

European Equity Market Contagion: An Empirical Application to Ireland's Sovereign Debt Crisis

*Shaen Corbet – Cian Twomey**

Abstract:

This paper examines the time-varying conditional correlations of daily European equity market returns during the Irish sovereign debt crisis. A dynamic conditional correlation (DCC) multivariate GARCH model is used to estimate to what extent the collapse of Irish equity markets and subsequent troika intervention in Ireland spilled over upon European equity markets during this crisis. During the Irish financial crisis from 2007 to 2010, strong contagion effects are uncovered between Irish equity markets and the investigated European equity markets. The contagion effects are found to ease dramatically in the period after troika intervention in Irish finances. This result supports the use of bailouts and external financial intervention as a mechanism to mitigate and absorb contagion associated with state-specific financial crises and if possible, should be considered as a primary response function in future cases of sovereign debt crisis.

Key words: Dynamic correlation; DCC GARCH; Contagion; Financial crises; Bailouts; Equity markets.

JEL classification: G01, G12, G15.

1 Introduction

Financial contagion phenomena have become more pronounced and aggressive in recent years, particularly after the onset of the United States subprime crisis in 2007 that triggered an international financial crisis that rippled throughout banks and financial markets around the world. The subprime crisis became evident in 2007 and exposed significant weaknesses in financial industry regulation, and indeed, the global financial system. Europe was over-exposed through excessive levels of debt being held in some countries. Institutionally in Ireland, banks' level of foreign borrowing increased from €15 billion to €110 billion between 2004 and 2008 (Ahearne, 2012). At a European level, problems arising from debt levels were exacerbated through the revelation in December 2009 that Greece had misstated its accounts, admitting that its level of debt had exceeded €300 billion {approximately 150% of GDP at the time} (Lavdas, Litsas and Skiadas, 2013). The high levels of debt were attributed to relaxed financial regulation, low taxation and high public expenditure. This was immediately followed by international

* Shaen Corbet; DCU Business School (DCUBS), Dublin City University, Dublin 9, Ireland; <shaen.corbet@dcu.ie>.

Cian Twomey; J.E. Cairnes School of Business and Economics, National University of Ireland, Galway (NUIG), Ireland; <cian.twomey@nuigalway.ie>.

accusations of 'severe irregularities' in Greek finances, as Eurostat¹ continued to revise debt figures upwards (Abboushi, 2011). This accelerated the European-wide crisis in already debt-burdened countries such as Portugal, Ireland, Italy and Spain, initiating a period of austerity across Europe.

This research examines the European crisis through the implementation of a three-stage Dynamic Conditional Correlation (DCC)-GARCH model to obtain information found in European equity markets related to contagion stemming from the Irish-specific sovereign debt crisis. There is particular emphasis placed on the implementation of the Irish bank guarantee and the intervention of the troika². The period from January 2002 to October 2013, inclusive of both events is investigated. The DCC-GARCH model was developed by Engle (2002), and was found to significantly improve upon the Constant Conditional Correlation (CCC)-GARCH model developed by Bollerslev (1990). This improvement stemmed from the relaxation of the constant correlation assumption by allowing time-varying correlation. The number of unknown parameters was also limited in the DCC-GARCH model. The main advantage of using this type of approach is the detection of time-varying conditional correlations, which captures dynamic investor behaviour in response to news and innovations. Contagion effects due to herding behaviour and flights-to-quality³ during turmoil periods can also be uncovered through these mechanisms (Syllignakis & Kouretas, 2011).

Forbes and Rigobon (2002) define contagion as a '*significant increase in the cross-market correlation during a turmoil period*'. Therefore, it is necessary to compare the correlation between equity markets during the pre-crisis period to the period of time defined as 'being in-crisis'. If two markets are moderately correlated during the period of stability, and a shock to one market leads to a significant increase in market co-movements, this can be defined as financial contagion. However, if two markets are moderately correlated during the two periods, this can sometimes be attributed to market interlinkages rather than contagion (Mighri & Mansouri, 2013). It is necessary to segregate these financial market phenomena. The application of the DCC-GARCH models have recently become a key focus of financial econometrics as the threat of widespread

¹ Eurostat is the statistical office of the European Union situated in Luxembourg. It is tasked to provide the European Union with statistics at the European level that enable comparisons between countries and regions.

² The troika refers to the combined intervention of the European Union (EU), European Central Bank (ECB) and the International Monetary Fund (IMF).

³ A flight to quality is defined as the actions of investors when moving their capital away from riskier investments to the safest possible investment vehicles. The flight is usually caused by uncertainty in the financial or international markets. However, at other times, this move may be an instance of investors cutting back on the more volatile investments for the conservative ones (diversifying) without much consideration of international markets.

contagion increased. The model can be used to shed light on underlying questions based on the time-varying effects of correlation within European equity markets, or the effects on equity market correlations during periods of crises, or indeed contagion effects stemming from a particular event.

The remainder of the paper is organised as follows. Section 2 discusses the evolution of the Irish-specific financial crises, while explaining the segregation of the specific time periods used in the DCC-GARCH methodologies. Section 3 focuses on the data and the descriptive statistics. Section 4 introduces the simple and adjusted correlation analysis, with section 5 introducing the dynamic conditional correlation (DCC-GARCH) model. Section 6 concludes.

2 The Irish financial crisis

Between 2008 and 2013, Ireland experienced one of the most severe economic downturns in living memory. This period was highlighted by collapsing equity markets, the nationalisation of Anglo Irish Bank, economic retraction, high unemployment, political uncertainty, a collapsed property market and mass emigration. Any one of these issues could instigate and fuel crisis alone, the combination of these issues provided the ingredients for an economic ‘perfect storm’. These events also occurred within the climate of one of the worst international financial environments ever experienced. Ireland entered recession in September 2008, with equity markets falling dramatically and five-year Credit Default Swap (CDS) spreads increasing⁴. The government pushed forward the 2009 budget in an attempt to increase taxation and cut public spending to bridge the gaps in Irish finances.

On the 29th of September 2008, the Irish government was forced to implement an unlimited bank guarantee of the six major Irish banks⁵. As public perceptions of the Irish banking system deteriorated and negative sentiment increased, this guarantee had to be taken as banks began to experience mass-withdrawals and the probability of a bank-run increased. The Irish banking and economic climate deteriorated more substantially over the following twenty-four months, until Irish government bond yields began to show the strain of the negative expectation based on Ireland’s financial credibility. This led to sovereign borrowing on international markets becoming too expensive and on the 21st of November 2010, the Irish state formally requested financial support from the European Union’s European Financial Stability Facility (EFSF) and the International Monetary Fund (IMF). The request was accepted by European finance ministers and on the 28th of

⁴ Increased Credit Default Swap (CDS) spreads indicate higher risk associated with the underlying insured product. This occurs as investors perceive a higher risk of insuring the underlying, or indeed a higher probability of default.

