The Shift-Contagion Effect Of Global Financial Crisis And The European Sovereign Debt Crisis On OECD Countries

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ABSTRACT

This article investigates shift-contagion as defined by Forbes and Rigobon (2002) in 16 OECD member economies during most recent financial crisis i.e. global financial crisis (2008-2009) and European sovereign debt crisis (2009-2012), using multivariate asymmetric dynamic conditional correlation model developed by Cappiello et al. (2006). The empirical analyses provide substantial evidence of shifts in the dynamic correlations and hence reconfirm shift-contagion during the global financial crisis that originated from U.S. However, there is no evidence in support of shift-contagion during the European sovereign debt crisis which originated from events in Greece. The results provide important implications for investors and policy makers.

Keywords: Global Financial Crisis; European Sovereign Debt Crisis; Asymmetric Dynamic Conditional Correlations; Shift Contagion

1. INTRODUCTION

Economic and financial crisis (2008-2009) had a profound impact not only on U.S economy but also on the global economy as well. Seeds of global financial crisis (GFC henceforth) can be traced to good times when Federal Reserve reduced Fund rate from 6.5% to 1.75% from May 2000 to December 2001. This definitely spurred a lot of liquidity along with large foreign capital inflows. This combination along with financially engineered products created perfect times for financial boom and perfect ground for the doom in the years to come. Most of the major financial giants like Merrill Lynch, Bear Stearns, Lehman Brothers, Citibank, Wells Fargo and Washington Mutual had deep roots in financially engineered products and securitization process. Ultimately good times ended and history revealed that, most of the perceived safe and sound financial institutions were not properly insulated from financial risk as they should have been. Good times of lower interest rates ended and Fed increased fund rate to 5.25% by 2006. Large number of bankruptcy applications were filed by mortgage loan borrowers and chain of defaults started taking place. This had reflective impact on other financial institutions around the globe as well, and thus exhibiting the phenomenon of contagion. All the major economies of the world in one way or the other were affected by the GFC. In summary the main causes of the crisis were high rise in housing demand, high defaults on low quality loans, increase in origination of mortgage backed securities (MBS), easily available credit with less supervision and due diligence and soft regulatory structure, weak underwriting standards, unsound risk management practices, increasingly complex financial products, high leveraged strategies, inadequate attention to known risk elements and relaxation in following domestic and international financial regulatory rules and principles.

The impact of GFC had not completely vanished; the birth of European sovereign debt crisis (ESDC henceforth) took place. The economic and financial events in late 2009 in Greece may be regarded as the epicenter of the ESDC. Most economies of Europe, such as, France and Spain, were affected by the crisis. Syllignakis and Kouretas (2010) while confirming this point of view substantiate that GFC had a critical effect on the convergence of stock markets of Central and Eastern Europe as they were partially integrated with the mature US stock markets.

In summary the individual economic factors which contributed to contagion were currency depreciation, budget deficits and rising debt levels (Syllignakis & Kouretas, 2011).

Despite much research on the subject little consensus is found on a single definition of contagion. For example, Eichengreen and Rose (1999) and Kaminsky and Reinhart (1999) define contagion as a situation where the information of crisis at one place increases the probability of domestic crisis elsewhere. Forbes and Rigobon (2002) introduced the concept of “Shift-Contagion” and defined it as “a significant increase in cross market linkages after a shock to an individual country (or group of countries)”. Gravelle et al. (2006) further formalized this idea and the term “Shift-Contagion” started gaining popularity. Distinction between interdependency and contagion has important implications for researchers, investors and the policy makers. High levels of correlation between two variables during normal period may represent interdependence but the same situation may represent contagion if a significant shift in correlations is observed. We base our analysis on the definition of contagion as proposed by Forbes and Rigobon (2002).

