***	0.5642***	0.5301***	0.4158***	0.4467***
		(0.0177)	(0.0140)	(0.0187)	(0.0163)	(0.0189)	(0.0232)
LM(2) statistic		0.180	0.962	0.083	1.442	0.559	0.550
$\mathrm{F-statistic}_{\mathrm{GFC\,\&\,ESDC}}$		644.27***	50.39***	659.27***	51.70***	94.13***	45.91***
$\mathrm{F-statistic}_{\mathrm{GFC}}$		92.67***	89.52***	114.38***	42.34***	68.85***	49.42***
$\mathrm{F-statistic}_{\mathrm{ESDC}}$		100.10***	2.30*	126.11***	75.54***	166.75***	55.66***
$\Delta(\mathrm{GFC-ESDC})$		0.627	0.253	0.656	0.198	-0.736	0.670
$\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$		2.192***	2.009***	2.646***	1.887**	9.087***	3.885***
Observations		2,869	2,869	2,869	2,869	2,869	2,869

Notes: The table reports estimated coefficients and standard errors in brackets for equation (10) in the text. LM(2) denotes the Breusch-Godfrey LM test statistic for autocorrelation allowing for up to two lags. $\mathrm{F-statistic}_{\mathrm{GFC\,\&\,ESDC}}$, $\mathrm{F-statistic}_{\mathrm{GFC}}$ and $\mathrm{F-statistic}_{\mathrm{ESDC}}$ test the joint significance of those dummy variables that correspond to both the GFC and the ESDC, only the GFC, only the ESDC respectively. The $\Delta(\mathrm{GFC-ESDC})$ reports the logarithmic change between the estimated coefficients that correspond to peak (i.e., the second phase) of each crisis and a positive value indicates that the impact of the ESDC has been more pronounced. The $\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$ tests the equality of the coefficients that correspond to peak of each crisis. ***,**,*: denote statistical significance at the 1, 5 and 10% significance level.

Table 6 – Panel B. Estimation results for cross-country, cross-sector financial contagion.

	Financials	Core EU	PIIGS	Core EU	Scandinavian	Scandinavian	PIIGS
	Health Care	PIIGS	Core EU	Scandinavian	Core EU	PIIGS	Scandinavian
GFC	d_1	-0.0006	0.0071***	-0.0028***	0.0082***	0.0003	-0.0021
		(0.0004)	(0.0004)	(0.0004)	(0.0007)	(0.0003)	(0.0003)
	d_2	0.0067***	0.0106***	-0.0028***	0.0109***	0.0032***	-0.0013**
		(0.0007)	(0.0007)	(0.0007)	(0.0011)	(0.0005)	(0.0006)
	d_3	0.0059***	0.0096***	-0.0028***	0.0109***	0.0032***	-0.0017*
		(0.0009)	(0.0011)	(0.0011)	(0.0014)	(0.0006)	(0.0010)
	d_4	0.0065***	0.0141***	-0.0059***	0.0142***	0.0030***	-0.0048***
		(0.0012)	(0.0015)	(0.0014)	(0.0018)	(0.0008)	(0.0013)
ESDC	d_5	0.0087***	0.0196***	-0.0006	0.0172***	0.0047***	0.0018
		(0.0014)	(0.0018)	(0.0017)	(0.0022)	(0.0010)	(0.0016)
	d_6	0.0091***	0.0255***	0.0088***	0.0220***	0.0046***	0.0118***
		(0.0017)	(0.0021)	(0.0021)	(0.0026)	(0.0012)	(0.0018)
	d_7	0.0086***	0.0249***	0.0084***	0.0222***	0.0041***	0.0113***
		(0.0019)	(0.0023)	(0.0024)	(0.0029)	(0.0013)	(0.0020)
	φ	0.9945***	0.9953***	0.9959***	0.9941***	0.9958***	0.9963***
		(0.0019)	(0.0018)	(0.0018)	(0.0018)	(0.0015)	(0.0018)
	c_0	0.2556***	0.3853***	0.4619***	0.4687***	0.2461***	0.3724***
		(0.0086)	(0.0132)	(0.0169)	(0.0107)	(0.0098)	(0.0177)
LM(2) statistic		1.590	1.055	2.967*	1.606	1.753	2.787*
$\mathrm{F-statistic}_{\mathrm{GFC\ \&\ ESDC}}$		314.07***	35.82***	444.24***	30.58***	106.72***	166.63***
$\mathrm{F-statistic}_{\mathrm{GFC}}$		181.41***	36.45***	98.77***	32.74***	35.24***	15.18***
$\mathrm{F-statistic}_{\mathrm{ESDC}}$		23.10***	53.09***	427.12***	43.62***	1.92**	336.20***
$\Delta(\mathrm{GFC-ESDC})$		0.302	0.877	4.160	0.699	0.376	9.812
$\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$		0.608***	8.703***	7.783***	5.886***	1.765**	3.997***
Observations		2,869	2,869	2,869	2,869	2,869	2,869