⁵ The six major Irish banks included Allied Irish Bank, Anglo Irish Bank, Bank of Ireland, Permanent TSB, Irish Nationwide and National Irish Bank.

November 2010, a bailout of €85 billion was agreed upon⁶. After the announcement of this bailout, there was an alleviation of some pressures on the Irish economy.

This analysis focuses on these dates to create differing periods of investigation. The aim of the paper is to investigate how much equity market contagion spread in Europe due to Irish influenced financial crisis. The first period is based on the relative period of calm, between the 1st of January 2002 and the beginning of the subprime crisis in the United States in June 2007. As the subprime crisis developed, significant frailties were uncovered in the Irish banking system that has since been identified as the beginning of the Irish economic crisis. The second period of investigation is based on the collapse of the Irish banking system and property market. This period is identified as that between the 1st of June 2007 and the 28th of November 2010, when the international bailout fund was given to the Irish government. The final period is that of the 29th of November 2010 to the 31st of October 2013. This period encompasses the period of relative stability experienced after the implementation of the international bailout. By investigating the period after the bailout, it may shed light on its success as European equity markets experienced an extremely volatile period thereafter due to the Greek financial crises. Reduced contagion stemming from Irish influenced crises would be a direct endorsement of bailout facilities as a medium of financial crises moderation.

3 Data and descriptive statistics

In this paper, we use daily price indices database. The sample period for all data is from January 1st 2002 until October 31st 2013. The stock market indices used are the ATHEX 20 for Greece, the FTSE 100 for the United Kingdom, the ISEQ 20 for Ireland, the OMX 30 for Sweden, the SSMI 20 in Switzerland, the BEL 20 for Belgium, the AEX 25 for the Netherlands and the IBEX 35 for Spain. The daily stock index returns are defined as the logarithmic differences of stock price indices and thus computed as $r_t = 100 \ln(x_t/x_{t-1})$ for $t = 1, 2, \dots, T$, where T , r_t , x_t and x_{t-1} are the total number of observations, the return at time t , the current stock price index and the lagged day's stock price index respectively.

Tables one and two report summary statistics for the included stock return series during the entire period of investigation from 2002 until 2013. It also includes statistics summarising the period before and after the start of the subprime crisis in

⁶ The €85 billion bailout fund consisted of €22.5 billion from the European Financial Stability Mechanism (EFSM), €22.5 billion from the International Monetary Fund (IMF), €22.5 billion from the European Financial Stability Facility (EFSF), €17.5 billion from the Irish sovereign National Pension Reserve Fund (NPRF) and bilateral loans from the United Kingdom, Sweden and Denmark.

the United States in June 2007, and before and after the arrival of international bailout assistance in Ireland. During the full sample of investigation, the Greek ATHEX 20 is found to be the most volatile exchange as measured by the standard deviation of 2.01%, while the SSMI in Switzerland is the least volatile with a standard deviation of 1.22%. Ireland experienced a standard deviation of 1.48%. The measure for skewness shows that stock returns are negatively skewed with the exception of Germany, Sweden, Switzerland and Belgium. This negative skewness indicates that large negative stock returns are more common than large positive returns. From the measure of excess kurtosis, the leptokurtic behaviour is apparent in all series with more pronounced fat tails in Greece (103.8). This implies that large shocks of either sign are more likely to be present and that the stock-return series may not be normally distributed.

Tab. 1: Descriptive statistics

	Greece	UK	Germany	France	Italy	Denmark	Ireland	Sweden	Switz	Belgium	Netherl	Spain
Panel A: The entire period: 01/01/2002 to 31/10/2013 (3070 observations)												
Mean	-0.0251	0.0081	0.0179	-0.0021	-0.0164	0.0255	-0.0082	0.0265	0.0083	0.0015	-0.0085	0.0058
Std. Dev	2.0140	1.2555	1.5631	1.5296	1.5351	1.3172	1.4767	1.4578	1.2231	1.3397	1.5363	1.5226
Minimum	-	-9.2645	-7.4334	-9.4715	-8.5991	-11.7231	-	-7.5126	-8.1078	-8.3193	-9.5903	-9.5858
Maximum	39.0385						13.9635					
Skew	40.5389	9.3842	10.7974	10.5946	10.8742	9.4963	9.7331	9.8650	10.7876	9.3339	10.0283	13.4836
Excess K	-0.2917	-0.1315	0.0490	-0.0721	-0.0303	-0.2755	-0.5821	0.0487	0.0481	0.0309	-0.0029	-0.1441
Excess K	103.803	10.0209	7.8346	8.3516	8.0311	9.5117	10.8847	7.8439	9.5448	9.0147	9.6960	8.9405
Panel B: The pre-crisis period: 01/01/2002 to 29/6/2007 (1427 observations)												
Mean	0.0438	0.0165	0.0306	0.0195	0.0188	0.0406	0.0349	0.0783	0.0258	0.0361	0.0055	0.0403
Std. Dev	1.0344	1.0413	1.5341	1.3351	1.0927	1.0556	0.9578	0.9836	1.1361	1.1289	1.4673	1.1585
Minimum	-6.1067	-5.5887	-6.3360	-6.0448	-5.0101	-5.5922	-6.1245	-4.8819	-5.7628	-4.9329	-7.1690	-5.2006
Maximum	4.9735	5.9037	7.5526	7.0022	6.4038	4.9698	4.7751	5.3495	6.2769	9.3339	9.5168	5.6942
Skew	-0.1779	-0.1869	-0.0200	0.0067	-0.0761	-0.3772	-0.7146	-0.4648	0.0426	0.3550	0.1275	0.0351
Excess K	5.1437	8.2025	6.5469	7.2960	6.4694	6.3369	7.6428	7.0645	8.0111	10.4880	8.3308	6.1855
Panel C: The subprime and Irish economic crisis: 2/7/2007 to 28/11/2010 (635 observations)												
Mean	-0.1398	-0.0198	-0.0202	-0.0578	-0.0879	-0.0152	-0.1422	-0.0145	-0.0413	-0.0691	-0.0577	-0.0531
Std. Dev	2.8305	1.6812	1.7519	1.8798	1.9047	1.7869	2.2342	1.8687	1.5054	1.7152	1.9084	1.9179
Minimum	-	-	-	-	-	-	-	-	-	-	-	-
Maximum	39.0385	-9.2646	-7.4334	-9.4715	-8.5991	-11.7232	13.9636	-7.5127	-8.1078	-8.3193	-9.5903	-9.5859
Skew	40.5390	9.3842	10.7975	10.5946	10.8743	9.4964	9.7331	9.8650	10.7876	9.2212	10.0283	13.4836
Excess K	0.3808	-0.0371	0.2424	0.2266	0.2035	-0.1265	-0.3319	0.2760	0.1965	-0.0133	-0.0168	0.2799
Excess K	88.1320	5.3125	6.2901	5.3309	5.0314	4.7922	3.4922	3.2179	6.2508	4.4310	5.9737	6.2536
Panel D: The troika bailout in Ireland and the Greek sovereign debt crisis: 29/11/2010 to 31/10/2013 (1006 observations)												
Mean	-0.0212	0.0248	0.0383	0.0220	0.0004	0.0445	0.0666	0.0216	0.0331	0.0189	0.0223	0.0095
Std. Dev	2.2511	1.0248	1.3737	1.4139	1.7513	1.0987	1.1236	1.3090	0.9924	1.1979	1.1217	1.6047
Minimum	-7.3664	-4.7792	-5.9947	-5.6346	-7.0442	-6.7809	-4.5191	-6.9681	-4.2428	-5.4925	-4.5689	-6.0008
Maximum	13.4311	3.9414	5.2104	6.0892	6.3863	3.9883	4.6662	6.0332	4.9029	5.3539	4.4257	5.8835
Skew	0.2402	-0.2613	-0.1923	-0.1453	-0.2575	-0.4431	-0.1943	-0.3529	-0.3582	-0.1051	-0.2340	0.0314
Excess K	2.5500	2.2609	2.6569	2.3646	1.4159	3.2174	1.6539	3.3719	3.7285	2.2428	2.1081	1.4052