In literature, we find the application of time varying conditional correlations between stock market returns, exchange rates returns, credit default swaps among many other financial variables to distinguish the stable and the crisis period. This methodology became widely used after the seminal work of Engle (2002)¹. Most of the research based on the model of Engle (2002) (now on as DCCE) and its various flavors revolve around the Asian financial crisis or the GFC e.g. Chiang et al. (2007) use the DCCE model to study the dynamic conditional correlations among nine Asian stock market returns from 1990 to 2003. They identify two phases of Asian crisis; first phase exhibits the contagion phenomenon whereas the second phase is characterized by herding (continued high correlations). Kuper and Lestano (2007) also apply the same model to daily data from March 3, 1995 to December 31, 2001 to study the dynamic correlations among the stock markets, the markets for foreign exchange and the money markets in Indonesia and Thailand during the Asian crisis. They observe no contagion between Thailand and Indonesia. Cheung et al. (2008) employ the same model on the stock market returns of U.S. and 11 EMEAP² economies while using weekly data to study the contagion effect of GFC. They use t-test to compare the means of the dynamic correlations to assess the contagion behavior and find no contagion between U.S. and 11 EMEAP economies but witness intra-regional contagion. They attribute this to indiscriminate treatment of regional markets by investors while facing common external shocks. Yiu et al. (2010) apply the Asymmetric Dynamic Conditional Correlation model of Cappiello et al. (2006) on the weekly stock market returns to study the contagion effect of Asian crisis and the GFC on a common factor representing Asia extracted through Principal Component Analysis (similar to Cheung et al., 2009) and each of 11 Asian countries. They find no contagion effect during the Asian crisis whereas contagion is evidenced during the GFC. Very few research articles have applied these techniques beyond the Asian countries. Syllignakis and Kouretas (2011) apply DCCE model to study short-run interdependencies and potential channels of contagion effects between the Central and Eastern European countries and the US, German and Russian stock markets on weekly stock market returns for the period 1997–2009. They provide evidence in favor of contagion effects due to herding behavior in Central and Eastern European markets around the 2007–2009 financial turmoil whereas the hypothesis of contagion is rejected for the Asian crisis, Russian crises, and the dot-com bubble. Kenourgios et al. (2011) employ the Asymmetric Generalized Dynamic Conditional Correlations model by Cappiello et al. (2006) on weekly stock market returns of BRIC³ and two developed countries i.e. U.S. and U.K to study contagion effect of five financial crises. They confirm contagion effect from crisis country to all other countries during different crisis under study and they reveal that BRIC markets are more prone to financial contagion while industry specific turmoil has larger impact than country-specific crisis. More recently, Tamakoshi et al. (2012) apply Asymmetric Dynamic Conditional Correlation model by Cappiello et al. (2006), on daily stock market returns from September 2008 to May 2010, of Greece and six European countries to study the contagion effects during Greek sovereign debt crisis. They reveal that there is significant decline in dynamic correlation during the crisis period which may offer diversification benefits hence no contagion.

¹ Engle (2002) introduced the methodology to estimate Dynamic Conditional Correlations (DCC). This methodology consists of two stages. In first stage, an appropriate univariate GARCH model is selected to fit to the data. In the second stage, the conditional correlations are estimated using the standardized errors from the first stage.

² EMEAP stands for the Executives’ Meeting of East Asia-Pacific Central Banks. It comprises central banks and monetary authorities of Australia, China, Hong Kong, Indonesia, Japan, Korea, Malaysia, New Zealand, the Philippines, Singapore, and Thailand.

³ BRIC stands for four emerging economies which include Brazil, Russia, India and China.

This paper studies the changes in the dynamics of conditional correlation of stock market returns of 16 OECD countries in times of crisis vis-à-vis tranquil period. Stock market data is used to study shift-contagion due to the fact that the stock market reactions could be triggered by the exchange rate dynamics followed by sovereign debt signals (Phylaktis & Ravazzolo, 2005). We analyze the contagion effect of two recent crises i.e. GFC and ESDC, by applying a robust technique of Asymmetric Dynamic Conditional Correlations (ADCC henceforth) introduced by Cappiello et al. (2006). ADCC GARCH helps to alleviate the dimensionality issue, and incorporates asymmetric impact of negative and positive shocks on the correlations. Moreover, the use of GARCH models for estimating correlations also overcomes the problem of heteroscedasticity of Pearson correlation coefficient raised by Forbes and Rigobon (2002). We avoid the application of DCC model by Engle (2002) due to inconsistency problem with the DCC estimators as identified by Aielli (2013). To the best of our knowledge, this paper is the first of its kind, in terms, of addressing the GFC and ESDC simultaneously by applying the ADCC EGARCH model on a huge data set of 16 OECD stock markets.