Notes: The table reports estimated coefficients and standard errors in brackets for equation (10) in the text. LM(2) denotes the Breusch-Godfrey LM test statistic for autocorrelation allowing for up to two lags. $\mathrm{F-statistic}_{\mathrm{GFC\ \&\ ESDC}}$, $\mathrm{F-statistic}_{\mathrm{GFC}}$ and $\mathrm{F-statistic}_{\mathrm{ESDC}}$ test the joint significance of those dummy variables that correspond to both the GFC and the ESDC, only the GFC, only the ESDC respectively. The $\Delta(\mathrm{GFC-ESDC})$ reports the logarithmic change between the estimated coefficients that correspond to peak (i.e., the second phase) of each crisis and a positive value indicates that the impact of the ESDC has been more pronounced. The $\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$ tests the equality of the coefficients that correspond to peak of each crisis. ***,**,*: denote statistical significance at the 1, 5 and 10% significance level.

Table 6 – Panel C. Estimation results for cross-country, cross-sector financial contagion.

	Financials	Core EU	PIIGS	Core EU	Scandinavian	Scandinavian	PIIGS
	Telecommunications	PIIGS	Core EU	Scandinavian	Core EU	PIIGS	Scandinavian
GFC	d_1	0.0025***	0.0060***	0.0064***	0.0065***	0.0037***	0.0070***
		(0.0002)	(0.0002)	(0.0005)	(0.0002)	(0.0001)	(0.0003)
	d_2	0.0099***	0.0139***	0.0111***	0.0104***	0.0073***	0.0112***
		(0.0005)	(0.0005)	(0.0010)	(0.0005)	(0.0003)	(0.0006)
	d_3	0.0101***	0.0133***	0.0118***	0.0102***	0.0076***	0.0112***
		(0.0009)	(0.0009)	(0.0013)	(0.0009)	(0.0007)	(0.0010)
ESDC	d_4	0.0138***	0.0173***	0.0166***	0.0126***	0.0112***	0.0171***
		(0.0014)	(0.0013)	(0.0016)	(0.0013)	(0.0010)	(0.0015)
	d_5	0.0171***	0.0224***	0.0206***	0.0153***	0.0133***	0.0217***
		(0.0017)	(0.0016)	(0.0020)	(0.0016)	(0.0013)	(0.0019)
	d_6	0.0214***	0.0268***	0.0267***	0.0190***	0.0167***	0.0282***
		(0.0021)	(0.0019)	(0.0024)	(0.0020)	(0.0016)	(0.0023)
	d_7	0.0188***	0.0260***	0.0246***	0.0183***	0.0136***	0.0263***
		(0.0025)	(0.0022)	(0.0027)	(0.0024)	(0.0019)	(0.0027)
	φ	0.9920***	0.9943***	0.9931***	0.9939***	0.9943***	0.9931***
		(0.0026)	(0.0023)	(0.0023)	(0.0023)	(0.0022)	(0.0023)
	c_0	0.4203***	0.3936***	0.4633***	0.4662***	0.3885***	0.3606***
		(0.0084)	(0.0126)	(0.0117)	(0.0124)	(0.0111)	(0.0114)
LM(2) statistic		0.653	0.664	1.228	1.414	1.389	0.485
$\mathrm{F-statistic}_{\mathrm{GFC\ \&\ ESDC}}$		107.11***	84.98***	46.90***	53.92***	51.28***	64.28***
$\mathrm{F-statistic}_{\mathrm{GFC}}$		200.83***	140.69***	44.10***	83.87***	78.25***	90.40***
$\mathrm{F-statistic}_{\mathrm{ESDC}}$		38.24***	42.13***	94.25***	50.46***	54.30***	92.41***
$\Delta(\mathrm{GFC-ESDC})$		0.769	0.653	0.875	0.604	0.822	0.926
$\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$		6.442***	8.054***	8.814***	5.279***	6.733***	9.004***
Observations		2,869	2,869	2,869	2,869	2,869	2,869

