University of the Aegean

Department of Business Administration

Business School

Empirical Analysis of Contagious Financial Crisis: The Key Role of Multivariate Dynamic Conditional Correlations, Copula Functions, Markov Regime Switching Models and Machine Learning

A dissertation submitted in fulfillment of the requirements for the degree of Doctor of Philosophy.

Elias Kampouris **December 2018** **Doctoral Thesis**

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ABSTRACT

This doctoral thesis studies the volatility spillover effects from shock events of financial crisis. To achieve this goal, individual research problems are empirically analyzed, aiming at a better understanding of the subject. The empirical analysis is divided into five parts/researches which cover fields of financial contagion in the global financial system focusing on the most recent crisis events.

The first part investigates the volatility spillover effects from South to North Eurozone during the Sovereign Debt Crisis. I propose the Dynamic Conditional Correlation (DCC) model and the BEKK model to identify possible linkages during the period 2005-2015. These two models are the most appropriate in quantifying the correlations and the variance-covariance matrices between asset markets. The findings showed that both models behave perfectly and are flexible in presenting the spillover effects. However, when it comes to figure illustration of conditional correlations, the ADCC model seems to fit better. Additionally, Spain and Italy are those countries which can produce significant damage on all Northern strong economies while Greece's negative shocks are capable of co-moving the French index. France, on the other hand, is the most correlated country with the South Eurozone. The findings support significant interesting contribution to the literate of contagion in capital markets.

The second part studies the spread of the Subprime Crisis and the European Sovereign Debt Crisis from Eurozone countries to the real economy by examining ten sectors in major developed and emerging stock markets. First, I employ Cappielo's et al. (2006) model and copula functions to detect and cross-check the correlations and the contagion thereafter. Second, I uncover evidence of correlation behavior between policy uncertainty indexes and stock market returns. The results demonstrate that no country and sector was immune to spillover effects, highlighting the limited effectiveness of policy makers for both the Subprime Crisis and the European Sovereign Debt Crisis. The empirical application provides evidence of significant volatility and tail dependence from the financial sector to many real sectors in the U.S. economy. Additionally, there is clear evidence that certain sectors, particularly Healthcare, Telecommunications, Utilities and Technology, were less severely affected by the crisis, as observed by Baur (2011).

The third part applies a dynamic conditional correlation DCC model to investigate the volatility spillovers and the interdependence between the Greek Debt crisis and the Cypriot financial crisis. The subprime mortgage crisis created large shocks to most major economies. Shortly after, the new economic framework obliged Greece to decrease its high deficit and public debt. Subsequently, the Cypriot financial crisis occurred after the credit event in Greece. Possible contagion channels were created after the Cypriot government's decision to impose a bank deposit levy in return for the bailout. The findings support the existence of contagion during the period 2008-2013. By 2015, the financial environment in both countries was quite different and this is evident in correlations in the last two years. Observing the behaviour of the correlations, I conclude that both economies are being “treated like lab rats” to test for austerity measures in order for the rest of the systemic countries to be secured from a possible transfer of the crisis from Greece to their own state.

The fourth part studies the effects of the June 2016 United Kingdom European Union membership referendum and the subsequently triggered article 50 on 43 major developed and emerging stock markets. I detect which countries are vulnerable to the transmission of the shock and which others have immunity during the period of turmoil. Specifically, on a bivariate basis, I use dependence dynamics through copulas with regime switching of Silva Filho et al. (2012) using intraday data returns to identify contagion among stock markets. The empirical results add significant evidence to the literature on the financial contagion from the Brexit to other countries for a very large sample thus far. Evidence shows that the methodology identified immediate financial contagion produced from the referendum results. However, the contagion was not sufficiently significant given the short duration. I suppose that the negative reaction in the markets was overall small and held only for a short period. In general, results showed instant financial contagion due to the shock and increased uncertainty from the referendum results; however, the shock and uncertainty were very limited, because a few days after the polling day, most stock exchange markets had fully recovered their losses. Additionally, no significant contagion produced from the trigger of article 50. The approach provides significant information not only to policymakers but also to investors about the stock market’s reaction to the expected Brexit.

Lastly, the fifth part of the research studies on ‘early warning systems’ (EWS) by investigating whether measures of contagion risk, which are based on modeling the global financial system as a network, can serve as early warning indicators and improve the performance of standard crisis prediction models. In doing so, I combine network analysis and machine learning algorithms to create an accurate model for predicting the vulnerable periods of contagion during shock events and crisis periods in stock exchange markets. The empirical results add significant evidence to the literature since few prior studies have focused on the network topologic metrics in the financial networks. Regarding the financial networks, they are interpreted by a significant percentage of the actual geographic location of the markets. In addition, the volatility of the correlations largely follows the volatility of the centralities where significant shocks in the correlations trigger huge volatility in all centralities. Based on this evidence I use hypothesis testing to determine the possibility of contagion risk inside the network. The results verify the presence of contagion risk on the dates where I observe a significant increase in the correlations and centralities. Regarding the empirical results of the machine learning approach to predict and forecast the contagion risk inside the financial network, the accuracy of the quadratic Support Vector Machine reached 98.8%, making the predictions fairly accurate. The model provides substantial information not only to policymakers (institutions) but also to investors about employing the financial market network as a useful device to improve the portfolio selection process by targeting a group of assets based on their centrality.

Keywords: Financial Crisis, Contagion, DCC, Asymmetric BEKK, Copula functions, Regime-Switching Models, Social Network Analysis, Forecasting, Machine Learning.

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1. INTRODUCTION

1.1. The aim of this thesis

Financial contagion is referred as the phenomenon where small turmoil in financial markets, which firstly affects only few countries or a particular territory of an economy, spreads to other sectors or other financial institutions whose economies were healthy before, in a way similar to a transmission of infection of medical illness. Financial contagion can occur both domestically and internationally. Domestically, typical is the example of Lehman Brothers giant, where bankruptcy has created a subsequent turmoil in the United States capital markets and then to the rest of the world. At international level, contagion is the transmission of the economic crisis through the markets (either indirectly or directly) to economies of emerging or developed countries. Considering the current form of the global financial system, which is characterized by high liquidity and large capital movements in the interbank market, the financial contagion is answered/transmitted both to the domestic economy (the country in which the crisis started) and to the other countries (global level).

Although several financial crises occurred in the past (with the presence of systemic risk), little is written in the international literature about financial contagion in capital markets. Both academic institutions and political organizations have focused on other elements of economic crises (weak policies for supervision of the financial system, etc.). The first time that there was a reference to capital market contagion was the Thai crisis in 1997 where the crisis spread very quickly to East Asia and then to Brazil and Russia, even affecting Europe and North America. In particular, the financial crisis began with the collapse of the Thai currency and the spread of the crisis in Indonesia, Malaysia, South Korea, Hong Kong and the Philippines in less than two months. Afterwards, literature began to be more enriched with the term contagion. Other examples of spillover effects are the 2007-08 Financial Crisis in the US and the Eurozone’s and Greece 2009 government Debt Crisis.

There are several categories that we can refer to contagion within financial crises. Some of these are the currency market crises as described by Goldfajn and Valdés (1997) and Kaminsky and Reinhart (2000). Another case is the transmission of the infection through financial institutions and the great interdependence that exists between them due to the circulation of securities (bonds in particular), as reported by Lagunoff and Schreft (2001) and Alen and Gale (2000). Among other cases of contagion, is through stock markets. Researchers in this case are trying to analyze the linking information that is experiencing high turbulence to liquidity sectors of the economy. Volatility in stock prices in one market appears to have strong impact on the value of equities in other markets, causing the latter to change equally. Calvo (1999) states that when investors in a market remove or liquidate some securities from their portfolio (possibly to offset their capital from a loss to another country or investment sector), this move may generate a transmission of this turmoil to other areas of the economy.

According to the literature, financial contagion can be quantified with econometric models that focus on rise in the values of correlation of stock returns within markets during the crises. Contagion is one of the main reasons for the introduction of rules on supervision and surveillance in the global financial system. Following the unfortunate events of the 2008 US crisis and the sovereign debt crisis in the Eurozone later on, effective policy-making to prevent a possible transmission of the crisis through markets is now a top priority for both central banks around the world and international institutions, such as the G-20 Council. Worldwide, where the financial system is huge and complex (with many investors and credit institutions), banking products such as Credit Default Swaps (CDSs) have made difficult and complicated the banking supervision in the sense that many investors keep different types of banking products in their portfolios for diversification and hedging. As mentioned above, Lehman Brothers' bankruptcy has caused a dramatic spread of the crisis to other markets globally. For this framework, understanding the reasons and the mechanism of contagion could help create effective “shock-management” policies, making the financial system more resilient and stable and less prone to challenges. Domestically, enforcement of supervisory rules and surveillance can help increase liquidity and limit exposure to risk that can, in turn, restrain the transmission of the crisis. Better understanding the mechanism of contagion could contribute not only to the literature but also to fiscal reform. In addition, maintaining high capital adequacy ratios can also balance banks' profitability and to shield the financial system from shocks and turbulences that may cause the crisis to spread to other regions.

In this Ph.D. dissertation, I attempt to identify the phenomenon of financial contagion using econometric models in various channels of markets and the economy, with a view to better understand and explain the phenomenon, in order to enrich the international literature in this field.

1.2. Elements of originality

An important element of the research is the limited literature on Eurozone's crisis regarding the transmission through stock exchange markets. It should be mentioned that by the time this thesis is written, the crisis in the Eurozone is still in progress. On a daily basis, we are witnessing events about possible transmissions of market uncertainty (from financial news) through many economies around the world. International institutions, central banks and governments, as well as the academic community, are struggling to shield the financial system and limit market infections whenever a financial crisis breaks out. This PhD thesis answered many of the problems that constitute the contagion theory in capital markets. The concluded evidence helps to better understand and explain the phenomenon and its spread mechanics. The findings provide significant information to the literature and contribute to the effectiveness of protecting the markets from imminent crises. The research analysis, as a whole, provides significant information so as to create a model that can assess the transmission of the crisis and the contagion risk from stock exchange markets to the real economy sectors and other channels such as bonds and CDS.

An important factor in a financial crisis is to reduce the costs resulting from it and to avoid misconduct in future crises. In this framework, this thesis answers to important issues about Early Warning Systems. No reference has been made to the literature about the impact of contagion on capital markets towards the real economy that focuses on the current financial crisis. In the same context, research expands on the impact of capital markets on other countries' economies by looking at significant dates of crisis. In addition, the findings contribute to the literature by measuring the volatility of stock, bond and CDS markets for the current financial crisis and the spreading of turmoil in other markets and regions. The main purpose is the examination of these variables at the same time in order to discover those channels in the financial system that is most vulnerable to the diffusion of the crisis.

Research also extends to the volatility of sovereign bonds and CDS (in particular those from high risk countries) in order to address the diffusion of information into markets. Studying different channels of contagion, we have a comprehensive view of how the crisis is spreading to markets because I quantify the phenomenon from many different factors and areas of the financial system. Previous research analyzes market contagion, but most of the published papers focus on the 2008 Global Financial Crisis, while much less has been written for the Eurozone's debt crisis. It should be emphasized that in this doctoral dissertation, as it was in progress, I investigated current disturbances of the global financial system and events such as Brexit. This gave the advantage to assess new data and compare the data with earlier approaches of the phenomenon of crisis and the transmission in capital markets. By approaching this issue, we are setting up strong foundation for enriching the literature on the transmission of the crisis from capital markets to economies in other countries.

1.3. Purpose and individual objectives

The purpose of the doctoral thesis is to investigate the existence of contagion channels in stock exchange markets. The contagion channels contain associated information whereby the infection of capital markets can be interpreted as the transmission of information from markets that started the crisis to markets that they were previously healthy by focusing on rapid increases in simultaneous volatility of the returns in other/different markets during the crisis period. To achieve this goal, individual research problems are addressed, aiming at a better understanding of the subject. In particular, the research is divided into five parts which cover fields of financial contagion in the global financial system focusing on the most recent crisis events (last twenty years).

More specifically, the first part of the research investigates the volatility spillover effects from South to North Eurozone during the Sovereign Debt Crisis. Centering on different periods of the crisis, I propose the Dynamic Conditional Correlation (DCC) model and the BEKK model to locate possible spillover during the period 2005-2015. Based on relationships of the Eurozone's major economies, I adopt asymmetric variations of the models in order to capture observations where returns tend to be affected by negative shocks more significantly than positive. These two models are the most appropriate in quantifying the correlations and the variance-covariance matrices between asset markets.

The second part studies the spread of the Subprime Crisis and the European Sovereign Debt Crisis from Eurozone countries to the real economy sectors by investigating ten (10) sectors in developed and emerging stock markets. First, I analyze different channels of contagion across Eurozone countries and sectors. Second, I employ Cappielo's et al. (2006) model and Copula functions to detect and cross-check the correlations and subsequently the contagion. The third implementation of this part of the research uncovers evidence of correlation behavior between policy uncertainty indexes and stock market returns. Motivated by the presence of various crisis events contained in the sample, I detect different behavior of interconnectedness between the US real economy sectors and the Eurozone stock markets.

The third part of the research applies a dynamic conditional correlation DCC model to investigate the turmoil period and the interdependence between the Greek Debt crisis and the Cypriot financial crisis. The subprime mortgage crisis created large shocks to most major economies. Shortly after, a Memorandum of Understanding obliged Greece to decrease its high deficit and public debt. Subsequently, the Cypriot financial crisis occurred after the credit event in Greece. Possible contagion channels were created after the Cypriot government's decision to impose a bank deposit levy in return for the bailout. However, as Greece and Cyprus are members of the Eurozone, and severely hit by the Eurozone crisis, it is necessary to examine if there exists interdependence between these two economies.

The fourth part of the research investigates the impacts of the June 2016 United Kingdom European Union membership referendum and the subsequent activated article 50 on 43 developed and developing stock markets. I find which countries are vulnerable against the transmission of the shock and which others have invulnerability amid the time of turmoil. In particular, on a bivariate basis, I use dependence dynamics through copulas with regime switching of Silva Filho et al. (2012) using intraday data returns to locate contagion among stock markets. The findings add critical information/evidence to the literature on the financial contagion from Brexit to different countries for an expansive sample up to date.

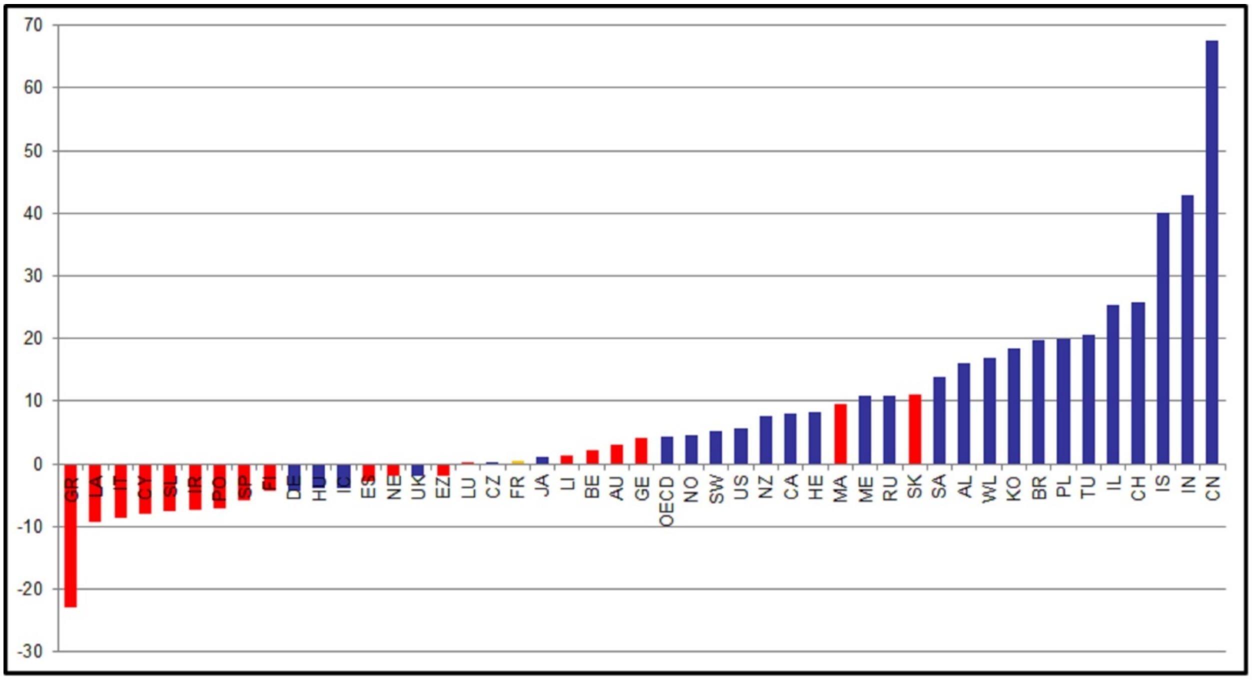
Lastly, the fifth part of the research studies on 'early warning systems' (EWS) by researching if measures of contagion risk, which depend on demonstrating the worldwide financial system as a network, can serve as early cautioning markers and enhance the performance of traditional crisis forecasting models. In doing so, I combine network analysis and machine learning algorithms to create an accurate model for predicting the vulnerable periods of contagion during shock events and crisis periods in stock markets.

1.4. Volatility spillover effects from South to North Eurozone during the Sovereign Debt Crisis

(*This section is based on Samitas and Kampouris (2017b), where Samitas is coauthor of the published paper*)

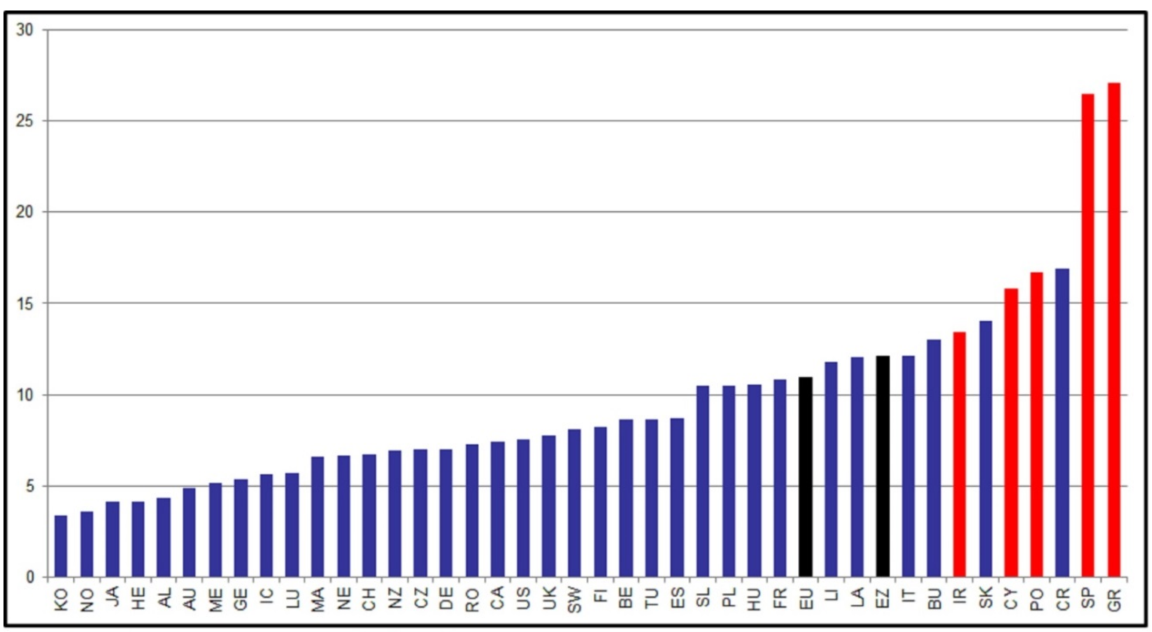
Obviously, the single market in Europe has been good for jobs and growth as well as it brought lasting peace to Europe. In addition, it helped new economies to integrate with the Western World and catch up while it improved the trade expansion. In this framework, the single currency seemed to be a great idea as the next step in European integration. However, in its present form, it is holding back growth and jobs creation (Figure 1.1.**)**. The current condition is alarmingly unsatisfactory; instead of partnership, we have lenders and indebted individuals, solid and powerless and one nation forcing its arrangement rationality on others. It appears that we are losing an entire age of youngsters (Figure 1.2.**)**. Eurozone split between North and South: North surges ahead while South lags further behind. It can be concluded that in order to invert the negative environment, more integration through financial institution union and debt pooling or break up the current structure are the principal things that should be done.

Figure 1. 1. Cumulative change in GDP 2007 - 2013



Notes: Eurozone in red. Source: Eurostat.

Figure 1. 2. Unemployment rates 2013



Notes:Eurozone MoU countries in red

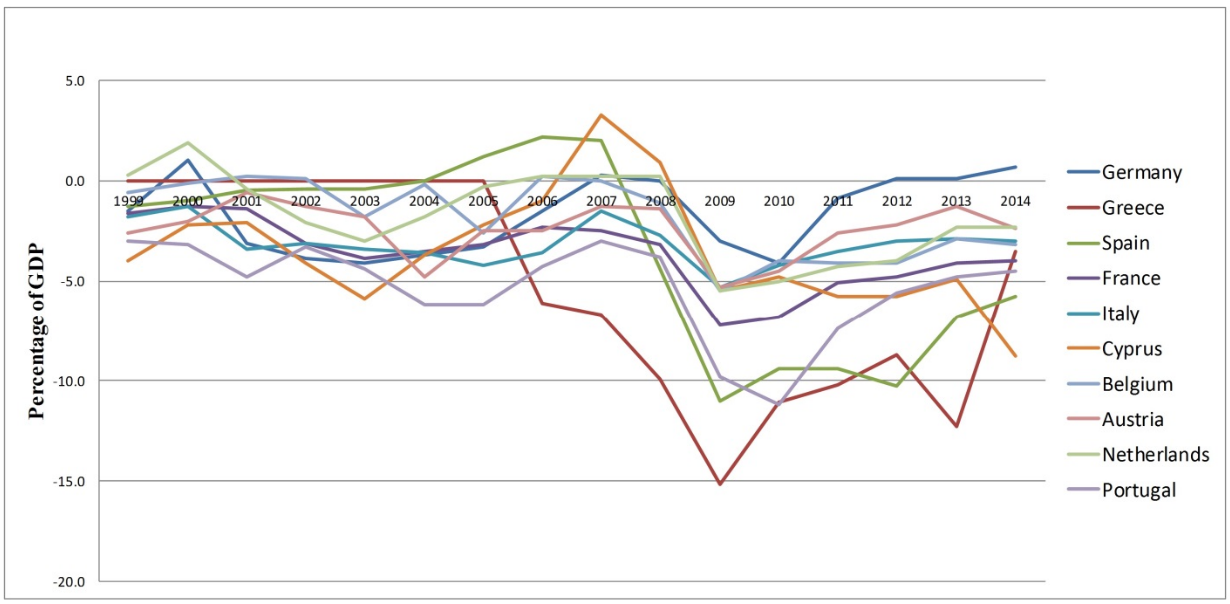
Tying smaller, ineffective and low-profitability development economies of the European South with a huge high-efficiency and high-development economy like Germany proved to be a wrong policy implication. As long as we have debts and fiscal policies that are split along national borders there can be no viable Economic Union. Namely, national borders should count less if monetary union is to succeed. Eurozone needs more solidarity between north and south, in both fiscal consolidation and policy implementation. There is no doubt that the root problem is the structure of the Eurozone and careful movements from politicians are needed. Despite claims to the contrary, the interests of European countries have never been as diverse as they are today. Governments are focusing on policies that are associated with national interests and not pan-European ones. Where policies have to be common, as in monetary policy, the national interests of the strong country-members dictate pan-European policies.

Considering these cases, it is crucial to investigate possible spillover effects that may be caused from South to North Eurozone during the Sovereign Debt Crisis. The European Debt Crisis is alluded as a multi-year turmoil recession period that has occurred in nearly the half of the Eurozone. Before the end of 2009 several economies of the Eurozone were not able refinance their government debt or to bail-out over-indebted banks under their supervision without the guide of third parties like the Institutions (IMF, ECB and European Commission). Greece, Ireland, Portugal, Spain and Cyprus directly faced sovereign debt problems and asked for a bailout. It became a perceived problem for the whole Eurozone since serious speculation of spillover effect to other states and a chance of break-up of the Eurozone were feasible. Focusing on different periods of the crisis, in the first part of the research, I propose the Asymmetric Dynamic Conditional Correlation (A-DCC) model of Cappiello et al. (2006) and the Asymmetric full BEKK model of Kroner and Ng (1998) to identify possible spillover effects during the period 2005-2015.

European Debt crisis began after the Subprime crisis and the subsequent recession in the late of 2009. The main features of the crisis are the high government deficits (Figure 1.3) and the accelerating debt levels (Figure 1.4). Eurozone economies faced harsh rise of interest rate spreads of government bonds due to investors’ doubts about the debt sustainability (Figure 1.5). Countries such as Ireland, Spain, Greece, Cyprus and Portugal accepted bailout programs from IMF, European Commission and ECB.

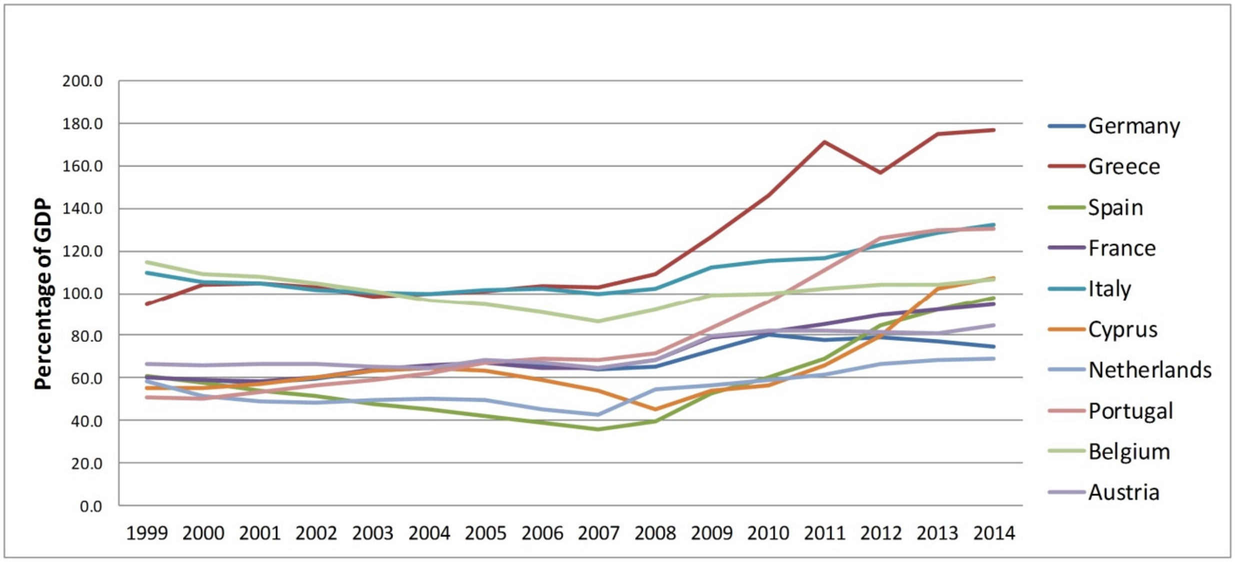
The causes of the Debt crisis vary by country. Factors such as the Financial Crisis of 2007-2008, the subsequent recession 2008-2012, the globalization of the financial system, the soft credit conditions the period 2002 - 2008 allowed high-risk lending and borrowing products as well as the fiscal policies of governments played substantial role at the resulted Eurozone crisis. Additionally, many analysts believe that the combination of international trade imbalances along with the structure of the Euro area as a currency union lacking fiscal union, conduced to the crisis, disarming Eurozone for a quickly respond. The aforementioned facts lead Eurozone to implement apart from bailout programs, a progression of financial support measures such as the European Financial Stability Facility (EFSF) and the European Stability Mechanism (ESM).

Figure 1. 3. General government deficit/surplus



Source: Eurostat.

Figure 1. 4. General Government Debt-to-GDP ratio



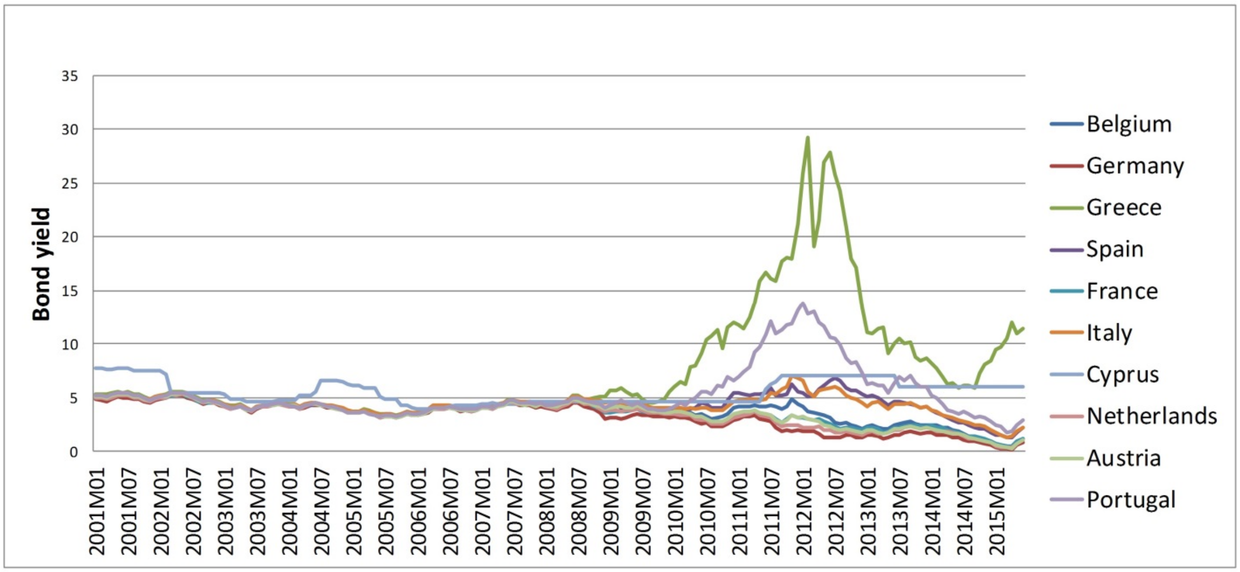
Source: Eurostat.

The impact of the crisis lead Eurozone to bailout several banks with recapitalization loans due to the severe capital losses. This act was necessary if we consider the possible significant spillover between their survival and the stability of financial sector. It should be noted that by January of 2009, ten central banks had already asked for a bailout. However, these bank recapitalizations blamed to be one of the core causes behind the rise in Debt-to-GDP ratios. Nonetheless, the Sovereign debt crisis, primary occurred to countries which had weak growth and competiveness as well as large pre-existing deficits and Debts-to-GDP ratios. A glaring example of these countries was Greece, Ireland, Portugal and Cyprus.

These countries presented negative growth (Figure 1.6) as well as rise in government Debts. Subsequently, they faced difficulties in refinancing their government Debt without the aid of Troika (IMF, ECB and European Commission). The bailout funds required the implementation of packages which included austerity measures such as privatization of public sector, structural reforms, fiscal consolidation and launch funds for supplemental bank recapitalization. By the summer of 2014, Ireland and Portugal seemed to have completed their programs while Greece and Cyprus still have not regained full market access. Spain, on the other hand, has not been primary hit by the crisis as the received package was only to fund a bank recapitalization without any aid support to the government. However, the unemployment rate in

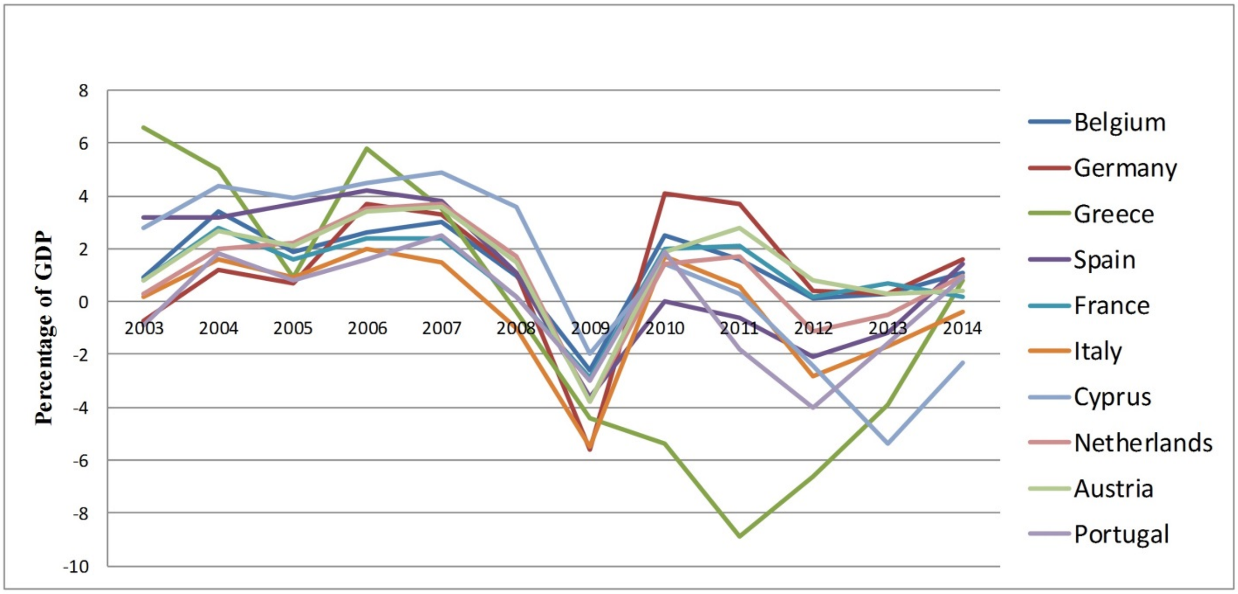
Spain climbed to 27% (second highest after Greece). Italy's condition was not much better either, if we consider that by the end of 2014 the unemployment rate exceeded 13% with a trend to go higher. The labor market effects in Spain and Greece, was one of the most severe causes of the European recession leading to subdued economic growth to the entire Union.

Figure 1. 5. Long term Government bond yields (10 year)



Source: Eurostat.

Figure 1. 6. Real GDP growth rate



Source: Eurostat.

To fight the crisis, governments focused on decreasing the expenditures and raising taxes. This policy contributed to high yield spreads on CDS especially in economies where deficits and sovereign debts were already high. On the other hand, by 2012, countries such as Germany, Finland, Austria, Netherlands and France profited from zero interest rates. Greece, in contrast, after two bailouts (€110 and €130 billion), austerity programs greatly decreased Public pensions and wages. However, France owned nearly 10% of Greece's sovereign debt and this caused terror to investors over a possible debt default inside the Eurozone. At this point, crucial was the role of the international news media that bombarded investors with a huge amount of unfavorable events, leading to doubts about who is fueling the crisis.

Considering the aforementioned analysis, contagion was considered possible. Despite the fact that only few countries directly faced sovereign debt problems and asked for bailout, it became a perceived problem for the whole Eurozone, leading to speculation of further contagion to different countries and a likely break-up of the Euro area.

1.5. The spread of the crisis from Eurozone countries to the global real economy

The global financial crisis of 2008, which was triggered by the U.S. subprime mortgage market collapse, was one of the most turbulent economic events in recent history. The Subprime Crisis was a notable example of systemic risk and the spillover effect, which led to the European sovereign debt crisis. The end of the Subprime Crisis in 2009 was followed by the Greek sovereign debt crisis in the fall of 2009. These events triggered a new cycle of uncertainty in the Euro area and fears of financial contagion to international stock markets.

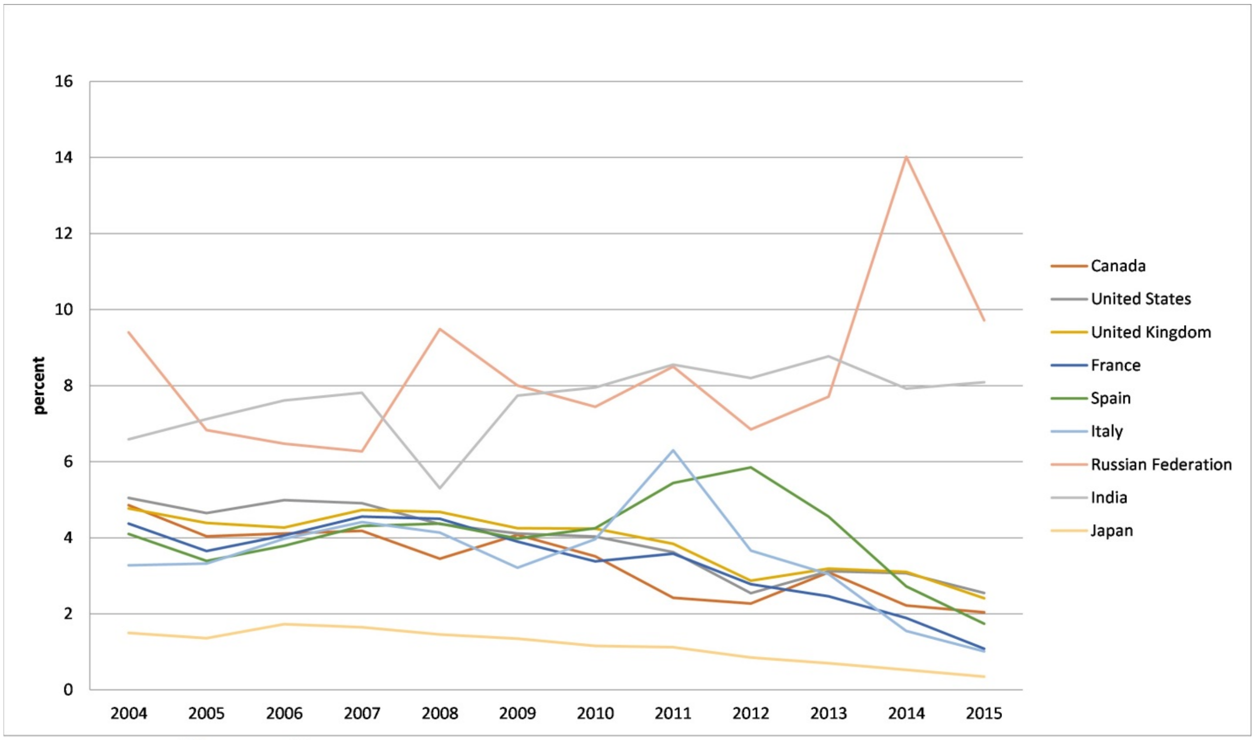
Forbes and Rigobon (2002) stated that contagion is a significant increase in market linkages after a substantial shock to one channel of the economy (or group of sectors, countries and markets). Specifically, contagion refers to the condition in which we observe the spread of financial disturbances from one country to others or from a specific financial channel to others. In addition, if two countries exhibit a high level of co-movement during tranquil periods, and they continue to be highly correlated after a shock to one of the markets, this may not constitute a financial contagion. Other researchers define contagion as an excessive increase in the correlation among the countries causing the crisis and all other countries (e.g. Nguyen and Liu, 2016).

From a methodological perspective, a dependence structure among market indices is the core issue for many studies. Many studies used multivariate GARCH models as an appropriate method for studying the transmission mechanism, the volatility and the correlation dynamics among financial markets. Other studies used copula functions to measure the contagion effect. The first attempt was made by Bollerslev et al. (1988) who proposed the VECH specification. Engle and Kroner (1995) proposed the BEKK model, which has the known issue of dimensionality. Bollerslev (1990) developed the Constant Conditional Correlation (CCC). Engle (2002) evolved the CCC model and proposed the dynamic conditional correlation (DCC) model in which the correlation is time varying and can capture the changes over time. Cappiello et al. (2006) modified Engle's (2002) variation and proposed the asymmetric (A-DCC) model to quantify the asymmetry in conditional variances and correlation dynamics. Conversely, copula functions have been employed in several studies measuring the financial contagion phenomenon (Rodriquez, 2007; Bhatti and Nguyen, 2012; Durante and Jaworski, 2010). Copulas are considered to be an advanced technique to investigate market dependence and have been widely used for this purpose.

Most studies conclude that financial contagion is the result of the lack of appropriate financial regulation. Many authors in the literature state that the top priority for domestic and the international organizations is regulation and the effective planning of the financial architecture. Much of the research in recent years showed that, if the organizations had followed a policy approach to this direction, we may not have witnessed harsh volatile periods over the Subprime and the Sovereign Debt crisis. At the international level, the financial system is constituted by linked balance sheets of a variety of intermediaries (see hedge funds and banks). In addition, the development of sophisticated financial products, such as CDS, has made financial regulation a trickier job. Understanding the reasons and the mechanisms of global financial contagion can help organizations improve the monetary policy and reduce the dramatic spread of the shocks.

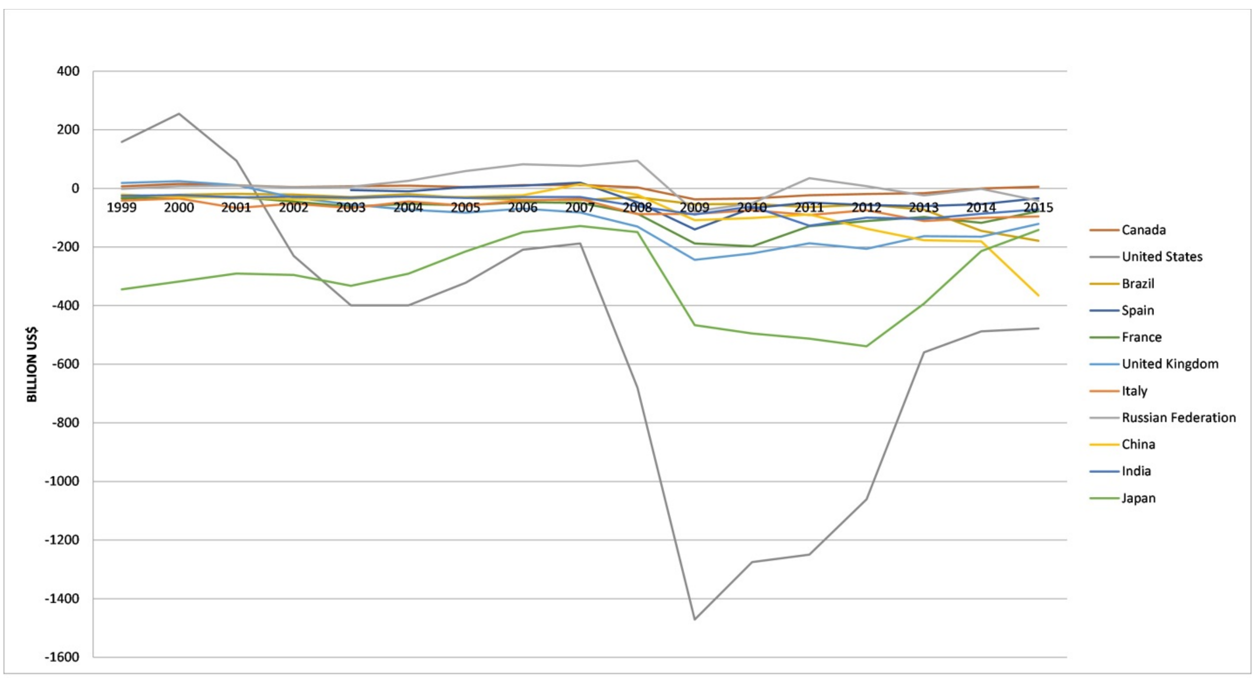
The Great Recession of the late 2000s was characterized by trade imbalances and debt bubbles, inadequate monetary policy, high private debt levels and increases in uncertainty. The uncertainty revealed the shadow banking system and the ineffective regulation in the U.S. and the European Union. The U.S. encountered persistent high unemployment in addition to low consumer confidence. Additionally, increases in foreclosures and personal bankruptcies and declines in house values were reported. Other effects were increasing debt and inflation. The increased uncertainty in the U.S. may be explained by both the private and public levels of debt, which were at historic highs. Conversely, the crisis in Europe generally progressed from the banking sector to the sovereign debt crisis; many European economies were required to bailout their banking systems. Furthermore, many countries embarked on austerity measures to reduce their budget deficits relative to GDP (see Figure 1.8). However, many major economies avoided recessions. A glaring example are the BRICs, where Brazil, Russia, China and India encountered slowing growth, but they did not enter recessions (see Figure 1.9, Figure 1.10 and Figure 1.11).

Figure 1. 7. Long term Government Bond Yield



source: Thomson Reuters

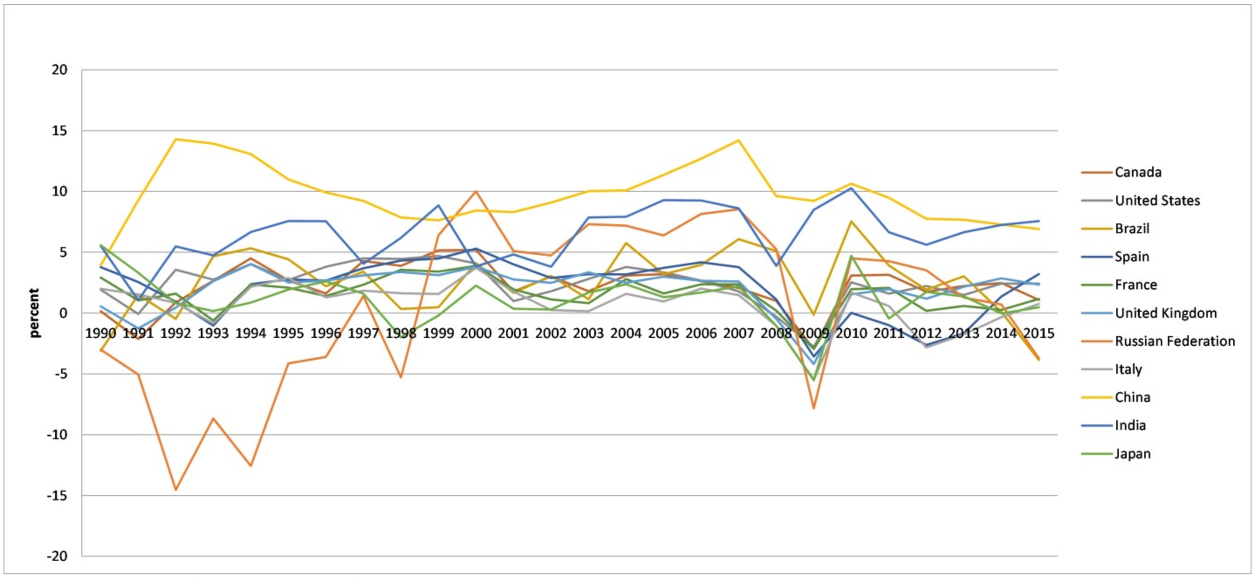
Figure 1. 8. Central Government Surplus/Deficit



source: Thomson Reuters

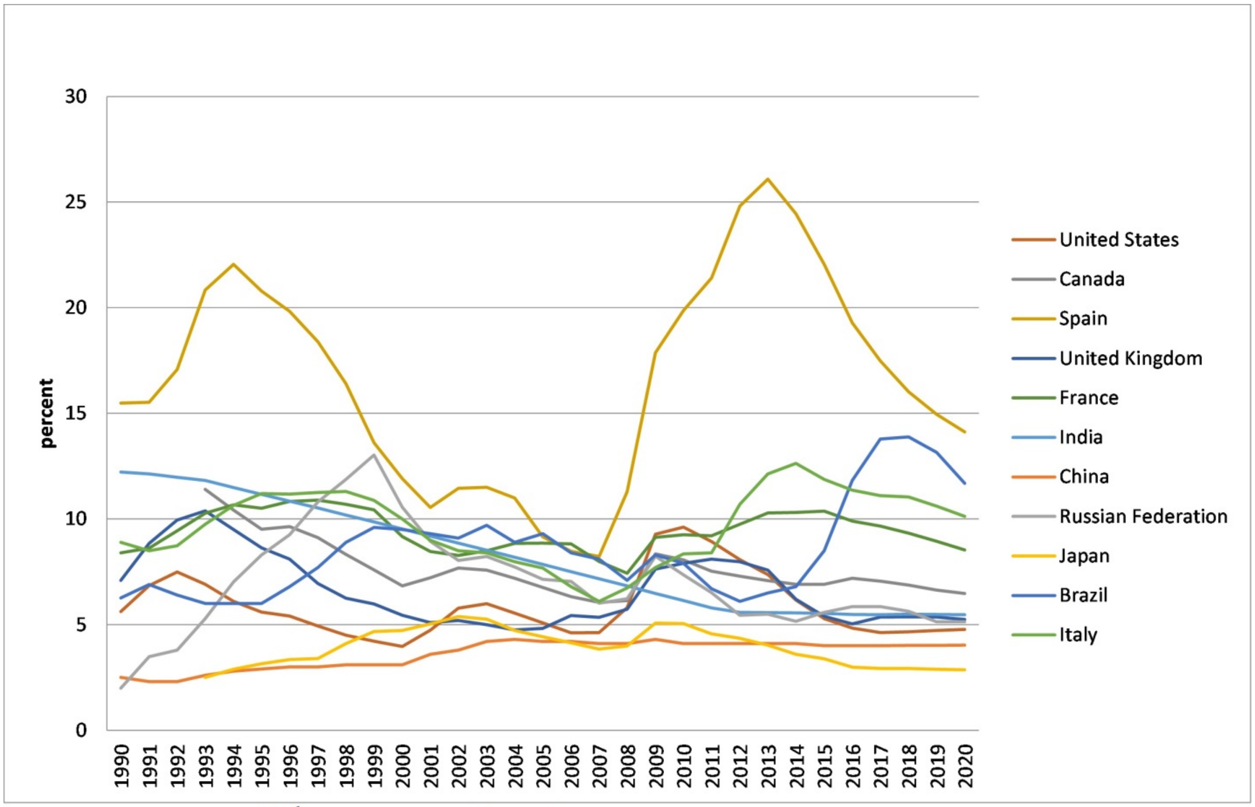
French financial institutions were holding the highest amount of Greek debt among the Eurozone; this caused uncertainty to investors over a possible default by the Greek government. This debt was estimated at approximately 65 billion euros, according to a recent (2015) French Senate report. The French economy encountered a rise in its unemployment rate (see Figure 1.10) and needed to enact austerity measures to increase competitiveness. In November 2012, the French Government announced an increase in the standard VAT and eco-taxes. In addition, the French presidential election that year became the first since 1981 in which an incumbent failed to gain a second term, when Nicolas Sarkozy lost to François Hollande. The same year, Standard & Poor's downgraded France in addition to Spain and Italy. Furthermore, Spain was struck directly by the Sovereign Debt crisis, as it was unable to refinance its over-indebted banks without the assistance of third parties such as Troika. Additionally, a crisis hit the Spanish labor market when the unemployment rate exceeded 26% in 2013. Spain's long-term 10-year bonds exceeded 6% (see Figure 1.7), encountering difficulties in accessing the bond market. In addition, the Debt to GDP ratio increased rapidly after 2008 (see Figure 1.11), creating concerns not only inside Spain but for the entire Eurozone. Entering areas with increased uncertainty, the Spanish economy was required to adopt several austerity measures to achieve fiscal consolidation. Lastly, Italy was not directly impacted by the Debt crisis but encountered many concerns regarding its banking system. These banking concerns resulted in one of the highest Debt to GDP ratios inside the Eurozone and an unemployment rate over 13%. As shown in Figures 1.7 to 1.11, France, Spain and Italy are countries with high rates of unemployment, high Debt to GDP ratios and small or negative GDP growth. These three countries cover a large proportion of the Eurozone, which creates significant concern about the future of the Eurozone and increases the uncertainty in the global financial environment (Samitas and Kampouris, 2017b).

Figure 1. 9. GDP Growth



source: Thomson Reuters

Figure 1. 10. Unemployment Rate

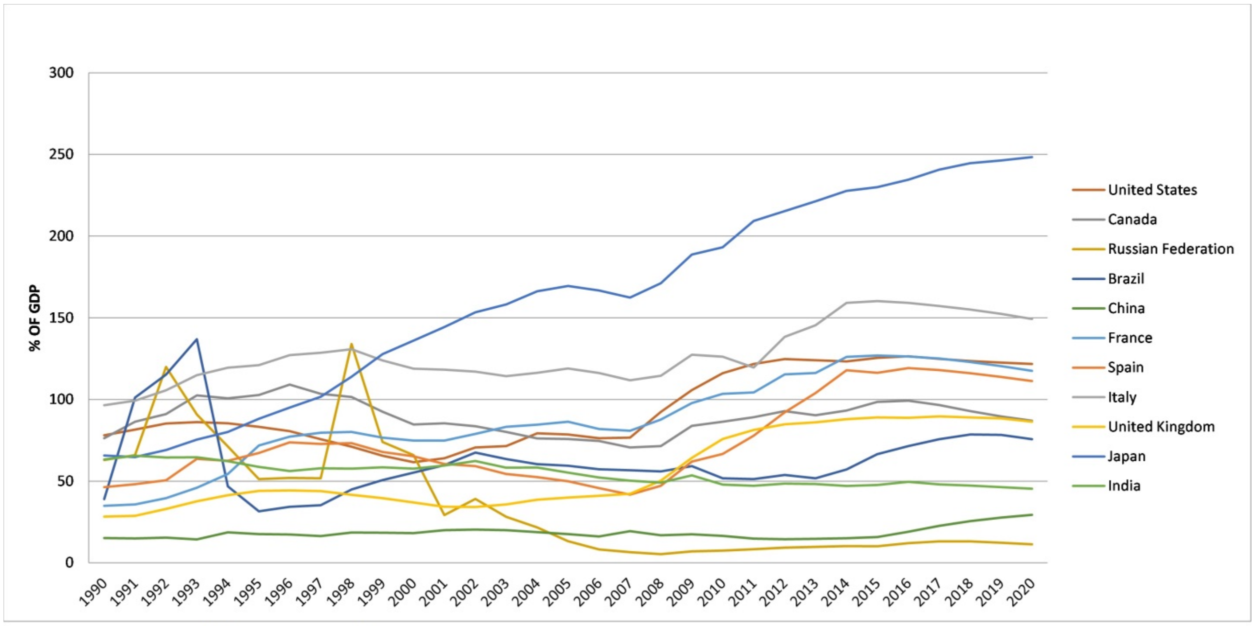


source: Thomson Reuters

Conversely, Germany benefited from the Debt crisis as it was estimated to have made more than €9 billion from the crisis as investors flocked to the safer but near zero interest rate of German federal government bonds (Thomson Reuters). By 2009, the deficits for Italy and Spain were estimated to be $42.96bn and $75.31bn, respectively, while Germany's trade surplus was $188.6bn. During the Sovereign Debt crisis, the German economy appeared to be one of the healthiest inside the Euro area; in addition, it has played a significant role in the structural reform of the entire Eurozone through today.

On the one hand, the BRIC economies (Brazil, Russia, India and China) have experienced a low Debt to GDP ratio (Figure 1.11) over the past two decades. The unemployment rates in these countries are small with the exception of Brazil, where it has increased during the period 2013-2015. China and India are rapidly growing economies, while Russia and Brazil experienced negative growth in 2015 (see Figure 1.9). On the other hand, the US, the UK, Japan and Canada are countries that have had low rates of unemployment and generally steady GDP growth the past two decades (see Figure 1.10).

Figure 1. 11. Gross Government Debt



source: Thomson Reuters

1.6. The interdependence of small economies

The 2008 Subprime crisis triggered an unexpected turmoil in the economic environment which resulted in large shocks in the global economy. International markets experienced a new economic framework, the consequences of which permanently changed the global banking sector. At the same time, Greece and some other Eurozone members with significant high government debt had trouble meeting their obligations. The rest of the Eurozone members and other European countries undervalued the situation. Since 2010, Greece adopted several austerity measures which had little effect. Following Greece, Cyprus employed a new economic model in 2013 as a result of the transmission of Greek Debt crisis. Under the pressure of the so called "Troika" (European Commission, International Monetary Fund, European Central Bank), the Cypriot government was forced to levy by 40% all bank deposits above 100.000 Euro. The investigation of possible spillovers between the two countries is the main issue examined in this study. The purpose in this part of the research is to measure, quantify and compare the co-movements between the Greek Debt crisis and the Cypriot Financial crisis as well as to determine whether the contagion phenomenon exists for these two economies.

Greece, as a member of the European Economic Community (EEC) from 1981, enjoyed several advantages through development programs provided by the European Union. During the last decade, government policies led to a substantial public deficit due to the inefficient management of the development programs. The 2004 Olympic Games and the non-productive public sector increased country's obligations. These needs were financed by bonds, which were not adequate to cover the country's costs. Tax evasion as well as political corruption led the country to a financial dead end. The 2008 Global Financial crisis revealed these problems in the Greek economy and woke up hedge funds as well as major credit rating firms which focused on the Greek economy and lost their confidence in Greece. Although the Eurozone seemed to be well secured, credit default swaps (CDS) focused on Greece. The consequences of these events forced the Greek government to implement a series of austerity measures in order to decrease its deficit and debt, which at the end of 2009, according to Eurostat, were 15.2% and 126.8% of GDP respectively.

The figures in Table 1.1 accurately depict Greece’s condition, which, since 2008, has been characterised by an economic impasse, accompanied with unemployment and significant liquidity problems. However, fundamental problems in the European Union's (E.U.) structure did not solve the volatility in Europe's economic environment. Investors who bet on the Eurozone's separation, took advantage of the conflicting interests between E.U. members and increased the pressure on countries with high debts and deficits. This resulted in a debt crisis for South European countries and Ireland. The problem appeared to be a nightmare not only for Greece but for the whole Eurozone. Additionally, markets were still cautious due to the pessimism in the global economic framework after the subprime crisis. Many other countries including Belgium, UK and France faced high debts and deficits. This resulted in extended recession in the Eurozone and all states realized that the crisis concerned PIIGS (Portugal, Italy, Ireland, Greece and Spain) as well as many other countries who were then faced with similar fiscal problems.

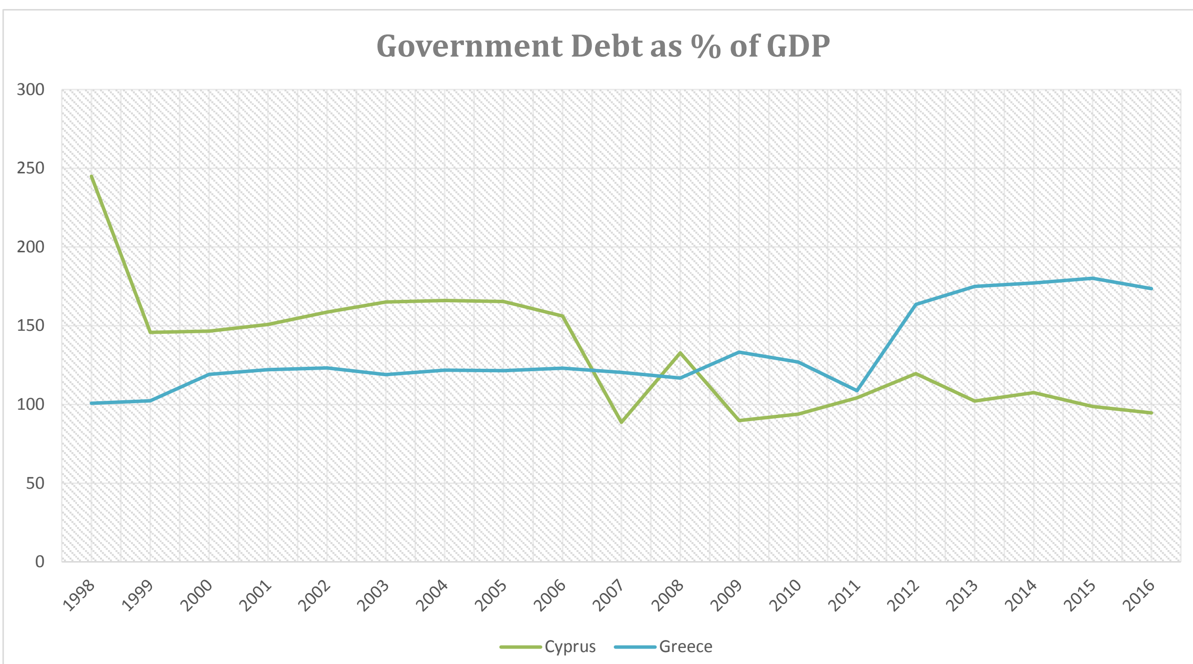
Table 1. 1. Greek Government debt and deficit (1995-2016)

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015 (forecasts)	2016
€ bilion	86.9	97.8	105.2	111.9	118.6	141	151.9	159.2	168	183.2	195.4	225.3	240.0	264.6	301.0	330.3	356.0	304.7	319.1	313.0	356.0	384.0
% GDP	97.9	100.3	97.5	95.4	94.9	104.4	104.7	102.6	98.3	99.8	101.2	103.4	103.1	109.3	126.8	146.0	171.3	156.9	174.9	176.3	184.0	186.0
GDP Growth	2.1	2.4	3.6	3.4	3.4	4.5	4.2	3.4	6.6	5	0.9	5.8	3.5	-0.4	-4.4	-5.4	-8.9	-6.6	-3.9	0.9	0.2	-0.4
Deficit	−9.1	−6.7	−5.9	−3.9	−3.1	−3.7	−4.5	−4.8	−5.7	−7.6	−5.5	-6.1	-6.7	-9.9	-15.2	-11.1	-10.1	-8.6	-12.2	-3.5	-3.35	-3.56

Source: Eurostat (1995-2013) & forecasts

Following the Greek debt crisis, Cyprus was hit by the domino effect of negative consequences. As can been seen from Figure 1.12, the Cypriot economy has passed into a recessionary stage after 2009. The country seemed to be well secured at the beginning of subprime crisis but some specific reasons triggered huge debt which surpassed the average level of the Eurozone. Some of these reasons were the non-performing loans, the exposure to the haircut of the Greek government bonds and the inability to raise liquidity from the markets to support the financial sector. This resulted in an increase in unemployment and a steep deterioration in output in the tourism and shipping sectors. Consequently, commercial properties declined by almost 30% and the banking sector faced liquidity problems from the exposure (€22 billion) to the Greek private sector. It is clear that the Cyprus crisis was different from the Greek crisis as the initial problem was the banking sector.

Figure 1. 12. Greek and Cypriot Government Debt as % of GDP



Source: World Bank & ECB Forecast

Cyprus has a very low tax rate and has thus attracted many foreign investors, including many Russians. As credit rating firms gradually downgraded their ratings for the Cypriot economy and the liquidity problem came to surface, Russia offered an emergency loan of 2.5 billion Euros (at 4.5% interest rate) to Cyprus in order to cover its financial gap through the international markets. Unfortunately, this solution did not solve the problem since the received loan did not include any funds for the recapitalisation of the banking sector after the haircut of the Greek government bonds. Table 1.2 depicts Moody's ratings for the Cypriot and the Greek government since 2001. It is clearly portrays the continued downgrade after 2010 for the former. The downgrading of the Cyprus economy led to a financial suffocation and a liquidity gap, which forced the Cypriot government to ask for a bailout from the European Financial Stability Facility (EFSF) on 25 June 2012. After several negotiations with the representatives of Troika, they came to an agreement for a bailout of €10 billion on 25th March 2013. In return, Cyprus had to impose a 40% bank deposit levy on all uninsured deposits above 100.000 euros and merge "Laiki Bank" merge with "Bank of Cyprus".

Table 1. 2. Moody's Rating regarding the Cypriot and the Greek Government

	Cyprus	Greece
25 September 2015		Caa3
1 July 2015		Caa3
29 April 2015		Caa2
1 August 2014		Caa1
12 April 2013	Ca	
22 March 2013	Caa3	
14 January 2013	Caa2	
29 November 2012		Caa3
19 November 2012	Caa1	
9 October 2012	Caa1	
12 June 2012	B2	
14 March 2012	B1	
2 March 2012		C
8 November 2011	Ba2	
10 August 2011	Baa1	
28 July 2011	Baa1	
25 July 2011		Ca
1 June 2011		Caa1
7 March 2011		B1
2 March 2011	Baa2	
13 January 2011	A3	
5 July 2010	A3	
14 June 2010		Ba1
27 May 2010	A2	
22 April 2010		A3
22 December 2009		A2
24 April 2007	A2	
24 September 2004	Baa1	
8 June 2004	A3	
5 August 2003	A3	
10 June 2003	A2	
4 November 2002		A1
20 March 2001	A2	

Additionally, if we look back in history for IMF's involvement, we will find that it usually causes a negative impact to people's quality of life. However, apart from the bad economic conditions, Cyprus decided to start the exploration of the natural gas fields inside country's maritime exclusive economic zone (EEZ). This provoked the opposition of neighbouring Turkey regarding the exploration of natural gas exclusively from Cyprus. Despite the Turkish government's threats, Cyprus had already came to an agreement with its neighbours, Egypt, Lebanon and Israel and had secured the support of Russia, USA and European Union since the Cypriot government was in line with the United Nation Convention of the Law of the Seas. These particularities together with Russian interests in Cyprus, created an entirely different economic environment compared to the Debt crisis that appeared in PIIGS. The aim of the third part of the research is to quantify the volatility spillovers among the Cypriot financial market and the financial market of Greece, during the period 2005 - 2015.

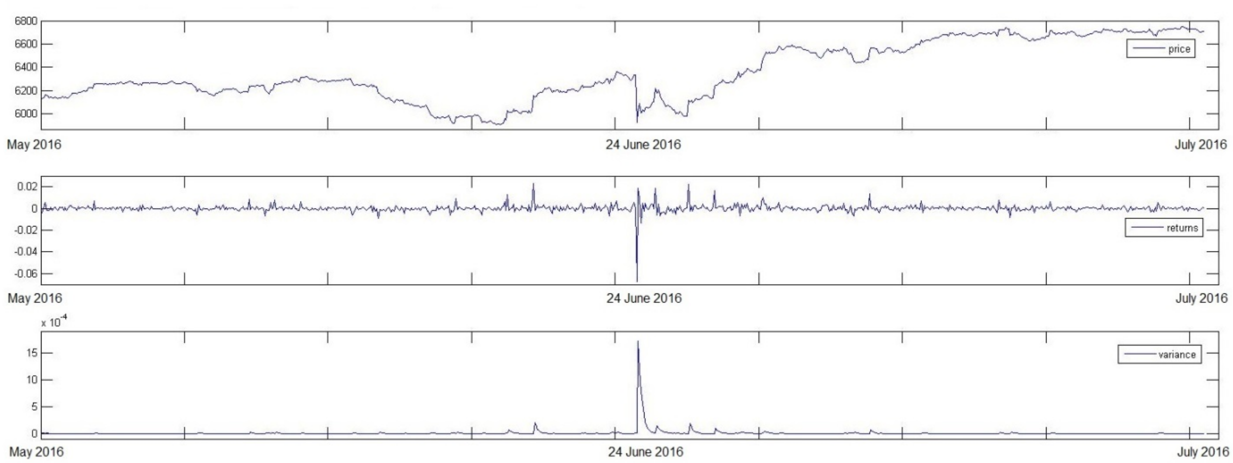
1.7. The case of Brexit: market reactions to the UK's referendum results

(*This section is based on Samitas and Kampouris (2017a), where Samitas is coauthor of the published paper*)

On Thursday, June 23, 2016, the EU referendum, also referred to as the United Kingdom European Union membership referendum, was held. The United Kingdom (UK) voted to relinquish its membership of the Union. These events are commonly known as Brexit, short for British Exit. The referendum had 51.9 percent of the voters opt to exit the EU. In the aftermath, the Great British Pound (GBP) fell 10 per cent against the US dollar (USD) and seven per cent against the Euro, marking the lowest levels since 1985. Moreover, the drop was historic, as the currency had never fallen from $1.50 to $1.37 within two hours, at any point before. Over USD 2 trillion was lost within the equities market globally. In four days, i.e. June 27, around £85 billion had been lost in terms of the FTSE 100 index, which had fallen by 500 points (Figure 1.13). On the same day, the FTSE 250, a domestically-focused Index, fell by 14 percent.

The Euro experienced its own fall, seeing a four percent decline against the US currency. Simultaneously, a surge was witnessed in the Japanese Yen and gold. At the same time, the prices of crude oil saw a dip, while DAX and CAC 40 experienced a 10 percent fall. The impact was also seen on the Greek ATHEX, Czech PX, IBEX 35, Polish WIG30 and Dutch AEX, which saw drops of eight to 15 percent. Sovereign bonds from the EU saw an increase in yields, with 10-year bonds from Italy and Spain jumping for early trades by as much as 40 percent. Markets from the Asia Pacific also suffered. China, India and South Korea reportedly attempted to control the impact and attempted to tackle the vulnerable market situation. On June 24, a sharp drop was seen in American markets from Canada to Brazil. The Australian dollar fell against the US dollar, and the Chinese Yuan and Yen saw one of the sharpest declines since 2011.

Figure 1. 13. FTSE 100, one month before and after referendum



UK's debt status was changed by Moody's from "stable" to "negative" on June 24, 2016. Similarly, Fitch Ratings changed UK's status from AA+ to AA, and Standard & Poor's reevaluated it to AA as well. The ripple effects could be seen in other countries; for instance, the South African rand saw its biggest-ever decline since 2008. Its value fell by eight percent against the dollar. Similar impacts were seen on the currencies of Kenya and Nigeria. UK's exit from the EU cast a shadow over economies and trade relations. Any countries with economic ties to the UK were impacted by the uncertainty that Brexit came part and parcel with.

Most stock markets became volatile following the vote. Central bankers said that they would try to maintain stability. After the vote, the International Monetary Fund (IMF) highlighted that world economic growth would shrink by 0.1 per cent, while UK's growth itself would face significant consequences. Article 50 was put into motion by the British government on March 29, 2017. This would move the country onwards on the path of withdrawal, and is expected to be completed by March 2019. Despite promises from Britain's Prime Minister that implementation of the law will be seen through at the domestic level, there has been no real effort to establish the relevant terms of withdrawal to date. At present, the UK continues to be a member of the EU. This research looks at the likelihood of financial contagion from the UK to both developed and emerging markets. The analysis will take into account the Brexit vote, and Article 50.

One remedy to possible financial contagion is increased financial supervision. This must be implemented strictly if it is to be effective. Organizations and institutions must work at the local and global front to efficiently plan financial architecture. Binding regulation with policy can help tackle the uncertain time that stems from a crisis. Within a financial environment, the balance sheets shared between different intermediaries are looked at, e.g. banks and hedge funds. Moreover, financial regulation has been made exceedingly difficult because of things like the CDS, which is an example of sophistical financial solutions that are hard to tackle. It is important to first understand how financial contagions operate. This helps stakeholders, including policymakers, authors and institutions, understand how aftershocks of an event such as Brexit can be controlled or reduced.

1.8. Financial Networks, Contagion and Predicting Shock Events: A Machine Learning Approach

The global financial crisis has underscored the role of financial connectedness as a potential source of systemic risk and macroeconomic instability. This crisis has also highlighted the need to better understand whether an increase in connectedness leads to a higher probability of a financial crisis. As we mentioned in section 1.5, Forbes and Rigobon (2002) stated that contagion is a significant increase in market linkages after a substantial shock to one channel of the economy (or group of sectors, countries and markets). Specifically, contagion refers to the condition in which we observe the spread of financial disturbances from one country to others or from a specific financial channel to others. In addition, if two indices exhibit a high level of comovement during tranquil periods, and they continue to be highly correlated after a shock to one of the markets, this may not constitute a financial contagion. Other researchers define contagion as an excessive increase in the correlation among the countries causing the crisis and all other countries (e.g., Masson,1998, 1999; Pericoli and Sbracia, 2003; Corsetti et al.,2005; Samitas and Tsakalos, 2013; Geraci and Gnabo, 2018; Baele L., 2005). Dornbusch et al. (2000) describe contagion as the dissemination of market disturbances, primarily with negative consequences, from one market to another. In addition, Bekaert et al. (2005) study contagion in financial markets as the condition that indices move more closely together during periods of crisis. However, Sachs et al. (1996) illustrate contagion as a significant increase in the cross-country correlations of stock market returns and volatilities.

The recent financial crisis has prompted considerable new research on the interconnectedness of the modern financial system and the extent to which it contributes to systemic fragility. Network connections diversify markets' risk exposures, but they also create channels through which shocks can spread by contagion. In the fifth part of the research, I build on the literature that links network connectivity in the global financial sector (channels of stock indices, sovereign bonds and CDS) to possible contagion risk during crisis periods. In particular, I compute dynamic conditional correlations between all pairs of stocks indices, sovereign bonds and CDS and create dynamic financial networks from them. The extracted networks are then used to detect possible risk of contagion during crisis periods. Subsequently, I introduce a machine learning approach to predict and forecast the possibility of contagion risk inside the financial networks.

1.9. Contribution

The contribution of this thesis is multidimensional. Each part of the research adds, individually, its own elements of originality to the literature of financial contagion. In particular, the first part of the research contributes to the existing literature by: i) examining possible co-movements between South and North Eurozone countries during the Eurozone Debt Crisis, ii) quantifying the dynamic conditional correlations of Spain, Italy, Greece, Cyprus and Portugal with Germany, Netherlands, France, Austria and Belgium and iii) employing full BEKK model for the same data and period to identify the contagion channels.

Subsequently, the second part of the research in this thesis differs from the existing literature in several ways. First, it examines the cross-country contagion effects of equity indices from France, Spain and Italy to the real economy during the Subprime crisis and the Eurozone Sovereign Debt crisis. The real economy sectors in the sample cover a wide range of major economies outside the Eurozone, namely BRICs, US, UK, Canada and Japan. This approach assumes that both crises caused significant uncertainty to investors' behavior, fueling the volatility among the markets. In addition, it identifies the countries that are vulnerable to the transmission of shocks and those that have immunity during crisis periods. France, Spain and Italy are now permanently in an alert mode while simultaneously attempting to consolidate their fiscal expenditures because of the fear that they will be the next economies that will confront fiscal problems and bank imbalances similar to those of Greece. Italy continues to encounter significant problems in the banking sector. Conversely, we have BRICs, the UK, the US, Canada and Japan, which, generally, until December 2015, appeared to be "healthy" economies with minor fluctuations in their indices. This part of the research tests this hypothesis and attempts to identify the sources of contagion for sectors of the real economy. France, Spain and Italy are part of the Eurozone, and they cover a large proportion of the Eurozone with their GDP size. Therefore, these countries can be characterized as "systemic" countries[1]. These countries appear to be condemned to continue fixing their fiscal positions to be immune to the Debt crisis. I excluded the German economy from our research, as it showed complete health during the European Debt crisis. Therefore, there is no evidence of contagion from the German economy to countries outside the Eurozone and particularly to their real economic sectors.

Second, it investigates the behavior of the correlations between the systemic Eurozone countries (see above) and the sectors of the real economy from major economies outside the Eurozone. Third, it adopts two approaches to cross-check the results. It includes the time-varying asymmetric dynamic conditional correlations (ADDC model) and the copula functions between each source of crisis, providing a robust analysis of financial contagion. Fourth, the sample period of 1998 to 2015 allows comparison of the contagion effects during different periods such as the Subprime crisis and the European Debt crisis. Fifth, it investigates evidence of the correlation behavior between the US policy uncertainty news and the fear factor indexes with

[1] Countries who are vulnerable to increase systemic risk, uncertainty and contagion both domestically and internationally.

sectors of the US real economy and the market indices of France, Spain and Italy. The evidence is interesting, as the comparison showed that there appears to be completely different correlation behavior between the sectors of the US economy and the Eurozone indices with the newspaper indexes.

The Asymmetric Dynamic Conditional Correlation (ADCC) model quantifies the conditional asymmetries in the correlation dynamics directly by estimating the correlation coefficients using standardized residuals. Conversely, copula functions are perfect for measuring the dependence between time series and spillover effects. I used copulas not only because of their methodological novelty but also to reassess the results from the ADDC model. The empirical results offer significant evidence to the literature thus far on the contagion hypothesis from the Eurozone to the sectors of major economies for a very large sample period. In addition, the empirical evidence provides significant information about the connection between the market indices and the policy uncertainty indexes.

The third part of the research contributes to the literature by: i) investigating relationships and covariance between the Greek and Cypriot stock market, ii) examining the new economic model (Bail-In) which was imposed on the Cypriot government, iii) quantifying the dynamic conditional correlation among Greece and Cyprus. Hence it is important to examine the level of dependence among the aforementioned stock markets.

The following part of this study adds to literature that already exists on the subject at hand. This part studies the Brexit vote and Article 50 and looks at their impact on different stock exchange markets. Moreover, it employs advanced methods to gauge and quantify the impact that UK's decision had on other countries and their economies. In particular, on a bivariate basis, I employ dependence dynamics via copulas and Silva Filho et al. (2012)'s regime switching. Intraday data returns have been used to locate contagion within different stock markets. Intraday data is imperative here because of its high frequency, and also because of the manner in which stock markets react to public information of importance. A large sample of 43 different economies has been used. This includes countries that are a part of the EU, and additionally includes other significant economies, such as the US, Japan, Canada, BRICS and the UK itself.

The paper assumes that the vote resulted in investors exhibiting volatile behavior, causing markets to become unstable. The study also looks at the countries that are susceptible to the aftershocks of such an event, and the ones that remain immune from any disruptions. The analysis also goes a step further by looking at the situation pre and post-referendum, and the situation subsequent to Article 50 coming into play, to outline the behavior of the correlations therein. It makes use of test hypotheses to look at the aftereffects of these events. Moreover, the empirical evaluation looks at both the FTSE 100 Index and the local FTSE 350 so that the impact on other markets can also be gauged. The evidence is interesting; the study has highlighted that after the immediate volatile scenario following the immediate financial contagion that resulted from the vote and subsequent events, there was no long-term damage. The negative impact seen on the markets was not monumentally significant and only persisted over a short course of time.

Copula functions are useful when quantifying the link between spillovers and time series. The Markov regime-switching models are additionally helpful in evaluating the regime-change states in terms of the given time series of correlations. The empirical results outline substantial indications for the literature about UK's financial contagion that was borne of Brexit and impacted other nations. The evidences pertain to a large sample period. Moreover, a good amount of information for implied hypotheses stems from this empirical data. It helps develop an understanding of the extent to which stock exchange markets experienced contagion.

The fifth part of the research contributes to the literature on 'early warning systems' (EWS) by investigating whether measures of contagion risk, which are based on modeling the global financial system as a network, can serve as early warning indicators and improve the performance of standard crisis prediction models. In doing so, I combine network analysis and machine learning algorithms to create an accurate model for predicting the vulnerable periods of contagion during shock events and crisis periods in stock exchange markets.

The work differs from others in several aspects:

- In most papers that contain dynamic conditional correlations, we see the contagion channels and then the source of the spillover effect. In this sample, I use 33 countries, selected by their GDP size and the best available data, and extracted correlations for all possible combinations. In particular, I calculated 528 pairs of correlations for stocks indices, sovereign bonds and CDS to cover all possible combinations for these countries. To the best of my knowledge, this has not been covered in the literature (see the literature review section). With this approach we have the ability to test and analyze the behavior of the correlations between countries and subsequently, quantify the extent of the interdependence in stock markets. Additionally, I categorize the dynamic conditional correlations based on the geographical position of the countries and provide significant evidence about how the markets react to financial crises.

- This is the first time that we extract and depict for a very large sample thus far and in a network form the global financial system of markets with joints of correlations for stocks indices, sovereign bonds and CDS. In this way, we have the ability to see the structure of the global financial networks for the first time, almost from the foundation of the Eurozone and beyond. Specifically, I create financial networks of stock indices, sovereign bonds and CDS and analyze factors such as which countries have the strongest ties, which are more vulnerable to transferring uncertainty to markets and which others are less prone to the most significant shocks during the financial crisis.
- I present the dynamic evolution of financial networks and consequently their centralities, along with the core nodes of the financial networks of stock indices, sovereign bonds and CDS, for a very large sample. In this way, we can observe not only how the networks mutate with the evolution of time but also which countries played the most important role in the global financial network of markets during the critical dates of the financial crisis. This enables me to say that market forces can be interpreted by other means (e.g., network centralities), thus giving further data to interpret and quantify the existence of contagion in the markets.
- The literature on financial contagion in networks is very limited. Using hypothesis testing I create a model from dynamic conditional correlations and dynamic centralities and analyze the possible existence of contagion risk inside the financial networks during periods of crisis. The model seems to be highly

accurate in that it detects many of the financial crises of the last eighteen years in the markets for all networks.

- Lastly, I introduce a machine learning approach that allows us to predict the contagion risk during periods of crisis in financial networks with accuracy that exceeds 98%. The model predicts most of the shocks in the global financial environment making it surprisingly accurate. In this framework, I incorporate new methods of measuring the spread of shocks within financial networks.

1.10. History of financial crisis and contagion

Contagion was first presented in July 1997. The currency crisis in Thailand immediately created a domino impact all through East Asia and afterward on to Russia and Brazil. Developed markets in North America and Europe were likewise experienced contagion. Relative prices of financial instruments moved and caused the fall of Long-Term Capital Management (LTCM). The contagion began from Thailand with the fall of the Thai baht. The spread began to Indonesia, the Philippines, Malaysia, South Korea and Hong Kong in under 2 months (Stijin and Forbers, 2001). After this crisis, an extensive volume of research papers were written focusing on financial contagion. However, there were occurrences of worldwide financial crisis that happened before the introduction of the term financial contagion.

Bordo and Murshid (2000) argue that the principal worldwide financial crisis occurred in 1825. Latin America's liberation in 1820s prompted an enormous inflow of capital from U.K. to fund the abuse of gold and silver mines and of sovereign loans to the recently autonomous republics. As new mechanical zones rising, an expansion in outside impact joined with a liberal monetary expansion after the Napoleonic Wars, there was an increase in irrationality on the London Stock Exchange. This brought about an increase of discount rate. Markets smashed in October, activating banking crisis 2 months after the fact, in December. The domino impact stunned the entire mainland. As the abroad loans were removed, the crisis spread rapidly to Latin

America. The decrease in venture and fares diminished tax revenues and prompted sovereign debt defaults over the entire locale.

One of the biggest world crises was the crash of the stock market on Wall Street in October 1929. The failure of 1929-1933 caused the collapse of commodity prices in many emerging economies. The rise of the stock market in New York in 1928 vanished US capital flows to Central Europe and Latin America and produced monetary crises in several countries (Australia, Argentina, Uruguay and Brazil) (Bordo and Murshid, 2000). The crash of Wall Street has sparked fears in the stock market worldwide; this is known as the Great Depression. The US crisis in 1929 was converted into the Great Depression until 1930 and 1931 because the Federal Reserve failed to alleviate the banking panic. The consequential collapse in world prices and production forced sovereign borrowers to reduce their debt service and then bankrupt, precipitating a collapse of foreign lending in 1931 (Bordo and Murshid, 2000).