The remainder of the paper is organized as follows. Section 2 describes empirical methodology. Section 3 presents the data, descriptive statistics and a little discussion on key dates of crisis. Section 4 contains our empirical analysis of the results whilst Section 5 offers some concluding remarks.

2. METHODOLOGY

We organize our study in three stages. At first stage we fit a univariate GARCH model to each series of stock returns⁴. At second stage, we estimate multivariate ADCC model of Cappiello et al. (2006) between the U.S and 15 OECD stock markets, and between Greece and 14 OECD stock markets. This is in contrast to Yiu et al (2010) and Tamakoshi et al. (2012), where they use a bi-variate framework. The advantage of using a multivariate ADCC lies in the fact that we can simultaneously estimate the pair-wise correlation coefficients for the stock market returns and study the phenomena of contagion (Syllignakis & Kouretas, 2011). Finally, we estimate an AR(1) model on the dynamic correlation with two dummy variable representing the GFC and ESDC. Each stage is further elaborated as under:

2.1 EGARCH Model Estimation (Stage 1)

We estimate a mean equation to retrieve the residuals needed to model variance equation; hence returns can be described by the following process:

$$r_t = \Phi_0 + \varepsilon_t, \quad (1)$$

$$\varepsilon_t \sim \text{idN}(0, \sigma_t^2)$$

where Φ_0 is a constant, r_t is returns at time t and ε_t is error term at time t .

Nelson (1991), introduced Exponential GARCH (EGARCH) which has advantage over the plain vanilla GARCH, as it permits good news and bad news to have a different impact on volatility by allowing bad news to have greater impact on volatility. The EGARCH model works in two steps, first it considers mean and then variance, it can be defined as:

$$\log(d_t) = \omega + \sum_{i=1}^p \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) + \sum_{i=1}^q \beta_i \log(d_{t-i}), \quad (2)$$

⁴ We test for various univariate GARCH models and find EGARCH(1,1) the most suitable based on likelihood ratio test, though the results are only presented for EGARCH to preserve space. The superiority of EGARCH in financial research compared to its other asymmetric counterparts is also well discussed in Alexander (2008) and Tsay (2010).

where ω, β and γ are all parameters for estimating conditional variance. β_i shows the impact of last period measures on conditional variance. α_i is a coefficient that indicates the past standardized residuals' influence on current volatility. Finally γ_i explains asymmetry effect in variance.

2.2 ADCC Model Estimation (Stage 2)

We estimate asymmetric DCC model developed by Cappiello et al. (2006) to derive the time-varying conditional correlations. We denote the standardized regression mentioned above as:

$$\bar{\varepsilon}_t = \varepsilon_t / \sqrt{d_t} \quad (3)$$

To capture asymmetric impacts, the negative standardized residuals are defined by

$$\bar{n}_t = \bar{\varepsilon}_t \text{ if } \bar{\varepsilon}_t < 0 \text{ and } \bar{n}_t = 0 \text{ otherwise} \quad (4)$$

Then by depicting the dynamics of conditional correlation matrix denoted by P_t , and unconditional correlation matrix between residuals denoted by $\bar{P}$, the asymmetric DCC (1, 1) model is represented as:

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1}, \quad (5)$$

$$Q_t = (\bar{P} - a_1 \bar{P} - b_1 \bar{P} - g_1 \bar{N}) + a_1 \varepsilon_{t-1} \varepsilon'_{t-1} + g_1 n_{t-1} n'_{t-1} + b_1 Q_{t-1}, \quad (6)$$

where a_1 and b_1 are scalars and Q_t is the conditional correlation matrix between standardized residuals. Q_t^* is a diagonal matrix with square root of i -th diagonal element of conditional correlation matrix on its i -th diagonal position. A necessary and sufficient condition to ensure that Q_t is positive definite for all realizations is that:

$$a^2 + b^2 + \delta g^2 < 1, \quad (7)$$

where δ represents maximum eigenvalue $\left[\bar{P}^{-1/2} \bar{N} \bar{P}^{-1/2} \right]$.