Source: Data is sourced from Bloomberg with all calculations completed by the authors.

Note: The above table represents the summary statistics of the daily equity market returns of the twelve investigated European states. The periods of investigation are based on the pre-crisis period, the Irish financial and subprime crises and the period thereafter troika intervention.

Tab. 2: Unconditional correlation matrix for stock returns

	Gre	UK	Ger	Fra	Ita	Den	Ire	Swe	Swi	Bel	Neth
UK	0.467										
Ger	0.451	0.830									
Fra	0.492	0.864	0.935								
Ita	0.485	0.806	0.867	0.875							
Den	0.448	0.587	0.556	0.603	0.551						
Ire	0.467	0.646	0.632	0.653	0.585	0.535					
Swe	0.460	0.746	0.783	0.789	0.737	0.581	0.568				
Swi	0.482	0.781	0.810	0.826	0.752	0.567	0.616	0.723			
Bel	0.515	0.769	0.811	0.848	0.794	0.600	0.618	0.725	0.754		
Neth	0.477	0.835	0.907	0.917	0.850	0.587	0.643	0.771	0.804	0.826	
Spa	0.476	0.807	0.867	0.870	0.822	0.567	0.629	0.761	0.761	0.786	0.821

Source: Data is sourced from Bloomberg with all calculations completed by the authors.

Note: The above table represents the conditional correlations between equity returns (January 2002 to October 2013).

Comparison of the Irish economic crises period from June 2007 until the bailout in November 2010 and the period thereafter offers some interesting results. European markets endured their harshest climates during the period of the Irish economic crises, a time where financial markets were gripped by the United States subprime crisis. Ireland possessed a standard deviation of 0.96% in the period before the crisis began. This standard deviation more than doubled to 2.23% as the Irish economic climate deteriorated, but reduced significantly to 1.12% after the implementation of the troika bailout. This presents evidence that the intervention of the troika in Ireland had a significant ‘calming’ effect across Irish equity markets. Greece was the worst affected European state during the periods under investigation. During the subprime and Irish economic crises, Greek returns exhibited a standard deviation of 3.06%, whereas this fell to 2.23% in the period after the Irish bailout. France, Italy, Sweden and the Netherlands all experienced standard deviations above 2% during the subprime crises, whereas only Greece experienced levels above 2% after 2010. Kurtosis is also found to have increased in Greece between the two periods, whereas in Ireland is fell from 7.65% to 3.49%. The results indicate that European countries reacted more substantially to the Irish economic crises, evident from large increases in European-wide risk. This can be attributed to the widespread shock that spread through European financial markets as Irish financial markets strained under its own economic pressures. It appears that the troika’s influence when bailing out Ireland may have stemmed the associated negative sentiment.

The international crises from 2007 to present has been identified by many observers as the worst since the great depression of the 1930s in the United States. The subprime crisis erupted in the second half of 2007 with the collapse of the subprime market in the United States. This directly impacted upon equity markets

in 2007 and continued until 2011, marked by a liquidity crisis and a credit crunch. The Irish and Greek sovereign debt crises escalated substantially in late 2008, but it only became abundantly clear through media coverage in December 2009 to what degree of damage had occurred, along with the depth of financial irregularities evident in Greek financial markets (Lavdas, Litsas and Skiadas, 2013). These crises are deemed to have continued to the time of completing this research, as Ireland and Greece are still in the midst of IMF intervention; while in Greece there have been continuous threats of default.

Table two represents the pair-wise unconditional correlation between the equity market returns. It must be emphasised that the considered equity markets are high correlated with each other, a fact present and found to have increased dramatically since the creation of the Euro as a currency in 1999. Simple correlation analysis was broadly used to measure the degree of financial contagion (Hardouvelis, Malliaropoulos & Priestley, 2006). This indicates that the indices are characterised by volatility clustering, revealing the presence of heteroskedasticity. This market phenomenon has been widely recognised and successfully captured by the ARCH and GARCH⁷ family models to adequately describe stock market returns' volatility dynamics. This is important because the DCC-GARCH models used in this research are based on the interdependence of stock markets in the form of second moments by modelling the time varying variance-covariance matrix for the sample. The extent of the Irish and Greek crisis are also clearly evident through sharp spikes in volatility in mid-2008.

4 Simple and adjusted correlation analysis

In order to measure the financial contagion phenomenon, we use the simple Pearson correlation approach as used by Calvo and Reinhart (1996). If the correlations significantly increase during a particular crisis period compared to a defined stability period (pre-crisis period), one can conclude that there exists a strengthening of links or indeed a transmission mechanism for shocks between the two markets (or a group of markets), thus detecting elements of financial contagion. If this increase is found to be statistically significant, the finding of market contagion is accepted, whereas if the results are not significant, this indicates only an interdependence phenomenon rather than financial contagion.