One of the factors of the Asian financial crisis of 1997 was the excessive lending by national banks. National banks continually borrowed from foreign countries and are constantly borrowing in their own country. At that time, it did not look exaggerated, but it looked like that afterwards. Bad loans were made, misunderstandings were raised risks, and the debt level continued to rise. Since the onset of the crisis, national equity betas have risen and average returns have fallen significantly (Maroney et al., 2004). The first problem on currency was the Thai Baht. With the Thai baht having issues, the debt of Thai organizations has doubled. This initiated the spreading of the crisis to other healthy countries. As this was the case, investors began to re-evaluate their investment in the region. This has led to the rapid disappearance of money flow, resulting in an emergence of the crisis.

The 2007-2008 crisis was portrayed as the most noticeably awful since the Great Depression of 1930 (Helleiner, 2011). Substantial financial institutions all through the world have been significantly influenced. The historical backdrop of the 2007-2008 crisis has brought about the blast in housing bubble in the United States and the ascent in housing mortgage defaults. Markowitz (2009) argues that this occurred because of the US Congress' command for the Federal National Mortgage to expand access to low-salary housing. Because of high default rates, numerous financial institutions were influenced in the United States. In spite of the fact that the US Government endeavored to protect the circumstance through liquidity portions, the crisis weakened further. Until March 2008, Bear Sterns, an American investment bank, has required the administration's endeavors to be safeguarded. At this stage, unmistakably the crisis had extended. Other financial institutions, for example, Lehman Bank and American International Group (AIG), started to feel the impacts of the crisis (Helleiner, 2011). The seriousness of this emergency has expanded and most American and European banks have pulled back their own international loans. This move has caused major monetary issues far and wide, particularly for those countries that depend intensely on worldwide loaning. Financial contagion was extremely seen, particularly in countries where monetary frameworks were defenseless because of nearby housing bubbles and account deficits. A portion of the nations influenced were, inter alia, Germany, Iceland, Spain, Britain and New Zealand (Helleiner, 2011). Numerous experts and governments have neglected to anticipate the genuine impacts of the crisis. As the significant economies of the world started to feel the effect of the crisis, relatively every economy was directly or by implication influenced. In particular, there was a fall in exports and commodity prices in real economy sectors.

Financial contagion can make financial influences and can deliver critical capital misfortune to the country's economy and financial frameworks. There are several classifications that clarify the mechanism of financial contagion, which are spillover effects and financial crisis caused by the impact of the behavior of the four components. The four components impacting financial globalization are governments, financial institutions, investors and borrowers (Schmukler, 2004).

The first branch, spill-over effects, can be considered as negative external factors. Spill-over effects are also known as fundamental element of contagion (Dornbusch et al., 2000). These impacts can occur either in worldwide level, influencing an extensive number of countries or at a provincial level, influencing just neighboring countries. Significant players, which are more than the biggest nations, ordinarily have a worldwide impact. Smaller nations are players who ordinarily have a local result. These types of coco-movements would not for the most part be infectious, but rather on the off chance that they happen amid a crisis period and their result is negative, it very well may be expressed as a contagion (Dornbusch et al., 2000).

The root causes of the transmission include macro-economic disturbances that have an international impact and local disturbances transmitted through trade links, competitive devaluations and financial links (Dornbusch et al., 2000). It can prompt some co-movements in capital flows and asset prices. Crises might be like the impacts of financial links. A financial crisis in a country can prompt direct economic repercussions, incorporating cuts in exchange credits, outside direct venture and other capital flows abroad (Dornbusch et al., 2000). Financial links originate from the globalization of the financial sector since economies around the globe endeavor to coordinate with the financial markets. Allen and Gale (2000) dissect financial contagion as a result of linkages between financial intermediaries. They gave a general equilibrium model to clarify a little stun of liquidity inclination in a zone that can spread from transmission over the economy and the likelihood of transmission emphatically relies upon the culmination of the structure of interregional claims. Lagunoff and Schreft (2001) proposed a dynamic stochastic game-theoretical model of financial delicacy, through which they clarify interconnected portfolios and installment commitments, create financial linkages between components of behavior, and in this way two related sorts of financial crisis can develop.

Trade links are another sort of stun that has its similitudes to basic crises and financial links. These sorts of volatility concentrate more on integrating, causing neighborhood impacts. Any major trading partner of a country in which a financial crisis has induced a sharp current depreciation could experience declining asset prices and large capital outflows or could become the target of a speculative attack as investors anticipate a decline in exports to the crisis country and hence a deterioration in the trade account (Dornbusch et al., 2000). Kaminsky and Reinhart (2000) express that trade links in goods and services and exposure to a typical creditor can clarify prior emergencies clusters, not just the debt crisis of the early 1980s and 1990s, yet additionally the observed historical pattern of contagion.

Competitive devaluation is likewise connected with financial contagion. Competitive devaluation, otherwise called a currency war: numerous countries rival each other to gain a competitive advantage with low trade rates for their currency. Devaluation in a country hit by a crisis lessens the export competitiveness of the countries with which it contends in third markets. This puts weight on the currencies of other countries; particularly in situations when those currencies don't drift unreservedly (Dornbusch et al., 2000). This action cause countries to act irrationally because of dread and uncertainty. On the off chance that countries expect that a currency crisis will prompt competitive devaluation, they will normally offer their holdings of securities of other countries, shorten their loaning, or decline to roll over loans to borrowers in those countries (Dornbusch et al., 2000).

Another case of contagion is a financial crisis, which is likewise alluded to irrational phenomena. For example, when a co-movement happens, notwithstanding when there are no worldwide stuns and interdependence and fundamentals are not factors (Dornbusch et al., 2000). It very well may be caused by any of the four factors of behavior (governments, financial institutions, investors and borrowers) who impact financial globalization. Contagion can be caused either by increased risk aversion, lack of confidence, and financial fears. King and Wadhwani (1990) say that under the correlated data channel, price changes in a single market are seen as having ramifications for the values of assets in different markets, making their prices change also. In a similar structure, Calvo (2004) contends for correlated liquidity shock channel: when some market members need to liquidate and pull back a portion of their assets to obtain cash, maybe in the wake of encountering a startling misfortune in another country and need to reestablish capital sufficiency proportions. This conduct will in the long run transmit the shock.

Out of the four factors (governments, financial institutions, investors, and borrowers), an investor's behavior is by all accounts a standout amongst the most critical one that can impact a country's financial system (Dornbusch et al., 2000). The different types of investor behaviors are considered rational or irrational and individually or collectively.

The primary kind of behavior is when investors make a move that is ex-risk separately sane however prompt unnecessary co-movements – extreme as in they can't be clarified by genuine essentials (Dornbusch et al., 2000). It very well may be classified into two sorts, liquidity and incentive problems and information asymmetries and coordination problems. On account of liquidity and incentive problems, a lessening in stock prices can result in lost cash for investors. These misfortunes may incite investors to auction securities in different markets to bring trade up out expectation of a higher recurrence of recoveries (Dornbusch et al., 2000). What's more, the liquidity issue is likewise a major issue for commercial banks. Incentive problems can likewise deliver same impacts as the liquidity issues. For instance, the first signs of a crisis may cause investors to sell their holdings in some countries, resulting in equity and different asset markets in economies to decline in value. This reason likewise diminishes in the currencies for these economies. On account of data asymmetries and coordination issues, investor's behavior can either be viewed as rational or irrational. This sub-category is when one group, or country, has more or significantly better information compared to another group or country. This can cause a market failure issue, which could possibly cause a financial crisis.

The second kind of investor behavior focuses on numerous equilibriums. It centers on the investor's behavioral changes when the financial market can have numerous equilibrium changes. In this manner, contagion happens when an emergency in one financial market makes another financial market move or hop to a bad equilibrium, described by depreciation, a drop in asset prices, capital outflows, or debt default (Dornbusch et al., 2000). The third sort of behavior is when there is an adjustment in the worldwide financial system. It can influence investors to modify their practices after a financial transaction happens universally or an initial crisis occurs. These practices can prompt overflow impact, causing contagion.

In the same framework, there are additionally some less-developed hypotheses for financial contagion. A few hypotheses for financial contagion, depend on changes in investors' psychology, attitude, and behavior, particularly after the Russian default in 1998. The initial steps of the exploration go back to early investigations of Mackay (1841). Regular early models of disease diffusion were connected to financial markets by Shiller (1984). Moreover, Kirman (1993) researched a model of impact that is persuaded by the scrounging behavior of ants, notwithstanding, material to the behavior of stock market investors. Given the choice between two indistinguishable heaps of nourishment, ants change occasionally from one heap to the other. He assumes that there are N ants and that each switch arbitrarily between heaps with likelihood ε (to keep the mistake of the framework if stalls out with all at one heap or the other), and copies an aimlessly picked other insect with likelihood δ (Morgan, 2008). Eichengreen et al. (2001) research on the transmission of crises inside markets for developing country debt. They found that the noteworthiness of changes in market sentiment has a tendency to be confined to the prototype region. Furthermore, they likewise found that market sentiments would more be able to impact prices yet less on quantities in Latin America, compared with Asian countries. On the top of that, a few papers center on geographic factors driving the contagion. For example, De

Gregorio and Valdes (2001) explore how the 1982 debt crisis, the 1994 Mexican crisis, and the 1997 Asian crisis spillover to different countries. Their outcomes demonstrated that a neighborhood effect is the most grounded determinant of which countries experience the contagion. No matter the fact that trade links and pre-crisis growth similarities are likewise critical, although to a lesser extent than the neighborhood effect.

2. LITERATURE REVIEW

As this thesis is based on five different parts of research, in order to quantify the contagion in capital markets, the literature is organized as follows: Section 2.1 covers the literature about interdependence, contagion and volatility spillover effects which is an introductory section about the current methodologies used in the literature of financial contagion. In section 2.2 I present the literature review for estimating and quantifying contagion. This is the most important part of the literature, as all parts of the research which covered in this thesis, based in this part of the literature review. In particular, section 2.2 contains the most modern and advanced methodologies used in the literature for analyzing contagion and most importantly, correlation between indices, which is the key measure among all techniques in this thesis. In most part, this section covers modern econometric techniques capable of extracting correlations, which are useful for analyzing evidence of contagion. In section 2.3 I display the literature review which covers financial contagion and correlation estimation with copulas. Copulas functions are considered to be an advanced technique to investigate market dependence and have been widely used for this purpose. Section 2.4 covers contagion calculation with regime-switching models. Markov regime-switching models are useful tools to calculate regime-change states on the specified time series of correlations. In section 2.5 I present the part of the literature that covers interdependence and contagion in financial networks. Structured networks and social network analysis seem to be an emerging and fast-growing literature for the case of stock markets and contagion. Lastly, section 2.6 covers the literature for machine learning for predictions in finance, in an attempt to predict the contagion risk which is covered and presented later in this thesis.

2.1 Interdependence, contagion and volatility spillovers

Financial contagion is frequently measured with respect to changes in the transmission of shocks from one index to another during periods of higher volatility associated with the crisis, often via correlation measures; see Forbes and Rigobon (2002)**,** Petmezas and Santamaria (2014), Luchtenberg and Vu (2015), Claeys and Vasicek (2014), Jung and Maderitsch (2014), Siebenbrunner et al. (2017) and Akca and Ozturk (2016). In this state, Li and Zhu (2014) found increased market co-movement thereafter, based on a nonparametric measure of the cross-market correlation. Applying their test to investigate contagion from the 1997 East Asian crisis and the 2007 Subprime crisis, the researchers found that international financial contagion existed due to the two financial crises. Similarly, Burzala (2016) analyzed contagion in the selected capital markets during the financial crisis of 2007–2009 and indicated that the rates of return in European markets studied react simultaneously to a much greater extent due to interdependencies than due to mutual contagion. However, Jin and An (2016) showed significant contagion effects from the U.S. to the BRICSs' stock although the degree of stock market reactions to such shocks differs from one market to another, depending on the level of integration with the international economy. Informational spillovers are also present in Cipollini et al. (2015), who argued that contagion occurs because trading activity in one market creates an informational cascade in another. Most prior studies employ classical time-domain analyses, and they usually use methods that test changes in correlation coefficients: Dungey and Gajurel (2015), Fry-McKibbin et al. (2014), Ait-Sahalia et al. (2015), Flavin and Sheenan (2015).

The emerging literature on the crisis in the euro area can be divided into the early and late definitions of contagion. MacDonald et al. (2014) constructed financial stress indices and employed multivariate analysis [Vector Autoregression (VAR) models] to explore the potential inter-reactions between the root causes of systemic risk. They used data from a wide range of series drawn from the money, equity and bond markets, as well as from the banking sector of each Eurozone country and found that countries were mostly responsive to their own financial shocks, while a degree of regionalism is also evident. Tola and Walti (2015) tested for the existence of financial contagion during this crisis, which they defined as the international transmission of country-specific shocks beyond the normal channels of financial interdependence. Mollah et al. (2016) found evidence of contagion in developed and emerging markets during the global and Eurozone crises, bearing policy implications for portfolio diversification between the US and other countries during crises. In accordance with Blatt et al. (2015), another strand of literature prefers to focus on structural breaks in the volatility of a given set of indexes. Consequently, the researchers argue that their model can locate the dates of contagion more precisely. Conversely, Shen et al. (2015) and Ludwig (2014) adopted a time-varying approach to test for contagion from the Eurozone to the Chinese economy and to the

Eurozone itself. Both studies confirm that crisis contagion easily occurs between countries that trade more often with each other.

2.2 Contagion and correlation estimation with multivariate GARCH models

Prior research on measuring cross-market linkages developed rapidly as modern approaches made their appearance. Earlier studies investigating the existence of contagion effects can be traced back in 1990's (King and Wadhwani, 1990; Lee and Kim, 1993; Calvo and Reinhart, 1996). The introduction of more advanced methods, created an ongoing debate among researchers about the identification of contagion on which economists can agree. More recent studies such as Dungey and Martin (2007) and Frank and Hesse (2009) investigated contagion and spillover effects and found significant evidence of increased volatility during the crisis periods. On the other hand, studies like Corsetti et al. (2005) didn't find any significant evidence of contagion among markets in their sample.

One of the most widely known approaches which are capable of measuring volatility transmission introduced from Engle and Kroner (1995), the so-called BEKK model (from Baba, Engle, Kraft and Kroner, 1990 - which is an unpublished manuscript). The BEKK model is one of the first methods that allows for dependence of conditional variances of one variable on the lagged values of another variable. Kroner and Ng (1998) introduced the asymmetric variation of the model which it can capture observations where returns tend to be affected by negative shocks more significantly than positive. However, huge drawback of this methodology is that it captures vast space if is it to measure many time series and full parameter matrices. Namely, over parameterized models have the problem of dimensionality.

Although a wide range of methodologies have been used, only few of them successfully identified and quantified the various channels that may transmit the spread across asset markets. Studies such as these implemented various econometric techniques to highlight and quantify the existence of contagion effects. A milestone methodology among these techniques is introduced by Engle (2002), who proposed the Dynamic Conditional Correlation (DCC) model. The huge advantage of this method, that overcomes previous approaches' limitations, was the ability of estimating time-varying conditional correlations among data series. This means that we have the ability to quantify not only the conditional correlation but also the co-movements in every single different observation of the sample. Since then, various studies adopted this approach (or modifications of it) to investigate for co-movements (Franses and Hafner, 2003; Billio and Pelizzon, 2003; Aielli, 2007).

Engle’s (2002) technique has been often used together with more sophisticated techniques, because it considers the possible time-varying nature of correlations and structural shifts in the data: Gomes and Taamouti (2016), Mobarek et al. (2016). There are also several multivariate extensions of the model proposed in the literature (see Pragidis et al.,2015). Yarovaya and Lau (2016) reported that the last two decades, after every shock and generated by the crisis, there been an increase in co-movements between emerging and developed stock markets. They also suggested that conditional correlation among the stock markets exhibits higher dependency when it is driven by negative shocks to the market. Another well-established statistical problem is the presence of autoregressive conditional heteroskedasticity, which can impact the linear test statistics. This finding led to a rise in the popularity of the ARCH models such as the structural GARCH models (Dungey et al., 2015).

Among other studies which used dynamic conditional correlations, Hwang (2014) used DCC-GARCH to investigate the spillover effects of the 2008 Financial crisis to Latin American stock markets and concluded that significant evidence confirms co-movements by showing persistently higher and more volatile conditional correlations during the crisis period. In the same framework, Kim and Kim (2013) also used DCC-GARCH model to test for linkages from 2008 Financial crisis to Korean market and other Asian markets. Their evidence showed exogenous shocks that transmitted to the domestic financial market and they are further expanded through the structural weakness of the domestic financial system.

In recent years and because of the Subprime crisis of 2008 many studies used conditional correlation modifications approaches to test for spillover effects among markets. Ahmad et al. (2013) adopted DCC models to examine the co-movements between PIIGS (Portugal, Italy, Ireland, Greece, and Spain) and BRIICKS (Brazil, Russia, India, Indonesia, China, South Korea and South Africa). The evidence indicated that Ireland, Italy and Spain appear to be more correlated with BRIICKS while Brazil, India, Russia, China and South Africa are strongly hit by the spillover effect during the Eurozone Debt crisis period. Similarly, Petmezas and Santamaria (2014) and Hemche et al. (2014) investigated the linkages in stock markets during the Subprime crisis period. Both studies showed evidence of significant increased correlations for most markets under consideration.

Cappiello et al. (2006) modified Engle's (2002) DCC model and proposed the Asymmetric variation of it. The A-DCC model has the ability to capture observations where returns tend to be affected by negative shocks more significantly than positive. Additionally, the A-DCC approach identify the coefficient of the asymmetric term between two indices (or more), implying that the dynamic conditional correlation of these return series is more significantly influenced by negative shocks. Tamakoshi and Hamori (2013) employed the A-DCC model to test for spillover effects during the recent European Debt crisis. They investigated five European financial institutions holding large amounts of Greek sovereign bonds and found increased correlations between several combinations after the crisis outbreak. They also stated presence of asymmetry for two specific institutions which implies that the conditional correlation of the indices is more significantly influenced by negative shocks than by positive innovations.

Following the same framework, Kenourgios (2014) investigated volatility contagion across U.S. and European stock markets during the Global Financial Crisis and the Eurozone Sovereign Debt Crisis. The results indicated the existence of contagion in cross-market volatilities. Kenourgios and Dimitriou (2014) and Karanasos et al. (2014) proposed the FIAPARCH–DCC model to investigate co-movements during the 2008 Financial crisis. Both studies found significant increased correlations across regional stock markets. On the other hand, Dimitriou et al. (2013) using the FIAPARCH–DCC technique for the Subprime crisis of 2008 stated that no spillover effects found for all BRICSs' economies that could be affect trades and financial sectors. Several other studies followed Engle's (2002) methodology and other variations of multivariate GARCH models to test for financial contagion (Rajwani and Kumar, 2015; Bekiros, 2014; Celik, 2012; Wang, 2013; Pesaran and Pesaran, 2007; Kazi and Wagan, 2014; Liow, 2012; Chiang et al., 2014; Kenourgios et al. (2016); Akhtaruzzaman and Shamsuddin (2016); Gómez-Puig and Sosvilla-Rivero (2016). Among other techniques, Chang and Cheng (2016), Boubaker et al. (2016) and Neaime (2016) used Granger causality tests and drew satisfactory conclusions for financial contagion.

The first part of the research investigates the volatility spillover effects from South to North Eurozone during the Sovereign Debt Crisis. Focusing on different phases of the crises, I propose the Dynamic Conditional Correlation (DCC) model and the BEKK model to identify possible linkages during the period 2005-2015. Additionally, in the second part of the research I analyze the spread of the Global Financial Crisis of 2007–2009 and the Eurozone Sovereign Debt crisis from the financial sector to the real economy by examining ten sectors in major and developed stock markets, similar to Baur (2011), Chiu et al. (2014), Pyun and An (2016). In particular, I employ Cappielo's et al. (2006) model and copula functions to detect and cross-check the correlations and the contagion thereafter. Furthermore, the third part of the research applies a dynamic conditional correlation DCC model to investigate the volatility spillovers and the interdependence between the Greek Debt crisis and the Cypriot financial crisis.

2.3 Correlation estimation with copulas

The copula approach has been employed by many authors, as it can model tail dependence in financial time series. This particular approach can capture the non-normality and the fat-tailedness of financial time series data (Horta et al.,2016; Arakelian and Dellaportas, 2012). Particularly, Silvapulle et al. (2016) employed a robust semi-parametric copula approach to estimate the bivariate joint distributions of bond yield spreads and the tail dependence parameters to establish the contagion effects among time-series. The researchers found that the contagion effect is demonstrated by a significant increase in the tail dependence from the pre-crisis (1999 to 2008) to the post-crisis period 2008 to 2013. Changqing et al. (2015) applied the dynamic Markov Regime Switching copula model to depict the contagion characteristics. They selected an appropriate model using goodness-of-fit testing to analyze the cross market lower tail dependency. The researchers found that the model can clearly distinguish the different states of the market correlation structure. While Poshakwale and Mandal (2015) show that the time-varying conditional copula depict a robust alternative model specification that uses a regime switching MGARCH model, Lee et al. (2015) state that the distinct copula model specifications with time-invariant and time-varying dependence structures are reliable for strong evidence of contagion. Other studies that tested the copula functions' efficiency are Horta et al. (2014) who examined the impact of the 2008 and 2010 financial crises on the Hurst exponents of the index returns representing the stock markets of the US, Greece, Belgium, France, Japan, the Netherlands, Portugal and the UK. The copula models showed increased correlation in the markets where the crises originated. Among other studies, Jin (2016) investigated the impact of the 2008 financial crisis on the behavior of Asian stock markets in terms of efficiency and contagion. Applying copula models, the researcher found a significant increase in the correlation, indicating the existence of financial contagion.

Copula functions are typically used by authors to illustrate tail dependence in financial time series, under the same framework (Bhatti and Nguyen, 2012; Durante and Jaworski, 2010). In addition, the models have the ability to detect fat-tailedness and non-normality within the markets in question. Ye et al. (2010) looked at the impact of the 2008 financial meltdown and highlighted that the models demonstrated a heightened correlation where the crises began. Zhu et al. (2013) studied Chinese banking to find the subprime crisis contagion through application of a change-point detection method, which was based on copula. Their study showed contagion between 2007 and 2009. Other work, Rodriguez (2007), Wen et al. (2012), Loaiza-Maya et al (2015), and Jayech (2016), employed copula function variations to examine different time series and contagions. Evidence of spillover and co-movements was found within all these works. Zhou and Gao (2010) analysed tail dependence of six major real estate securities markets to monitor the co-movements by using symmetrized Joe-Clayton (SJC) copula. The results showed that international markets display different strength and dynamics of tail dependence. On the other hand, Zimmer (2014) proposed copula-based approach to model co-movements in house prices and found strong contemporaneous tail dependence among US census divisions and other OECD countries, indicating that extreme price movements in different areas tend to happen in tandem.

Copula functions are used in the case of Brexit, which is covered in part four of the research. Specifically, I measure the spillover effects from the UK to 43 developed and emerging economies that the Brexit referendum produced. On a bivariate basis, I employ dependence dynamics through copulas with regime switching of Silva Filho et al. (2012) to identify contagion among stock markets. In addition, copula functions, in static mode, are also used in the case of contagion from the financial sector to the real economy, which is covered in part two of the research.

2.4 Contagion calculation with regime-switching models

Several studies took help from econometric models of contagion, which intertwined many different elements. One example is the Markov regime-switching model, which has been proposed in this study. Lopes and Nunes (2012) consider a Markov regime-switching vector autoregression conditional heteroskedastic model with time-varying transition possibilities, where there is room for changing correlations. Through use of this model, they found that the interest rates in Portugal and Spain, subsequent to the 1992 Monetary System crisis, had varying impacts on the transition probability from non-crisis to crisis state. On the other hand, the evidence demonstrated strong contagion for both the countries.

Under a Markov regime-switching VAR framework, Guo et al. (2011) looked at the global impact of contagion. The study found that regimes presented themselves at the start of the 2007 subprime crisis. Changqing et al. (2015) used a dynamic copula model to highlight the characteristics of the contagion. They evaluated the lower tail dependency across multiple markets. The study found that the model was able to differentiate the many states of market correlation. Akay et al. (2013) used a dynamic factor framework with Markov regime switching. They looked time variation and contagion under a risk-adjusted return framework. Their empirical work isolated three regimes, i.e. high mean, low and crash. Another example of the Markov model was found in the work of Ye et al. (2016), whose study focused on detecting contagion in the US and some EU economies. The study made use of a quantile regression model with parameters isolated through the calculation for maximum likelihood. The study reported that interdependence between EU nations and the US substantially increased at the time of crisis.

As I already mentioned in the end of the previous subsection, regime-switching models are used in the case of Brexit, which is covered in part four of the research. Dynamics through copulas with regime switching of Silva Filho et al. (2012) is one of the most modern techniques in the literature to identify contagion among stock markets.

2.5 Financial networks, interdependence and contagion in finance

Modern banking systems and stock markets are highly interconnected. Despite various benefits, linkages between banks carry the risk of contagion (Babus, 2016). Hausenblas et al. (2015) examined possible contagion risk within the Czech banking system via the channel of interbank exposures of domestic banks, which are aggravated by a liquidity channel and an asset price channel. They used a computational model of the size and structure of interbank exposures as well as balance sheet and regulatory characteristics of individual banks in the network. They found that the potential for contagion due to credit losses on interbank exposures was rather limited. On the other hand, Minoiu et al. (2015) examined the ability of connectedness in the global network of financial linkages to predict systemic banking crises. Their results indicated that increases in a country's own connectedness and decreases in its neighbors' connectedness are associated with a higher probability of banking crises after controlling for macroeconomic fundamentals.

In the same framework, Tse et al. (2010) constructed networks to study correlations between closing prices for US stocks. The nodes were the stocks, and the connections were determined by cross correlations of the variations of the stock prices, price returns and trading volumes within a chosen period of time. They found that variations in stock prices are strongly influenced by a relatively small number of stocks. Similarly, Qiao et al. (2015) modeled the currency networks through the use of REER (real effective exchange rate). Using the MST (minimum spanning tree) approach and the rolling-window method, they constructed time-varying and correlation-based networks with which they investigated the linkage effects among different currencies. The study demonstrated that obvious linkage effects exist among currency networks and the euro (EUR), which has been confirmed as a predominant world currency. Likewise, Eryigit and Eryigit (2009) reported the results of an investigation of properties of the networks formed by the cross-correlations of stock market indices. Their analysis showed that North American and European markets are much more strongly connected among themselves compared to the integration with the other geographical regions. Similar evidence was found by Brida and Risso (2010) and Kantar et al. (2011) as it relates to the German and Turkish economies, respectively. Among other studies, Yang et al (2014), Chen et al. (2015), Eom et al.

(2009), Coelho et al. (2007), Ulusoy et al. (2012) and Tabak et al. (2010) used extensive variations of constructed networks to study the correlations and possible spillovers effects in the data.

Within a dynamic financial network framework, Sensoy and Tabak (2014) proposed dynamic spanning trees constructed by the ARMA-FIEGARCH-cDCC process to evaluate Asia-Pacific stock market interconnections. They found that the network shrinks over time and that the Hong Kong market was the key player. In addition, they observed an increased interdependence between Asia-Pacific stock markets over the last two decades, which is evidence for a contagion effect during the 1997 and 2008 financial crises. Qiao et al. (2016) used a (DCC) method to identify the linkage effects of the Chinese stock market, and further detected the influence of network linkage effects on the magnitude of security returns across different industries. They analyzed stock interdependence within the network of the China Securities Index (CSI) industry index basket, observing that obvious linkage effects existed among stock networks. The two aforementioned papers used time-varying highest centrality measures to analyze the dynamic evolution of the network structure. This purpose fulfills the investigation for network stability and the extent of shrinkage during a stock market crisis.

In the fifth part of the research, I use the correlations from the (ADCC) model to construct networks from the dynamic minimum spanning tree (MST) technique and subsequently to extract centrality measures to investigate the core nodes and possible contagion effects within the networks.

2.6 Machine learning for predictions in finance

In the fifth part of the research I introduce a machine learning approach to predict and forecast the risk of contagion inside the financial network. Machine learning is a subset of artificial intelligence in the field of computer science that often uses statistical techniques to give the model the ability to "learn" with data without being explicitly programmed (Samuel, 1959). Machine learning tasks are typically classified into two broad categories, depending on whether there is a learning "signal" or "feedback" available to a learning system. In the first case we have “supervised learning” where the model is presented with example inputs and their desired outputs, given by a "teacher", and the goal is to learn a general rule that maps inputs to outputs. As special cases, the input signal can be only partially available, or restricted to special feedback (Russell and Norvig, 2010). In the second case, we have “unsupervised learning” where no labels are given to the learning algorithm, leaving it on its own to find structure in its input. Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means to an end (feature learning) (Jordan and Bishop, 2004). Another categorization of machine learning tasks arises when one considers the desired output of a machine-learned system: classification, regression and clustering. In classification, inputs are divided into two or more classes, and the learner must produce a model that assigns unseen inputs to one or more (multilabel classification) of these classes. In regression, also a supervised problem, the outputs are continuous rather than discrete. Lastly, in clustering, a set of inputs is be divided into groups. Unlike in classification, the groups are not known beforehand, making this typically an unsupervised task.

Machine learning has started to enter in the modern literature of finance as we see an increasing number of applications in the field of prediction and forecasting. Gogas et al. (2018) applied an SVM-based (Support Vector Machine) methodology for forecasting the bankruptcy of U.S. financial institutions over the period 2007–2013 using financial data taken from the banks’ publicly available financial statements. Their model exhibited a 99.22% overall forecasting accuracy and outperformed the Ohlson’s score. In this framework, Hu et al. (2018) proposed a neural network optimized by the improved sine cosine algorithm; the results showed that the model is suitable for predicting the directions of the S&P 500 and DJIA Indices. Similarly, Ticknor (2013) proposed neural networks to forecast financial market behavior. The results indicated that the proposed model performed as well as the more advanced models without the need for preprocessing of data. Likewise, Rather et al. (2015) proposed linear and nonlinear models for stock market prediction and found that Recurrent Neural Network model produces satisfactory predictions compared to statistical models. Among other studies, Zahedi and Rounaghi (2015), Gocken et al. (2016), Malagrino et al. (2018) and Chatzis et al. (2018) used extensive variations of machine learning and deep learning algorithms to investigate contagion among time series, and all found significant evidence of accuracy for prediction and forecasting. As far as I are aware, there is no application in the finance literature that combines machine learning, network analysis and financial contagion inside the financial network that we apply in this paper.

At this point, I must mention why I select machine learning over statistical modeling. Regarding the aforementioned literature on machine learning and from a traditional data analytics standpoint, machine learning is a calculation that can learn from information without depending on rules-based programming. Measurable displaying is a formalization of connections between factors in the information as scientific conditions. Both machine learning and statistics share a similar objective: Learning from the data. Machine learning requires no earlier suppositions about the fundamental connections between the factors. We just input all the data we have, and the calculation forms the information and finds designs, which we can use to make predictions on the new dataset. Generally, machine learning is applied to high dimensional datasets, while statistical modeling can be used for low dimensional datasets. Regarding forecasting and prediction, using statistics (e.g., moving average), we take restricted inferences: infer from one feature, learn from some data, and prone to outliers. This is where machine learning methods come to the rescue. The ultimate goal of machine learning is to learn and to predict the data correctly. They are intended to be used for a more complex data. Regarding the fact that our sample includes both high dimensional and complex data, I deploy a machine learning approach for prediction and forecasting.

3. METHODOLOGICAL STRATEGY

3.1. Data and descriptive statistics

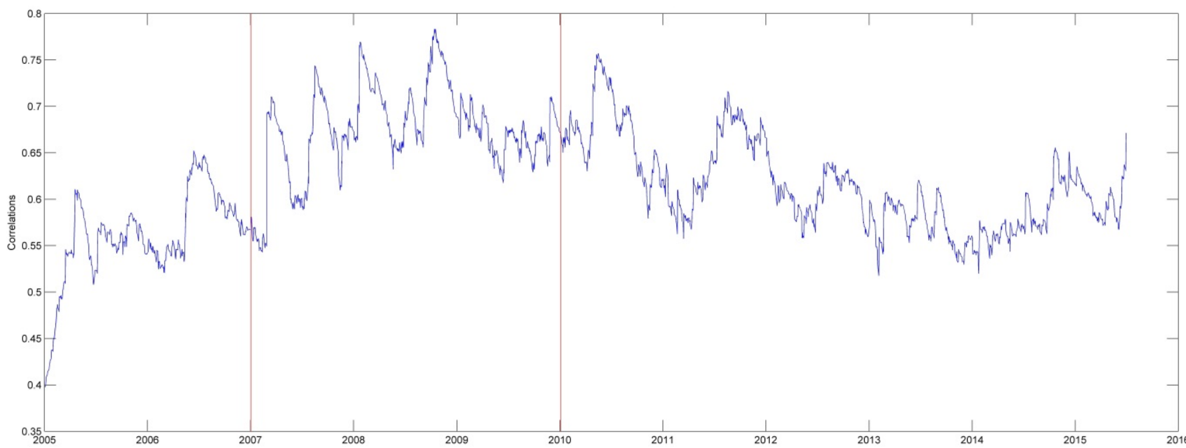
The data used in this thesis was obtained from many different channels. In particular, I used stock indices, sovereign Bonds and CDS, real economy sectors and policy uncertainty indexes. Each part of the research contains different combination of the data. The data samples and the descriptive statistics for each different stages of the research are presented in the following subsections.

3.1.1. First part: The case of South and North Eurozone countries

(*This section is based on Samitas and Kampouris (2017b), where Samitas is coauthor of the published paper*)

To measure the effect of the sovereign debt crisis in Eurozone, I follow the literature and try to identify the linkages by which a crisis is transferred to other countries. The sample includes daily return observations beginning on January 4, 2005, until June 30, 2015. The examination period is divided into 3 subperiods: a) The early Eurozone period (January 4, 2005, to December 28, 2006), b) the subprime crisis period (January 2, 2007, to December 30, 2009) and c) the Eurozone debt crisis period (January 4, 2010, to June 30, 2015). I consider 2010 as the initial year of the crisis due to the wake of Great Recession, which was characterized by overly high government structural deficits and accelerating debt levels. I run a robustness test about the period selection. Specifically, using the DCC model presented below, I extract all possible correlations from the countries included in this paper. I then estimate the average correlation from all extracted correlations. The average correlation also depicts Eurozone interdependence. Using Yamamoto and Perron's (2013) technique about structural breaks, I calculate the possible structural breaks on Eurozone interdependence. The results showed two structural breaks (Figure 3.1): the first in early 2007 and the second at the beginning of 2010 (red vertical lines). Figure 3.1 shows increased correlations for Eurozone interdependence between 2007 and 2010. The evidence of the structural breaks shows that the research is in line about the selection of the crisis period. The sample comprises ten European economies, which are divided into two groups: the "South Eurozone" including the five economies of Italy (FTSE MIB), Spain (IBEX 35), Greece (FTSE/ATHEX), Cyprus (CYSMMAPA) and Portugal (PSI 20) and the "North Eurozone", which includes five of the strongest northern economies in Eurozone: Germany (DAX), France (CAC 40), Belgium (BEL 20), Austria (ATX) and the Netherlands (AEX index). Data is obtained from Bloomberg.

Figure 3. 1. Eurozone Interdependence



The summary statistics of our sample are presented in Table 3.1. The mean value is lower than the median for all indices. Four of the indices skew positive (Spain, France, Cyprus and Greece), while all ten have kurtosis much higher than 3. The Dutch index (AEX) is the most negatively skewed (-0.2465) and has the highest level of kurtosis (12.2989), indicating that extreme changes tend to occur more frequently. The lowest and the highest average return is recorded for the Cypriot index, which has at the same time the highest standard deviation indicating the extent of volatility in the market. On the other hand, the Belgian market is the least volatile (0.0128). None of the indices is normally distributed based on the Jarque-Bera statistic. Thus, AR(1)-GJR-GARCH is an appropriate specification to capture asymmetry and excess kurtosis. Additionally, all indices exhibit ARCH effects. However, in all indices ARCH(1) was adequate according to the AIC and BIC. Finally, augmented Dickey–Fuller tests for the presence of unit roots can convincingly be rejected for all indices.

Table 3. 1. Descriptive Statistics of the indices

	IBEX 35 Spain	AEX Netherlands	ATX Austria	BEL 20 Belgium	CAC 40 France	CYSMMAPA Cyprus	DAX Germany	FTSE/ATHEX LARGE CA Greece	FTSE MIB Italy	PSI 20 Portugal
Mean	0.0001	0.0001	0.0000	0.0001	0.0001	-0.0009	0.0003	-0.0006	-0.0001	-0.0001
Median	0.0008	0.0006	0.0007	0.0004	0.0004	-0.0004	0.0010	0.0000	0.0007	0.0003
Maximum	0.1348	0.1003	0.1202	0.0922	0.1059	0.1696	0.1080	0.1637	0.1087	0.1020
Minimum	-0.0959	-0.0959	-0.1025	-0.0832	-0.0947	-0.1552	-0.0743	-0.1384	-0.0860	-0.1038
Std. Dev.	0.0152	0.0134	0.0166	0.0128	0.0143	0.0275	0.0137	0.0235	0.0158	0.0128
Skewness	0.1101	-0.2465	-0.2402	-0.1495	0.0128	0.1102	-0.1770	0.1236	-0.0492	-0.1678
Kurtosis	9.7152	12.2989	8.8465	9.4909	9.5988	7.7537	8.7615	6.7628	7.8028	9.9435
Jarque-Bera	4777.62	9176.99	3641.93	4468.43	4608.44	2396.75	3526.37	1504.95	2442.32	5114.44
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	0.24	0.21	-0.12	0.22	0.17	-2.28	0.73	-1.55	-0.31	-0.28
Sum Sq. Dev.	0.59	0.46	0.70	0.41	0.52	1.92	0.47	1.41	0.63	0.42
Observations	2540	2540	2540	2540	2540	2540	2540	2540	2540	2540
ADF test	-50.42	-51.16	-47.23	-49.07	-53.13	-44.96	-50.12	-47.94	-51.43	-47.37
ARCH(1) test	95.47	110.18	245.40	183.06	100.97	89.21	100.30	48.23	75.50	85.55

Notes: ADF test critical values: 1% level = -3.4327, 5% level = -2.8625, 10% level = -2.5673.
ARCH test critical values: 1% level = 6.6349 (a=0.01).

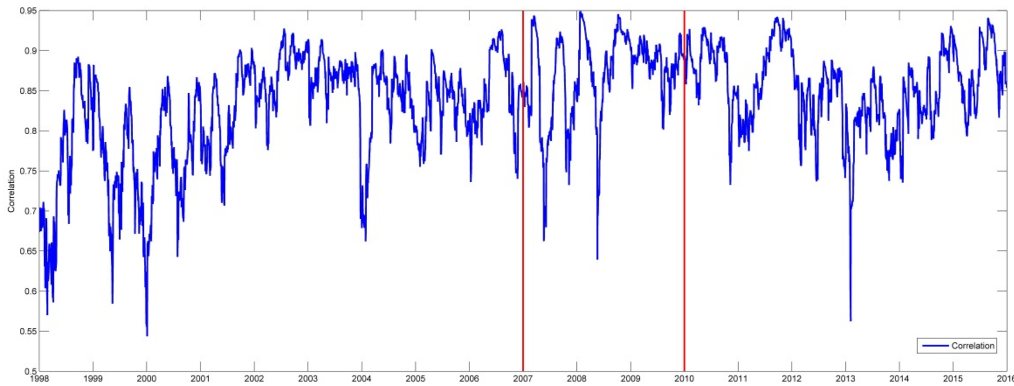
3.1.2. Second Part: the case of contagion in real economy and the key role of policy uncertainty

To measure the impact of the Sovereign Debt crisis on the rest of the world's major economies, I act in accordance with the literature. I attempt to identify linkages, co-movements and contagion channels by which the crisis is transmitted to other countries. In this approach, it is substantial to measure the interdependence ratio that can be derived from the correlations of the applied econometric models. As Greece encounters the most severe impact of the Sovereign Debt crisis, seems reasonable to international investors that the most serious transmission channel of the crisis is the Eurozone. There is no doubt that the Institutions (ECB, E.C.) of the

Eurozone are afraid of this case, particularly if the transmission channels include "systemic" economies such as Spain, Italy or even France.

The sample includes daily return observations beginning on January 1st 1998 until December 31st 2015. The sample is divided into 3 periods: a) The Early Eurozone period (1st January 1998 until 29th December 2006), b) the Subprime crisis period (1st January 2007 until 31st December 2009) and c) the Eurozone Debt crisis period (1st January 2010 until 31st December 2015). The most challenging issue in this approach is the selection of the appropriate periods. The initial year of the Debt crisis is considered 2010, as it was a year characterized by high government structural deficits and accelerating debt levels combined with the Great Recession. I run a robustness test about the period selection. Specifically, using the DCC model presented below, I extract all possible correlations from the countries included in this paper (major indices). Then I estimate the average correlation from all extracted correlations. The average correlation also depicts the global interdependence. Using Yamamoto and Perron's (2013) technique about structural breaks, I calculate the possible structural breaks on global interdependence. The results showed two structural breaks (Figure 3.2): the first in early 2007 and the second at the beginning of 2010 (red vertical lines). Figure 3.2 shows increased correlations for global interdependence between 2007 and 2010. The sample is constituted by 3 Eurozone economies, which I assume can transmit the crisis to healthy economies outside the Eurozone to the rest of the world. These countries are France (CAC 40 index), Spain (IBEX 35) and Italy (FTSE MIB). In addition, I select 10 sectors of major economies that it is believed that can produce a severe impact on the global financial environment. These economies were selected by their GDP size; they are as follows: the United Kingdom, the United States, BRIC economies, Canada and Japan. The BRIC economies are composed of the countries of Brazil, Russia, India and China. The sectors that I included for the analysis are as follows: Oil and Gas, Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications, Utilities, Financials and Technology. There are 50 price index sectors overall; ten sectors for each economy (the US, the UK, BRIC, Canada and Japan). Due to the lack of data for certain time series, I included a generalized index for BRIC countries. The generalized index of BRICs was the sole index that had data for all sectors for eighteen years of the time series (1998 to 2015) that I included in the analysis. Therefore, I did not separate the BRIC economies to test the transmission of the Debt crisis to the sectors of each country individually. Data is obtained from Thomson Reuters DataStream.

Figure 3. 2. Global interdependence



The descriptive statistics of our research are presented in Table 3.2. Unfortunately, due to the lack of dimensionality, I only present the summary statistics of the three Eurozone indexes divided by the corresponding period (Early, Subprime crisis and Debt crisis period). However, the whole sample of the sectors for each economy is available upon request. The mean value is positive for all indexes in the Early Eurozone period and negative for the Subprime crisis period. In addition, in most cases, the mean value is lower than the median. The Subprime crisis period was the most volatile, and the Early Eurozone period was the least, according to the standard deviation. Six indexes present negative skewness, while all nine have kurtosis higher than 3. All indexes for all periods present high values of skewness and kurtosis, indicating that, in all cases, extreme changes tend to occur more frequently. In all periods, none of the indexes are normally distributed according to the Jarque-Bera test. In this case, I propose the AR(1)-GJR-GARCH (Glosten-Jagannathan-Runkle GARCH model of Glosten et al., 1993) as it fits properly to locate asymmetry and excess kurtosis channels through the time series. The Early Eurozone period covers 2347 observations, the Subprime crisis 784, and the Debt crisis period 1565. The augmented Dickey–Fuller test for the presence of unit roots is rejected for all indices. Engle's test for residual heteroscedasticity showed that we should reject the null hypothesis of no conditional heteroscedasticity and conclude that there are significant ARCH effects in the return series on all cases. Finally, the Ljung-Box Q-test for the presence of autocorrelation showed that most time series rejected the null hypothesis that the residuals are not autocorrelated.

Table 3. 2. Descriptive Statistics

	FRANCE CAC 40	IBEX 35	FTSE MIB INDEX	FRANCE CAC 40	IBEX 35	FTSE MIB INDEX	FRANCE CAC 40	IBEX 35	FTSE MIB INDEX
	EARLY EUROZONE PERIOD			SUBPRIME CRISIS PERIOD			DEBT CRISIS PERIOD		
Mean	0.0003	0.0003	0.0002	-0.0004	-0.0002	-0.0007	0.0001	-0.0001	-0.0001
Median	0.0002	0.0005	0.0004	0.0000	0.0002	0.0000	0.0003	0.0000	0.0000
Maximum	0.0700	0.0632	0.0763	0.1059	0.1012	0.1088	0.0922	0.1348	0.1068
Minimum	-0.0768	-0.0734	-0.0787	-0.0947	-0.0959	-0.0860	-0.0563	-0.0687	-0.0704
Std. Dev.	0.0142	0.0139	0.0137	0.0184	0.0179	0.0184	0.0135	0.0153	0.0164
Skewness	-0.1112	-0.1895	-0.1526	0.1521	-0.0129	0.0674	-0.0285	0.2544	-0.1049
Kurtosis	5.7632	5.8353	6.2534	8.9108	8.4400	8.3126	6.1711	8.1730	5.4274
Jarque-Bera	751.48	800.21	1044.17	1144.34	966.74	922.59	655.93	1761.88	387.10
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	0.6141	0.6677	0.5295	-0.3421	-0.1696	-0.5779	0.1638	-0.2240	-0.0820
Sum Sq. Dev.	0.4747	0.4524	0.4381	0.2660	0.2508	0.2651	0.2861	0.3663	0.4192
Observations	2347.00	2347.00	2347.00	784.00	784.00	784.00	1565.00	1565.00	1565.00
ADF Test	-47.926	-47.790	-48.719	-30.680	-29.320	-28.421	-39.569	-37.296	-40.489
ARCH Test	79.576	77.230	94.491	28.688	40.047	30.302	31.606	21.320	22.802
Ljung-Box Q-test									
5 Lags (P - Values)	0.0116	0.1804	0.0000	0.0000	0.0004	0.0000	0.0649	0.0000	0.0829
10 Lags (P - Values)	0.0125	0.0364	0.0000	0.0000	0.0014	0.0000	0.0938	0.0000	0.1132
15 Lags (P - Values)	0.0014	0.0019	0.0000	0.0000	0.0007	0.0000	0.3056	0.0000	0.2421
h	1	0	1	1	1	1	0	1	0
	1	1	1	1	1	1	0	1	0
	1	1	1	1	1	1	0	1	0

Notes: Engle test for residual heteroscedasticity showed that we should reject null hypothesis of no conditional heteroscedasticity and conclude that there are significant ARCH effects in the return series on all cases. h and pValue are vectors containing three elements corresponding to tests at each of the three lags. The first element of each output corresponds to the test at lag 5, the second element corresponds to the test at lag 10, and the third element corresponds to the test at lag 15. h = 1 indicates the rejection of the null hypothesis that the residuals are not autocorrelated. pValue indicates the strength at which the test rejects the null hypothesis. Since all three are less than 0.01, there is strong evidence to reject the null hypothesis that the residuals are not autocorrelated.

3.1.3. Third Part: the case of interdependence of small economies

In order to measure the conditional correlations between Greece and Cyprus and present the significance of the evidence, first I need to split the data into two major subgroups. The sample is divided into two periods. The first period covers the 2008 Global Financial Crisis (GFC) and the second the Eurozone Debt Crisis (EDC). The GFC covers the period from January 4, 2005 till December 31, 2009, while the EDC the events from January 4, 2010 till June 30, 2015 (date that Greek capital market closed after the law-enforcement of capital controls). Furthermore, the sample contains daily returns of Stocks indices from the Greek and the Cypriot market. I assume in this part of the research that the EDC period was an internal issue for Greece and Cyprus and not a Eurozone problem. Major Banks, Credit Rating Institutions and Eurozone members determined this problem as individual problem of Greece and Cyprus, which in fact later became a Eurozone problem despite their expectations.

The summary statistics of our sample are presented in Table 3.3. Both indices (Greece and Cyprus) are negative skewed in GFC period while they are positive skewed in the EDC period. Likewise, both indices have kurtosis higher than 3 in the GFC period. However, in the EDC period only Cyprus exhibits kurtosis higher than 3 while the Greek index scores 2.7289. In both periods the lowest and the highest average return is recorded for the Cypriot index, which has at the same time the highest standard deviation indicating the extent of volatility in the market. None of the indices is normally distributed based on the Jarque-Bera statistic. In this case, the AR(1)-GJR-GARCH is an appropriate specification in order to capture asymmetry and excess kurtosis in both indices. Furthermore, both indices exhibit ARCH effects. However, the absence of an ARCH effect is rejected uniformly up to 5 lags.

Table 3. 3. Descriptive Statistics - Global Financial Crisis and Eurozone Debt Crisis

	GFC period		EDC period	
	Greece	Cyprus	Greece	Cyprus
Mean	-0.0003	0.0004	-0.0009	-0.0021
Maximum	0.1028	0.1212	0.1637	0.1696
Minimum	-0.0980	-0.1214	-0.1384	-0.1553
Std. Dev.	0.0186	0.0237	0.0273	0.0305
Skewness	-0.2176	-0.0576	0.2332	0.2248
Kurtosis	4.3864	3.7505	2.7289	4.5761
Jarque-Bera	983.62	712.78	423.16	1167.2
Probability	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	1215	1215	1325	1325
ARCH(5) test	51.612	28.992	11.055	15.993
	[0.0000]	[0.0000]	[0.0000]	[0.0000]

3.1.4. Fourth Part: spillover effects from the case of Brexit

(*This section is based on Samitas and Kampouris (2017a), where Samitas is coauthor of the published paper*)

This analysis tries to highlight the impact that Brexit and Article 50 had in terms of contagion and co-movements pertaining to other countries. An important aspect of this approach is to quantify the ratio of interdependence that can be gauged from the applied econometric model's correlations. The UK is an important entity when it comes to the stock exchange markets of the world, and is also a part of the EU. This is the reason that it is only logical to assume that the Eurozone is the most serious transmission channel. Moreover, capital markets around the world, within developed and developing economies, fear losses.

Intraday data returns between January 1, 2016 and September 30, 2017 (30-minute close price frequency) were used to evaluate the impact that the Brexit vote had on global markets. The time duration was six months before the vote and six months after Article 50 was set in motion. Stock markets experience immediate impact upon facing public information that has great significance, and this was the reason that intraday data was used. A 30-minute frequency was used because some countries do not support this data for greater frequencies, and it helps find most data that is available. Major indexes from Europe, EU, Africa, Asia, South and North America, Eurozone and BRICS were used. Thompson Reuters DataStream was used for sample data, which covered 44 countries. This, alongside the descriptive statistics of this study, can be found in Table 3.4. The GDP size was used to select countries. The trading hours of the stock exchange markets under discussion proved to be a limitation for this study. For instance, the London Stock Exchange has hours that are different from other exchanges, especially when one tries to take into context Japan or Australia (Table 3.5). Therefore, countries such as Australia, Japan, etc. were excluded from the sample so that only counties with similar trading hours could be analyzed.

For 16 countries, the mean value is lower than the median, as illustrated through the statistics. Countries that were the most volatile include Greece, Italy and Brazil. Countries such as Estonia, Malaysia and Lithuania were the least volatile. A majority of the indexes were negatively skewed and 28 of them demonstrated kurtosis that was more than 3. Most indexes in question demonstrated high values of kurtosis and skewness, highlighting that massive changes take place frequently. The Jarque-Bera test outlines that no index was distributed normally. For this, residuals were used from MA, AR and ARMA models, based on whatever fit best. AR (1) fit well in most cases, and helped find excess kurtosis and asymmetry through the time series. For all instances, the minimum value was chosen to be the announcement of the results. This indicates that the resultant contagion raised problems because of its size.

Table 3. 4. Descriptive Statistics

	Mean	Standard Error	Median	Standard Deviation	Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Jarque - Bera	Probability
FTSE 100	-9.84E-18	0.0004	-4.96E-06	0.0087	7.50E-05	2.5662	0.0500	0.0703	-0.0356	0.0347	119.13	0.00
FTSE 350	5.47E-18	0.0004	8.20E-05	0.0085	7.20E-05	3.4607	-0.1279	0.0739	-0.0397	0.0342	218.12	0.00
Austria	7.14E-18	0.0005	7.05E-04	0.0115	1.31E-04	5.3321	-0.8699	0.1113	-0.0738	0.0375	572.47	0.00
Belgium	5.42E-18	0.0005	1.91E-04	0.0097	9.35E-05	6.0645	-0.8112	0.0968	-0.0664	0.0304	717.15	0.00
Cyprus	7.46E-07	0.0004	-7.66E-05	0.0081	6.50E-05	1.9915	-0.1431	0.0680	-0.0390	0.0290	72.77	0.00
Estonia	2.83E-18	0.0002	-5.06E-05	0.0048	2.33E-05	2.0435	0.1063	0.0388	-0.0193	0.0195	76.05	0.00
Finland	-5.54E-18	0.0005	3.76E-05	0.0106	1.13E-04	10.8973	-1.2975	0.1201	-0.0880	0.0322	2,287.13	0.00
France	-1.23E-17	0.0005	-2.15E-04	0.0110	1.20E-04	8.7940	-0.9104	0.1244	-0.0842	0.0402	1,468.76	0.00
Germany	5.42E-18	0.0005	3.55E-04	0.0107	1.14E-04	4.9547	-0.6722	0.1051	-0.0712	0.0340	479.19	0.00
Greece	9.79E-07	0.0008	2.48E-04	0.0167	2.79E-04	14.4852	-1.7146	0.2155	-0.1446	0.0710	4,031.66	0.00
Ireland	8.56E-07	0.0006	-1.27E-04	0.0117	1.37E-04	16.4124	-1.9861	0.1444	-0.0990	0.0453	5,165.76	0.00
Italy	-1.18E-17	0.0007	4.14E-04	0.0156	2.44E-04	9.8563	-1.0161	0.1751	-0.1251	0.0500	1,845.00	0.00
Latvia	-3.53E-18	0.0004	-8.07E-04	0.0090	8.18E-05	21.4819	2.6888	0.1114	-0.0289	0.0825	8,949.17	0.00
Lithuania	-3.18E-18	0.0002	-7.41E-05	0.0042	1.78E-05	1.7266	-0.2487	0.0331	-0.0187	0.0144	58.16	0.00
Netherlands	-1.01E-17	0.0004	2.38E-04	0.0093	8.64E-05	3.8349	-0.3756	0.0847	-0.0526	0.0321	277.03	0.00
Portugal	5.98E-18	0.0005	2.71E-04	0.0109	1.19E-04	4.8015	-0.7628	0.1022	-0.0700	0.0322	461.62	0.00
Slovakia	1.10E-06	0.0005	-2.46E-04	0.0097	9.41E-05	2.5984	0.0528	0.0843	-0.0353	0.0490	121.60	0.00
Slovenia	1.31E-06	0.0003	-1.87E-04	0.0062	3.84E-05	1.4765	-0.2511	0.0474	-0.0278	0.0195	43.54	0.00
Spain	-9.17E-18	0.0006	1.97E-04	0.0131	1.72E-04	18.0138	-1.9150	0.1611	-0.1239	0.0372	6,186.36	0.00
Denmark	8.87E-06	0.0005	3.51E-05	0.0114	1.29E-04	4.1049	-0.4463	0.1059	-0.0532	0.0527	320.33	0.00
Sweden	1.31E-06	0.0005	-2.16E-04	0.0103	1.07E-04	10.1858	-1.0143	0.1186	-0.0826	0.0360	1,965.09	0.00
Hungary	2.37E-06	0.0004	6.74E-05	0.0094	8.81E-05	2.1275	-0.3127	0.0845	-0.0456	0.0389	88.83	0.00
Poland	1.82E-06	0.0004	-2.81E-04	0.0088	7.74E-05	1.9878	-0.2118	0.0744	-0.0447	0.0297	74.48	0.00
Czech Republic	6.19E-07	0.0004	1.35E-04	0.0086	7.40E-05	3.6811	-0.6801	0.0771	-0.0420	0.0351	279.84	0.00
Bulgaria	6.27E-06	0.0003	-2.10E-04	0.0065	4.23E-05	9.6479	0.1771	0.0854	-0.0466	0.0388	1,688.88	0.00
Croatia	4.53E-07	0.0003	1.66E-04	0.0062	3.91E-05	4.9949	-0.7765	0.0538	-0.0308	0.0229	497.68	0.00
Turkey	3.46E-05	0.0005	-3.74E-04	0.0112	1.26E-04	4.7510	-0.5586	0.1124	-0.0717	0.0406	432.83	0.00
Switzerland	2.16E-06	0.0004	2.11E-04	0.0086	7.44E-05	1.6459	-0.2119	0.0638	-0.0345	0.0292	51.85	0.00
Norway	6.10E-06	0.0005	-3.22E-04	0.0114	1.29E-04	2.1782	-0.1318	0.0936	-0.0490	0.0445	86.82	0.00
Brazil	1.58E-05	0.0007	-1.58E-04	0.0147	2.16E-04	4.1907	-0.3360	0.1540	-0.0894	0.0646	326.87	0.00
Russia	2.72E-06	0.0005	-3.26E-04	0.0099	9.86E-05	1.0086	-0.1475	0.0724	-0.0415	0.0309	19.69	0.00
India	2.93E-05	0.0004	-3.07E-04	0.0077	6.00E-05	2.0162	-0.0205	0.0678	-0.0344	0.0333	73.24	0.00
South Africa	5.38E-06	0.0004	-2.99E-04	0.0093	8.70E-05	1.1565	-0.1870	0.0656	-0.0342	0.0314	26.26	0.00
US	5.79E-06	0.0003	-2.27E-04	0.0068	4.59E-05	3.9633	-0.4605	0.0607	-0.0364	0.0242	300.49	0.00
Mexico	5.28E-06	0.0004	-1.70E-05	0.0076	5.77E-05	3.7876	-0.4356	0.0749	-0.0461	0.0288	274.07	0.00
Argentina	-3.87E-05	0.0007	-5.61E-04	0.0144	2.07E-04	1.5014	0.0720	0.1028	-0.0538	0.0490	40.79	0.00
Indonesia	-1.60E-05	0.0003	-2.55E-04	0.0073	5.28E-05	3.4029	-0.0103	0.0686	-0.0407	0.0279	209.70	0.00
Saudi Arabia	-1.06E-04	0.0005	-1.83E-04	0.0105	1.10E-04	4.4682	-0.7637	0.0945	-0.0546	0.0399	405.48	0.00
Thailand	1.04E-04	0.0003	-1.88E-04	0.0070	4.84E-05	6.2229	0.0512	0.0773	-0.0320	0.0453	703.99	0.00
UAE	-1.63E-05	0.0005	-3.13E-04	0.0101	1.02E-04	5.2863	0.3063	0.0979	-0.0467	0.0512	514.45	0.00
Malaysia	3.48E-05	0.0002	-1.20E-04	0.0044	1.96E-05	1.5801	0.1164	0.0332	-0.0130	0.0202	45.80	0.00
Israel	1.96E-06	0.0003	1.13E-04	0.0060	3.60E-05	4.3007	-0.8533	0.0490	-0.0316	0.0174	389.51	0.00
Hong Kong	1.07E-04	0.0005	9.08E-05	0.0097	9.49E-05	1.9657	-0.3666	0.0712	-0.0390	0.0322	78.98	0.00
Pakistan	1.18E-04	0.0004	-1.71E-04	0.0093	8.67E-05	4.0847	-0.5955	0.0818	-0.0470	0.0347	328.86	0.00
Nigeria	1.07E-04	0.0005	-3.88E-04	0.0109	1.19E-04	2.8656	0.0047	0.0888	-0.0458	0.0430	146.77	0.00

Notes: The indices for each economy are the following: UK - FTSE, Austria - ATX, Belgium - BFX, Cyprus - CYFT, Estonia - OMXTGI, Finland - OMXH25, France - FCHI, Germany - GDAXI, Greece - ATG, Ireland - ISEQ, Italy - FTMIB, Latvia - OMXRGI, Lithuania - OMXVGI, Netherlands - AAX, Portugal - PSI20, Slovakia - SAX, Slovenia - SBITOP, Spain - IBEX, Denmark - OMXC20, Sweden - OMXS60, Hungary - BUX, Poland - WIG, Czech Republic - PX, Bulgaria - SOFIX, Croatia - CRBEX, Turkey - XU100, Switzerland - SSMI, Norway - OBXP, Brazil - BVSP, Russia - MCX10, India - BSESN, South Africa - JDALS, USA - SPX, Mexico - MXX, Argentina - IBG, Indonesia - JKSE, Saudi Arabia - TASI, Thailand - SETI, UAE - DFMGI, Malaysia - KLSE, Israel - TA100, Hong Kong - HSI, Pakistan - KSE, Nigeria - NGSE30. Data obtained from Thompson Reuters DataStream.

Table 3. 5. World Stock Exchanges with a corresponding time zone

Stock Exchange	Trading Hours	Time Zone
New York Stock Exchange (NYSE)	09:30-16:00	UTC-5
Tokyo Stock Exchange (TSE)	09:00-11:30 12:30-15:00	UTC+9
London Stock Exchange (LSE)	08:00-16:30	UTC
Hong Kong Stock Exchange (HKE)	09:30-16:00	UTC+8
National Stock Exchange of India (NSE)	09:00-15:30	UTC+5:30
Bolsa de Valores, Mercadorias & Futuros de Sao Paulo (BM&F Bovespa)	10:00-17:00	UTC-3
Australian Securities Exchange (ASX)	10:00-16:00	UTC+10
Frankfurt Stock Exchange - Deutsche Borse (FWB)	09:00-20:00	UTC+1
Russian Trading System (RTS)	09:30-19:00	UTC+3
Johannesburg Stock Exchange (JSE)	09:00-17:00	UTC+2
Dubai International Financial Exchange-now NASDAQ Dubai (DIFX)	10:00-14:00	UTC+4
Shanghai Stock Exchange (SSE)	09:15-11:30 13:00-15:00	UTC+8
New Zealand Stock Exchange (NZSX)	10:00-17:00	UTC+12
Toronto Stock Exchange (TSX)	09:30-16:00	UTC-5

Notes: Local trading hours for 14 Stock Exchange markets globally.

3.1.5. Fifth Part: financial networks and contagion

In this part of the analysis, I attempt to identify spillover and contagion evidence that information from stocks indices, Sovereign Bonds and CDS is transferred negatively from one country to others inside a financial network constructed by correlations. In addition, I introduce a new model, based on machine learning approach, to predict and forecast risk of contagion inside a network of stocks, bonds and CDS. The first step in this approach is to measure the interdependence ratio that can be drawn from the correlations of the applied econometric model. Because I am analyzing the stock exchange market environment globally, the major key players in this field are the Eurozone, UK, USA and Asian markets. Additionally, there is no doubt that all other major emerging and developed economies of the world are capable of strong co-movements and contagion in capital markets.

To measure the interdependence ratio from the correlations, I use weekly data returns: for stocks: from 01 Jan 2004 until 31 December 2016; for 10-Year Bond Yield: from 1 September 2006 until 31 December 2016; and for 5-Year CDS: from 19 December 2008 until 31 December 2016. I use major stock indices from each country taken from Eurozone, European Union, Europe, North and South America, Africa and Asia. Sample data obtained from Thompson Reuters DataStream cover 33 economies (Stocks, Bonds and CDS). The countries are presented in Table 3.6, along with the descriptive statistics of our research. The countries are selected by their GDP size and the best available data regarding that all should have stock, bond and CDS markets. Due to this limitation, we excluded countries such as India, Canada and Switzerland from the sample.

Table 3. 6. Descriptive Statistics

		Mean	Median	Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count	Jarque- Bera Probability
UK	Stocks	0.001	0.002	0.025	0.001	15.346	-1.389	0.362	-0.236	0.126	0.474	679	0.00
	Bonds	-0.002	-0.002	0.055	0.003	3.978	0.356	0.510	-0.241	0.269	-1.292	539	0.00
	CDS	-0.003	-0.001	0.074	0.006	4.479	0.073	0.770	-0.421	0.349	-1.217	420	0.00
Austria	Stocks	0.001	0.004	0.036	0.001	14.491	-1.735	0.514	-0.341	0.172	0.527	679	0.00
	Bonds	-0.004	-0.005	0.135	0.018	31.298	-0.041	2.252	-1.345	0.908	-2.182	539	0.00
	CDS	-0.004	-0.001	0.085	0.007	3.837	0.098	0.771	-0.386	0.386	-1.594	420	0.00
Belgium	Stocks	0.001	0.004	0.028	0.001	13.601	-1.834	0.352	-0.261	0.091	0.487	679	0.00
	Bonds	-0.004	-0.006	0.098	0.010	20.524	-0.434	1.334	-0.799	0.535	-1.955	539	0.00
	CDS	-0.002	-0.001	0.085	0.007	3.143	-0.160	0.775	-0.445	0.329	-0.924	420	0.00
Finland	Stocks	0.001	0.004	0.031	0.001	4.460	-0.844	0.325	-0.203	0.122	0.883	679	0.00
	Bonds	-0.004	-0.007	0.184	0.034	44.044	0.502	3.420	-1.689	1.730	-2.363	539	0.00
	CDS	-0.002	0.000	0.080	0.006	7.343	-0.218	0.886	-0.481	0.405	-0.903	420	0.00
France	Stocks	0.000	0.003	0.030	0.001	8.866	-1.213	0.375	-0.251	0.124	0.326	679	0.00
	Bonds	-0.003	-0.004	0.110	0.012	29.572	0.874	1.846	-0.884	0.962	-1.703	539	0.00
	CDS	-0.001	-0.005	0.087	0.008	4.235	0.072	0.874	-0.482	0.392	-0.433	420	0.00
Germany	Stocks	0.002	0.005	0.030	0.001	8.204	-1.010	0.393	-0.243	0.149	1.079	679	0.00
	Bonds	0.005	-0.007	2.161	4.671	276.267	7.908	68.250	-28.000	40.250	2.752	539	0.00
	CDS	-0.002	0.000	0.089	0.008	4.851	0.378	0.885	-0.412	0.473	-0.777	420	0.00
Greece	Stocks	-0.002	0.001	0.044	0.002	2.471	-0.570	0.401	-0.225	0.176	-1.233	679	0.00
	Bonds	0.001	0.000	0.070	0.005	33.925	-2.591	1.090	-0.779	0.310	0.552	539	0.00
	CDS	0.003	0.000	0.225	0.051	238.401	-13.384	4.538	-3.999	0.539	1.441	420	0.00
Ireland	Stocks	0.000	0.005	0.033	0.001	15.497	-1.876	0.451	-0.317	0.134	0.292	679	0.00
	Bonds	-0.003	-0.001	0.069	0.005	16.145	0.088	1.006	-0.592	0.414	-1.587	539	0.00
	CDS	-0.003	-0.007	0.080	0.006	3.710	0.060	0.677	-0.348	0.329	-1.178	420	0.00
Italy	Stocks	0.000	0.003	0.033	0.001	5.966	-1.212	0.348	-0.244	0.105	-0.334	679	0.00
	Bonds	-0.001	0.000	0.044	0.002	4.042	0.106	0.393	-0.203	0.191	-0.790	539	0.00
	CDS	0.000	0.000	0.102	0.010	3.872	-0.151	1.017	-0.512	0.505	-0.108	420	0.00
Lithuania	Stocks	0.002	0.002	0.027	0.001	18.432	-0.056	0.456	-0.208	0.248	1.181	679	0.00
	Bonds	-0.003	0.000	0.114	0.013	36.530	-0.600	1.952	-1.138	0.814	-1.629	539	0.00
	CDS	-0.006	0.000	0.054	0.003	3.541	-0.076	0.442	-0.223	0.219	-2.312	420	0.00
Netherlan	Stocks	0.001	0.003	0.029	0.001	13.658	-1.612	0.395	-0.271	0.124	0.426	679	0.00
	Bonds	0.064	-0.007	1.642	2.696	227.631	13.843	36.200	-8.000	28.200	34.317	539	0.00
	CDS	-0.003	0.000	0.080	0.006	5.849	-0.580	0.818	-0.539	0.279	-1.133	420	0.00
Portugal	Stocks	-0.001	0.002	0.028	0.001	5.420	-1.154	0.291	-0.206	0.085	-0.361	679	0.00
	Bonds	0.000	-0.001	0.052	0.003	4.298	-0.096	0.553	-0.311	0.242	-0.039	539	0.00
	CDS	0.003	0.000	0.108	0.012	5.642	-0.132	1.168	-0.683	0.485	1.051	420	0.00
Spain	Stocks	0.000	0.004	0.032	0.001	5.460	-0.979	0.349	-0.238	0.111	0.195	679	0.00
	Bonds	-0.002	-0.001	0.049	0.002	6.460	-0.752	0.545	-0.353	0.192	-0.987	539	0.00
	CDS	-0.001	0.000	0.096	0.009	1.467	0.023	0.761	-0.357	0.404	-0.231	420	0.00
Denmark	Stocks	0.002	0.005	0.029	0.001	8.736	-1.346	0.342	-0.225	0.117	1.286	679	0.00
	Bonds	-0.004	-0.006	0.246	0.061	148.149	7.093	6.067	-2.015	4.052	-2.417	539	0.00
	CDS	-0.004	0.000	0.077	0.006	7.570	0.124	0.903	-0.454	0.448	-1.741	420	0.00
Hungary	Stocks	0.002	0.002	0.034	0.001	7.654	-0.969	0.420	-0.269	0.152	1.224	679	0.00
	Bonds	-0.002	-0.003	0.041	0.002	2.766	0.664	0.306	-0.132	0.174	-0.894	539	0.00
	CDS	-0.003	-0.001	0.071	0.005	9.081	0.870	0.767	-0.285	0.482	-1.332	420	0.00
Poland	Stocks	0.001	0.003	0.027	0.001	3.795	-0.732	0.287	-0.171	0.116	0.909	679	0.00
	Bonds	-0.001	-0.001	0.032	0.001	4.227	0.266	0.344	-0.176	0.168	-0.437	539	0.00
	CDS	-0.003	0.000	0.077	0.006	8.386	0.815	0.898	-0.365	0.533	-1.253	420	0.00
Czech Rep	Stocks	0.001	0.002	0.031	0.001	15.294	-1.508	0.460	-0.305	0.156	0.350	679	0.00
	Bonds	-0.004	-0.003	0.059	0.004	5.331	0.451	0.565	-0.267	0.298	-2.083	539	0.00
	CDS	-0.004	0.000	0.078	0.006	15.413	0.500	1.084	-0.525	0.559	-1.497	420	0.00

Table 3.6. Descriptive Statistics (continued)

		Mean	Median	Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count	Jarque- Bera Probability
Norway	Stocks	0.001	0.005	0.034	0.001	8.221	-1.155	0.416	-0.248	0.168	0.937	679	0.00
	Bonds	-0.002	0.000	0.046	0.002	2.735	0.116	0.384	-0.184	0.199	-0.920	539	0.00
	CDS	-0.001	0.000	0.068	0.005	4.016	0.370	0.689	-0.330	0.359	-0.487	420	0.00
Brazil	Stocks	0.001	0.004	0.036	0.001	3.843	-0.273	0.392	-0.223	0.168	1.016	679	0.00
	Bonds	0.000	0.000	0.027	0.001	3.677	0.246	0.282	-0.122	0.160	-0.245	539	0.00
	CDS	-0.001	-0.004	0.074	0.005	2.080	0.260	0.603	-0.238	0.365	-0.332	420	0.00
Russia	Stocks	0.002	0.005	0.046	0.002	9.626	0.175	0.655	-0.282	0.373	1.577	679	0.00
	Bonds	0.000	0.000	0.046	0.002	20.031	1.788	0.636	-0.230	0.406	0.238	539	0.00
	CDS	-0.003	-0.003	0.091	0.008	6.800	-0.418	1.053	-0.628	0.425	-1.456	420	0.00
China	Stocks	0.001	0.000	0.039	0.002	2.261	0.060	0.343	-0.170	0.173	0.816	679	0.00
	Bonds	0.000	0.000	0.026	0.001	6.754	-0.667	0.284	-0.186	0.098	-0.079	539	0.00
	CDS	-0.001	0.000	0.078	0.006	3.099	-0.322	0.722	-0.427	0.295	-0.610	420	0.00
South Afri	Stocks	0.002	0.004	0.024	0.001	3.474	-0.113	0.231	-0.098	0.133	1.681	679	0.00
	Bonds	0.000	-0.001	0.023	0.001	8.246	0.818	0.286	-0.104	0.182	0.012	539	0.00
	CDS	-0.002	-0.003	0.080	0.006	3.202	0.491	0.677	-0.265	0.412	-0.702	420	0.00
USA	Stocks	0.001	0.002	0.024	0.001	9.737	-0.972	0.314	-0.201	0.114	0.714	679	0.00
	Bonds	-0.001	-0.004	0.049	0.002	1.079	0.270	0.366	-0.189	0.177	-0.664	539	0.00
	CDS	-0.002	0.000	0.075	0.006	5.529	-0.028	0.727	-0.419	0.308	-0.892	420	0.00
Mexico	Stocks	0.002	0.004	0.028	0.001	6.759	-0.239	0.365	-0.179	0.186	1.665	679	0.00
	Bonds	0.000	-0.001	0.027	0.001	11.109	0.354	0.372	-0.205	0.167	-0.100	539	0.00
	CDS	-0.002	-0.003	0.079	0.006	1.785	0.065	0.605	-0.258	0.347	-0.887	420	0.00
Argentina	Stocks	0.004	0.006	0.041	0.002	3.477	-0.724	0.377	-0.238	0.139	2.772	679	0.00
	Bonds	-0.002	0.000	0.105	0.011	8.975	-0.348	1.160	-0.575	0.584	-0.823	539	0.00
	CDS	-0.005	0.000	0.129	0.017	78.794	-5.029	2.514	-1.720	0.794	-2.270	420	0.00
South Kor	Stocks	0.001	0.004	0.029	0.001	9.139	-1.019	0.400	-0.229	0.170	0.943	679	0.00
	Bonds	-0.002	-0.003	0.028	0.001	2.740	0.589	0.240	-0.104	0.136	-0.853	539	0.00
	CDS	-0.005	-0.002	0.082	0.007	2.617	-0.016	0.753	-0.405	0.348	-2.114	420	0.00
Indonesia	Stocks	0.003	0.005	0.031	0.001	7.198	-1.174	0.349	-0.233	0.116	2.054	679	0.00
	Bonds	-0.001	-0.001	0.033	0.001	5.155	0.406	0.327	-0.145	0.182	-0.390	539	0.00
	CDS	-0.004	-0.004	0.077	0.006	2.891	0.120	0.663	-0.292	0.370	-1.498	420	0.00
Thailand	Stocks	0.001	0.004	0.028	0.001	12.884	-1.543	0.374	-0.267	0.108	0.742	679	0.00
	Bonds	-0.001	-0.003	0.040	0.002	7.207	0.097	0.494	-0.283	0.211	-0.669	539	0.00
	CDS	-0.003	-0.004	0.072	0.005	2.725	-0.124	0.629	-0.372	0.257	-1.327	420	0.00
Malaysia	Stocks	0.001	0.002	0.017	0.000	4.007	-0.792	0.164	-0.097	0.067	0.744	679	0.00
	Bonds	0.000	0.000	0.025	0.001	6.423	0.950	0.231	-0.093	0.137	-0.027	539	0.00
	CDS	-0.002	-0.003	0.081	0.007	1.667	0.097	0.635	-0.307	0.327	-0.710	420	0.00
Hong Kon	Stocks	0.001	0.004	0.030	0.001	3.281	-0.321	0.295	-0.178	0.117	0.569	679	0.00
	Bonds	-0.001	-0.003	0.065	0.004	3.408	0.524	0.596	-0.260	0.336	-0.795	539	0.00
	CDS	-0.002	0.000	0.077	0.006	8.247	-0.335	0.783	-0.416	0.368	-0.970	420	0.00
Philippine	Stocks	0.002	0.003	0.028	0.001	5.616	-0.792	0.312	-0.202	0.110	1.567	679	0.00
	Bonds	-0.001	-0.002	0.041	0.002	14.151	0.036	0.578	-0.333	0.244	-0.650	539	0.00
	CDS	-0.003	-0.007	0.071	0.005	1.973	-0.112	0.550	-0.279	0.270	-1.345	420	0.00
Australia	Stocks	0.001	0.003	0.023	0.001	6.241	-1.043	0.263	-0.172	0.091	0.541	679	0.00
	Bonds	-0.001	-0.002	0.033	0.001	0.540	0.202	0.205	-0.096	0.108	-0.706	539	0.00
	CDS	-0.003	0.000	0.085	0.007	8.926	-0.562	0.984	-0.588	0.396	-1.256	420	0.00
Japan	Stocks	0.001	0.003	0.029	0.001	5.926	-1.058	0.313	-0.220	0.092	0.399	679	0.00
	Bonds	0.002	-0.007	0.570	0.324	292.827	11.719	17.042	-5.917	11.125	1.207	539	0.00
	CDS	-0.001	-0.001	0.078	0.006	5.176	0.677	0.798	-0.318	0.479	-0.485	420	0.00

Notes: The indices for each economy are the following: UK - FTSE, AUSTRIA - ATX, BELGIUM - BFX, FINLAND - OMXH25, FRANCE - FCHI, GERMANY - GDAXI, GREECE - ATG, IRELAND - ISEQ, ITALY - FTMIB, LITHUANIA - OMXVGI, NETHERLANDS - AAX, PORTUGAL - PSI20, SPAIN - IBEX, DENMARK - OMXC20, HUNGARY - BUX, POLAND - WIG, CZECH REPUBLIC - PX, NORWAY - OBXP, BRAZIL - BVSP, RUSSIA - MCX10, CHINA - SSEC, SOUTH AFRICA - JDALS, USA - SPX, MEXICO - MXX, ARGENTINA - IBG, SOUTH KOREA - KOSPI, INDONESIA - JKSE, THAILAND - SETI, MALAYSIA - KLSE, HONG - KONG - HSI, PHILIPPINES - PSEi, AUSTRALIA - S&P/ASX 200, JAPAN - N225. 10 year sovereign bond yields and 5 year sovereign cds. Data obtained from Thompson Reuters DataStream.

The descriptive statistics show that the mean value is lower than the median in most cases for stocks and then for CDS. Bonds have mean value higher than the median. In addition, in Stock indices the mean value is positive in most cases. Conversely, Bonds and CDS show negative mean value in most cases. Additionally, Bonds were the most volatile, whereas Stocks were the least volatile bases on standard deviations. In case of Stocks and CDS, most indexes are negative skewed. On the other hand, Bonds showed to be positive skewed. In almost all cases for Stocks, Bonds and CDS data showed that kurtosis were higher than 3. All indexes present high values of skewness and kurtosis, indicating that extreme changes tend to occur more frequently. Finally, the Jarque-Bera test showed that none of the indexes are normally distributed. For this case, I used the residuals from the AR, MA and ARMA models, depending on which one fits better. However, in almost all cases, the AR (1) fit properly to locate asymmetry and excess kurtosis through the time series.

3.2. EMPIRICAL APPROACH

Following the structure of this thesis, in this section I analyze the empirical approach for the whole research and different stages of the experimentation. Specifically, the subsections below describe the empirical approaches which are used in all stages of the research. In most cases, dynamic conditional correlations are used with many variations; namely, multivariate GARCH models, dynamic copula functions and dependence dynamics with the regime switching.

3.2.1. Methodological approach for quantifying contagion inside the Eurozone – The case of South and North Eurozone countries

(*This section is based on Samitas and Kampouris (2017b), where Samitas is coauthor of the published paper*)

Testing for volatility is one of the most important components of financial series. Numerous varieties of ARCH models have been proposed and tested in empirical studies. This component of the research focuses on investigating co-movements between the southern and northern parts of the Eurozone. I differentiate the study from others by employing the A-DCC model of Cappielo et al. (2006) and the asymmetric BEKK model of Kroner and Ng (1998) to check and compare the behavior of conditional correlation of each model as well as the dependence among the following markets. In most cases, the literature showed that the A-DCC model produces satisfactory results because it not only captures the time varying conditional correlations between indices but also has the ability to test for leverage effect – asymmetry in variances (where negative shocks at time $t-1$ have a stronger impact on variance at time t than positive shocks). However, the asymmetric BEKK model depicts many similarities with the A-DCC model, as it can do virtually anything the other model can. The analysis focuses on daily financial returns. In this study, GJR – GARCH models are adapted into the A-DCC model to check for linkages among assets. In addition, the procedure is rerun with the same indices and period but with the asymmetric BEKK model this time to compare the results.

3.2.1.1. Asymmetric BEKK model

The BEKK model is designed to ensure the positive definiteness of the variance covariance matrix H_t. Engle and Kroner (1995) proposed the following basic form of the BEKK model:

$$H_t = CC' + \sum_{j=1}^{q} A_j e_{t-j} e'_{t-j} A'_j + \sum_{i=1}^{p} B_i H_{t-i} B'_i$$

where A_j, B_i and C are N × N parameter matrices, and C is a lower triangular matrix. The decomposition of the constant term into a product of two triangular matrices is to ensure the positive definiteness of H_t. A_j is a matrix of ARCH coefficients that capture the ARCH effects, and B_i is a matrix of GARCH coefficients capturing the GARCH effects. Kroner and Ng (1998) introduced the asymmetric variation of the BEKK model:

$$H_t = CC' + \sum_{j=1}^{q} A_j e_{t-j} e'_{t-j} A'_j + \sum_{i=1}^{p} B_i H_{t-i} B'_i + \sum_{k=1}^{o} G_k h_{t-k} h'_{t-k} G'_k$$

where the G_k matrix captures the asymmetries in the conditional variance-covariance matrix. The aforementioned equation in the bivariate case can be denoted as:

$$C = \begin{bmatrix} C_{11} & 0 \\ C_{21} & C_{22} \end{bmatrix}; A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}; B = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}; G = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix}$$

The diagonal elements in matrix A show the impact of past shocks on the current conditional variance, and the diagonal elements in Matrix B represent the impact of past volatility on the current conditional variance. The off-diagonal parameters represent the volatility spillover effects. The parameter A_{21} is the volatility spillover from market 2 to market 1, and A_{12} indicates the spillover from market 1 to market 2. Namely, A_{21} emphasizes the cross-effect for lagged residual 2 on variance 1, and A_{12} is the cross effect for lagged residual 1 on variance 2. Hence, the statistical significance of these parameters indicates the volatility spillover and how the first index affects the second. It should be mentioned that the BEKK model becomes symmetric if asymmetric coefficients are statistically jointly equal to 0.