Notes: The table reports estimated coefficients and standard errors in brackets for equation (10) in the text. LM(2) denotes the Breusch-Godfrey LM test statistic for autocorrelation allowing for up to two lags. $\mathrm{F-statistic}_{\mathrm{GFC\ \&\ ESDC}}$, $\mathrm{F-statistic}_{\mathrm{GFC}}$ and $\mathrm{F-statistic}_{\mathrm{ESDC}}$ test the joint significance of those dummy variables that correspond to both the GFC and the ESDC, only the GFC, only the ESDC respectively. The $\Delta(\mathrm{GFC-ESDC})$ reports the logarithmic change between the estimated coefficients that correspond to peak (i.e., the second phase) of each crisis and a positive value indicates that the impact of the ESDC has been more pronounced. The $\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$ tests the equality of the coefficients that correspond to peak of each crisis. ***,**,*: denote statistical significance at the 1, 5 and 10% significance level.

Table 6 – Panel D. Estimation results for cross-country, cross-sector financial contagion.

	Financials	Core EU	PIIGS	Core EU	Scandinavian	Scandinavian	PIIGS
	Industrials	PIIGS	Core EU	Scandinavian	Core EU	PIIGS	Scandinavian
GFC	d_1	0.0008	-0.0027***	0.0028***	-0.0030***	0.0010*	0.0039***
		(0.0007)	(0.0005)	(0.0003)	(0.0003)	(0.0006)	(0.0006)
	d_2	0.0063***	0.0010	0.0054***	-0.0010***	0.0043***	0.0084***
		(0.0009)	(0.0008)	(0.0005)	(0.0004)	(0.0007)	(0.0009)
	d_3	0.0073***	0.0008	0.0054***	-0.0008*	0.0051***	0.0083***
		(0.0012)	(0.0011)	(0.0006)	(0.0004)	(0.0009)	(0.0013)
ESDC	d_4	0.0088***	0.0039***	0.0064***	0.0008	0.0066***	0.0099***
		(0.0014)	(0.0014)	(0.0008)	(0.0005)	(0.0010)	(0.0017)
	d_5	0.0120***	0.0079***	0.0086***	0.0013**	0.0084***	0.0137***
		(0.0016)	(0.0018)	(0.0009)	(0.0006)	(0.0012)	(0.0021)
	d_6	0.0144***	0.0108***	0.0102***	0.0034***	0.0110***	0.0162***
		(0.0018)	(0.0021)	(0.0010)	(0.0007)	(0.0013)	(0.0024)
	d_7	0.0141***	0.0106***	0.0102***	0.0036***	0.0106***	0.0160***
		(0.0019)	(0.0022)	(0.0011)	(0.0008)	(0.0014)	(0.0026)
	φ	0.9945***	0.9947***	0.9972***	0.9980***	0.9960***	0.9942***
		(0.0022)	(0.0022)	(0.0016)	(0.0014)	(0.0021)	(0.0023)
	c_0	0.6277***	0.5850***	0.6774***	0.6681***	0.5922***	0.5558***
		(0.0113)	(0.0125)	(0.0213)	(0.0298)	(0.0167)	(0.0125)
LM(2) statistic		1.060	1.212	0.270	2.919*	3.158*	0.564
$\mathrm{F-statistic}_{\mathrm{GFC\,\&\,ESDC}}$		26.19***	112.44***	27.34***	43.99***	23.53***	53.09***
$\mathrm{F-statistic}_{\mathrm{GFC}}$		35.57***	189.34***	23.49***	57.96***	25.44***	75.71***
$\mathrm{F-statistic}_{\mathrm{ESDC}}$		20.30***	32.64***	19.54***	62.46***	36.52***	19.99***
$\Delta(\mathrm{GFC-ESDC})$		0.827	2.380	0.630	4.453	0.935	0.660
$\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$		6.522***	6.684***	6.555***	8.996***	7.265***	4.567***
Observations		2,869	2,869	2,869	2,869	2,869	2,869