Forbes and Rigdon (2002) and Mansourti (2013) argue that analysts need to be careful when interpreting increases in simple correlation as evidence of financial

⁷ Autoregressive Conditional Heteroskedasticity (ARCH) models are used to characterise and model observed time series. They are used whenever there is reason to believe that, at any point in a series, the terms will have a characteristic size, or variance. In particular ARCH models assume the variance of the current error term of innovation to be a function of the actual sizes of the previous time periods; error terms, where the variance is often related to the squares of previous innovations.

contagion. This can be attributed to the fact that the return correlation can increase when equity markets become volatile. The authors have proposed a correction of the correlation coefficients for the conditional heteroskedasticity. Forbes and Rigobon (2002) propose to adjust the correlation coefficients in the following way:

$$\rho^* = \rho / \sqrt{1 + \delta(1 - \rho^2)} \quad (1)$$

where $\rho = \sigma_{ij}/\sigma_i\sigma_j$ is the unadjusted correlation coefficient between a crisis market I and non-crisis market j, ρ^* is the adjusted correlation coefficient and $\delta = (\sigma_{it}^h/\sigma_{it}^l) - 1$ is the change in high period (crisis period) volatility against the low period (stability period) volatility. To compute the adjusted correlation coefficients, the crisis (turmoil) period is used as the high volatility period and the stable period as the low volatility period. By calculating the adjusted correlation coefficient for each crisis period and the stability period, it possible to investigate contagion effects. By calculating ρ_h^* , which represents the adjusted correlation coefficient during a crisis period and ρ_l^* denotes the adjusted correlation coefficient during the stable period, it is possible to investigate contagion effects. If $\rho_h^* > \rho_l^*$, the hypothesis of no contagion is accepted, whereas if $\rho_h^* < \rho_l^*$ indicates a rejection of the hypothesis of no contagion, thus there are contagion effects present. To test the significance of these changes in linkages between stock markets during crisis, Forbes and Rigobon (2002) compare the adjusted correlation coefficient in the crisis period (ρ_h^*) with the adjusted one in the stable period (ρ_l^*). A significant positive difference between both adjusted correlation adjusted correlation values indicates the existence of financial contagion effects. If contagion exists, co-movement during the crisis period would be more significant than that of the stable period. To test for pair-wise, cross-market significance, we use the Fisher's Z transformation test as used by Mighri and Mansouri (2013). It is described as:

$$Z^* = (z_h^* - z_l^*) / \text{var}(z_h^* - z_l^*) \quad (2)$$

where $z_h^* = (1/2) \ln(1 + \rho_h^*)/(1 - \rho_h^*)$ is the Fisher transformation of correlation coefficients in the crisis period and $z_l^* = (1/2) \ln(1 + \rho_l^*)/(1 - \rho_l^*)$ is the Fisher transformation of correlation coefficients in the stable periods. Fisher's Z transformation as used by Billio & Pelizzon (2003) and Lee et al. (2007) to convert standard coefficients to normally distributed Z variables. The critical values for the Fisher's Z test at the 1%, 5% and 10% levels are 1.28, 1.65 and 1.96 respectively. Therefore, any Z test statistic greater than those critical values indicate likely contagion while any test statistic less than or equal to those critical values indicates the alternative, namely no contagion.

The empirical results are summarised in table three. It reports the adjusted and unadjusted correlation coefficients between Ireland and the other international indices included in this research. The stability period is denoted as that between the 1st of January 2002 and the 29th of June 2007. The Irish economic crisis is deemed to have started in conjunction with the beginning of the United States subprime crisis and ended at the point of troika intervention, thus the period selected is that between the 1st of July 2007 and the 28th of November 2010. The final period is based on the post-troika intervention period from the 29th of November 2010 until the 31st of October 2013. The total period simply includes the three selected periods. The correlations between stock market returns are compared before and after the start of the Irish crisis and before and during the European sovereign debt crisis. Financial contagion effects are measured by the statistical significance of the adjusted correlation coefficients in the crisis period compared to those of the stability period.

Tab. 3: Tests of significant increases in correlation coefficients

	Stable period	Irish economic crisis			Post-troika intervention			Z (Z*) test	
	ρ_t	ρ_t	ρ_t^*	% ↑	ρ_t	ρ_t^*	% ↑	Z (Subprime)	Z* (European)
UK	0.6339	0.7001	0.9437	34.8	0.7545	0.6644	-11.9	5.57139***	11.11850***
Ger	0.5179	0.6426	0.9320	45.0	0.7555	0.7911	4.7	31.70240***	5.74420***
Fra	0.6096	0.7189	0.9120	26.9	0.7855	0.7895	0.5	1.91013**	8.04822***
Ita	0.5685	0.6768	0.9145	34.6	0.6922	0.8512	22.9	14.2915***	3.97755***
Den	0.5234	0.6628	0.9116	37.5	0.6492	0.6384	-1.7	14.6101***	12.03430***
Gre	0.4425	0.3988	0.8470	112.4	0.3815	0.7872	106.3	23.2513***	8.05080***
Swe	0.5687	0.6648	0.9758	46.7	0.7264	0.6686	-7.9	4.43076***	14.01660***
Swi	0.5768	0.6844	0.9233	34.9	0.7118	0.6106	-12.9	15.4060***	17.39710***
Bel	0.5785	0.7145	0.9514	33.2	0.7895	0.8394	6.3	7.77307***	6.29160***
Neth	0.5934	0.6851	0.9123	33.2	0.7969	0.7924	-0.6	2.13476***	8.39478***
Spa	0.5608	0.6850	0.9145	33.5	0.6595	0.8728	32.3	13.5858***	3.31484***

Source: Data is sourced from Bloomberg with all calculations completed by the authors.

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively. The percentage increase is based on the increase between the correlation coefficient between the crisis period investigated and the stable period between January 2002 and June 2007. The subprime crisis again represents the period between June 2007 and November 2010, while the estimated period of post-troika intervention in Ireland is between November 2010 and October 2013.

As evident in table three, the effects of the Irish economic crisis in Europe are very strong. The reported results show that financial contagion effects based on adjusted correlation coefficients are statistically significant (computed without adjusting for heteroskedasticity). After this adjustment, the countries included all present a rejection of the null hypothesis of no contagion during the Irish economic crises. Greek equity markets present the strongest relationship with Irish equity markets, which is expected due to the core economic difficulties found in both countries. The most interesting results are based on the period after troika

intervention. The United Kingdom, Denmark, Sweden, Switzerland and the Netherlands offer results accepting the null hypothesis of no contagion after the Irish financial bailout. This presents interesting evidence supporting the use of bailouts as a medium of crises moderation, as it appears that it alleviated pressures stemming from Irish financial difficulties on these countries. The main problematic states in Europe though, still share significant contagion characteristics in the period after troika intervention in Ireland, indicating that market fears were still present based on the interconnectiveness of Ireland with Germany, France, Italy, Greece, Belgium and Spain. The contagion statistics are strongest for the interconnectiveness of Ireland and Greece, Spain and Italy. These results present evidence that the adjustment for heteroskedasticity has a significant impact on the correlation coefficients between equity markets and on the financial contagion tests. The high values and statistical significance of the Z tests confirm the strength of Irish contagion effects across European equity markets.