2.3 AR(1) Model Estimation (Stage 3)

At this last stage, we apply an Autoregression (AR) model, with one lag and two dummy variables representing the GFC and the ESDC, on asymmetric dynamic conditional correlations to check for the hypothesis that GFC and ESDC have significant impact on the dynamics of correlations between the U.S. stock market and each of 15 OECD markets on one hand, and Greece stock market and each of 14 OECD stock markets on the other. The AR(1) model is presented as under:

$$AD\hat{C}C_t = \delta_0 + \delta_1 AD\hat{C}C_{t-1} + \xi_1 GFC_t + \xi_2 ESDC_t + \nu_t. \quad (8)$$

3. THE DATA AND DESCRIPTIVE STATISTICS

We use weekly Wednesday to Wednesday returns in percentage terms of benchmark equity indices of 16 OECD countries (U.S, Canada, Finland, France, Germany, Ireland, Italy, Netherlands, Spain, Denmark, Norway,

Sweden, U.K, Australia, Japan, and Greece). We use weekly returns to preserve the adequacy of data and avoid the market microstructure biases at daily frequencies. Further, equity indices are obtained in U.S. dollars to avoid the influence of country specific factors such as inflation and at the same time incorporate exchange rate fluctuations in our study.

Analyzing crisis requires understanding of the chronological events that shape up the crisis. It is difficult to come out with a unanimous agreement on the periods of GFC and ESDC, therefore we base our analysis on the chronology of events as given in the literature. The date of the GFC is based upon the study of Aït-Sahalia et al. (2012), Aloui et al. (2011), Kowalski and Shachmurove (2011), and Blancheton and al. (2011) among many others. All these articles treat 15 September 2008 as the start of GFC, since we use weekly data and the same does not fall in our data set therefore we have taken the nearest date i.e. 17 September 2008 as the start of crisis. Tamakoshi and al. (2012), Arnold (2012), and Chudik and Fratzscher (2012) refer different dates for ESDC. We prefer to follow the date as in Tamakoshi and al. (2012) because of the strong reasoning that on 5 November 2009 the Greek government announced an unexpected fiscal deficit of 12.7% of GDP instead of 6%, and the public debt projections of 135% of the GDP by the end of 2011, lead towards the nation's economic collapse. This also changed investor perceptions not only in Greece and Europe but all around the globe and hence the demarcation of ESDC. Similar to the GFC, the date 5 November 2009 does not fall in our data so we have taken the nearest date of 11 November 2009 as the beginning of ESDC.

Our data set starts from 7 January 2004 and ends at 23 May 2012. Descriptive statistics are provided in Table 1. It is interesting to note that the mean returns of the weekly data were negative for most of the countries for both the crisis except for U.S. and Sweden⁵. In U.S., the returns are negative for GFC but positive during the ESDC whereas for Sweden the returns were positive for GFC but negative for ESDC. As expected, there is increase in standard deviation during both crisis periods for all the countries. The returns are characterized by negative skewness during both the crisis except for Australia which is positively skewed during the ESDC. Further the returns exhibit excess kurtosis. The Jarque–Bera statistics are significant for all return series and hence rejects the assumption of normality.

Table 1: Summary Statistics (07/01/2004 – 23/05/2012)