Notes: The table reports estimated coefficients and standard errors in brackets for equation (10) in the text. LM(2) denotes the Breusch-Godfrey LM test statistic for autocorrelation allowing for up to two lags. $\mathrm{F-statistic}_{\mathrm{GFC\,\&\,ESDC}}$, $\mathrm{F-statistic}_{\mathrm{GFC}}$ and $\mathrm{F-statistic}_{\mathrm{ESDC}}$ test the joint significance of those dummy variables that correspond to both the GFC and the ESDC, only the GFC, only the ESDC respectively. The $\Delta(\mathrm{GFC-ESDC})$ reports the logarithmic change between the estimated coefficients that correspond to peak (i.e., the second phase) of each crisis and a positive value indicates that the impact of the ESDC has been more pronounced. The $\mathrm{t-statistic}_{\mathrm{GFC-ESDC}}$ tests the equality of the coefficients that correspond to peak of each crisis. ***,**,*: denote statistical significance at the 1, 5 and 10% significance level.

Table 7. Synchronisation of GFC and ESDC Crises phases.

	GFC Phase 2		ESDC Phase 2		ESDC Phase 3	
Country	Crisis Transition Date	Sync	Crisis Transition Date	Sync	Crisis Transition Date	Sync
Denmark	22/09/08	5	07/05/10	13	19/08/11	34
Finland	22/09/08	5	11/05/10	16	12/09/11	57
Sweden	22/09/08	5	11/05/10	16	13/09/11	58
Austria	22/09/08	5	—	—	—	—
Belgium/Lux	22/09/08	5	11/05/10	16	—	—
France	22/09/08	5	11/05/10	16	11/08/11	26
Germany	30/09/08	13	—	—	12/09/11	57
Netherlands	22/09/08	5	11/05/10	16	01/11/11	107
UK	22/09/08	5	—	—	—	—
Portugal	07/10/08	20	29/04/10	5	12/07/2011	-2
Italy	22/09/08	5	07/05/10	13	11/07/2011	-3
Greece	20/10/08	28	05/05/10	11	30/08/2011	45
Ireland	30/09/08	8	24/11/10	211	—	—
Spain	22/09/08	5	05/05/10	11	11/08/2011	27

Notes: The Synchronisation variable ($Sync_{i,m}$) is given in equation 11, with the respective bench crisis $T_{C_{bench}}$ dates being 16/09/2008 for GFC Phase 2, 23/4/2010 for ESDC Phase 2 and 15/7/2011 for ESDC Phase 3. The crisis transition date column reports the estimated $T_{C_{i,m}}$from the Markov-Switching model on the conditional volatilities of the equity indices. Calculations have been done for each business sector separately and here we report the average values. A "—" indicates that the specific market has neither been affected by that particular phase of the crisis nor any phase that followed.