5 Dynamic correlation analysis and results

The simple and adjusted correlation analysis underlines the significance of equity market volatility in a selected period of investigation. Nevertheless, stock market behaviour is expected to vary continuously in response to shocks and crises. Moreover, correlation may vary over time and increase during periods of high volatility and turmoil. In this analysis, we employ a multivariate GARCH model with Dynamic Conditional Correlation (DCC) that allows for time-varying conditional correlation as proposed by Engle (2002). In a first step, we specify the mean equation as follows:

$$r_t = \mu_0 + \mu_1 r_{t-1} + \mu_2 r_{t-1}^{Ire} + \mu_3 r_{t-2}^{Ire} + \varepsilon_t \quad (3)$$

where $r_t = (r_{1t}, r_{2t}, \dots, r_{nt})'$ and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{nt})'$. Also $\varepsilon_t = H_t^{1/2} z_t$ and $\varepsilon_t / F_{t-1} \sim N(0, H_t)$. $z_t: (n \times 1)$ is denoted as a vector of i.i.d. errors such that $E(z_t) = 0$ and $E(z_t z_t') = 1$. Finally, $H_t \equiv \{h_{ij}\}_t \forall i, j = 1, 2, \dots, n$ is an $(n \times n)$ matrix of conditional variances and covariances of r_t conditional to previous returns. In the mean equation, we include an AR(1) term and the one-day lagged Irish equity index returns as a measure of the impact of the Irish equity markets on European equity markets during the investigated crises. In a second step, we specify a multivariate conditional variance as: $H_t \equiv D_t R_t D_t$ where $R_t = \{\rho_{ij}\}_t$ is an $(n \times n)$ conditional symmetric correlation matrix of ε_t at time t and $D_t = \text{diag}\{\sqrt{h_{it}}\}$ is an $(n \times n)$ diagonal matrix of conditional standard deviations of ε_t at time t . The elements in the diagonal matrix D_t are the standard deviations from univariate GARCH models:

$$h_{it} = \omega_i + \sum_{i=1}^q \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^p \beta_j h_{t-j} \quad (4)$$

where $\omega_i > 0$; $\alpha_i \geq 0$; $\beta_j \geq 0$ and $\sum_{i=1}^q \alpha_i + \sum_{j=1}^p \beta_j < 1$. The elements of $H_t \equiv D_t R_t D_t$ are $[H_t]_{ij} = \sqrt{h_{it} h_{jt}} \rho_{ij,t}$. As proposed by Engle (2002), the DCC-GARCH model is designed to allow for a two-stage estimation of the conditional variance matrix h_t . In the first stage, univariate GARCH (1,1) volatility models are fitted for each of the stock return residuals and estimates of $\sqrt{h_{it}}$ are obtained. In the second stage, stock return residuals are transformed by their estimated standard deviations from the first stage as $z_{it} = \varepsilon_{it} / \sqrt{h_{it}}$. Then, the standardised residual z_{it} is used to estimate the correlation parameters. The dynamics of the correlation in the standard DCC-GARCH model could be expressed as follows:

$$Q_t = (1 - a - b)\bar{Q} + az_{t-1}z'_{t-1} + bQ_{t-1} \quad (5)$$

where $a \geq 0, b \geq 0$ and $a + b < 1$. $Q_t = [q_{ij,t}]$ is the time-varying covariance matrix of z_t and $\bar{Q} = E(z_t z'_t)$ is a $(n \times n)$ unconditional covariance matrix of z_t . In addition, Q_0 , the starting value of Q_t should be positive to guarantee that H_t would also be positive. In a bivariate setting, the conditional covariance could be expressed as follows:

$$q_{ij,t} = (1 - a_{ij} - b_{ij})\bar{q}_{ij} + a_{ij}z_{i,t-1}z_{j,t-1} + b_{ij}q_{ij,t-1} \quad (6)$$

When specifying the form of the conditional correlation matrix R_t , two requirements have to be considered. The first is that the covariance matrix H_t has to be positive and the second is that all the elements in the conditional correlation matrix R_t have to be equal or less than unity. To ensure both of these requirements in the DCC-GARCH model, the correlation matrix R_t could be decomposed as:

$$R_t = Q_t^{*-1/2} Q_t Q_t^{*-1/2} \quad (7)$$

where $Q_t^* = \text{diag}(Q_t) = \begin{bmatrix} \sqrt{q_{11,t}} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sqrt{q_{nn,t}} \end{bmatrix}$ and $R_t = \begin{bmatrix} 1 & \dots & \rho_{1n,t} \\ \vdots & \ddots & \vdots \\ \rho_{1n,t} & \dots & 1 \end{bmatrix}$ is

a correlation matrix with ones on the diagonal and off-diagonal elements are less than one in absolute value as long as Q_t is positive. The correlation coefficient can therefore be expressed as: $\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}} \forall i, j = 1, 2, \dots, n; i \neq j$. As noted by Engle (2002), the DCC model could be estimated by using a two-step approach to maximise the log-likelihood function. If we let θ denote the parameters in D_t and ϑ , the parameters in R_t , then the log-likelihood is:

$$l_t(\theta, \vartheta) = \left[-\frac{1}{2} \sum_{t=1}^T n \log(2\pi) + \log|D_t|^2 + \varepsilon_t' D_t^{-2} \varepsilon_t \right] + \left[-\frac{1}{2} \sum_{t=1}^T \log|R_t| + z_t' R_t^{-1} z_t - z_t' z_t \right] \quad (8)$$

The first part of the log likelihood function is volatility, which is the sum of the individual GARCH likelihoods. The log-likelihood function can be maximised in the first stage over the parameters D_t . Given the estimated parameters in the first stage, the correlation component of the likelihood function in the second stage is maximised to estimate the correlation coefficients.

Tab. 4: Estimation results from the bivariate AR(1)-DCC-GARCH(1,1) model

	United Kingdom		Germany		France		Italy		Denmark		Greece	
	UK	Ireland	Germany	Ireland	France	Ireland	Italy	Ireland	Denmark	Ireland	Greece	Ireland
Mean eq.												
μ_0	0.0390 (0.025)	0.0440 (0.009)	0.0555 (0.026)	0.0452 (0.051)	0.0141 (0.053)	0.0106 (0.637)	0.0211 (0.389)	0.0016 (0.094)	0.0515 (0.011)	0.0485 (0.006)	0.0571 (0.008)	0.0306 (0.136)
μ_1	0.1198 (0.000)	0.1791 (0.000)	-0.1834 (0.114)	0.1142 (0.004)	-	-	-	0.1078 (0.000)	0.0168 (0.178)	0.0549 (0.000)	0.0156 (0.085)	0.0235 (0.000)
μ_2	-	0.2436 (0.000)	-	0.2955 (0.000)	-	0.3172 (0.000)	-	0.3225 (0.000)	-	0.3577 (0.000)	-	0.2813 (0.000)
Var eq.												
ω_{10}	0.0152 (0.000)	0.0252 (0.000)	0.0213 (0.000)	0.0221 (0.000)	0.0265 (0.000)	0.0255 (0.000)	0.0134 (0.000)	0.0230 (0.000)	0.0376 (0.000)	0.0225 (0.000)	0.0012 (0.603)	0.0197 (0.000)
α_i	0.0798 (0.000)	0.0842 (0.000)	0.0818 (0.000)	0.0961 (0.000)	0.0861 (0.000)	0.0923 (0.000)	0.0729 (0.000)	0.0901 (0.000)	0.0729 (0.000)	0.0808 (0.000)	0.0569 (0.000)	0.0905 (0.000)
β_i	0.9068 (0.000)	0.9011 (0.000)	0.9096 (0.000)	0.8955 (0.000)	0.9012 (0.000)	0.8947 (0.000)	0.9215 (0.000)	0.8967 (0.000)	0.9001 (0.000)	0.9059 (0.000)	0.9355 (0.000)	0.9005 (0.000)
Mul. DCC												
$\rho_{i,Ireland}$	0.6721 (0.000)		0.6824 (0.000)		0.6958 (0.000)		0.6243 (0.000)		0.5539 (0.000)		0.3789 (0.000)	
α_i	0.0179 (0.000)		0.0255 (0.000)		0.0367 (0.000)		0.0259 (0.005)		0.0263 (0.000)		0.0756 (0.000)	
β_i	0.9560 (0.000)		0.9639 (0.000)		0.9323 (0.000)		0.9482 (0.000)		0.9541 (0.000)		0.7463 (0.000)	