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
RUSA	0.036	9,639	-16,451	2,486	-1.143	9,932	970,166
RCAN	0,073	7,833	-15,263	2,434	-0,940	7,400	416,883
RFIN	-0,046	9,606	-13,730	3,289	-0,547	4,847	83,935
RFR	-0,039	11,127	-14,796	2,920	-0,901	6,799	322,020
RGER	0,103	10,942	-16,804	3,091	-1,190	7,926	544,929
RIRL	-0,115	14,881	-17,576	3,631	-0,619	7,061	328,240
RITA	-0,170	11,659	-14,735	3,238	-0,590	5,944	183,144
RNL	-0,037	9,401	-15,706	2,971	-0,831	6,201	236,757
RSP	-0,055	11,881	-12,490	3,069	-0,397	4,942	80,174
RDM	0,189	11,578	-18,276	2,891	-0,934	8,564	627,223
RNOR	0,201	19,711	-20,120	3,681	-0,949	8,637	644,202
RSWE	0,098	13,196	-14,770	2,963	-0,570	6,009	188,507
RUK	0,037	6,872	-12,732	2,457	-0,926	6,144	242,406
RAUS	0,048	12,016	-11,530	2,397	-0,548	6,443	237,644
RJPN	-0,052	14,794	-21,126	3,129	-0,928	9,363	799,850
RGRE	-0,422	14,527	-19,440	4,529	-0,518	4,697	71,974

4. EMPIRICAL ANALYSIS

4.1 EGARCH Model Estimation (Stage 1)

In Table 2, we present the parameter estimates of univariate EGARCH(1,1) for all the 16 OECD countries stock market returns. Similar to Tamakoshi et al. (2012) and Yiu et al. (2010) most of the parameters in the mean

⁵ Descriptive statistics for the sub-periods are not provided to preserve space. Contact authors for information.

equation are not significant except for Canada, Ireland, Denmark, Norway and Australia, whereas the parameters of the variance equations and the asymmetric terms are statistically significant for all the OECD stock markets therefore exhibiting a good fit to the data. The Ljung and Box (1978) Q statistics for serial correlation show that the null hypothesis of no autocorrelation up to the 20th order is accepted, confirming no serial autocorrelation in the standardized residuals and the squared standardized residuals. Also, the diagnostic tests reveal no evidence of ARCH effects in the residuals.

Table 2: EGARCH(1,1) Model for the Entire Period (07/01/2004 – 23/05/2012) for 16 OECD Countries

	EGARCH(1,1) Parameters					Diagnostics		
	Φ_0	ω	α_1	β_1	γ_1	Q(20)	Q ² (20)	ARCH
RUSA	0,020 (0,087)	0,275* (0,092)	0,148** (0,051)	0,801*** (0,052)	0,382* (0,077)	28.595 [0.096]	22.451 [0.213]	1.124 [0.322]
RCAN	0,162*** (0,090)	0,207** (0,098)	0,159*** (0,085)	0,826* (0,051)	0,147** (0,066)	24.345 [0.228]	16.002 [0.592]	0.860 [0.639]
RFIN	0,092 (0,130)	0,308* (0,085)	-0,054*** (0,028)	0,919* (0,027)	0,181* (0,041)	23.819 [0.250]	13.020 [0.790]	0.657 [0.868]
RFR	0,019 (0,108)	0,470* (0,171)	-0,064** (0,038)	0,796* (0,055)	0,347* (0,087)	29.145 [0.085]	23.484 [0.173]	1.094 [0.353]
RGER	0,179 (0,124)	0,894* (0,248)	-0,066** (0,040)	0,702* (0,053)	0,461* (0,113)	33.417 [0.030]	25.006 [0.125]	1.218 [0.235]
RIRL	0,234*** (0,136)	0,454*** (0,243)	0,099*** (0,055)	0,785* (0,073)	0,61** (0,069)	18.120 [0.580]	22.949 [0.193]	1.044 [0.409]
RITA	0,025 (0,102)	0,187* (0,072)	0,281*** (0,145)	0,865* (0,035)	0,164* (0,053)	29.451 [0.079]	10.164 [0.926]	0.490 [0.970]
RNL	0,031 (0,114)	0,370** (0,155)	-0,060** (0,038)	0,835* (0,055)	0,233* (0,072)	23.710 [0.255]	26.205 [0.095]	1.356 [0.141]
RSP	0,124 (0,117)	0,525* (0,179)	0,078*** (0,045)	0,766* (0,055)	0,334* (0,094)	22.088 [0.336]	13.781 [0.743]	0.679 [0.847]
RDM	0,505* (0,098)	0,155** (0,069)	0,116*** (0,065)	0,791* (0,047)	0,160** (0,076)	17.861 [0.597]	23.084 [0.187]	1.155 [0.291]
RNOR	0,316** (0,141)	2,116* (0,799)	0,074** (0,053)	0,578* (0,114)	0,317* (0,110)	26.998 [0.135]	35.817 [0.007]	1.432 [0.103]
RSWE	0,102 (0,112)	0,313* (0,077)	-0,100* (0,027)	0,904* (0,025)	0,291* (0,061)	27.309 [0.127]	13.014 [0.791]	0.629 [0.891]
RUK	0,050 (0,095)	0,360* (0,110)	-0,033** (0,017)	0,793* (0,047)	0,343* (0,084)	28.069 [0.108]	19.786 [0.345]	1.060 [0.391]
RAUS	0,190** (0,092)	0,234** (0,098)	0,068** (0,049)	0,805* (0,047)	0,259* (0,090)	21.804 [0.351]	14.296 [0.710]	0.668 [0.858]
RJPN	0,039 (0,121)	1,387* (0,328)	-0,039*** (0,021)	0,722* (0,068)	0,322* (0,087)	24.581 [0.218]	7.720 [0.983]	0.318 [0.998]
RGRE	0,073 (0,168)	0,242*** (0,142)	0,066** (0,047)	0,888* (0,033)	0,075*** (0,061)	24.922 [0.204]	17.054 [0.519]	0.861 [0.637]