3.2.1.2. Asymmetric Dynamic Conditional Correlation model

To measure the co-movements and contagion I identify the channels by which the shocks are transferred to other countries. In this case, it is significant to measure the interdependence ratio that can be derived from the correlations of the applied econometric models. I employ Cappielo's et al. (2006) model to detect the correlations. The Asymmetric Dynamic Conditional Correlation (ADCC) model quantifies the conditional asymmetries in the correlation dynamics directly by estimating the correlation coefficients using standardized residuals. This technique has been often used together with more sophisticated techniques, because it considers the possible time-varying nature of correlations and structural shifts in the data.

In this sample, all indexes present high values of skewness and kurtosis, indicating that, in all cases, extreme changes tend to occur more frequently. In this case, a model such as the AR(1)-GJR-GARCH (Glosten-Jagannathan-Runkle GARCH model of Glosten et al., 1993) fits properly to locate asymmetry and excess kurtosis channels through the time series. In this stage of research, I employ GJR –GARCH models into the A-DCC model to check for co-movements among assets.

The ADCC model of Cappiello et al. (2006) can produce satisfactory evidence because it captures the time varying conditional correlations between indices and simultaneously it has the ability to test for leverage effect; asymmetry in variances (where negative shocks at time t−1 tend to have stronger impact in the variance at time t than positive shocks). The ADCC model is designed as such to allow for two-stage estimation of the conditional covariance matrix. In the first stage, I proceed to data cleaning for all-time series. In most cases, an AR (1) model was adequate for the residuals. Then a univariate GARCH model is estimated for each return series. Regardless of the fact that in the literature we can find numerous univariate GARCH models, I applied the GJR-GARCH model of Glosten et al. (1993). The GJR-GARCH model is capable of capturing asymmetry and excess kurtosis in cases when data is not normally distributed.

The GJR-GARCH model uses the following form for conditional heteroskedasticity:

$$\sigma_t^2 = \omega + (a + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

where

$$I_{t-1} = \begin{cases} 0 \; if \; r_{t-1} \geq \mu \\ 1 \; if \; r_{t-1} < \mu \end{cases}$$

We find many papers in the literature that assure the GJR-GARCH model provide the empirically observed fact that negative shocks at time t−1 have a stronger impact on the variance at time *t* than positive shocks. The observed asymmetry should be the leverage effect. The increase in risk was believed to originate from the increased leverage induced by a negative shock. The authors believe that the increase in risk originate from the increased leverage induced by a negative shock. The generalized model to capture more lags has the following form [GJR-GARCH (p, q)]:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (a + \gamma I_{t-1}) \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta \sigma_{t-1}^2$$

The best lags can be chosen from the Akaike Information Criterion and the Bayesian Information Criterion. However, in nearly all cases, p=1 and q=1 best fits the data.

The second stage of the ADCC estimation uses the residuals taken from the univariate GARCH models and transformed by their estimated standard deviations. Subsequently, the results are used to estimate the parameters of the conditional correlations for the A-DCC model. The A-DCC model estimates the conditional asymmetries in dynamic conditional correlations and explains the heteroskedasticity directly by estimating the correlation parameters using the standardized residuals from the first stage of estimation. In Engle’s (2002) DCC model, the correlation matrix R_t in addition to the variance covariance matrix H_t are time varying and have the following decomposition:

$$H_t = D_t R_t D_t$$

where $D_t = diag\{\sqrt{h_{i,t}}\}$ is the diagonal matrix of the conditional standard deviations and $R_t = \{\rho_{ij,t}\}$ the correlation matrix, which is time varying. The correlation matrix can be also denoted as:

$$R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1}$$

$$\text{where } Q_t = [1-\alpha(1)-\beta(1)]\Gamma + \alpha(L)\eta_{t-1}\eta'_{t-1} + \beta(L)Q_{t-1}$$

Qt^* is a diagonal matrix with a square root of the i^{th} diagonal of Qt on its i^{th} diagonal position. Namely, in the Q_t matrix, the model estimates the elements of correlations, which are calculated by the coefficients. Cappiello et al. (2006) presented a transformation of the original DCC model, which has the ability to capture asymmetries in the conditional variances, covariances and correlations of the time series. This asymmetric variation of the DCC model has the following form:

$$Q_t = (1-a-b)\bar{Q} - q\bar{N} + az_{t-1}z'_{t-1} + bQ_{t-1} + gn_{t-1}n'_{t-1}$$

where α and β are the scalar parameters, g the asymmetry coefficient and $\bar{Q}$ and $\bar{N}$ are the unconditional correlation matrices of z_t and n_t. The ADCC model, as the literature review showed, is suitable for quantifying the correlation and subsequently the dependence among stock market time series.

3.2.2. Empirical approach for measuring spillover effects in real economy and policy uncertainty indexes

We employ ADCC model and copulas functions to identify and cross-check contagion channels among stock markets. Until recently, the literature has provided us with many different approaches to choose from and investigate for financial contagion. Although the literature review provided important methodologies, in most cases, the ADCC model in addition to the copulas functions allow authors to make satisfactory conclusions about their results. Both methodologies provide reactions, behaviour, shocks, crashes, interdependence and correlation among the time series under investigation. This paper focuses on interdependence and correlation and the combination of these two approaches can help us compare the results with similar cases. Our analysis focuses on daily stock market returns. In this paper, we employ GJR –GARCH models into the A-DCC model to check for co-movements among assets. Additionally, we rerun the procedure with copula functions this time for the same indices and period to cross-check the results.

3.2.2.1. Copula functions

Copulas functions have many applications. Most notable of them are the following: risk management, portfolio decision, dependence between time series and spillover effects. Copulas functions are employed in this part of the research to crosscheck the results and clarify whether the behavior of the correlations between stock markets are positive or negative. Copula functions were introduced by Abe Sklar (1959). Copulas are restricted to $[0, 1]^2$ of a bivariate distribution function where margins are uniform in [0, 1]. Namely, what Sklar said was that H is a bivariate distribution function with margins F(x) and G(y), and a copula function exists such that:

$$H(x, y) = C\big(F(x), G(y)\big)$$

For continuous conditional distributions, Patton (2009, 2012) stated Sklar's theorem: Let F be the conditional distribution of $X|Z, G$ be the conditional distribution of $Y|Z,$ and H be the joint conditional distribution of $X|Y, Z$. Assume that F and G are continuous in x and y, and let $\mathfrak{z}$ be the support of Z. Then exists a unique conditional copula C exists such that:

$$H(x|y, z) = C(F(x|z), G(y|z)|z), \forall (x, y) \in \mathbb{R}x\mathbb{R} \; and \; each \; z \in \mathfrak{z}$$

In this part of the research, I adopt a Gaussian copula, a Clayton copula and a symmetrized Joe-Clayton copula to identify the evidence needed to produce a conclusion. The literature has provided us with many different copula functions that can be used in a variety of cases. However, the most popular for captured interdependence are those that are applied in this thesis. Copula functions are used in this study because we want to reconfirm that the ADCC results measure the time series dependence with different parameters.

The Gaussian copula has the following form:

$$C_N(u; v; \rho) = \Phi_\rho\big(\Phi^{-1}(u), \Phi^{-1}(v)\big)$$

$$C_N(u; v; \rho) = \frac{1}{\sqrt{1-\rho^2}} exp\left\{\frac{\Phi^{-1}(u)^2 + \Phi^{-1}(v)^2 - 2\rho\Phi^{-1}(u)\Phi^{-1}(v)}{2(1-\rho^2)} + \frac{\Phi^{-1}(u)^2\Phi^{-1}(v)^2}{2}\right\}$$

$$\rho \in (-1, 1)$$

The Clayton copula (Kimeldorf and Sampson copula in Joe,1997) form is presented below:

$$C_C(u;v;\theta) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-1/\theta}$$

$$C_C(u;v;\theta) = (1-\theta)(uv)^{-\theta-1}\left(u^{-\theta} + v^{-\theta} - 1\right)^{-2-1/\theta}$$

$$\theta \in [-1, \infty)\backslash\{0\}$$

and the symmetrized Joe-Clayton copula is defined as:

$$C_{SJC}(u, v|\tau^U, \tau^L) = 0.5\left(C_{JC}(u, v|\tau^U, \tau^L) + C_{JC}(1-u, 1-v|\tau^U, \tau^L) + u + v - 1\right)$$

$$\tau^U \in (0,1), \tau^L \in (0,1)$$

The symmetrized Joe–Clayton (SJC) copula is clearly only a slight modification of the original Joe–Clayton copula; however, by construction, it is symmetric when $\tau^{U} = \tau^{L}$. The τ^{U} and τ^{L} conclude the upper and the lower tails of the distribution, respectively. The main advantage of copula functions is that they are simple and that they help authors define the nonparametric measures of dependence for pairs of random variables.

3.2.3. Methodology for calculating the case of interdependence of small economies

In this part research, the DCC model of Engle (2002) was employed (please see section 3.2.1.2.) in order to test the behaviour of correlations between the Greek and the Cypriot market. A major advantage of this model is the ability to test for dependence among markets. Until now, the literature has provided us with a variety of models to investigate the contagion phenomenon and spillover effects. However, despite the fact that we may choose from several different methodologies, the literature provided some interesting evidence. In most cases, the DCC model has allowed authors to reach some satisfactory conclusions. The DCC model is an appropriate specification in quantifying the interdependence among markets because it is flexible and allows time-varying correlations and covariance matrixes.

This methodology helps us to quantify the dependence among the two crises and the other markets. This model is quite familiar and useful in quantifying the dependence and the contagion phenomenon and used by many authors (Jithendranathan 2005; Gupta and Donleavy 2009; Gjika and Horváth 2013) because it captures time-varying conditional correlations between financial indices.

3.2.4. Empirical approach for quantifying the impact of Brexit

(*This section is based on Samitas and Kampouris (2017a), where Samitas is coauthor of the published paper*)

The following part of the study looks at the methodology employed to examine the impact of the results' announcement, and Article 50 being put into motion. This part of the study sees the deployment of dependence dynamics via regime-switching copulas (Silva Filho et al., 2012). Intraday data returns have been used to isolate contagion within stock markets (30-minute close price). Current literature highlights many different methods that can be used to examine financial contagion. The literature review has delved into significant methods of inquiry; however, the copula functions remain dominant in terms of allowing authors reach satisfactory conclusions about their findings, see the copula-GARCH models (Jondeau and Rockinger, 2006). The same can be seen applied in Panchenko (2006), Huang et al. (2009), etc. More technical detail can be found in Kim and Nelson (1999), Wang (2003) and Hamilton (1994; 2005). For a basic understanding of the models, refer to Tsay (2002), Brooks (2002) and Alexander (2008). This study applies its own approach while drawing from the literature. It highlights crashes, behavior, interdependence, correlation and shocks in the time series being studied.

For this purpose, I start by using a time-varying copula functions, from where the regime switching and dependence dynamics are extracted. This draws from the Silva Filho et al. (2012) approach as discussed. After this, the sample is divided into three main parts i.e. the period before the referendum, the period after it, and finally the period after Article 50 is triggered. Once again, the correlations are extracted from the time-varying normal copula, for these periods. This is done to see if the correlations experienced an increase (implying the presence of contagion) in the post-referendum and Article 50 periods. Subsequently, hypotheses were developed to account for the spillover from the approach employed. The main aim was to find crucial points and see if they are linked to the vote and article 50, and thereby confirm whether there was a financial contagion within the time series under observation. All calculations, for the UK and other countries, were made on bivariate basis.

3.2.4.1. Dependence dynamics Copulas

This section of the paper looks at the copula functions of Silva Filho et al. (2012) to elaborate on whether there is a negative or positive correlation between the different markets under examination. The process revolves around a time-varying dependence framework. The parameter for dependence is given room to grow, as per Patton (2006) via ARMA (1,10) restricted process. In addition, the intercept term relies on a two-state Markov chain (MC) that is hidden. Marginal distributions are estimated during the first step, and the parameter for dependence is estimated through copulas during the second. Tail dependence is used to measure the spillover effect. To make sure that the dependence structure is multivariate, and not as a result of marginal misspecification, with respect to asymmetry, the univariate skewed-t GARCH models were used.

Copulas: basic theory

According to Schweizer and Sklar (1983), an n-dimensional copula $C(u_1, . . . , u_n)$ is a multivariate distribution function in $[0, 1]^n$ whose marginal distributions are uniform in the [0, 1] interval. For any joint distribution $H(x_1, . . . , x_n)$ with marginals

$F_1(x_1), \dots, F_n(X_n)$, we have

$$H(x_1, \dots, x_n) = C\big(F_1(x_1), \dots, F_n(X_n)\big).$$

If $F_1,\dots, F_n$ are continuous, then the copula C associated to H is unique and may be obtained by

$$C(u_1, \ldots, u_n) = H\left(F_1^{(-1)}(u_1), \ldots, F_n^{(-1)}(u_n)\right),$$

where $u_1 = F_1(x_1), \ldots, u_n = F_n(x_n)$.

The density function related to the joint distribution can be easily obtained because $F_1, \ldots, F_n$ and C are n-differentiable. Thus, in a bivariate case the density function is given by

$$h(x_1, x_2) = c\big(F_1(x_1), F_2(x_2)\big) \prod_{i=1}^{2} f_i(x_i)$$

where h is the density function associated with H, f_i is the density function for each marginal, and the copula density c is obtained by differentiating the joint distribution, which can be written as

$$c\big(F_1(x_1), \ldots, F_n(x_n)\big) = \frac{h\left(F_1^{(-1)}(u_1), F_2^{(-1)}(u_2)\right)}{\prod_{i=1}^{2} f_i\left(F_i^{(-1)}(u_i)\right)}.$$

The term elliptical is used for the Gaussian (normal) copula due to its link to a quadratic form of correlation between the marginals. The dependence structure related to this copula is the linear correlation coefficient which belongs to the [−1, 1] interval. A symmetric distribution function exists when it comes to this copula. The literature has also used other copulas, many of which are Archimedean. For a comparison, emphasis is placed on tail dependence, which allows for an investigation into the model that has the capacity to reproduce empirical or stylized facts about the markets under study. Moreover, this measure can be seen as the likelihood that an extreme event could hit a market, because this event is taking place in another market. This analysis was conducted through use of four copula functions:

Normal copula

has no tail dependence and its dependence parameter is the linear correlation coefficient.

$$C_N(u_1, u_2 | \rho) = \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-\rho^2)}}$$

$$* \, exp\left\{\frac{-(r^2 - 2\rho rs + s^2)}{2(1-\rho^2)}\right\} drds, \qquad \rho \in (-1, 1).$$

Gumbel copula

has only upper tail dependence.

$$C_G(u_1, u_2|\theta) = exp\left(-\left((-\log u_1)^\theta + (-\log u_2)^\theta\right)^{\frac{1}{\theta}}\right), \theta \in [1, +\infty).$$

Symmetrized Joe-Clayton copula

$$C_{SJC}(u_1, u_2|\tau^U, \tau^L) = 0.5 * \left(C_{JC}(u_1, u_2|\tau^U, \tau^L) + C_{JC}(1-u_1, 1-u_2|\tau^U, \tau^L) + u_1 + u_2 - 1\right),$$

where C_{JC} is the Joe-Clayton copula given by

$$C_{JC}(u_1, u_2|\tau^U, \tau^L) = 1 - \left(1 - \{[1-(1-u_1)^k]^{-\gamma} + [1-(1-u_2)^k]^{-\gamma} - 1\}^{-\frac{1}{\gamma}}\right)^{-\frac{1}{k}},$$

with $k = \frac{1}{\log_2(2-\tau^U)}, \gamma = -\frac{1}{\log_2(\tau^L)}$ $and\ \tau^U, \tau^L \in (0, 1)$.

The SJC has both upper and lower tail dependence parameters while Clayton has only lower. Its own dependence parameters, τ^U and τ^L, are the measures of dependence of the upper and lower tail, respectively. Using these four copulas we cover all possible options to capture asymmetry while estimating the dynamic interdependence.

3.2.4.2. Copula – GARCH models

If $x_t = (x_{1t}, x_{2t}), t = 1,2, \ldots,$ is a 2-dimensional time series vector, we can represent the copula – GARCH model as follows:

$$H(x_t|\mu, h_t) = C_{\theta ct}\left(F_1(x_{it}|\mu_1, h_{1t}), F_2(x_{2t}|\mu_2, h_{2t})\right),$$

where $C_{\Theta ct}$ is the copula function with time-varying dependence parameter θ_{ct} and $F_i(x_{it}|\mu_i, h_{it}), i = 1, 2$, are the marginal distributions specified as a univariate GARCH model. A GARCH (1, 1) model can be described as:

$$x_{it} = \mu_i + h_{it}^{1/2}\varepsilon_{it}$$

$$h_{it} = \omega_i + \beta_\iota h_{it-1} + a_i\varepsilon_{it-1}^2,$$

where h_{it} is the conditional variance, ε_{1t}, $t = 1, 2, \ldots$, are i.i.d. random variables, ω_i, β_i, $\alpha_i > 0$ and $\alpha_i + \beta_i < 1$ assuring $h_{it} > 0$. Also, ε_{1t} has a skewed t distribution, where its density is given by:

$$g(z|\nu, \lambda) = \begin{cases} bc\left(1 + \dfrac{1}{\nu - 2}\left(\dfrac{bz + a}{1 - \lambda}\right)^2\right)^{-\frac{(\nu+1)}{2}} & z < -a/b \\ bc\left(1 + \dfrac{1}{\nu - 2}\left(\dfrac{bz + a}{1 - \lambda}\right)^2\right)^{-\frac{(\nu+1)}{2}} & z \geq -\dfrac{a}{b}, \end{cases}$$

where the constants α, b and c are obtained by:

$$a = 4\lambda c\left(\frac{\nu - 2}{\nu - 1}\right), b^2 = 1 + 3\lambda - a^2,$$

$$c = \frac{\Gamma\left(\frac{\nu + 1}{2}\right)}{\sqrt{\pi(\nu - 2)\Gamma\left(\frac{\nu}{2}\right)}},$$

with ν and λ representing the number of degrees of freedom and asymmetry, respectively. As discussed earlier, the dependence parameter is allowed to vary over time. Its time evolution follows a restricted ARMA (1, 10) process, where the intercept term switches according to a first order Markov chain, such as:

$$\Theta_{ct,S_t} = \Lambda\left(\omega_c^{S_t} + \beta_c\theta_{ct-1} + \psi_t\right),$$

where $S_t \sim$ Markov (P). S_t may assume two possible states (regimes), and P is a 2*2 transition matrix for these states. Ψt represents the mean absolute difference between u_1 and u_2. Λ is a logistic transformation of each copula function to constrain the dependence parameter in a fixed interval. Θ_{ct} is the measure of dependence except for the normal copula that has no tail dependence.

3.2.4.3.Copulas estimation

The log-likelihood of the model is as follows:

$$l(\theta|x_t) = \sum_{t=1}^{T} \log\left(C_{\theta_{ct}}\left(F_1(x_{1t}|\theta_1), F_2\langle x_{2t}|\theta_2|\theta_{ct,S_t}\rangle\right) * \prod_{i=1}^{2} f_{it(x_{it}|\theta_i)} \right),$$

where $\theta_i = \mu_i$, h_{it}, $i = 1, 2$, and θ is a vector with all model parameters. The inference function for margins by Joe and Xu (1996) consists of estimating the parameters of the univariate marginal distributions in the first step and then using these estimates to calculate the dependence parameters in the second step. The marginal distributions are modeled as univariate GARCH processes, and the dependence parameters are specified by the copula function choice. The dependence parameter Θ_{ct} depends on a non-observable discrete variable S_t, which follows a Markov chain. This estimation is made with the approach by Kim and Nelson (1999). The log-likelihood can be rewritten as:

$$l(\theta|x_t) = \sum\nolimits_{t=1}^{T} \log\left(C_{\theta_{ct}}\left(F_1(x_{1t}|\mu_1, h_{1t}, \theta_1), F_2(x_{2t}|\mu_2, h_{2t}, \theta_2)\middle|\theta_{ct,S_t}\right) \prod_{i=1}^{2} f_{it}(x_{it}|\mu_1, h_{it}, \theta_i) \right)$$

$$= \sum_{t=1}^{T} \log f_{1t}\,(x_{1t}|\mu_1, h_{1t}; \theta_1) + \sum_{t=1}^{T} \log f_{2t}\,(x_{2t}|\mu_2, h_{2t}; \theta_2)$$

$$+ \sum_{t=1}^{T} \log C_t\left(u_{1t}, u_{2t}\middle|\mu_1, \mu_2, h_{1t}, h_{2t}; \theta_{ct,S_t}\right)$$

$$l(\theta|x_t) = \ell_{f1}(\theta_1) + \ell_{f2}(\theta_2) + \ell_c\left(\theta_{ct,S_t}\right),$$

where $\ell_{f1}(\theta_1) = \sum_{t=1}^{T} \log f_{1t}(x_{1t}|\mu_1, h_{1t}; \theta_1), \ell_{f2}(\theta_2) = \sum_{t=1}^{T} \log f_{2t}(x_{2t}|\mu_2, h_{2t}; \theta_2)$ and $\ell_c\left(\theta_{ct,S_t}\right) = \sum_{t=1}^{T} \log C_t\left(u_1, u_2\middle|\mu_1, \mu_2, h_{1t}, h_{2t}; \theta_{ct,S_t}\right)$, and $\ell_{f1}(\theta_1)$ and $\ell_{f2}(\theta_2)$ are log-likelihood functions from the estimation of marginal distributions in the first step. Next, we calculate the $\ell_c(\theta_{ct,S_t})$, considering the non-observable variables. The decomposition of c_t is as follows:

$$\ell_c = \sum_{t=1}^{T} \log\left(\sum_{S_t=0}^{1} c_t(u_1, u_2|S_t, w_{t-1})Pr\langle S_t|w_{t-1}\rangle\right).$$

The states S_t are non-observable. To evaluate this log-likelihood, we calculate the weights $Pr\langle S_t|w_{t-1}\rangle$ for $S_t = 0$ and $S_t = 1$. Applying the Kim and Nelson (1999) approach (Kim's filter), we get the algorithm below:

Prediction of S_t

$$\Pr\langle S_t = l|w_{t-1}\rangle = \sum_{k=0}^{1} p_{kl}^{t-1} Pr(S_{t-1} = k|w_{t-1})$$

for $l = 0,1$ and $p_{kl}^{t-1} = Pr(S_t = l|S_{t-1} = k, w_{t-1})$, the transition probabilities between the states k and l.

Filtering of S_t

$$\Pr\langle S_t = l|w_t\rangle = \frac{c_t(u_1, u_2|S_t = l, w_{t-1})Pr\langle S_t = l|w_{t-1}\rangle}{\sum_{k=0}^{1} c_t(u_1, u_2|S_t = k, w_{t-1})Pr\langle S_t = k|w_{t-1}\rangle}$$

where $w_t = [w_{t-1}, u_{1t}, u_{2t}]$. This filter gives the probability distribution of S_t considering the information of t. The smoothing process works as follows:

a) With the aforementioned filtering process, we obtain $Pr(S_t = l|w_t)$ for $l = 0, 1$ and $t = 1,\ldots,T$.
b) The smoothing process initializes in $t = T$ and reverses recursively, with $Pr(S_t = l|w_t)$ being equal to the filtered probability in $t = T$.
c) For each $t = T - 1, T - 2,\ldots,1$, the smoothed probability distribution $Pr(S_t = l|w_t)$ is given by:

$$Pr(S_t = l|w_t) = \sum_{k=0}^{1} \frac{p_{lk}(t)Pr(S_t = l|w_t)Pr(S_{t+1} = k|w_t)}{\sum_{j=0}^{1} p_{jk}(t)Pr(S_t = j|w_t)}$$

where $p_{lk}(t) = Pr(S_{t+1} = k|S_t = l, w_t)$ are the transition probabilities between the states l and k. The applied econometric methodology belongs to Silva Filho et al. (2012); more technical information about the methodology can be found in their paper.

Once the model's calculations were complete, the study settled on a hypothesis to define the contagion. Given that the vote took place on June 24, 2015, and Article 50 was set into motion on March 29, 2017, the problems were found with when and how speedily news went through the markets in question. Negative information could travel to other nations before the actual shock date (factor of fear) or after it (shockwave result). It was assumed that the Markov regime-switching change is linked to the contagion that took place either six days after or six days before the event (±6 days):

$$\boldsymbol{Hypothesis\ 1}: M.R.S.change\ \pm 6\ days\ from\ the\ event$$

However, there is no clear specification on the contagion being present by setting time margins around the event. For instance, assuming a six-day period may seem logical, but if the interaction time could be smaller in other economies within the sample. What if this were true for, let's say, USA, France, Italy, etc.? A shorter interaction time denotes a more significant interdependence and interconnection, and ergo a much stronger contagion. To tackle this, another hypothesis was set up, i.e. the Markov regime-switching change of three days before and after the event (news about the vote result and the implementation of Article 50) is linked to stronger contagion (±3 days):

$$\boldsymbol{Hypothesis\ 2}: M.R.S.change\ \pm 3\ days\ from\ the\ event$$

The second hypothesis is significant to this study because it acts as a scale for the data regarding the contagion that is under investigation herein. It is interesting to see the reaction of stock markets, where a significantly larger reaction is witnessed a day after an event, as opposed to a week after it. This rapid pace of reaction demonstrates that economies share a deeper connection to each other when it comes to information regarding any positive or negative event.

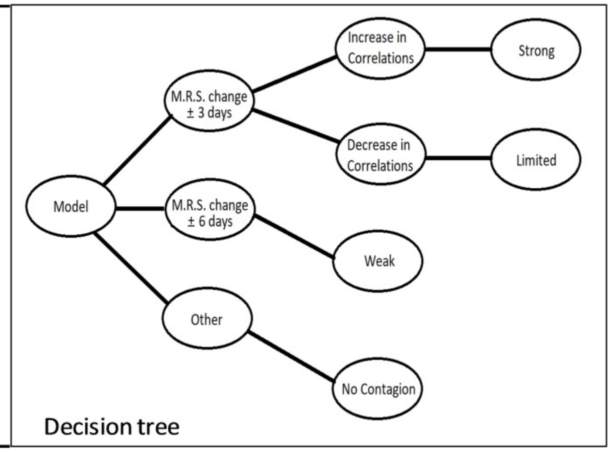
The sample is divided into three sub-periods in the next step of the methodology. The period before the vote, after the vote, and the phase after Article 50 was triggered. Correlations are then derived from the normal copula from these sub-periods to see whether there was an increase in the correlations (and ergo, contagion) during the period after the vote, and within the time that Article 50 was put into motion. In addition, more assumptions are created around the behavior of correlations before and after both events have taken place. In specific, a hypothesis was created to address the presence of strong contagion in the event that an increase was present in terms of correlation:

$$\boldsymbol{Hypothesis\ 3}: increase\ in\ correlations\ after\ the\ event$$

Specification of contagions is a problem that manifests differently in literature. Every author has their own explanation for it, based on the methods they are using. This analysis looks to outline the kind of contagion between different nations. Figure 3.3 highlights specific details about the contagion, as per the hypotheses developed for this study. “No contagion” is a situation where neither of the first two hypotheses correspond to the calculated results. “Weak contagion” is the situation where only the first hypothesis holds true. “Limited contagion” is the situation where the second hypothesis holds true. “Strong contagion” is the situation where the second and third hypothesis corresponds to the calculated results. Strong contagion specifications show that the situation conforms to the Markov regime-switching change state during a short amount of time, i.e. within a timeframe of three days. It was also observed that the correlation saw an increase once Article 50 was triggered. Therefore, the assumptions mentioned above outline that there was a clear possibility of a contagion existing between the different markets.

Figure 3. 3. Contagion specification

Hypothesis 1:	Significant Markov Regime Switch change (+/-) less than 6 days
Hypothesis 2:	Significant Markov Regime Switch change (+/-) less than 3 days
Hypothesis 3:	Increase in correlations after the event
No contagion:	none of the first three hypotheses
Weak contagion:	Hypothesis 1
Limited contagion:	Hypothesis 2
Strong contagion:	all of the hypotheses



3.2.5. Empirical methodological approach for quantifying and predict the contagion within financial networks

To measure the interdependence and the contagion risk specification, I selected the most modern and advanced econometric techniques in accordance with the literature. In addition, I apply machine learning approach to create an accurate and reliable model to predict and forecast possible risk of contagion inside a financial network.

The methodological strategy is as follows: First, an Asymmetric Dynamic Conditional Correlation (ADCC) model of Cappielo's et al. (2006) is applied to extract the correlations (please see section 3.2.1.2). Second, the correlations are transformed to distance metrics between each pair. Third, the distance metrics are used to construct financial networks by the Minimum Spanning Tree (MST) technique of Kruskal’s (1956) algorithm. Fourth, I extract centralities (betweenness, degree, eigenvector and closeness) from the created networks to measure the most important countries (key-nodes) inside the financial networks. It should be noted that the centralities are extracted for all dynamic conditional correlations for all indices (Stock, Bonds and CDS). Specifically, I analyze weekly centralities in accordance with the data of our sample. With the track of weekly centralities we intent to measure the behavior of centralities as long as the key-player countries for first, second and third place (ranking) of each centrality category. Fifth, a hypothesis is settled on to describe the risk of contagion inside the financial network.

Sixth, I introduce a machine learning approach to predict and forecast the risk of contagion inside the financial network.

To measure the co-movements and contagion we identify the channels by which the shocks are transferred to other countries. In this case, it is significant to measure the interdependence ratio that can be derived from the correlations of the applied econometric models. We uncover evidence of correlation behavior of stocks indices, sovereign Bonds and CDS markets returns. The Asymmetric Dynamic Conditional Correlation (ADCC) model quantifies the conditional asymmetries in the correlation dynamics directly by estimating the correlation coefficients using standardized residuals. This technique has been often used together with more sophisticated techniques, because it considers the possible time-varying nature of correlations and structural shifts in the data.

In this sample, all indexes present high values of skewness and kurtosis, indicating that, in all cases, extreme changes tend to occur more frequently. In this case, I believe that a model such as the AR(1)-GJR-GARCH (Glosten-Jagannathan-Runkle GARCH model of Glosten et al., 1993) fits properly to locate asymmetry and excess kurtosis channels through the time series (see section 3.2.1.2 for GJR-GARCH model). In this part of the research, I employ GJR –GARCH models into the A-DCC model to check for co-movements among assets. As the sample is constituted of 33 countries, the correlation matrix for Stock indices contains 528 pairs in order to have each correlation for all possible combinations. All calculations are made for bivariate case and I repeated the procedure for Bonds and CDS.

3.2.5.1. Financial networks

The extracted correlations are transformed to distance metrics between each pair of indices as in Matenga (1999):

$$d_{ij}^{t} = \sqrt{2\left(1 - \rho_{ij}^{t}\right)}$$

Matenga (1999) additionally said that linkages between stock returns can be analyzed by applying a straightforward change of the components of the correlation matrix of returns into distances. An associated diagram is developed in which the "hubs" compare to organizations (countries in our case) and the "separations", or "edges", between them are acquired from the suitable change of the correlation coefficients. This equation satisfies the necessities of separation. Next, the N×N distance matrix is utilized to decide the Minimum Spanning Tree (MST) which is developed utilizing Kruskal's (1959) calculation. In particular, I use Kruskal's calculation to develop a Minimum Spanning Tree (MST) for inspecting the degree and advancement of reliance among indices. A concise portrayal of MST development is proposed by Mantegna (1999):

- Step 1. See each record as hub and linkage impact as edge in a network. Think about every hub as a separated branch, and sort the edges by their weights which signify the level of linkage impacts among records.
- Step 2. Go through the network once and look through an edge with the base weight and guarantee no shut circle is made. This edge is added to the minimum spanning tree set if every one of the necessities is met. Something else, keep on crossing the system to look for a next edge with the base weight.
- Step 3. Recursively rehash the previous strides, until the point that n-1 edges have been recognized (if the network has n hubs, the minimum spanning tree ought to have n−1 edges since there are no shut circles in MST). At that point, the seeking procedure ends and the network's minimum spanning tree are acquired by choosing the most critical connections between the record returns.

After the construction of the financial networks, I extract the centralities to measure the most important countries inside the financial networks. The extracted centralities are on a weekly basis in order to analyze their behavior. The constructed financial networks are 679 for Stocks indices (weekly data from 01 Jan 2004 until 31 December 2016), 539 for 10-year Sovereign Bonds (weekly data from 01 September 2006 until 31 December 2016) and 420 for 5 Years CDS (weekly data from 19 December 2008 until 31 December 2016). I tracked the centralities of networks and observed and analyzed their behavior thereafter. The procedure is repeated for second and third highest centrality scores of all categories and for Stocks, Bonds and CDS. I used the most well-known centrality types of the literature as it may be assumed that they are sufficient to extract accurate and reliable results about the most key-nodes players of the financial networks. The centralities used in this particular part of the research are: betweenness, degree, eigenvector and closeness.

Betweenness centrality

Betweenness centrality measures the number of times a node behaves as a bridge between two other nodes whose path passes through it. The betweenness centrality list can be represented to as

$$C_B(n_i) = \sum_{f<d} \frac{g_{fd}(n_i)}{g_{fd}}$$

where g_{fd} is the total number of shortest paths from f to node d and $g_{fd}(n_i)$ is the number of those paths that pass through n_i. The standardized version is calculated as

$$C'_B(n_i) = \frac{C_B(n_i)}{[(g-1)(g-2)/2]}$$

Basically, a central hub is between two other (or more) hubs that have not teamed up/collaborated with one another but rather have associated with the central hub.

Degree centrality

Degree centrality measures the connections to which the hub is associated. As such, degree centrality estimates the occasions an actor interacted with different others. The degree centrality of a network is as per the following:

$$C_D = \frac{\sum_{i=1}^{g} [C_d(n^*) - C_d(n_i)]}{[(g-1)(g-2)]}$$

The $C_d(n_i)$ in the numerator are the g hubs degree indices, while $C_d(n^*)$ is the biggest watched value. Be that as it may, eigenvector centrality estimates a hub's impact over different hubs inside the network.

Eigenvector centrality

For a given network, if vertex I is connected to vertex j and Rij is the contiguousness matrix, the eigenvector centrality is ascertained by the eigenvector condition $\lambda e = Re$ and is expressed as

$$e_i = \frac{\sum_J R_{ij} e_j}{\lambda}$$

where e is the eigenvector of R_{ij} and λ the related eigenvalue. The eigenvalue is required so that the conditions have nonzero arrangements. There will be a wide range of eigenvalues for which an eigenvector arrangement exists. Be that as it may, just the best eigenvalue results in the favored centrality measure. It is sensible to assume that just the biggest eigenvalue λ is the coveted measure to ascertain the eigenvector centrality (Bonacich, 1987). Hubs with high eigenvector centrality are hubs that are associated with numerous different hubs, which thus are associated with numerous others.

Closeness centrality

Lastly, closeness centrality is based on shortest paths and is defined as the range of collaboration in terms of connected nodes. The closeness centrality C_c of a hub n is characterized as

$$C_c = \left[\frac{\sum_{J=1}^{N} d(n_i n_j)}{N-1}\right]^{-1}$$

where $d(n_i n_j)$ is the length of the shortest path between two hubs n_i and n_j. The closeness centrality of every hub is a number somewhere in the range of 0 and 1. The higher a hub's closeness centrality is, the lower its separation is from all other associated hubs.

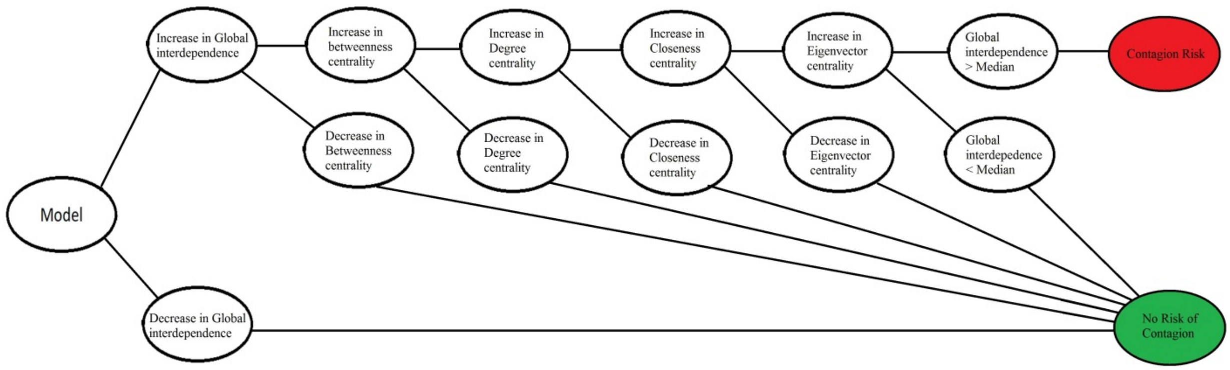
3.2.5.2. Contagion Risk specification

In the next step I make a hypothesis to determine the case whether there is a chance of contagion risk within the network based on the available data of weekly correlations and the corresponding centralities. As the results showed and I discuss them in the next section, it is observed increase in centralities at the points where it also observed increase in correlations for all cases of first, second and third highest centralities. Specifically, at the dates where the global economy faced financial crisis (see Figure 3). The sharp increase in correlation shows that we have high level of interdependence and increased possibility of financial contagion at this date. It is believed that there is a connection between countries' correlations and the extracted centralities of the financial networks. This connection, triggers dynamics of contagion risk from the key-node players. To put it clearer, I assume that the structure of the networks favors the appearance of contagion when we have simultaneously increase in already high correlations and the centralities. To answer this assumption I make a hypothesis the case where I observe contagion risk inside the network when we:

- Have increase in correlations (Global interdependence),
- increase in all four categories of centrality and
- the correlation is higher than the median value (the nodes with lower-than-median values are less well connected than those with higher values).

In all other cases I assume that there is no possibility of contagion risk inside the networks. A visual explanation of our model and the hypothesis is depicted in Figure 3.4.

Figure 3. 4 Contagion risk specification



Decision tree

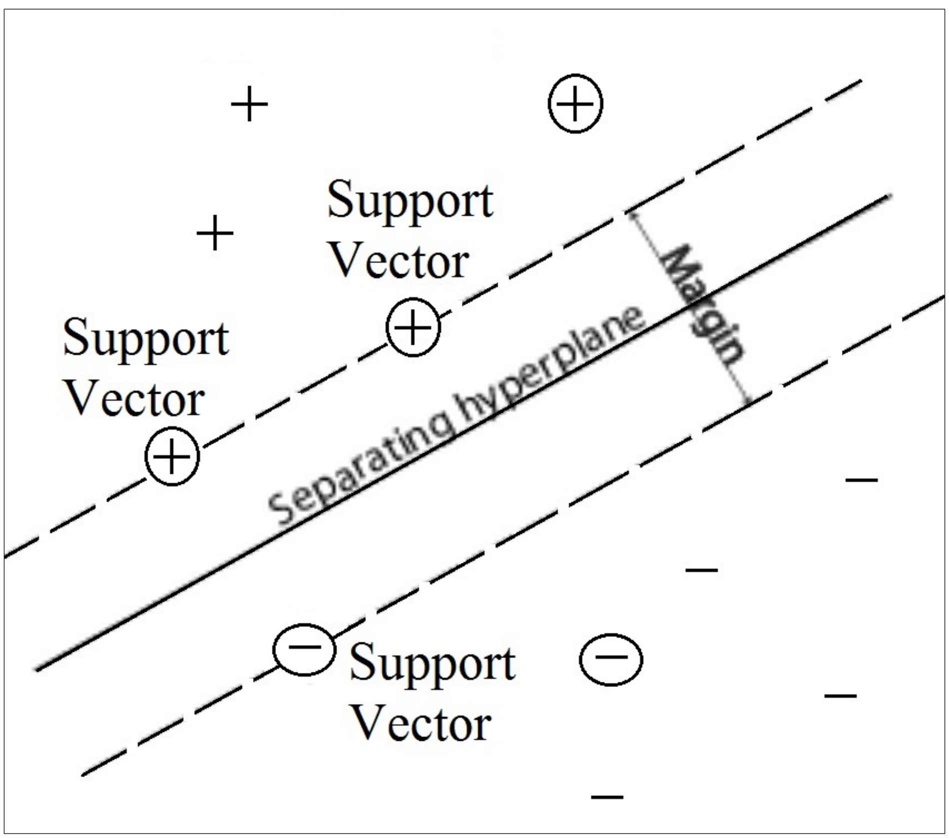
3.2.5.3. Forecasting with machine learning

In the last step of the methodological approach I attempt to create a model in order to predict and forecast the contagion risk possibility that described previously. In this step I applied several machine learning algorithms in order to find the most accurate. Specifically, I used decision trees, discriminant analysis, logistic regression classifies, Support Vector Machines (linear, quadratic and cubic), nearest neighbor classifiers and ensemble classifiers. However, in all cases, the SVM quadratic was the most accurate. As I followed this approach of forecasting and due to the lack of dimensionality, I present here only the mathematical approach of SVM quadratic algorithm. We can use a support vector machine (SVM) when the data has exactly two classes. This might be the most reasonable explanation, why the SVM quadratic algorithm is the most accurate algorithm in our data.

SVMs are supervised learning models with related learning calculations that break down information utilized for grouping and relapse investigation. Given an arrangement of preparing precedents, each set apart as having a place with either of two classifications, a SVM training calculation constructs a model that appoints new models to one classification or the other. A SVM model is a portrayal of the precedents as focuses in space, mapped with the goal that the models of the different classifications are partitioned by a reasonable hole that is as wide as could reasonably be expected. New examples are then mapped into that same space and anticipated to have a place with a classification in light of which side of the hole they fall.

A SVM characterizes information by finding the best hyperplane that isolates all information purposes of one class from those of alternate class. The best hyperplane for a SVM implies the one with the biggest edge between the two classes. Edge implies the maximal width of the chunk parallel to the hyperplane that has no inside information focuses. The support vectors are the information indicates that are nearest the isolating hyperplane; these focuses are on the limit of the chunk. Figure 3.5 represents these definitions, with + demonstrating information purposes of sort 1, and – showing information purposes of sort – 1.

Figure 3. 5. Hyperplane for an SVM



3.2.5.4. SVM quadratic algorithm

Mathematical Formulation: Primal

The model follows Hastie et al. (2008) and Christianini and Shawe-Taylor (2000). The information for training is an arrangement of focuses (vectors) x_j alongside their classes y_j. For some measurement d, the $x_j \epsilon R^d$, and the $y_j = \pm 1$. The condition of a hyperplane is:

$$f(x) = x'\beta + b = 0$$

where, $\beta \in R^d$ and b is a genuine number. The accompanying issue characterizes the best separating hyperplane (i.e., the choice limit). Discover β and b that limit $\|b\|$ with the end goal that for all information focuses (x_j, y_j):

$$y_j f(x_j) \geq 1$$

The support vectors are the xj on the limit, those for which $y_j f\left(x_j\right) = 1$. This equation is generally gives the proportion of limiting $\|b\|$. This is a quadratic programming issue. The ideal arrangement $\left(\hat{\beta}, \hat{b}\right)$ empowers characterization of a vector *z* as takes after:

$$class(z) = sign\left(z'\hat{\beta} + \hat{b}\right) = sign(\hat{f}(z))$$

$\hat{f}(z)$ is the order score and speaks to the separation *z* is from the choice limit.

Mathematical Formulation: Dual

It is computationally more straightforward to tackle the double quadratic programming problem. To get the double, take positive Lagrange multipliers α_j increased by every requirement, and subtract from the objective function:

$$L_P = \frac{1}{2}\beta'\beta - \sum_j a_j(y_j(x_j'\beta + b) - 1)$$

where we look for a stationary point of L_p over β and b. setting the gradient of L_p to 0, we get:

$$\beta = \sum_j a_j y_j x_j$$

$$0 = \sum_j a_j y_j$$

Substituting into L_p, we get the dual L_D:

$$L_D = \sum_j a_j - \frac{1}{2}\sum_j \sum_k \alpha_j \alpha_k y_j y_k x_j' x_k$$

Which we maximaze over $a_j \geq 0$. In general, many α_j are 0 at the maximum. The nonzero α_j in the solution to the dual problem define the hyperplane, as seen in $\beta = \sum_j a_j y_j x_j$, which gives β as the sum of $a_j y_j x_j$. The data points x_j corresponding to nonzero α_j are the support vectors. The derivative of L_D with respect to a nonzero α_j is 0 at an optimum. This gives:

$$y_j f(x_j) - 1 = 0$$

In particular, this gives the value of b at the solution, by taking any j with nonzero α_j.

4. EMPIRICAL RESULTS

This section contains all the empirical results from the applied methodologies for all stages of the research. In particular, subsection 4.1 presents the empirical results and the discussion for the case of contagion within South and North Eurozone countries. Subsection 4.2 displays the empirical evidence from the case of contagion in real economy and the key role of policy uncertainty. Additionally, subsection 4.3 depicts the results from the research of interdependence of small economies while subsection 4.4 concludes the empirical results from the case of contagion from Brexit. Lastly, subsection 4.5 I provide evidence and discussion from the analysis of financial networks and risk contagion specification and prediction.

4.1. Empirical results and discussion for the case of contagion within South and North Eurozone countries

(*This section is based on Samitas and Kampouris (2017b), where Samitas is coauthor of the published paper*)

4.1.1. Spillover effects

The results of the asymmetric DCC two-stage estimation are presented in Table 4.1.1 and Table 4.1.2. The data is divided into 3 sub-periods: a) the early Eurozone period (January 4, 2005, to December 28, 2006), b) the subprime crisis period (January 2, 2007, to December 30, 2009) and c) the Eurozone debt crisis period (January 4, 2010, to June 30, 2015). First, I proceed with the estimation of the GJR-GARCH(1,1) for the first stage of the process; then, in the second stage of estimations, the Asymmetric Dynamic Conditional Correlation (A-DCC) model of Cappielo (2006) is employed, which guarantees the dependent conditional correlation matrix to be positive definite on the parameters. I observe the g term in each period to conclude for the existence of asymmetric movements, and I also examine if the sum of terms α and β is less than *1* to conclude for contagion effect. In general, if terms α and β are found to be positive and with a sum lower than the unique ($a+b<1$), in the majority of the cases, this supports the existence of dynamic conditional correlations and subsequently the contagion phenomenon. The g term has to be greater than zero to imply the presence of asymmetric movements.

Table 4.1. 1. Univariate Estimations GJR - GARCH (1,1)

	Greece	Austria	Belgium	France	Germany	Netherlands	Cyprus	Portugal	Italy	Spain
Early Eurozone Period										
ω	1.12E-05 *	8.64E-06 ***	4.91E-06 **	4.40E-06 ***	7.38E-06 **	4.04E-06 *	2.98E-06 *	3.60E-06	7.51E-06 **	1.00E-05 ***
t-stat	1.517	3.610	2.200	2.592	1.692	1.485	1.169	1.020	2.137	2.529
a	6.96E-10	0.0113	0.0046	3.35E-10	1.71E-07	1.97E-07 *	1.31E-01 ***	5.60E-02	9.73E-08	1.06E-08 **
t-stat	0.093	0.377	0.307	0.094	0.423	1.247	3.491	0.842	0.412	1.795
g	0.1466 **	0.2112 ***	0.2063 **	0.1733 ***	0.2148 **	0.1725 *	-0.0623 *	0.1097	0.2523 **	0.22739 **
t-stat	2.032	2.871	1.908	3.070	2.034	1.433	-1.511	1.026	2.176	2.216
b	0.8125 ***	0.7974 ***	0.7861 ***	0.8414 ***	0.7879 ***	0.8371 ***	0.8948 ***	0.7825 ***	0.7255 ***	0.7026 ***
t-stat	8.104	18.963	9.641	18.328	7.636	8.377	25.246	4.732	6.862	6.796
Subprime Crisis										
	Greece	Austria	Belgium	France	Germany	Netherlands	Cyprus	Portugal	Italy	Spain
ω	4.98E-06 **	8.14E-06 *	6.14E-06 **	4.73E-06 ***	5.03E-06 ***	2.68E-06 **	8.28E-06 *	5.76E-06 ***	3.08E-06 **	5.69E-06 **
t-stat	1.750	1.350	1.793	2.382	2.565	2.189	1.620	2.445	2.064	2.245
a	5.34E-02 ***	2.55E-02	2.07E-02 *	8.33E-08 *	1.52E-08	2.98E-08	4.83E-02 **	3.48E-02 **	1.92E-02	1.66E-07 ***
t-stat	2.438	0.927	1.344	1.306	0.479	0.913	1.757	1.641	1.184	9.967
g	0.1473 ***	0.1619 ***	0.1869 ***	0.1855 ***	0.1669 ***	0.1808 ***	0.1342 ***	0.2114 ***	0.1438 ***	0.1729 ***
t-stat	3.334	2.473	3.381	3.929	3.393	4.827	2.329	2.957	3.581	3.703
b	0.8728 ***	0.8773 ***	0.8659 ***	0.8945 ***	0.8989 ***	0.9051 ***	0.8841 ***	0.8327 ***	0.8988 ***	0.8921 ***
t-stat	29.550	15.498	22.472	41.367	39.339	53.125	19.120	19.685	47.071	35.559
Debt Crisis										
	Greece	Austria	Belgium	France	Germany	Netherlands	Cyprus	Portugal	Italy	Spain
ω	1.64E-05 *	3.17E-06 **	3.73E-06	6.40E-06 ***	4.41E-06 **	3.33E-06 **	1.74E-06	8.98E-06 ***	7.53E-06 ***	5.08E-06 **
t-stat	1.485	2.240	1.031	2.445	1.808	1.888	0.921	2.763	2.547	1.943
a	4.84E-02 **	7.03E-09 **	9.84E-08	9.20E-08 ***	1.68E-06 ***	2.19E-07	1.32E-01 ***	1.89E-02	8.67E-10	5.14E-08
t-stat	2.015	1.690	0.906	2.612	4.374	0.906	5.637	0.868	0.203	0.600
g	0.0420 *	0.0954 ***	0.1514 **	0.2141 ***	0.1691 ***	0.1915 ***	-0.0475 *	0.1384 ***	0.1181 ***	0.1523 ***
t-stat	1.398	3.781	1.869	3.378	2.636	2.786	-1.416	3.856	3.569	3.224
b	0.9109 ***	0.9329 ***	0.8934 ***	0.8591 ***	0.8869 ***	0.8790 ***	0.8918 ***	0.8603 ***	0.9103 ***	0.9038 ***
t-stat	27.260	49.971	13.074	21.565	20.102	20.235	56.961	23.304	36.348	29.963

Notes: The lag length is determined by the AIC and BIC criteria.

*** Denote statistical significance at 1% level.

** Denote statistical significance at 5% level.

* Denote statistical significance at 10% level.

Table 4.1. 2. ADCC results - co-movements South and North Eurozone

		Early Eurozone Period			Subprime Crisis			Debt Crisis		
		a	g	b	a	g	b	a	g	b
Greece	ATX Austria	7.00E-09	0.135045 **	0.87065 ***	5.64E-09	5.17E-02 *	0.92645 ***	1.39E-08	8.68E-03	0.989269 ***
	Bel20 Belgium	8.14E-09	0.065433	0.89367 ***	3.29E-04	4.39E-02 *	0.95715 ***	5.70E-09	1.15E-08	0.996518 ***
	CAC40 France	3.46E-02	0.023997	0.91587 ***	4.05E-08	5.50E-02	0.94205 ***	3.59E-07	2.18E-02 **	0.980711 ***
	DAX Germany	2.72E-02	0.000002	0.93127 ***	5.58E-08	5.90E-02 **	0.92822 ***	1.83E-08	1.08E-02	0.981626 ***
	AEX Netherlands	2.02E-02	0.032502	0.91966 ***	6.90E-04	5.36E-02	0.94654 ***	1.48E-05	1.32E-01	2.86E-05
Cyprus	ATX Austria	2.73E-08	3.55E-02 *	0.97182 ***	1.20E-02	9.89E-02 **	0.86375 ***	2.31E-08	6.19E-03 *	0.995848 ***
	Bel20 Belgium	6.03E-03	6.58E-03	0.93566 ***	9.97E-08	2.09E-01 ***	0.80373 ***	1.52E-03	1.82E-02 *	0.981581 ***
	CAC40 France	1.98E-04	4.23E-02	0.91895 ***	2.73E-02	1.10E-01 **	0.84783 ***	2.15E-06	2.86E-02 ***	0.976822 ***
	DAX Germany	3.43E-03	4.02E-02	0.00004	3.29E-02 *	1.26E-01 **	0.78156 ***	3.27E-03	1.42E-02 *	0.981348 ***
	AEX Netherlands	1.52E-02	3.84E-02	0.00004	1.93E-02	1.08E-01 **	0.86681 ***	1.58E-03	2.57E-02 *	0.974005 ***
Portugal	ATX Austria	2.81E-09	2.96E-02 **	0.98369 ***	3.14E-08	5.16E-02 **	0.93589 ***	1.14E-02	9.52E-02 **	0.806045 ***
	Bel20 Belgium	6.17E-09	2.63E-01 **	0.73333 ***	7.54E-02 **	5.97E-02	0.68065 ***	2.52E-02 *	2.77E-02	0.910956 ***
	CAC40 France	3.90E-07	4.44E-01 **	0.05515	2.09E-02 *	8.35E-02 ***	0.91354 ***	2.29E-02 *	2.90E-02	0.912515 ***
	DAX Germany	7.23E-09	2.94E-02	0.94555	2.37E-03	7.22E-02 **	0.92420 ***	5.00E-03	4.78E-02 **	0.93905 ***
	AEX Netherlands	3.10E-09	2.92E-02	0.95512 **	4.70E-02 *	7.29E-02 **	0.86911 ***	1.88E-02	7.06E-02 **	0.86396 ***
Italy	ATX Austria	3.13E-08	1.47E-01 *	0.62063	2.32E-03	9.82E-02 **	0.83473 ***	5.45E-02 **	4.66E-02 *	0.833502 ***
	Bel20 Belgium	7.15E-03	7.77E-02 **	0.90357 ***	8.81E-03	1.03E-01 **	0.90772 ***	0.017818	0.048485 **	0.931103 ***
	CAC40 France	4.36E-02 *	4.52E-02	0.82089 ***	5.49E-03	1.18E-01 ***	0.91246 ***	1.77E-03	8.04E-02 ***	0.926336 ***
	DAX Germany	2.19E-08	6.18E-02 **	0.88863 ***	2.25E-02	1.48E-01 ***	0.83264 ***	2.62E-02	7.47E-02 **	0.875701 ***
	AEX Netherlands	9.05E-02 **	3.83E-02	0.75081 ***	2.73E-02 *	7.85E-02 **	0.90717 ***	7.08E-03	7.59E-02 ***	0.927882 ***
Spain	ATX Austria	5.21E-09	4.71E-02	0.90883 **	1.44E-05	1.13E-01 *	0.83022 ***	6.30E-02 ***	2.52E-03	0.796444 ***
	Bel20 Belgium	4.09E-09	5.44E-02 **	0.93853 ***	3.19E-02	7.57E-02 *	0.82977 ***	4.17E-02 *	1.33E-08	0.899549 ***
	CAC40 France	2.11E-08	5.56E-02 *	0.92276 ***	3.73E-02 *	9.67E-02 *	0.80417 ***	4.10E-02 ***	4.59E-07	0.930645 ***
	DAX Germany	4.58E-02 *	5.63E-02	0.83340 ***	5.18E-02 *	8.56E-02 *	0.79005 ***	3.94E-02 ***	7.17E-09	0.902641 ***
	AEX Netherlands	3.18E-08	8.62E-02 **	0.88377 ***	7.11E-09	1.11E-01 *	0.88103 ***	4.27E-02 ***	2.76E-03	0.919718 ***

Notes: Asymmetric Dynamic Conditional Correlation results. g parameter shows the asymmetric term in the DCC model

*** Denote statistical significance at 1% level.

** Denote statistical significance at 5% level.

* Denote statistical significance at 10% level.

As we can see from Table 4.1, univariate estimations are, in most cases, statistically significant, which guarantees the absence of normality in the indices. On the other hand, in the ADCC estimations (Table 4.1.2) we observe that the subprime crisis period includes the most statistically significant parameters. This seems to be reasonable, as the 2008 financial crisis caused a severe impact (shocks) on many capital markets around the world, especially in the Eurozone. Moreover, the g term for the presence of asymmetry in variances is statistically significant in almost all estimations for the subprime crisis period. In addition, terms *a* and *b* were found to be positive, and their sum was lower than 1 in all cases. Thus, the spillover effects exist in all estimations.

The results of the full asymmetric BEKK model are presented in Tables 4.1.3, 4.1.4 and 4.1.5 for each period, respectively. I carried out the procedure again with the ABEKK model of Kroner and Ng (1998) for the same periods and indices to compare the results with the ADCC model. I selected the full BEKK model because in the bivariate case coefficients display the impact among the indices more clearly. Unlike in the ADCC model, the debt crisis period seems to have the most statistically significant parameters and the early Eurozone period the least. The subprime crisis and debt crisis periods seem to have produced vast amounts of spillover effects in other markets. More importantly, asymmetric terms seem to be more prominent in the debt crisis period compared to the ADCC model.

Table 4.1. 3. Asymmetric Full BEKK estimations - Early Eurozone Period

	Greece					Cyprus					Portugal					Italy					Spain				
Coefficients	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands
C11	0.004	0.003	0.003	0.003	0.003	0.001	0.000	0.004	0.001	0.005	0.002	0.002	0.002	0.002	0.001	0.002	0.002	0.002	0.002	0.001	0.002	0.002	0.003	0.003	0.002
C12	0.001	0.001	0.000	0.001	0.001	0.004	-0.007	0.001	0.002	0.000	0.001	0.001	0.002	0.001	0.000	0.001	0.002	0.002	0.002	0.001	0.002	0.002	0.002	0.002	0.002
C22	0.003	0.002	0.002	0.002	0.002	0.003	0.002	0.002	0.003	0.002	0.003	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001
A11	-0.042	-0.027	0.084	-0.016	0.031	0.241	0.176	0.288	0.243	0.188	0.156	0.183	0.114	0.106	0.166	-0.032	0.022	-0.023	-0.017	0.432	0.029	0.071	0.088	0.221	0.080
A21	-0.015	-0.145	0.018	-0.082	-0.149	0.138	-0.006	-0.009	-0.114	-0.033	0.024	0.020	0.032	-0.043	0.030	0.003	0.010	0.004	-0.020	-0.412	0.059	-0.088	0.043	0.006	-0.018
A12	0.047	0.002	0.000	0.003	-0.009	-0.159	-0.117	-0.047	0.042	-0.017	-0.045	0.000	-0.052	0.015	0.021	0.020	0.032	0.015	0.013	0.196	0.012	0.052	-0.001	-0.009	0.005
A22	0.041	0.035	0.002	0.073	0.043	0.136	0.126	0.045	0.252	0.187	0.086	0.027	0.010	0.160	-0.132	0.069	0.018	0.013	0.014	-0.159	-0.009	-0.005	0.083	0.215	0.004
G11	0.218	0.280	0.317	0.329	0.289	0.200	0.248	0.296	0.031	0.196	0.067	0.346	0.153	0.242	0.097	0.335	0.300	0.267	0.412	0.094	0.195	0.144	0.265	0.270	0.184
G21	0.202	0.088	0.108	0.186	0.167	0.020	-0.091	0.001	0.290	-0.031	0.110	0.060	0.094	0.095	0.147	-0.023	0.120	0.153	0.024	0.282	0.074	0.119	0.057	0.021	0.189
G12	0.013	0.049	0.024	0.016	0.026	0.040	0.109	0.080	0.012	0.036	0.117	0.049	0.046	0.033	-0.011	0.026	0.095	0.047	0.035	0.094	0.109	0.123	0.002	0.011	0.130
G22	0.373	0.367	0.350	0.368	0.335	0.171	0.101	0.319	0.278	0.197	0.415	0.428	0.228	0.368	0.420	0.408	0.339	0.373	0.393	0.296	0.376	0.197	0.316	0.281	0.239
B11	0.884	0.921	0.907	0.910	0.925	0.943	0.920	0.901	0.952	0.920	0.939	0.870	0.934	0.915	0.948	0.915	0.926	0.892	0.896	0.973	0.937	0.929	0.904	0.881	0.918
B21	0.007	-0.029	-0.032	-0.026	-0.047	-0.071	-0.001	-0.096	0.068	-0.031	-0.020	0.003	-0.024	-0.006	-0.019	-0.008	-0.027	0.020	-0.011	-0.059	-0.013	0.013	-0.008	-0.005	-0.010
B12	-0.036	-0.007	0.021	-0.003	-0.001	-0.001	0.023	0.020	-0.030	0.012	-0.010	-0.025	-0.002	-0.021	0.116	-0.004	-0.018	-0.033	0.012	0.081	-0.021	-0.032	0.039	0.009	-0.008
B22	0.907	0.915	0.914	0.917	0.934	0.869	0.935	0.906	0.852	0.922	0.903	0.896	0.937	0.903	0.863	0.904	0.920	0.938	0.893	0.852	0.909	0.957	0.896	0.886	0.927

Notes: Bivariate full ABEKK model estimations. C parameters shows the lower tringular matrix. G parameters depict the asymmetric term for the BEKK model.

BLUE: Denote statistical significance at 1% level.

GREEN: Denote statistical significance at 5% level.

RED: Denote statistical significance at 10% level.

Table 4.1. 4. Asymmetric Full BEKK estimations - Subprime Crisis Period

	Greece					Cyprus					Portugal					Italy					Spain				
Coefficients	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands
C11	0.003	0.004	0.006	-0.006	-0.003	-0.008	0.003	0.006	0.006	0.007	0.004	0.001	0.004	0.003	0.003	0.000	0.002	0.005	0.003	0.002	0.006	-1.250	0.004	0.004	0.003
C12	0.001	0.004	0.002	-0.005	-0.002	-0.004	0.001	0.002	0.001	0.001	0.004	0.004	0.003	0.005	0.003	-0.001	0.004	0.004	0.003	0.002	0.006	-1.311	0.003	0.003	0.002
C22	0.003	0.000	0.000	0.002	0.002	0.004	0.003	0.002	0.003	-0.002	0.003	0.002	0.002	0.002	0.001	0.005	0.000	0.001	0.002	0.001	0.000	0.001	0.001	0.002	-0.001
A11	0.096	0.127	0.071	0.138	-0.120	0.070	0.084	0.015	0.020	0.035	0.068	0.069	0.078	0.041	0.161	0.076	0.130	0.041	0.205	0.051	0.021	-0.082	0.041	0.076	0.012
A21	-0.098	0.011	0.088	-0.017	-0.078	-0.091	0.066	-0.070	-0.018	-0.003	0.003	-0.001	0.021	0.053	-0.109	-0.055	-0.006	-0.005	-0.015	0.035	-0.112	0.052	0.026	0.021	-0.038
A12	0.212	-0.070	-0.054	-0.023	-0.018	0.057	0.067	-0.009	-0.011	0.027	-0.017	0.013	0.031	-0.145	-0.078	-0.073	0.011	-0.013	0.123	0.036	0.052	-0.265	-0.006	-0.010	-0.023
A22	-0.014	0.004	0.044	0.046	0.091	0.068	0.080	0.120	0.002	0.048	0.011	0.022	0.021	0.077	-0.044	-0.044	0.078	-0.016	-0.010	0.011	0.003	0.157	-0.010	0.047	-0.010
G11	0.127	0.221	0.185	0.170	0.336	0.101	0.235	0.332	0.264	0.284	0.179	0.226	0.183	0.282	0.162	0.167	0.111	0.118	0.320	0.077	0.165	0.426	0.179	0.250	0.093
G21	-0.073	-0.029	0.117	0.010	0.113	0.044	0.078	-0.043	0.012	0.032	0.032	-0.136	0.086	0.095	0.206	0.084	0.008	0.048	-0.002	0.036	0.013	0.103	0.065	0.013	0.060
G12	-0.169	0.101	0.000	0.030	0.005	-0.081	0.087	0.090	0.075	-0.004	0.033	0.113	-0.021	0.063	-0.025	0.008	0.145	0.033	-0.092	0.027	0.013	0.166	0.110	0.001	0.138
G22	0.127	0.275	0.090	0.246	0.381	0.128	0.241	0.149	0.325	0.136	0.201	0.220	0.233	0.248	0.284	0.185	0.280	0.110	0.441	0.214	0.083	0.379	0.109	0.231	0.014
B11	0.977	0.942	0.936	0.927	0.915	0.949	0.936	0.922	0.948	0.940	0.940	0.930	0.940	0.919	0.930	0.953	0.952	0.952	0.917	0.952	0.934	0.873	0.943	0.934	0.946
B21	-0.001	0.024	-0.074	0.002	0.023	-0.003	0.061	0.026	-0.002	0.011	-0.008	0.064	-0.023	0.021	-0.027	0.065	0.032	-0.018	0.014	-0.002	-0.052	-0.015	-0.012	-0.011	-0.010
B12	0.029	-0.022	0.039	-0.034	-0.007	0.010	-0.083	-0.031	-0.006	-0.019	0.007	-0.034	0.016	-0.072	0.009	-0.026	-0.076	0.008	0.005	-0.004	0.008	-0.075	0.006	0.003	0.011
B22	0.966	0.927	0.957	0.937	0.939	0.940	0.930	0.943	0.938	0.941	0.945	0.940	0.942	0.944	0.941	0.943	0.924	0.953	0.921	0.946	0.945	0.929	0.954	0.935	0.967

BLUE: Denote statistical significance at 1% level.
GREEN: Denote statistical significance at 5% level.
RED: Denote statistical significance at 10% level.

Table 4.1. 5. Asymmetric Full BEKK estimations - Debt Crisis Period

	Greece					Cyprus					Portugal					Italy					Spain				
Coefficients	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands	ATX Austria	Bel20 Belgium	CAC40 France	DAX Germany	AEX Netherlands
C11	0.006	0.000	0.006	0.008	0.007	-0.008	0.006	0.003	0.006	0.006	0.003	0.004	0.003	0.004	0.004	0.004	-0.003	0.006	0.003	0.004	0.003	0.004	0.004	0.003	0.003
C12	0.002	0.003	0.002	0.001	0.000	0.000	0.000	-0.001	0.000	-0.001	0.001	0.001	0.001	0.001	0.002	0.003	0.006	0.004	0.000	0.002	-0.001	0.003	0.003	0.002	0.002
C22	0.002	0.007	0.001	-0.001	0.002	0.003	-0.002	0.003	-0.003	0.003	0.003	-0.002	0.002	0.001	0.002	-0.003	-0.038	0.001	0.001	0.002	0.002	0.002	0.002	0.001	0.001
A11	0.108	0.028	0.139	0.118	0.182	-0.012	-0.049	0.231	0.183	0.134	0.192	0.054	0.069	0.055	0.136	0.116	0.017	0.013	-0.014	0.112	0.009	-0.006	-0.008	0.130	0.113
A21	-0.096	0.031	-0.031	0.063	-0.057	0.043	0.096	0.023	-0.012	0.110	-0.021	0.137	0.015	-0.003	0.002	-0.133	0.006	0.129	-0.111	-0.188	-0.093	-0.046	-0.021	-0.049	-0.114
A12	-0.042	0.005	0.002	-0.034	-0.036	-0.002	-0.006	0.009	0.012	-0.002	0.017	-0.098	-0.005	0.001	0.003	-0.029	-0.007	-0.008	0.144	0.070	0.005	-0.024	-0.005	0.013	-0.020
A22	0.052	-0.010	0.010	0.027	-0.048	0.174	0.254	0.020	0.192	0.081	0.071	0.185	0.016	0.073	0.049	0.009	0.005	0.026	0.152	-0.109	0.086	0.030	0.005	-0.033	-0.071
G11	0.150	0.264	0.126	0.288	0.271	0.069	0.113	0.068	0.084	0.125	0.219	0.316	0.227	0.278	0.306	0.195	0.001	0.099	0.165	0.157	0.205	0.060	0.113	0.100	0.334
G21	-0.012	-0.036	-0.040	-0.105	-0.136	0.007	0.122	-0.004	-0.036	0.058	0.021	0.032	0.003	0.053	-0.047	0.057	0.003	-0.265	-0.088	0.090	0.155	-0.012	0.015	0.056	0.137
G12	0.080	0.041	0.141	0.098	0.012	0.027	0.010	0.024	0.049	0.036	0.014	0.110	0.025	-0.025	0.059	0.054	0.017	0.080	0.016	0.072	0.071	0.040	0.015	-0.043	0.102
G22	0.240	0.249	0.266	0.252	0.402	0.063	0.057	0.308	0.116	0.173	0.129	0.266	0.300	0.166	0.329	0.142	0.016	0.021	0.203	0.175	0.094	0.036	0.106	0.265	0.350
B11	0.954	0.943	0.950	0.913	0.931	0.956	0.967	0.949	0.939	0.946	0.929	0.925	0.934	0.915	0.911	0.956	0.964	0.913	0.940	0.940	0.969	0.956	0.953	0.949	0.906
B21	0.032	0.023	0.029	0.065	0.039	0.032	0.032	0.063	0.073	0.105	-0.003	-0.018	-0.004	-0.022	0.024	-0.050	0.003	0.014	-0.006	-0.003	-0.086	0.003	-0.003	-0.001	0.029
B12	-0.011	-0.018	-0.024	-0.025	0.014	-0.002	-0.003	-0.019	-0.010	-0.009	0.015	0.005	0.003	0.028	-0.011	0.026	-0.004	-0.008	0.042	-0.009	0.020	-0.001	0.001	-0.002	-0.027
B22	0.941	0.941	0.938	0.967	0.924	0.942	0.938	0.939	0.928	0.932	0.949	0.923	0.928	0.960	0.918	0.925	0.957	0.965	0.932	0.946	0.912	0.957	0.951	0.943	0.949

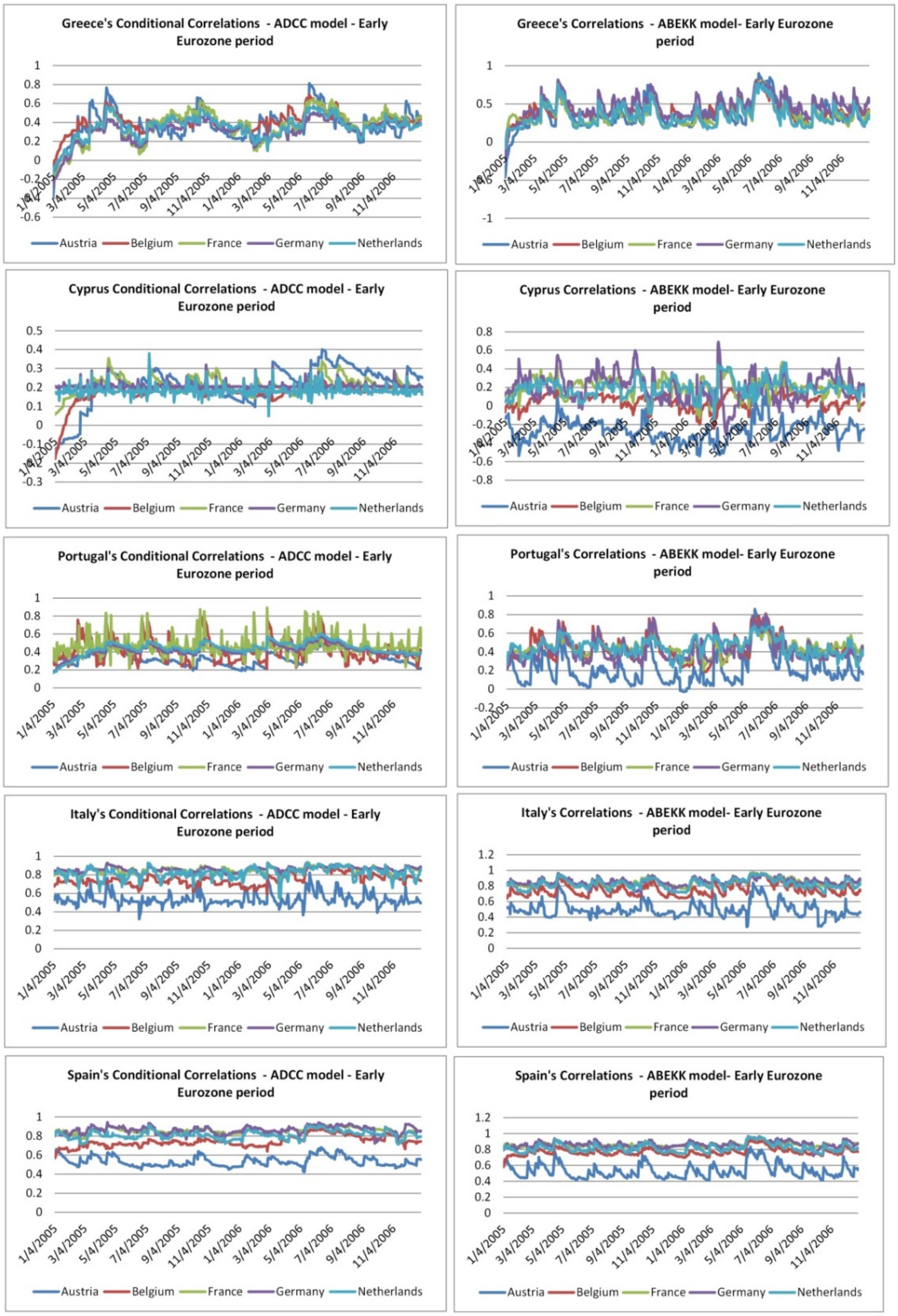
BLUE: Denote statistical significance at 1% level.
GREEN: Denote statistical significance at 5% level.
RED: Denote statistical significance at 10% level.

According to the ADCC model, during the early Eurozone period I observe a minor spillover effect from Italy and Spain to France, Netherlands and Germany, while asymmetric coefficients are more prominent for Portugal, Italy and Spain. This means that returns tend to be affected by negative shocks more significantly than positive. On the other hand, the ABEKK model showed that the Cyprus spillover impact is extremely low (A12) while DAX's fluctuations tend to produce large impact on Cypriot economy (G21). Table 4.6 shows the outline of correlations for both models. Figure 4.1.1 illustrates correlations $R_{(t)}$ for both ADCC and ABEKK models for the early Eurozone period. Spain and Italy are the most correlated with the northern countries; average correlations exceed 0.70 and Portugal and Greece come next, whereas Cyprus has the lowest values (under 0.20). Additionally, Portugal, Greece and Cyprus present volatile correlations with strong northern economies while Spain and Italy are more stable, as seen in Figure 4.1.1. Lastly, Greece and Cyprus showed an upward trend of conditional correlations with the countries of the northern Eurozone, as seen from Figure 4.1.1**.** This evidence can be confirmed from both models.

Table 4.1. 6. Conditional and unconditional correlations for DCC and ABEKK models

		Early Eurozone Period			Subprime Crisis			Debt Crisis		
		Unconditional correlation ADCC	Average conditional ADCC	Average Correlation ABEKK	Unconditional correlation ADCC	Average conditional ADCC	Average Correlation ABEKK	Unconditional correlation ADCC	Average conditional ADCC	Average Correlation ABEKK
Greece	ATX Austria	0.2521	0.3688	0.3579	0.6500	0.6753	0.5299	0.2835	0.3901	0.3991
	Bel20 Belgium	0.3609	0.4005	0.4069	0.5672	0.6233	0.6152	0.3549	0.3682	0.3611
	CAC40 France	0.3601	0.3602	0.3594	0.6206	0.6524	0.5066	0.1307	0.3560	0.3546
	DAX Germany	0.3475	0.3129	0.4566	0.5883	0.6207	0.6507	0.2592	0.3330	0.3482
	AEX Netherlands	0.3227	0.3487	0.3454	0.5899	0.6381	0.6385	0.3513	0.3602	0.3574
Cyprus	ATX Austria	-0.0657	0.2102	-0.2583	0.5275	0.5645	0.6203	-0.5613	0.2117	0.2195
	Bel20 Belgium	0.1751	0.1726	0.0566	0.4192	0.5059	0.1419	-0.0136	0.2079	0.2126
	CAC40 France	0.1542	0.2126	0.2062	0.4986	0.5452	0.2958	-0.1031	0.2044	-0.0476
	DAX Germany	0.2044	0.2080	0.2007	0.4845	0.5201	0.4890	0.0116	0.1872	0.1721
	AEX Netherlands	0.1779	0.1817	0.1924	0.4828	0.5414	0.1310	-0.0219	0.1909	0.1782
Portugal	ATX Austria	-0.9999	0.3307	0.2192	0.6448	0.6781	0.6889	0.6345	0.6510	0.5710
	Bel20 Belgium	0.3209	0.4270	0.4354	0.6941	0.6958	0.7067	0.6955	0.7086	0.6959
	CAC40 France	0.4420	0.4631	0.4484	0.6299	0.6996	0.7226	0.6849	0.6971	0.5797
	DAX Germany	0.3809	0.4217	0.4199	0.6632	0.6957	0.6423	0.6154	0.6604	0.5371
	AEX Netherlands	0.3766	0.4396	0.4542	0.6558	0.6855	0.6736	0.6414	0.6608	0.6487
Italy	ATX Austria	0.5120	0.5354	0.4971	0.7337	0.7469	0.5190	0.7505	0.7508	0.6247
	Bel20 Belgium	0.7148	0.7497	0.7536	0.7987	0.8176	0.4802	0.8112	0.8221	0.3051
	CAC40 France	0.8484	0.8507	0.8494	0.8765	0.8998	0.9143	0.8597	0.8601	0.8165
	DAX Germany	0.8482	0.8597	0.8552	0.8707	0.8761	0.8851	0.7999	0.8048	0.0755
	AEX Netherlands	0.8201	0.8206	0.8253	0.8312	0.8559	0.7961	0.7850	0.7970	0.8376
Spain	ATX Austria	0.4889	0.5344	0.5315	0.7284	0.7478	0.6437	0.7423	0.7381	0.0737
	Bel20 Belgium	0.7142	0.7417	0.7682	0.7957	0.7988	1.0000	0.8165	0.8133	0.8326
	CAC40 France	0.8425	0.8576	0.8650	0.8853	0.8870	0.8876	0.8549	0.8492	0.8642
	DAX Germany	0.8536	0.8616	0.8651	0.8709	0.8712	0.8329	0.7891	0.7853	0.7797
	AEX Netherlands	0.7894	0.8121	0.8185	0.8176	0.8347	0.8440	0.7940	0.7873	0.7798

Figure 4.1. 1. Early Eurozone Period. Correlations $R_{(t)}$ for ADCC and ABEKK models

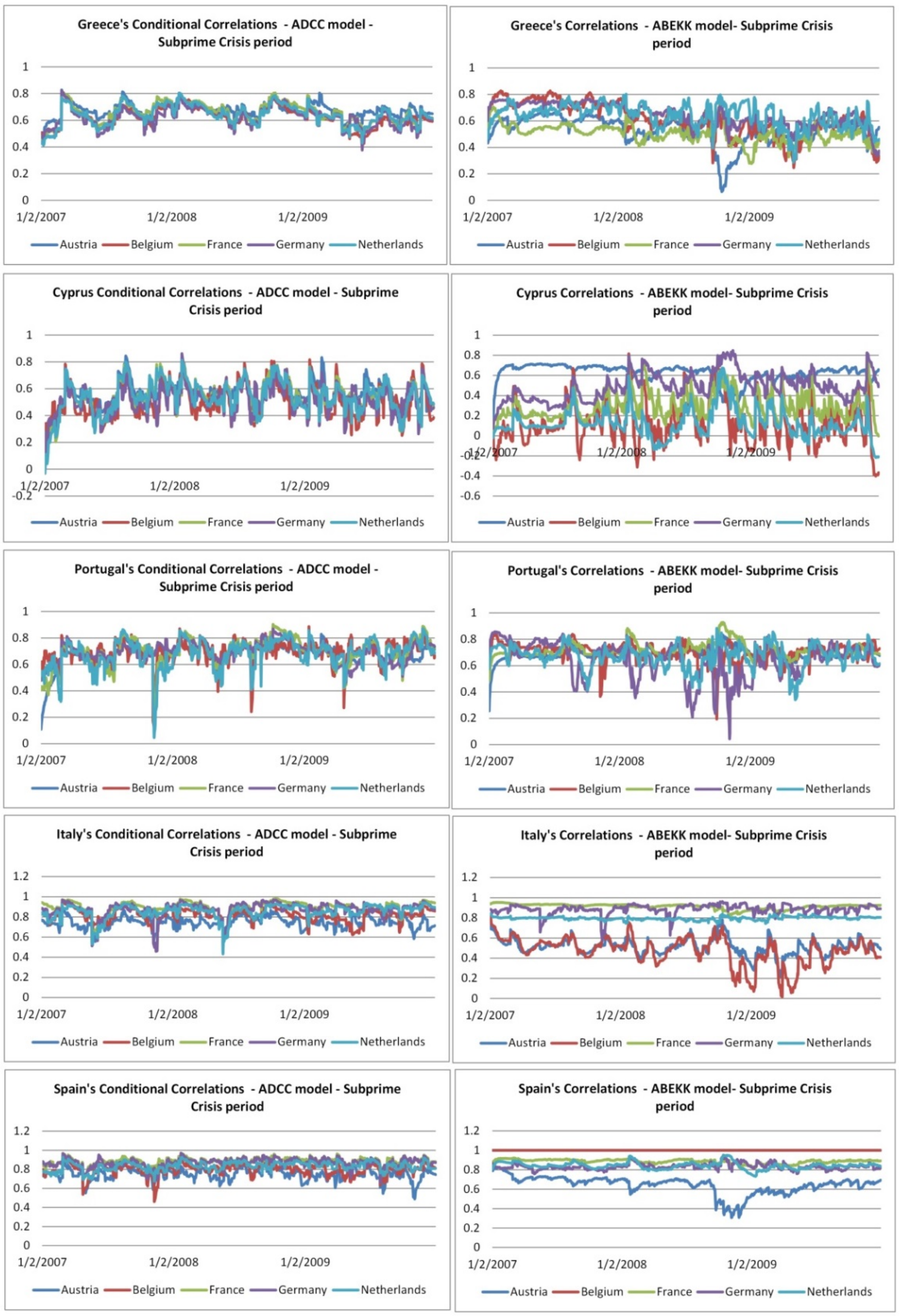


Notes: Left column shows the Correlations of ADCC while the right column belongs to ABEKK. Generally, correlations for both models have similar behavior. However, there is a continuous negative correlation between Cyprus and Austria, which is quite unusual compared to the ADCC where all correlations vary near 0.20.