	Sweden		Switzerland		Belgium		Netherlands		Spain		Ireland	
	Sweden	Ireland	Switzerland	Switz	Belgium	Ireland	Netherl	Ireland	Spain	Spain	Ireland	Ireland
Mean eq.												
μ_0	0.0525	0.0516	0.0344	0.0344	0.0343	0.0222	0.0409	0.0454	0.0417	0.0417	0.0289	0.0289
					(0.055)	(0.037)	(0.021)	(0.066)	(0.061)	(0.017)	(0.082)	(0.202)
μ_1					-0.1085	0.0688	0.0425	-	-	-	-	-
					0.0464	(0.000)	0.0345	0.0285	0.1603	0.0509	0.0255	0.1027
					(0.003)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.070)	(0.000)
μ_2					-	0.2666	0.2371	0.2455	-	0.3141	-	0.3011
					-	(0.000)	(0.000)	(0.000)	-	(0.000)	-	(0.000)
Var eq.												
ω_{i0}					0.0227	0.0235	0.0198	0.0207	0.0237	0.0180	0.0214	0.0217
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_i					0.0682	0.0938	0.0792	0.0833	0.0945	0.0831	0.0815	0.0874
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_i					0.9179	0.8952	0.9029	0.9039	0.8893	0.9047	0.9072	0.9019
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mult DCC												
$\rho_{i,irreiland}$					0.6385	0.6338	0.6338	0.6640	0.6872	0.6872	0.6221	0.6221
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_i					0.0303	0.0296	0.0296	0.0241	0.0283	0.0283	0.0281	0.0281
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_i					0.9407	0.9510	0.9510	0.9566	0.9585	0.9585	0.9496	0.9496
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Source: Data is sourced from Bloomberg with all calculations completed by the authors.

Note: The above table reports the estimates of the return and conditional variance equations as well as the DCC parameters. T-statistics are located below the estimated coefficients. In the variance equation, α_i represents the ARCH term, β_1 the GARCH term and ω_{i0} representing the constant of the variance equation. In the multivariate DCC-GARCH results, $\rho_{i,Ireland}$ represents the correlation between the investigated country and Ireland.

Table 4 reports the estimates of the return and conditional variance equations as well as the DCC parameters. The constant terms in the mean equation (μ_0) is significantly different from zero for all the stock returns apart from Italy, France, Greece and Spain. With the exception of Germany and Denmark, the μ_1 term is significantly negative for the remaining stock markets. According to Antoniou et al. (2005), the negativity of the AR(1) term in the mean equation is due to the existence of positive feedback trading in developed markets, while the positivity of this parameter in emerging markets is due to price friction or partial adjustment. The results indicate that all the markets under investigation would be deemed to be developed in this view. The μ_2 coefficient is statistically positive and significant for all markets when modelled against Ireland. The effects of Irish equity returns on the returns of those markets is on average highly significant and large in magnitude, ranging from 0.23 in Switzerland to 0.36 in Denmark. All are positive, which represents the direct influence of Irish equity markets on the investigated countries during this period. The coefficients for the lagged variance (β_i) are positive and statistically significant at the 1% level for all stock markets. The parameters α_i in the variance equations are statistically different from zero for all stock returns. This justifies the suitability of the DCC GARCH⁸ (1,1) specification as the best fitting model to capture time-varying volatility. Moreover, the $\alpha_1 + \beta_1$ is very close to unity in all the markets investigated, indicating a high short-term persistence of the conditional variance. Therefore, the volatility in the GARCH models displays a high persistence.

Table 4 also reports the estimates of the bivariate DCC(1,1) model. The parameters α and β of the DCC(1,1) models respectively capture the effects of standardised lagged shocks ($\epsilon_{t-1}, \epsilon'_{t-1}$) and the lagged dynamic conditional correlation effect (Q_{t-1}) on current dynamic conditional correlation. The statistical significance of these coefficients in each pair of equity markets investigated indicates the existence of time-varying dynamic correlations. When $\alpha_1 = 0$ and $\beta_1 = 0$, we obtain Bollerslev's (1990) Constant Conditional Correlation (CCC) model. The estimated coefficients α_1 and β_1 are all positive and satisfy the inequality constraint of $\alpha_1 + \beta_1 < 1$ in each of the pairs of stock markets investigated. As shown in table 4, the parameter α is statistically significant in all the pairs

⁸ Alternative specifications (DCC (2.1), DCC (1.2), DCC (2.2), etc.) have been tested, but parameters were not significant and the log likelihood did not improve.

investigated. The parameter β_1 is also highly significant. The significance of both the DCC parameters reveals a considerable time-varying co-movement and thus a high persistence of the conditional correlation. The sum of these parameters are very close to unity, thus implying that the volatility displays a high level of persistence. Also, since $\alpha_1 + \beta_1 < 1$, the dynamic correlations revolve around a constant level and the dynamic process appears to be mean reverting. The unconditional correlation pairs of the standardised innovations are also listed from the estimated for the twelve GARCH models with the Irish equity market. The value of the correlations vary between a high of 0.69 for France and a low of 0.38 for Greece.