Notes: ** *, **, and * indicate statistical significance at 10%, 5% and 1% respectively. The numbers in parentheses are the Standard Errors of estimations and the numbers inside square brackets are the p-values. Q(20) and Q²(20) are the Ljung–Box Q-statistic of order 20 computed on the standardized residuals and squared standardized residuals, respectively. ARCH(20) is the non heteroskedasticity statistic of order 20.

4.2 ADCC Model Estimation (Stage 2)

The estimated parameter of standardized residuals (a), and the parameter of innovation in the dynamics of the conditional correlation matrix (b) are all significant at 1% significance level with estimated values of 0.117 and 0.899 respectively. The magnitude and significance of these parameters permit us to verify the time-varying co-movement between the markets. In contrast to Yiu et al. (2010) and Tamakoshi and al. (2012), the parameter of the standardized negative residuals (g) is higher than zero (i.e. 0.215) and significant at 1% significance level. This implies that the dynamic correlations react more to negative news than the positive news. Further, the significance of

the asymmetric term strengthens our argument for using asymmetric dynamic correlation model rather than using a plain vanilla dynamic correlation model of Engle (2002).

4.3 AR(1) Model Estimation (Stage 3)

Tables 3 and 4, present the AR(1) model estimates of the dynamic conditional correlations for the U.S. stock market and each of the 15 remaining OECD countries, and the Greece stock market and each of the 14 OECD countries respectively.

Table 3: AR(1) Models for the ADCC between U.S. and Each of 15 OECD Countries

	δ_0	δ_1	ξ_1	ξ_2	R Square
corr_us_can	0,122* (0,020)	0,835* (0,026)	0,009* (0,003)	0,004** (0,002)	0,764
corr_us_fin	0,122* (0,019)	0,814* (0,028)	0,011* (0,004)	0,006** (0,003)	0,739
corr_us_fr	0,122* (0,021)	0,846* (0,026)	0,007* (0,003)	0,004** (0,002)	0,783
corr_us_ger	0,118* (0,020)	0,841* (0,026)	0,008* (0,003)	0,004** (0,002)	0,773
corr_us_irl	0,113* (0,018)	0,825* (0,028)	0,006 (0,004)	0,007** (0,003)	0,722
corr_us_ita	0,110* (0,019)	0,844* (0,026)	0,009* (0,003)	0,004*** (0,002)	0,771
corr_us_nl	0,115* (0,019)	0,847* (0,026)	0,006** (0,003)	0,003 (0,002)	0,750
corr_us_sp	0,075* (0,016)	0,885* (0,024)	0,007*** (0,004)	-0,001 (0,003)	0,792
corr_us_dm	0,090* (0,015)	0,843* (0,026)	0,011* (0,004)	0,008** (0,003)	0,780
corr_us_nor	0,106* (0,016)	0,814* (0,028)	0,015* (0,004)	0,013* (0,003)	0,783
corr_us_swe	0,100* (0,018)	0,854* (0,026)	0,005 (0,003)	0,003 (0,002)	0,754
corr_us_uk	0,153* (0,023)	0,802* (0,029)	0,009* (0,003)	0,007* (0,002)	0,744
corr_us_aus	0,138* (0,019)	0,768* (0,032)	0,013* (0,004)	0,012* (0,003)	0,707
corr_us_jpn	0,078* (0,014)	0,857* (0,025)	0,008** (0,004)	0,003 (0,003)	0,769
corr_us_gre	0,065* (0,011)	0,852* (0,026)	0,010** (0,005)	-0,002 (0,003)	0,760