The ADCC model showed asymmetric impact during the subprime crisis period in almost all cases (*g* parameter). However, only Portugal and Spain seem to produce some spillover effects to other countries. On the other hand, with the ABEKK model we observed that six out of ten statistically significant coefficients (A12) are negative (eight in A21), which means that the weight on cross effect impact to the other index is negative. According to the ABEKK model, southern countries did not affect the north in the subprime crisis period. Additionally, Spain has the most statistically significant asymmetric parameters (G12). Among others, France is the most connected with Italy and Spain (above 0.88 – Table 4.1.6); the most possible explanation is that these countries as neighbors share more transactions than the others. During the subprime crisis period, all southern countries increased correlations with northern countries. Still, Spain and Italy retained the leading correlation level, which exceeded 0.80. Like the previous period, Portugal, Greece and Cyprus come next, though with substantially increased levels of correlations (Table 4.1.6). According to Figure 4.1.2, almost all correlations are intensely volatile, much higher than the early Eurozone period. The 2008 financial crisis is responsible for this volatile behavior in capital markets, which are stigmatized by the most significant economic events of recent years.

Focusing now on the Eurozone debt crisis, the ADCC model showed that Spain had a huge impact on all northern countries. However, this impact is symmetric (statistically insignificant g parameters – Table 4.1.2). The asymmetric coefficients that we can tell apart are those of Italy and Cyprus, while Greece's negative shocks seem to affect French economy. This is consistent with the assumption that, since France holds nearly 10% of Greece's sovereign debt, investors were fueled by worry over a possible debt default inside the Eurozone. This can also be confirmed from the ABEKK model (G12 – Table 4.1.5); however, this impact has a low spillover effect but is capable of moving the CAC40 index. The ABEKK model showed that the Italian index can significantly affect the DAX. Moreover, Spain and Italy's negative shocks seem to be more significant than positive in almost all estimations (G12).

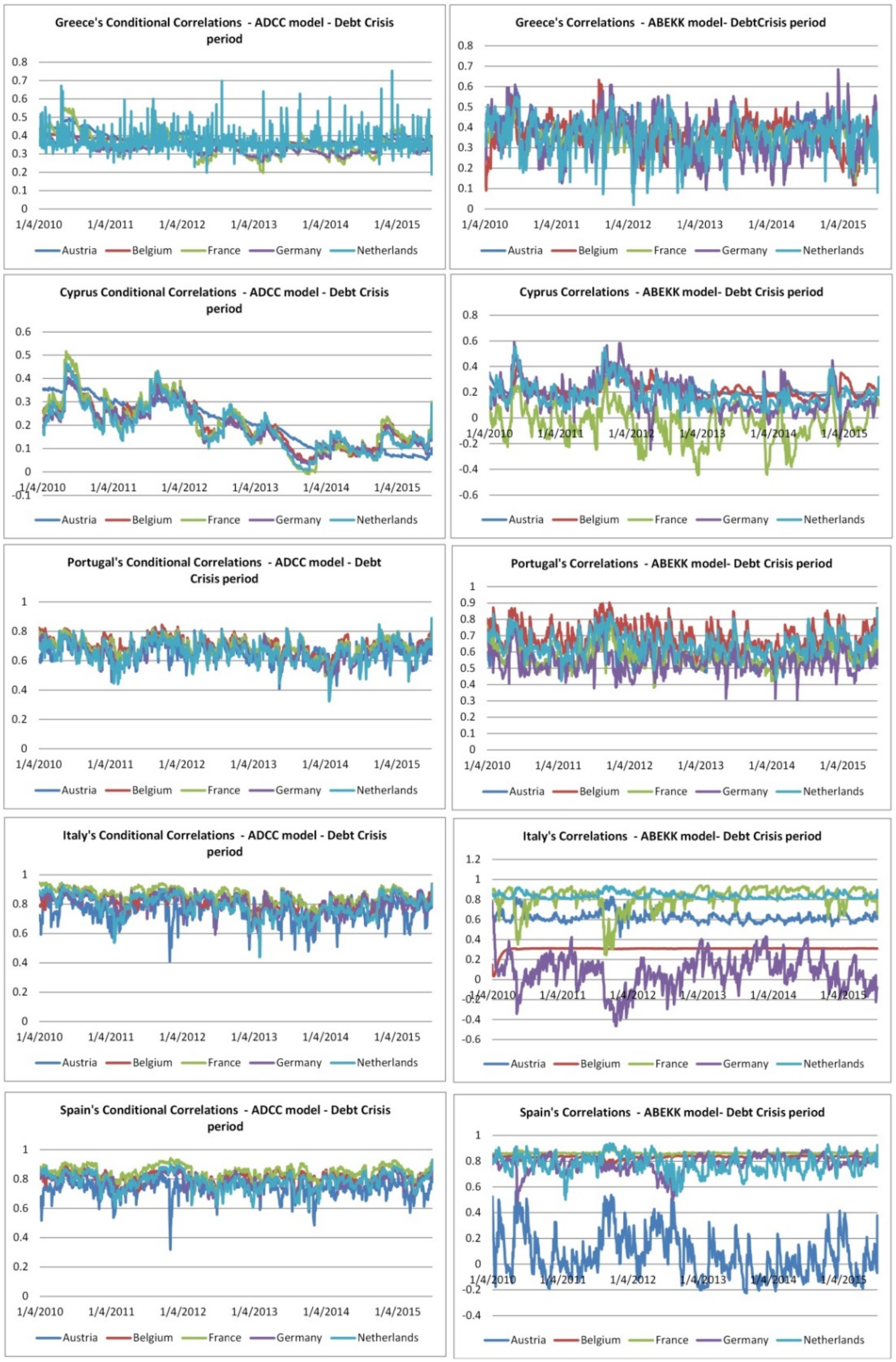
Figure 4.1. 2. Subprime Crisis Period. Correlations R(t) for ADCC and ABEKK models



Notes: In the Subprime crisis period, correlations for both models look similar no matter the large volatility. However, the ABEKK model looks that produce unreliable results in cases of: Cyprus – Austria, Italy – Netherlands, Spain – Belgium and Spain – France. Specifically, in case of Spain and Belgium correlations is completely inelastic and close to 1 in all observations of this period. Automatically, this shows statistical insignificance of this estimation.

Correlations decreased for all indices compared to the previous period (Table 4.1.6). However, they are at higher levels than the early Eurozone period. Likewise, the order of correlations from first to last is the same with the two previous periods: Spain and Italy in the leading positions, while Cyprus is for the third consecutive time the least correlated country with the strong economies of the northern Eurozone. As can be concluded from the results, Cyprus can only produce minor spillover effects to the European economies. This is alarming for other small economies (with small GDPs) of the Eurozone: if they abandon healthy economic positions in the near future, they will be in danger of receiving bail-in/out programs that will affect only the local economy. Namely, the contagion phenomenon will be extremely weak. The French index remained the most correlated with Spain and Italy, indicating that the CAC40 index is highly connected with neighboring countries; both models confirm this assumption. Lastly, I found that all correlations in the debt crisis period (Figure 4.1.3) are more highly volatile than the two previous periods. This behavior is in line with the cloud of uncertainty that covers the European economies due to the debt crisis, especially after the events in Greece, which featured high deficits and debt-to-GDP ratios in the middle of 2009 and the subsequent downgrade by credit rating firms.

Figure 4.1. 3. Debt Crisis Period. Correlations R(t) for ADCC and ABEKK models



Notes: In the Debt crisis period, correlations for both models look similar no matter the large fluctuations produced by the prolonged uncertainty. However, the ABEKK model looks that produce inelastic results in cases of: Italy – Belgium, Italy – Germany, Spain – France and Spain - Austria. Similarly to the previous period, in case of Italy and Belgium correlations is completely inelastic and close to 1 in all observations of the period. This shows statistical insignificance of these estimations. On the other hand, the ADCC model shows that it is more stable and reliable in all cases.

Convincingly, both models behave well and are flexible in presenting the spillover effects and the contagion phenomenon. However, regarding the illustration of conditional correlation, the ADCC model seems to fit better. This assumption can be explained by the unusual results that the ABEKK model showed in some of the estimations, while the ADCC model produced more reasonable estimations. The ABEKK model is very good at investigating and analyzing the parameters; however, regarding visual illustration with figures (correlations – $R_{(t)}$), the ADCC model seems to be more stable and logical in estimations not only with large samples (as the debt crisis period had over 1300 observations) but also with small ones (under 500 in the early Eurozone period).

As far as the estimations are concerned, Spain and Italy can produce significant damage to all strong northern strong, as confirmed by both models (ADCC and ABEKK). Moreover, the French economy is most correlated with Spain and Italy during the subprime and debt crisis periods; both models reach these same results. In addition, Greece’s negative shocks are capable of moving the French index. The involvement of France in Greek sovereign debt still produces fear in investors. Both the ADCC and the ABEKK behave similarly in this case. Moreover, Cyprus’s contagion ability is extremely low in all periods; this might be a lesson to other small economies of the Eurozone about the low spillover effects of these countries. In case of fiscal problems, that may require recapitalization of the economy and the banks (bailout); “contagion blackmailing” will no longer be a wild card in negotiations with institutions regarding these countries. Greece, on the other hand, is a cautionary tale for spillover effects in terms of political contagion, as discussed below.

The subprime crisis had the highest levels of conditional correlations, which proves that large economic events have significant effects on the big economies of the Eurozone. However, the debt crisis period presented lower levels of conditional correlations but higher degrees of fluctuations than the previous period. This volatile behavior may stem from the extensive uncertainty that prevails in the Eurozone due to the fear of debt default of southern Eurozone countries, the so-called “PIIGS”.

The uncertainty in capital markets during the debt crisis period can be clearly explained by the results. The Eurozone's economic policy of the last five years seems to have not minimized the speculation of a possible bankruptcy of a member country. This risk first originated in Greece in the middle of 2009 (Samitas and Tsakalos, 2013). Even today, credit rating agencies issue consecutive downgrades not only for Greece but also for other large countries of the southern Eurozone, such as Italy and Spain. Despite reassuring statements of the European Council that there is no chance of a possible debt default inside the Euro area, political uncertainty continues to swirl around Eurozone countries.

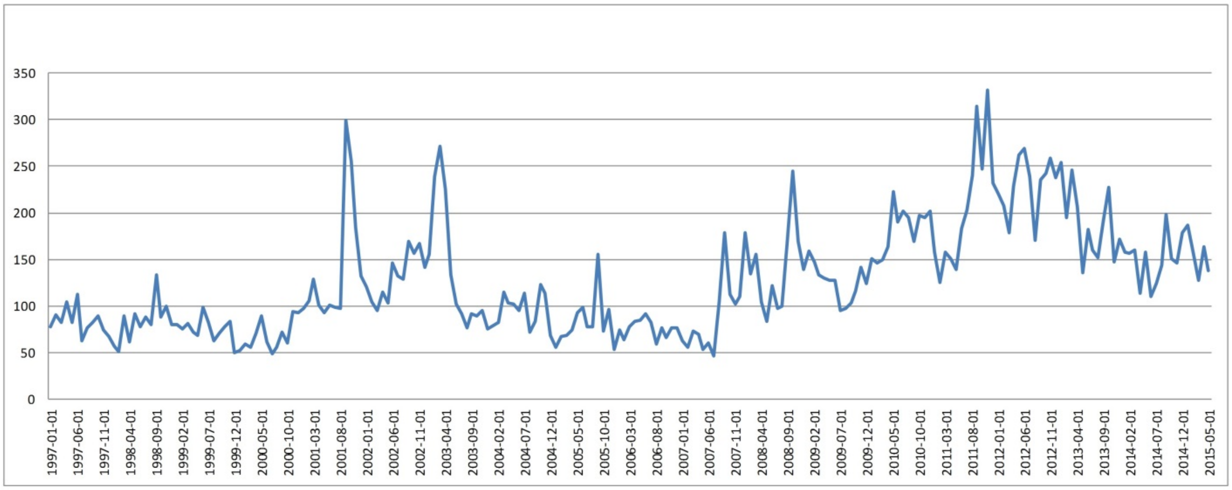
Regarding the results, one major question arises. Why does the French index have so much spillover potential on southern economies? According to the Observatory of Economic Complexity in 2016 the top export destinations of France are Germany ($85.4B), Belgium-Luxembourg ($47.4B), the United Kingdom ($41.5B), the United States ($40.3B) and Italy ($39.5B). The top import origins are Germany ($119B), Belgium-Luxembourg ($56B), China ($53.2B), Italy ($49.8B) and Spain ($41.7B). On the other hand, the top export destinations of Spain are France ($41.7B), Germany ($31.7B), Portugal ($25.2B), the United Kingdom ($22B) and Italy ($21.7B). The top import origins are Germany ($43.3B), France ($35.2B), China ($25.9B), Italy ($21.2B) and the United Kingdom ($14.5B). Additionally, the top export destinations of Italy are Germany ($61.3B), France ($49.8B), the United States ($40.8B), the United Kingdom ($28.1B) and Switzerland ($22.5B). The top import origins are Germany ($70.2B), France ($39.5B), China ($33.2B), the Netherlands ($27.3B) and Russia ($22.9B). Spain, France and Italy clearly share a large percentage of imports and exports among each other. The fact that France's top partner is Germany is not tested in this paper, as it only focuses on spillover effects from southern to northern countries, not the opposite.

The key results of this stage of the research provide significant guidance to fund managers and investors. The DCC model provides more realistic, accurate and elastic results; the BEKK approach in some cases showed inelastic curves in the correlations. Thus, the figure illustration seems to be not sufficiently adequate to produce safe conclusions. So, funds and investors should always prioritize the use of the ADCC model if they want to account for stock exchange co-movements, spillover effects and contagion. Regarding the results, funds and investors should be advised that there are strong dynamics connecting the vulnerable economies of Spain and Italy with northern Eurozone countries. Specifically, the size of these countries (in terms of GDP) can explain the increased interdependence compared with other countries inside the Eurozone. Thus, it seems logical that funds and investors should always have fiscal vulnerability and the continuous uncertainty from these two countries in mind. Lastly, investors should also remember the strong interconnection of the French economy with southern Eurozone countries, especially Spain and Italy. French interior fiscal and political problems seem to be the core contributing factor to the increased correlations with the southern economies. On the other hand, the increased market correlation of the France-Spain-Italy triangle seems to be based on neighborhood issues; large commercial and state transactions between the three very large countries contribute to global import and exports. Fund managers and investors in the European stock markets should take all these parameters extracted from the results into account in considering opportunities for better portfolio diversification.

4.1.2. The case of political contagion

The latest evidence from the Eurozone shows that southern "allies" are already split. Greece's statements about bailouts, austerity measures and debt sustainability differ from those of Cyprus and Spain (who previously were supposed to be on the side of Greeks) after the 2015 Greek elections. However, it is crucial that there be homogenous views when making significant decisions inside the Union that promote a global alliance. Figure 4.1.4 depicts the current economic political uncertainty in Europe. This diversification of policies creates concerns about the future of the EMU and exposes the fear of a weakening euro. Typical examples of these concerns are the recent statements of the United Kingdom about a possible "Brexit". There is no doubt that the Eurozone lacks a stable political and financial environment.

Figure 4.1. 4. Economic Policy Uncertainty Index for Europe



Notes: The index increased rapidly due to the 2008 Financial Crisis and remained that high till today with major periodic fluctuations. This behavior of the index stems from the lack of economic and monetary policy in the Eurozone which in turn leads to persistent political uncertainty. Source: www.policyuncertainty.com.

The EU currently lacks consensus and a proper space for debate. The financial contagion seems to be shifting to political contagion. Although the negotiations at this stage appear to be positive, there are now more political issues than economic/technocratic. Negotiations about the bailout programs and debt sustainability are positive when completed on time and quickly and efficiently (which supports a strong Eurozone that is flexible enough to react and take crucial decisions that may prevent a new financial crisis). Otherwise, like in 2015 in Greece, the government uses negotiations to gain more time to create a sustainable solution while also trying to achieve a withdrawal of the loaners' hard line. However, there is a huge risk of financial contagion through capital markets under these circumstances. Moreover, before the agreement on the Greece's new program, the Greek market suffered from serious economic suffocation due to a lack of liquidity and capital controls. Simultaneously, many businesses are going bankrupt, and the private sector is sinking even more. This complicated condition creates confusion among people and capital markets; it has led to several months of stagnation that is harmful to the whole Eurozone. On the other hand, Greece was trapped in seeking to find an exit to growth (after years of recession) and does not desire to continue strict austerity measures, despite the IMF and German policy proposals.

Failing to find a solution, along with a subsequent rift between Greece and its lenders, will lead to a new shock in the markets, the impact of which will be difficult to predict. How long will the ECB and Mario Draghi keep the diffusion of crisis constant before it spreads to Italy, Spain and even France? The EU perhaps is ready for a possible “Grexit”, which at this stage seems to be manageable, although it will not prevent the crisis from spreading to the aforementioned countries, particularly if the country has received such a rebuke from markets and credit rating firms such as Greece in recent years.

Considering the economic political uncertainty index (Figure 4.1.4) and the political uncertainty of the results (in correlations of the models) we can state that there is political contagion within Eurozone. As long as the economically strong northern countries continue to treat Greece as a “lab” of austerity and Greece is unable to solve quickly and efficiently its interior political instability, it may be assumed that this condition will continue to create political contagion. Political contagion is the exacerbation of political fear about issues such as cleavage or risk policy. Consequently, Eurozone member countries will potentially struggle to find allies to negotiate core issues of their own interest. In particular, countries that are considered allies of Greece in negotiation issues are now diversifying their statements due to the political contagion (i.e., from Greece) in an attempt to avoid similar debates and discussions inside their own states (for example, if austerity is the solution for the Eurozone). Obviously, powerful countries such as Spain, Italy and France have already differentiated themselves from Greece in terms of how to address the crisis.

Improving the climate requires political and economic stability. Stability occurs only when there can be a final agreement about debt sustainability in the Eurozone. Wrong decisions can lead to uncharted paths and political contagion due to the fear of the financial contagion that caused the instability in Greece. Not finding a solution might leave a country without allies in the Eurozone. For example, if a country had 10 allies to negotiate within the Euro Group, it will lose 3 while the risk for GREXIT increases. Countries that were willing to help Greece will be forced to lose confidence in the continuation of the negotiations and the good economic framework in the Eurozone.

Additionally, political contagion is particularly dangerous for the entire Eurozone. The Eurozone, in its current form, can only manage small-scale crises, as in the case of Greece

(Samitas and Tsakalos, 2013), Cyprus and even Portugal. While the Greek government imposed a referendum to Greek people in order to ensure a strong negotiation strategy against Brussels, the subsequent capital control measures made a huge impact only on the interior of the country (locally). This indicates that ECB and Mario Draghi have kept the spillover effect low despite the uncertainty and skepticism remaining in the Eurozone. However, what would occur if Italy, Spain or France experienced a significant financial shock? In these cases the ratio of the country GDP to the total EU are enormous, and a crisis could lead to a global economic event much greater than the subprime crisis.

The financial institutions of the Eurozone should pay close attention to the scenario of political contagion from Greece to other countries, especially Italy and Spain; those two countries could produce an uncontrollable contagion effect on the entire Eurozone economy. Looking more closely at the political uncertainty index and the volatile behavior of the correlations with the debt crisis period, it is easy to understand that we are in the whirl of the debt crisis inside the Eurozone. Eurozone institutions examine all these possible scenarios to avoid economic events similar to those of 2008 financial crisis. Additionally, it can be stated that these scenarios are capable of splitting Eurozone or at least changing the form we know today.

4.2. Empirical evidence from the research in real economy and the key role of policy uncertainty

The results of the ADCC model are presented in Tables 4.2.1, 4.2.2 and 4.2.3. First, I proceed with the estimation of the GJR-GARCH (1, 1) model that covers the first part of the ADCC process. The second part is the estimation of the ADCC model of Cappielo (2006), which ensures the dependent conditional correlation matrix to be positive definite on the parameters. We must note that the estimations of the univariate GJR – GARCH (1, 1) model for all periods and correlations are 159 (3 Eurozone indexes and 50 sectors of economies for 3 time periods); in addition, due to dimensionality, I did not present them in this thesis. However, the estimations are available upon request.

The *g* parameter in the ADCC results shows the existence of asymmetric movements. The DCC model works as any other GARCH model, where $\alpha+\beta<1$. This condition, in addition to the g term, supports the presence of dynamic conditional correlations and subsequently, evidence for interdependence. The positive g parameter guarantees the existence of asymmetric movements. The asymmetric movements support the fact that negative shocks at time $t-1$ have a stronger impact on the variance at time t than positive shocks.

Table 4.2. 1ADCC results. Co-movements between France and sectors of real economy

	Early Eurozone Period			**Subprime Crisis**			**Debt Crisis**		
	a	**g**	**b**	**a**	**g**	**b**	**a**	**g**	**b**
US-DS Oil & Gas	1.59E-02	8.35E-04	9.74E-01 ***	2.57E-02	1.07E-05	9.60E-01 ***	5.06E-02 **	2.98E-03	9.04E-01 ***
UK-DS Oil & Gas	3.19E-02 ***	5.77E-09	9.62E-01 ***	3.15E-02 **	7.02E-02 **	9.20E-01 ***	5.86E-02 **	6.36E-02 **	8.67E-01 ***
BRIC-DS Oil & Gas	3.17E-03	2.95E-02 **	9.51E-01 ***	4.25E-02 *	1.00E-06	9.21E-01 ***	2.27E-02 **	3.91E-02 *	9.40E-01 ***
JAPAN-DS Oil & Gas	1.88E-02	4.54E-05	3.45E-01	1.10E-08	3.87E-03	9.83E-01 ***	1.39E-08	2.32E-02 *	9.66E-01 ***
CANADA-DS Oil & Gas	1.46E-02 **	7.61E-09	9.49E-01 ***	2.56E-02 **	2.85E-02	9.47E-01 ***	4.99E-02 **	2.17E-03	9.03E-01 ***
US-DS Basic Mats	2.86E-02 **	4.25E-09	9.56E-01 ***	1.43E-02	7.10E-03	9.74E-01 ***	3.41E-02	9.57E-07	8.12E-01 ***
UK-DS Basic Mats	2.24E-02 **	4.85E-02 ***	9.48E-01 ***	1.23E-02	6.63E-02 **	9.32E-01 ***	2.09E-02 *	3.58E-02 **	9.51E-01 ***
BRIC-DS Basic Mats	3.42E-02 ***	4.43E-07	9.14E-01 ***	2.90E-02 **	1.65E-08	9.32E-01 ***	5.02E-09	1.79E-02 **	9.90E-01 ***
JAPAN-DS Basic Mats	3.90E-06	4.59E-02	9.38E-02	1.08E-02	6.24E-04	9.74E-01 ***	8.81E-03	1.40E-07	9.49E-01 ***
CANADA-DS Basic Mats	2.00E-02 ***	5.59E-03	9.68E-01 ***	2.57E-02 **	2.49E-08	9.60E-01 ***	5.27E-03	5.10E-03	9.75E-01 ***
US-DS Industrials	3.17E-02 *	3.29E-09	8.88E-01 ***	9.96E-03	1.98E-07	9.83E-01 ***	6.64E-02 **	7.04E-08	5.87E-01 **
UK-DS Industrials	2.08E-02 ***	2.14E-02 **	9.67E-01 ***	8.60E-02 **	4.37E-02	6.26E-01 ***	3.77E-02 **	5.15E-02 **	8.68E-01 ***
BRIC-DS Industrials	1.14E-02 *	3.46E-03	9.73E-01 ***	2.29E-02	7.12E-05	9.26E-01 ***	2.65E-02 **	1.14E-02	9.34E-01 ***
JAPAN-DS Industrials	1.24E-02	1.54E-03	4.34E-01	1.16E-02	8.03E-03	9.59E-01 *	3.10E-02	1.41E-06	2.74E-01
CANADA-DS Industrials	2.83E-07	1.51E-02 **	9.87E-01 ***	1.20E-08	7.61E-08	9.99E-01 ***	8.88E-09	3.81E-02 *	9.46E-01 ***
US-DS Consumer Gds	1.38E-02 **	8.81E-09	9.77E-01 ***	4.01E-03	2.81E-08	5.23E-01	2.44E-02	1.54E-02	9.07E-01 ***
UK-DS Consumer Gds	2.18E-02 ***	2.87E-02 **	9.61E-01 ***	1.80E-03	8.91E-02 **	9.21E-01 ***	3.84E-02 **	8.18E-02 **	8.59E-01 ***
BRIC-DS Consumer Gds	1.75E-02 **	9.30E-03 *	9.54E-01 ***	4.20E-03	5.67E-02	9.63E-01 ***	1.32E-08	3.18E-02 **	9.78E-01 ***
JAPAN-DS Consumer Gds	1.62E-02 *	1.42E-02 **	3.52E-01 *	6.69E-03 *	5.18E-08	9.86E-01 ***	6.31E-03	1.35E-02	9.53E-01 ***
CANADA-DS Consumer Gds	8.08E-03 **	1.45E-02 *	9.78E-01 ***	3.88E-02	2.80E-07	1.82E-06	3.74E-03 **	7.07E-09	9.94E-01 ***
US-DS Health Care	1.25E-02 *	8.94E-09	9.77E-01 ***	2.62E-02	1.37E-06	4.59E-02	9.24E-04	3.20E-07	9.99E-01 ***
UK-DS Health Care	2.57E-02 **	1.01E-02	9.63E-01 ***	3.71E-02	2.61E-08	9.42E-01 ***	3.21E-02	7.44E-02 **	8.90E-01 ***
BRIC-DS Health Care	5.24E-03	1.30E-08	9.76E-01 ***	3.56E-02	6.18E-08	4.12E-07	1.70E-02 *	1.37E-02	9.59E-01 ***
JAPAN-DS Health Care	1.85E-07	2.07E-02	1.40E-05	3.19E-10	5.16E-10	2.80E-01	1.08E-02	6.35E-08	9.60E-01 ***
CANADA-DS Health Care	1.58E-02	1.34E-02	9.00E-01 ***	2.48E-08	6.19E-03	9.85E-01 ***	3.06E-02	8.90E-04	9.23E-01 *
US-DS Consumer Svs	1.39E-02	2.35E-08	9.17E-01 ***	1.00E-02	2.94E-07	9.79E-01 ***	7.77E-02 **	6.13E-08	5.76E-01 ***
UK-DS Consumer Svs	3.07E-02 **	2.35E-02	9.50E-01 ***	2.90E-02	4.24E-02 *	8.83E-01 ***	5.39E-02 ***	3.30E-02 *	8.75E-01 ***
BRIC-DS Consumer Svs	5.91E-03	2.08E-02 *	9.79E-01 ***	3.32E-02	5.74E-02	7.69E-01 ***	1.91E-02 *	3.35E-02 **	9.45E-01 ***
JAPAN-DS Consumer Svs	9.56E-07	5.45E-02 *	3.95E-01	2.09E-02 *	3.21E-06	9.57E-01 ***	3.06E-06	1.57E-02	9.75E-01 ***
CANADA-DS Consumer Svs	2.24E-02	6.97E-03	8.51E-01 ***	1.88E-07	1.14E-02	9.62E-01 **	4.89E-08	1.59E-02	9.51E-01 **
US-DS Telecom	2.19E-02 *	2.63E-08	8.18E-01 ***	3.56E-03	7.48E-08	6.03E-01	3.94E-04	2.07E-02 *	9.85E-01 ***
UK-DS Telecom	1.00E-02	2.31E-02	9.72E-01 ***	7.85E-02 *	1.56E-01	1.41E-01	3.78E-02 **	7.49E-02 **	8.67E-01 ***
BRIC-DS Telecom	1.57E-03	1.29E-02 *	9.66E-01 ***	1.22E-07	9.93E-02 **	8.78E-01 ***	1.08E-03	2.32E-02 ***	9.85E-01 ***
JAPAN-DS Telecom	1.59E-09	5.12E-09	9.99E-01 ***	2.85E-08	1.31E-02	9.69E-01 ***	6.89E-03	4.62E-08	9.63E-01 ***
CANADA-DS Telecom	7.83E-03	2.50E-02	9.62E-01 ***	1.47E-06	5.46E-06	1.00E+00 ***	7.18E-09	4.42E-09	9.71E-01 ***
US-DS Utilities	9.45E-03 **	2.09E-08	9.79E-01 ***	1.84E-02 *	5.96E-08	9.52E-01 ***	5.13E-03 *	4.82E-03	9.92E-01 ***
UK-DS Utilities	1.01E-02 **	3.74E-02 ***	9.60E-01 ***	2.57E-02 *	3.65E-02 *	9.45E-01 ***	1.96E-02 *	6.41E-02 **	9.05E-01 ***
BRIC-DS Utilities	6.68E-03	1.48E-02	9.48E-01 ***	1.73E-02	8.75E-04	9.06E-01 ***	2.89E-02 *	1.79E-02	9.43E-01 ***
JAPAN-DS Utilities	4.16E-03	2.81E-02 *	9.38E-01 ***	2.56E-08	2.52E-02	9.83E-01 ***	6.71E-03	5.12E-08	9.71E-01 ***
CANADA-DS Utilities	1.14E-02	7.97E-04	9.73E-01 ***	6.34E-08	4.37E-02	8.90E-01 ***	1.17E-04	5.69E-02 **	9.38E-01 ***
US-DS Financials	2.53E-02 *	3.48E-09	9.39E-01 ***	4.50E-02	6.34E-07	4.92E-01 ***	2.26E-02 **	1.05E-02	9.10E-01 ***
UK-DS Financials	5.07E-02 *	7.03E-07	9.40E-01 ***	1.53E-08	4.35E-02 **	9.74E-01 ***	1.54E-02 **	5.90E-02 **	9.27E-01 ***
BRIC-DS Financials	2.88E-02 ***	1.91E-07	9.06E-01 ***	5.48E-02 *	3.42E-08	1.03E-07	2.50E-08	2.85E-02 *	9.79E-01 ***
JAPAN-DS Financials	1.48E-08	8.02E-02 **	3.62E-01 **	1.33E-02	1.64E-02	9.37E-01 ***	6.40E-03	1.25E-02	9.59E-01 ***
CANADA-DS Financials	2.29E-02 **	1.07E-02	9.37E-01 ***	7.56E-02 **	2.04E-07	9.94E-07	8.82E-08	2.88E-02 **	9.55E-01 ***
US-DS Technology	8.37E-03 *	1.07E-08	9.51E-01 ***	2.08E-07	1.47E-02	9.90E-01 ***	5.74E-02	1.33E-08	7.91E-01 ***
UK-DS Technology	5.74E-10	1.37E-02 *	9.91E-01 ***	8.09E-03	5.72E-02 *	9.20E-01 ***	1.10E-02	4.77E-02 **	9.01E-01 ***
BRIC-DS Technology	1.79E-04	2.64E-02 *	9.74E-01 ***	3.25E-09	9.76E-03	9.62E-01 ***	1.62E-02	6.77E-02 *	8.37E-01 ***
JAPAN-DS Technology	1.29E-02	1.14E-05	7.22E-01 ***	7.63E-03	5.21E-03	9.67E-01 ***	1.11E-02	3.77E-07	9.44E-01 ***
CANADA-DS Technology	7.71E-09	1.64E-02 **	9.87E-01 ***	2.28E-08	1.23E-02	9.07E-01 ***	3.77E-07	9.69E-03	9.94E-01 ***

Notes: Asymmetric Dynamic Conditional Correlation results. g parameter shows the asymmetric term in the DCC model

*** Denote statistical significance at 1% level.

** Denote statistical significance at 5% level.

* Denote statistical significance at 10% level.

Table 4.2. 2. ADCC results. Co-movements between Spain and sectors of real economy

US-DS Oil & Gas	1.14E-02	3.11E-08	0.978101 ***	2.15E-02	8.84E-03	0.963342 ***	7.14E-03	2.19E-02	0.968464 ***
UK-DS Oil & Gas	1.74E-02 ***	4.61E-03	0.977989 ***	2.36E-02 *	6.09E-02 **	0.931718 ***	2.73E-02 *	5.02E-02 *	0.889244 ***
BRIC-DS Oil & Gas	2.75E-08	4.19E-02 **	0.948622 ***	2.48E-02 **	1.02E-02	0.939195 ***	4.34E-03	3.75E-02 **	0.963752 ***
JAPAN-DS Oil & Gas	9.93E-03	1.34E-06	0.466614 *	3.13E-09	7.63E-03	0.978676 ***	4.61E-09	2.79E-02 **	0.969788 ***
CANADA-DS Oil & Gas	1.04E-02 **	2.40E-08	0.966601 ***	2.78E-02 **	2.92E-02 *	0.94606 ***	8.22E-03	1.69E-02	0.973304 ***
US-DS Basic Mats	2.08E-02	1.79E-04	0.967915 ***	2.11E-02	5.63E-07	0.966193 ***	1.92E-08	2.56E-02	0.959338 *
UK-DS Basic Mats	1.94E-02 **	3.62E-02 **	0.95437 ***	3.54E-02 **	2.45E-02	0.920734 ***	4.90E-04	4.72E-02 ***	0.96789 ***
BRIC-DS Basic Mats	8.40E-03	1.05E-08	0.987556 ***	1.16E-02	1.26E-02	0.930871 ***	2.16E-03	2.82E-02	0.974623 ***
JAPAN-DS Basic Mats	5.17E-08	2.31E-02	3.93E-06	3.14E-08	1.77E-02	0.97797 ***	1.15E-03	1.34E-02	0.961525 ***
CANADA-DS Basic Mats	1.28E-02 **	1.45E-02 **	0.976989 ***	2.99E-02 **	1.02E-07	0.940678 ***	1.10E-08	1.84E-03	0.979936 ***
US-DS Industrials	2.95E-02 **	1.38E-07	0.902891 ***	1.35E-08	3.27E-08	0.998988 ***	5.83E-02 **	6.91E-07	0.400359 *
UK-DS Industrials	1.82E-02 **	2.91E-02 **	0.965252 ***	6.52E-02 *	8.52E-08	0.804471 ***	1.85E-02	4.20E-02	0.916277 ***
BRIC-DS Industrials	1.98E-03	1.27E-03 **	0.997215 ***	5.57E-08	4.58E-02	0.920494 ***	7.57E-03	2.44E-02	0.957499 ***
JAPAN-DS Industrials	7.34E-04	3.10E-02	3.28E-05	3.55E-04	1.88E-02 **	0.977755 ***	5.59E-03	4.71E-03	0.965979 ***
CANADA-DS Industrials	1.00E-08	2.11E-02 ***	0.985729 ***	9.33E-10	3.39E-09	0.996791 ***	6.19E-09	5.10E-02	0.944729
US-DS Consumer Gds	1.29E-02	1.47E-09	0.980482 ***	1.18E-03	1.67E-08	0.84043 **	1.86E-02	3.04E-03	0.922805 ***
UK-DS Consumer Gds	1.40E-02 **	2.64E-02 **	0.970491 ***	1.49E-02	7.88E-02 **	0.922116 ***	2.48E-02	7.81E-02 **	0.891028 ***
BRIC-DS Consumer Gds	7.57E-03 **	2.52E-08	0.988392 ***	6.86E-03	3.55E-02	0.972319 ***	5.06E-03	2.98E-02 **	0.966844 ***
JAPAN-DS Consumer Gds	1.89E-02 **	1.14E-02 *	0.70344 ***	5.40E-03	8.52E-03	0.970751 ***	1.10E-02	9.08E-03	0.953065 ***
CANADA-DS Consumer Gds	9.19E-03 ***	2.53E-03	0.985345 ***	7.97E-04	7.31E-05	0.059379	9.48E-03 *	2.55E-08	0.96318 ***
US-DS Health Care	9.35E-03 **	4.97E-08	0.986103 ***	3.51E-03	7.45E-03	0.000234	1.44E-03	1.48E-02	0.97604 ***
UK-DS Health Care	1.63E-02 ***	2.95E-02 **	0.96439 ***	4.45E-02 **	7.21E-07	0.926964 ***	1.49E-02 *	6.79E-02 **	0.91232 ***
BRIC-DS Health Care	8.02E-03 **	2.08E-07	2.47E-05	1.37E-02	1.45E-07	3.22E-06	5.00E-08	2.29E-02 **	0.978502 ***
JAPAN-DS Health Care	5.16E-03	6.36E-09	0.990736 ***	1.87E-08	9.87E-03	0.977311	9.49E-03	3.26E-08	0.958896 ***
CANADA-DS Health Care	1.02E-07	1.87E-02 **	0.98321 ***	9.81E-08	5.74E-08	0.000184	5.29E-09	2.55E-02 **	0.980082 ***
US-DS Consumer Svs	3.48E-02 **	2.56E-06	0.881942 ***	3.10E-02 **	0.00E+00	3.28E-05 ***	3.65E-07	1.81E-02	0.96204 ***
UK-DS Consumer Svs	1.88E-02 **	3.97E-02 ***	0.953505 ***	3.81E-02 *	4.24E-02	0.899674 ***	2.54E-02 *	4.32E-02 **	0.914162 ***
BRIC-DS Consumer Svs	1.15E-02	1.25E-02	0.979497 ***	1.47E-01 **	5.67E-08	0.301971	2.03E-09	4.84E-02 ***	0.963394 ***
JAPAN-DS Consumer Svs	1.50E-07	6.23E-02 *	1.32E-05	4.91E-03	2.58E-02	0.946776 ***	2.39E-03	7.01E-03	0.971224 ***
CANADA-DS Consumer Svs	1.19E-02	9.96E-08	0.765198 ***	1.10E-08	2.06E-08	6.59E-05	7.39E-08	2.23E-02 *	0.333488
US-DS Telecom	1.92E-02 *	7.91E-09	0.855514 ***	2.21E-02	6.36E-08	0.762709 **	4.34E-10	2.02E-02 **	0.981391 ***
UK-DS Telecom	1.89E-02 ***	7.73E-03	0.96548 ***	2.00E-02	2.59E-02	0.928809 ***	1.53E-02	3.05E-02 *	0.950676 ***
BRIC-DS Telecom	4.54E-03	1.33E-02	0.95719 ***	2.45E-08	8.23E-02	0.896741 ***	3.66E-04	3.10E-02 **	0.975733 ***
JAPAN-DS Telecom	2.08E-07	2.76E-06	0.000779	6.93E-09	1.36E-08	1.37E-05	5.34E-03	1.58E-07	0.961687 ***
CANADA-DS Telecom	7.01E-03	2.64E-02 *	0.959227 ***	1.10E-02	3.69E-08	4.6E-07	3.30E-08	4.17E-03	0.972936 ***
US-DS Utilities	1.73E-02 **	6.57E-08	0.964249 ***	8.99E-02 ***	7.16E-07	0.490223 **	2.95E-03	3.87E-03	0.994606 ***
UK-DS Utilities	1.54E-02 ***	1.99E-02 **	0.969973 ***	2.96E-02 **	4.12E-02 *	0.924677 ***	1.51E-02	5.74E-02 *	0.924942 ***
BRIC-DS Utilities	2.69E-03	4.11E-02 **	0.927348 ***	6.73E-03	1.31E-01	0.051929	5.59E-03	3.46E-02 **	0.958588 ***
JAPAN-DS Utilities	8.33E-03	3.31E-02	0.727102 **	2.49E-06	3.29E-02	0.962454 ***	3.81E-03	1.59E-02	0.967083 ***
CANADA-DS Utilities	1.34E-02	1.31E-02	0.96083 ***	2.31E-03	3.25E-02	0.910393 ***	2.67E-08	3.73E-02 **	0.96849 ***
US-DS Financials	3.57E-02 **	8.37E-06	0.904249 ***	5.95E-02 **	1.26E-07	0.602695 ***	4.08E-02 *	6.62E-08	0.720692 **
UK-DS Financials	2.04E-02 ***	1.67E-02 **	0.969979 ***	7.99E-02 ***	1.10E-08	0.79619 ***	5.09E-02 **	1.65E-02	0.881548 ***
BRIC-DS Financials	2.96E-02 ***	2.11E-08	0.907246 ***	5.49E-02 **	7.42E-08	4.04E-07	2.00E-09	2.76E-02 **	0.972772 ***
JAPAN-DS Financials	1.98E-02 *	7.07E-08	0.856249 ***	5.08E-08	2.87E-02	0.954423 ***	5.39E-03	1.41E-02	0.95953 ***
CANADA-DS Financials	1.35E-02 **	2.19E-02	0.941705 ***	6.95E-02	6.72E-08	8.1E-07	7.23E-03	1.79E-02	0.958128 ***
US-DS Technology	1.50E-02	6.90E-10	0.965036 ***	4.28E-07	2.11E-06	0.999023 ***	3.97E-02 *	2.66E-09	0.797743 ***
UK-DS Technology	1.61E-07	9.70E-03	0.994586 ***	1.10E-02	6.35E-02 **	0.897282 ***	2.79E-02	8.26E-03	0.87401 ***
BRIC-DS Technology	9.99E-08	2.07E-02 ***	0.982243 ***	6.57E-08	0.00E+00	0.964249 ***	6.39E-09	4.34E-02	0.883955 ***
JAPAN-DS Technology	1.66E-02 ***	1.96E-07	0.847429 ***	1.10E-03	1.24E-02	0.970982 ***	1.02E-02	1.57E-04	0.964788 ***
CANADA-DS Technology	1.73E-08	1.59E-02	0.984504 ***	1.76E-10	8.62E-03	0.875026 ***	3.64E-09	6.40E-03 *	0.995789 ***

Notes: Asymmetric Dynamic Conditional Correlation results. g parameter shows the asymmetric term in the DCC model

*** Denote statistical significance at 1% level.

** Denote statistical significance at 5% level.

* Denote statistical significance at 10% level.

Table 4.2. 3. ADCC results. Co-movements between Italy and sectors of real economy

US-DS Oil & Gas	9.46E-03 **	9.21E-09	0.986579 ***	2.55E-02	5.18E-03	0.956716 ***	3.32E-03	2.22E-02 *	0.980815 ***
UK-DS Oil & Gas	2.33E-02 **	9.10E-03	0.968109 ***	4.52E-02 **	5.84E-02 *	0.907529 ***	1.35E-02 *	9.22E-02 ***	0.892096 ***
BRIC-DS Oil & Gas	2.67E-06	4.43E-02 ***	0.956628 ***	5.50E-02 **	6.83E-08	0.906322 ***	1.98E-02 *	1.46E-02	0.960675 ***
JAPAN-DS Oil & Gas	3.76E-06	7.20E-02 **	0.165644 *	1.16E-08	2.20E-04	0.98628 ***	1.56E-03	8.00E-08	4.74E-05
CANADA-DS Oil & Gas	1.40E-02 **	1.87E-08	0.97154 ***	2.55E-02 **	3.48E-02 *	0.946056 ***	7.00E-03	2.55E-02 *	0.974849 ***
US-DS Basic Mats	1.40E-02 **	9.40E-10	0.982872 ***	2.22E-02 **	5.25E-07	0.965184 ***	1.86E-08	2.07E-02	0.964947 ***
UK-DS Basic Mats	4.26E-02 ***	4.42E-02 **	0.916697 ***	2.77E-02 **	4.67E-02 *	0.930997 ***	6.88E-03 *	3.62E-02 **	0.967271 ***
BRIC-DS Basic Mats	1.05E-02 *	1.64E-08	0.97877 ***	3.59E-02 **	1.36E-07	0.908449 ***	5.15E-03	1.34E-02	0.984358 ***
JAPAN-DS Basic Mats	4.76E-03	1.59E-02	0.92202 ***	8.33E-03	1.91E-05	0.965991 ***	1.31E-02	3.97E-07	7.2E-06
CANADA-DS Basic Mats	1.28E-02 *	1.12E-02	0.979409 ***	2.80E-02 **	2.35E-06	0.953946 ***	1.40E-03	9.92E-08	0.976348 ***
US-DS Industrials	1.44E-02 *	2.02E-07	0.967582 ***	1.09E-08	6.08E-03	0.996381 ***	5.00E-03	1.81E-02 *	0.962341 ***
UK-DS Industrials	2.00E-02 **	2.35E-02 *	0.966482 ***	4.71E-02	3.27E-02	0.863592 **	3.91E-02 *	3.19E-02 *	0.899926 ***
BRIC-DS Industrials	3.00E-09	1.83E-03 ***	0.9985 ***	8.06E-03	3.75E-02	0.920229 ***	1.74E-02 *	9.37E-03	0.95311 ***
JAPAN-DS Industrials	2.82E-06	6.52E-02 **	3.03E-05	7.18E-03	1.23E-02	0.958683 ***	1.35E-02 *	1.01E-07	2E-06
CANADA-DS Industrials	2.00E-03	1.65E-02 *	0.984063 ***	1.59E-08	2.56E-03	0.998421 ***	1.15E-09	2.99E-02 *	0.966894 ***
US-DS Consumer Gds	2.46E-02 **	1.97E-09	0.949112 ***	5.36E-03	1.35E-05	0.434901 ***	6.84E-02 **	1.06E-06	0.541187 ***
UK-DS Consumer Gds	1.60E-02 **	4.62E-02 **	0.956723 ***	2.85E-07	8.92E-02 *	0.924581 ***	1.82E-02	8.73E-02 ***	0.879467 ***
BRIC-DS Consumer Gds	1.05E-02	9.76E-03	0.977337 ***	2.65E-03	4.98E-02 *	0.968004 ***	5.90E-08	2.77E-02 ***	0.98215 ***
JAPAN-DS Consumer Gds	2.01E-02	1.32E-02 **	0.573217 *	3.41E-03	4.61E-03	0.97182 ***	8.11E-03	1.19E-07	0.931782 ***
CANADA-DS Consumer Gds	5.76E-03 **	1.60E-02	0.983984 ***	6.86E-03	1.35E-07	0.989785 ***	2.59E-08	1.95E-08	0.697777
US-DS Health Care	9.67E-03 *	1.87E-07	0.985194 ***	3.16E-02	1.98E-06	7.01E-06	6.10E-06	3.68E-05	0.999706 ***
UK-DS Health Care	2.56E-02 ***	1.48E-02 *	0.958935 ***	1.27E-02	2.96E-02	0.953407 ***	4.25E-03	9.34E-02 ***	0.913017 ***
BRIC-DS Health Care	3.60E-07	2.36E-07	0.999841 ***	5.62E-02	1.09E-06	9.45E-06	3.38E-10	1.27E-02 **	0.990487 ***
JAPAN-DS Health Care	7.04E-03	1.21E-07	0.970267	1.04E-08	8.06E-03	0.970608	5.26E-03	5.89E-09	0.958597 ***
CANADA-DS Health Care	1.27E-03	1.95E-02 **	0.979331 ***	4.64E-09	6.74E-03	0.973003 ***	3.46E-03	8.59E-03	0.980859 ***
US-DS Consumer Svs	1.34E-03	1.51E-02	0.970159 ***	3.09E-02	2.54E-02	0.396976 *	8.42E-10	1.57E-02	0.975446 ***
UK-DS Consumer Svs	3.05E-02 **	3.85E-02 **	0.936633 ***	2.44E-02 *	4.49E-02 *	0.914895 ***	3.34E-02 **	1.98E-02	0.910413 ***
BRIC-DS Consumer Svs	2.48E-07	2.97E-02 **	0.975172 ***	7.42E-03	5.78E-02 *	0.865331 ***	3.00E-03	2.65E-02	0.975802 ***
JAPAN-DS Consumer Svs	1.38E-03	1.69E-02 *	0.948115 ***	4.71E-03	1.95E-02	0.942689 ***	3.82E-02	9.93E-08	3.5E-06
CANADA-DS Consumer Svs	6.51E-03	3.71E-03	0.98925 ***	6.11E-09	1.37E-08	0.961909 ***	1.55E-02	1.19E-06	0.398435
US-DS Telecom	6.06E-03	1.44E-02	0.966897 ***	3.79E-03	1.23E-07	0.607279	6.18E-09	2.66E-02 *	0.979298 ***
UK-DS Telecom	1.32E-02 *	3.56E-02 **	0.960474 ***	5.90E-02 *	1.96E-01	0.563892 **	1.13E-02	4.39E-02 *	0.948099 ***
BRIC-DS Telecom	3.04E-03	1.92E-02 **	0.968235 ***	1.40E-02	8.73E-02 *	0.847434 ***	1.11E-03	2.14E-02 **	0.986369 ***
JAPAN-DS Telecom	2.95E-07	2.52E-02 **	2.03E-05	2.51E-09	2.29E-02	0.971901 ***	2.37E-07	3.42E-07	0.000543
CANADA-DS Telecom	1.11E-02	1.48E-02	0.961012 ***	2.63E-07	9.08E-07	0.999806 ***	4.26E-07	2.69E-03	0.972378 ***
US-DS Utilities	1.22E-02 **	1.76E-08	0.947886 ***	2.29E-02	8.94E-08	0.908991 ***	4.01E-03 *	3.02E-03	0.994022 ***
UK-DS Utilities	9.08E-03	4.21E-02 *	0.955962 ***	2.75E-02 *	5.31E-02 **	0.93824 ***	1.92E-02	5.77E-02 *	0.913369 ***
BRIC-DS Utilities	2.54E-03	2.33E-02 *	0.953692 ***	1.10E-01 **	2.20E-06	0.15844	2.15E-02 *	4.53E-03	0.960697 ***
JAPAN-DS Utilities	6.52E-09	2.04E-02	0.807511 ***	4.72E-09	3.07E-02 **	0.97917 ***	4.31E-08	4.68E-08	0.904428 ***
CANADA-DS Utilities	1.92E-02 **	7.51E-03	0.947379 ***	9.51E-07	4.19E-02 *	0.88783 ***	4.93E-08	4.06E-02 **	0.962132 ***
US-DS Financials	2.39E-02 **	2.60E-09	0.945154 ***	2.80E-02	1.27E-06	0.549928 ***	3.49E-08	3.61E-02 *	0.957827 ***
UK-DS Financials	4.43E-02 ***	3.16E-02 **	0.93312 ***	5.47E-02 **	1.69E-08	0.857418 ***	1.30E-02	6.02E-02 **	0.925352 ***
BRIC-DS Financials	1.61E-02 *	1.01E-02	0.930482 ***	4.03E-02	1.80E-07	5.33E-07	5.62E-04	9.58E-03	0.993867 ***
JAPAN-DS Financials	1.43E-02	1.12E-02	0.873528 ***	5.73E-03	2.59E-02	0.941646 ***	5.72E-02 **	5.73E-07	3.69E-06
CANADA-DS Financials	4.79E-03 *	2.20E-02 **	0.97876 ***	2.91E-02	2.48E-06	8.82E-06	5.04E-07	2.32E-02 *	0.971834 ***
US-DS Technology	7.46E-04	2.30E-03	0.997909 ***	4.18E-02	1.50E-06	0.487315 *	4.21E-02 *	3.01E-07	0.759702 ***
UK-DS Technology	1.44E-10	1.20E-02 ***	0.993302 ***	2.03E-02 *	5.46E-02 **	0.921577 ***	5.37E-02 **	6.89E-07	0.806245 ***
BRIC-DS Technology	2.25E-02 *	2.69E-03	0.77055 ***	3.49E-09	1.85E-02	0.957039 ***	7.12E-10	2.28E-02 **	0.979232 ***
JAPAN-DS Technology	1.27E-03	6.91E-02 *	1.34E-05	4.91E-03	6.97E-03	0.968194 ***	2.22E-02	4.22E-09	5.59E-08
CANADA-DS Technology	7.91E-09	1.36E-02 *	0.991214 ***	4.09E-08	2.80E-02	0.922114 ***	1.13E-09	9.02E-03 **	0.994524 ***

Notes: Asymmetric Dynamic Conditional Correlation results. g parameter shows the asymmetric term in the DCC model

*** Denote statistical significance at 1% level.

** Denote statistical significance at 5% level.

* Denote statistical significance at 10% level.

The univariate estimations are, in most time series, statistically significant; this highlights the absence of normality in the indexes. The ADCC results (Table 4.2.1, 4.2.2 and 4.2.3) note that the statistically significant parameters for each period are mixed. However, the Sovereign Debt crisis period contains the most statistically significant parameters of the *g* term; this shows the presence of asymmetry in variances. Table 4.2.4, 4.2.5 and 4.2.6 show the conditional and unconditional correlations for the ADCC model in addition to the results of the copula functions for all periods and estimations. There is evidence that can be derived from the correlations. To understand this evidence more effectively, I created two more Tables (4.2.7, 4.2.8) where correlations are categorized by country and by sector, respectively.

The average conditional correlation ADCC shows similar behavior to the copulas functions. This finding means that, where we observe a higher conditional correlation of the ADCC model, there was also incremental correlations for the copula functions. This conclusion can be confirmed for all cases and estimations. Furthermore, the Gaussian copula was very close to the average ADCC correlations; in most cases, the difference was less than $\pm$ 5%. This finding is very interesting, as it shows that the average ADCC correlation is nearly the same as the Gaussian copula correlation. Regarding only the correlations and the investigation for interdependence, it is preferable to solely use the Gaussian copula, as it can be calculated much faster and easier than the ADCC approach. This statement covers only the average correlation; time varying copulas are not the focus of this research.

Table 4.2. 4. Conditional and unconditional correlations between France and real economy sectors for ADCC model and copulas

	Early Eurozone Period						Subprime Crisis						Debt Crisis					
	Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula		Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula		Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula	
US-DS Oil & Gas	0.2030	0.2052	0.2202	0.2982	0.0262	0.1376	0.5748	0.5314	0.5481	0.9758	0.3604	0.4377	0.4992	0.5024	0.5330	0.8491	0.3495	0.3751
UK-DS Oil & Gas	0.5492	0.5041	0.5266	0.8637	0.3367	0.3877	0.5210	0.6800	0.7323	1.8116	0.5245	0.6421	0.5641	0.6133	0.6634	1.2966	0.4526	0.5202
BRIC-DS Oil & Gas	0.2580	0.3453	0.3632	0.4956	0.1146	0.2439	0.6383	0.6156	0.6262	1.2775	0.3880	0.5349	0.4842	0.5704	0.5918	1.0225	0.3542	0.4508
JAPAN-DS Oil & Gas	0.1177	0.1177	0.1117	0.1478	0.0000	0.0470	0.2110	0.2590	0.2915	0.4410	0.0617	0.2329	0.1054	0.2060	0.2300	0.2791	0.0341	0.1086
CANADA-DS Oil & Gas	0.1541	0.1554	0.1468	0.1732	0.0024	0.0461	0.3644	0.4744	0.5039	0.8942	0.2592	0.4298	0.4603	0.4594	0.4915	0.7075	0.2978	0.3139
US-DS Basic Mats	0.3835	0.3695	0.3772	0.5363	0.1971	0.2467	0.5587	0.5815	0.5588	1.0251	0.3794	0.4557	0.5440	0.5432	0.5656	0.9207	0.3739	0.4032
UK-DS Basic Mats	-0.0472	0.5103	0.5349	0.8357	0.2704	0.3918	0.6519	0.7309	0.7333	1.7713	0.5606	0.6220	0.5099	0.6342	0.6866	1.3547	0.4679	0.5362
BRIC-DS Basic Mats	0.2313	0.2354	0.2459	0.3013	0.0358	0.1254	0.6619	0.6522	0.6701	1.3596	0.4326	0.5473	-0.9988	0.5450	0.5775	0.9736	0.3616	0.4277
JAPAN-DS Basic Mats	0.2210	0.2267	0.2145	0.3010	0.0105	0.1501	0.2845	0.3028	0.3597	0.5415	0.1397	0.2736	0.2336	0.2320	0.2286	0.3135	0.0051	0.1598
CANADA-DS Basic Mats	0.2972	0.3533	0.3634	0.5063	0.1408	0.2421	0.4100	0.3798	0.3526	0.6411	0.0987	0.3510	0.1970	0.2435	0.2598	0.3389	0.0614	0.1552
US-DS Industrials	0.4323	0.4293	0.4449	0.6463	0.2745	0.2918	0.6759	0.6342	0.6185	1.2349	0.4245	0.5130	0.6383	0.6363	0.6466	1.1671	0.4676	0.4733
UK-DS Industrials	-0.4054	0.5590	0.5752	1.0272	0.3373	0.4608	0.8503	0.8483	0.8580	2.8219	0.6550	0.7440	0.7708	0.7787	0.8157	2.1301	0.6457	0.6614
BRIC-DS Industrials	0.1829	0.2123	0.2052	0.2597	0.0063	0.1165	0.4949	0.4960	0.5284	0.9395	0.2291	0.4485	0.4442	0.4651	0.4814	0.7529	0.2149	0.3675
JAPAN-DS Industrials	0.2660	0.2663	0.2480	0.3453	0.0428	0.1693	0.2900	0.3204	0.3611	0.5611	0.1135	0.2944	0.2367	0.2364	0.2281	0.3191	0.0061	0.1664
CANADA-DS Industrials	0.1718	0.3893	0.4205	0.6097	0.2347	0.2798	0.7237	0.5584	0.5855	1.0942	0.3255	0.4913	0.4332	0.4977	0.5301	0.8457	0.3027	0.3892
US-DS Consumer Gds	0.4196	0.4122	0.4219	0.6198	0.2682	0.2827	0.5903	0.5902	0.5595	1.0906	0.3565	0.4833	0.5686	0.5782	0.5965	1.0399	0.4101	0.4463
UK-DS Consumer Gds	-0.4245	0.4157	0.4117	0.6133	0.1812	0.3058	0.6287	0.7038	0.7326	1.7449	0.5242	0.6216	0.6243	0.6619	0.7062	1.4786	0.4923	0.5670
BRIC-DS Consumer Gds	0.2057	0.2436	0.2467	0.3009	0.0615	0.1164	-0.9999	0.5021	0.5737	1.0243	0.3661	0.4455	0.1616	0.4980	0.5276	0.8043	0.3089	0.3606
JAPAN-DS Consumer Gds	0.2248	0.2271	0.2096	0.2902	0.0177	0.1386	0.2742	0.2973	0.3362	0.5152	0.0949	0.2687	0.1820	0.2223	0.2182	0.3053	0.0009	0.1610
CANADA-DS Consumer Gds	0.1539	0.3324	0.3435	0.4635	0.1745	0.2040	0.4752	0.4747	0.4608	0.8058	0.1111	0.4240	0.4644	0.4559	0.4802	0.7496	0.2357	0.3609
US-DS Health Care	0.3091	0.3025	0.2842	0.3847	0.1125	0.1718	0.5419	0.5417	0.5219	0.9839	0.2672	0.4639	-0.9996	0.5298	0.5495	0.9003	0.3311	0.4061
UK-DS Health Care	0.4028	0.4895	0.5278	0.9090	0.3182	0.4153	0.5449	0.5222	0.5463	0.9463	0.3240	0.4294	0.4254	0.5286	0.5861	0.9985	0.3570	0.4432
BRIC-DS Health Care	0.1125	0.1194	0.0966	0.1018	0.0007	0.0087	0.3973	0.3968	0.4095	0.6509	0.1286	0.3380	0.2628	0.3321	0.3361	0.4774	0.0841	0.2447
JAPAN-DS Health Care	0.2118	0.2142	0.1943	0.2679	0.0124	0.1244	0.2088	0.2088	0.2440	0.3724	0.0491	0.1935	0.2031	0.1977	0.1743	0.2315	0.0017	0.1023
CANADA-DS Health Care	0.2838	0.3005	0.3287	0.4525	0.1297	0.2093	0.2139	0.2846	0.3358	0.5129	0.0529	0.2817	0.1945	0.2044	0.2508	0.2959	0.0723	0.1075
US-DS Consumer Svs	0.4182	0.4173	0.4456	0.6532	0.3099	0.2828	0.5966	0.5779	0.5588	1.0745	0.3510	0.4784	0.5800	0.5771	0.5863	1.0029	0.3786	0.4387
UK-DS Consumer Svs	0.6155	0.7057	0.7317	1.6971	0.5008	0.6152	0.8106	0.8171	0.8292	2.3531	0.6358	0.6938	0.7547	0.7593	0.7999	2.0011	0.6075	0.6488
BRIC-DS Consumer Svs	-0.9996	0.2371	0.2381	0.3320	0.0102	0.1767	0.6200	0.6254	0.6516	1.2138	0.4465	0.4960	0.4560	0.5389	0.5489	0.9124	0.3048	0.4172
JAPAN-DS Consumer Svs	0.2078	0.2183	0.2045	0.2906	0.0031	0.1499	0.2733	0.2636	0.3088	0.4530	0.1029	0.2261	0.1074	0.2021	0.1807	0.2328	0.0055	0.0968
CANADA-DS Consumer Svs	0.4011	0.4039	0.4085	0.5867	0.2150	0.2720	0.4840	0.5164	0.5384	0.9350	0.2364	0.4496	0.4141	0.4448	0.4809	0.7619	0.1829	0.3791
US-DS Telecom	0.3393	0.3380	0.3582	0.4848	0.2081	0.2099	0.5421	0.5420	0.5276	0.9371	0.3323	0.4311	0.0798	0.4339	0.4752	0.7032	0.2721	0.3242
UK-DS Telecom	0.4708	0.6011	0.6483	1.1748	0.4252	0.4879	0.5979	0.6028	0.6394	1.2566	0.4529	0.5080	0.4189	0.4953	0.5685	0.9615	0.3351	0.4318
BRIC-DS Telecom	0.3250	0.3732	0.3697	0.5360	0.1281	0.2692	0.5087	0.5652	0.6069	1.1824	0.3742	0.5058	-0.9699	0.5166	0.5388	0.8711	0.2839	0.4038
JAPAN-DS Telecom	0.2536	0.1744	0.1606	0.2077	0.0218	0.0718	0.1151	0.1834	0.2059	0.3339	0.0019	0.1921	0.1511	0.1472	0.1300	0.1616	0.0001	0.0505
CANADA-DS Telecom	0.1419	0.2803	0.3208	0.4223	0.1291	0.1902	-0.5812	0.4060	0.4467	0.6721	0.2438	0.3202	0.2728	0.2613	0.2841	0.3850	0.0648	0.1850
US-DS Utilities	0.2081	0.1982	0.1971	0.2625	0.0420	0.1097	0.5265	0.5224	0.5260	0.9452	0.2851	0.4417	-1.0000	0.4056	0.4348	0.6081	0.2449	0.2730
UK-DS Utilities	0.1126	0.3717	0.4059	0.5940	0.2107	0.2781	0.4441	0.6079	0.6274	1.2132	0.4230	0.5108	0.4361	0.5021	0.5649	0.8907	0.3634	0.3878
BRIC-DS Utilities	0.3133	0.3535	0.3539	0.5004	0.1113	0.2508	0.6136	0.6103	0.6206	1.2147	0.3820	0.5143	0.4829	0.5286	0.5485	0.9050	0.3108	0.4110
JAPAN-DS Utilities	0.0346	0.1192	0.1138	0.1400	0.0035	0.0313	-0.9995	0.0779	0.1086	0.1538	0.0013	0.0477	0.1330	0.1320	0.1111	0.1339	0.0002	0.0294
CANADA-DS Utilities	0.1313	0.1468	0.1404	0.1829	0.0048	0.0594	0.3645	0.4121	0.4420	0.7544	0.1052	0.4010	0.1705	0.3267	0.3977	0.5402	0.2004	0.2462
US-DS Financials	0.4071	0.4027	0.4204	0.6050	0.2605	0.2729	0.5671	0.5660	0.5341	0.9738	0.3269	0.4478	0.6023	0.6068	0.6173	1.1203	0.4240	0.4710
UK-DS Financials	0.7291	0.7023	0.7231	1.6648	0.5245	0.6034	0.5209	0.8395	0.8398	2.4669	0.6761	0.6914	0.7592	0.7954	0.8342	2.3964	0.6474	0.7004
BRIC-DS Financials	0.3425	0.3390	0.3326	0.4585	0.1058	0.2232	0.6177	0.6168	0.6235	1.1872	0.4249	0.4914	0.2644	0.5364	0.5578	0.9537	0.3073	0.4355
JAPAN-DS Financials	0.1781	0.1934	0.1761	0.2523	0.0003	0.1291	0.2864	0.3136	0.3579	0.5361	0.1115	0.2756	0.1803	0.2188	0.2003	0.2596	0.0098	0.1096
CANADA-DS Financials	0.3387	0.3576	0.3779	0.5417	0.1883	0.2521	0.5556	0.5544	0.5605	1.0225	0.2905	0.4732	0.5058	0.5569	0.5993	1.0326	0.3624	0.4535
US-DS Technology	0.3975	0.3972	0.3853	0.5147	0.2535	0.2138	0.4014	0.5594	0.5537	0.9747	0.3700	0.4342	0.5620	0.5587	0.5699	0.9254	0.4044	0.3980
UK-DS Technology	0.5104	0.6201	0.6382	1.1169	0.4291	0.4649	0.7427	0.7630	0.7868	1.9108	0.6082	0.6297	0.5743	0.6059	0.6502	1.2124	0.4324	0.4977
BRIC-DS Technology	-0.0445	0.1801	0.1761	0.2077	0.0229	0.0646	0.3574	0.3809	0.4147	0.6581	0.1610	0.3309	0.2330	0.2827	0.3191	0.4471	0.0798	0.2213
JAPAN-DS Technology	0.2566	0.2566	0.2346	0.3175	0.0303	0.1494	0.2980	0.3145	0.3746	0.5697	0.1335	0.2906	0.2257	0.2233	0.2204	0.3056	0.0017	0.1600
CANADA-DS Technology	0.0865	0.3605	0.3882	0.5441	0.1833	0.2560	0.2648	0.2742	0.2670	0.4265	0.0154	0.2478	-0.1963	0.2341	0.2765	0.3334	0.1007	0.1283

Table 4.2. 5. Conditional and unconditional correlations between Spain and real economy sectors for ADCC model and copulas

	Early Eurozone Period						Subprime Crisis						Debt Crisis					
	Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula		Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula		Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula	
US-DS Oil & Gas	0.1785	0.1731	0.1774	0.2405	0.0175	0.0968	0.4748	0.4662	0.4843	0.7982	0.2817	0.3821	0.3429	0.4540	0.4713	0.6819	0.2776	0.3112
UK-DS Oil & Gas	0.4006	0.4316	0.4532	0.6513	0.2762	0.2918	0.4042	0.5980	0.6390	1.3245	0.4288	0.5446	0.4950	0.5291	0.5721	0.9161	0.3712	0.3952
BRIC-DS Oil & Gas	0.1959	0.3180	0.3480	0.4649	0.1326	0.2178	0.5858	0.5815	0.5883	1.1433	0.3208	0.5064	0.3429	0.4906	0.5255	0.7767	0.3121	0.3463
JAPAN-DS Oil & Gas	0.0985	0.0985	0.0963	0.1249	0.0000	0.0327	0.1377	0.2033	0.2390	0.3738	0.0172	0.2070	0.0075	0.1745	0.1880	0.2116	0.0368	0.0541
CANADA-DS Oil & Gas	0.1397	0.1367	0.1292	0.1448	0.0061	0.0222	0.3133	0.4345	0.4517	0.7472	0.2210	0.3727	0.2946	0.4157	0.4370	0.5820	0.2400	0.2582
US-DS Basic Mats	0.3600	0.3501	0.3612	0.5114	0.1858	0.2313	0.5521	0.5222	0.5129	0.8613	0.3332	0.3991	0.4426	0.4936	0.5062	0.7665	0.3038	0.3494
UK-DS Basic Mats	0.1727	0.4603	0.4759	0.6983	0.2494	0.3246	0.6688	0.6766	0.6741	1.4145	0.4755	0.5546	0.2365	0.5476	0.5918	0.9587	0.3756	0.4158
BRIC-DS Basic Mats	0.2538	0.2498	0.2434	0.3067	0.0185	0.1386	0.6018	0.6065	0.6167	1.1986	0.3538	0.5173	0.2761	0.4723	0.5133	0.7828	0.3023	0.3558
JAPAN-DS Basic Mats	0.1952	0.1979	0.1902	0.2569	0.0060	0.1168	0.0838	0.2565	0.3119	0.4654	0.1139	0.2349	0.1304	0.1769	0.1737	0.2266	0.0011	0.0970
CANADA-DS Basic Mats	-0.1141	0.3270	0.3398	0.4534	0.1203	0.2094	0.3444	0.3224	0.3058	0.5413	0.0559	0.3065	0.2066	0.2299	0.2351	0.3049	0.0293	0.1422
US-DS Industrials	0.3946	0.3916	0.4062	0.5770	0.2352	0.2643	1.0000	0.5615	0.5760	1.0418	0.3951	0.4527	0.5682	0.5667	0.5648	0.9007	0.3839	0.3895
UK-DS Industrials	-0.5607	0.5028	0.5199	0.8395	0.3078	0.3848	0.7953	0.7909	0.7958	2.1123	0.5858	0.6705	0.6248	0.6469	0.6775	1.2487	0.5117	0.4838
BRIC-DS Industrials	0.1992	0.2373	0.2026	0.2662	0.0039	0.1256	0.4285	0.4803	0.5045	0.9144	0.2166	0.4422	0.3198	0.4039	0.4248	0.6082	0.1639	0.3003
JAPAN-DS Industrials	0.2081	0.2114	0.2059	0.2828	0.0155	0.1337	0.0839	0.2745	0.3159	0.4902	0.0873	0.2611	0.1726	0.1894	0.1782	0.2376	0.0008	0.1087
CANADA-DS Industrials	-0.0361	0.3552	0.3948	0.5395	0.2221	0.2387	0.6250	0.5101	0.5376	0.9279	0.2822	0.4376	0.3081	0.4283	0.4595	0.6573	0.2684	0.2981
US-DS Consumer Gds	0.4021	0.3836	0.3852	0.5591	0.2161	0.2628	0.5466	0.5449	0.5331	0.9644	0.3429	0.4368	0.5043	0.5081	0.5210	0.7891	0.3402	0.3499
UK-DS Consumer Gds	-0.6371	0.3658	0.3687	0.5458	0.1496	0.2766	0.5838	0.6646	0.6840	1.4649	0.4800	0.5655	0.4023	0.4917	0.5448	0.8265	0.3455	0.3638
BRIC-DS Consumer Gds	0.2861	0.2761	0.2651	0.3260	0.0635	0.1331	-0.9996	0.4898	0.5262	0.8844	0.3067	0.4017	0.2821	0.4429	0.4796	0.7027	0.2418	0.3290
JAPAN-DS Consumer Gds	0.1746	0.1790	0.1668	0.2369	0.0003	0.1151	0.2126	0.2692	0.3043	0.4617	0.0789	0.2407	0.1593	0.1862	0.1741	0.2273	0.0003	0.0991
CANADA-DS Consumer Gds	0.2637	0.3172	0.3192	0.4062	0.1790	0.1627	0.4474	0.4474	0.4359	0.7327	0.1270	0.3841	0.3923	0.3915	0.4014	0.5647	0.1800	0.2712
US-DS Health Care	0.2890	0.2757	0.2475	0.3293	0.0894	0.1389	0.4874	0.4879	0.4862	0.8630	0.2216	0.4238	0.4060	0.4791	0.4836	0.7224	0.2597	0.3399
UK-DS Health Care	-0.1203	0.4287	0.4495	0.7031	0.2521	0.3335	0.4825	0.4635	0.4865	0.7861	0.2891	0.3617	0.3185	0.4321	0.4750	0.6680	0.2660	0.3024
BRIC-DS Health Care	0.1254	0.1254	0.1079	0.1338	0.0000	0.0334	0.3741	0.3740	0.3771	0.6294	0.0722	0.3426	0.0410	0.2960	0.3098	0.4163	0.0586	0.2082
JAPAN-DS Health Care	0.2117	0.2037	0.1764	0.2378	0.0061	0.1045	0.0946	0.1752	0.2082	0.3380	0.0242	0.1796	0.1711	0.1645	0.1436	0.1729	0.0004	0.0550
CANADA-DS Health Care	-0.0040	0.2679	0.2961	0.3981	0.1063	0.1833	0.2773	0.2773	0.3013	0.4533	0.0567	0.2454	-0.1222	0.2108	0.2355	0.2653	0.0559	0.0874
US-DS Consumer Svs	0.4047	0.4004	0.4163	0.6076	0.2508	0.2779	0.5602	0.5579	0.5397	0.9683	0.3451	0.4367	0.4569	0.4980	0.5074	0.7682	0.3088	0.3477
UK-DS Consumer Svs	0.3975	0.6335	0.6548	1.2792	0.4307	0.5239	0.7557	0.7690	0.7915	1.9623	0.6125	0.6399	0.6069	0.6350	0.6772	1.2402	0.4934	0.4862
BRIC-DS Consumer Svs	-0.9968	0.2575	0.2426	0.3501	0.0037	0.1935	0.6130	0.6063	0.6097	1.0745	0.3962	0.4589	0.2086	0.4786	0.5004	0.7545	0.2580	0.3530
JAPAN-DS Consumer Svs	0.1710	0.1782	0.1715	0.2375	0.0003	0.1120	0.1565	0.2385	0.2870	0.4450	0.0769	0.2306	0.1275	0.1548	0.1385	0.1590	0.0015	0.0415
CANADA-DS Consumer Svs	0.3703	0.3702	0.3813	0.5484	0.1753	0.2625	0.4872	0.4872	0.5061	0.8409	0.2154	0.4130	0.3896	0.3925	0.4082	0.5839	0.1583	0.2887
US-DS Telecom	0.3178	0.3167	0.3255	0.4351	0.1597	0.1938	0.5219	0.5206	0.5028	0.8616	0.2980	0.4053	0.2105	0.4043	0.4275	0.5953	0.2251	0.2745
UK-DS Telecom	0.5370	0.5625	0.5942	0.9958	0.3937	0.4310	0.5773	0.6010	0.6184	1.1636	0.4412	0.4792	0.3389	0.4424	0.4915	0.7434	0.2831	0.3397
BRIC-DS Telecom	0.3450	0.3802	0.3824	0.5832	0.1186	0.3003	0.4421	0.5234	0.5701	1.0993	0.3066	0.4943	0.2104	0.4629	0.4897	0.7182	0.2450	0.3356
JAPAN-DS Telecom	0.1438	0.1438	0.1376	0.1876	0.0040	0.0750	0.1803	0.1803	0.1892	0.3092	0.0030	0.1736	0.1141	0.1113	0.1019	0.1154	0.0000	0.0196
CANADA-DS Telecom	0.1537	0.2754	0.3101	0.4201	0.0962	0.2034	0.3585	0.3585	0.3956	0.5713	0.2025	0.2711	0.1866	0.1944	0.2126	0.2583	0.0478	0.0955
US-DS Utilities	0.2121	0.1996	0.1640	0.2145	0.0373	0.0732	0.4974	0.4937	0.4902	0.8285	0.2759	0.3915	-1.0000	0.3582	0.3886	0.5137	0.1936	0.2282
UK-DS Utilities	0.0361	0.3647	0.3753	0.5285	0.1841	0.2463	0.5038	0.5821	0.6066	1.1889	0.3982	0.5097	0.3268	0.4329	0.4836	0.6767	0.3018	0.2929
BRIC-DS Utilities	0.2739	0.3466	0.3615	0.5363	0.1068	0.2765	0.5830	0.5883	0.5831	1.1541	0.2918	0.5152	0.3200	0.4515	0.4888	0.7218	0.2490	0.3377
JAPAN-DS Utilities	0.0756	0.0928	0.0921	0.1190	0.0001	0.0273	-0.1684	0.0701	0.0884	0.1501	0.0000	0.0593	0.0190	0.1047	0.0971	0.1122	0.0000	0.0172
CANADA-DS Utilities	0.0485	0.1349	0.1307	0.1704	0.0013	0.0584	0.3455	0.3845	0.4119	0.6607	0.1079	0.3532	0.0032	0.2932	0.3528	0.4405	0.1751	0.1825
US-DS Financials	0.3908	0.3847	0.3926	0.5558	0.2164	0.2587	0.5353	0.5327	0.5181	0.8825	0.3365	0.4028	0.5622	0.5602	0.5522	0.9115	0.3533	0.4056
UK-DS Financials	-0.1493	0.6448	0.6553	1.3294	0.4524	0.5344	0.8099	0.8045	0.8083	2.0981	0.6690	0.6415	0.7450	0.7450	0.7610	1.6865	0.5764	0.5880
BRIC-DS Financials	0.3505	0.3456	0.3385	0.4824	0.0829	0.2463	0.5939	0.5929	0.5876	1.1383	0.3674	0.4931	0.3212	0.4677	0.4916	0.7437	0.2538	0.3521
JAPAN-DS Financials	0.1721	0.1718	0.1550	0.2207	0.0000	0.1061	0.2086	0.2955	0.3461	0.5166	0.1177	0.2647	0.1445	0.1887	0.1691	0.2075	0.0081	0.0706
CANADA-DS Financials	0.2743	0.3247	0.3535	0.4973	0.1642	0.2327	0.5493	0.5479	0.5413	0.9313	0.3333	0.4252	0.4570	0.4986	0.5244	0.8049	0.3111	0.3665
US-DS Technology	0.3710	0.3639	0.3439	0.4630	0.2072	0.1978	1.0000	0.4962	0.5193	0.8441	0.3502	0.3806	0.4988	0.4969	0.4958	0.7226	0.3232	0.3184
UK-DS Technology	0.0889	0.5699	0.5847	0.9757	0.3763	0.4262	0.6924	0.7100	0.7278	1.5590	0.5514	0.5680	0.5056	0.5085	0.5388	0.8151	0.3605	0.3484
BRIC-DS Technology	-0.1369	0.1768	0.1574	0.2044	0.0074	0.0773	0.3000	0.3519	0.3821	0.6282	0.1047	0.3342	0.1925	0.2389	0.2660	0.3616	0.0365	0.1773
JAPAN-DS Technology	0.2067	0.2068	0.1937	0.2658	0.0059	0.1262	0.2266	0.2906	0.3504	0.5416	0.1094	0.2845	0.1893	0.1839	0.1760	0.2310	0.0002	0.1033
CANADA-DS Technology	0.1575	0.3282	0.3588	0.5028	0.1418	0.2446	0.2544	0.2594	0.2448	0.3759	0.0128	0.2116	-0.0981	0.2071	0.2266	0.2826	0.0442	0.1142

Table 4.2. 6. Conditional and unconditional correlations between Italy and real economy sectors for ADCC model and copulas

	Early Eurozone Period						Subprime Crisis						Debt Crisis					
	Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula		Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula		Unconditional correlation ADCC	Average conditional ADCC	Gaussian Copula	Clayton Copula	SJC Copula	
US-DS Oil & Gas	0.2438	0.2070	0.2068	0.2768	0.0275	0.1198	0.5301	0.4987	0.5164	0.8528	0.3537	0.3858	0.1073	0.4579	0.4892	0.7181	0.3035	0.3224
UK-DS Oil & Gas	0.4101	0.4615	0.4832	0.7312	0.2964	0.3313	0.5019	0.6192	0.6578	1.4944	0.4234	0.5923	0.4604	0.5377	0.5847	0.9672	0.3790	0.4193
BRIC-DS Oil & Gas	0.1572	0.3309	0.3496	0.4672	0.1276	0.2212	0.5991	0.5755	0.5892	1.1782	0.3538	0.5132	0.4741	0.5254	0.5493	0.8718	0.3333	0.3919
JAPAN-DS Oil & Gas	0.0785	0.0898	0.0986	0.1344	0.0000	0.0381	0.1906	0.2133	0.2248	0.3482	0.0176	0.1894	0.1919	0.1919	0.1990	0.2402	0.0248	0.0829
CANADA-DS Oil & Gas	0.1455	0.1371	0.1296	0.1575	0.0001	0.0441	0.2952	0.4510	0.4810	0.8127	0.2747	0.3912	0.0689	0.4105	0.4499	0.6077	0.2633	0.2659
US-DS Basic Mats	0.4056	0.3465	0.3547	0.4853	0.1817	0.2166	0.5679	0.5462	0.5310	0.8890	0.3828	0.3941	0.4501	0.4908	0.5204	0.7796	0.3273	0.3470
UK-DS Basic Mats	0.3259	0.4539	0.4731	0.6970	0.2113	0.3374	0.5667	0.6688	0.6923	1.5208	0.5107	0.5755	0.3499	0.5751	0.6136	1.0142	0.3994	0.4338
BRIC-DS Basic Mats	0.2133	0.2106	0.2177	0.2800	0.0108	0.1267	0.6233	0.6140	0.6359	1.2374	0.3959	0.5203	0.2480	0.4881	0.5207	0.7970	0.3217	0.3576
JAPAN-DS Basic Mats	0.1492	0.1770	0.1812	0.2370	0.0244	0.0902	0.2598	0.2639	0.3009	0.4474	0.1040	0.2253	0.2013	0.2012	0.1827	0.2536	0.0003	0.1236
CANADA-DS Basic Mats	-0.1559	0.3318	0.3365	0.4716	0.0924	0.2360	0.3933	0.3624	0.3387	0.5770	0.1252	0.3078	0.2132	0.2220	0.2357	0.2981	0.0355	0.1323
US-DS Industrials	0.4272	0.4202	0.4299	0.6005	0.2701	0.2634	1.0000	0.5782	0.5815	1.0441	0.4327	0.4422	0.5336	0.5631	0.5876	0.9443	0.4051	0.4006
UK-DS Industrials	-0.4371	0.5097	0.5230	0.8519	0.2944	0.3974	0.7900	0.7936	0.7827	2.1754	0.5580	0.6874	0.6722	0.6814	0.7154	1.4137	0.5275	0.5353
BRIC-DS Industrials	0.1331	0.1988	0.1756	0.2369	0.0012	0.1109	0.4422	0.4821	0.5091	0.8821	0.2463	0.4220	0.3811	0.4095	0.4227	0.6160	0.1721	0.3047
JAPAN-DS Industrials	0.1923	0.1992	0.1969	0.2565	0.0201	0.1096	0.2184	0.2672	0.2955	0.4527	0.0741	0.2398	0.2076	0.2075	0.1856	0.2609	0.0002	0.1327
CANADA-DS Industrials	0.1772	0.3635	0.3932	0.5585	0.1955	0.2625	1.0000	0.5314	0.5535	0.9895	0.3189	0.4542	0.3339	0.4396	0.4782	0.6974	0.2833	0.3156
US-DS Consumer Gds	0.4195	0.4063	0.4118	0.5909	0.2586	0.2681	0.5468	0.5467	0.5196	0.9258	0.3585	0.4180	0.5196	0.5172	0.5343	0.8282	0.3597	0.3644
UK-DS Consumer Gds	-0.5907	0.3759	0.3717	0.5476	0.1727	0.2679	0.5261	0.6292	0.6504	1.3380	0.4502	0.5390	0.4552	0.5269	0.5707	0.9026	0.3695	0.3964
BRIC-DS Consumer Gds	0.1500	0.2488	0.2332	0.2824	0.0670	0.1020	-1.0000	0.4878	0.5528	0.9413	0.3471	0.4177	-0.1826	0.4385	0.4704	0.6625	0.2634	0.2975
JAPAN-DS Consumer Gds	0.1749	0.1785	0.1757	0.2386	0.0181	0.1026	0.2454	0.2684	0.2901	0.4353	0.0741	0.2244	0.1966	0.1966	0.1768	0.2447	0.0000	0.1212
CANADA-DS Consumer Gds	-0.3208	0.3362	0.3420	0.4508	0.1829	0.1925	0.4847	0.4288	0.4340	0.7272	0.1327	0.3822	0.4075	0.4075	0.4284	0.6258	0.1940	0.3047
US-DS Health Care	0.3170	0.2985	0.2769	0.3653	0.1170	0.1571	0.4868	0.4864	0.4653	0.8262	0.2399	0.4036	-0.2853	0.4763	0.4947	0.7393	0.2810	0.3405
UK-DS Health Care	0.3314	0.4374	0.4838	0.7780	0.2736	0.3656	0.3970	0.4812	0.5016	0.8031	0.3112	0.3671	0.2838	0.4520	0.4949	0.7099	0.2612	0.3296
BRIC-DS Health Care	0.9999	0.1171	0.0885	0.1126	0.0000	0.0219	0.4108	0.4098	0.4161	0.6579	0.1413	0.3392	-0.2288	0.3089	0.3137	0.4421	0.0545	0.2304
JAPAN-DS Health Care	0.1847	0.1793	0.1678	0.2138	0.0195	0.0775	0.1464	0.1815	0.2009	0.3069	0.0314	0.1528	0.1652	0.1617	0.1345	0.1727	0.0001	0.0614
CANADA-DS Health Care	0.0640	0.2737	0.3012	0.4072	0.1090	0.1861	0.2150	0.2509	0.2932	0.4380	0.0521	0.2362	0.1271	0.2087	0.2392	0.2702	0.0644	0.0884
US-DS Consumer Svs	0.3548	0.4009	0.4256	0.4256	0.2798	0.2671	0.5494	0.5503	0.5222	0.8997	0.3596	0.4043	0.4433	0.5047	0.5275	0.8164	0.3273	0.3674
UK-DS Consumer Svs	0.5558	0.6379	0.6544	1.2772	0.4202	0.5255	0.7318	0.7524	0.7608	1.8127	0.5645	0.6243	0.6484	0.6571	0.6995	1.3690	0.4945	0.5315
BRIC-DS Consumer Svs	-0.2701	0.2157	0.2221	0.3180	0.0003	0.1779	0.5922	0.6071	0.6254	1.1105	0.4385	0.4612	0.2549	0.4882	0.5042	0.7734	0.2777	0.3589
JAPAN-DS Consumer Svs	0.1211	0.1696	0.1687	0.2284	0.0058	0.0979	0.1811	0.2259	0.2607	0.3757	0.0743	0.1837	0.1636	0.1634	0.1373	0.1735	0.0002	0.0621
CANADA-DS Consumer Svs	0.2755	0.3708	0.3793	0.5604	0.1639	0.2746	0.4849	0.4892	0.4976	0.8081	0.2332	0.3960	0.3993	0.3992	0.4247	0.6370	0.1553	0.3222
US-DS Telecom	0.2770	0.3286	0.3480	0.4577	0.1875	0.1967	0.5157	0.5155	0.4920	0.8019	0.3164	0.3736	0.1106	0.4097	0.4414	0.6384	0.2311	0.3000
UK-DS Telecom	0.3757	0.5529	0.5876	0.9946	0.3636	0.4372	0.5470	0.5653	0.6001	1.0876	0.4281	0.4565	0.3030	0.4605	0.5137	0.7964	0.2885	0.3686
BRIC-DS Telecom	0.2707	0.3550	0.3377	0.4890	0.1036	0.2467	0.5152	0.5572	0.5795	1.1047	0.3494	0.4861	-0.9723	0.4691	0.4918	0.7278	0.2650	0.3367
JAPAN-DS Telecom	0.1046	0.1080	0.1153	0.1573	0.0019	0.0480	-0.0345	0.1681	0.1924	0.3162	0.0057	0.1759	0.1285	0.1285	0.1036	0.1260	0.0000	0.0288
CANADA-DS Telecom	0.2022	0.2675	0.3038	0.4076	0.1132	0.1874	-0.9728	0.3732	0.3910	0.5972	0.1912	0.2965	0.2090	0.2090	0.2315	0.2897	0.0464	0.1184
US-DS Utilities	0.2066	0.2012	0.1928	0.2432	0.0425	0.0887	0.5065	0.5025	0.5088	0.8508	0.3128	0.3923	-0.9999	0.3746	0.4008	0.5464	0.2042	0.2479
UK-DS Utilities	0.0959	0.3523	0.3703	0.5195	0.1683	0.2451	0.0587	0.5593	0.5937	1.0822	0.3944	0.4703	0.3565	0.4367	0.4928	0.6859	0.3146	0.2928
BRIC-DS Utilities	0.2693	0.3380	0.3389	0.4931	0.0980	0.2517	0.6172	0.6148	0.6153	1.1928	0.3872	0.5057	0.4551	0.4734	0.4965	0.7717	0.2687	0.3620
JAPAN-DS Utilities	0.0807	0.0950	0.0929	0.1223	0.0002	0.0270	-0.9183	0.0713	0.0867	0.1300	0.0008	0.0323	0.1130	0.1132	0.0924	0.1169	0.0000	0.0232
CANADA-DS Utilities	0.1026	0.1365	0.1309	0.1740	0.0006	0.0596	0.3365	0.3786	0.4013	0.6367	0.0944	0.3433	0.0645	0.3024	0.3504	0.4502	0.1549	0.2005
US-DS Financials	0.4041	0.3947	0.4068	0.5771	0.2393	0.2631	0.5400	0.5394	0.5106	0.8644	0.3555	0.3925	0.4963	0.5595	0.5790	0.9721	0.3828	0.4223
UK-DS Financials	0.5175	0.6541	0.6792	1.4295	0.4722	0.5579	0.8142	0.8121	0.8018	2.2193	0.6509	0.6708	0.7396	0.7673	0.7893	1.9073	0.5984	0.6307
BRIC-DS Financials	0.3125	0.3258	0.3204	0.4361	0.0850	0.2130	0.5955	0.5950	0.5905	1.0951	0.3969	0.4681	-0.9951	0.4799	0.4996	0.7783	0.2659	0.3682
JAPAN-DS Financials	0.1366	0.1488	0.1387	0.1968	0.0003	0.0861	0.2187	0.2785	0.3195	0.4753	0.0831	0.2477	0.1906	0.1899	0.1650	0.2104	0.0040	0.0801
CANADA-DS Financials	0.0089	0.3267	0.3598	0.5052	0.1694	0.2358	0.5357	0.5354	0.5447	0.9730	0.3347	0.4465	0.4288	0.5054	0.5476	0.8535	0.3306	0.3840
US-DS Technology	0.0657	0.4065	0.3699	0.4946	0.2298	0.2094	0.5429	0.5414	0.5251	0.8342	0.3851	0.3632	0.5027	0.5014	0.5164	0.7634	0.3561	0.3291
UK-DS Technology	-0.0384	0.5567	0.5598	0.9165	0.3268	0.4159	0.6551	0.7003	0.7249	1.5727	0.5214	0.5783	0.5430	0.5405	0.5702	0.9264	0.3636	0.4051
BRIC-DS Technology	0.1808	0.1822	0.1630	0.1974	0.0217	0.0607	0.3234	0.3716	0.3957	0.6404	0.1372	0.3313	-0.0003	0.2515	0.2778	0.3725	0.0668	0.1728
JAPAN-DS Technology	0.1840	0.1916	0.1831	0.2385	0.0094	0.0993	0.2556	0.2799	0.3274	0.4970	0.1016	0.2564	0.1955	0.1954	0.1796	0.2456	0.0002	0.1178
CANADA-DS Technology	-0.2522	0.3364	0.3629	0.4886	0.1517	0.2269	0.2027	0.2449	0.2492	0.3938	0.0178	0.2264	-0.5084	0.2201	0.2528	0.3006	0.0822	0.1098

Overall, the correlations in both methodologies (ADCC and copulas) present the same behavior. Correlations increase rapidly in the Subprime crisis period and subsequently decrease in the Debt crisis period, but generally correlations remained higher than the first period (Early Eurozone period). Table 8 present the correlations categorized by country. The UK appears to be the most correlated market with the Eurozone countries in all periods. In second place is the US market, followed by BRICs, Canada and Japan. At this point, we must note that the Canadian market had higher correlations than BRICs only in the Early Eurozone period. In the periods that followed, this changed in all cases; BRICs were found to have higher correlations than the Canadian market. Additionally, the French economy appears to be the most correlated with the remainder of the major economies in all periods according to Table 4.2.7.