Boyer et al. (2006) show that contagion can either be investor induced through portfolio rebalancing or fundamental based. The latter can be associated to the interdependence phenomenon (Forbes and Rigobon, 2002) while the former case is described in behavioural finance literature as herding. Hirshleifer and Teoh (2003) argue that this herding behaviour can occur since investors are following other investors and characterise it as convergence of behaviour. Herding behaviour is defined as a group of investors trading in the same direction over a period of time. Using the dynamic conditional correlation measure, Jeon and Moffett (2010) and Syllignakis and Kouretas (2011) find herding behaviour in financial markets during crises periods. Also, it is crucial to check whether the selected equity index time series display evidence of multivariate ARCH effects and test the ability of multivariate GARCH specifications to capture the volatility linkages between equity markets. Kroner and Ng (1998) have confirmed the fact that only a few diagnostic tests are available for multivariate GARCH-class models compared to the diverse range of diagnostic tests devoted to its univariate counterparts.

Finally, we examine the DCC-GARCH model's change in behaviour between the period of stability and period of crises. In a first stage analysis, we estimate the impact of external shocks on the dynamic conditional correlation features. The influence of the subprime crisis in Europe has some particularly interesting effects. Through the use two dummy variables denoting the Irish economic crises and the period after the troika bailout, the different sub-classes allow us to investigate the dynamic features of the correlation coefficient changes associated with the Irish crisis, in terms of the pairwise correlations between the eleven equity markets investigated and that of Ireland. Following Chiang et al. (2007), we regress the time-varying correlation model as follows:

$$\rho_{ij,t} = \omega_{ij} + \sum_{p=1}^p \varphi_p \rho_{ij,t-p} + \sum_{k=1}^2 \alpha_k DM_{k,t} + e_{ij,t} \quad (9)$$

where $\rho_{ij,t}$ is the pair-wise conditional correlation coefficient between the stock return i of the Irish equity market and the stock returns j of the eleven European exchanges included. DM_{1t} is a dummy variable denoting the Irish financial crisis

denoting the period between July 2007 and November 2010. DM_{2t} is a dummy variable denoting the period after troika intervention from November 29th 2010, until October 2013. The Irish crisis is the first phase of the investigation with 635 observations and the second dummy term possesses 1,006 observations. The value of the dummy variables are set equal to unity for the crises periods and one otherwise. We use the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC) to determine the lag length of the above equation. From the descriptive statistics of the time-varying correlation series, we find significant heteroskedasticity in all cases. Therefore, the conditional variance equation is assumed to follow a GARCH(1,1) specification including two dummy variables, $DM_{k,t}$ ($k = 1,2$):

$$h_{i,t} = A_0 + A_1 \varepsilon_{t-1}^2 + B_1 h_{i,t-1} + \sum_{k=1}^2 d_k DM_{k,t} \quad (10)$$

where $A_0 > 0$, $A_1 \geq 0$, $B_1 \geq 0$ and $A_1 + B_1 < 1$. The estimation results for the time-varying correlations are reported in table 5. In the mean equation, the coefficient d_1 is statistically significant in all the countries investigated. This indicates that the subprime crisis is significantly different from that of the pre-crisis period included. This finding indicates the existence of contagion phenomenon between Irish equity markets and the included markets in this investigation during the Irish financial crisis. The largest coefficient is based on the correlation between Spain and Ireland (0.25) while the lowest is between Sweden and Ireland (0.03). In the second phase of the investigation focusing on the period after the troika bailout in Ireland, the estimate of the second dummy variable provides significant results for all the pair-wise investigations. The largest coefficient is based on the correlation between equity markets in Ireland and Spain (0.12) while the lowest is again based on the correlation between Irish and Swedish equity markets (0.01). The estimates of the shock-squared errors (A_1) and lagged variance (B_1) are highly significant for all pair-wise relationships investigated, indicating the presence of clustering phenomenon. These findings indicate more volatility changes in the conditional correlation coefficients during the Irish economic crisis than the period after the troika financial bailout in Ireland. The substantial reduction in contagion after the bailout offers significant support towards its use as a mechanism in crises moderation. In fact, the large statistics shows the true extent of how serious the Irish problem was across European equity markets, and the significant reduction in contagion coefficients prove that the bailout eased European-wide equity volatility rather than Irish equity volatility alone.

Tab. 5: GARCH model testing changes in dynamics conditional correlations of stock market returns during the International financial crisis

	UK	Ger	Fra	Ita	Den	Gre	Swe	Swit	Bel	Neth	Spain
Mean											
eq.											
ω_{ij}	0.0009 (0.019)	0.0003 (0.343)	0.0008 (0.009)	0.0005 (0.003)	0.0014 (0.000)	0.0017 (0.001)	0.0009 (0.040)	0.0001 (0.687)	0.0018 (0.000)	0.0009 (0.016)	0.0006 (0.008)
φ_1	0.9023 (0.000)	0.8381 (0.000)	0.8596 (0.000)	0.8544 (0.000)	0.9315 (0.000)	0.8233 (0.000)	0.8835 (0.000)	0.9075 (0.000)	0.8253 (0.000)	0.8346 (0.000)	0.9443 (0.000)
φ_2	0.0703 (0.003)	0.1765 (0.000)	0.1470 (0.000)	0.1760 (0.000)	0.0603 (0.057)	0.1005 (0.003)	- (0.000)	0.1500 (0.000)	0.1011 (0.000)	0.1351 (0.000)	0.1019 (0.000)
φ_3	-	-	-	-	-	0.0576 (0.013)	0.0928 (0.001)	- (0.037)	0.0528 (0.016)	-	0.0521 (0.048)
Var											
eq.											
ω_{ij}	0.0014 (0.000)	0.0013 (0.000)	0.0013 (0.000)	0.0015 (0.000)	0.0136 (0.000)	0.0132 (0.000)	0.0152 (0.000)	0.0137 (0.000)	0.0129 (0.000)	0.0135 (0.000)	0.0137 (0.000)
α_1	0.1261 (0.000)	0.1629 (0.000)	0.1901 (0.000)	0.2684 (0.000)	0.1018 (0.000)	0.1256 (0.000)	0.1275 (0.000)	0.2032 (0.000)	0.2295 (0.000)	0.1481 (0.000)	0.2082 (0.000)
β_1	0.8690 (0.000)	0.5256 (0.000)	0.8092 (0.000)	0.7203 (0.000)	0.8795 (0.000)	0.8679 (0.000)	0.8662 (0.000)	0.7802 (0.000)	0.7670 (0.000)	0.8392 (0.000)	0.7597 (0.000)
d_1	0.1812 (0.000)	0.1847 (0.000)	0.1494 (0.000)	0.2385 (0.000)	0.1284 (0.000)	0.1407 (0.000)	0.0319 (0.000)	0.1615 (0.000)	0.2121 (0.000)	0.1737 (0.000)	0.2538 (0.000)
d_2	0.0751 (0.000)	0.0643 (0.000)	0.0643 (0.000)	0.1011 (0.000)	0.0784 (0.000)	0.0846 (0.000)	0.0156 (0.000)	0.0515 (0.000)	0.0828 (0.000)	0.1076 (0.000)	0.1185 (0.000)

Source: Data is sourced from Bloomberg with all calculations completed by the authors.