Notes: ** *, **, and * indicate statistical significance at 10%, 5% and 1% respectively.

Table 4: AR(1) Models for the ADCC between Greece and Each of 14 OECD Countries

	δ_0	δ_1	ξ_1	ξ_2	R Square
corr_gre_can	0,062* (0,012)	0,864* (0,025)	0,010** (0,004)	0,000 (0,003)	0,766
corr_gre_fin	0,071* (0,013)	0,863* (0,025)	0,005 (0,004)	0,000 (0,003)	0,751
corr_gre_fr	0,072* (0,014)	0,877* (0,024)	0,005 (0,004)	-0,002 (0,003)	0,787
corr_gre_ger	0,075* (0,014)	0,867* (0,024)	0,007 (0,004)	-0,003 (0,003)	0,783
corr_gre_irl	0,061* (0,012)	0,877* (0,024)	0,004 (0,005)	-0,001 (0,003)	0,775
corr_gre_ita	0,073* (0,014)	0,877* (0,023)	0,006*** (0,004)	-0,001 (0,003)	0,792
corr_gre_nl	0,074* (0,014)	0,872* (0,024)	0,006 (0,004)	-0,003 (0,003)	0,792
corr_gre_sp	0,086* (0,015)	0,855* (0,026)	0,005 (0,004)	-0,001 (0,003)	0,741
corr_gre_dm	0,034* (0,008)	0,916* (0,020)	0,005 (0,005)	0,000 (0,004)	0,844
corr_gre_nor	0,060* (0,011)	0,874* (0,023)	0,008 (0,004)	-0,001 (0,003)	0,784
corr_gre_swe	0,071* (0,013)	0,863* (0,025)	0,003 (0,004)	-0,004 (0,003)	0,762
corr_gre_uk	0,078* (0,014)	0,857* (0,026)	0,007 (0,004)	-0,002 (0,003)	0,756
corr_gre_aus	0,060* (0,012)	0,878* (0,024)	0,005 (0,004)	0,000 (0,003)	0,778
corr_gre_jpn	0,041* (0,009)	0,898* (0,022)	0,004 (0,004)	-0,002 (0,003)	0,820

Notes: ***, **, and * indicate statistical significance at 10%, 5% and 1% respectively.

The mean term (δ_0) in the AR(1) model reveals that the shocks in one market are positively or negatively correlated with other market (Yiu et al., 2010). For U.S. and each of the 15 OECD stock markets, the mean terms are all statistically significant at 1% level. Further, the shocks in U.S. stock market impact the U.K stock market (0.15) the most as shown in Figure 1, and the Greece stock market (0.06) the least, whereas the U.S. stock markets approximately equally affects the Canadian, French and Finland stock markets (0.12).

Figure 1: Asymmetric Dynamic Conditional Correlations between U.S and U.K Stock Markets

Figure (2) Asymmetric Dynamic Conditional Correlations between Greece and Spain Stock Markets

For Greece and each of 14 OECD stock markets, the mean parameters are also statistically significant at 1% level. The shocks in Greece stock market impact the Spain stock market (0.086) the most as shown in Figure 2 and the Denmark stock market (0.034) the least, whereas Greece stock market approximately equally impacts Sweden and Finland stock markets (.071).