Table 4.2. 7. Correlations categorized by country

	FRANCE CAC 40		SPAIN IBEX 35		ITALY FTSE MIB	
			Early Eurozone Period			
	correlation	% change	correlation	% change	correlation	% change
US	0.3513		0.3230		0.3417	
UK	0.5601		0.5048		0.5089	
BRIC	0.2634		0.2681		0.2485	
JAPAN	0.1941		0.1635		0.1528	
CANADA	0.3159		0.2925		0.2960	
			Subprime Crisis			
US	0.5577	58.73%	0.5173	60.18%	0.5239	53.33%
UK	0.7220	28.90%	0.6746	33.64%	0.6674	31.13%
BRIC	0.5593	112.38%	0.5270	96.55%	0.5412	117.81%
JAPAN	0.2745	41.42%	0.2447	49.69%	0.2358	54.35%
CANADA	0.4414	39.72%	0.4081	39.49%	0.4115	39.03%
			Debt Crisis			
US	0.5473	-1.85%	0.4869	-5.88%	0.4973	-5.07%
UK	0.6625	-8.24%	0.5612	-16.81%	0.5840	-12.49%
BRIC	0.4921	-12.02%	0.4348	-17.51%	0.4440	-17.97%
JAPAN	0.1970	-28.24%	0.1588	-35.12%	0.1653	-29.91%
CANADA	0.3868	-12.38%	0.3378	-17.23%	0.3481	-15.40%

In Table 4.2.8, I categorized the correlations by sectors. Specifically, I categorized the sectors by the period and market of correlation. The evidence here is worth noting. In all periods, “financials” is the sector that depicts the most increased correlations, followed by “Industrials” and “Consumer Services”. Surprisingly, significant sectors such as “Health Care” and “Utilities” were in the last positions in all cases.

Table 4.2. 8. Correlations categorized by sector

	FRANCE CAC 40				SPAIN IBEX 35				ITALY FTSE MIB			
	Correlations	% change	Ranking	Position change	Correlations	% change	Ranking	Position change	Correlations	% change	Ranking	Position change
Early Eurozone Period												
Oil & Gas	0.2696		9		0.2362		9		0.2494		9	
Basic Mats	0.3431		6		0.3196		6		0.3083		6	
Industrials	0.3750		3		0.3428		4		0.3410		3	
Consumer Gds	0.3264		7		0.3027		7		0.3080		7	
Health Care	0.2858		8		0.2579		8		0.2624		8	
Consumer Svs	0.4011		2		0.3706		2		0.3645		2	
Telecom	0.3625		5		0.3428		3		0.3304		5	
Utilities	0.2400		10		0.2262		10		0.2249		10	
Financials	0.4025		1		0.3766		1		0.3755		1	
Technology	0.3637		4		0.3284		5		0.3312		4	
Subprime Crisis												
Oil & Gas	0.5262	95.18%	5	+4	0.4686	98.39%	6	+3	0.4827	93.52%	5	+4
Basic Mats	0.5322	55.10%	4	+2	0.4805	50.38%	5	+1	0.4954	60.69%	4	+2
Industrials	0.5809	54.91%	1	+2	0.5347	55.99%	3	+1	0.5375	57.61%	2	+1
Consumer Gds	0.5231	60.24%	6	+1	0.4899	61.88%	4	+3	0.4808	56.09%	6	+1
Health Care	0.4012	40.38%	10	-2	0.3637	41.04%	10	-2	0.3687	40.49%	10	-2
Consumer Svs	0.5687	41.80%	3	-1	0.5393	45.50%	2	0	0.5292	45.17%	3	-1
Telecom	0.4726	30.39%	7	-2	0.4460	30.09%	7	-4	0.4434	34.20%	7	-2
Utilities	0.4555	89.76%	9	+1	0.4299	90.04%	9	+1	0.4332	92.65%	9	+1
Financials	0.5806	44.25%	2	-1	0.5575	48.01%	1	0	0.5528	47.21%	1	0
Technology	0.4689	28.91%	8	-4	0.4332	31.92%	8	-3	0.4360	31.65%	8	-4
Debt Crisis												
Oil & Gas	0.4861	-7.62%	5	0	0.4258	-9.13%	4	+2	0.4396	-8.93%	4	+1
Basic Mats	0.4516	-15.14%	6	-2	0.3940	-18.00%	6	-1	0.4050	-18.24%	6	-2
Industrials	0.5316	-8.48%	2	-1	0.4540	-15.10%	2	+1	0.4691	-12.73%	2	0
Consumer Gds	0.4945	-5.46%	4	+2	0.4141	-15.47%	5	-1	0.4267	-11.24%	5	+1
Health Care	0.3689	-8.04%	10	0	0.3230	-11.19%	10	0	0.3285	-10.91%	10	0
Consumer Svs	0.5119	-9.99%	3	0	0.4391	-18.59%	3	-1	0.4506	-14.85%	3	0
Telecom	0.3851	-18.52%	9	-2	0.3338	-25.15%	9	-2	0.3459	-22.00%	9	-2
Utilities	0.3952	-13.24%	7	+2	0.3451	-19.71%	7	+2	0.3533	-18.44%	7	+2
Financials	0.5523	-4.88%	1	+1	0.4959	-11.06%	1	0	0.5082	-8.05%	1	0
Technology	0.3941	-15.95%	8	0	0.3339	-22.94%	8	0	0.3506	-19.60%	8	0

Notes: Columns near correlations denote rankinks in each period of the data.

The methodology uses the ADCC model of Cappiello (2006) to identify and simultaneously quantify the contagion channels among the time series. I rerun the approach again with copula functions for the same periods and indices to compare the estimated correlations with the ADCC model.

During the Early Eurozone period, according to the correlations of Tables 4.2., 4.2.5 and 4.2.6, we observe a weak spillover effect. The overall average was near 0.3164 to 0.3215 (ADCC and Gaussian copula respectively). All the indexes show that they are more connected with the UK and the US, respectively. This finding can be also confirmed from Table 4.2.7, which show close to 0.56 for the UK and 0.35 for the US. See also Figures 4.2.1 to 4.2.9 which illustrate the correlations $R_{(t)}$ for the ADCC model for the Early Eurozone period, the Subprime crisis and the Sovereign Debt crisis period, respectively. Evidence show that there appears to be an upward trend for UK and US indexes for all sectors and cases.

Figure 4.2. 1. Correlations $R_{(t)}$ in Early Eurozone Period – France with real economy sectors

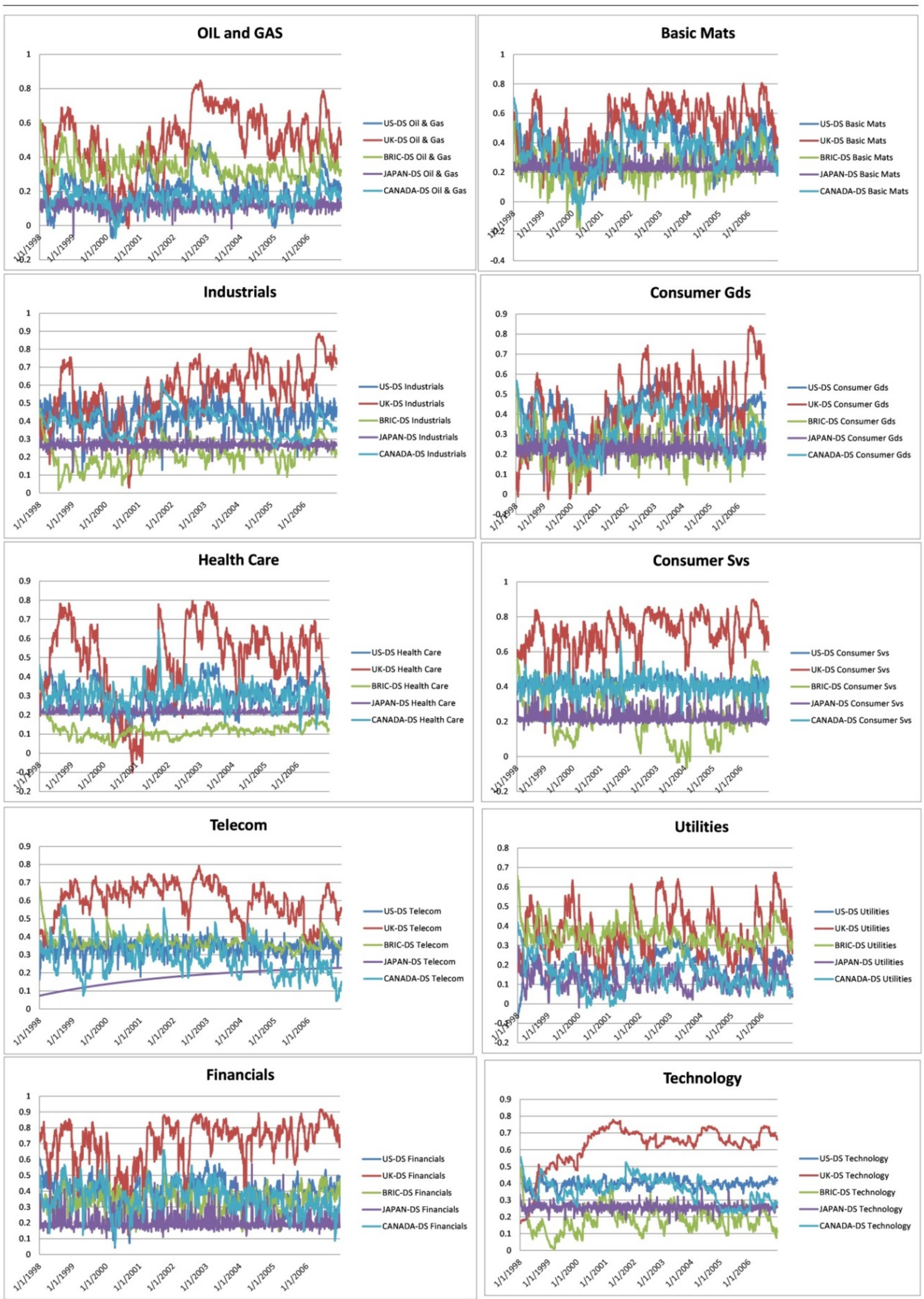


Figure 4.2. 2. Correlations $R_{(t)}$ in Early Eurozone Period – Spain with real economy sectors

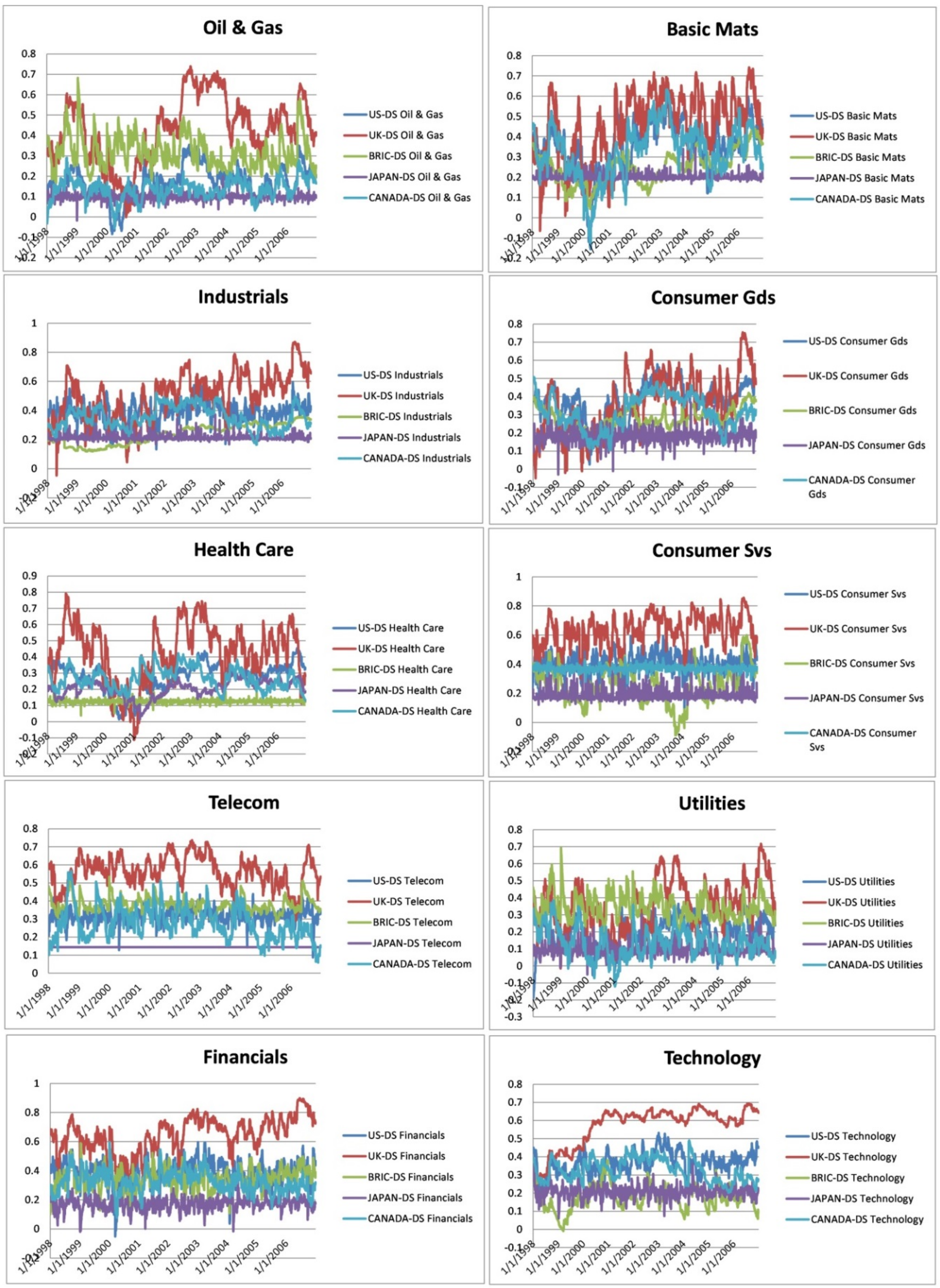
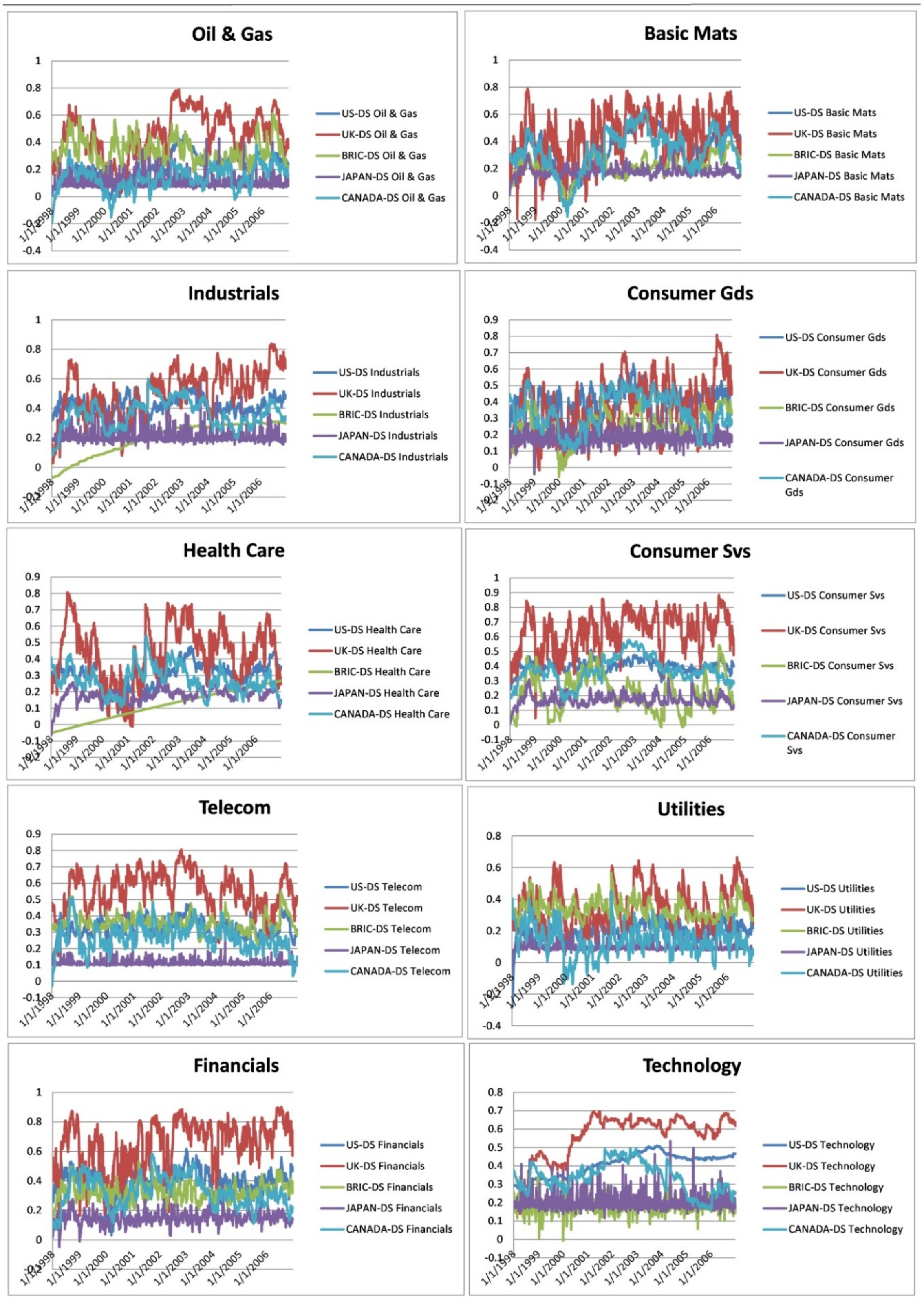


Figure 4.2. 3. Correlations $R_{(t)}$ in Early Eurozone Period – Italy with real economy sectors



During the Subprime crisis period, we observe increased correlations in all cases of the estimations. The order of correlations did not change significantly. This finding means that the UK and BRICs are the leading economies that present the most increased conditional correlations between their sectors and the Eurozone countries; BRICs are now in second place, marginally in front of the US (their correlations were very close, lower than 2%). The most notable evidence is that, in all cases, France, Spain and Italy clearly depict the events of the crisis on the "Oil and Gas" and "Basic Materials" sectors; we observe a harsh volatile period between April to October of 2008. Nevertheless, this finding was observed only with these two specific sectors of each economy.

Focusing on the Debt crisis period, we observe a decrease in all correlations in all cases. However, the correlations for both models (ADCC and copula functions) remained at higher levels than the Early Eurozone period. The order of correlations is the same as the first period, which means that the UK and the US are in first place; the US economy surpassed the level of interdependence of BRICs with the Eurozone countries. It can be stated that there was a small downward trend in the correlations for certain sectors.

The French economy was the most correlated with the sectors of the countries that were explored in this research. This finding means that, if a possible financial shock is produced in the European stock markets, the French economy can transmit the financial contagion to the rest of the world economies including the UK and the US more easily than Spain or Italy can. Conversely, the UK was the most correlated economy with the Eurozone countries; this can provide a logical explanation as it occurs due to geographical and European Union reasons. The UK is geographically excessively close to the Eurozone area, and it is also a member of the European Union, which makes the stock markets more correlated and eventually produces more interdependence. This finding applies only to the sample period (until 31st December 2015); things in stock markets may change rapidly, specifically after strong events like the UK's withdrawal from the European Union via Brexit in June of 2016 (Samitas and Kampouris, 2017a; Samitas et al., 2017).

Figure 4.2. 4. Correlations $R_{(t)}$ in Subprime crisis – France with real economy sectors

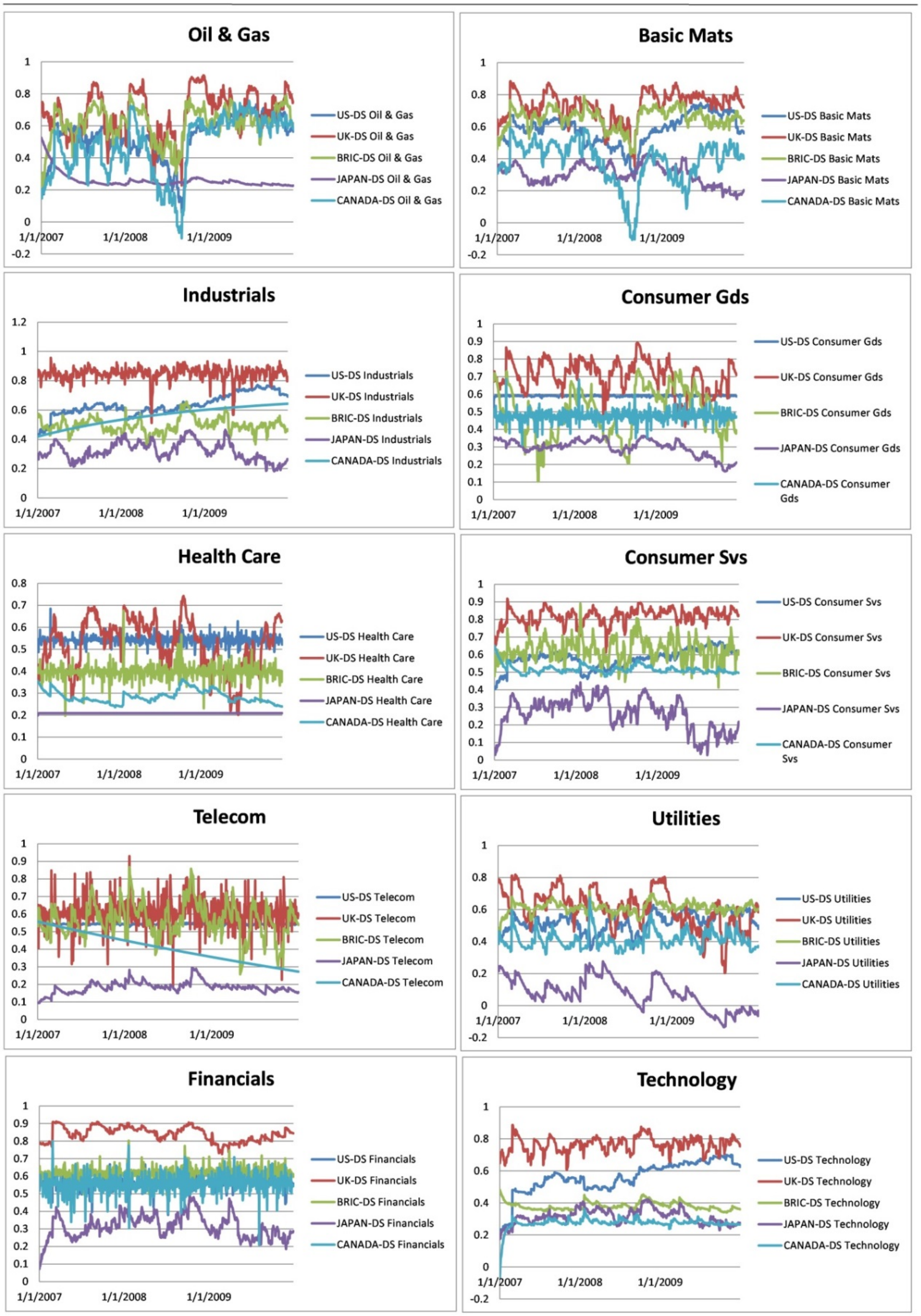


Figure 4.2. 5. Correlations R(t) in Subprime crisis – Spain with real economy sectors

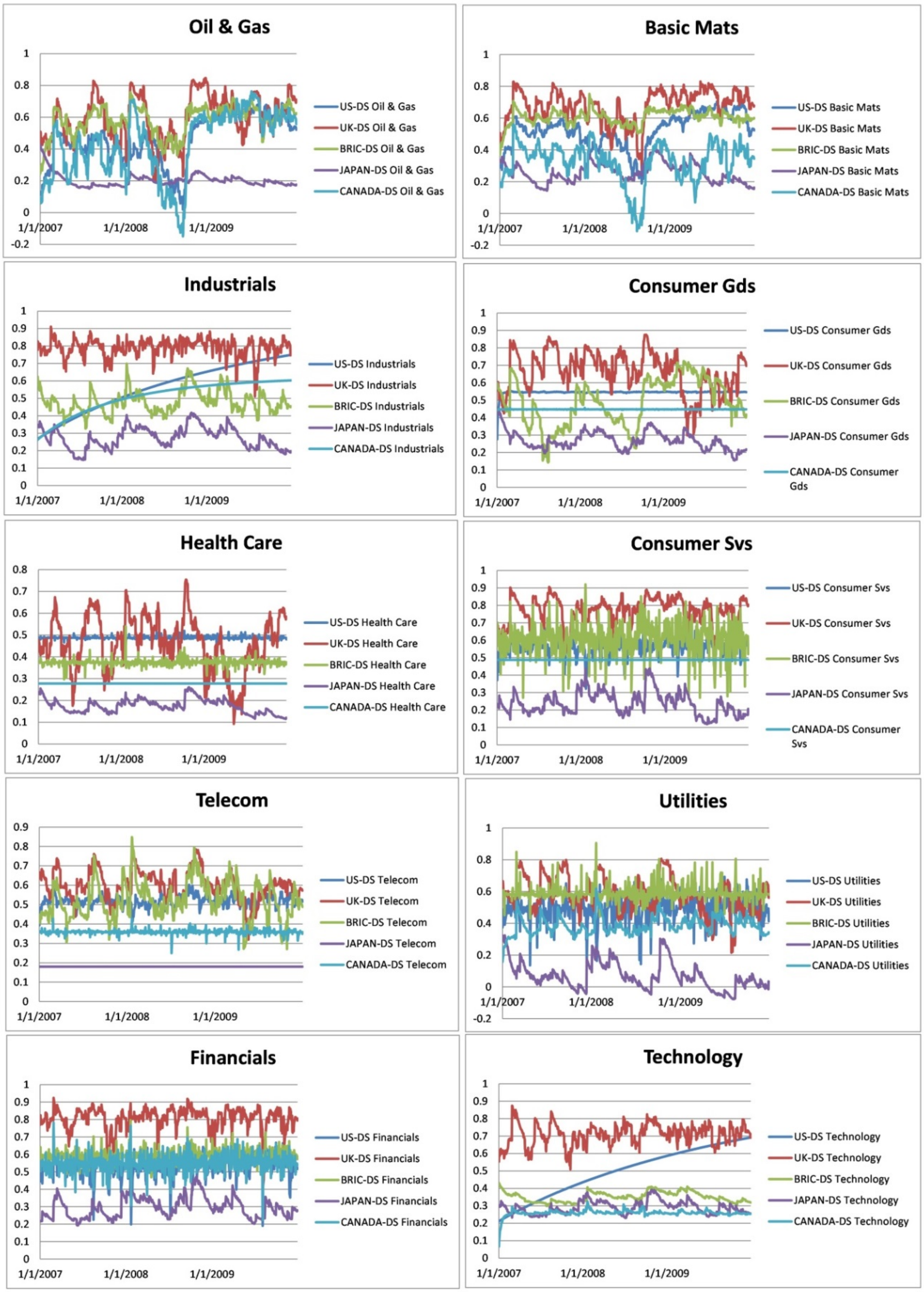
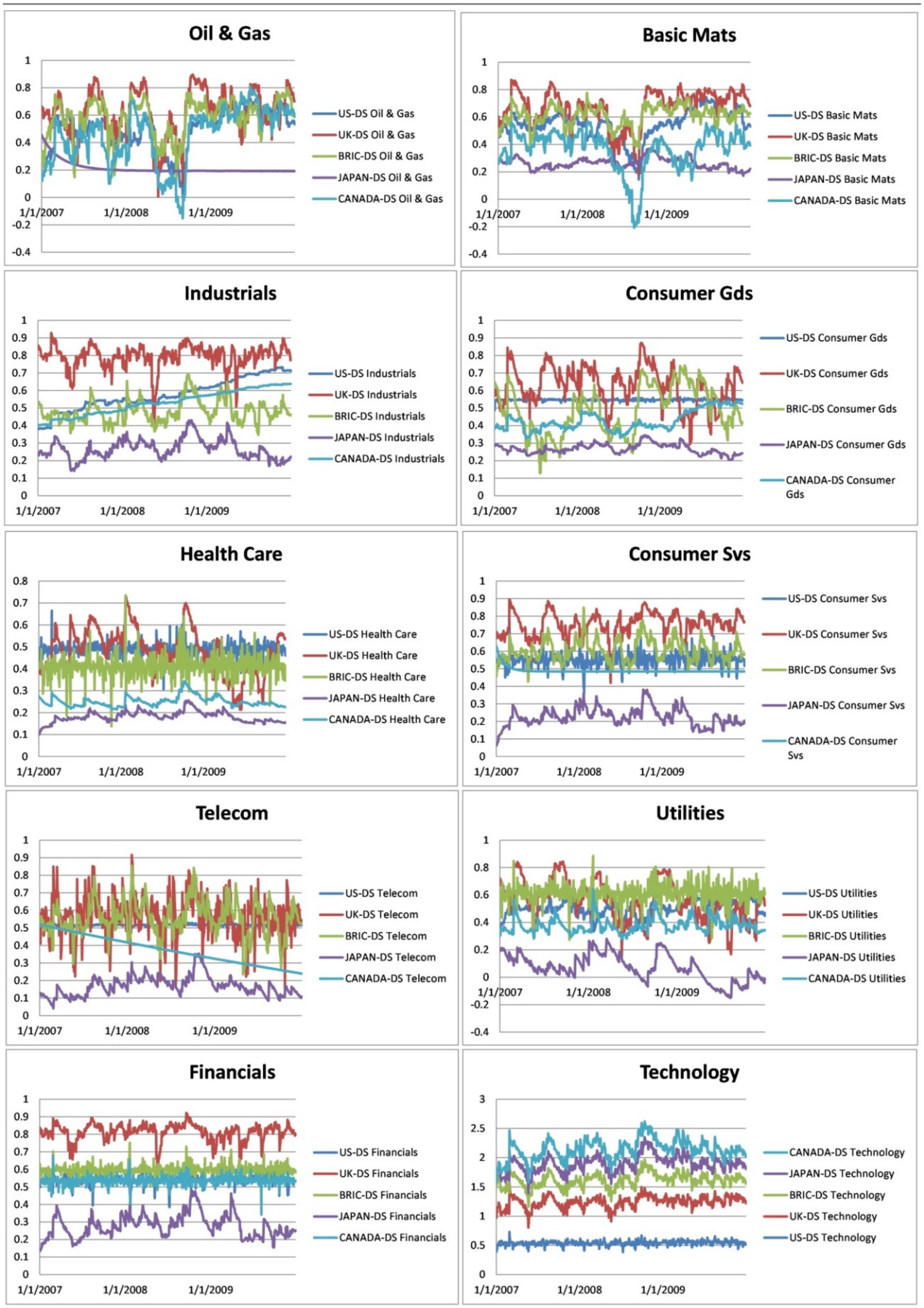


Figure 4.2. 6. Correlations R(t) in Subprime crisis – Italy with real economy sectors



As we expected, the correlations in all sectors increased in the Subprime crisis period and decreased in the Debt crisis period. This finding is reasonable, since the Subprime crisis was a turbulent period. However, in all estimations, the correlations remained higher than the Early Eurozone period. Considering that the global financial crisis of 2008 began with the US economy, I extend the research one step further and assume the probability of whether a European economy can produce shock transmissions to the US economy. Subsequently, the size of the US economy will produce a new form of financial crisis, similar or worse, than the Subprime crisis. History shows that the stock markets are unpredictable regardless of how well-secured the global banking system is. Based on this assumption, I investigate the possibility of whether a European economy can produce shocks to the US economy. The US economy is the core of the global financial system; if this system collapses, there is a possibility that the world financial environment will encounter a new crisis that may be worse than the Subprime crisis.

If France, Spain and Italy, as Eurozone's largest economies countries, are capable of producing a new form of Sovereign Debt crisis in the Eurozone, there is a possibility, due to the domino effect and the increasing policy uncertainty for the investors, that the new form of crisis would result in a transmission of the crisis from the Eurozone to the US economy. The market uncertainty in the US stock market system surely can produce significant shocks to the global financial environment. The US economy is the largest market in the world; in addition, it has previously proved in 2008 that it powers the rest of the world and provides the pace to the markets and subsequently, to development. Considering the aforementioned analysis, I extend the research one step further by investigating whether there is any connection via the fear factor and the policy uncertainty indexes with the European indices and the US sector price indices over the US economy.

Figure 4.2. 7. Correlations R(t) in Debt crisis – France with real economy sectors

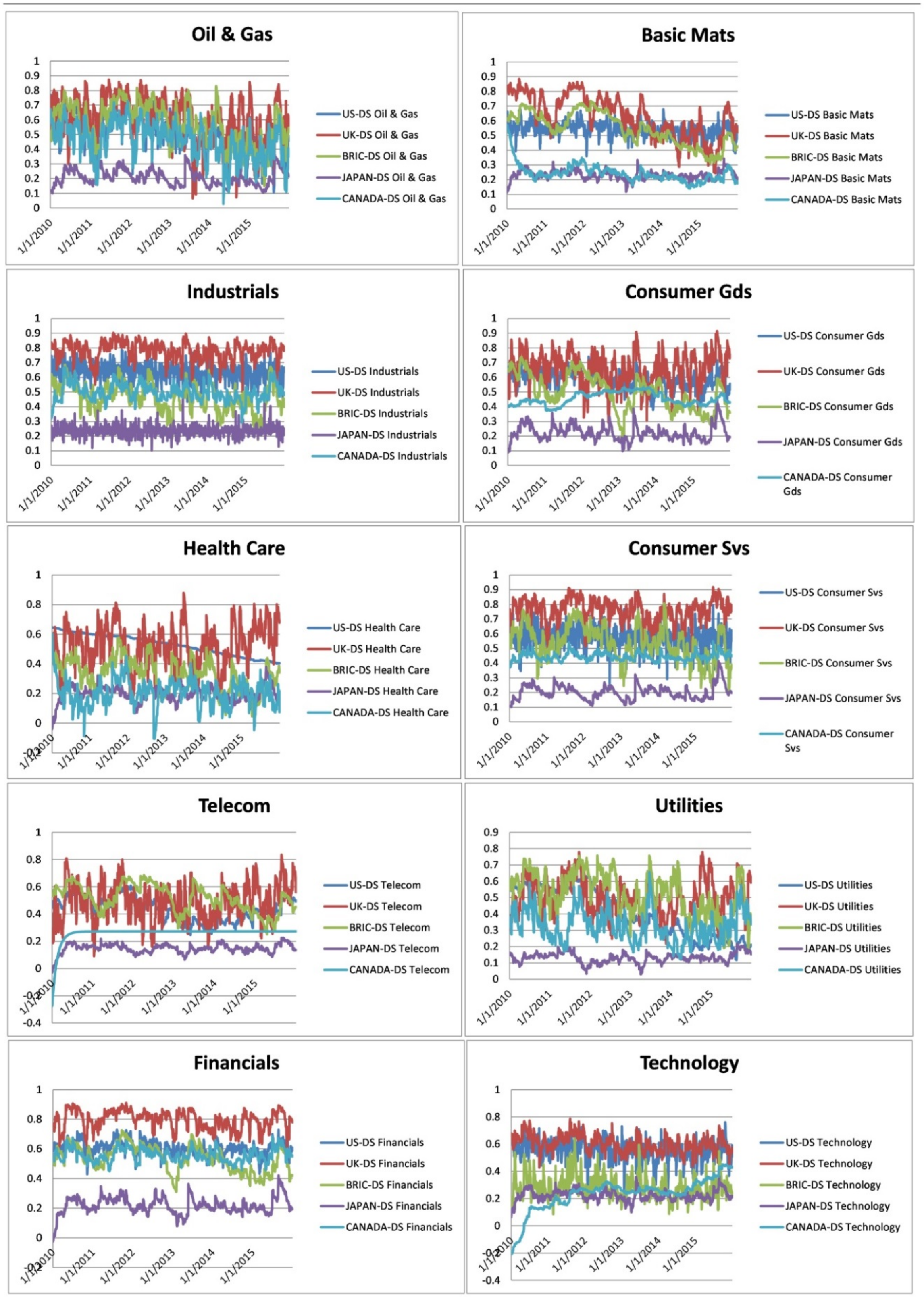


Figure 4.2. 8. Correlations R(t) in Debt crisis – Spain with real economy sectors

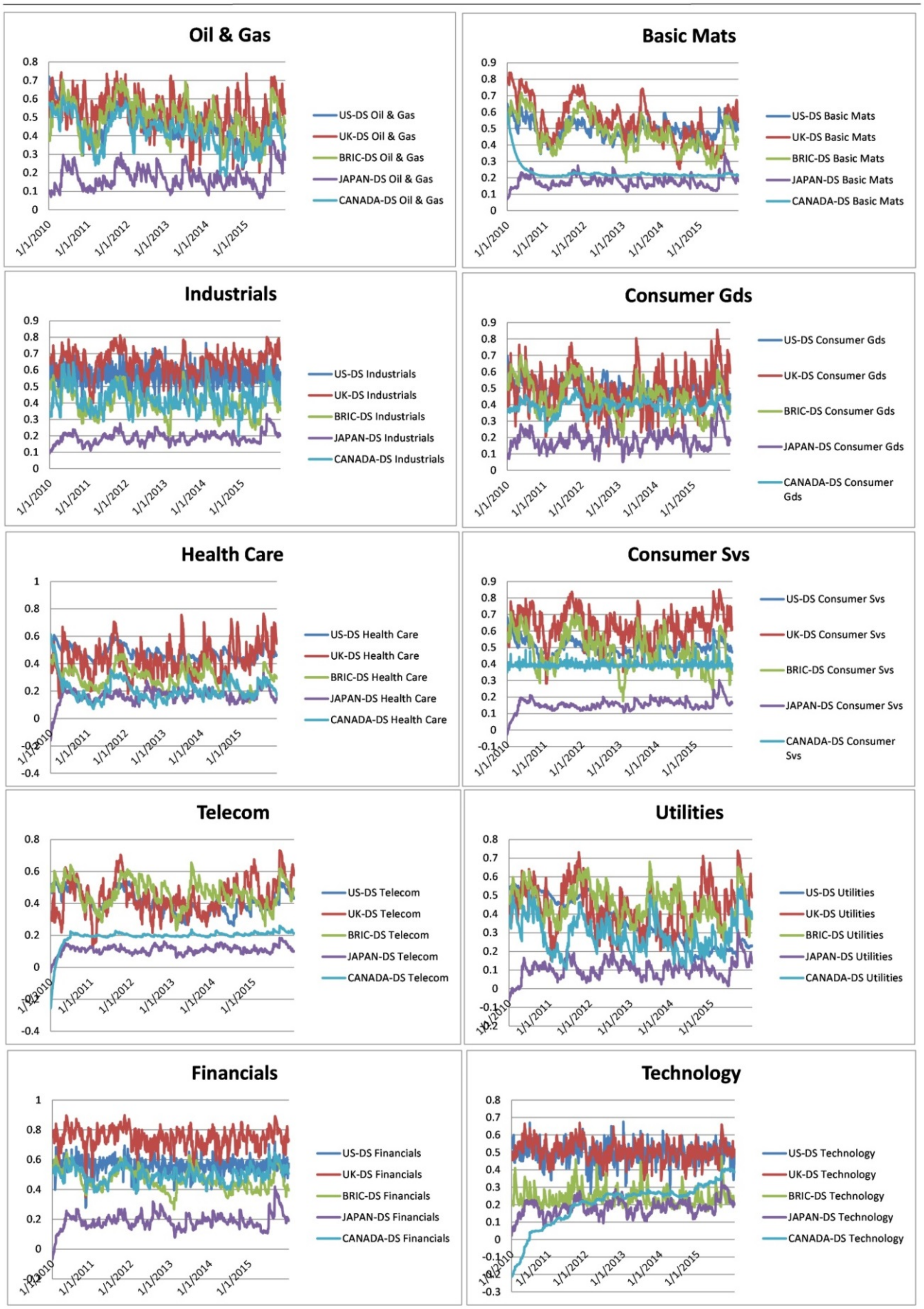
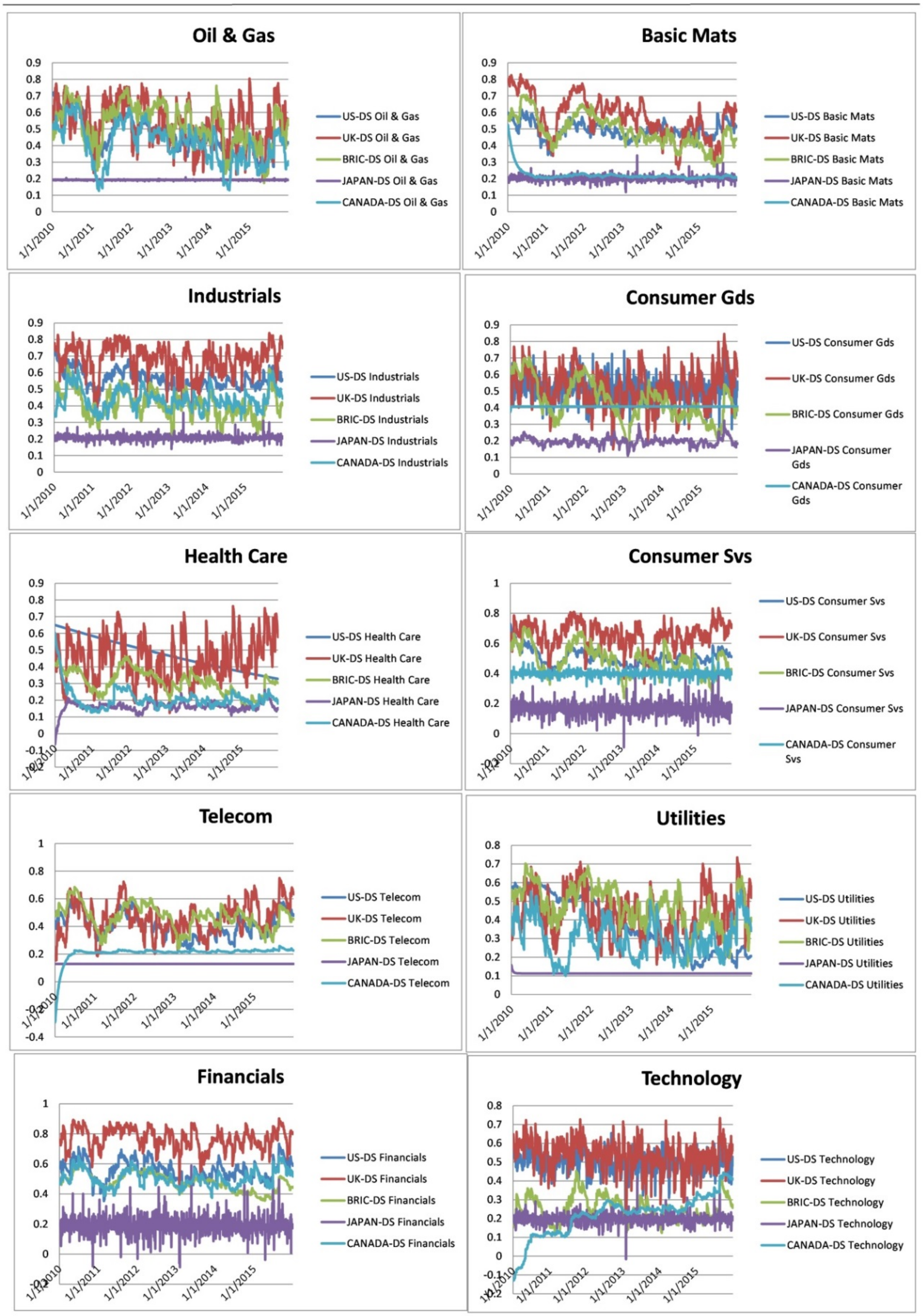


Figure 4.2. 9. Correlations R(t) in Debt crisis – Italy with real economy sectors



First, I assess the correlation of the VIX index, which is calculated by Chicago Board Options Exchange (CBOE), with the following indices: CAC40, IBEX35 and FTSE MIB along with the sectors of the US economy. The VIX index, which is often referred to as the fear index and represents the market's expectation of stock market volatility over the next 30-day period (a month). The VIX index is a popular measure, as it calculates the implied volatility of S&P 500 index options.

Second, I explore the correlations of sectors of the US economy and the European indices with the US Equity Market Uncertainty index. The US Equity Market Uncertainty index is a daily index by the policyuncertainty.com and is calculated by analyzing news articles containing terms related to the equity market uncertainty. The news articles are from the Access World News Bank service. The index covers well over 1000 newspaper articles related to the United States. The index is constructed by performing month by month searches of each article for terms related to economic and policy uncertainty. The index has a contemporaneous daily correlation with the VIX index, 0.30 according to the policyuncertainty.com. The data was obtained from Thomson Reuters DataStream.

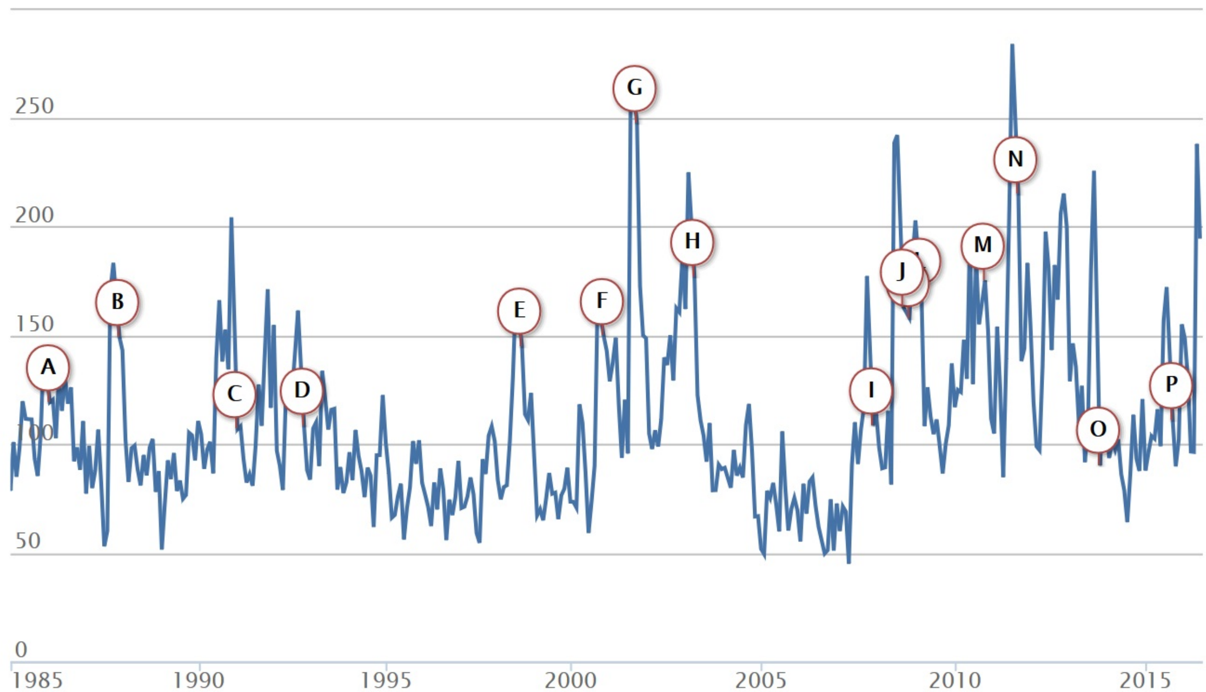
Third, I investigate the correlation between the US sector price indices and the European indexes with the Economic Policy Uncertainty index (EPU), also from policyuncertainty.com. The main difference with the US Equity Market Uncertainty index is that the EPU index is a daily news index. The measurement of the index contains at least one term, from the following: economic or economy, uncertainty, legislation, deficit or Federal Reserve. Particularly, the EPU index covers monetary policy, taxes, fiscal policy, health care, national security, entitlement programs, regulation, financial regulation, trade policy and a sovereign Debt crisis.

In all cases, I used GJR – GARCH (1, 1) on all estimations after data cleaning, which were performed on all time – series. Due to the dimensionality problem, I only present the models' parameters, unconditional and average dynamic conditional correlations. I also depict these results using the figures below. Before proceeding to the discussion of the results, I must note that these indexes (VIX, EPU, and US Equity Market Uncertainty) are not ordinary indexes for volatility investigation. Therefore, a positive or negative correlation is not the focus in this paper. In this section of our research, I attempt to identify the possible correlation behavior and the relationship between the European indices and the US sector price indexes with these three indexes of the fear factor and the policy uncertainty.

The goal is to extract these channels that illustrate the difference in the behavior of the correlations between European markets and the sectors of the US economy. The assumption is which portion (family) of indexes produces more impact on the fear factor and the policy uncertainty in the US economy. These two terms (fear factor and policy uncertainty) can clearly illustrate the economic condition in the US economy according to Figure 4.2.10.

Table 4.2.9 shows the parameters, the unconditional correlations and the mean conditional correlations of the VIX index with CAC40, IBEX 35 and FTSE MIB and the sectors of the US economy. In all cases, the correlations are negative. In this research, we only observe the behavior of correlations as these indexes are not ordinary market indexes because they measure events from newspapers, not transactions. There are clearly different behaviors in correlations with all periods (see Figure 4.2.11). Assuming that the Subprime crisis was a period with large shocks, I conclude that the correlation with the VIX index decreases with all indexes. However, in all periods, CAC40, IBEX35 and FTSE MIB have correlations with the VIX index that are much higher than with all sectors of the US economy. It appears that the VIX index is affected more by the sectors of its own US economy.

Figure 4.2. 10. US Economic Policy Uncertainty Index



Notes: A: Balanced Budget Act - Dec 1985, B: Black Monday - 1987, C: 1st Gulf War - 1990, D: Clinton Election - 1992, E: Russian Crisis/LTCM - Aug 1998, F: Bush Election Controversy - Oct 2000, H: 2nd Gulf War - Feb 2003, I: Large Interest Rate Cuts, Stimulus - Dec 2007, J: Lehman and TARP - Sep 2008, K: Obama Election - Oct 2008, L: Banking Crisis - Jan 2009, M: 2010 Midterm Elections - Sep 2010, N: Debt Ceiling Dispute - Jul 2011, O: Government Shutdown and Debt Ceiling - Dec 2013, P: China Slowdown - Aug 2015.

Table 4.2. 9. Parameters, unconditional correlations and the mean conditional correlations – VIX index

	Early Eurozone Period			Subprime Crisis			Debt Crisis		
	a	g	b	a	g	b	a	g	b
FRANCE CAC 40	1.60E-02 ***	3.07E-08	9.40E-01 ***	5.87E-02 **	5.31E-02	1.94E-01	5.14E-02 ***	4.50E-08	6.81E-01 ***
SPAIN IBEX 35	3.47E-02 **	3.93E-08	8.46E-01 ***	2.90E-02 *	1.49E-02	7.20E-01 **	7.17E-03	4.67E-03	9.83E-01 ***
ITALY FTSE MIB	1.01E-02	5.04E-07	9.81E-01 ***	6.14E-02 **	1.37E-01 *	2.67E-01 *	6.33E-03	3.16E-03	9.88E-01 ***
US-DS Oil & Gas	2.46E-02 ***	1.81E-07	9.65E-01 ***	5.08E-02 **	1.18E-07	9.18E-01 ***	4.38E-02 ***	1.37E-09	9.32E-01 ***
US-DS Basic Mats	4.03E-02 ***	6.50E-08	9.42E-01 ***	3.46E-02 ***	6.67E-09	9.50E-01 ***	3.64E-02 ***	1.62E-08	9.19E-01 ***
US-DS Industrials	3.22E-02 ***	1.94E-03	9.40E-01 ***	1.61E-02 ***	3.72E-03	9.71E-01 ***	5.06E-02	1.43E-09	8.61E-01 **
US-DS Consumer Gds	5.45E-02 ***	6.51E-03	9.04E-01 ***	4.00E-02 ***	1.02E-02	9.27E-01 ***	5.96E-02	1.10E-09	8.52E-01 ***
US-DS Health Care	1.96E-02 ***	1.82E-03	9.73E-01 ***	2.19E-01 ***	7.89E-02 *	3.84E-01 *	4.97E-02 ***	1.98E-09	8.76E-01 ***
US-DS Consumer Svs	4.07E-02 ***	8.81E-09	9.18E-01 ***	7.08E-02 **	6.93E-03	8.37E-01 ***	7.14E-02	3.64E-11	8.49E-01 **
US-DS Telecom	1.18E-02 *	1.18E-08	9.50E-01 ***	7.37E-02 **	2.07E-07	2.23E-01	4.13E-02 **	1.61E-09	9.14E-01 ***
US-DS Utilities	3.35E-02 **	8.64E-03	9.16E-01 ***	2.96E-02 ***	9.32E-09	9.39E-01 ***	8.63E-03	4.91E-11	9.91E-01 ***
US-DS Financials	2.86E-02 **	2.68E-09	9.49E-01 ***	7.52E-02 ***	2.24E-02	6.36E-01 ***	8.76E-02	1.21E-08	7.86E-01 **
US-DS Technology	2.54E-02 **	7.22E-08	8.93E-01 ***	7.96E-02 **	7.10E-02 *	3.38E-06	5.01E-02 **	1.57E-08	8.81E-01 ***

	Early Eurozone Period		Subprime Crisis		Debt Crisis	
	Unconditional correlation ADCC	Average conditional ADCC	Unconditional correlation ADCC	Average conditional ADCC	Unconditional correlation ADCC	Average conditional ADCC
FRANCE CAC 40	-0.3742	-0.3733	-0.5512	-0.5314	-0.5248	-0.5231
SPAIN IBEX 35	-0.3657	-0.3640	-0.5063	-0.4885	-0.6107	-0.4654
ITALY FTSE MIB	-0.3943	-0.3716	-0.5576	-0.5031	-0.6470	-0.4732
US-DS Oil & Gas	-0.3840	-0.3824	-0.6708	-0.6445	-0.6898	-0.6807
US-DS Basic Mats	-0.5645	-0.5499	-0.7187	-0.7084	-0.7273	-0.7249
US-DS Industrials	-0.7307	-0.6982	-0.9430	-0.7901	-0.7948	-0.7925
US-DS Consumer Gds	-0.6549	-0.5919	-0.9086	-0.7665	-0.7664	-0.7634
US-DS Health Care	-0.6746	-0.5830	-0.7923	-0.7226	-0.7215	-0.7170
US-DS Consumer Svs	-0.6945	-0.6917	-0.7986	-0.7677	-0.7728	-0.7688
US-DS Telecom	-0.5359	-0.5367	-0.6679	-0.6662	-0.5716	-0.5651
US-DS Utilities	-0.4661	-0.4104	-0.6671	-0.6414	0.9844	-0.5414
US-DS Financials	-0.6836	-0.6790	-0.7859	-0.7581	-0.7688	-0.7658
US-DS Technology	-0.6396	-0.6389	-0.7812	-0.7575	-0.7144	-0.7118

Notes: *** Denote statistical significance at 1% level.
** Denote statistical significance at 5% level.
* Denote statistical significance at 10% level.

Figure 4.2. 11. Behavior of Correlations – VIX index

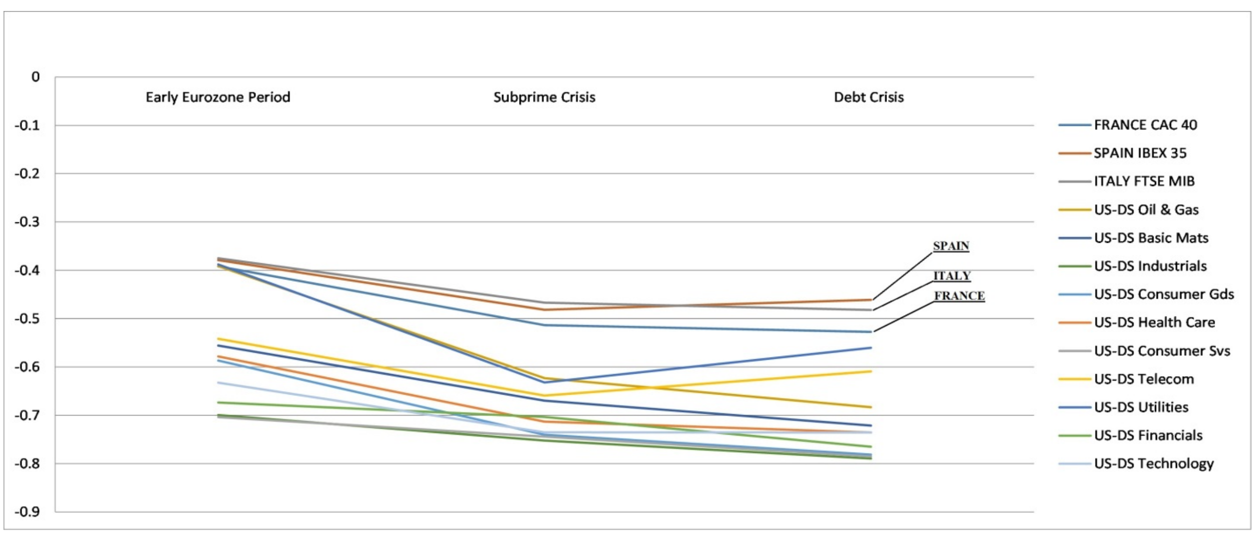


Table 4.2.10 presents the correlations with the US Equity Economic Uncertainty index. The results show that the correlations are also marginally negative with this index. While the Early Eurozone period showed no significant evidence, in the Subprime crisis period, the European indices have the most negative correlations. Subsequently, in the Debt crisis period, we observe a huge upward trend for these three indexes, as shown with the correlations in Figure 4.2.12. Moreover, in the Debt crisis period, the European indices capture the highest correlations; most are close to zero as all correlations are negative.

The correlations with the US Equity Economic Uncertainty index depict no significant evidence about which correlation produces more impact (lower or higher). However, it is clear that the European indexes behave differently than the sectors of the US economy. It can be assumed that the more negative the correlation is, the higher the impact and the interdependence is. Therefore, it appears that there was higher impact by the European indexes on the US Equity Economic Uncertainty index in the Subprime crisis period. However, this condition changed completely in the Debt crisis period, as the sectors of the US economy presented the most negative correlations.

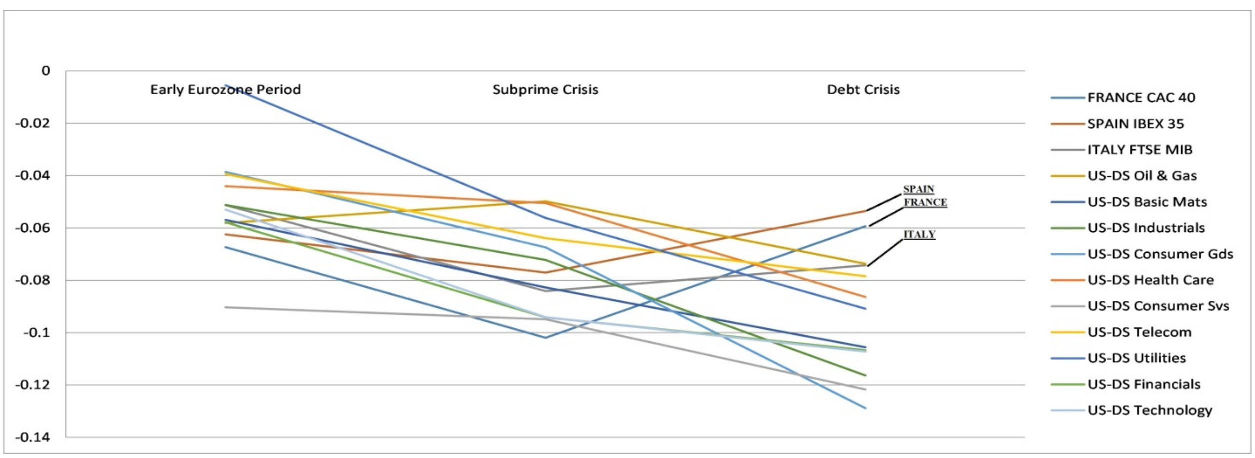
Table 4.2. 10. Parameters, unconditional correlations and the mean conditional correlations – US Equity Econ Uncertainty index

	Early Eurozone Period			Subprime Crisis			Debt Crisis		
	a	g	b	a	g	b	a	g	b
FRANCE CAC 40	1.56E-02	3.13E-08	9.25E-01 ***	3.03E-08	8.13E-08	1.39E-05	3.90E-07	2.65E-07	1.79E-04
SPAIN IBEX 35	3.21E-02	1.84E-07	2.63E-06	1.52E-07	2.99E-07	5.42E-05	1.54E-06	6.42E-07	7.68E-05
ITALY FTSE MIB	1.01E-02	6.10E-03	2.28E-04	1.14E-08	8.46E-08	2.50E-05	6.37E-03	6.84E-08	2.97E-05
US-DS Oil & Gas	2.96E-03	3.51E-04	9.91E-01 ***	9.61E-11	2.37E-10	9.89E-01 ***	2.61E-02	1.71E-08	6.84E-01
US-DS Basic Mats	5.54E-03	6.82E-08	9.25E-01 ***	1.14E-07	4.51E-02	1.14E-01	2.80E-02	9.69E-08	1.20E-01
US-DS Industrials	1.50E-02	2.84E-08	9.02E-01	2.97E-08	7.10E-08	9.83E-01 ***	7.01E-02 **	1.29E-07	5.22E-01 **
US-DS Consumer Gds	8.00E-07	6.21E-07	2.49E-04	1.72E-08	3.27E-08	9.87E-01	5.82E-02 **	1.13E-07	6.20E-01 **
US-DS Health Care	6.57E-03	4.93E-08	9.06E-01 ***	6.48E-09	2.32E-08	9.98E-01 ***	4.64E-02 *	8.11E-08	5.15E-01 *
US-DS Consumer Svs	1.50E-02	4.56E-08	8.71E-01 ***	2.69E-09	1.62E-08	9.82E-01 ***	8.50E-02 **	2.47E-07	2.98E-01 **
US-DS Telecom	4.17E-02 *	5.80E-08	6.17E-01	8.52E-07	5.34E-02	3.48E-01	1.22E-07	6.69E-03	9.92E-01 ***
US-DS Utilities	3.31E-02 **	6.62E-08	7.02E-01 ***	8.85E-09	9.98E-09	9.30E-01 ***	5.00E-02 *	6.54E-02	4.08E-01 **
US-DS Financials	5.06E-02 **	1.07E-08	4.48E-01 ***	9.73E-09	1.89E-08	9.92E-01 ***	6.95E-02 **	1.05E-06	3.61E-01 **
US-DS Technology	1.97E-08	2.50E-08	9.37E-01 ***	1.82E-07	1.74E-01 *	1.96E-01	8.86E-02 **	1.34E-07	1.00E-01

	Early Eurozone Period		Subprime Crisis		Debt Crisis	
	Unconditional correlation ADCC	Average conditional ADCC	Unconditional correlation ADCC	Average conditional ADCC	Unconditional correlation ADCC	Average conditional ADCC
FRANCE CAC 40	-0.0652	-0.0663	-0.1238	-0.1238	-0.0374	-0.0374
SPAIN IBEX 35	-0.0647	-0.0646	-0.0994	-0.0994	-0.0266	-0.0266
ITALY FTSE MIB	-0.0543	-0.0534	-0.1067	-0.1067	-0.0627	-0.0628
US-DS Oil & Gas	-0.0385	-0.0543	-0.1073	-0.0439	-0.0509	-0.0509
US-DS Basic Mats	-0.0568	-0.0587	-0.1035	-0.0948	-0.0952	-0.0960
US-DS Industrials	-0.0427	-0.0453	-0.0691	-0.0795	-0.1015	-0.1030
US-DS Consumer Gds	-0.0412	-0.0412	-0.0560	-0.0793	-0.1235	-0.1256
US-DS Health Care	-0.0372	-0.0392	0.0581	-0.0734	-0.0673	-0.0683
US-DS Consumer Svs	-0.0789	-0.0800	-0.0840	-0.1061	-0.1073	-0.1108
US-DS Telecom	-0.0336	-0.0342	-0.0869	-0.0741	-0.3295	-0.0550
US-DS Utilities	0.0005	0.0002	-0.0580	-0.0594	-0.1217	-0.1011
US-DS Financials	-0.0542	-0.0542	-0.0897	-0.1021	-0.1028	-0.1037
US-DS Technology	-0.0573	-0.0605	-0.1504	-0.1159	-0.1015	-0.1019

Notes: *** Denote statistical significance at 1% level.
** Denote statistical significance at 5% level.
* Denote statistical significance at 10% level.

Figure 4.2. 12.Behavior of Correlations – US Equity Econ Uncertainty index



Focusing on the EPU index, the correlations fluctuate around zero, as shown in Table 4.2.11 and Figure 4.2.13. It is also clear that the European indexes behave completely different from the US economic sectors. The EPU index behaves similar to the previous two indices of the fear factor and the policy uncertainty (VIX and US Equity Economic Uncertainty index). This finding means that negative correlations in the indexes show higher impact. Based on this statement, the sectors of the US economy produce a higher impact on the policy uncertainty of the United States than the European indexes. It appears that policy uncertainty in the US was affected more by its own sectors than by the Eurozone indexes. In addition, this finding means that the Debt crisis affected the US economy less than the domestic sectors of the same US economy.

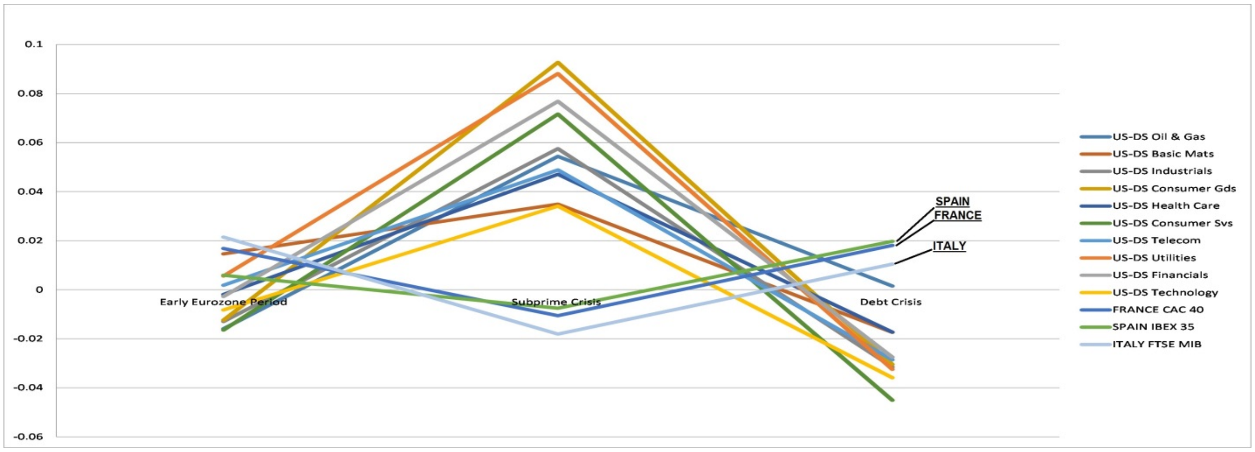
Table 4.2. 11. Parameters, unconditional correlations and the mean conditional correlations – EPU index

	Early Eurozone Period			Subprime Crisis			Debt Crisis		
	a	g	b	a	g	b	a	g	b
FRANCE CAC 40	4.257E-08	2.042E-02	8.684E-01 ***	3.235E-07	4.826E-07	3.116E-01	2.245E-03	1.652E-08	9.512E-01 ***
SPAIN IBEX 35	9.566E-10	3.265E-09	6.986E-01	1.151E-02	1.149E-07	7.183E-01 ***	2.780E-02 **	3.310E-08	8.378E-01 ***
ITALY FTSE MIB	6.663E-03	4.670E-03	8.935E-01 ***	1.267E-05	1.867E-05	2.414E-01	4.059E-08	2.508E-02	3.032E-06
US-DS Oil & Gas	1.137E-08	1.812E-08	9.412E-01 ***	4.135E-08	3.918E-08	7.621E-01 ***	5.033E-09	1.176E-08	4.517E-06
US-DS Basic Mats	3.873E-08	1.733E-02	8.828E-01 ***	2.836E-09	7.276E-09	9.624E-01 ***	7.332E-10	2.797E-09	9.979E-01 ***
US-DS Industrials	4.002E-07	5.866E-02 **	7.399E-01 ***	2.576E-08	1.822E-01	1.795E-07	1.515E-08	6.185E-08	2.348E-05
US-DS Consumer Gds	9.132E-08	3.188E-02	8.381E-01	1.297E-05	2.342E-01 *	2.211E-05	1.712E-08	2.563E-08	9.134E-01 ***
US-DS Health Care	2.466E-09	1.532E-08	9.262E-01 **	5.614E-08	9.022E-03	9.553E-01	4.549E-08	4.672E-08	8.663E-01 **
US-DS Consumer Svs	3.601E-07	8.157E-02 *	6.279E-01 ***	1.838E-08	4.477E-08	9.629E-01 ***	7.805E-08	1.118E-02	3.522E-06
US-DS Telecom	4.378E-09	1.622E-08	9.740E-01 ***	1.580E-02	3.891E-01 ***	3.589E-04	8.643E-10	2.197E-09	9.906E-01 ***
US-DS Utilities	2.689E-08	6.996E-08	9.387E-01	8.135E-09	1.694E-08	6.881E-01 ***	6.744E-03	3.850E-07	1.361E-05
US-DS Financials	1.204E-07	5.938E-02	2.317E-01	2.240E-09	1.591E-08	9.825E-01 ***	2.702E-08	2.347E-08	8.651E-01 ***
US-DS Technology	4.232E-02 **	1.597E-06	3.009E-06	4.918E-08	1.152E-01	3.008E-07	2.061E-08	1.767E-03	9.957E-01 ***

	Early Eurozone Period		Subprime Crisis		Debt Crisis	
	Unconditional correlation ADCC	Average conditiona l ADCC	Unconditional correlation ADCC	Average conditional ADCC	Unconditional correlation ADCC	Average conditional ADCC
US-DS Oil & Gas	-0.0183	-0.0159	0.0536	0.0544	0.0015	0.0015
US-DS Basic Mats	-0.0105	0.0146	0.0371	0.0349	-0.0435	-0.0174
US-DS Industrials	-0.0538	-0.0130	0.0358	0.0575	-0.0315	-0.0315
US-DS Consumer Gds	-0.0489	-0.0124	0.0693	0.0927	-0.0295	-0.0305
US-DS Health Care	-0.0031	-0.0019	0.0175	0.0471	-0.0171	-0.0173
US-DS Consumer Svs	-0.0563	-0.0165	0.0770	0.0716	-0.0468	-0.0451
US-DS Telecom	0.0048	0.0018	0.0091	0.0488	-0.0458	-0.0286
US-DS Utilities	0.0051	0.0056	0.0881	0.0881	-0.0325	-0.0325
US-DS Financials	-0.0152	-0.0028	0.0835	0.0768	-0.0274	-0.0275
US-DS Technology	-0.0083	-0.0083	0.0197	0.0341	-0.1397	-0.0359

Notes: *** Denote statistical significance at 1% level.
** Denote statistical significance at 5% level.
* Denote statistical significance at 10% level.

Figure 4.2. 13. Behavior of Correlations - EPU index



To conclude the aforementioned assumptions, I run further robustness tests. I used the same model GJR – GARCH (1, 1) – ADCC (1, 1) to explore the correlation of the American S&P 500 index with European indexes and the sectors of the US economy to compare the impact of the correlations in each case of the family indexes. The results are presented in Table 4.2.12 and Figure 4.2.14. The evidence shows that the European indexes behave differently than the sectors of the US economy. In all periods, the indexes present correlations lower than the sectors of the US economy, which is in accordance with our assumption regarding the indexes of the fear factor and policy uncertainty.

However, this assumption can only be made for the Debt crisis period. Additionally, only the VIX index is completely in accordance with the results of the S&P 500 index; the correlations show similar behavior for all indexes (regardless that, in the VIX index, the correlations were negative). Therefore, there appears to be a connection in the behavior of the correlations. Regarding the EPU and the US Equity Economic Uncertainty indexes (which show higher correlations in the Subprime crisis period for the European indices), the Subprime crisis period was a period with large fluctuations and strong volatility in the markets. This finding means that the assumption of the higher impact in the sector of the US economy than the European economy cannot be confirmed for the Subprime crisis period; it can only be confirmed for the Debt crisis period. Subsequently, newspaper news and information cannot clearly be correlated with the stock market indices in the Subprime crisis period, which was a period with large fluctuations, harsh volatility and huge economic and policy uncertainty. Simultaneously, it is de facto difficult to assess correlation between newspaper news and information with the time – series from stock markets to test for volatility, interdependence, and crisis transmission, particularly in cases where the periods are asymmetric and extremely volatile such as the Subprime crisis period.