Note: T-statistics are located below the estimated coefficients of the GARCH model based on the conditional correlations of European stock market returns. In the variance equation, α_1 represents the ARCH term and β_1 represents the GARCH term. d_1 is a dummy variable denoting the Irish financial crisis's impact upon the selected countries (July 2007 to November 2010). d_2 is a dummy variable denoting the period after troika intervention in Ireland (November 29th 2010 to October 2013) and its associated impact on the investigated countries.

Overall, these results suggest that when the Irish-specific crisis began in 2007, combined with rumours of a Greek sovereign debt default, market correlations are found to have varied intensely and this variability appears to be persistent over time. The results indicate herding behaviour within European markets during the crises, but this phenomenon appears to have been significantly higher during the Irish financial crisis. Germany and the problematic states of Greece, Spain, France and Italy show dramatic contagion increases during the Irish sovereign debt crises. These results represent European-wide fear and show that contagion spread through the main problematic states and indeed Germany, a sovereign state viewed by investors as a barometer of European-wide financial health given its leading status and financial strength.

The empirical analysis of the patterns of time-varying correlation coefficients during the Irish financial crisis of 2007-2010, provides evidence supporting the presence of significant contagion effects due to herding behaviour in European

equity markets. Indeed, the high correlation coefficients, during crisis periods, imply that the benefit from international diversification, by holding a portfolio consisting of diverse stocks from the contagious equity markets in Europe, decline. Furthermore, the statistical inference of the high volatility of conditional correlation coefficients during the investigated crises periods may have misled investment manager's portfolio decisions. Moreover, the findings in this paper are important for policy makers in Europe since the instability created by equity market contagion significantly hinders development and growth. The results found in this paper reiterate the importance that European policymakers focus on methods of closing channels of contagion during crisis periods to decrease the instability of European markets as a whole.

6 Conclusions

This paper is a contribution to the existing empirical literature on financial market contagion. It focuses on the increase in the strength of the transmission of the Irish sovereign debt crisis between 2007 and 2010, to eleven of the European equity markets. To measure potential contagion phenomena, we first use the adjusted correlation approach of Forbes and Rigobon (2002). The main empirical findings of this analysis presents evidence of financial contagion mechanisms in all pairs of stock markets investigated. Then, we have extended this analysis by taking into account the dynamic feature of the conditional correlation coefficients between the European equity markets investigated. We used the multivariate DCC-GARCH modelling structure to investigate the existence of increased correlation patterns during denoted financial crisis periods. The results indicate the existence of financial contagion effects due to herding behaviour in European equity markets between 2007 and 2013. We find statistically significant effects of the Irish financial crisis on the dynamic conditional correlations with the main European equity markets during the crises. These effects are found to be stronger during the initial Irish economic crisis. The alleviation of these effects in the period after troika intervention in the Irish financial system offer evidence supporting bailouts as a mechanism of stemming equity market contagion.

The use of bailouts as a mechanism to ease contagion during crises is supported and is found to have been largely successful during the Irish financial crisis. Given this result, it may be necessary to implement bailout mechanisms as a primary response in future economic crises. This result also raises moral hazard issues, primarily to what extent these issues can be mitigated if a sovereign state knows that it will be bailed out in the event of economic turmoil. Perhaps, the implementation of high interest rates on each unit of funding provided through the bailout mechanism (but less than sovereign borrowing rates) would reduce any moral hazard issues. Performance incentives could also aid recovery speed, but

this would have to be carefully controlled. During the implementation of a bailout facility, all parties involved must not lose sight that the immediate alleviation of financial market chaos is the primary goal, which stems directly from the restoration of investor confidence. The next goal should be to generate economic growth to enable repayment of the financial facility. If this cannot be generated, the recipient of the financial assistance will most likely enter a debt-spiral leading to further medium to long term financial crisis. If the alternative to not implementing a financial bailout is financial and economic collapse, the bailout mechanism should be viewed as the better option between two unwanted and potentially catastrophic financial outcomes.

References

- Abboushi, A., 2011. Analysis and outlook of the Greek financial crisis', *Journal of Global Business Management* 1, 1-8.
- Ahearne, A., 2012. Debt still a huge challenge despite our foreign assets, *Irish Independent*, 9th of March.
- Antoniou, A., Koutmos, G., Percli, A., 2005. Index futures and positive feedback trading: evidence from major stock exchanges, *Journal of Empirical Finance* 2, 219-238.
- Billio, M., Pelizzon, L., 2003. Volatility and shocks spillover before and after EMU in European stock markets, *Journal of Multinational Financial Management* 1, 323-340.
- Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *Review of Economics and Statistics* 1, 498-505.
- Boyer, B., Kumagai, T., Yuan, K., 2006. How do crises spread? Evidence from accessible and inaccessible stock indices, *Journal of Finance* 1, 957-1003.
- Calvo, S., Reinhart, C., 1996. Capital flows to Latin America: is there evidence of contagion effects? In: Calvo, Goldstein, Hochreiter (Eds.), *Private Capital Flows to Emerging Markets after the Mexican Crisis*. Institute for International Economics, Washington, DC.
- Engle, R. F., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business and Economic Statistics* 3, 339-350.
- Forbes, K., Rigobon, R., 2002. No Contagion, Only Interdependence: Measuring Stock Market Co-Movements, *Journal of Finance* 5, 2223-2261.
- Hardouvelis, G. A., Malliaropoulos, D., Priestley, R., 2006. EMU and European Stock Market Integration, *The Journal of Business* 1, 365-392.

Corbet, S. – Twomey, C.: *European Equity Market Contagion: An Empirical Application to Ireland's Sovereign Debt Crisis*.

Hirshleifer, D., Teoh, S. H., 2003. Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management* 1, 25-66.

Jeon, J. Q., Moffett, C. M., 2010. Herding by foreign investors and emerging market equity returns: Evidence from Korea, *International Review of Economics and Finance* 1, 698-710.

Kroner, K. F., Ng, V. K., 1998. Modelling asymmetric comovements of asset returns, *The Review of Financial Studies* 1, 817-844.

Lavdas, K. A., Litsas, S. N., Skiadas, D. V., 2013. *Stateness and sovereign debt, Greece in the European conundrum'*, Lexington Books, ISBN 978-0-7391-8126-3.

Lee, H. Y., Wu, H. C., Wang, Y. J., 2007. Contagion effect in financial markets after the South-East Asia Tsunami, *Research in International Business and Finance* 1, 281-296.

Mighri, Z., Mansouri, F., 2013. Dynamic Conditional Correlation Analysis of Stock Market Contagion: Evidence from the 2007-2010 Financial Crises, *International Journal of Economics and Financial Issues* 3, 637-661.

Syllignakis, M. N., Kouretas, G. P., 2011. Dynamic correlation analysis of financial contagion: Evidence from the central and eastern European markets, *International Review of Economics and Finance* 1, 717-732.