The coefficients of the AR terms (δ_1) are all statistically significant at 1% significance level for all the equations and for both the, U.S. and each of 15 OECD countries, and the Greece and each 14 OECD countries. The values of all coefficients are less than unity hence reconfirming the stationary property of the model. The coefficient of determination (R^2) measures the goodness of fit of an estimated regression to the data. R^2 ranges between 0.71 and 0.80 for the AR(1) models of U.S. and each of the 15 OECD countries and between 0.74 and 0.84 for Greece and each of the 14 OECD countries. Compared to Yiu and al. (2010) our AR(1) models evidence better fit to the data.

The dummy variables for GFC (ξ_1) and ESDC (ξ_2) for AR(1) models on the asymmetric dynamic conditional correlations between U.S. and each of 15 OECD countries reveal some interesting results. The parameter estimates for the GFC are all statistically significant at 10% significance level except for the Ireland and Sweden stock markets whereas the parameter estimates for the ESDC are also mostly significant except for Netherlands, Spain, Sweden, Japan, and Greece. The non significance of the estimates of ESDC dummy variable reveals that there was no contagion from Greece to U.S. This may be due to the fact that U.S. banks have little direct exposure amounting to \$7.3 billion to Greece. The significance of remaining 10 OECD countries may be attributed to the after effect of the GFC and the probability of default by U.S in July-August 2011, rather than directly attributing it to the events in Greece. Our finding reconfirm most of the research on GFC contagion on advanced economies of the world as already discussed in the text.

The parameter estimates of the dummy variables for GFC (ξ_1)⁶ and ESDC (ξ_2) for AR(1) models on the asymmetric dynamic conditional correlations between Greece and each of the 14 OECD countries are almost non significant except for Canada and Italy which are significant at 10% significance level for the GFC dummy. This enables us to deduce the notion of no strong evidence of contagion effects on OECD stock markets due the economic and financial events in Greece. Three important reasons may be put forward to support our findings. First, Greece being a comparatively small economy⁷ has negligible impact on rest of the OECD member countries (e.g Nelson et al., 2011, p. 2). Second, the crisis in European countries mainly emerged from domestic mishandling of unsustainable levels of public debt (e.g. in Greece, Ireland, Portugal, and Spain), hence economic and financial events in one country may not substantial impact other countries. Blundell-Wignall and Slovik (2010) provide similar explanation; they find that the financial institutions are heavily burdened by the sovereign debt of the domestic country. Third, international monetary institutions such as European Central Bank (ECB) and International Monetary Fund (IMF) were quick enough in responding to crisis in each country and prevented them from spreading to other countries in the region (Nelson et al., 2011, p. 5). Our result contradicts that of Tamakoshi and al. (2012). This contradiction is mainly because of two methodological issues. First, they use daily stock market returns which may incorporate market microstructure biases (e.g. Kenourgios et al., 2011). Second, they take a dataset of stock market returns of seven European countries including that of U.K whose opening and closing times do not match with rest of the countries and hence may induce contemporaneous mean relations between the markets.

5. CONCLUSION

This paper investigates shift-contagion among 16 OECD member economies during global financial crisis (2008-2009) and European sovereign debt crisis (2009-2012). To this end, we apply asymmetric dynamic conditional correlation model developed by Cappiello et al. (2006) in a multivariate frame work. Our results provide interesting results. First, our results reconfirm the impact of shift-contagion in most of the advanced countries of the world as presented in the literature. Second, we find no strong evidence of shift-contagion during the European sovereign debt crisis. This may be attributed to comparatively small magnitude of Greek economy in the world, the crisis in European countries originate and impact the domestic economies, and lastly, international financial institutions such as IMF and ECB were efficient in responding to the country specific needs at times of default and

⁶ The dummy variable is introduced for GFC between the dynamic correlations of Greece and each of OECD country to perform robust test to observe if the methodology under consideration reveals expected results. We do not expect to observe any significant shifts between the dynamic correlations of Greece and each of OECD during GFC.

⁷ 42nd economy in the world and contributes a paltry 3% to the GDP of European Union.

prevented them from becoming an international phenomenon. The extension of current work is possible as ESDC is an ongoing phenomenon so a revision of the current work may yield further insight into the contagion dynamics.

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