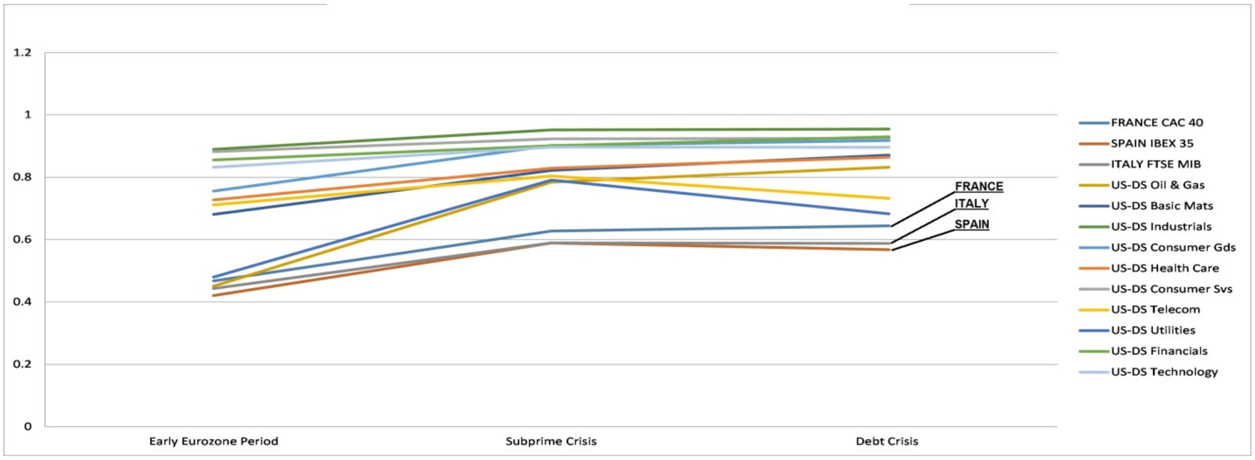
Table 4.2. 12. Parameters, unconditional correlations and the mean conditional correlations – S&P 500 index

	Early Eurozone Period			Subprime Crisis			Debt Crisis		
	a	g	b	a	g	b	a	g	b
FRANCE CAC 40	2.25E-02	1.18E-08	8.82E-01 **	4.48E-09	1.12E-02	9.93E-01 ***	8.73E-02 *	1.03E-08	5.58E-01 **
SPAIN IBEX 35	2.63E-02	1.72E-08	9.01E-01 ***	1.72E-09	3.09E-03	9.98E-01 ***	6.52E-02 **	1.06E-07	4.86E-01 **
ITALY FTSE MIB	1.25E-02	4.80E-09	9.74E-01 ***	1.53E-06	6.04E-03	9.96E-01 ***	9.15E-02 ***	3.24E-07	4.39E-01 ***
US-DS Oil & Gas	2.09E-02 ***	1.17E-03	9.75E-01 ***	3.85E-02 ***	3.61E-02 *	9.28E-01 ***	3.44E-02 **	6.29E-02 **	9.19E-01 ***
US-DS Basic Mats	3.07E-02 ***	2.42E-02 **	9.56E-01 ***	6.28E-02 **	1.15E-02	9.12E-01 ***	2.92E-02 **	3.57E-02 *	9.26E-01 ***
US-DS Industrials	2.01E-02 **	3.91E-02 ***	9.53E-01 ***	6.70E-10	1.36E-08	9.67E-01 ***	5.20E-02 *	4.59E-02 *	8.46E-01 ***
US-DS Consumer Gds	3.01E-02 ***	3.90E-02 ***	9.49E-01 ***	4.47E-02 **	2.57E-02	9.19E-01 ***	1.99E-02	9.82E-02 ***	8.84E-01 ***
US-DS Health Care	3.28E-02	1.39E-03	9.61E-01 ***	6.50E-02 ***	1.01E-07	9.21E-01 ***	3.37E-02 *	1.46E-01 ***	7.94E-01 ***
US-DS Consumer Svs	3.10E-02	7.17E-03	9.58E-01 ***	8.75E-03	7.62E-02 ***	9.37E-01 ***	6.95E-02 ***	2.15E-02	8.56E-01 ***
US-DS Telecom	1.14E-03	1.96E-02 *	9.71E-01 ***	3.45E-02 **	7.90E-08	9.31E-01 ***	3.20E-03	1.22E-01 **	8.94E-01 ***
US-DS Utilities	3.82E-02 **	8.20E-07	9.48E-01 ***	6.68E-02 **	1.32E-08	8.79E-01 ***	3.45E-02 *	4.57E-02 *	9.18E-01 ***
US-DS Financials	1.03E-02 *	4.04E-02 ***	9.68E-01 ***	2.54E-07	3.87E-02 **	9.78E-01 ***	4.57E-03	1.03E-01 **	8.90E-01 ***
US-DS Technology	3.41E-02 ***	2.63E-07	9.43E-01 ***	4.58E-02 **	2.68E-02	8.91E-01 ***	9.09E-03	1.61E-01 ***	8.11E-01 ***

	Early Eurozone Period		Subprime Crisis		Debt Crisis	
	Unconditional correlation ADCC	Average conditional ADCC	Unconditional correlation ADCC	Average conditional ADCC	Unconditional correlation ADCC	Average conditional ADCC
FRANCE CAC 40	0.4653	0.4639	0.3884	0.6454	0.6454	0.6422
SPAIN IBEX 35	0.4312	0.4278	1.0000	0.5854	0.5761	0.5741
ITALY FTSE MIB	0.4631	0.4505	0.6987	0.6005	0.5854	0.5741
US-DS Oil & Gas	0.4436	0.4590	0.8193	0.7747	0.7545	0.8030
US-DS Basic Mats	-0.0285	0.6973	0.8734	0.8288	0.8384	0.8516
US-DS Industrials	0.8416	0.8843	0.9558	0.9515	0.9476	0.9473
US-DS Consumer Gds	-0.4375	0.7658	0.9101	0.9008	0.8795	0.8941
US-DS Health Care	0.7666	0.7460	0.8380	0.8162	0.8285	0.8406
US-DS Consumer Svs	0.8744	0.8775	0.8843	0.9148	0.9120	0.9101
US-DS Telecom	0.6714	0.6966	0.7869	0.7794	0.5946	0.6798
US-DS Utilities	0.5491	0.5173	0.7789	0.7627	0.5929	0.6384
US-DS Financials	0.6267	0.8617	0.4590	0.9071	0.9130	0.9227
US-DS Technology	0.8398	0.8357	0.9001	0.8914	0.8631	0.8707

Notes: *** Denote statistical significance at 1% level.
** Denote statistical significance at 5% level.
* Denote statistical significance at 10% level.

Figure 4.2. 14.Behavior of Correlations – S&P 500 index



4.3. Empirical analysis of interdependence in small economies

The estimations of the DCC model are presented in Table 4.3.1 and Table 4.3.2 respectively in the two-stage process. Table 4.3.1 presents the univariate estimations AR(1) – GJR GARCH (1,1) for both indices. The *g* coefficient, which shows the leverage effect, is significant only in case of Greece in the GFC period. This guarantees the absence of normality in the index. However, in all other cases the absence of normality is not strong enough.

Table 4.3. 1. Univariate estimations AR(1) – GJR – GARCH (1,1)

	GFC Period							
	Greece				Cyprus			
	Coefficient	**Std.Error**	**t-value**	**t-prob**	**Coefficient**	**Std.Error**	**t-value**	**t-prob**
Cst(M)	0.0004	0.0004	1.080	0.2802	0.0016	0.0005	3.341	0.0009
AR(1)	0.0891	0.0299	2.975	0.0030	0.1163	0.0311	3.741	0.0002
Cst(ω)	0.0359	0.0142	2.524	0.0117	0.0518	0.0373	1.389	0.1650
ARCH(Alpha1)	0.0482	0.0174	2.770	0.0057	0.0905	0.0279	3.242	0.0012
GARCH(Beta1)	0.8770	0.0236	37.080	0.0000	0.8745	0.0420	20.81	0.0000
GJR(Gamma1)	0.1276	0.0360	3.543	0.0004	0.0685	0.0508	1.348	0.1778
	EDC Period							
	Greece				**Cyprus**			
	Coefficient	**Std.Error**	**t-value**	**t-prob**	**Coefficient**	**Std.Error**	**t-value**	**t-prob**
Cst(M)	-0.0005	0.0007	-0.720	0.4714	-0.0005	0.0003	-1.491	0.1362
AR(1)	0.0458	0.0334	1.372	0.1703	0.1630	0.0461	3.535	0.0004
Cst(ω)	0.1620	0.1025	1.581	0.1142	0.0078	0.0057	1.366	0.1721
ARCH(Alpha1)	0.0496	0.0239	2.078	0.0379	0.2131	0.0531	4.011	0.0001
GARCH(Beta1)	0.9111	0.0310	29.360	0.0000	0.8667	0.0169	51.14	0.0000
GJR(Gamma1)	0.0389	0.0292	1.333	0.1829	-0.0827	0.0634	-1.304	0.1924

Figure 4.3.1 and Figure 4.3.2 show the return time-series for each period respectively. Additionally, Figure 4.3.3 and Figure 4.3.4 show the univariate conditional variance for each index. We observe extensive volatility from the outbreak of the GFC in mid-2008 until mid-2013. Table 4.3.2 shows the Dynamic Conditional Correlations of the two stock markets. The unconditional correlation is statistically significant only in the case of the EDC period (0.883). The ARCH parameter α was higher in the GFC period (0.06) which means that shocks were more significant in the first period than the second (0.034). On the other hand, the GARCH parameter β was higher in the EDC period which concludes the extent of volatility in the market during the EDC period. It is evident that if terms a and b are found to be positive and their sum is lower than one ($a+b<1$), this implies the existence of dynamic conditional correlations. As can be seen, the results support the presence of correlations over time and the existence of a

contagion effect. Furthermore, the analysis shows significant increase during the crash period among the indices.

Table 4.3. 2. Dynamic Conditional Correlations

	GFC Period			
	Coefficient	**Std.Error**	**t-value**	**t-prob**
UnCon. Corr	0.0464	0.7101	0.065	0.9479
alpha	0.0604	0.0173	3.494	0.0005
beta	0.9378	0.0187	50.260	0.0000

	EDC Period			
	Coefficient	**Std.Error**	**t-value**	**t-prob**
UnCon. Corr	0.8834	0.0624	14.160	0.0000
alpha	0.0328	0.0087	3.773	0.0002
beta	0.9672	0.0106	91.400	0.0000

Figure 4.3. 1. Returns GFC period

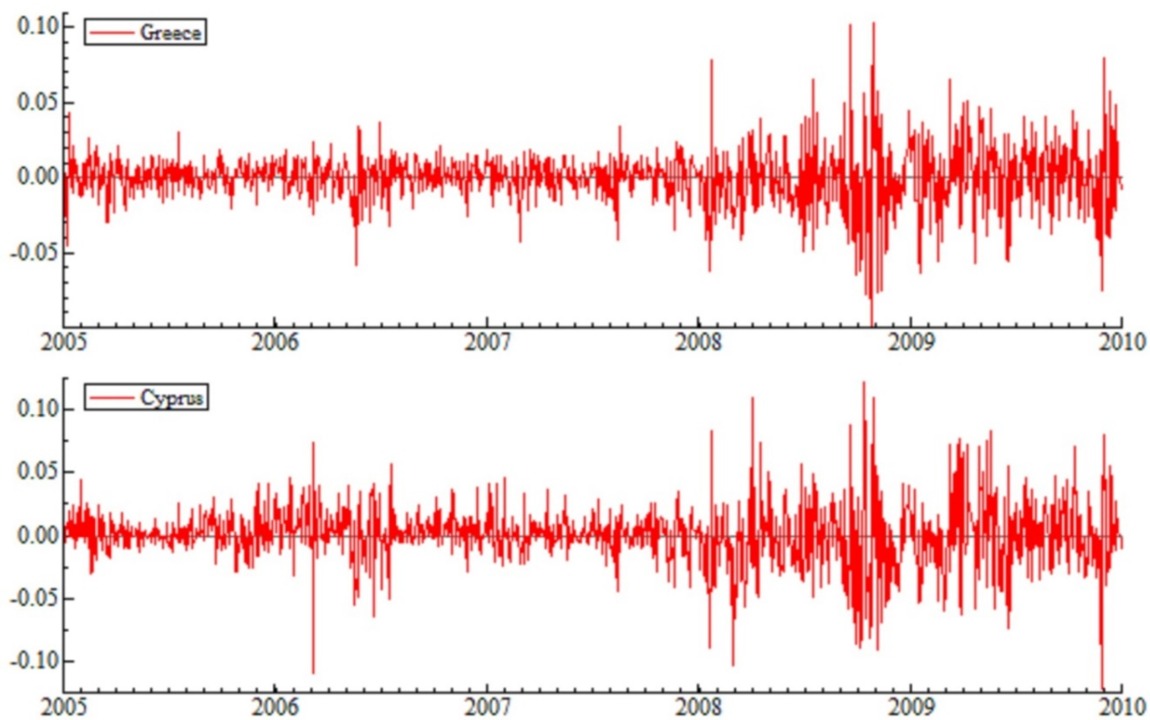
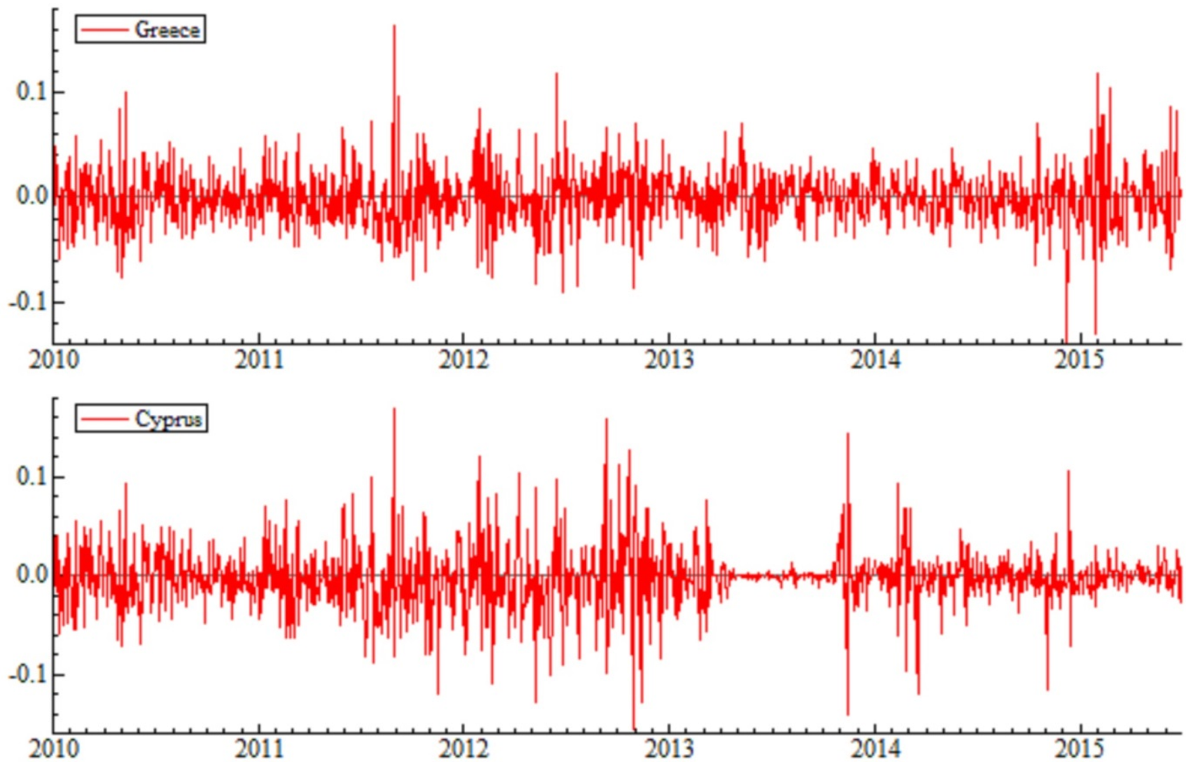


Figure 4.3.2. Figure 4.3. 2. Returns EDC period



Covariances and conditional correlations are presented in Figures 4.3.5 to 4.3.8 for each period separately. The covariance is not that much different from the aforementioned assumption that a close connection between the two economies exists from 2008 to 2013, the period that includes the GFC and the subsequent crisis first in Greece (2010) and then in Cyprus (2012-13). Furthermore, the results also show that the two markets are closely connected to each other. This leads to the immediate conclusion of an increased level of interdependence between the two indices in this specific period. Focusing now on the conditional correlation, we observe from Figure 8 that this starts from negative values and continues with an upward trend until the value of 0.80. However, in the EDC period (Figure 4.3.8), it can be observed that the behaviour of the correlation is completely different; from 2010 to 2014, the data present a negative trend until the values start to rise again. As of mid-2015, Cyprus looks almost ready to stop the recapitalisation from the Institutions. On the other hand, the Greek economy is still in the opposite position; economic uncertainty is again the core of the events as the current condition shows that Greek debt is not sustainable. On top of that, capital controls seem to have affected the stability of the economy. However, this situation in Greece seems to affect the Cypriot economy because of the interdependence, as shown in our findings (Figure 4.3.8).

Figure 4.3. 3. Univariate Conditional Variances GFC period

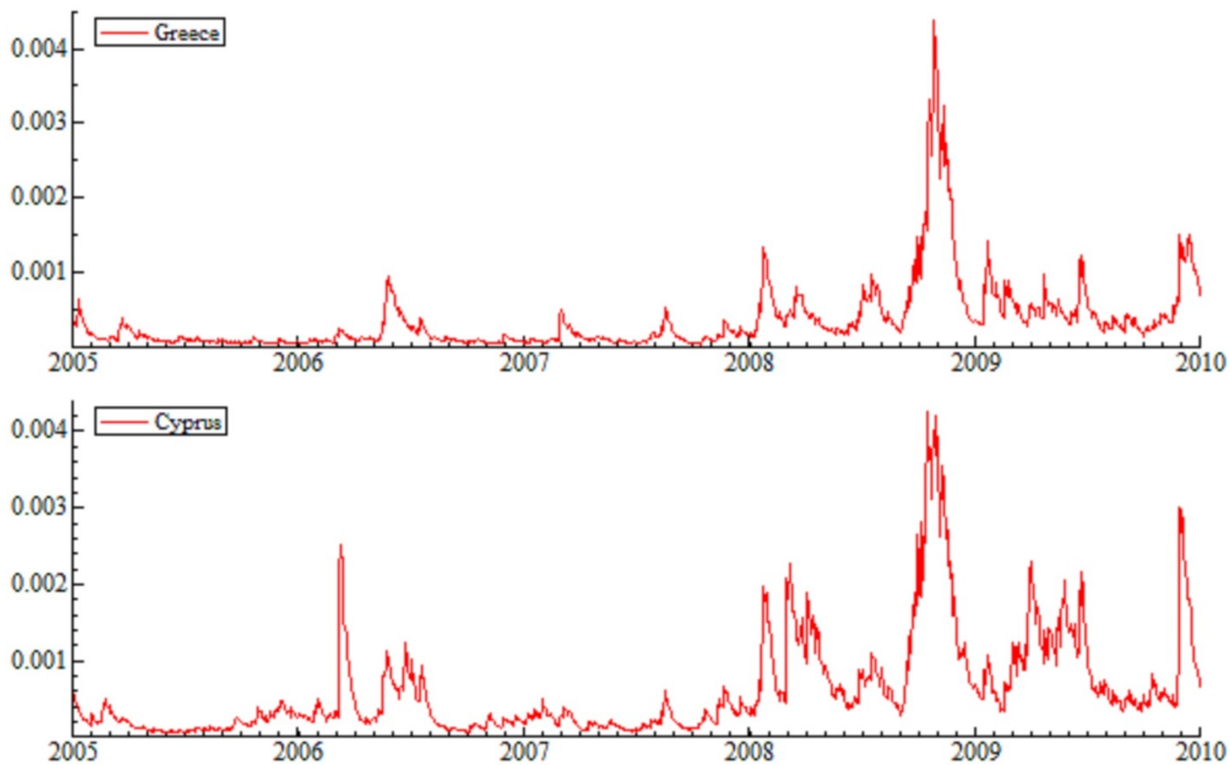
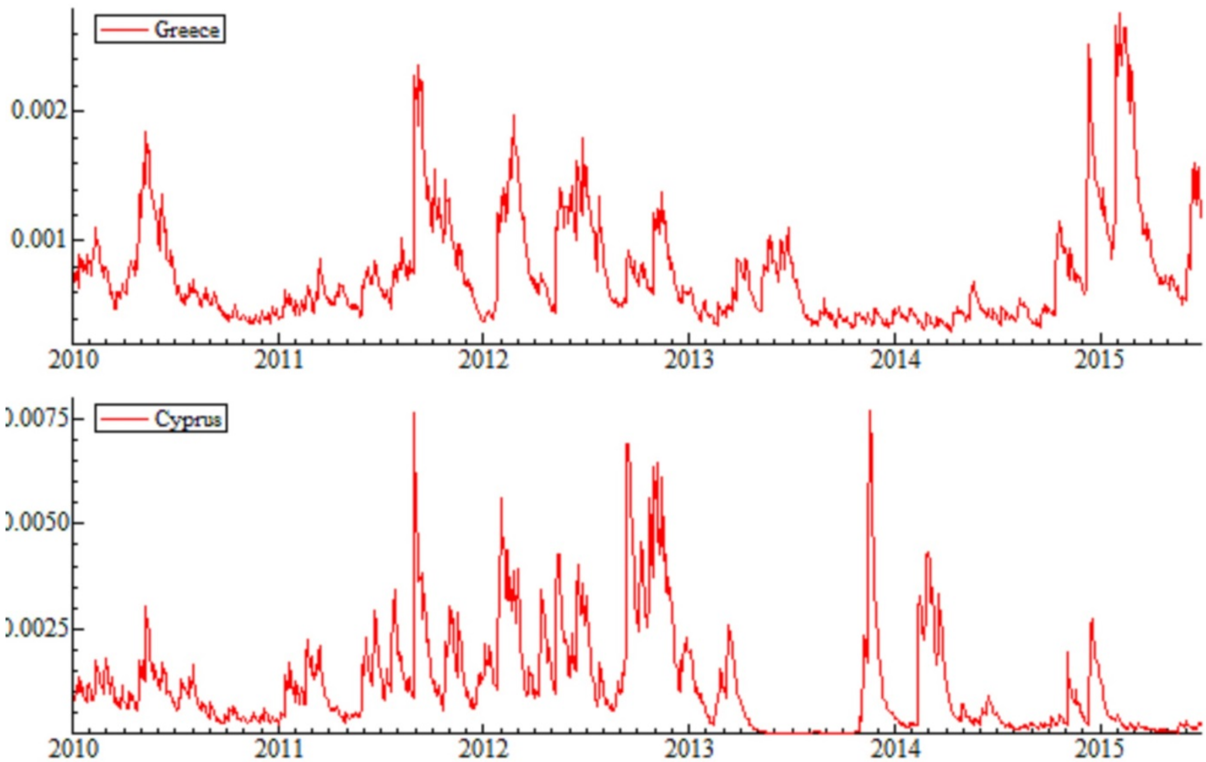


Figure 4.3. 4. Univariate Conditional Variances EDC period



The descriptive statistics of the conditional correlations are presented in Table 4.3.3. The average conditional correlation is marginally lower in the EDC period (0.5066). However, the standard deviation is higher in the second period (0.3512). In all estimations, indices are negative skewed and platykurtic, while the Jarque-Bera test ensures the absence of normality in correlations for both periods. Lastly, the GFC period shows lower maximum correlation values and higher minimums compared to the EDC period.

Table 4.3. 3. Correlations' Descriptive Statistics

	GFC Period	EDC Period
Mean	0.5524	0.5066
Maximum	0.9020	0.9401
Minimum	-0.2288	-0.1519
Std. Dev.	0.2999	0.3512
Skewness	-0.7417	-0.4168
Kurtosis	-0.6474	-1.4606
Jarque-Bera	132.62	156.13
Probability	[0.0000]	[0.0000]

Figure 4.3. 5. GFC Covariance

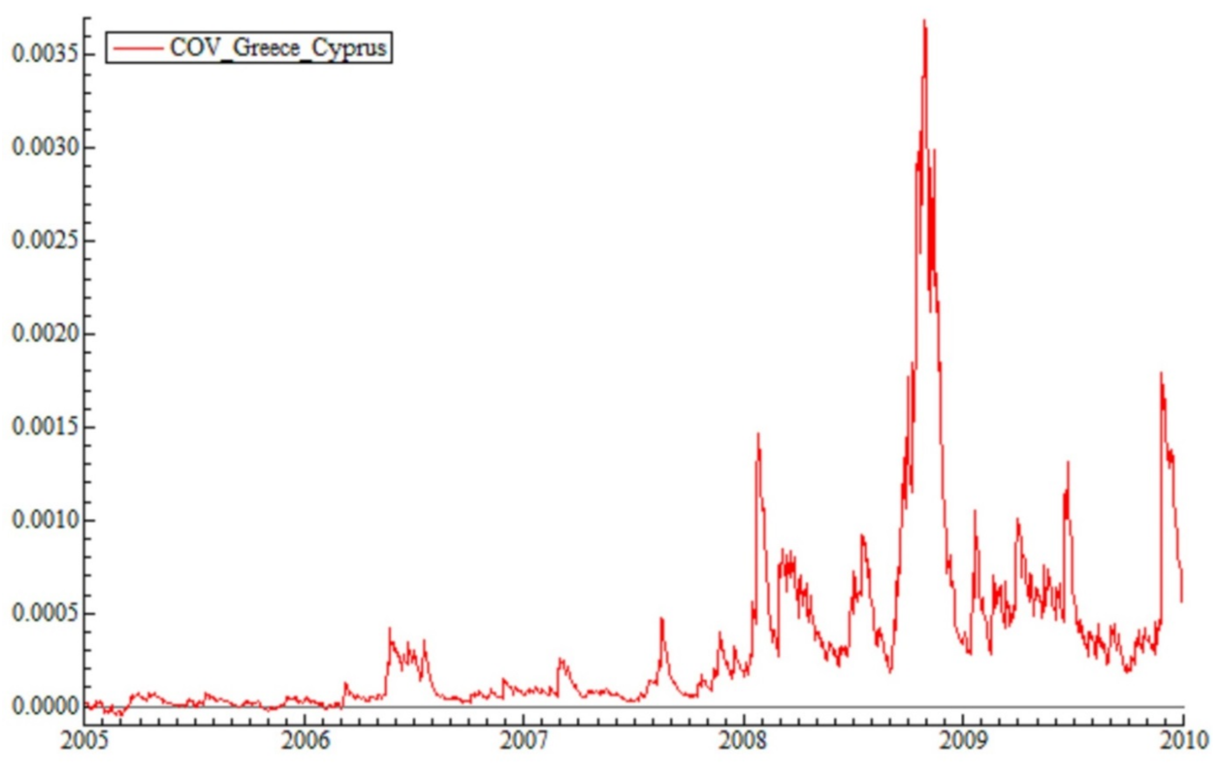
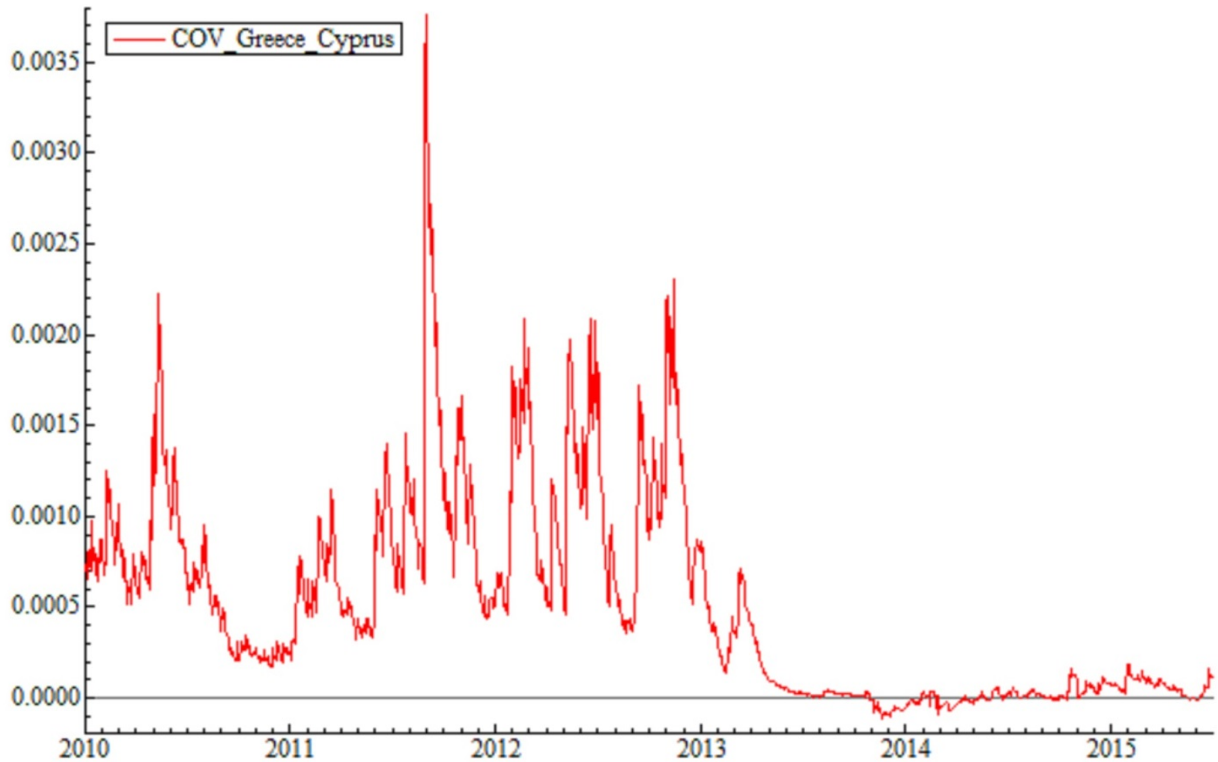


Figure 4.3. 6. EDC Covariance



Overall, the GFC increased the level of dependence, with extremely high volatility, between the two indices. The turmoil period in the global financial environment affected many other major countries including the Eurozone and thereafter, smaller economies faced also substantial problems, as a result of the financial contagion phenomenon. In the meantime, the relationship between the two economies remained high. However, with reference to the rest of the European economies, it is reasonable to suppose that Greek market dynamics are weak and its power to produce shocks to other markets it is relatively limited. While all the international markets were trying to recover from the subprime crisis, the Greek problem was underestimated by all major economies inside the Eurozone. The aforementioned condition in Greece raised a huge subject for investigation due to the fears of spillover effects from Greece's sovereign debt to other countries right after the subprime crisis.

Figure 4.3. 7. GFC Correlations

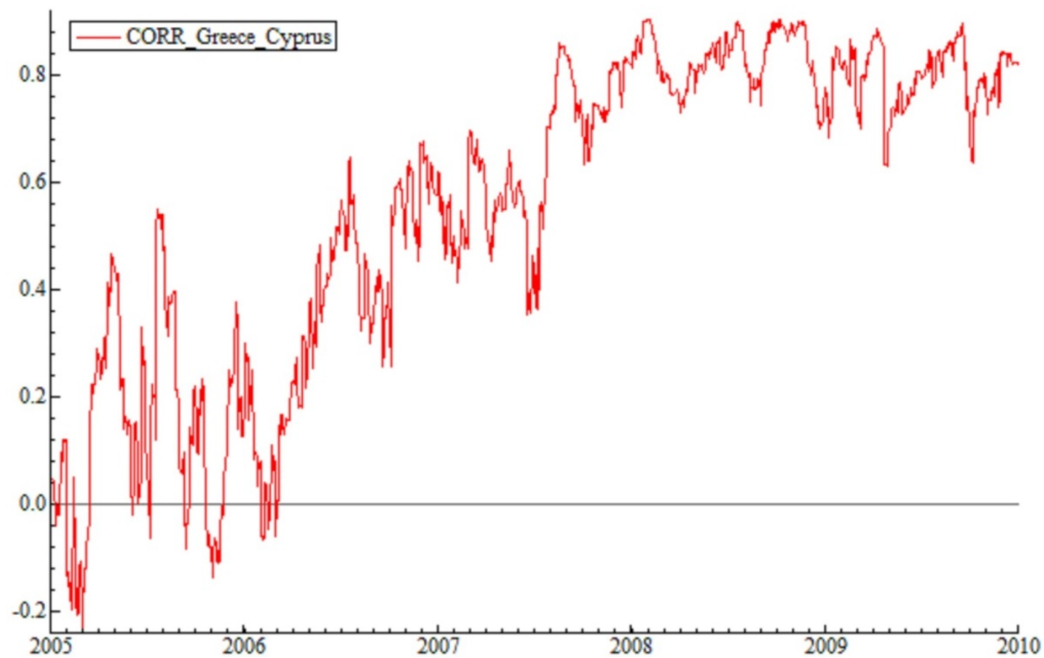


Figure 4.3. 8. EDC Correlations

The main issue of the Institutions (IMF, EC and ECB) in the Greek Debt crisis was whether a small country, that covers the 2.5% of Eurozone's GDP, can affect the entire European region. This devastating scenario forced the Eurozone and the IMF to focus on this new threat for the global economy. In the meantime, the majority of the developed economies were trying to recover from the subprime crisis and protect their economies from similar spillover effects. Thus, interested parties attempted to confront the new threat at an early stage. Greece adopted many austerity measures (such as 10% cut to bonuses, freezes in public-sector salaries and increases in VAT) in order to produce savings and decrease the high government deficit. Unfortunately, the measures were not enough and the recession deepened, consumption decreased rapidly and the Greek Government was unable to stabilise tax revenue. All the upcoming rescue packages did not change the condition in Greece; tax collection inefficiency as well as delays in public sector's much needed reorganisation were the biggest challenges. Eurozone's inability to successfully resolve the problem in Greece created serious doubts about the effectiveness of the program. Shortly after, the Eurozone began to feel pressured from credit rating firms. Hence, in January 2012, Standard & Poor's downgraded France (from AAA rating to AA+) and this was the first shock in Eurozone area.

It may be reasonable to suppose that the austerity measures implemented in Greece cannot provide any flexibility to increase GDP and decrease the deficit to a sustainable level. In addition, this is the first time that a Eurozone country faces such a severe financial crisis. This threat of financial contagion led Eurozone members as well as investors and governments to study carefully the possibility of a domino effect in Greece. In case of a Grexit, some expect great losses to several major economies, which are difficult to calculate at this stage. In such a scenario, it is likely that we would face more attempts from countries to withdraw from the Eurozone area and especially from the rest of the PIIGS. Despite the claims that the financial condition in the Eurozone is tranquil, stock markets are attracted by rumours and information. Thus, a domino effect is still possible regardless of the opposite beliefs of interested parties. The Greek Debt crisis is similar the ones in Italy and Portugal, while the banking crisis of Cyprus resembles those of Ireland, Spain and Iceland.

As for the Cypriot Financial crisis, the new economic model (bail-in) applied in Cyprus, affected only the local area while the spillover effects to other countries were low. It may be assumed that the program of Cyprus is ineffective because three and a half years later, the Cypriot economy presents negative GDP growth and high unemployment. Besides, major economies and investors had a great opportunity to implement a new model in a small country (with low spillover effects as it seems to be) in order to gain profits from it. Cyprus had a significant banking sector compared to the size of the country, well organized, and foreigners (including many Russians) had placed large amounts of money in the local economy. In addition, the country invested a lot in the exploration of the natural gas in the maritime exclusive economic zone and the agreements with Israel and USA are now the next great challenges to lead the economy to development.

The two crises are faced differently by the Eurozone. The events and the structure of the economies had different specifications. The Cyprus case was a great opportunity to implement a new economic model (the bail-in) based on the mechanism of the banking sector that turns the depositors into shareholders. At the same time, Greece's bad fiscal condition let the Institutions take advantage of the situation; Greece's contagion ability is also very poor, thus letting the Institutions test numerous different fiscal policies on the real economy of Greece, which is now completely destroyed. It seems that both countries look like lab rats for austerity measures in order for big economies to test for the effectiveness of their policies. The different scope of approach may explain the drop of covariances and correlations after 2013 in the estimations (Figure 4.3.6 and Figure 4.3.8); even though both economies are facing serious problems and traditionally have great interdependence, it seems that by 2013 this correlation had dropped significantly.

4.4. Empirical results for the effects of the June 2016 United Kingdom European Union membership referendum (Brexit)

(*This section is based on Samitas and Kampouris (2017a), where Samitas is coauthor of the published paper*)

Figures 4.4.1 through 4.4.11 highlight the smoothing probabilities with respect to the high dependence regime. The figures have been split into quadrants, where each illustrates the derivations from each bivariate case shared between a country and the UK. More specifically, every quadrant has a subfigure that outlines the smoothing probabilities for FTSE 350 and FTSE 100. Every subfigure includes 4 copula segments. Furthermore, the vertical red lines illustrate the announcement of the vote result on June 24, 2016, and the putting into motion of Article 50, on March 29, 2017.

The dates for the vote and Article 50's initiation were captured in only a few cases by regime switching copulas. Moreover, elevated levels of volatility were depicted during the pre and post referendum period. Take a look at Figures 4.4.12 through 4.4.22 to examine the dependence dynamics isolated by copulas that were derived by estimation. The dependence dynamics are furthermore highlighted for both FTSE 350 and FTSE 100 since each figure is further segmented into quadrants for each copula family. The figures for smoothing probabilities illustrate vertical red lines to highlight the results of the vote on June 24, 2016, and the initiation of Article 50 on March 29, 2017.

A linear correlation coefficient is depicted in the first subfigure, the normal copula's dependence parameter. the tail dependence of Gumbel, SJC and Clayton copulas can be seen in the other subfigures. The results indicate that a low dependence regime has no tail dependence. On the other hand, tail dependence is positive for a regime with high dependence. When the vote date was near, i.e. when the results had been announced, increased dependence was observed. This holds true for all copulas. Article 50's initiation did not lead to any significant changes, for FTSE 100 or FTSE 350.

Table 4.4.1 outlines the results from the second step, whereby the sample has been split into three categories, i.e. the time before and after the vote, and the time after Article 50 was initiated. The correlations were derived from the normal time-varying and regime-switching copula, to see if the correlations experienced a rise during the second or third period. In terms of the post vote timeframe, the correlations experienced a hike in 36 countries under FTSE 100 and 26 under FTSE 350. In terms of the third period, the correlations experienced a rise for 29 nations under FTSE 100, and 25 under FTSE 350. Lastly, Tables 4.4.2 ad 4.4.3 demonstrate the results for the hypotheses that were formulated for this study. They furthermore highlight the resulting contagion specification to elaborate on the spillover that stems from the different approaches used. For the contagion that resulted from the vote, take a look at Table 4.4.2. The results from the initiation of Article 50 can be examined in Table 4.4.3.

Table 4.4. 1. Average time varying correlation and percent change

	FTSE 100					FTSE 350				
	Pre referendum	Post referendum	% change	After Article 50	% change	Pre referendum	Post referendum	% change	After Article 50	% change
Austria	0.8201	0.8278	0.0094	0.8291	0.0016	0.8219	0.8298	0.0095	0.8317	0.0023
Belgium	0.9731	0.9722	-0.0010	0.9714	-0.0008	0.8706	0.8598	-0.0123	0.8560	-0.0044
Cyprus	0.9720	0.9797	0.0079	0.9796	0.0000	0.9891	0.9964	0.0074	0.9964	0.0000
Estonia	0.7278	0.7634	0.0490	0.7981	0.0454	0.9600	0.9668	0.0071	0.9668	0.0000
Finland	0.8621	0.8691	0.0081	0.8706	0.0018	0.8672	0.8725	0.0061	0.8737	0.0014
France	0.9105	0.8932	-0.0190	0.8884	-0.0054	0.8186	0.7722	-0.0566	0.7587	-0.0175
Germany	0.9761	0.9789	0.0029	0.9792	0.0003	0.9791	0.9814	0.0024	0.9816	0.0002
Greece	0.8223	0.8225	0.0003	0.8206	-0.0023	0.8129	0.8118	-0.0014	0.8089	-0.0036
Ireland	0.9951	0.9979	0.0028	0.9979	0.0000	0.7079	0.7115	0.0051	0.7130	0.0021
Italy	0.7429	0.7323	-0.0143	0.7292	-0.0041	0.7514	0.7375	-0.0185	0.7330	-0.0061
Latvia	-0.9053	-0.9106	0.0059	-0.9114	0.0008	-0.8525	-0.8562	0.0044	-0.8572	0.0011
Lithuania	0.9771	0.9842	0.0073	0.9843	0.0001	0.9908	0.9979	0.0072	0.9979	0.0000
Netherlands	0.9958	0.9970	0.0012	0.9970	0.0000	0.9831	0.9828	-0.0003	0.9824	-0.0004
Portugal	0.6908	0.6768	-0.0203	0.6715	-0.0079	0.7075	0.6945	-0.0185	0.6889	-0.0079
Slovakia	0.8645	0.8700	0.0063	0.8733	0.0038	0.0355	0.0303	-0.1463	0.0382	0.2624
Slovenia	0.2988	0.3107	0.0400	0.3118	0.0033	0.3158	0.3271	0.0358	0.3282	0.0034
Spain	0.8750	0.8914	0.0188	0.8955	0.0046	0.8797	0.8720	-0.0087	0.8695	-0.0028
Denmark	0.9407	0.9411	0.0004	0.9405	-0.0007	0.8356	0.8326	-0.0036	0.8312	-0.0017
Sweden	0.6293	0.6454	0.0255	0.6504	0.0079	0.8643	0.8681	0.0043	0.8688	0.0009
Hungary	0.4698	0.5043	0.0735	0.5216	0.0344	0.5042	0.5371	0.0652	0.5543	0.0321
Poland	0.9947	0.9989	0.0042	0.9989	0.0000	0.9940	0.9980	0.0041	0.9980	0.0000
Czech Republic	0.7574	0.8138	0.0745	0.8284	0.0179	0.9936	0.9977	0.0041	0.9978	0.0000
Bulgaria	-0.9177	-0.9192	0.0016	-0.9183	-0.0010	-0.8694	-0.8670	-0.0028	-0.8651	-0.0022
Croatia	-0.9497	-0.9649	0.0160	-0.9673	0.0025	-0.0081	-0.0391	3.8239	-0.0540	0.3786
Turkey	0.6545	0.6678	0.0202	0.6747	0.0104	0.5395	0.5528	0.0247	0.5611	0.0151
Switzerland	0.5105	0.5534	0.0841	0.5719	0.0335	0.8624	0.8670	0.0054	0.8683	0.0014
Norway	-0.5390	-0.5005	-0.0715	-0.4904	-0.0201	0.9916	0.9945	0.0030	0.9946	0.0000
Brazil	0.9610	0.9672	0.0064	0.9682	0.0011	0.9248	0.9315	0.0072	0.9333	0.0020
Russia	0.7297	0.7210	-0.0119	0.7251	0.0057	0.6450	0.6218	-0.0360	0.6289	0.0114
India	0.4076	0.4691	0.1508	0.4774	0.0178	-0.4634	-0.4100	-0.1151	-0.4015	-0.0207
South Africa	0.7373	0.7697	0.0440	0.7817	0.0155	0.9211	0.9345	0.0145	0.9396	0.0055
US	0.6045	0.6653	0.1006	0.6967	0.0472	0.6458	0.6788	0.0511	0.6997	0.0307
Mexico	0.9127	0.9186	0.0065	0.9205	0.0020	0.8640	0.8682	0.0049	0.8694	0.0013
Argentina	0.9861	0.9897	0.0036	0.9890	-0.0007	0.9901	0.9942	0.0042	0.9938	-0.0004
Indonesia	0.8669	0.8778	0.0126	0.8834	0.0064	0.9178	0.9268	0.0098	0.9304	0.0039
Saudi Arabia	0.1379	0.1848	0.3406	0.1749	-0.0537	0.1356	0.1794	0.3228	0.1699	-0.0526
Thailand	0.7610	0.7628	0.0024	0.7620	-0.0010	0.7222	0.7192	-0.0042	0.7150	-0.0058
UAE	0.8532	0.8857	0.0381	0.8888	0.0036	-0.0201	0.0397	-2.9806	0.0464	0.1672
Malaysia	-0.8775	-0.8798	0.0026	-0.8783	-0.0017	-0.8187	-0.8175	-0.0015	-0.8151	-0.0029
Israel	0.3701	0.4067	0.0990	0.4119	0.0129	-0.2032	-0.1718	-0.1546	-0.1653	-0.0379
Hong Kong	0.4215	0.5325	0.2632	0.5422	0.0182	0.7470	0.8079	0.0815	0.8170	0.0113
Pakistan	0.0590	0.0549	-0.0700	0.0544	-0.0092	0.4056	0.4051	-0.0013	0.4039	-0.0030
Nigeria	-0.2581	-0.2597	0.0063	-0.2612	0.0059	0.2801	0.2846	0.0163	0.2841	-0.0017

As discussed before, the vote results' announcement was taken as the benchmark for the minimum value for all the different indices being studied. This points to the fact that financial contagion took place instantly. While we know that a contagion did in fact exist, the real question is the size of said contagion and how it could be quantified. The results clearly show that the MRS copula isolated the results in just a handful of cases (see Table 4.4.2). The study's findings demonstrate that the referendum results lead to an immediate contagion. Despite the instant impact, its significance is questionable because it lacked a substantial enough time period. The negative outcome, while instant and significant in the very short run, was overall small and only persisted over a small timeframe. Moreover, Article 50 being set into motion had little to no impact. Additionally, with regards to the first, second and third hypotheses, the result of the vote demonstrated significant contagion for seven different nations no the FTSE, including the US and Greece. This essentially proves that any relevant shocks experienced by the markets in question in developed economies (like the US) or within volatile economies (like that of Greece) would lead to instant negative impact. The corresponding contagion for FTSE 350 was restricted to Argentina and the US. Apart from these two, contagion was found to be weak for all other cases. In terms of the impact that Article 50 had, the impact was seen mostly in Estonia, Hong Kong and Croatia.

Figure 4.4. 1. Smoothed probabilities for high dependence regime (Austria, Belgium, Cyprus and Estonia)

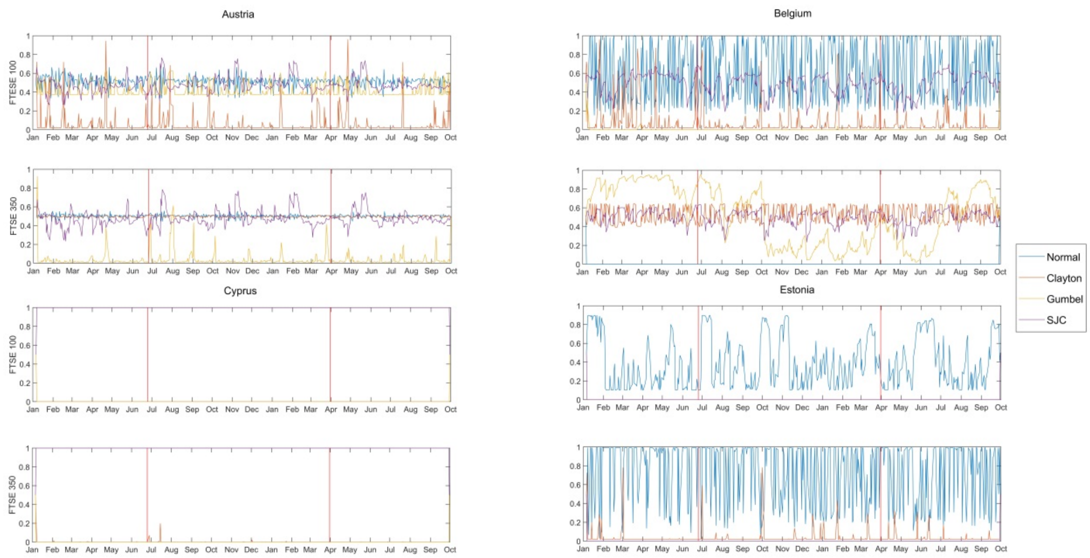


Figure 4.4. 2. Smoothed probabilities for high dependence regime (Finland, France, Germany and Greece)

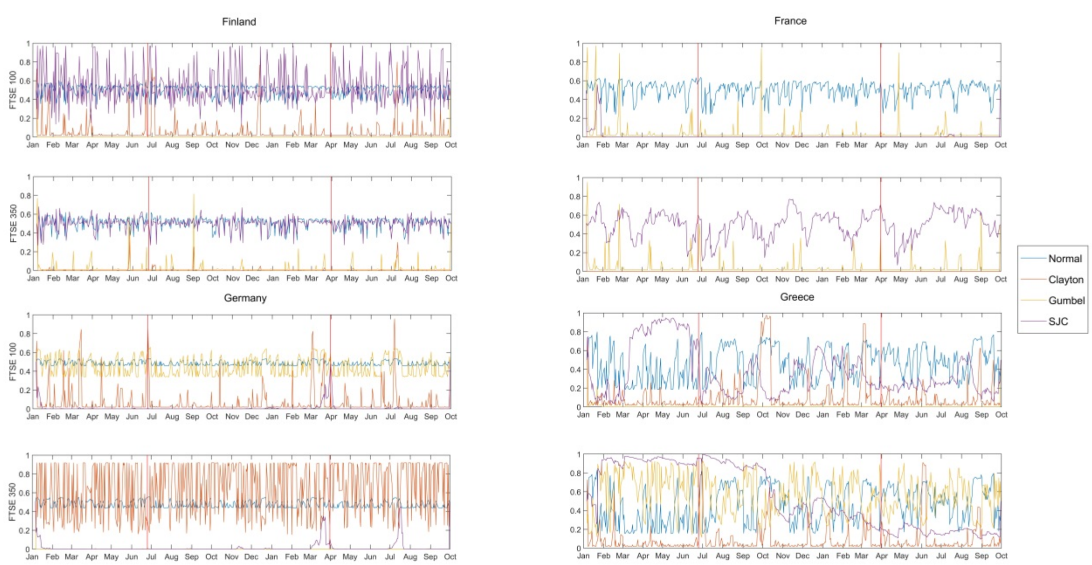


Figure 4.4. 3. Smoothed probabilities for high dependence regime (Ireland, Italy, Latvia and Lithuania)

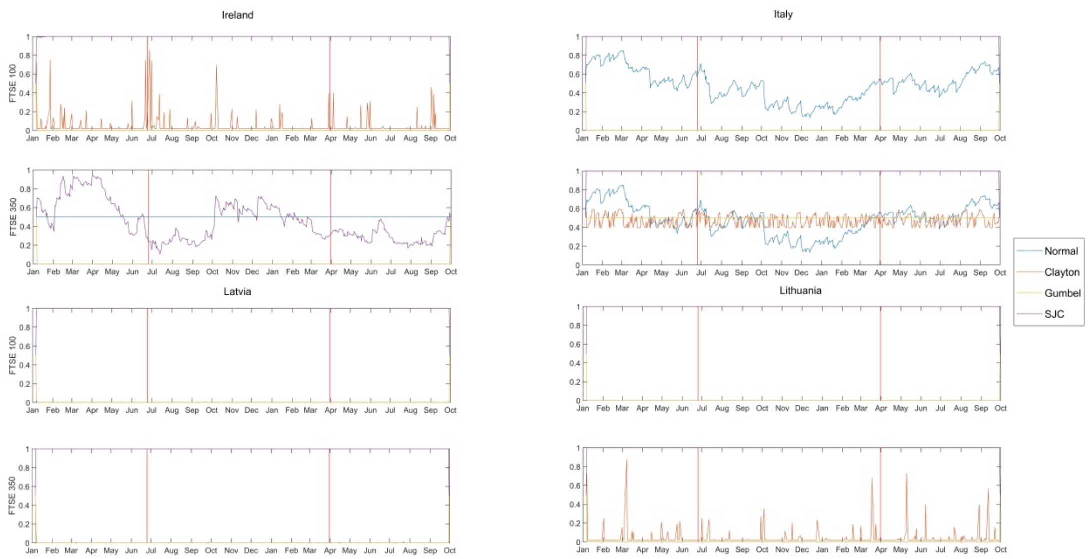


Figure 4.4. 4. Smoothed probabilities for high dependence regime (Netherlands, Portugal, Slovakia and Slovenia)

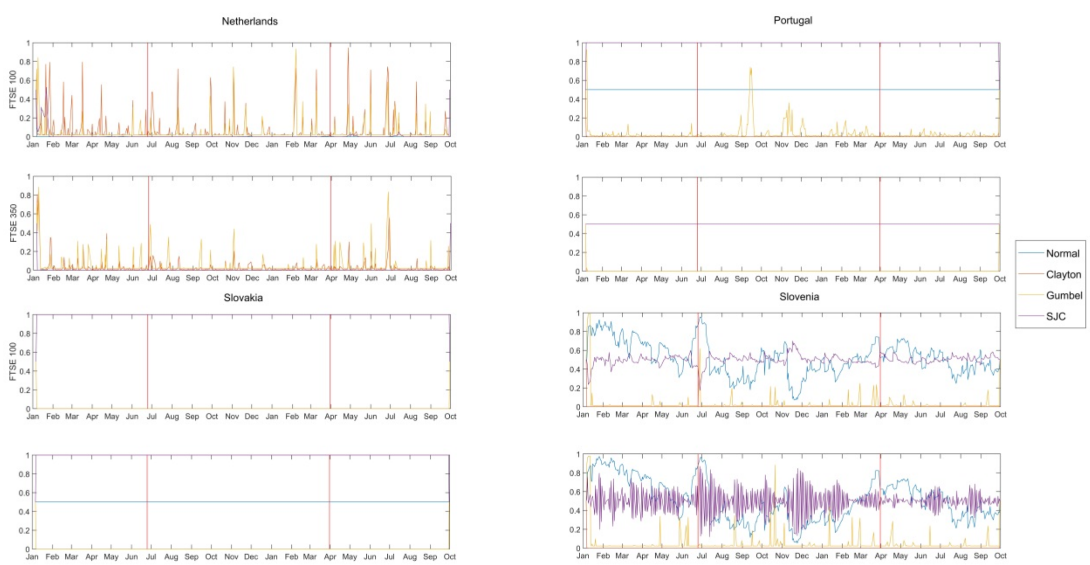


Figure 4.4. 5. Smoothed probabilities for high dependence regime (Spain, Denmark, Sweden and Hungary)

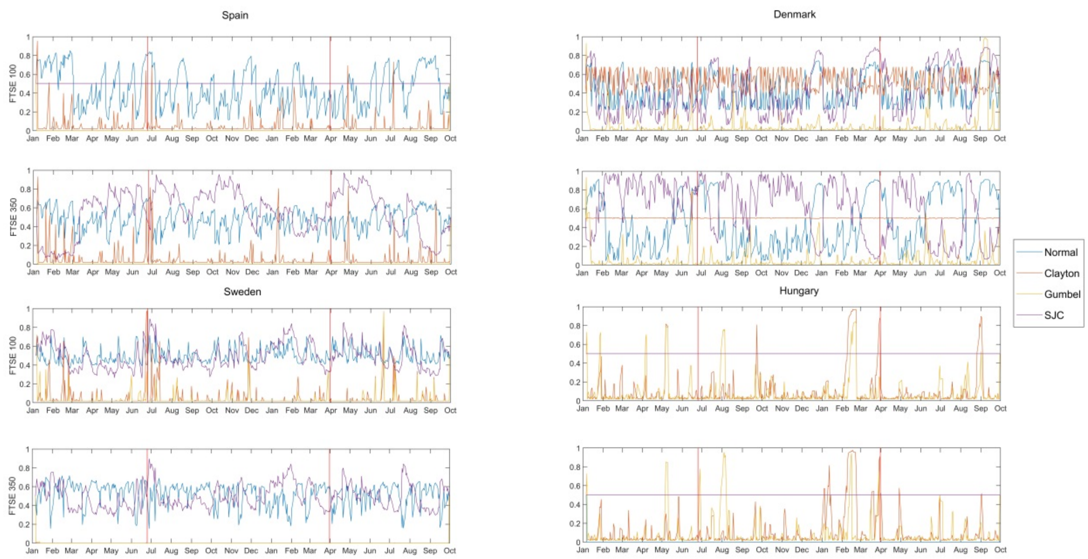


Figure 4.4. 6. Smoothed probabilities for high dependence regime (Poland, Czech Republic, Bulgaria and Croatia)

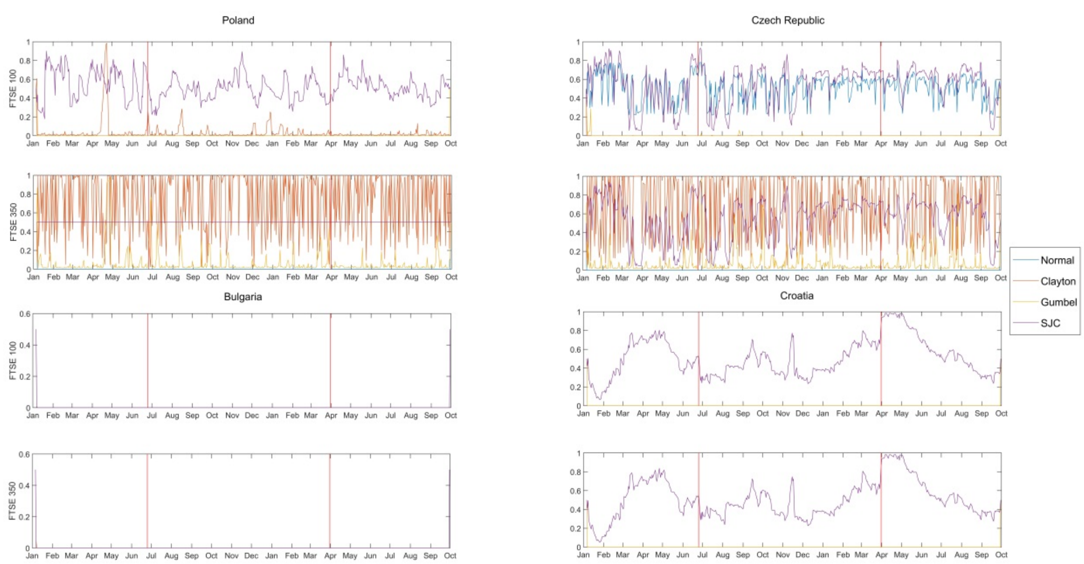


Figure 4.4. 7. Smoothed probabilities for high dependence regime (Turkey, Switzerland, Norway and Brazil)

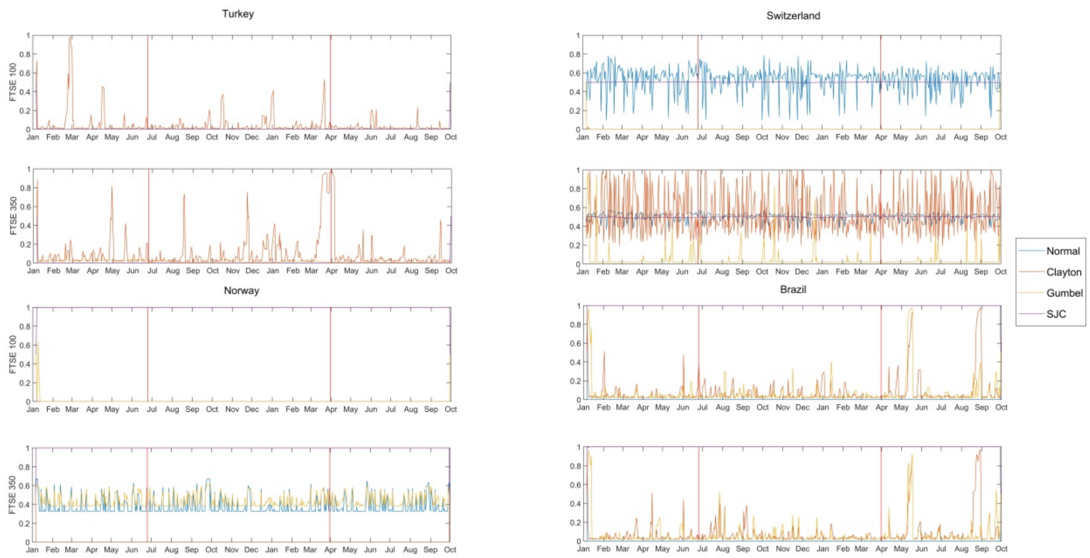


Figure 4.4. 8. Smoothed probabilities for high dependence regime (Russia, India, South Africa and USA)

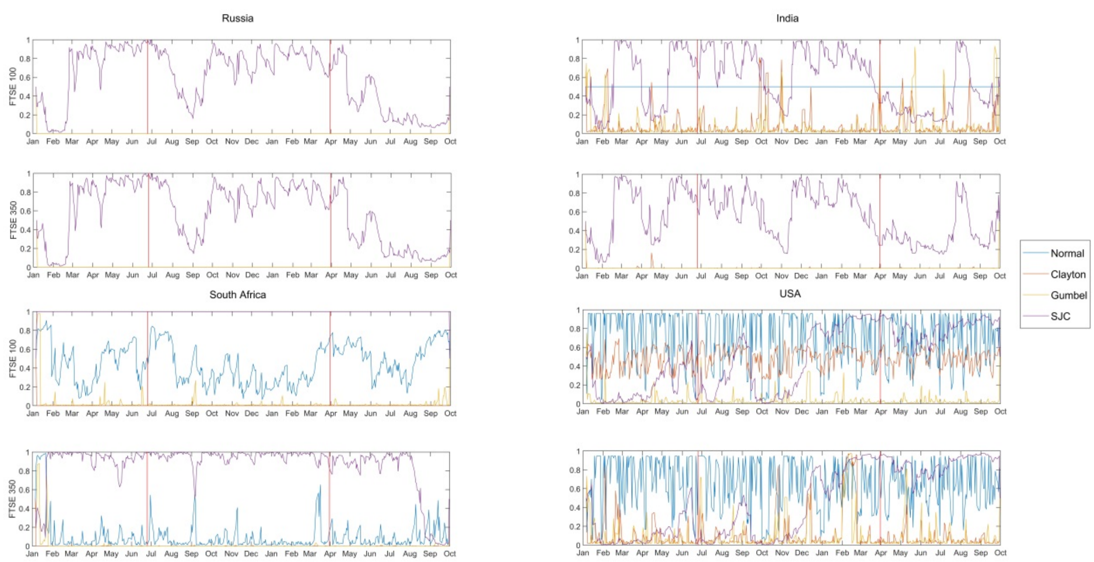


Figure 4.4. 9. Smoothed probabilities for high dependence regime (Mexico, Argentina, Indonesia and Saudi Arabia)

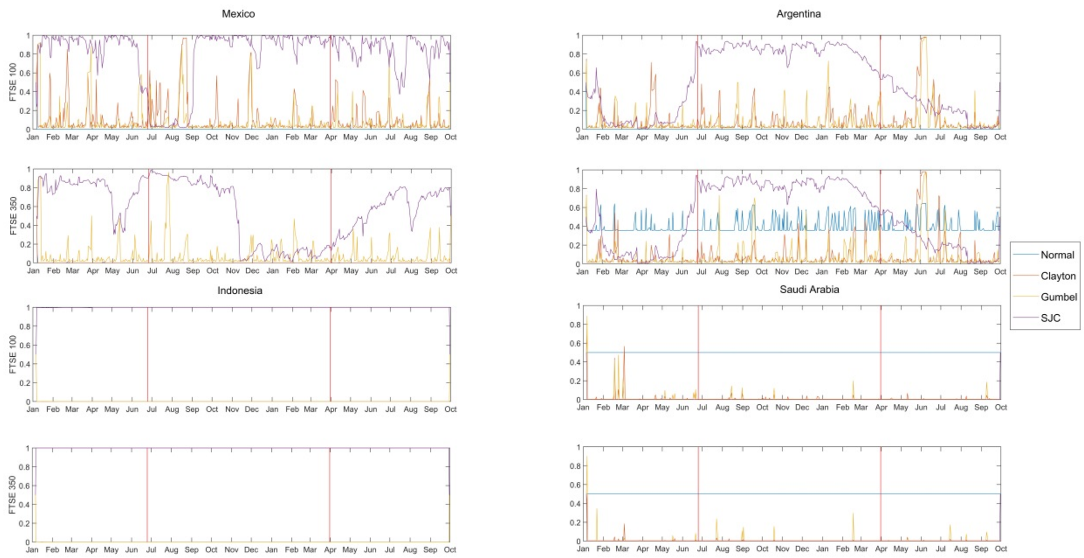


Figure 4.4. 10. Smoothed probabilities for high dependence regime (Thailand, UAE, Malaysia and Israel)

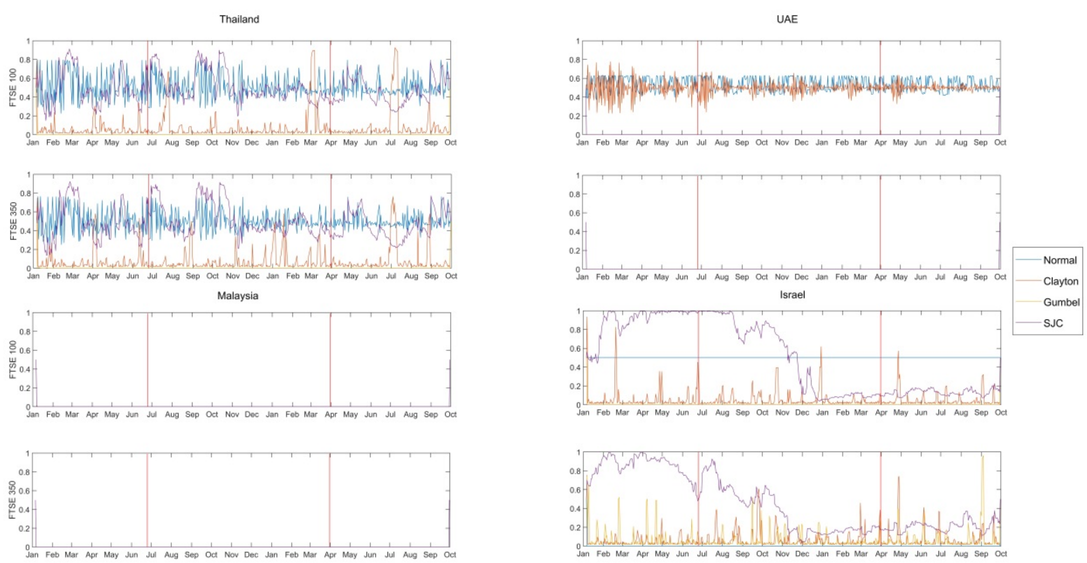
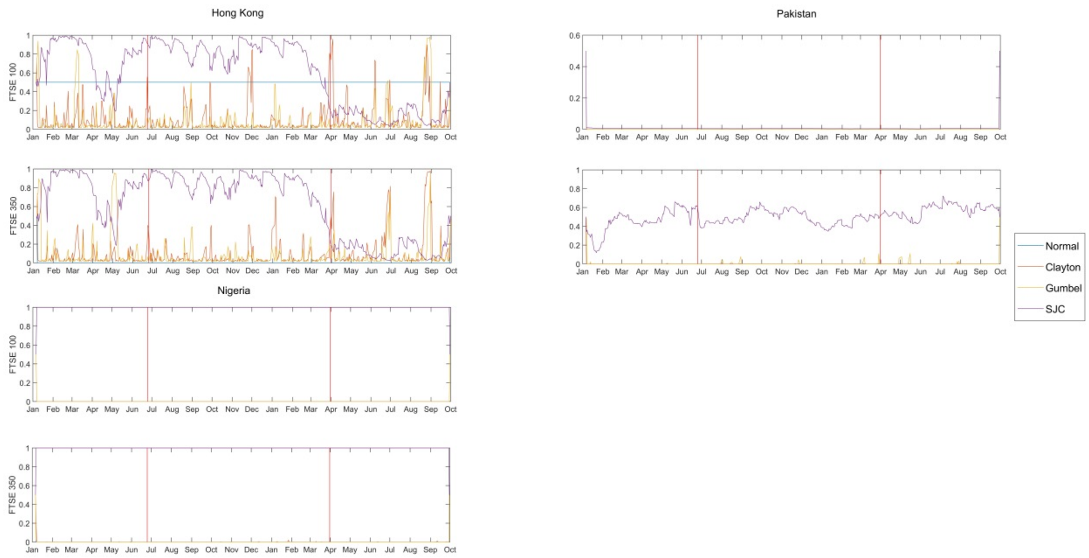


Figure 4.4. 11.Smoothed probabilities for high dependence regime (Hong Kong, Pakistan and Nigeria)



During the time before the referendum, the GBP experienced a drop against the dollar, hitting a seven-year low. This was during the time that UK was holding renegotiations (February 19, 2016). HSBC economists issued a warning that the GBP could sink further. They also pointed out that if the Sterling experienced a decline, the Euro would also follow a similar trend. European analysts talked about UK's potential exit at the time the main ingredient behind Euro's fall. US interest rates, low Eurozone growth, fears about emerging markets (such as China) combined with the possibility of Brexit at the time created a high level of instability for stock markets during January and February of 2016. On June 14, 2016, polls highlighted a rising likelihood that Brexit would happen, leading to the FTSE 100 losing GBP 98 billion as it fell by two percent.

Table 4.4. 2. Summary contagion results from referendum

	FTSE 100				FTSE 350			
	Hypothesis 1: Significant Markov Regime Switch change near referendum date (+/-) less than 6 days	Hypothesis 2: Significant Markov Regime Switch change near referendum date (+/-) less than 3 days	Hypothesis 3: Increase in correlations after the announcement of referendum results	contagion type	Hypothesis 1: Significant Markov Regime Switch change near referendum date (+/-) less than 6 days	Hypothesis 2: Significant Markov Regime Switch change near referendum date (+/-) less than 3 days	Hypothesis 3: Increase in correlations after the announcement of referendum results	contagion type
Austria	×	×	✓	*no*	×	×	✓	*no*
Belgium	×	×	×	*no*	✓	×	×	*weak*
Cyprus	×	×	✓	*no*	×	×	✓	*no*
Estonia	✓	×	✓	*weak*	×	×	✓	*no*
Finland	×	×	✓	*no*	×	×	✓	*no*
France	✓	×	×	*weak*	✓	×	×	*weak*
Germany	×	×	✓	*no*	✓	×	✓	*weak*
Greece	✓	✓	✓	*strong*	×	×	×	*no*
Ireland	×	×	✓	*no*	×	×	✓	*no*
Italy	×	×	×	*no*	×	×	×	*no*
Latvia	×	×	✓	*no*	×	×	✓	*no*
Lithuania	×	×	✓	*no*	×	×	✓	*no*
Netherlands	×	×	✓	*no*	×	×	×	*no*
Portugal	×	×	×	*no*	×	×	×	*no*
Slovakia	×	×	×	*no*	×	×	×	*no*
Slovenia	✓	✓	✓	*strong*	✓	×	✓	*weak*
Spain	✓	×	✓	*weak*	✓	×	×	*weak*
Denmark	×	×	✓	*no*	×	×	×	*no*
Sweden	✓	✓	✓	*strong*	✓	×	✓	*weak*
Hungary	×	×	✓	*no*	×	×	✓	*no*
Poland	✓	×	✓	*weak*	×	×	✓	*no*
Czech Republic	×	×	✓	*no*	×	×	✓	*no*
Bulgaria	×	×	✓	*no*	×	×	×	*no*
Croatia	×	×	✓	*no*	×	×	✓	*no*
Turkey	×	×	✓	*no*	×	×	✓	*no*
Switzerland	×	×	✓	*no*	×	×	✓	*no*
Norway	×	×	×	*no*	×	×	✓	*no*
Brazil	×	×	✓	*no*	×	×	✓	*no*
Russia	×	×	×	*no*	×	×	×	*no*
India	×	×	✓	*no*	×	×	×	*no*
South Africa	✓	✓	✓	*strong*	×	×	✓	*no*
US	✓	✓	✓	*strong*	✓	✓	✓	*strong*
Mexico	✓	✓	✓	*strong*	×	×	✓	*no*
Argentina	✓	✓	✓	*strong*	✓	✓	✓	*strong*
Indonesia	×	×	✓	*no*	×	×	✓	*no*
Saudi Arabia	×	×	✓	*no*	×	×	✓	*no*
Thailand	×	×	✓	*no*	✓	×	×	*weak*
UAE	×	×	✓	*no*	×	×	×	*no*
Malaysia	×	×	✓	*no*	×	×	×	*no*
Israel	×	×	✓	*no*	✓	×	×	*weak*
Hong Kong	×	×	✓	*no*	×	×	✓	*no*
Pakistan	×	×	×	*no*	×	×	×	*no*
Nigeria	×	×	✓	*no*	×	×	✓	*no*

On the other hand, during the post vote period, the FTSE fell by nine percent going from 6338.10 to 5806.13. This happened within the first 10 minutes of trading on the London Stock Exchange on the morning of June 24, 2016. However, a recovery was seen after another 90 minutes passed with the values pushing back to 6091.27 and finally resting at 6162.97 at closing. On June 27, 2016, FTSE 100 consistently fell and lost around two percent of its value. Similarly, a drop of 2.5 percent or 450 points was witnessed on the US Dow Jones Industrial Average. This drop took place in less than 30 minutes. By mid-afternoon on June 27, 2016, the GBP had hit its lowest value in 31 years, falling 11 per cent in just two days. Around GBP 85 billion were lost on the FTSE 100 as a result. Despite this, the FTSE recovered in just two days, i.e. by June 29, 2016, it has pulled back almost all its losses. The study results highlight tranquil correlations. No contagion was witnessed in any other nations (see Tables 4.4.2 and 4.4.3).

Table 4.4. 3. Summary contagion results from article 50

	FTSE 100				FTSE 350			
	Hypothesis 1: Significant Markov Regime Switch change near article 50 date (+/-) less than 6 days	Hypothesis 2: Significant Markov Regime Switch change near article 50 date (+/-) less than 3 days	Hypothesis 3: Increase in correlations after the announcement of article 50 results	contagion type	Hypothesis 1: Significant Markov Regime Switch change near article 50 date (+/-) less than 6 days	Hypothesis 2: Significant Markov Regime Switch change near article 50 date (+/-) less than 3 days	Hypothesis 3: Increase in correlations after the announcement of article 50	contagion type
Austria	×	×	✓	*no*	×	×	✓	*no*
Belgium	×	×	×	*no*	×	×	×	*no*
Cyprus	×	×	×	*no*	×	×	✓	*no*
Estonia	✓	✓	✓	*strong*	✓	✓	×	*limited*
Finland	×	×	✓	*no*	×	×	✓	*no*
France	×	×	×	*no*	✓	✓	×	*limited*
Germany	×	×	✓	*no*	✓	×	✓	*weak*
Greece	×	×	×	*no*	×	×	×	*no*
Ireland	×	×	✓	*no*	×	×	✓	*no*
Italy	×	×	×	*no*	×	×	×	*no*
Latvia	×	×	✓	*no*	×	×	✓	*no*
Lithuania	×	×	✓	*no*	×	×	✓	*no*
Netherlands	×	×	✓	*no*	×	×	×	*no*
Portugal	×	×	×	*no*	×	×	×	*no*
Slovakia	×	×	✓	*no*	×	×	✓	*no*
Slovenia	×	×	✓	*no*	×	×	✓	*no*
Spain	×	×	✓	*no*	×	×	×	*no*
Denmark	✓	×	×	*weak*	×	×	×	*no*
Sweden	×	×	✓	*no*	×	×	✓	*no*
Hungary	×	×	✓	*no*	×	×	✓	*no*
Poland	×	×	✓	*no*	×	×	✓	*no*
Czech Republic	×	×	✓	*no*	×	×	✓	*no*
Bulgaria	×	×	×	*no*	×	×	×	*no*
Croatia	✓	✓	✓	*strong*	✓	✓	✓	*strong*
Turkey	×	×	✓	*no*	✓	×	✓	*weak*
Switzerland	×	×	✓	*no*	×	×	✓	*no*
Norway	×	×	×	*no*	×	×	✓	*no*
Brazil	×	×	✓	*no*	×	×	✓	*no*
Russia	×	×	✓	*no*	×	×	✓	*no*
India	×	×	✓	*no*	×	×	×	*no*
South Africa	×	×	✓	*no*	×	×	✓	*no*
US	×	×	✓	*no*	×	×	✓	*no*
Mexico	×	×	✓	*no*	×	×	✓	*no*
Argentina	×	×	×	*no*	×	×	×	*no*
Indonesia	×	×	✓	*no*	×	×	✓	*no*
Saudi Arabia	×	×	×	*no*	×	×	×	*no*
Thailand	×	×	×	*no*	×	×	×	*no*
UAE	×	×	✓	*no*	×	×	✓	*no*
Malaysia	×	×	×	*no*	×	×	×	*no*
Israel	×	×	✓	*no*	×	×	×	*no*
Hong Kong	✓	✓	✓	*strong*	✓	✓	✓	*strong*
Pakistan	×	×	×	*no*	×	×	×	*no*
Nigeria	×	×	✓	*no*	×	×	×	*no*

The results highlight that the Brexit poll led to an instant impact on stock markets in other countries. The shock of the news created instability in the UK and for countries linked to it. However, this issue was limited and lasted only a few days. Almost all markets recovered fully from the original event. If and when the UK manages to completely withdraw from the EU, the results of this study imply that capital markets will suffer no contagion. There was no long-term damage to any of the markets and the UK did not cause financial contagion to other nations. Whenever a “hard” Brexit takes place, the markets will be able to sustain its weight. Whatever issues occur will only last in the shorter term, and markets will be able to push back soon.

It is pertinent to note, however, that the Brexit will cause serious economic damage to both the EU and the UK. The banking and private sector will suffer alongside the European Single Market. Citizens of the EU have ease of mobility and movement, meaning that they can live and work anywhere within the EU. It remains to be seen what part of this mobility and freedom will be retained post the "hard" Brexit that is expected. Around 2-3 million EU citizens have made the UK their home. Moreover, around 1.2 million British citizens have chosen to live in a number of EU countries. What happens to both sets of people is anyone's guess at this point in time.

In addition, the vote results led to instability for businesses. This instability can be a huge problem for businesses. It is important now more so than ever to reassure the business community and encourage spending and investment. In terms of the banking sector, the five largest banks in the UK saw a fall of around 21 percent in share prices right after the vote. In addition, banks that are from outside the UK also experienced a 10 percent drop. By June 24, 2016, day-end, while many banks had recovered, some continued to suffer, including Barclays and RBS Group, which stuck to their 10 percent drop. As a result, Moody's, Fitch Group and Standard & Poor's produced negative statements about the vote. The Bank of England attempted to tackle the problem by releasing GBP 150 billion in lending. Their aim was to reduce the countercyclical capital buffers that are topically held by banks. The problems outlined herein first presented themselves after the vote, and again once Article 50 was triggered.

Figure 4.4. 12. Depedence dynamics (Austria, Belgium, Cyprus and Estonia)

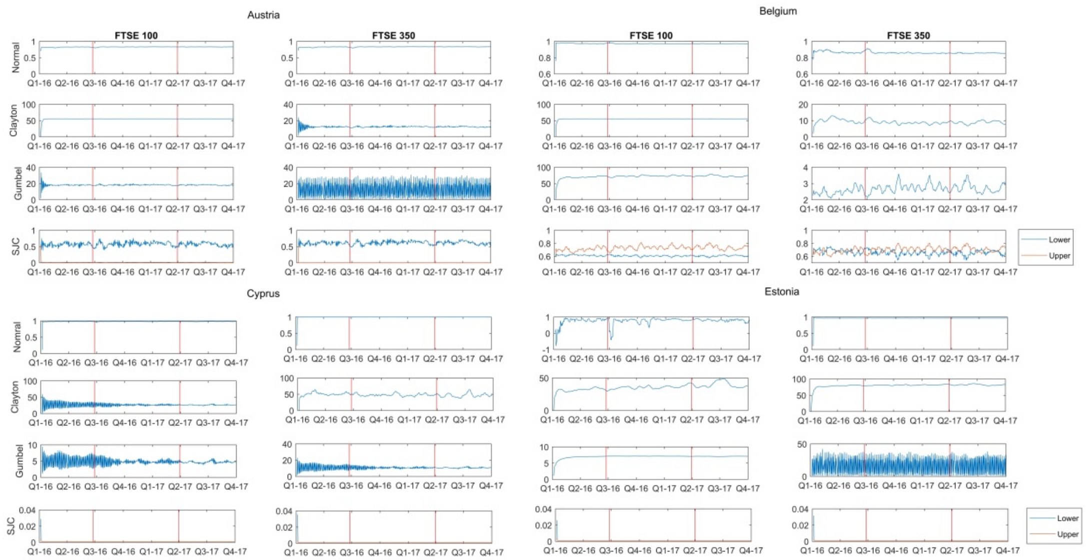


Figure 4.4. 13. Depedence dynamics (Finland, France, Germany and Greece)

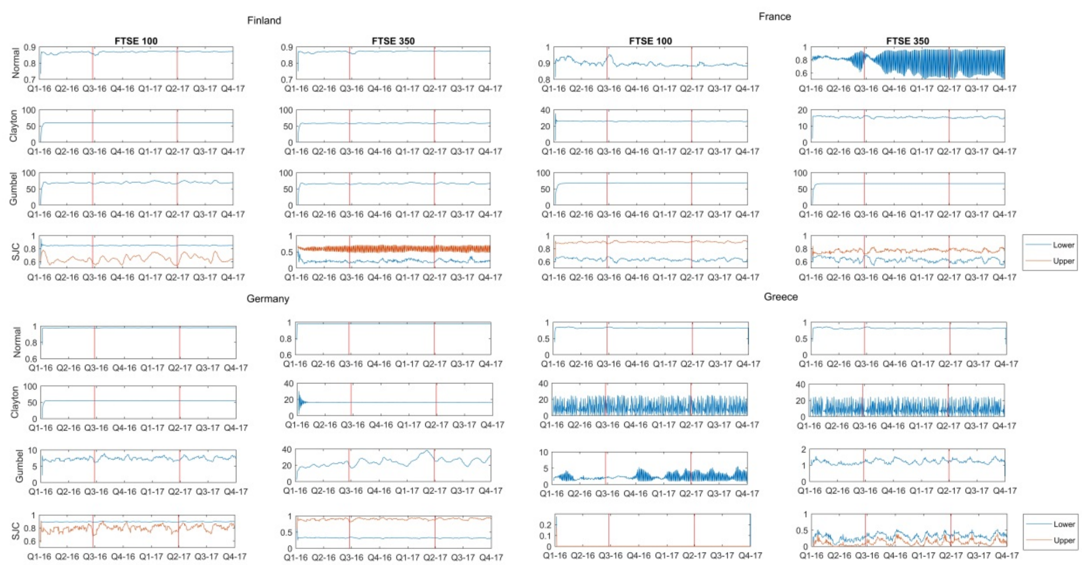


Figure 4.4. 14. Depedence dynamics (Ireland, Italy, Latvia and Lithuania)

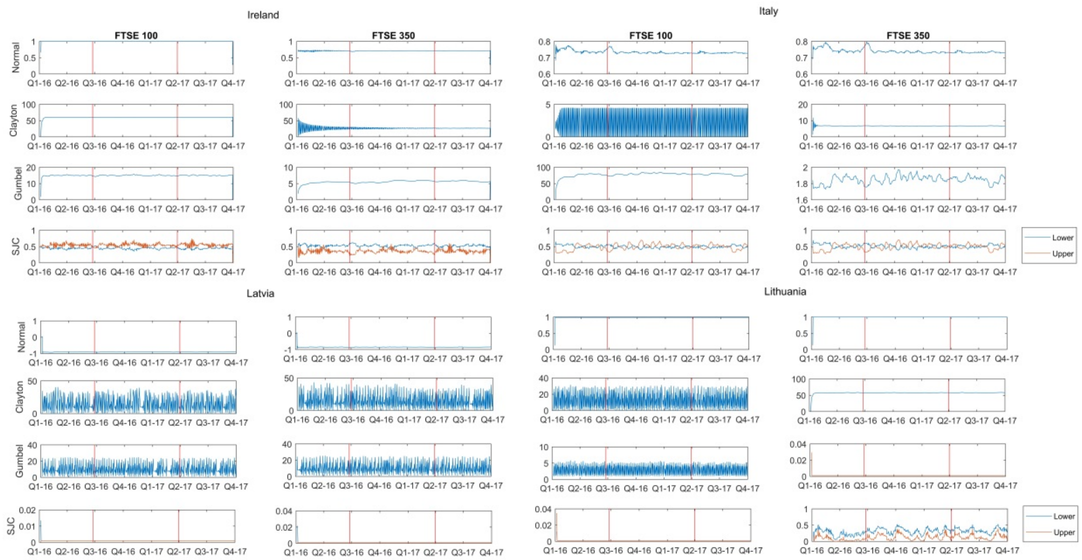


Figure 4.4. 15. Depedence dynamics (Netherlands, Portugal, Slovakia and Slovenia)

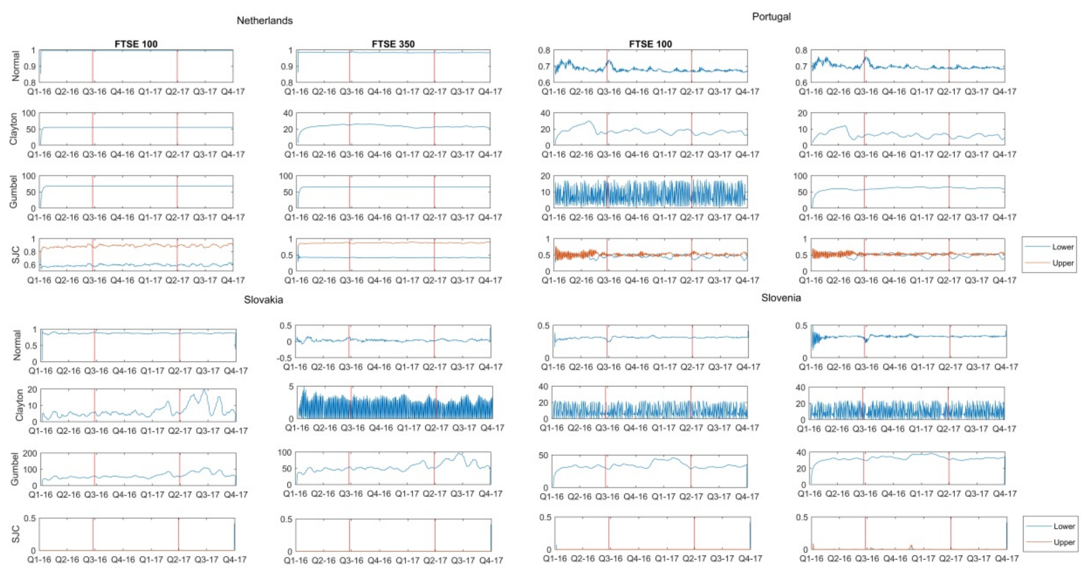


Figure 4.4. 16. Depedence dynamics (Spain, Denmark, Sweden and Hungary)

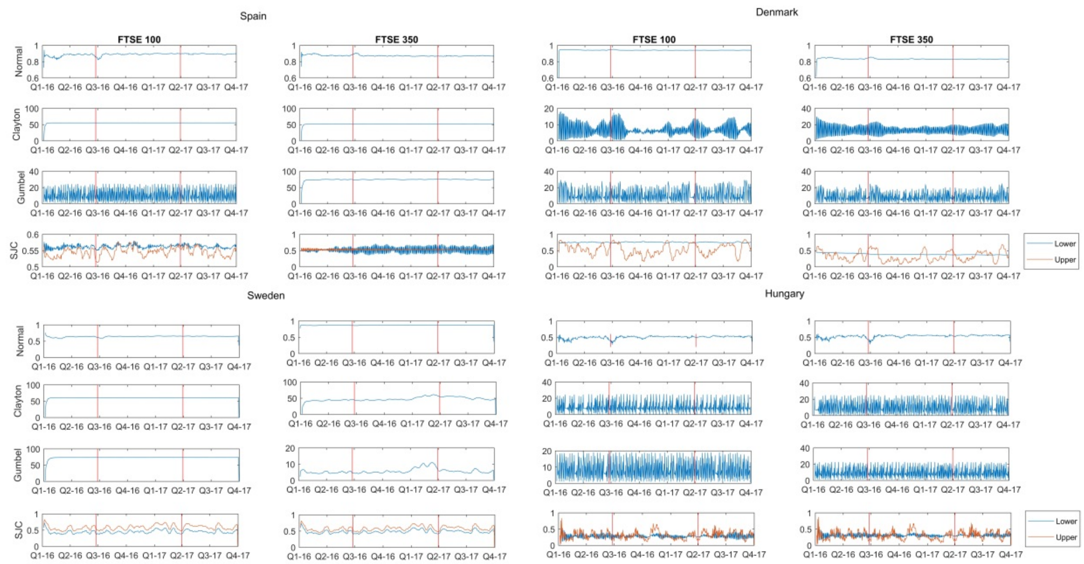


Figure 4.4. 17. Depedence dynamics (Poland, Czech Republic, Bulgaria and Croatia)

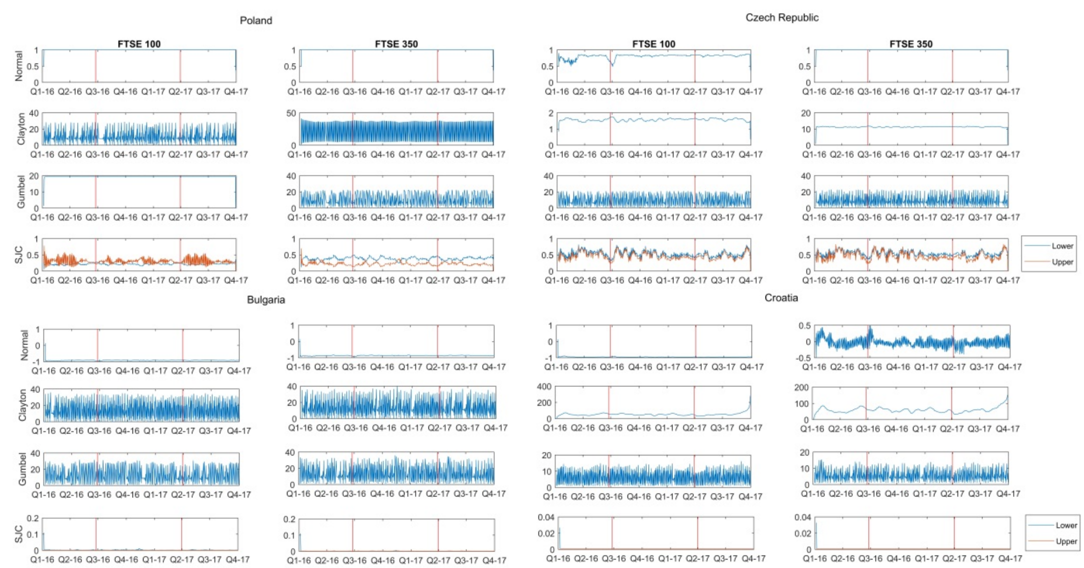


Figure 4.4. 18. Depedence dynamics (Turkey, Switzerland, Norway and Brazil)

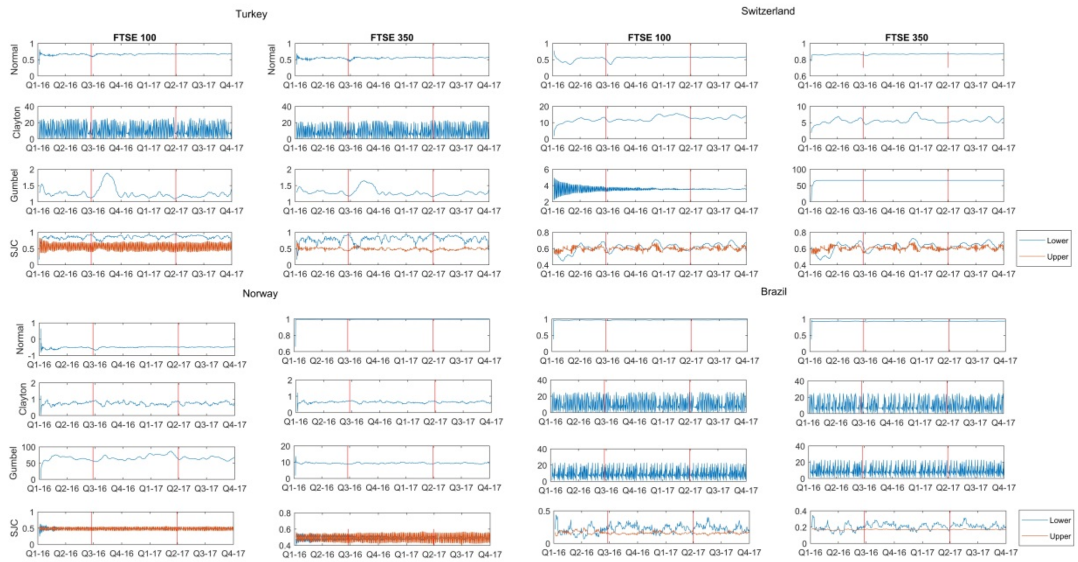


Figure 4.4. 19. Depedence dynamics (Russia, India, South Africa and USA)

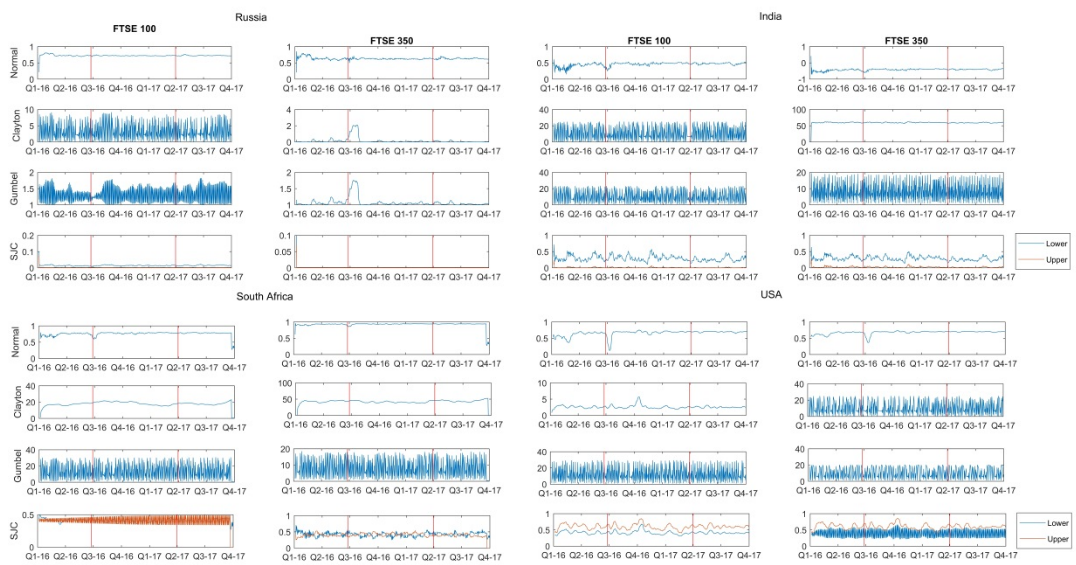


Figure 4.4. 20. Depedence dynamics (Mexico, Argentina, Indonesia and Saudi Arabia)

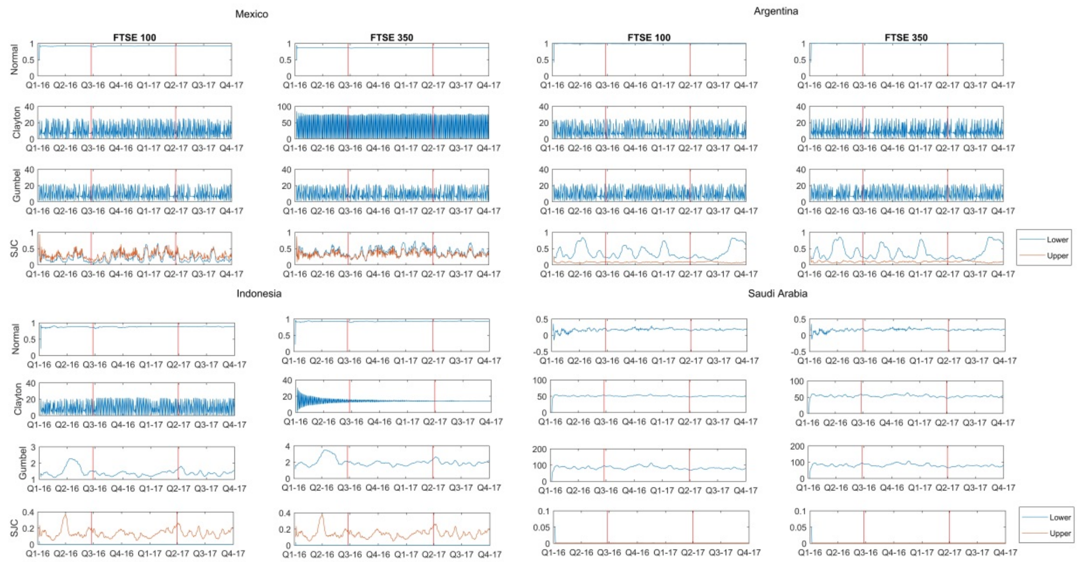


Figure 4.4. 21. Depedence dynamics (Thailand, UAE, Malaysia and Israel)

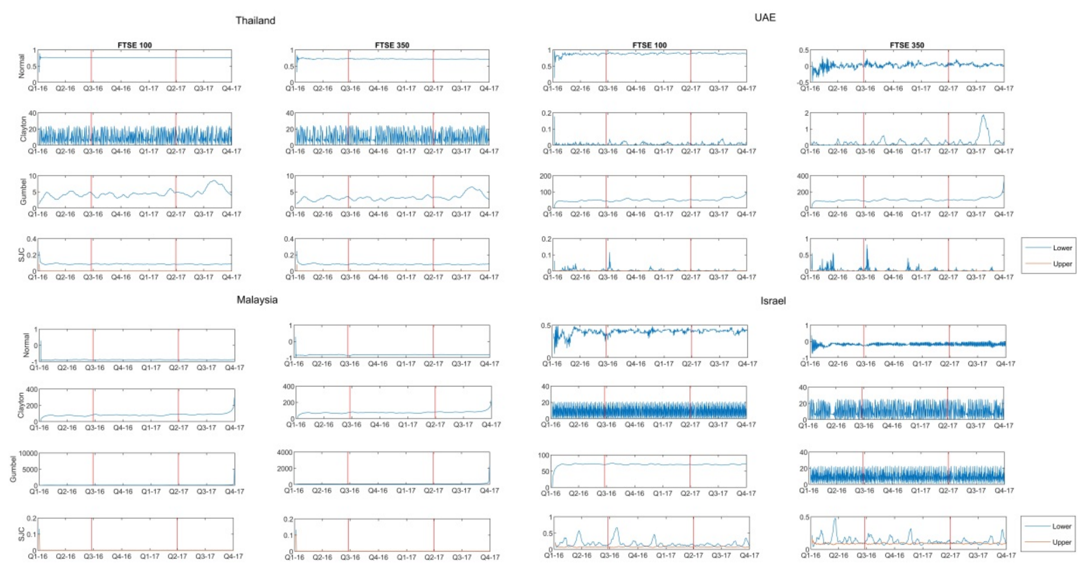
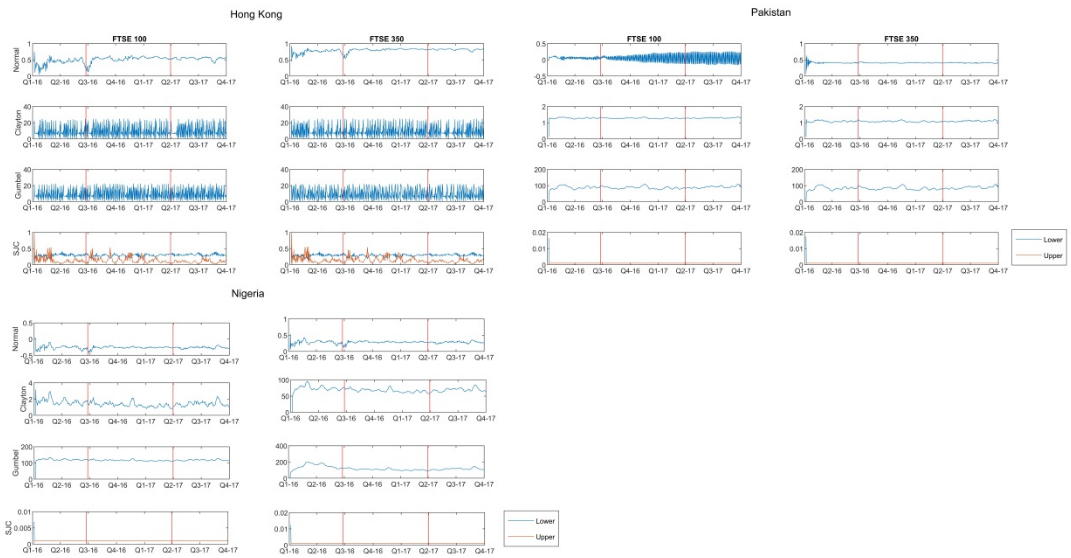


Figure 4.4. 22. Depedence dynamics (Hong Kong, Pakistan and Nigeria)



4.5. Empirical analysis of Financial Networks, Contagion and Predicting Shock Events with Machine Learning

In Figure 4.5.1 we see the evolution of correlations grouped in geographic regions. As we can see, in the case of stock indices, an instant increase in correlations is related to financial crisis across time. The most important evidence of this figure is that all regional correlations have almost identical behavior, specifically in the case of Eurozone, Asia/Pacific and American markets. This shows that even though that stock exchange markets open at different hours and are in different locations, the dynamics of the markets seem to share similar behavior of conditional correlations when we are referring to stock indices. This behavior is the same for the entire duration of our data. CDS also seem to follow the same behavior of correlation with the stock indices. However, this is not the case for bond yields.

Figure 4.5. 1. Global Interdependence (Asymmetric Dynamic Conditional Correlation)

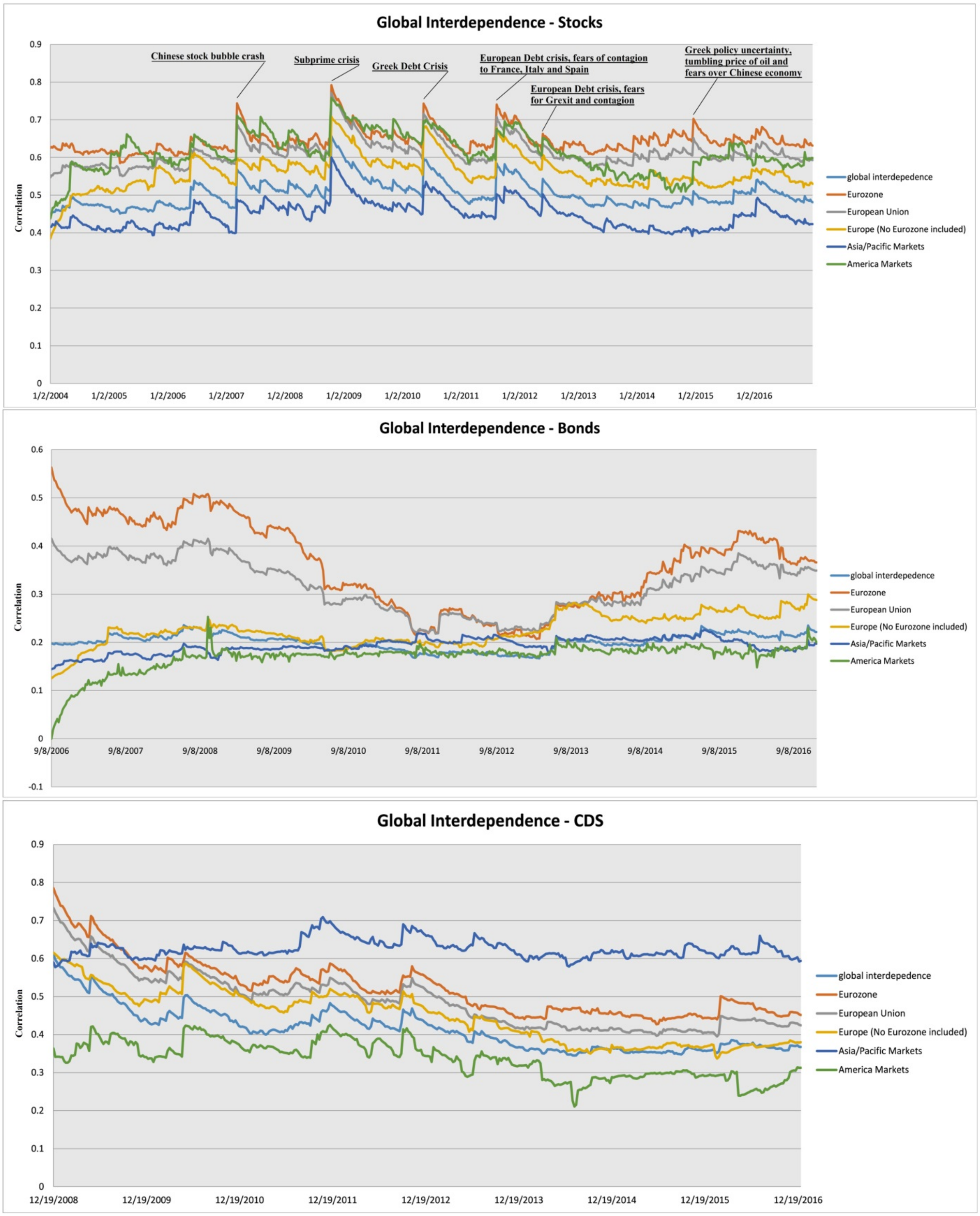


Figure 4.5.2 depicts structural information on stocks, bonds and CDS financial networks. Specifically, the financial networks extracted from average correlations of the entire sample each time. As we can see, the topological structure of the three financial networks (stocks, bonds and CDS) are quite close to the real location of the countries. Namely, the correlations (connected countries) are more connected to their neighbors instead of others in all networks. For example, in the stocks' network, we see that Eurozone countries are connected, as are American countries, while the same thing happens with Asian countries (different colors). This explains that the created networks are interpreted by a significant percentage of the actual geographic location of the markets. This evidence can verify the significance of our model and work as a robustness test for the extracted financial networks. The topological structure gives a logical explanation about the connectivity of the networks in all cases of stocks, bonds and CDS. This behavior of the correlations seems to be based on neighborhood issues; large commercial and state transactions between countries contribute to global imports and exports.

Regarding the characteristics, the Eurozone and Europe in general seem to connect with the countries of America and Asia in all networks. Specifically, as we stated previously, the conversion of correlations to network distance extracts a geographical structural very close to the real location and neighborhood of the countries. This can be answered for all three networks. Similarly, evidence of topological properties was found in Eryigit and Eryigit (2009) and Kantar et al. (2011); however, this evidence was for a different kind of financial network. A vital viewpoint in the network investigations is that we find that indices of the same geographical locale nature rush together, which gives proof of the synchronization of stock market indices' clustering behaviors to their territorial properties and affirms the network as the picture of the genuine financial condition hypothetically and experimentally. That is, there gives off an impression of being a more prominent clustering impact among the indices having a place with related district zones than those of different ones. In addition, Eurozone countries that have common currency show that they have strong weighted connection to a great extent and they depict remarkably high correlations in the entire sample. This can be confirmed for all networks. Asian countries present strong connectivity in the networks of bonds and CDS. Conversely, the conversion of correlations to network distance show that the American markets do not depict any statistical significance in the networks of bonds and CDS in terms of the location in the network and their neighborhood; they are dispersed in both financial networks.

It is worth noting that the financial network of bonds has many similarities with the network of CDS as far as the allocation of countries is concerned. It seems that there is a structure in these two networks (bonds and CDS) that is completely different with the financial network of stock indices. We believe that this behavior stems from the nature of the networks; the target of stock owners is to maximize their index, while in the case of bonds and CDS it is to stay as low as possible. Countries' bond yield shows the interest rate of lending money for the general government. Similarly, sovereign CDS include failure to pay on the coupons or principals of their bonds or restructuring those agreements. Thus, it is important for a country that sovereign bonds and CDS remain as low as possible.

Figure 4.5. 2. Financial Networks of Stocks Indices, Bonds and CDS

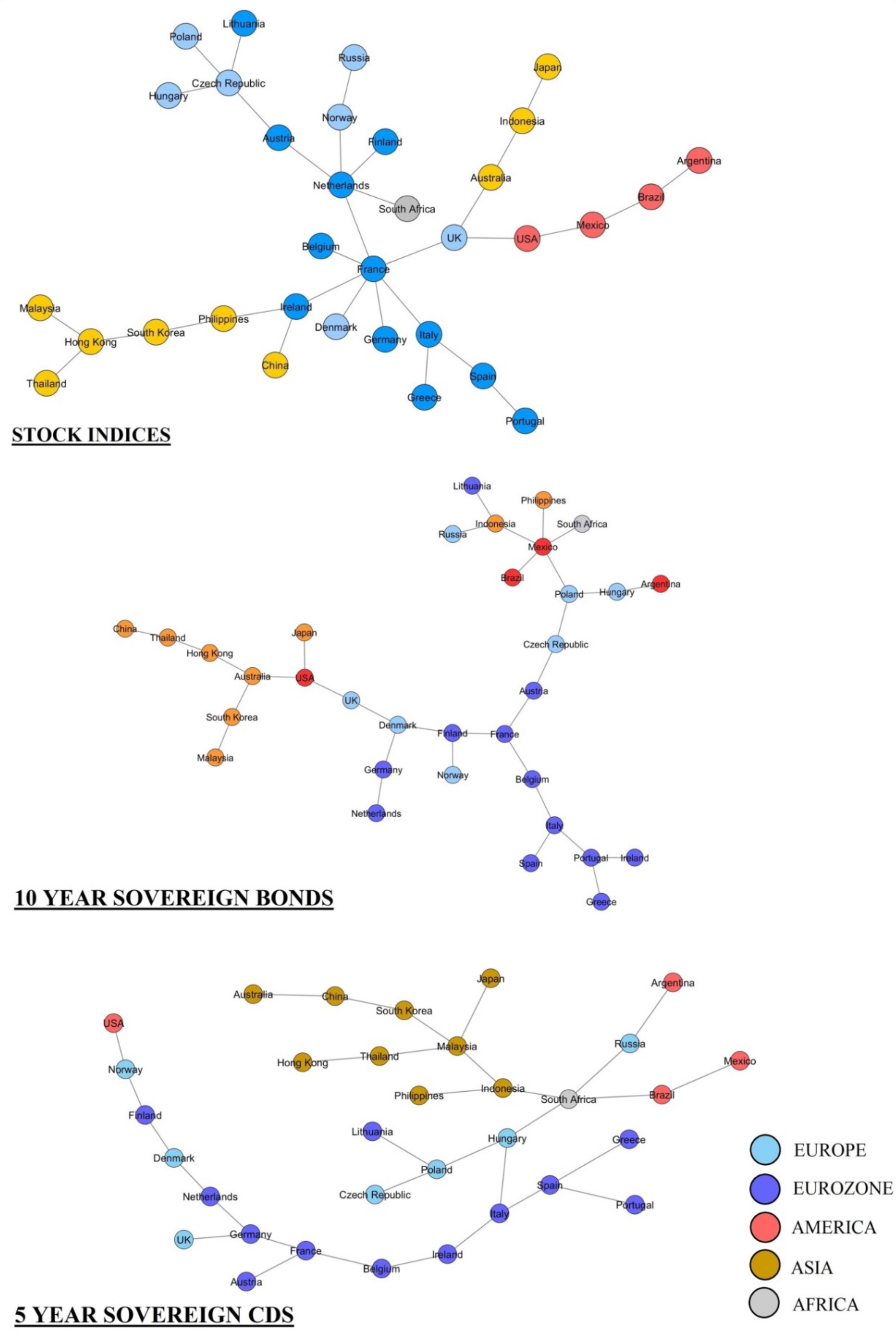


Table 4.5.1 shows the centrality rankings of countries for the stock networks. Due to the lack of space, the financial networks of bonds and CDS are available from the authors upon request. Figures 4.5.3, 4.5.4 and 4.5.5 depict the overall weighted financial networks of stocks, bonds and CDS and their corresponding centrality. In stock and bond networks, France seems to be the most central country followed by the Netherlands and the UK. For the case of France, this is in line with Kantar et al. (2011), Eryigit and Eryigit (2009) and Gilmore et al. (2008). European and more specifically, Eurozone countries dominate the networks and act as central nodes. In this case, the Eurozone works as a joint distribution with the American and the Asian markets. Similarly, evidence of the Eurozones' predominant network center is also found in Qiao et al. (2015).

Table 4.5. 1. Descriptive Statistics

		Mean	Median	Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count	Jarque- Bera Probability
UK	Stocks	0.001	0.002	0.025	0.001	15.346	-1.389	0.362	-0.236	0.126	0.474	679	0.00
	Bonds	-0.002	-0.002	0.055	0.003	3.978	0.356	0.510	-0.241	0.269	-1.292	539	0.00
	CDS	-0.003	-0.001	0.074	0.006	4.479	0.073	0.770	-0.421	0.349	-1.217	420	0.00
Austria	Stocks	0.001	0.004	0.036	0.001	14.491	-1.735	0.514	-0.341	0.172	0.527	679	0.00
	Bonds	-0.004	-0.005	0.135	0.018	31.298	-0.041	2.252	-1.345	0.908	-2.182	539	0.00
	CDS	-0.004	-0.001	0.085	0.007	3.837	0.098	0.771	-0.386	0.386	-1.594	420	0.00
Belgium	Stocks	0.001	0.004	0.028	0.001	13.601	-1.834	0.352	-0.261	0.091	0.487	679	0.00
	Bonds	-0.004	-0.006	0.098	0.010	20.524	-0.434	1.334	-0.799	0.535	-1.955	539	0.00
	CDS	-0.002	-0.001	0.085	0.007	3.143	-0.160	0.775	-0.445	0.329	-0.924	420	0.00
Finland	Stocks	0.001	0.004	0.031	0.001	4.460	-0.844	0.325	-0.203	0.122	0.883	679	0.00
	Bonds	-0.004	-0.007	0.184	0.034	44.044	0.502	3.420	-1.689	1.730	-2.363	539	0.00
	CDS	-0.002	0.000	0.080	0.006	7.343	-0.218	0.886	-0.481	0.405	-0.903	420	0.00
France	Stocks	0.000	0.003	0.030	0.001	8.866	-1.213	0.375	-0.251	0.124	0.326	679	0.00
	Bonds	-0.003	-0.004	0.110	0.012	29.572	0.874	1.846	-0.884	0.962	-1.703	539	0.00
	CDS	-0.001	-0.005	0.087	0.008	4.235	0.072	0.874	-0.482	0.392	-0.433	420	0.00
Germany	Stocks	0.002	0.005	0.030	0.001	8.204	-1.010	0.393	-0.243	0.149	1.079	679	0.00
	Bonds	0.005	-0.007	2.161	4.671	276.267	7.908	68.250	-28.000	40.250	2.752	539	0.00
	CDS	-0.002	0.000	0.089	0.008	4.851	0.378	0.885	-0.412	0.473	-0.777	420	0.00
Greece	Stocks	-0.002	0.001	0.044	0.002	2.471	-0.570	0.401	-0.225	0.176	-1.233	679	0.00
	Bonds	0.001	0.000	0.070	0.005	33.925	-2.591	1.090	-0.779	0.310	0.552	539	0.00
	CDS	0.003	0.000	0.225	0.051	238.401	-13.384	4.538	-3.999	0.539	1.441	420	0.00
Ireland	Stocks	0.000	0.005	0.033	0.001	15.497	-1.876	0.451	-0.317	0.134	0.292	679	0.00
	Bonds	-0.003	-0.001	0.069	0.005	16.145	0.088	1.006	-0.592	0.414	-1.587	539	0.00
	CDS	-0.003	-0.007	0.080	0.006	3.710	0.060	0.677	-0.348	0.329	-1.178	420	0.00
Italy	Stocks	0.000	0.003	0.033	0.001	5.966	-1.212	0.348	-0.244	0.105	-0.334	679	0.00
	Bonds	-0.001	0.000	0.044	0.002	4.042	0.106	0.393	-0.203	0.191	-0.790	539	0.00
	CDS	0.000	0.000	0.102	0.010	3.872	-0.151	1.017	-0.512	0.505	-0.108	420	0.00
Lithuania	Stocks	0.002	0.002	0.027	0.001	18.432	-0.056	0.456	-0.208	0.248	1.181	679	0.00
	Bonds	-0.003	0.000	0.114	0.013	36.530	-0.600	1.952	-1.138	0.814	-1.629	539	0.00
	CDS	-0.006	0.000	0.054	0.003	3.541	-0.076	0.442	-0.223	0.219	-2.312	420	0.00
Netherlan	Stocks	0.001	0.003	0.029	0.001	13.658	-1.612	0.395	-0.271	0.124	0.426	679	0.00
	Bonds	0.064	-0.007	1.642	2.696	227.631	13.843	36.200	-8.000	28.200	34.317	539	0.00
	CDS	-0.003	0.000	0.080	0.006	5.849	-0.580	0.818	-0.539	0.279	-1.133	420	0.00
Portugal	Stocks	-0.001	0.002	0.028	0.001	5.420	-1.154	0.291	-0.206	0.085	-0.361	679	0.00
	Bonds	0.000	-0.001	0.052	0.003	4.298	-0.096	0.553	-0.311	0.242	-0.039	539	0.00
	CDS	0.003	0.000	0.108	0.012	5.642	-0.132	1.168	-0.683	0.485	1.051	420	0.00
Spain	Stocks	0.000	0.004	0.032	0.001	5.460	-0.979	0.349	-0.238	0.111	0.195	679	0.00
	Bonds	-0.002	-0.001	0.049	0.002	6.460	-0.752	0.545	-0.353	0.192	-0.987	539	0.00
	CDS	-0.001	0.000	0.096	0.009	1.467	0.023	0.761	-0.357	0.404	-0.231	420	0.00
Denmark	Stocks	0.002	0.005	0.029	0.001	8.736	-1.346	0.342	-0.225	0.117	1.286	679	0.00
	Bonds	-0.004	-0.006	0.246	0.061	148.149	7.093	6.067	-2.015	4.052	-2.417	539	0.00
	CDS	-0.004	0.000	0.077	0.006	7.570	0.124	0.903	-0.454	0.448	-1.741	420	0.00
Hungary	Stocks	0.002	0.002	0.034	0.001	7.654	-0.969	0.420	-0.269	0.152	1.224	679	0.00
	Bonds	-0.002	-0.003	0.041	0.002	2.766	0.664	0.306	-0.132	0.174	-0.894	539	0.00
	CDS	-0.003	-0.001	0.071	0.005	9.081	0.870	0.767	-0.285	0.482	-1.332	420	0.00
Poland	Stocks	0.001	0.003	0.027	0.001	3.795	-0.732	0.287	-0.171	0.116	0.909	679	0.00
	Bonds	-0.001	-0.001	0.032	0.001	4.227	0.266	0.344	-0.176	0.168	-0.437	539	0.00
	CDS	-0.003	0.000	0.077	0.006	8.386	0.815	0.898	-0.365	0.533	-1.253	420	0.00
Czech Rep	Stocks	0.001	0.002	0.031	0.001	15.294	-1.508	0.460	-0.305	0.156	0.350	679	0.00
	Bonds	-0.004	-0.003	0.059	0.004	5.331	0.451	0.565	-0.267	0.298	-2.083	539	0.00
	CDS	-0.004	0.000	0.078	0.006	15.413	0.500	1.084	-0.525	0.559	-1.497	420	0.00

Table 4.5.1. Descriptive Statistics (continued)

		Mean	Median	Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count	Jarque- Bera Probability
Norway	Stocks	0.001	0.005	0.034	0.001	8.221	-1.155	0.416	-0.248	0.168	0.937	679	0.00
	Bonds	-0.002	0.000	0.046	0.002	2.735	0.116	0.384	-0.184	0.199	-0.920	539	0.00
	CDS	-0.001	0.000	0.068	0.005	4.016	0.370	0.689	-0.330	0.359	-0.487	420	0.00
Brazil	Stocks	0.001	0.004	0.036	0.001	3.843	-0.273	0.392	-0.223	0.168	1.016	679	0.00
	Bonds	0.000	0.000	0.027	0.001	3.677	0.246	0.282	-0.122	0.160	-0.245	539	0.00
	CDS	-0.001	-0.004	0.074	0.005	2.080	0.260	0.603	-0.238	0.365	-0.332	420	0.00
Russia	Stocks	0.002	0.005	0.046	0.002	9.626	0.175	0.655	-0.282	0.373	1.577	679	0.00
	Bonds	0.000	0.000	0.046	0.002	20.031	1.788	0.636	-0.230	0.406	0.238	539	0.00
	CDS	-0.003	-0.003	0.091	0.008	6.800	-0.418	1.053	-0.628	0.425	-1.456	420	0.00
China	Stocks	0.001	0.000	0.039	0.002	2.261	0.060	0.343	-0.170	0.173	0.816	679	0.00
	Bonds	0.000	0.000	0.026	0.001	6.754	-0.667	0.284	-0.186	0.098	-0.079	539	0.00
	CDS	-0.001	0.000	0.078	0.006	3.099	-0.322	0.722	-0.427	0.295	-0.610	420	0.00
South Afri	Stocks	0.002	0.004	0.024	0.001	3.474	-0.113	0.231	-0.098	0.133	1.681	679	0.00
	Bonds	0.000	-0.001	0.023	0.001	8.246	0.818	0.286	-0.104	0.182	0.012	539	0.00
	CDS	-0.002	-0.003	0.080	0.006	3.202	0.491	0.677	-0.265	0.412	-0.702	420	0.00
USA	Stocks	0.001	0.002	0.024	0.001	9.737	-0.972	0.314	-0.201	0.114	0.714	679	0.00
	Bonds	-0.001	-0.004	0.049	0.002	1.079	0.270	0.366	-0.189	0.177	-0.664	539	0.00
	CDS	-0.002	0.000	0.075	0.006	5.529	-0.028	0.727	-0.419	0.308	-0.892	420	0.00
Mexico	Stocks	0.002	0.004	0.028	0.001	6.759	-0.239	0.365	-0.179	0.186	1.665	679	0.00
	Bonds	0.000	-0.001	0.027	0.001	11.109	0.354	0.372	-0.205	0.167	-0.100	539	0.00
	CDS	-0.002	-0.003	0.079	0.006	1.785	0.065	0.605	-0.258	0.347	-0.887	420	0.00
Argentina	Stocks	0.004	0.006	0.041	0.002	3.477	-0.724	0.377	-0.238	0.139	2.772	679	0.00
	Bonds	-0.002	0.000	0.105	0.011	8.975	-0.348	1.160	-0.575	0.584	-0.823	539	0.00
	CDS	-0.005	0.000	0.129	0.017	78.794	-5.029	2.514	-1.720	0.794	-2.270	420	0.00
South Kor	Stocks	0.001	0.004	0.029	0.001	9.139	-1.019	0.400	-0.229	0.170	0.943	679	0.00
	Bonds	-0.002	-0.003	0.028	0.001	2.740	0.589	0.240	-0.104	0.136	-0.853	539	0.00
	CDS	-0.005	-0.002	0.082	0.007	2.617	-0.016	0.753	-0.405	0.348	-2.114	420	0.00
Indonesia	Stocks	0.003	0.005	0.031	0.001	7.198	-1.174	0.349	-0.233	0.116	2.054	679	0.00
	Bonds	-0.001	-0.001	0.033	0.001	5.155	0.406	0.327	-0.145	0.182	-0.390	539	0.00
	CDS	-0.004	-0.004	0.077	0.006	2.891	0.120	0.663	-0.292	0.370	-1.498	420	0.00
Thailand	Stocks	0.001	0.004	0.028	0.001	12.884	-1.543	0.374	-0.267	0.108	0.742	679	0.00
	Bonds	-0.001	-0.003	0.040	0.002	7.207	0.097	0.494	-0.283	0.211	-0.669	539	0.00
	CDS	-0.003	-0.004	0.072	0.005	2.725	-0.124	0.629	-0.372	0.257	-1.327	420	0.00
Malaysia	Stocks	0.001	0.002	0.017	0.000	4.007	-0.792	0.164	-0.097	0.067	0.744	679	0.00
	Bonds	0.000	0.000	0.025	0.001	6.423	0.950	0.231	-0.093	0.137	-0.027	539	0.00
	CDS	-0.002	-0.003	0.081	0.007	1.667	0.097	0.635	-0.307	0.327	-0.710	420	0.00
Hong Kon	Stocks	0.001	0.004	0.030	0.001	3.281	-0.321	0.295	-0.178	0.117	0.569	679	0.00
	Bonds	-0.001	-0.003	0.065	0.004	3.408	0.524	0.596	-0.260	0.336	-0.795	539	0.00
	CDS	-0.002	0.000	0.077	0.006	8.247	-0.335	0.783	-0.416	0.368	-0.970	420	0.00
Philippine	Stocks	0.002	0.003	0.028	0.001	5.616	-0.792	0.312	-0.202	0.110	1.567	679	0.00
	Bonds	-0.001	-0.002	0.041	0.002	14.151	0.036	0.578	-0.333	0.244	-0.650	539	0.00
	CDS	-0.003	-0.007	0.071	0.005	1.973	-0.112	0.550	-0.279	0.270	-1.345	420	0.00
Australia	Stocks	0.001	0.003	0.023	0.001	6.241	-1.043	0.263	-0.172	0.091	0.541	679	0.00
	Bonds	-0.001	-0.002	0.033	0.001	0.540	0.202	0.205	-0.096	0.108	-0.706	539	0.00
	CDS	-0.003	0.000	0.085	0.007	8.926	-0.562	0.984	-0.588	0.396	-1.256	420	0.00
Japan	Stocks	0.001	0.003	0.029	0.001	5.926	-1.058	0.313	-0.220	0.092	0.399	679	0.00
	Bonds	0.002	-0.007	0.570	0.324	292.827	11.719	17.042	-5.917	11.125	1.207	539	0.00
	CDS	-0.001	-0.001	0.078	0.006	5.176	0.677	0.798	-0.318	0.479	-0.485	420	0.00

Notes: The indices for each economy are the following: UK - FTSE, AUSTRIA - ATX, BELGIUM - BFX, FINLAND - OMXH25, FRANCE - FCHI, GERMANY - GDAXI, GREECE - ATG, IRELAND - ISEQ, ITALY - FTMIB, LITHUANIA - OMXVGI, NETHERLANDS - AAX, PORTUGAL - PSI20, SPAIN - IBEX, DENMARK - OMXC20, HUNGARY - BUX, POLAND - WIG, CZECH REPUBLIC - PX, NORWAY - OBXP, BRAZIL - BVSP, RUSSIA - MCX10, CHINA - SSEC, SOUTH AFRICA - JDALS, USA - SPX, MEXICO - MXX, ARGENTINA - IBG, SOUTH KOREA - KOSPI, INDONESIA - JKSE, THAILAND - SETI, MALAYSIA - KLSE, HONG - KONG - HSI, PHILIPPINES - PSEi, AUSTRALIA - S&P/ASX 200, JAPAN - N225. 10 year sovereign bond yields and 5 year sovereign cds. Data obtained from Thompson Reuters DataStream.

Figures 4.5.9 to 4.5.80 in the supplementary online appendix show the dynamic evolution of the centralities across time for the first, second and third highest central country each time. In addition, I provide the corresponding frequency of the most central countries in first, second and third position across the sample for all networks. As far as the dynamic presence of the frequency of the countries, for all centralities, in the networks of stock indices, France, the Netherlands and the UK seem to dominate their appearance in the first and most central positions. In the bond networks – except for the above three – we see the presence of Finland, which is also a European country. Lastly, in the CDS networks we do not observe any statistical significance; however, there is a slight precedence for the country of France. France seems to be the most central and most important core node for the global financial markets network.

Figure 4.5. 3. Overall Network of Stocks' Indices – Centrality analysis

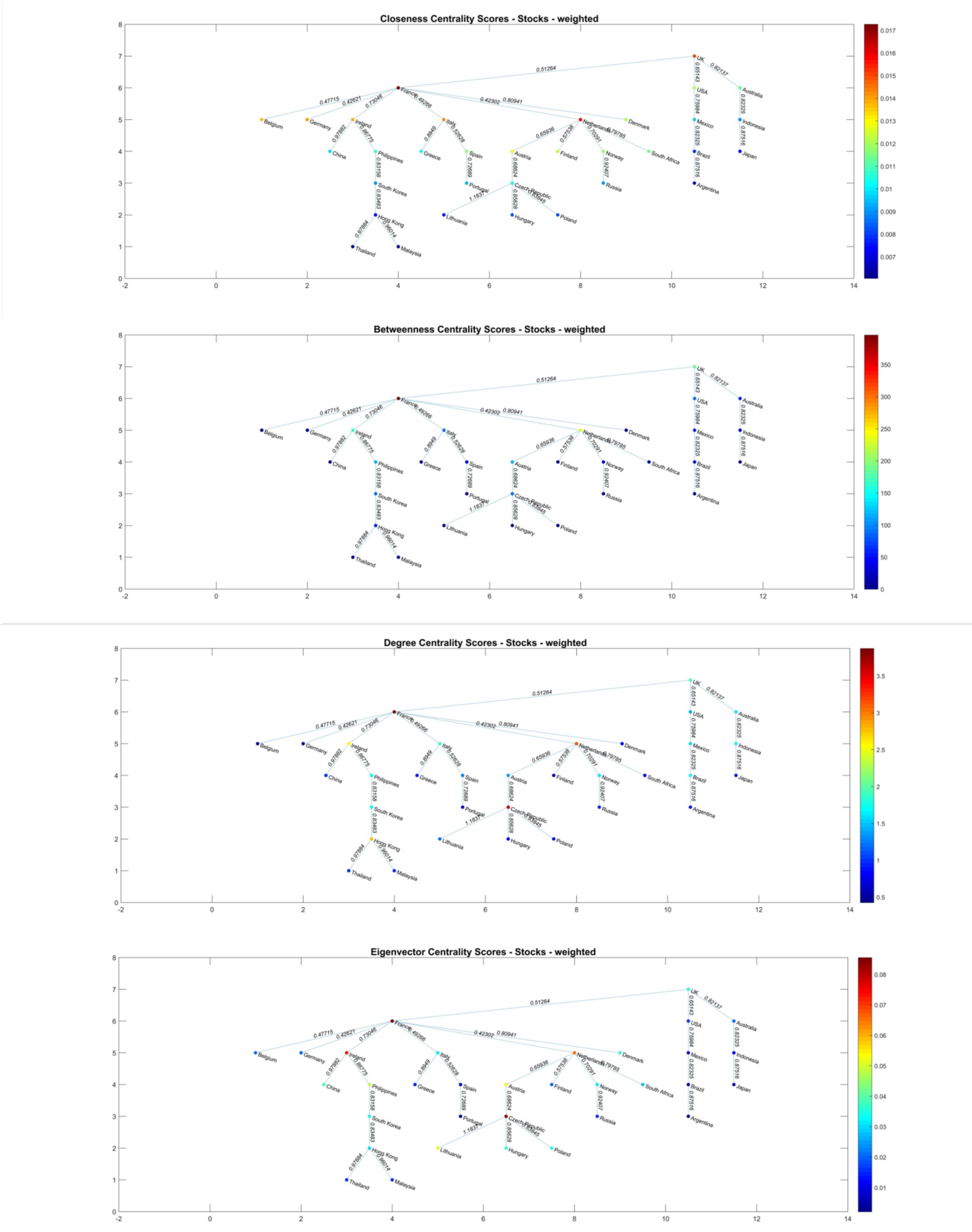


Figure 4.5. 4. Overall Network of Sovereign Bonds – Centrality analysis

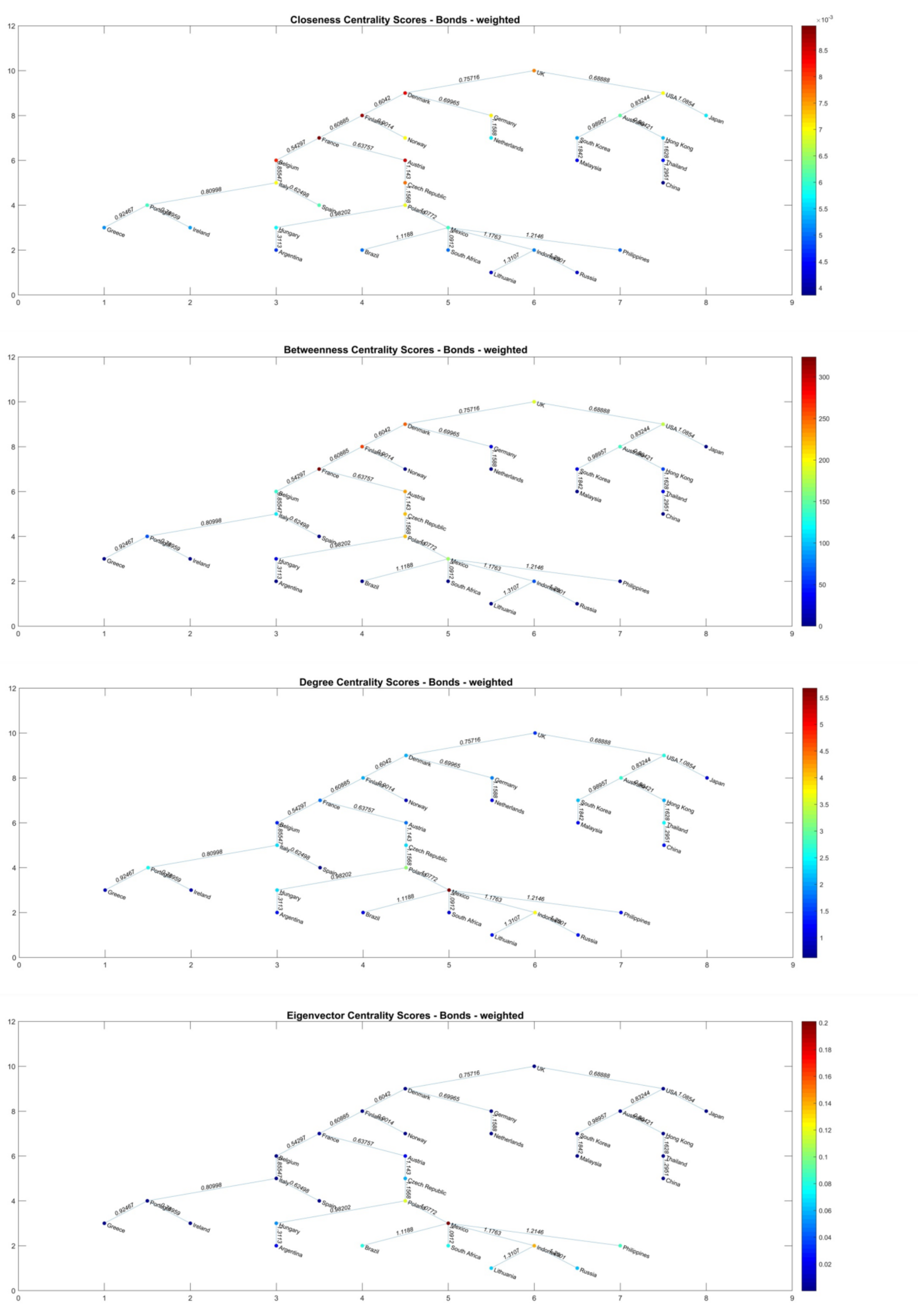
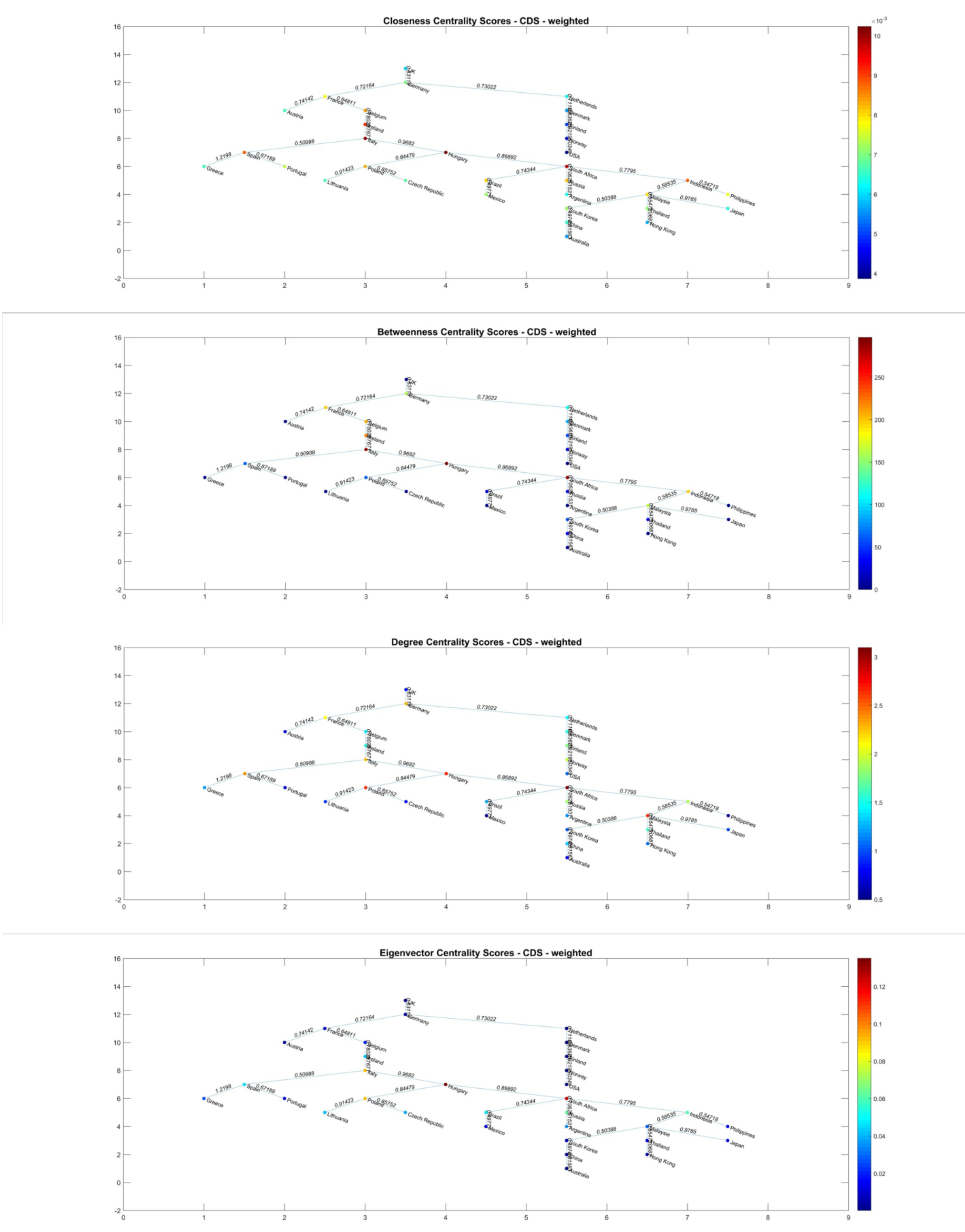


Figure 4.5. 5. Overall Network of Sovereign CDS – Centrality analysis



Besides, the dynamic evolution examination of network structure recommends that the system is generally steady over the time. Specifically, the Eurozone contains the most central hubs and are exceedingly related to different indices, which may for the most part be credited to the vital position of the comparing countries of Europe. In this sense, they play essential roles in the stock networks and may reliably extend generous effects on the spread of fundamental shocks in the worldwide financial framework. Thus, regulators and investors should remember that the central hubs in the stock network merit more consideration as the significant changeless wellspring of financial risk supervision of the tremendous universe of stock markets, in spite of the viewpoint of financial risk supervision or income interest. So, eye-catching changes have occurred in the system amid two remarkable periods: the U.S. subprime crisis and the European debt crisis. It is clearly noticed that the system's interdependence relationship reinforced considerably, implying that the network co-movements' variety may mostly begin from the infection impact of persuasive financial crises in reality.

The most significant evidence from these Figures (4.5.9 to 4.5.80) is that the volatility of the correlations (global interdependence) largely follows the volatility of the centralities. Specifically, significant shocks in the correlations trigger considerable volatility in all centralities (including all four of them). This can also be answered for the second and third most central countries in all three network categories (stocks, bonds and CDS). In addition, the bigger the correlation shock is, the greater the volatility of the centralities will be. This also happens in all cases of networks and centralities, despite the fact that the nature of bond and CDS indices is to remain as low as possible and are completely different from the stock indices.

Based on this evidence and the fact we have not seen anything such as this before, as mentioned in the methodology section, we form a hypothesis to determine whether there is a chance of contagion risk inside the network. The results of the contagion risk specification inside the dynamic networks of stocks, bonds and CDS are presented in the upper subfigures of Figures 4.5.6, 4.5.7 and 4.5.8. The hypothesis is correct, as the results verify the presence of contagion risk for the dates where we observe a significant increase in the correlations (global interdependence) and centralities. Specifically, in most cases where I observe a considerable increase in correlations I identified an increased possibility of contagion risk (red vertical lines).

The lower subfigures of Figures 4.5.6, 4.5.7 and 4.5.8 present the empirical results of the machine learning approach to predict and forecast the risk of contagion inside the financial network. In particular, they show the prediction of risk contagion using a quadratic Support Vector Machine. The SVM model reached 98.8% accuracy, thus making the predictions extremely accurate. As we can see in blue vertical lines the model predicted most of the significant financial crises over the last 15 years in the network of stock indices. The prediction accuracy is also significant in bonds and CDS.

Figure 4.5. 6. Contagion Risk specification and prediction - Network of Stocks' Indices

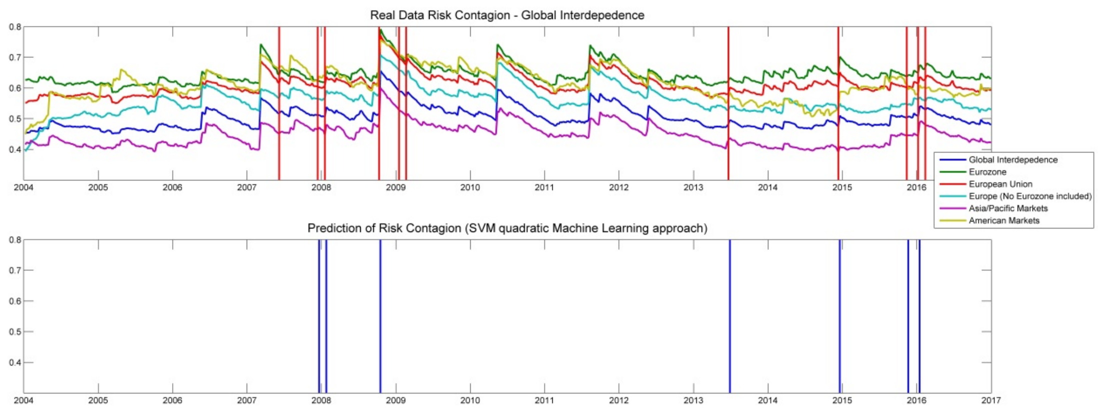


Figure 4.5. 7. Contagion Risk specification and prediction - Network of Sovereign Bonds

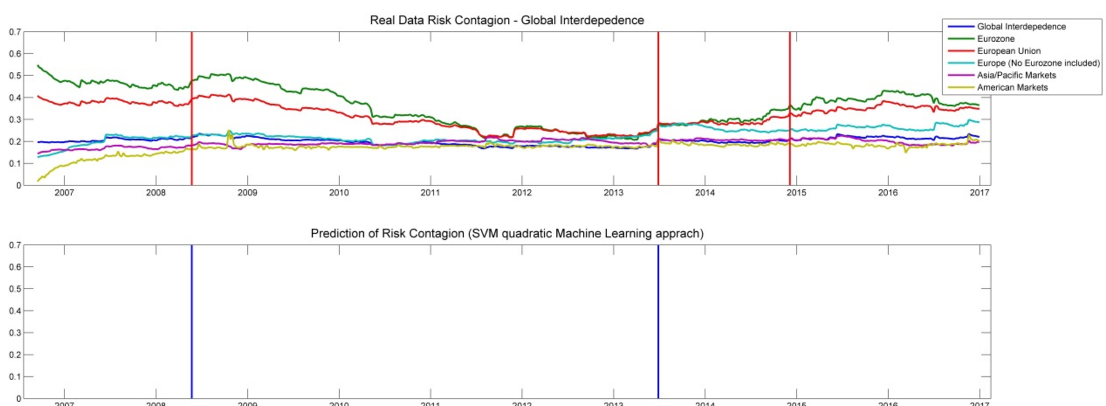


Figure 4.5. 8. Contagion Risk specification and prediction - Network of Sovereign CDS

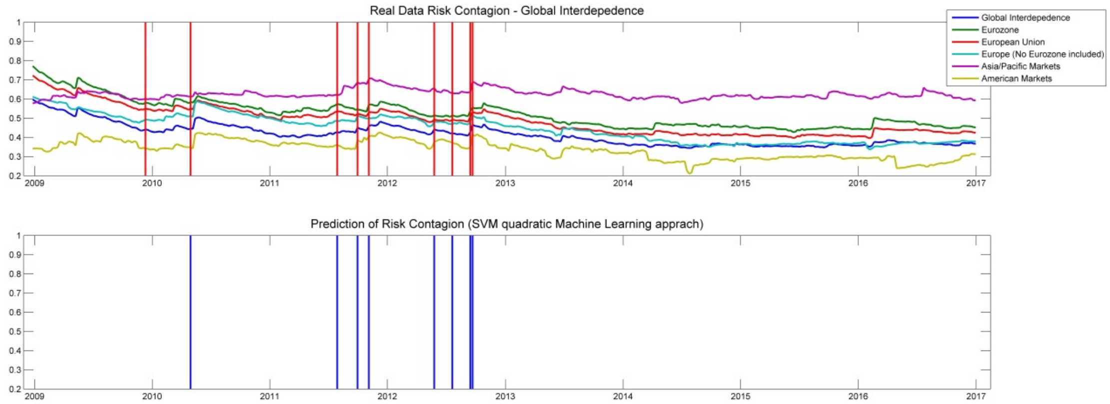


Table 4.5.2 shows the characteristics of risk contagion prediction for the network of stock indices. The tables for the bonds and CDS machine learning characteristics are available from the authors upon request. The accuracy of the classification in machine learning models is validated by the holdout method, which parts the data into training and test sets (traditionally 2/3 training set and 1/3 test set assignment) and assesses the execution of the training model on the test set. In addition to overall accuracy, the method allows us to assess sensitivity and specificity, i.e., True Positive Rate and Negative Rate, respectively. In the same framework, I report the False Positive Rate as well as the False Negative Rate. Be that as it may, these rates are proportions that neglect to uncover their numerators and denominators. The Receiver Operating Characteristic (ROC) is an effective method to express a model's diagnostic ability. ROC provides diagnostic information along with the commonly used Area Under the Curve (AUC).

As I mentioned earlier, the accuracy of the machine learning models exceeded 98%. This verifies that the approach is highly effective in predictions of contagion specification inside the financial networks. However, the statistical significance of the model is highly accurate only when I make predictions from the created model of the referenced data, for example, when I only create a model from the data of the 1st highest central countries and for the stock indices network and make predictions for this network. We did not notice any statistical significance after using the created model in other data categories such as 2nd and 3rd highest central countries and from different financial networks (bonds or CDS). The model extracts significant evidence of predictions only when we use it for the same data from which it was created.

The evidence of the predictions is quite accurate compared to the real data (red and blue vertical lines of Figures 4.5.6, 4.5.7 and 4.5.8). Taking a closer look at Table 4.5.2, we observe that only in several cases did the model make false predictions. The evidence along with the stability of the machine learning model show that we can now use additional methods instead of dynamic conditional correlations to predict and forecast the risk of financial contagion inside the financial networks of markets. The overall methodological approach contributes to the existing literature, giving motivation for further research into this particular field in finance and the spillover effects in networks.

Table 4.5. 2. Contagion Risk prediction – Quadratic SVM Training process

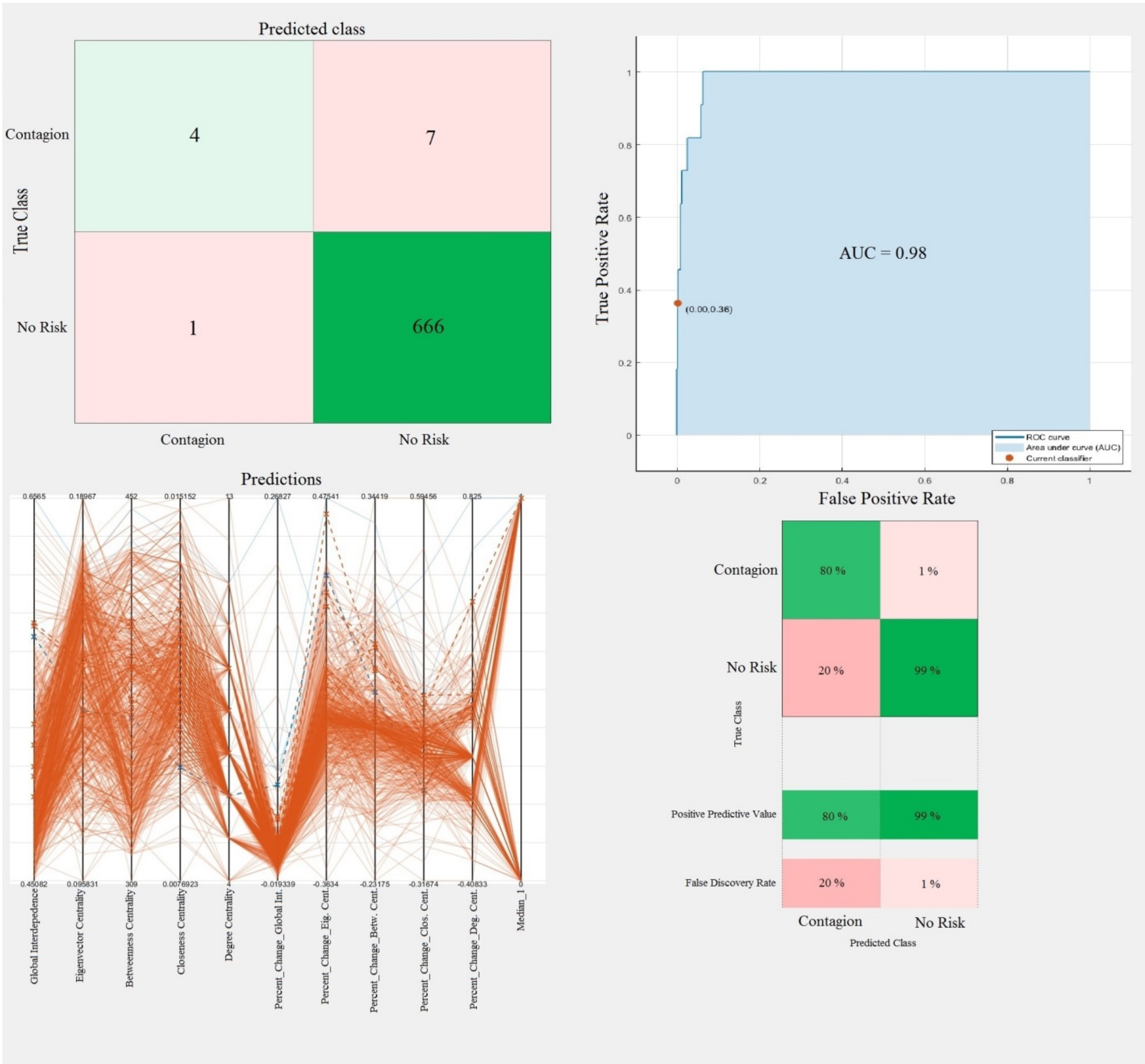


Table 4.5.2. Contagion Risk prediction – Quadratic SVM Training process (continued)

Also, this exploration clears up the benefit evaluating component of stock market. Though stock market networks have been extensively explored, I have extended this line of study to the effects of network topological properties on stock returns. The model shows that dynamic correlations and centralities tend to keep pace together, along these lines speaking to confirm that future stock returns are essentially influenced by the degree of the increased interdependence for a given stock in the concerned stock markets. Indeed, the closeness for a stock speaks to the level of its inborn correlation chance. All the more particularly, the stock index with the most connections with its system acquires the biggest expected returns among the central hubs, while the stock that is most impacted by its 'center' gets bigger risk premium among periphery hubs. From the viewpoint of trade factors, stock market investors have a tendency to be risk averse, and this inclination amplifies during crisis periods. Moreover, investors require significant yields for those benefits set at the center point of the network structure as a premium for the amplified contagion risk. Along these lines, network co-movement assumes a basically vital job in deciding the asset pricing mechanism and merits a positive risk cost. This evidence is also in line with Qiao et al. (2016).

The proof in this part of the research is huge since few of earlier investigations have concentrated on the system topologic measurements in the financial networks. From an economic perspective, our methodology provides fundamental insights to construct a diversified portfolio or manage risk in terms of their topological location information in stock networks. In particular, investors may lessen the repeating investments of profoundly related resources when making portfolio allocations, and they can center around the patterns of the territorial nations that compare to their holding resources when settling on investment decisions. Along these lines, the proposed technique gives shrewd implications that encourage investors and regulators in investigating stocks in view of the most central countries and features that they should give careful consideration to the "core" hubs as opposed to monitor each node inside the system. Similar assumptions are also made by Qiao et al. (2016).

5. CONCLUSIONS

Prior work has documented several different methodologies to test for co-movements or linkages between assets. However, only few of them focused on testing and comparing the ability of the two most well-known multivariate GARCH models, the ADCC of Cappiello et al. (2006) and the ABEKK of Kroner and Ng (1998). In the first part of the research I tested the spillover effects from South to North Eurozone countries. I implemented an Asymmetric DCC model with GJR-GARCH models in the first stage of estimation to investigate the existence not only for asymmetry but also the behavior of the multivariate dynamic conditional correlation. I reran the process again with ABEKK models and return data series for the same period to compare the two different approaches and found that the ABEKK model is good in investigating and analyzing the parameters. However, even though both models behave perfectly and are flexible in presenting the spillover effects and the contagion phenomenon, when it comes to figure illustration of conditional correlations, the ADCC model seems to fit better.

The results from South and North Eurozone countries showed increased correlations between indices during the Subprime Crisis period. Despite that Eurozone Debt Crisis period presented lower correlation levels than the previous, the variances of the assets were much more volatile. The Eurozone Debt Crisis had lower impact on the economies but with high sense of uncertainty because of the increased volatile correlations between South and North Eurozone countries. These turbulent correlations are driven by the events in the Eurozone economy the last five years and primary from Greece. Furthermore, French index (CAC40) found to be the most correlated one with Spain and Italy for all three periods. The most possible interpretation is that as these countries are neighbors, they share more transactions. Additionally, Spain and Italy are the countries which can produce the most significant damage on all Northern strong economies while Greece’s negative shocks are capable of co-moving the French index (CAC 40). This interpretation stems from the involvement of France in Greek sovereign debt, which till today, is producing fear to investors. At the same time, Cyprus contagion ability is extremely low in all periods and this gives a lesson to the rest small economies of Eurozone to be always aware of keeping their fiscal problems under control.

In addition, as Eurozone does not deliver a sustainable solution for the debt crisis, it seems that the financial contagion shifted to a political contagion. Political contagion is a condition, in which country-members will struggle to find allies in order to negotiate basic issues of their own interests inside the EU. Namely, countries that are considered as allies would avoid solidarity because they would fear the political contagion (i.e. from Greece) and consider avoiding similar debate and discussion inside their own states. It is clear that current Eurozone policies are not conducive to growth or to a healthy future for the single currency as a true European partnership. Divisions are growing and European Institutions should deliver more. It may be assumed that country-members need fundamental reforms to bring prosperity back to Europe and subsequently get the unemployed back into jobs.

Finally, considering the existence of uncertainty in European markets, drawn from the evidence, we can conclude that Eurozone economies suffer critical pressure the last five years. After the outbreak of the Debt Crisis, originated in Greece (with the Government's high deficit), a new regime of creditworthiness started by rating each country individually. This condition increased the risk of debt default in Southern countries that face difficulties all these years in reorganizing their economic structure in order to decrease their deficits and subsequently, their Debts. Despite the fact that Brussels Group reassures the rest of the Eurozone that there won't be a Grexit, capital markets and subsequently, the investors, have not been fully convinced. It should not be forgotten that it is difficult to quantify the impact of a possible Grexit. The background of all these events hide one huge risk, which is the possibility of another country, member of EMU, to come close to economic suffocation, similar to Greece. This scenario will cause extremely high contagion impact if we are referring to "systemic" countries like Spain or Italy. Here comes the case of France, which struggles to find a quick solution on Greece's problem because it fears that it will be next. Assuming that this onerous possibility is feasible, then we might be talking about the end of the Eurozone or at least in the form that we know it today. Therefore, it is my strongly belief that European Institutions should apply a new monetary policy in the Eurozone while they should also come to an agreement with a sustainable solution about the Sovereign Debt of country-members.

Focusing now on the second part of the research, the case of financial contagion in real economy and the key role of policy uncertainty, I began the investigation where I finish the first part of the research. In particular, as the first study showed that French index (CAC40) was found to be the most correlated one with Spain and Italy while Spain and Italy are the countries which can produce the most significant damage on all Northern strong economies, I investigated the spread of the Subprime Crisis and the European Sovereign Debt Crisis from Eurozone countries to the real economy by examining ten sectors in major developed and emerging stock markets. France, Spain and Italy are countries with high rates of unemployment, high Debt to GDP ratios and small or negative GDP growth. These three countries cover a large proportion of the Eurozone, which creates significant concern about the future of the Eurozone and increases the uncertainty in the global financial environment.

The political reaction to the Eurozone crisis has been reluctant, as it was regularly moderated by questions with respect to the results of fiscal problems in Spain, Italy and France. The Eurozone nations, which are powerless against a bailout, fear a prompt default inside the Eurozone, as the spread of a financial crisis may trigger an implosion of the European banking system and the finish of the Eurozone itself, causing the "mother of all financial crises" (Eichengreen, 2010). In the second part of the research, we measure the spillover from key Eurozone markets to the real economy sectors of major economies on a bilateral basis, adapting the asymmetric dynamic conditional correlation model of Cappiello et al. (2006) and copula functions to explain common developments. I use the daily return data on equity spreads of three Eurozone economies (France, Spain and Italy) and 10 real economy sectors of the US, the UK, BRICs, Canada and Japan over a unique long-term sample from January 1998 to December 2015 that covers both the tranquil period as well as two financial crises (Subprime crisis and Eurozone Debt crisis). I identify three phases during this period: a pre-crisis phase until 2006, a first crisis phase (Subprime crisis) until 2009 and a second crisis phase (Eurozone Debt crisis) from 2010 to the end of the sample. Based on the hypothesis that a possible domino effect from a vulnerable major Eurozone economy would transmit huge policy uncertainty to the U.S. financial market, triggering a new era of global recession due to the size and significance of the U.S. economy, I extend the research one step further. Motivated by this assumption, first, I test the correlation behavior in different periods from the Eurozone countries to the indexes of policy uncertainty and the fear factor in the U.S. economy. Second, procedure repeated for the U.S. real economy sectors to provide robust evidence regarding what index drives the policy uncertainty and the fear factor in the U.S. economy.

The findings of this research have important implications for understanding the policy uncertainty and the financial contagion in the euro area. The framework I implement distinguishes each channel of contagion and finds that the Debt crisis period contains the most statistically significant parameters of the *g* term, which refer to the presence of asymmetry in variances. The results indicate that the average ADCC correlation is nearly the same as the Gaussian copula correlation. Additionally, correlations in both methodologies (ADCC and copulas) present the same behavior: correlations increase rapidly in the Subprime crisis period and subsequently decrease in the Debt crisis period; however, generally, correlations remained higher than the first period (Early Eurozone period). Furthermore, the UK's sectors show that it is the most correlated market with the Eurozone countries in all periods. Conversely, the French economy appears to be the most correlated with the remainder of the major economies in all periods. Specifically, in all periods, "financials" is the sector that depicts the most increased correlations, followed by "Industrials" and "Consumer Services". Surprisingly, significant sectors such as the "Healthcare, Telecommunications, Utilities and Technology" depict weak contagion effects. However, regarding the case of pure contagion, only in the Subprime crisis period and for the "Oil and Gas" and "Basic Materials" sectors did I clearly observe pure contagion between Eurozone countries and the economies of the rest of the world. Considering the investigation regarding whether there is any connection via the fear factor and the policy uncertainty indexes with the European indices and the US sector price indices over the US economy, I find that the VIX, US Equity Economic Uncertainty and EPU indexes are affected more by the sectors of the U.S. economy itself. The correlations show that the European indexes behave differently than the sectors of the US economy. It is clear that there appears to be a connection in the behavior of the correlations. Based on this statement, the sectors of the US economy produce a higher impact on the policy uncertainty of the United States than the European indexes. It appears that the policy uncertainty in the US is affected more by its own sectors than by the Eurozone economies; this means that the Debt crisis affected the US economy less than the local sectors itself. Further robustness tests showed that the S&P 500 index was correlated more with the sectors of the US economy than with the Eurozone indices.

The structure created in the second part of the research enhances the ability to observationally understand the elements of financial contagion. The technique enables the information to uncover both the different periods in the advancement of moves from nonemergency to emergency shocks and beyond, and the changing idea of the spillover between indices those distinctive periods. Consequently, the framework can help not only policy makers but also provide significant information to the investors about portfolio diversification.

As far as the third part of the research is concerned, a DCC Model was applied to investigate the existence of interdependence during the Greek Debt crisis and the Cypriot Financial crisis. Despite that the subprime crisis, the correlation between the two stock markets has increased; it appears that the turmoil period continued until the end of 2013. South European countries faced several problems due to their high sovereign debt. This condition was followed by strict austerity measures. PIIGS as well as Cyprus had to adopt difficult economic policies which caused huge problems to their people's lives. Despite the European Commission's statements about tranquil economic environment in Eurozone, investors and credit rating firms remain doubtful about the effectiveness of the applied economic policy in all these countries.

The evidence of this study showed significant increased correlations between Greece and Cyprus during the period from 2008 to 2013. This is the fundamental reason why Eurozone sought a quick and secure solution for the Debt crisis in Euro area. It has to be noted that there is a huge risk that this spillover effect is transmitted to other countries, especially after recent speculations about a possible Grexit. It is evident from the literature that contagion exists as Italy, Spain, Portugal and Ireland are already facing difficulties in decreasing their debt. Moreover, credit rating firms are distrustful about the European economic environment as they can downgrade major economies such as France. On the contrary, results for the Cypriot Financial crisis showed that Cyprus can also affect the Greek economy to some extent. However, the impact of the economic events in Cyprus seems to not have produced shocks to other economies. The most possible reason for this market behaviour is that Cyprus, as a small country and economy, does not have the power to produce spillover effects on bigger economies. It can therefore be assumed that Cyprus was used as an experiment to adopt the new economic model (bail-in) easily without the risk of further impact. In addition, the new economic policy was convenient to hit the Russian interests in the Island as Russian firms took advantage of the tax benefits there.

Finally, Greece is the easiest country for Eurozone to address the Debt crisis because of its small economy in comparison with other countries of PIIGS like Italy and Spain (which also face debt issues). Therefore, the rest of the Eurozone members are focusing on the Greek economy to gain more time in order to noiselessly decrease the deficit and debt of other countries with significant systemic risk. Simultaneously, they apply austerity measures to improve their own financial condition to avoid focus and a possible downgrade from credit rating firms. Greece should make a new start with reforms over the economic structure in order to surpass the current problems and to move forward to development. The development policies for business and innovation play an important role in this field. Policies that are aimed at this direction will most likely have a positive GDP growth. Cyprus, on the other hand, was forced to apply an economic program that affected only the local economy, hence the impact was very limited. Secondly, it is apparent that the bail-in was manageable for Eurozone. Moreover, if there was any case of contagion, Eurozone would have been able to act much differently in order to limit the exposure of other countries. Besides, according to Eurozone and investor predictions, the Cypriot economy has slowed down significantly and GDP growth has been negative for many consecutive years. In addition, interested parties have their attention on natural gas exploration which is the next big challenge for the Cypriot government.

Eurozone policies and restrictions have made a hostile economic environment for member countries with high debt and a weak banking sector. Investors take advantage of this condition in the Eurozone because they gain profits from the credit default swaps. In addition, credit rating firms have the ability to set the interest rate for public debt. As member countries do not have the power to cover their needs and as long as the Eurozone does not give an end to this financial condition with political decisions, the economic war in Europe will hardly come to an end. Greece and Cyprus were the experiment for austerity measures in order to be tested for the effectiveness of the applied policies. By 2015, the financial environment in both countries has differentiated a lot and this can be confirmed from the decrease in correlations the last two years.

As the Ph.D. programme was in progress, in June 2016, the United Kingdom voted in favor of leaving the EU in the European Union membership referendum. Due to the huge shock to stock markets, it was considered of great importance to look into the possibility of Brexit to result in financial contagion from the UK to other countries. The UK will be withdrawing from the EU because of what is now commonly known as the British Exit or Brexit. A referendum held regarding the same on June 23, 2016, resulted in a 51.9 percent vote in favor of Britain leaving the EU. Following this, on March 29, 2017, Article 50 was triggered by the government, initiating the process for the country to leave the EU. However, the separation is easier said than done, and the ensuing aftermath has included both economic and political consequences and complications for not just the UK, but other nations as well. A day after the vote, on June 24, 2016, the LSE market experienced a drop of 9.1 percent within the initial 10 minutes of trading. The market closed for business with a three percent decline. The stock exchange markets experienced a negative reaction to the news, and the impact of the vote could be seen almost immediately. By June 27, 2016, market losses had risen to over USD 3 trillion. The GBP dropped to its lowest value in 31 years. This study looks at the spillover impact of the Brexit vote. It looks at the UK along with 43 other countries that consist of both developed and developing economies.

Major indexes from all the countries were used for this study. The sample consisted of the EU, Europe, Eurozone, South and North America, Asia, Africa and BRICS. Dependence dynamics were used on a bivariate basis via Silva Filho et al. (2012)'s regime switching copulas. Intraday data returns were used to isolate contagion within the different stock markets (30-minute close price from January 1, 2016 to September 30, 2017).

To start with, the dependence dynamics and the regime-switching were extracted from the time-varying copula. This approach was based on Silva Filho et al. (2012)'s work. After this, the sample was split into three categories, namely, the period before the referendum, after the referendum, and timeframe after Article 50 was triggered. Correlations were once against extracted from the time-varying normal copula to deduce if there was an increase, and therefore contagion, in correlations during the period after the vote, and also the period after Article 50 was initiated. Lastly, hypotheses were created to evaluate the spillover effects from the approach used.

The findings of this study have significant implications for comprehending the financial contagion from the UK to other countries. The framework used differentiates between the contagion evidence and outlines that there were only a small number of cases where the period of the vote, and the period after Article 50 was initiated, became a problem. Moreover, the time period before and after the vote illustrated elevated levels of instability (high dependence regime), as opposed to the time after Article 50 was put into motion. Increased dependence was witnessed close to the date of the vote. On the other hand, no noteworthy change was seen after Article 50 was triggered, as opposed to when the vote actually took place. This is true for both the FTSE 100 and FTSE 350. Stock exchange markets experienced a downturn as a result of the vote. For all indices studied, the minimum value was the time period when the result for the vote was announced (June 24, 2016, 10:30 AM). The announcement led to an instant contagion. However, because of its insignificant duration, the contagion cannot be taken as significant itself. The adverse impact was insignificant and only persisted for a short period of time. Moreover, in terms of the FTSE 100, seven countries experienced strong contagion, including the US and Greece. In terms of the FTSE 350, this contagion was restricted to Argentina and the US. Apart from these cases, for all other countries the contagion was negligible.

In terms of the significance of Article 50 being triggered, a significant contagion only existed for Estonia, Hong Kong and Croatia. The results demonstrate that the Brexit vote led to an instant and substantial contagion to other stock exchanges. The instant impact was owed to the uncertainty that the announcement brought. However, this shock was limited and only lasted a few days after the vote had been held. Almost all markets in question recovered from their losses within the next few days. Based on these results, it can be assumed that the UK had no financial contagion for other nations. Despite this, there is a possibility, in the longer run, the Brexit vote and Article 50 will lead to economic contraction for both the UK and the EU, given how intertwined their economies have been up till now. The banking and private sector, alongside the European Single Market will suffer deep impact from these events.

The structure created on account of Brexit advances our capacity to exactly comprehend and measure the elements of financial contagion. The model in this part of the research enables the confirmation to uncover both different periods in the co-movements (regime-switching change) from quiet to violent periods and past to the transitional idea of the spillover impacts between indices during the pre-referendum, post-referendum and the trigger of article 50. Thus, the model gives critical data not exclusively to policymakers but also to investors about the stock markets' response to the foreseen Brexit.

Lastly, in the fifth part of the research I attempt to identify spillover and contagion evidence showing that information from stock indices, sovereign bonds and CDS is transferred from one country to others inside a financial network constructed by correlations. In addition, I introduce a new model, based on a machine learning approach, to predict and forecast contagion risk inside a network of stocks, bonds and CDS. To measure the interdependence ratio from the correlations, I use weekly data returns. I use major stock indices, the 10-year bond yield and 5-year CDS from each country taken from Eurozone, European Union, Europe, North and South America, Africa and Asia. Sample data cover 33 economies (stocks, bonds and CDS) and are selected by their GDP size and the best available data with the consideration that all should have stock indices, bonds and CDS markets. First, on bivariate basis, I apply an Asymmetric Dynamic Conditional Correlation (ADCC) model of Cappielo et al. (2006) to extract the correlations. Second, I transform the correlations to distance metrics between each pair using Matenga's (1999) formula. Third, I use the extracted distance metrics to construct financial networks by the Minimum Spanning Tree (MST) technique of Kruskal's (1956) algorithm. Fourth, from the weekly financial networks, I extract centralities (betweenness, degree, eigenvector and closeness on weekly basis) to measure the most important countries (key nodes). Specifically, I analyze weekly centralities in accordance with the data of our sample. Tracking weekly centralities, I measure the behavior of centralities as the key player countries for first, second and third place (ranking) of each centrality category. Next, I settle on a hypothesis to justify the contagion risk inside the financial networks. The specification of the financial contagion risk is as follows: increase in correlations (global interdependence), increase in all four categories of centrality and the correlation is higher than the median value (the nodes with lower-than-median values are less well connected than those with higher values). In all other cases, I believe that there is no possibility of contagion risk inside the networks. In the last step of the methodological approach I attempt to create a model to predict and forecast the contagion risk possibility. I applied several machine learning algorithms to determine which one is the most accurate. Specifically, I used decision trees, discriminant analysis, logistic regression classifiers, Support Vector Machines (linear, quadratic and cubic), nearest neighbor classifiers and ensemble classifiers. However, in all cases, the SVM quadratic was the most accurate. Support vector machines (SVM) is designed to fit perfectly when the data have exactly two classes. This might be the most reasonable explanation as to why the SVM quadratic algorithm is the most accurate algorithm in our data.

The findings have important implications for understanding and predicting the financial contagion inside networks. Regarding the global interdependence of stock indices, an instant increase in correlations is related to financial crisis across the time. In addition, all regional correlations have almost identical behavior, specifically in the case of the Eurozone, Asia/Pacific and American markets. Different operation hours of stock markets and locations do not seem to affect the main regional interdependence. As far as financial networks are concerned, the topological structure of the three financial networks (stocks, bonds and CDS) are quite close to the real location of the countries. Namely, we see that Eurozone countries are connected, as are American countries; the same thing also happens with Asian countries. The financial networks are interpreted by a significant percentage of the actual geographic location of the markets. This evidence can verify the significance of our model and work as a robustness test for the extracted financial networks. This behavior of the correlations seems to be neighborhood driven in that transactions between countries contribute to global imports and exports. In addition, the Eurozone countries that have a common currency show a strong weighted connection to a significant extent, and they depict remarkably high correlations in the entire sample. The financial network of bonds has many similarities with the CDS network as far as the location of countries is concerned. I believe that this behavior stems from the nature of the networks; the target of stocks is to maximize their index, while in the case of bonds and CDS is to stay as low as possible. In the stock and bond networks, France seems to be the most central country followed by the Netherlands and the UK. A little gathering of "old" EU markets, sharing elevated amounts of improvement as well as close topographical nearness, has reliably comprised the most firmly connected arrangement of markets. The Eurozone dominates the networks and acts as a joint distribution with the American and the Asian markets. Additionally, as far as the dynamic presence of the frequency of the countries is concerned, for all centralities in the networks of stock indices, France seems to be the most central and most important core node for the global financial markets network. The most significant evidence from financial networks is that the volatility of the correlations (global interdependence) largely follows the volatility of the centralities where significant shocks in the correlations trigger huge volatility in all centralities. Based on this evidence I use hypothesis testing to determine the possibility of contagion risk inside the network. The results verify the presence of contagion risk on the dates where I observe a significant increase in the correlations (global interdependence) and centralities. Regarding the empirical results of the machine learning approach to predict and forecast the contagion risk inside the financial network, the accuracy of the quadratic Support Vector Machine reached 98.8%, making the predictions extremely accurate. The model predicted most of the significant financial crises the last 15 years in the network of stock indices. This verifies that our approach is highly effective in predicting contagion inside financial networks. However, the model extracts significant evidence of predictions only when I use it for the same data from which it was created. The evidence on the predictions are highly accurate compared to the real data; only in few cases did the model make false predictions. This evidence allows us to expand the literature and use additional methods instead of dynamic conditional correlations to predict and forecast the risk of financial contagion inside the financial networks of markets.

The framework developed in the fifth part of the research enriches our ability to empirically understand as well as quantify spillover and contagion evidence regarding information from stock indices, sovereign bonds and CDS that is transferred negatively from one country to another inside a financial network constructed by correlations. In addition, based on a machine learning approach, the model in this study allows us to predict and forecast contagion risk. Consequently, the model provides substantial information not only to policymakers (institutions) but also to investors about possible contagion risk inside a financial network. The real commitment of the research is to employ the financial market network as a valuable tool to enhance the portfolio choice process by focusing on a group of assets based on their centrality. Moreover, these outcomes are vital for the design of policies that help develop stock markets, and additionally for scholastics and professionals. Consequently, through this examination, regulators can focus on checking the center hubs to guarantee the general stability of the whole market, while investors can upgrade their portfolio allocations or investment decision-making.

To conclude, combining the evidence and the contribution from all five parts of the research, we can state that this thesis provide significant information. Policymakers (institutions) and investors can benefit in many different ways: stock markets' reaction to the anticipated Brexit, portfolio diversification, contagion risk specification within a financial network and prediction using a machine learning approach. The methodology in this thesis can be extended also in several directions. A further direction I plan to pursue in the future is to expand the parameters and propose more sophisticated econometric techniques to quantify financial contagion. In addition, motivated by the results of the fifth study about financial contagion and the involvedness of machine learning models, my future work on financial contagion will be focused on 'early warning systems' (EWS). In particular, deep learning approaches from the family of Recurrent Neural Networks (RNN), specifically Long Short-Term Memory (LSTM) models. Currently, these models can be used for effective forecasting in time series.

APPENDIX

Figures 4.5. 9. to 4.5.80. Dynamic evolution of the centralities across time for the 1st, 2nd and 3rd highest central country each time

Figure 4.5.9.Betweenness Centrality - Stocks - 1st highest

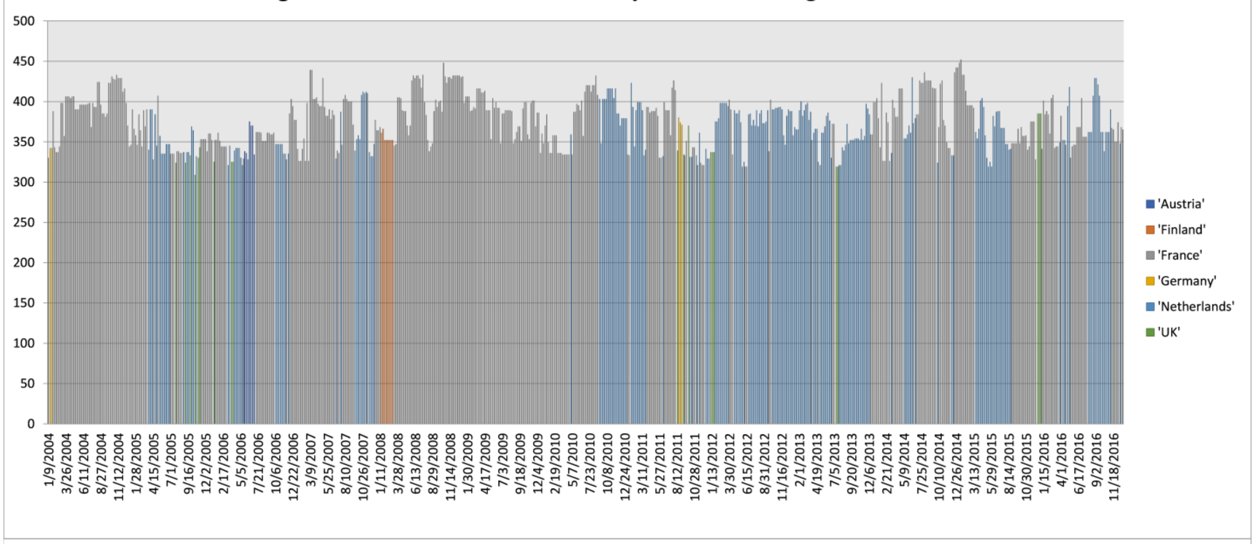


Figure 4.5.10.Betweenness Centrality - Stocks - 1st highest - Frequency

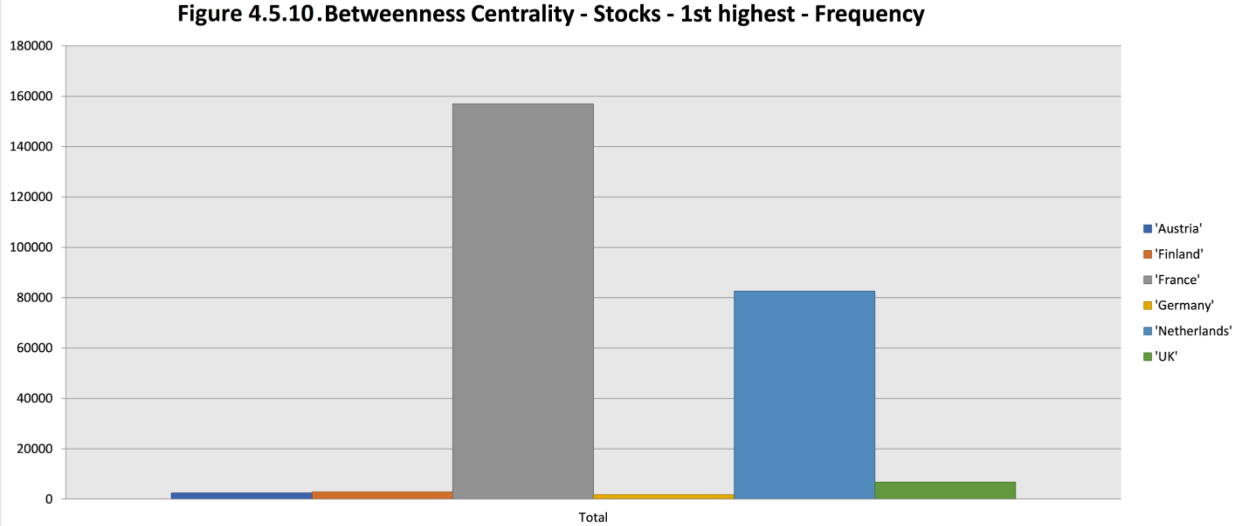


Figure 4.5.11. Closeness Centrality - Stocks - 1st highest

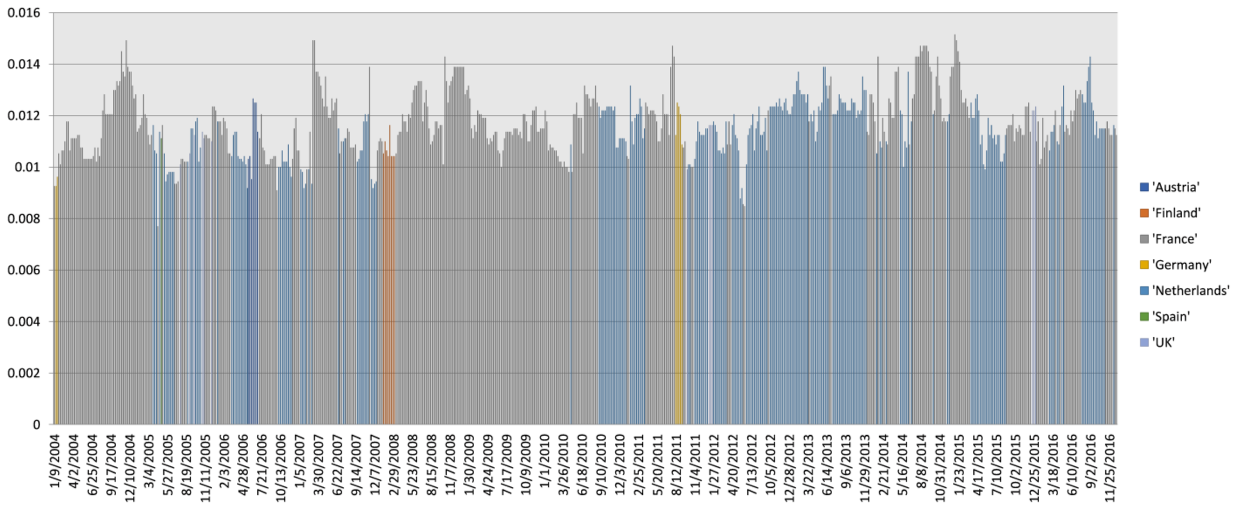


Figure 4.5.12. Closeness Centrality - Stocks - 1st highest - Frequency

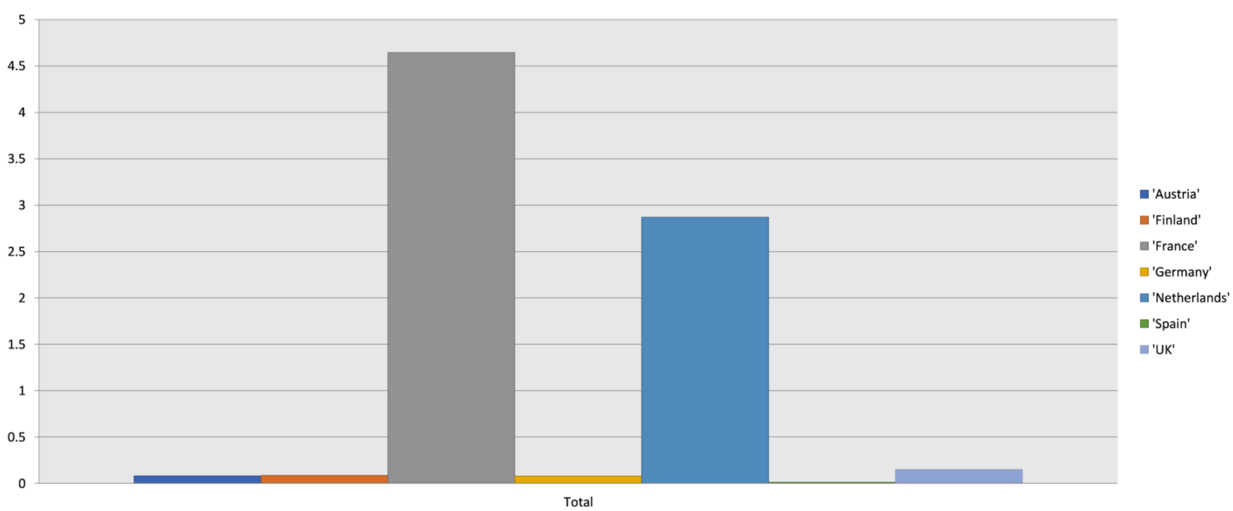


Figure 4.5.13.Degree Centrality - Stocks - 1st highest

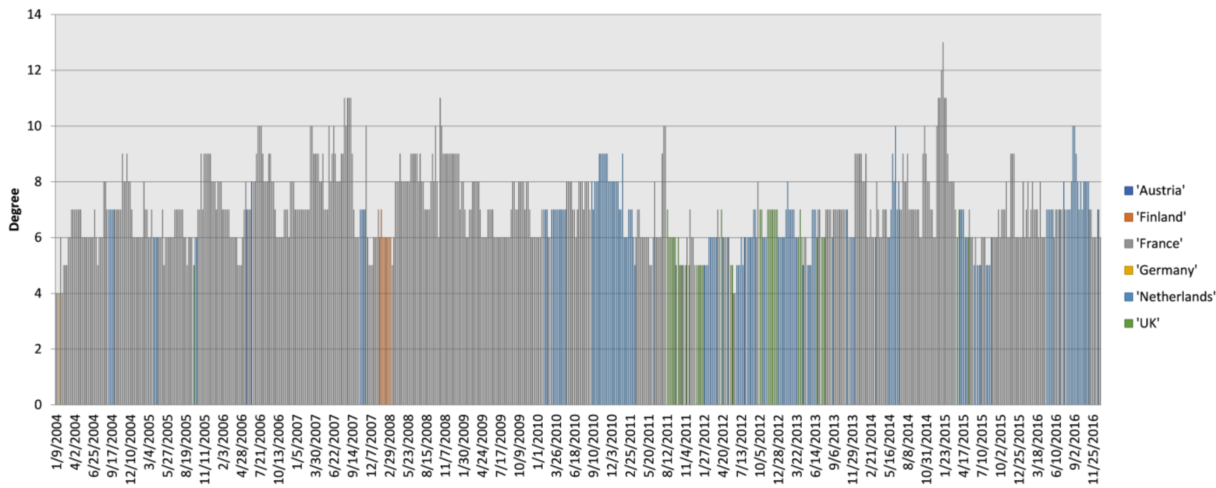
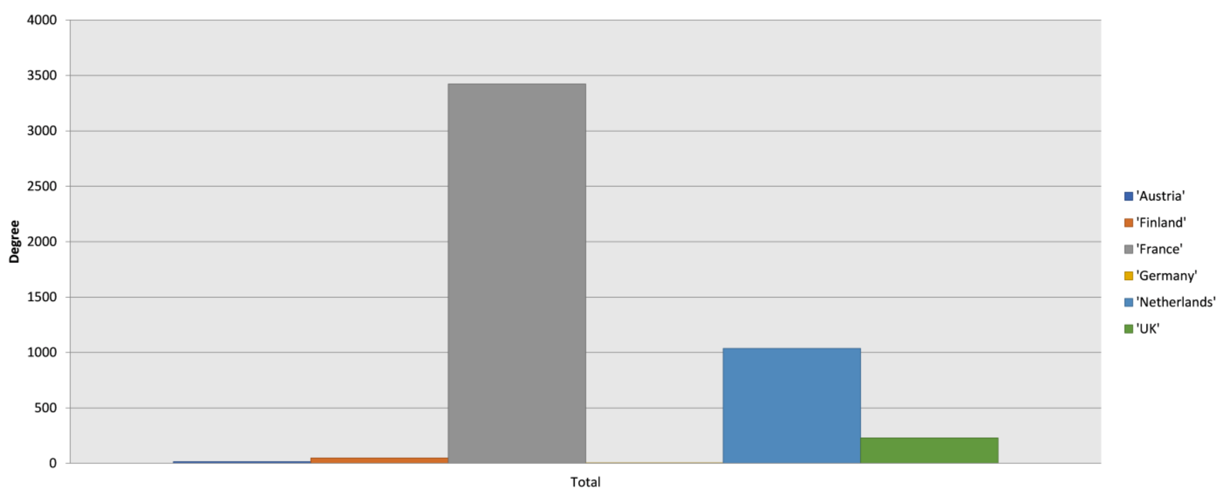


Figure 4.5.14.Degree Centrality - Stocks - 1st highest - Frequency



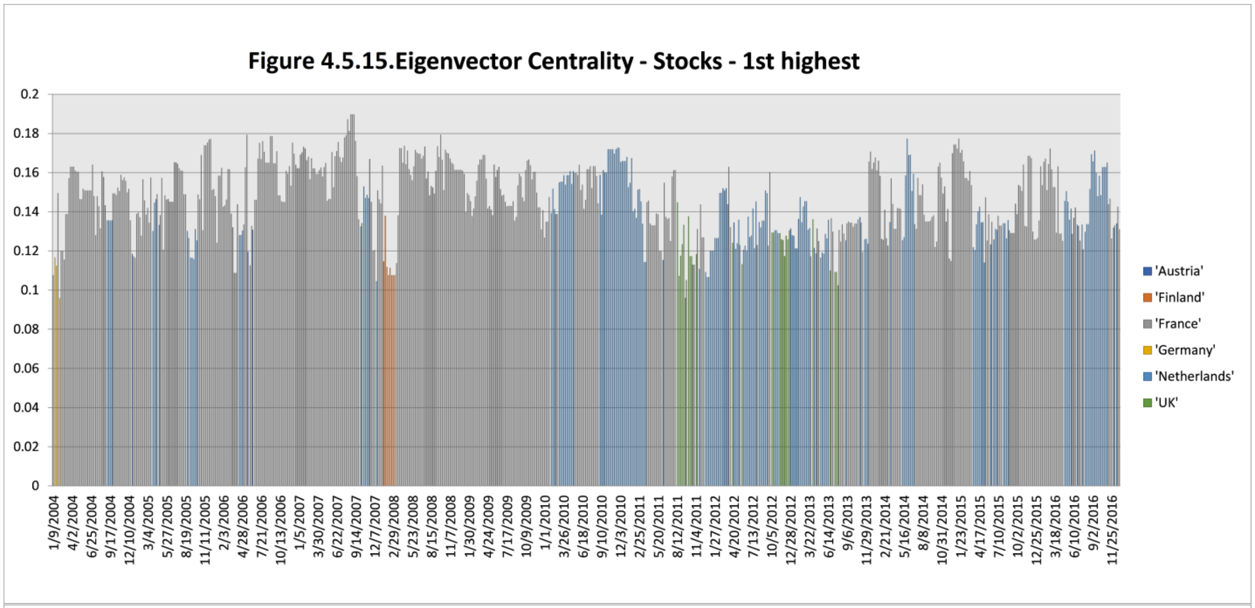


Figure 4.5.15.Eigenvector Centrality - Stocks - 1st highest
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
'Austria'
'Finland'
'France'
'Germany'
'Netherlands'
'UK'

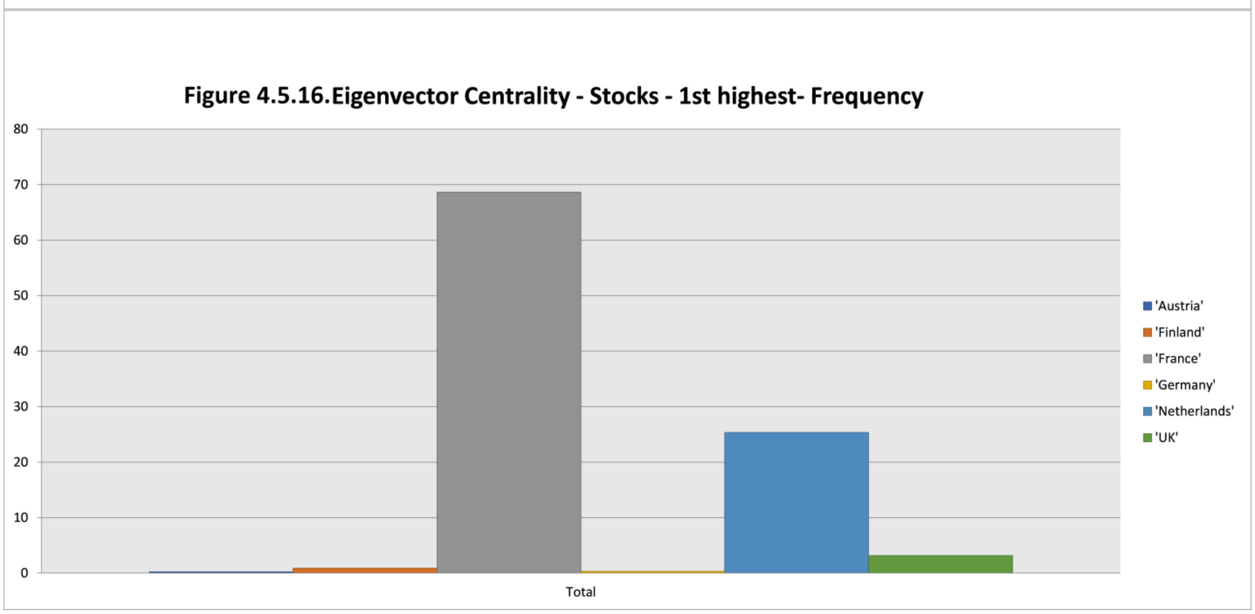


Figure 4.5.16.Eigenvector Centrality - Stocks - 1st highest- Frequency
80
70
60
50
40
30
20
10
0
Total
'Austria'
'Finland'
'France'
'Germany'
'Netherlands'
'UK'

Figure 4.5.17. Betweenness Centrality - Stocks - 2nd highest

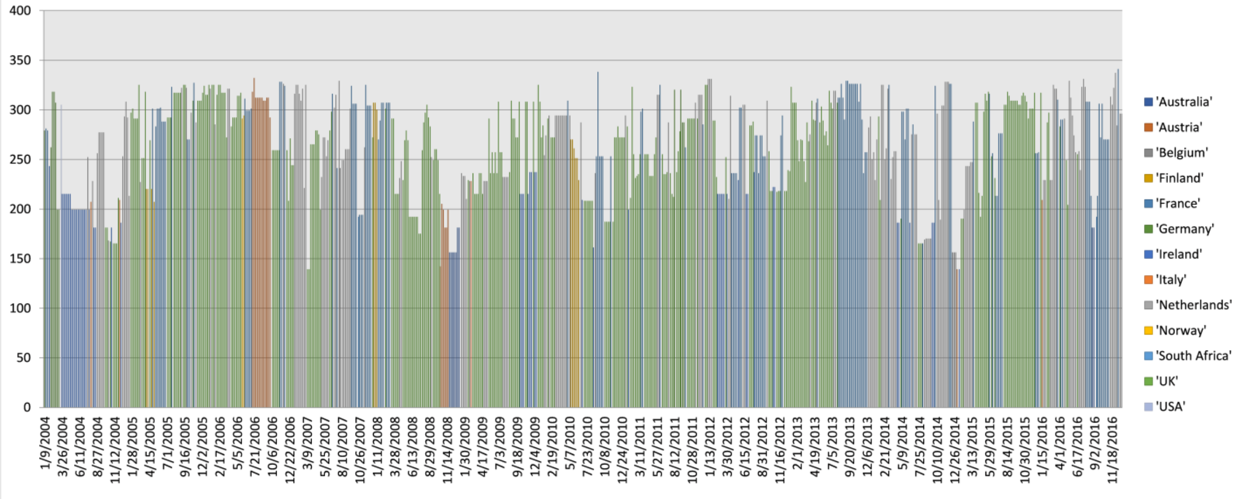


Figure 4.5.18. Betweenness Centrality - Stocks - 2nd highest - Frequency

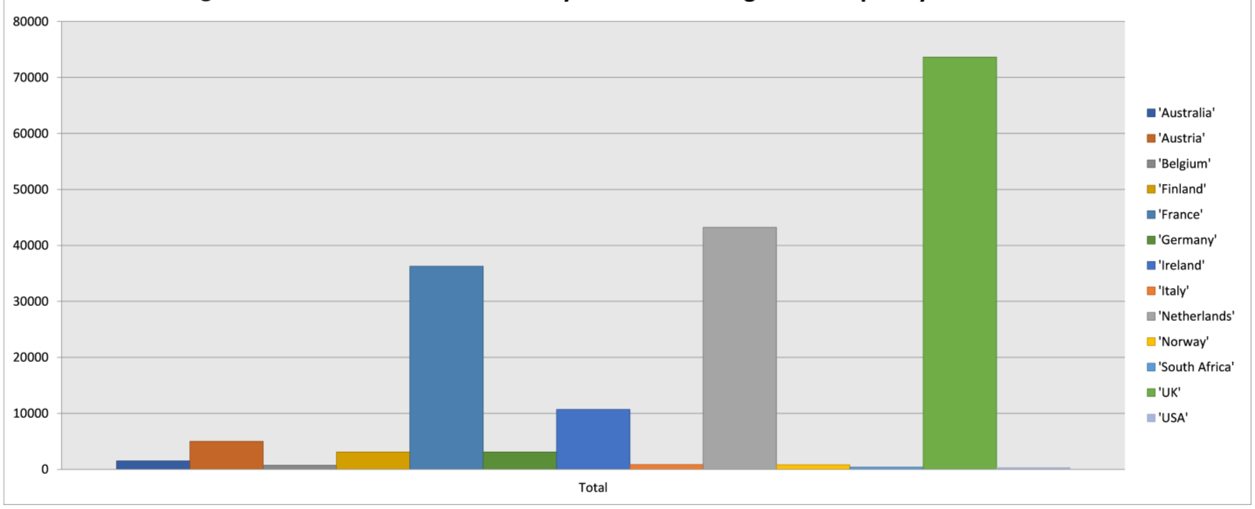


Figure 4.5.19.Closeness Centrality - Stocks - 2nd highest

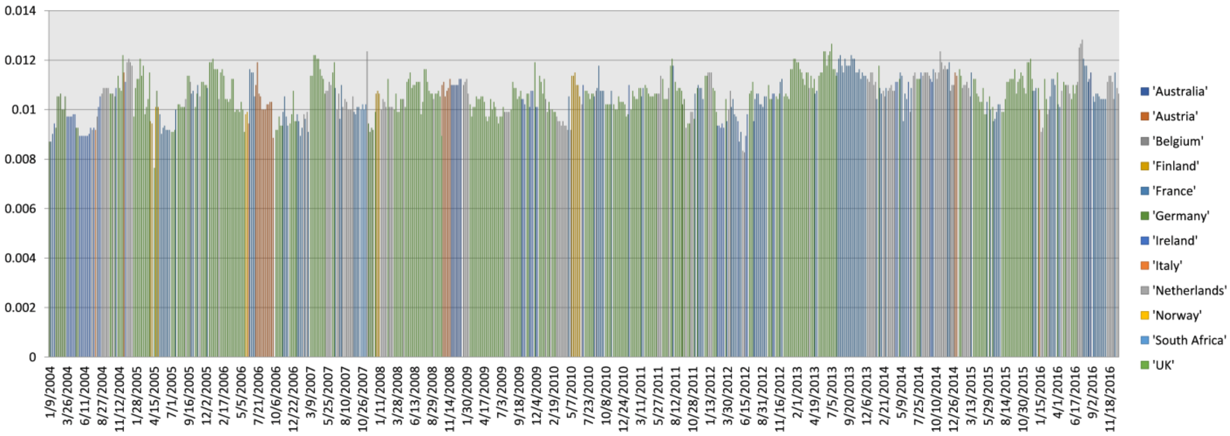


Figure 4.5.20.Closeness Centrality - Stocks - 2nd highest - Frequency

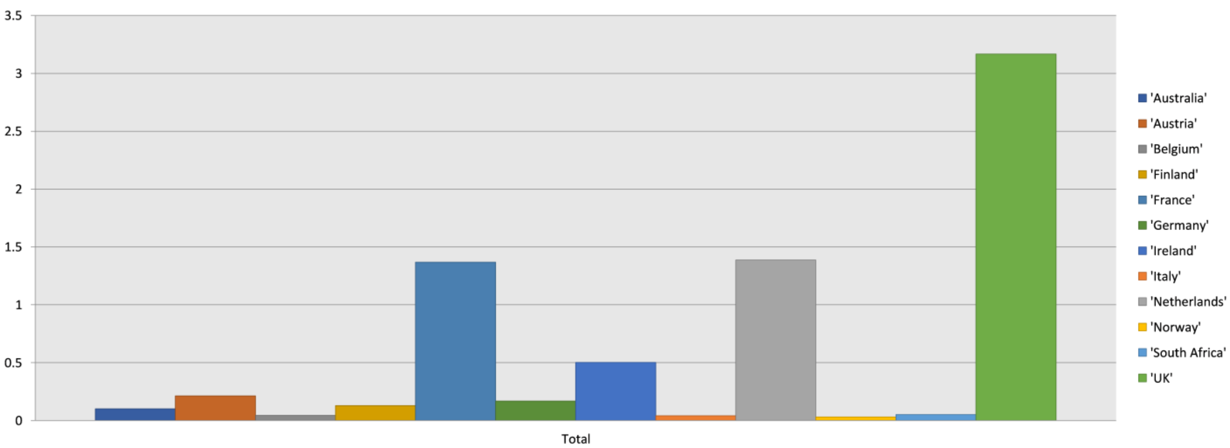


Figure 4.5.21.Degree Centrality - Stocks - 2nd highest

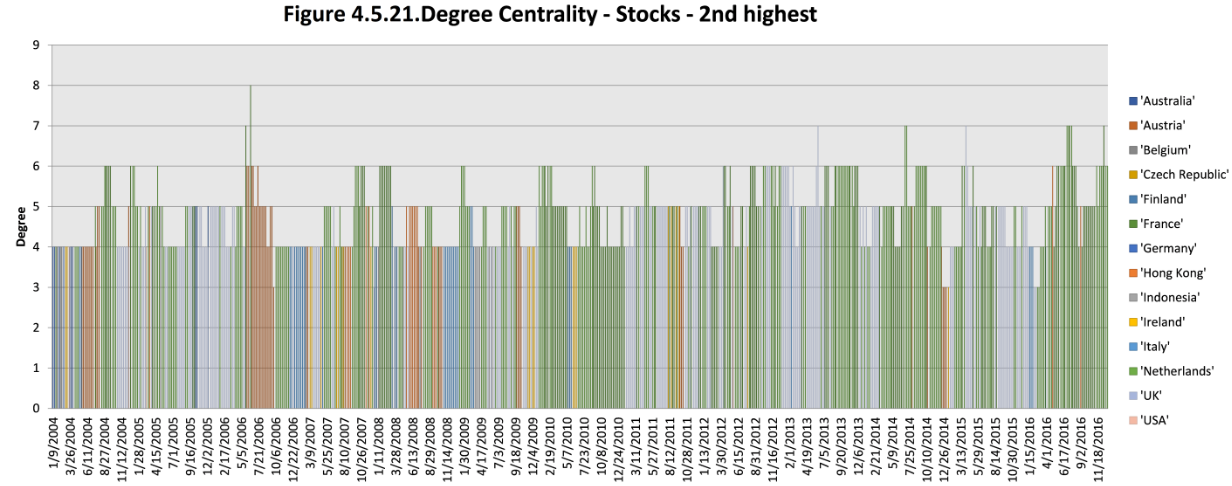


Figure 4.5.22.Degree Centrality - Stocks - 2nd highest - Frequency

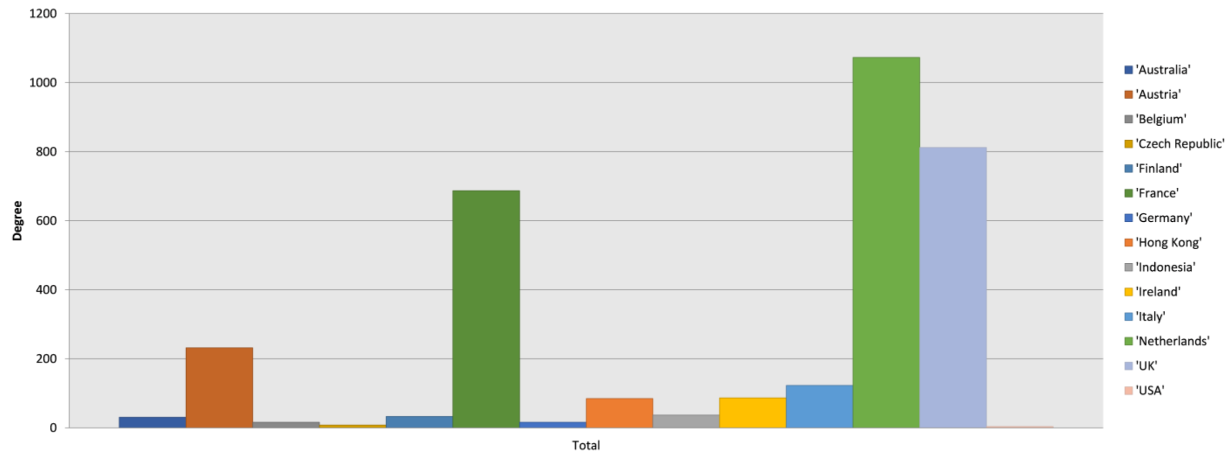


Figure 4.5.23.Eigenvector Centrality - Stocks - 2nd highest

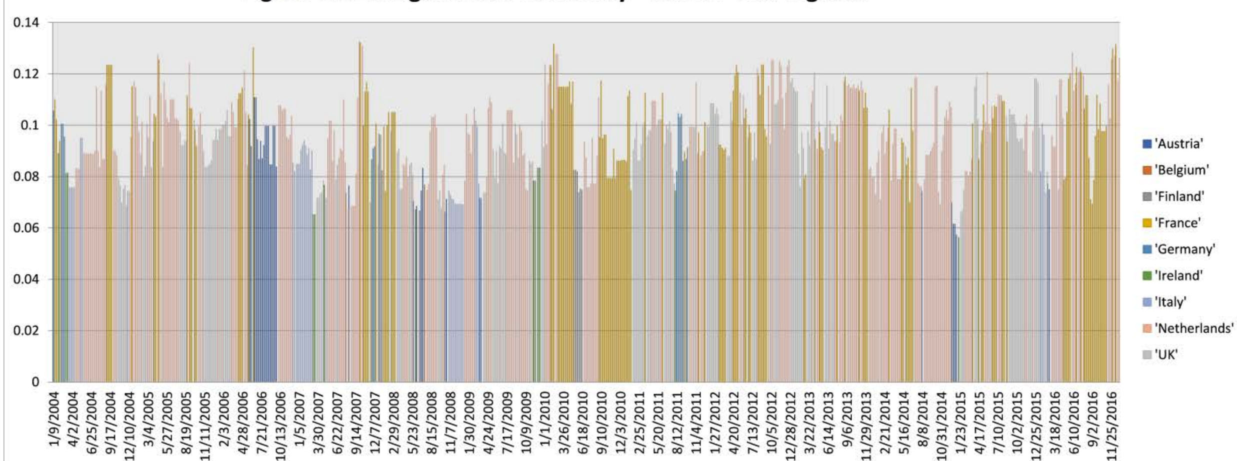


Figure 4.5.24.Eigenvector Centrality - Stocks - 2nd highest - Frequency

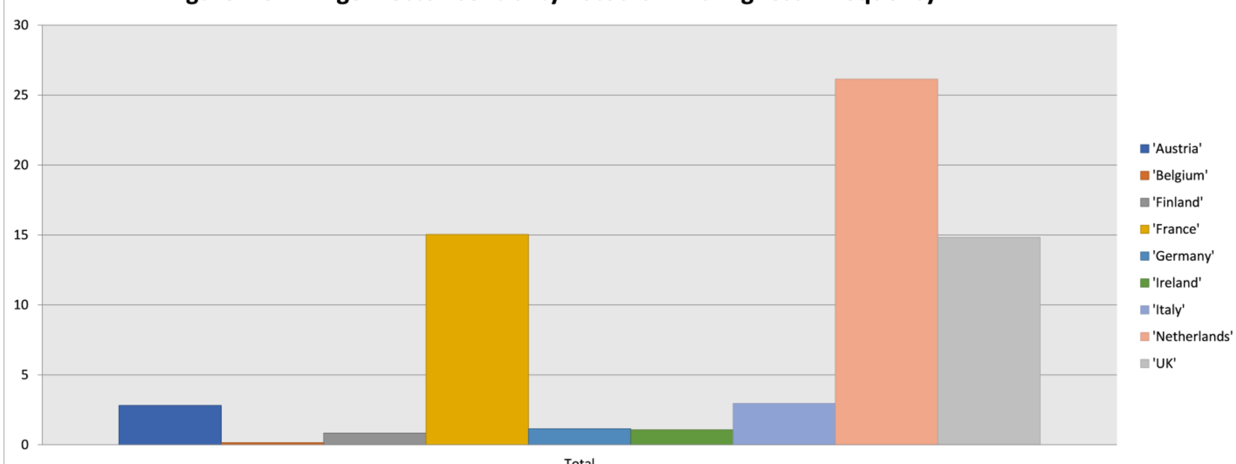


Figure 4.5.25.Betweenness Centrality - Stocks - 3rd highest

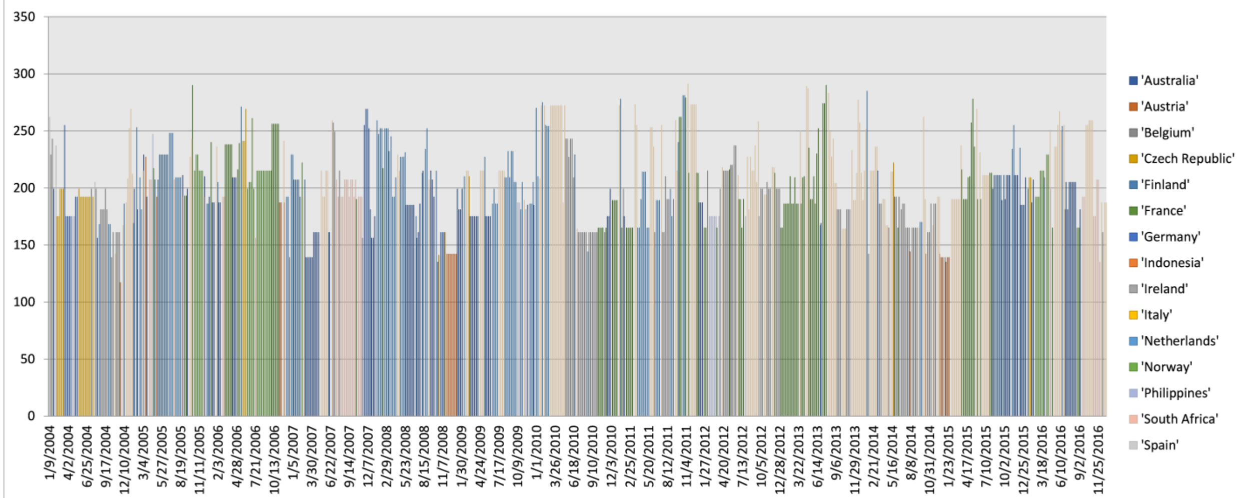


Figure 4.5.26.Betweenness Centrality - Stocks - 3rd highest - Frequency

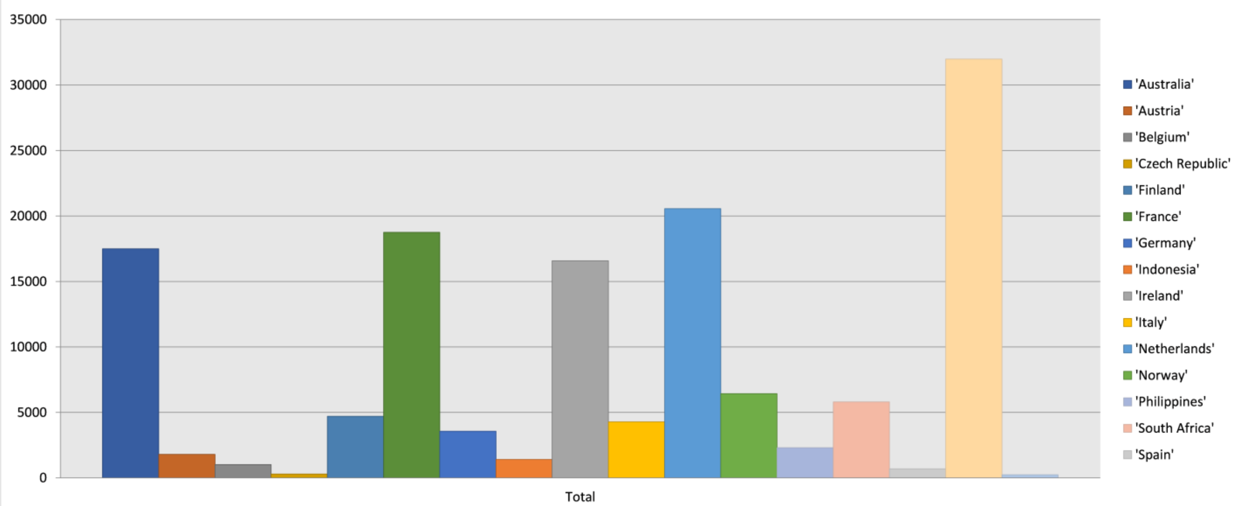


Figure 4.5.27.Closeness Centrality - Stocks - 3rd highest

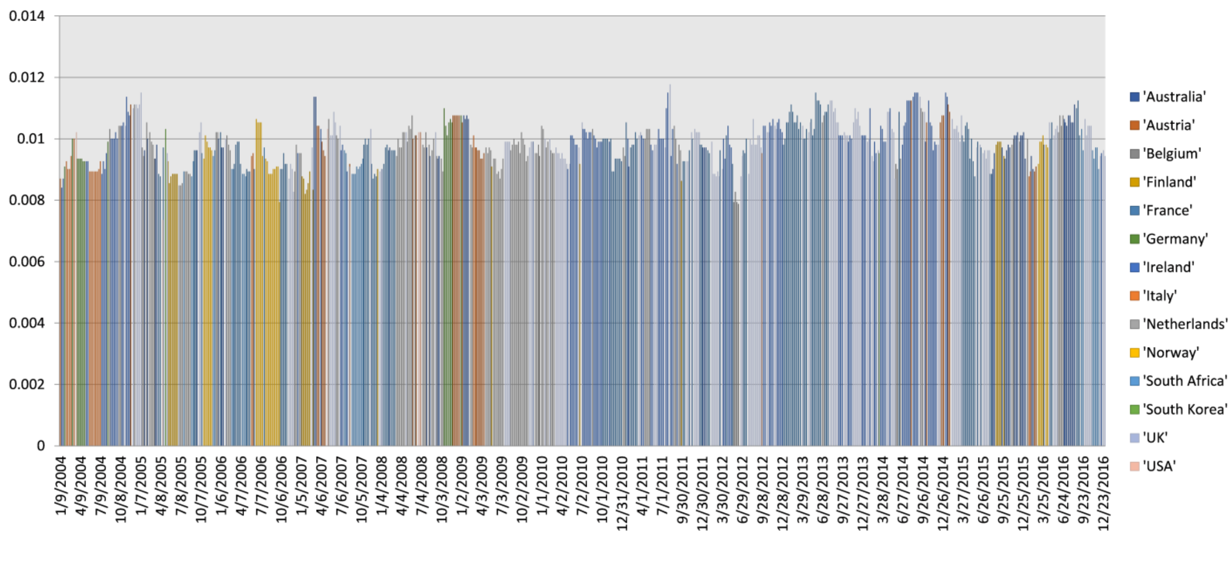


Figure 4.5.28.Closeness Centrality - Stocks - 3rd highest - Frequency

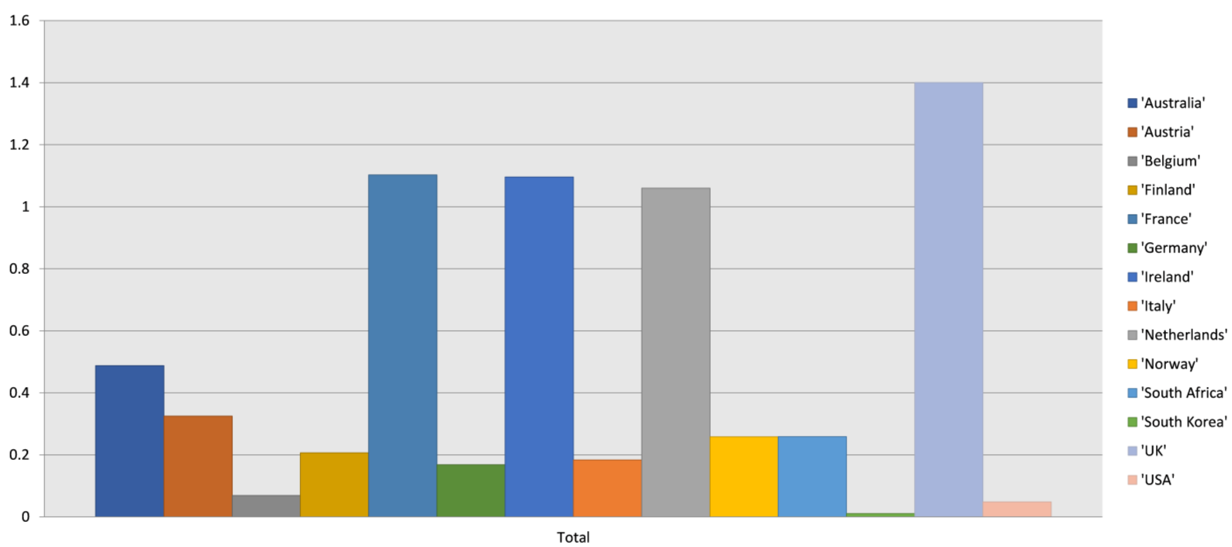


Figure 4.5.29. Degree Centrality - Stocks - 3rd highest

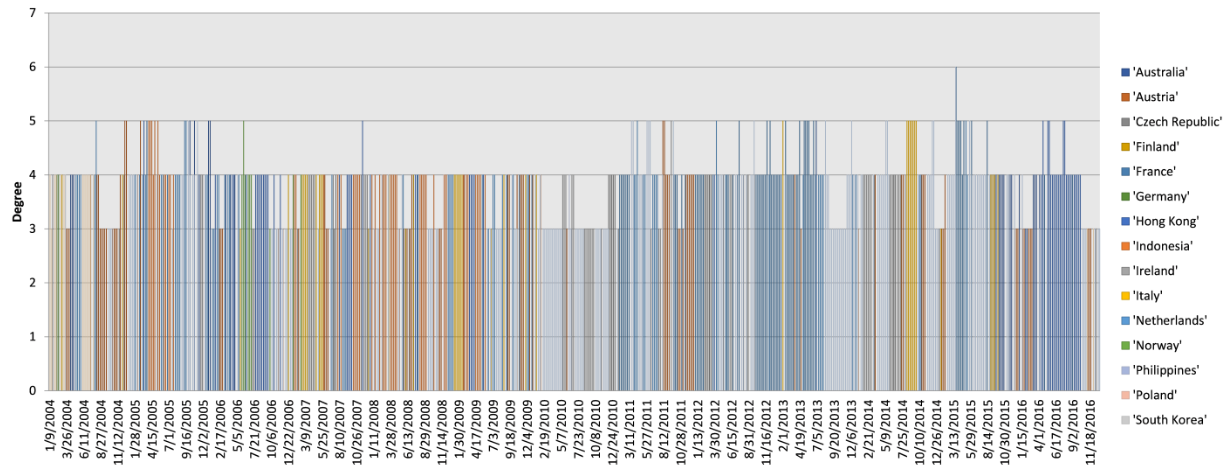


Figure 4.5.30. Degree Centrality - Stocks - 3rd highest - Frequency

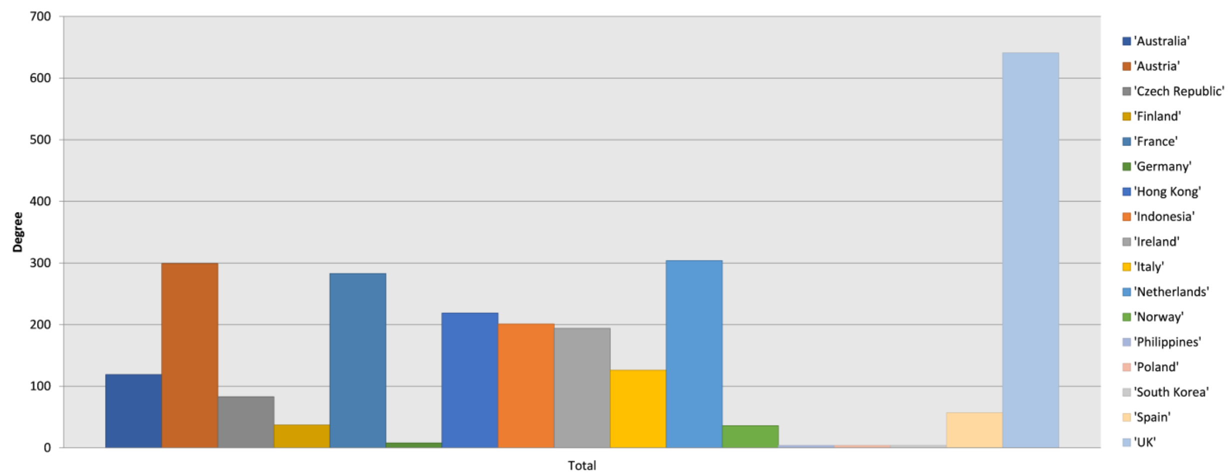


Figure 4.5.31.Eigenvector Centrality - Stocks - 3rd highest

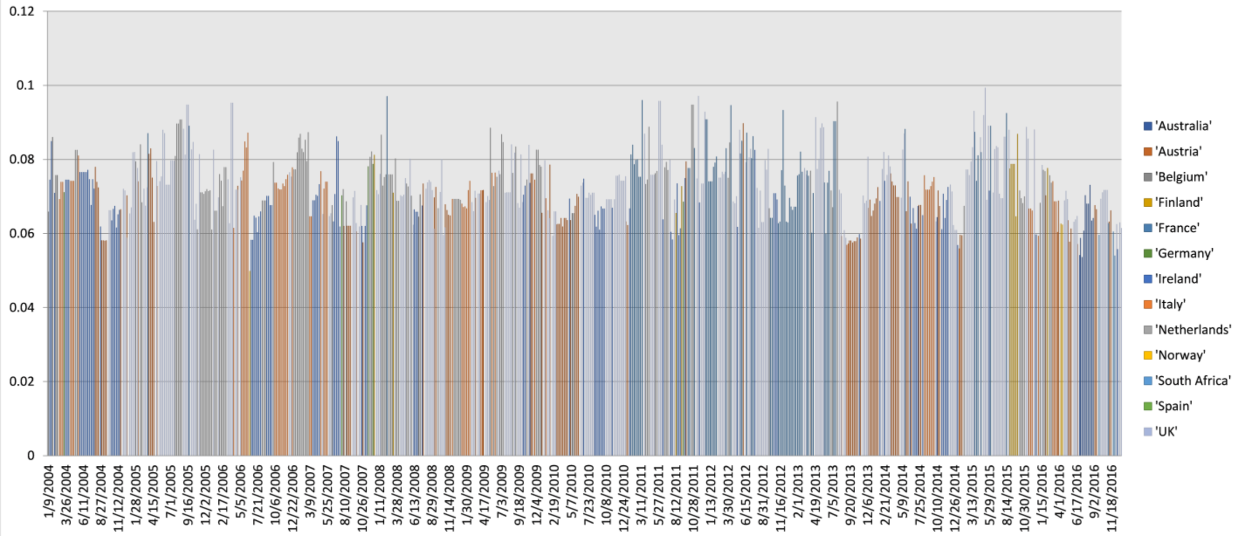
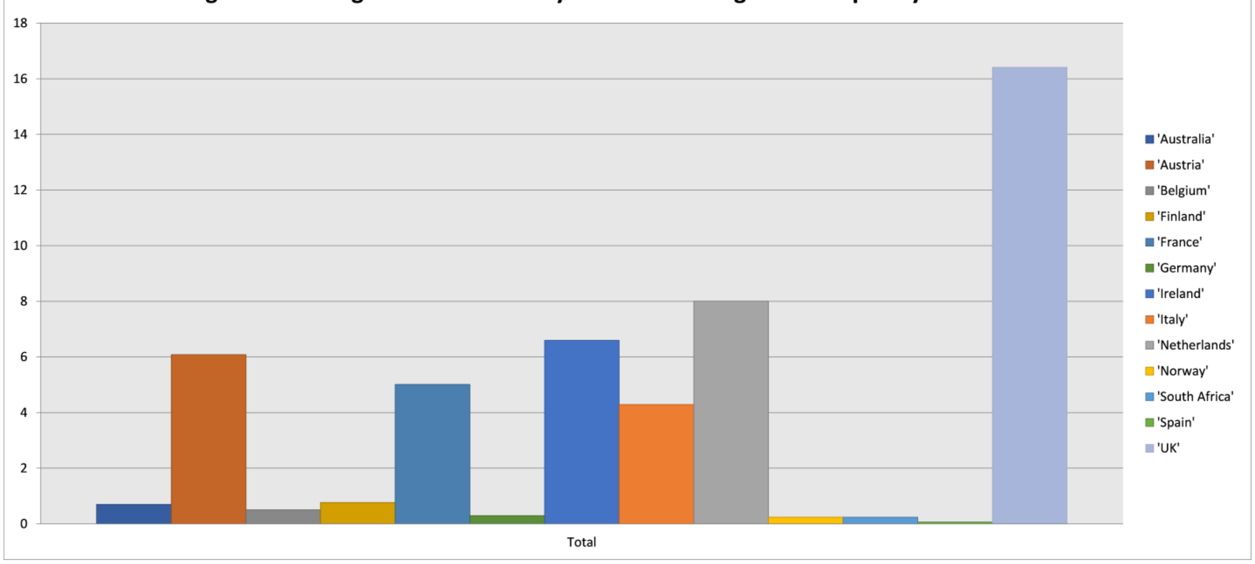


Figure 4.5.32.Eigenvector Centrality - Stocks - 3rd highest - Frequency



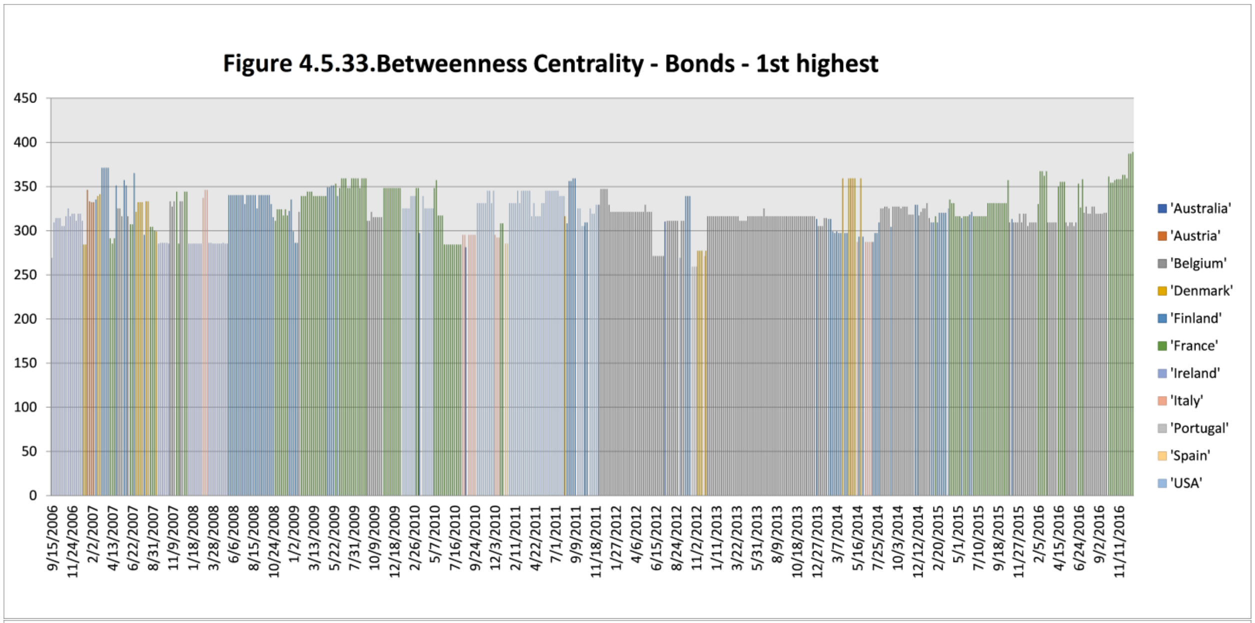


Figure 4.5.33.Betweenness Centrality - Bonds - 1st highest
450
400
350
300
250
200
150
100
50
0
'Australia'
'Austria'
'Belgium'
'Denmark'
'Finland'
'France'
'Ireland'
'Italy'
'Portugal'
'Spain'
'USA'

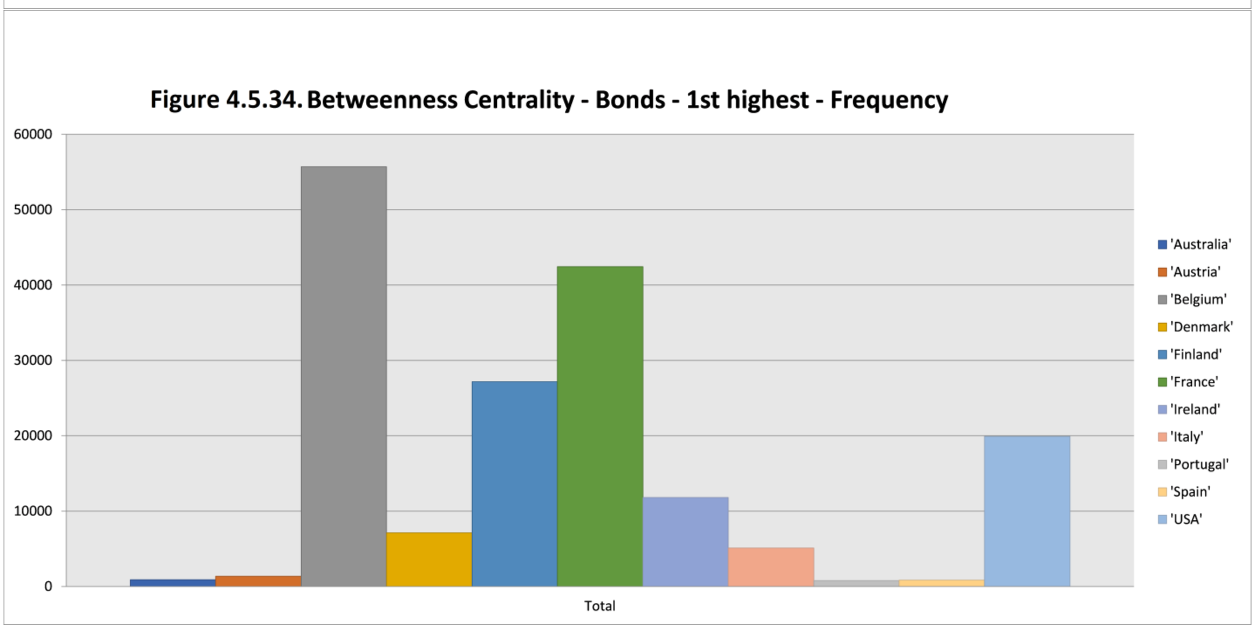


Figure 4.5.34. Betweenness Centrality - Bonds - 1st highest - Frequency
60000
50000
40000
30000
20000
10000
0
Total
'Australia'
'Austria'
'Belgium'
'Denmark'
'Finland'
'France'
'Ireland'
'Italy'
'Portugal'
'Spain'
'USA'

Figure 4.5.35.Closeness Centrality - Bonds - 1st highest

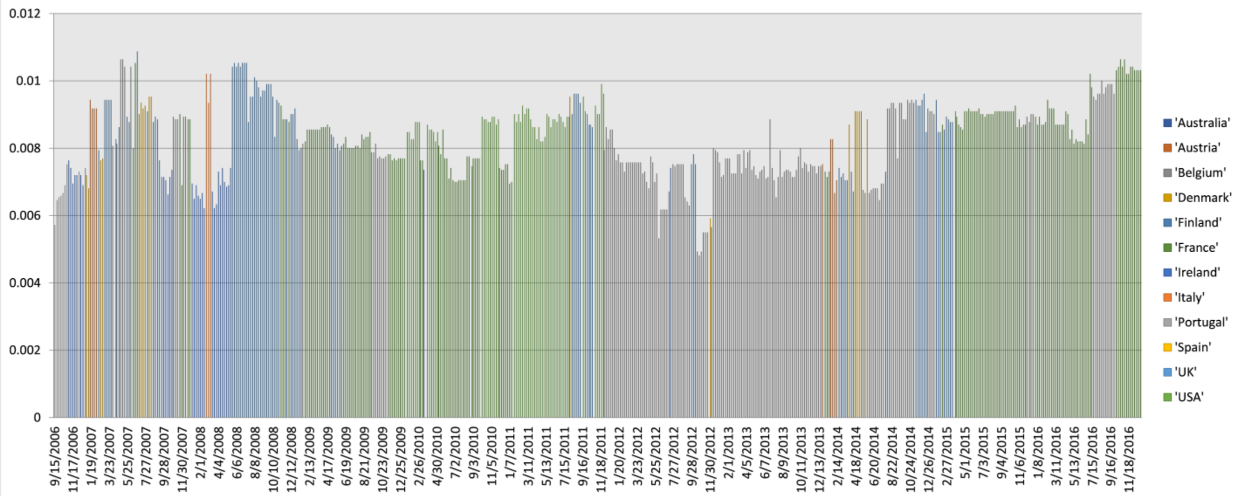
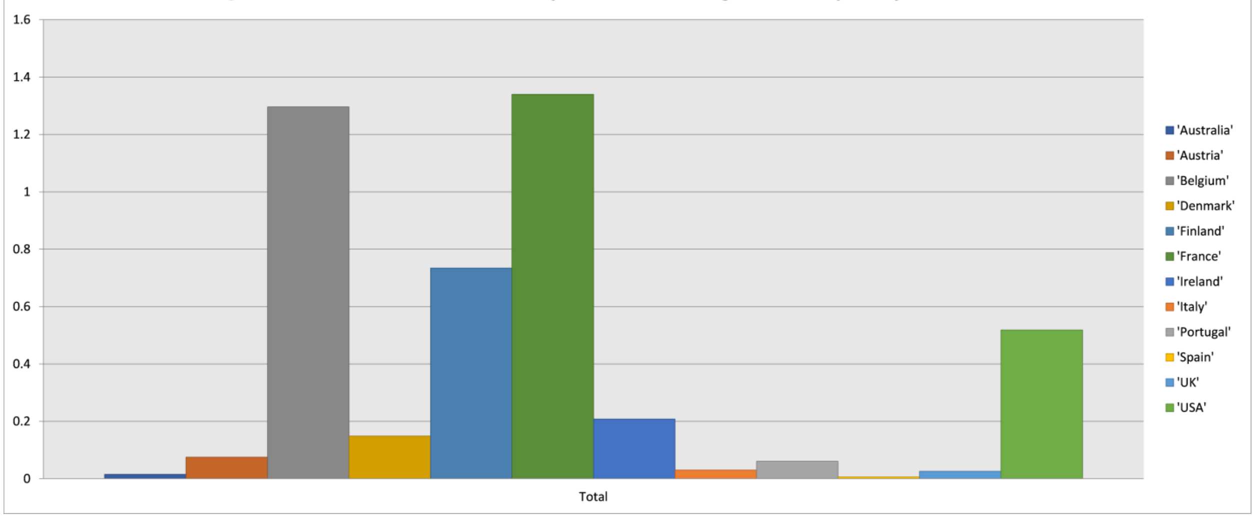


Figure 4.5.36.Closeness Centrality - Bonds - 1st highest - Frequency



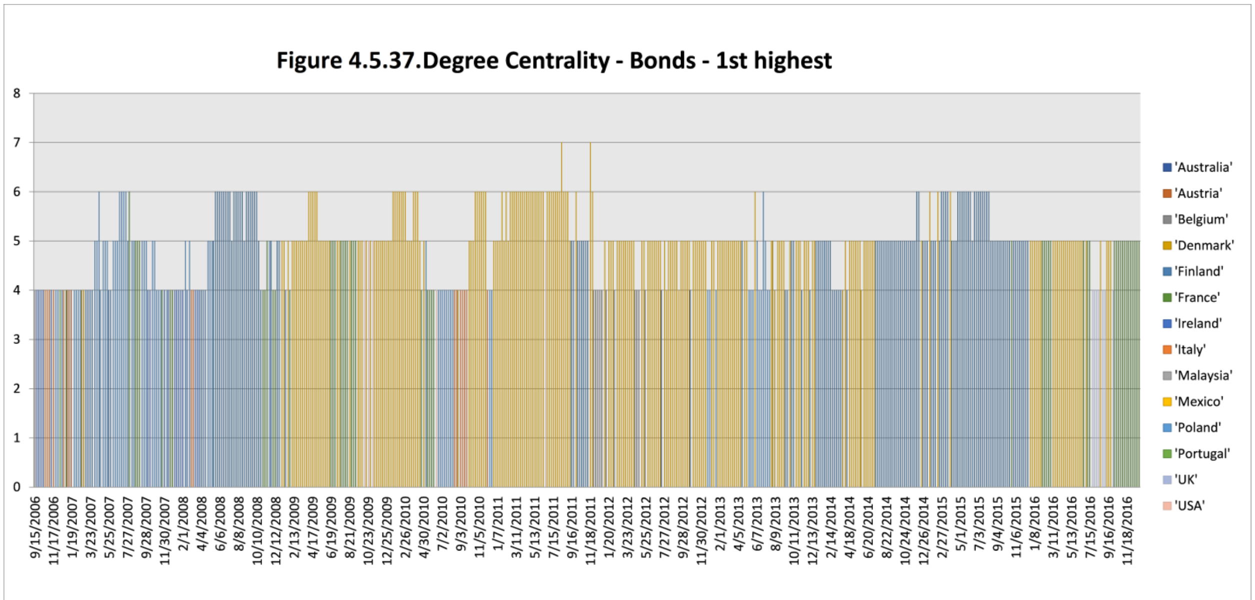


Figure 4.5.37.Degree Centrality - Bonds - 1st highest
'Australia'
'Austria'
'Belgium'
'Denmark'
'Finland'
'France'
'Ireland'
'Italy'
'Malaysia'
'Mexico'
'Poland'
'Portugal'
'UK'
'USA'

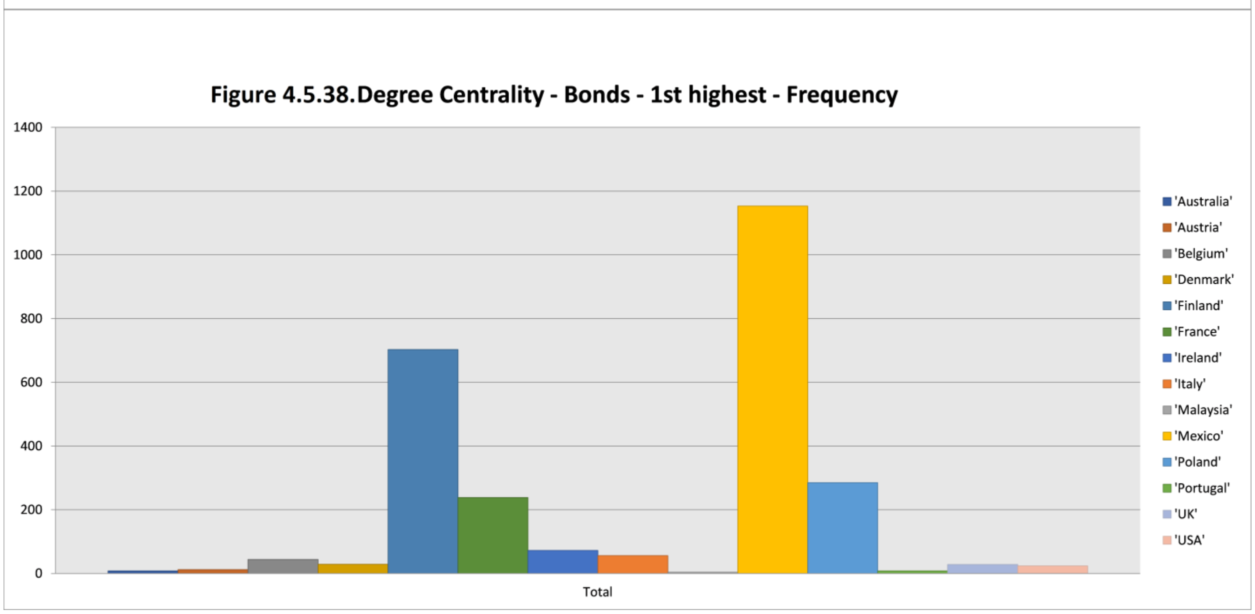


Figure 4.5.38.Degree Centrality - Bonds - 1st highest - Frequency
Total
'Australia'
'Austria'
'Belgium'
'Denmark'
'Finland'
'France'
'Ireland'
'Italy'
'Malaysia'
'Mexico'
'Poland'
'Portugal'
'UK'
'USA'

Figure 4.5.39.Eigenvector Centrality - Bonds - 1st highest

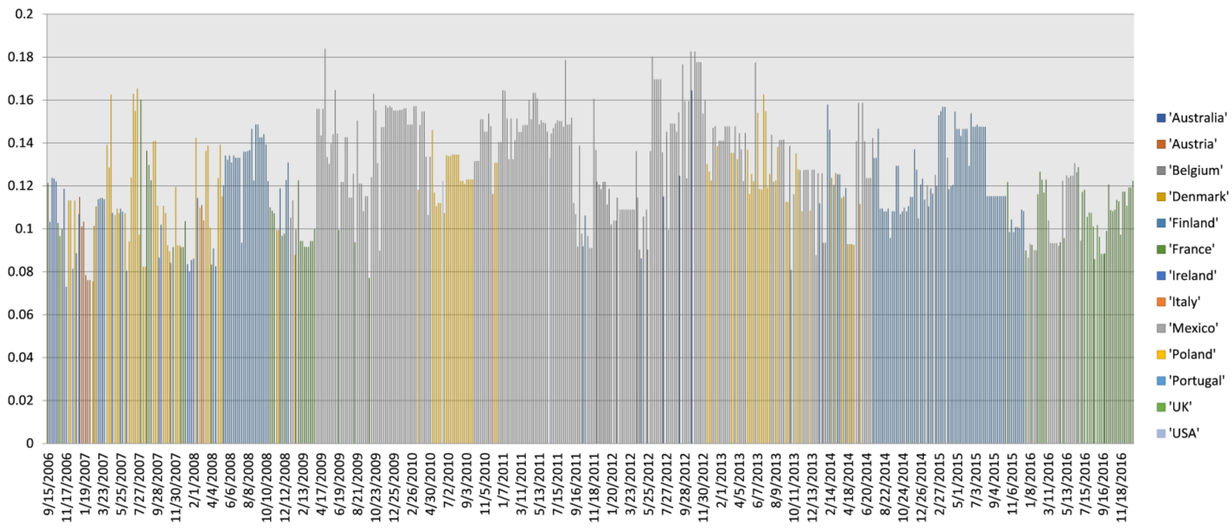


Figure 4.5.40.Eigenvector Centrality - Bonds - 1st highest - Frequency

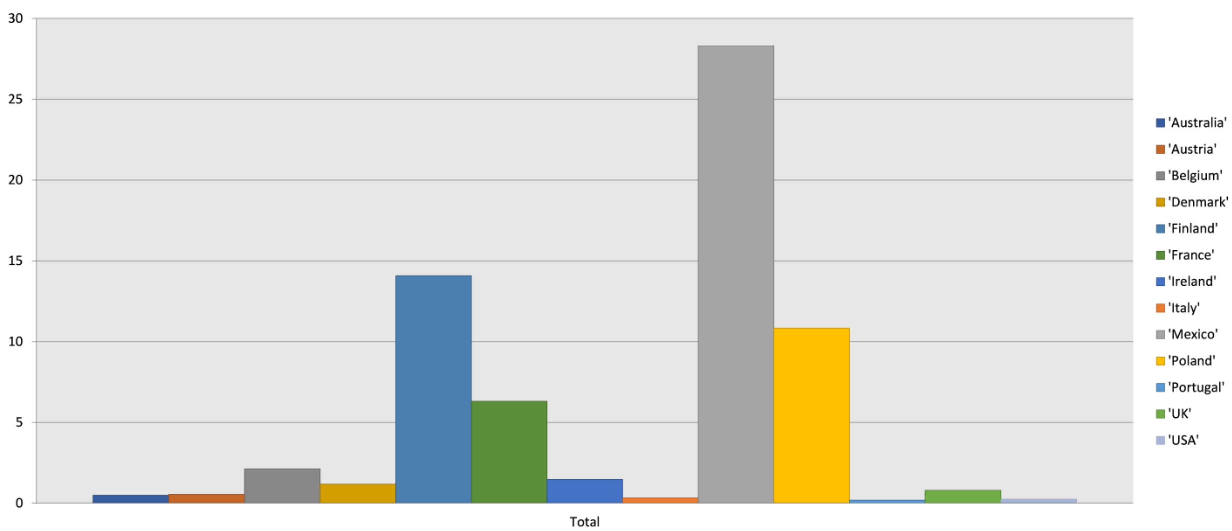


Figure 4.5.41.Betweenness Centrality - Bonds - 2nd highest

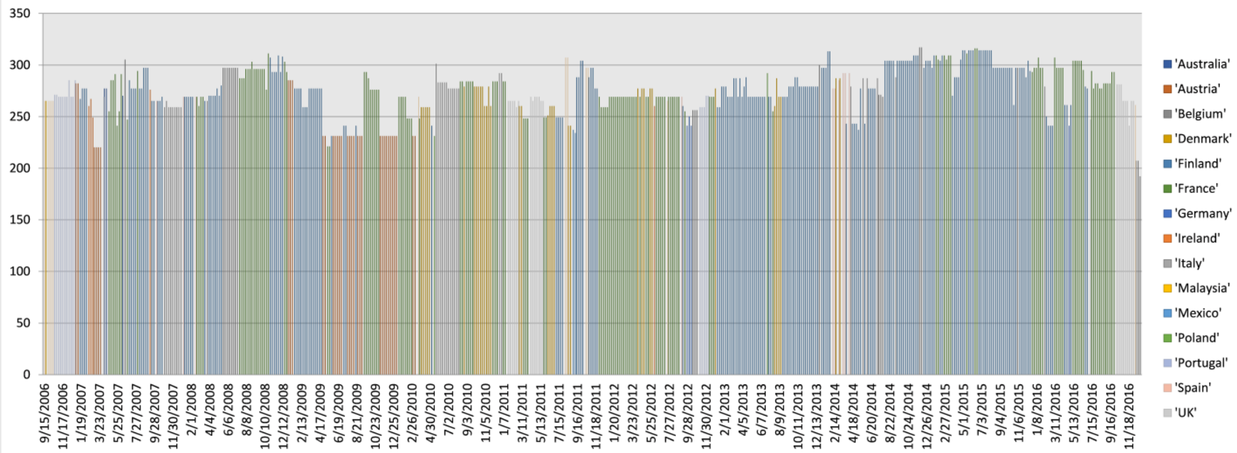


Figure 4.5.42.Betweenness Centrality - Bonds - 2nd highest - Frequency

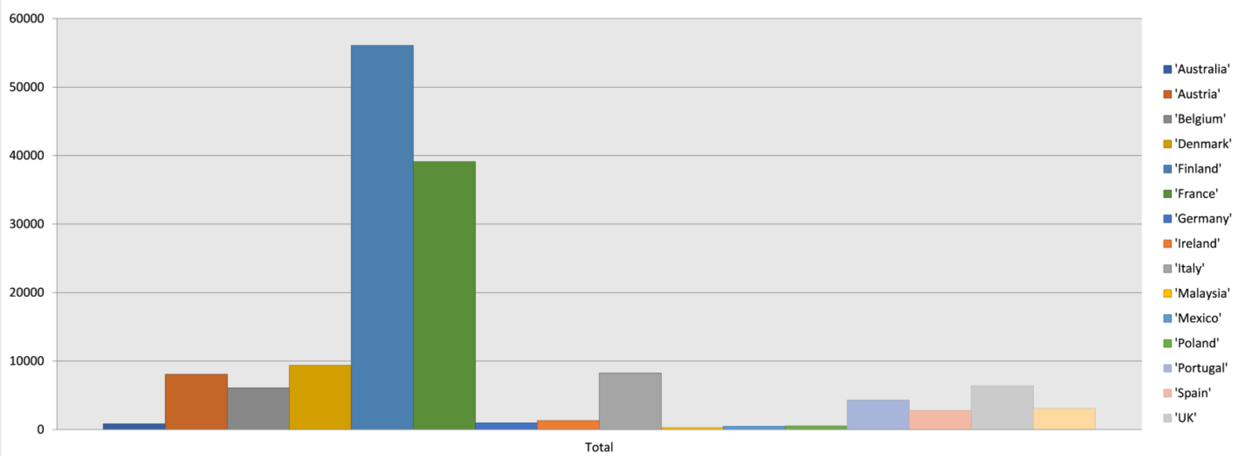


Figure 4.5.43.Closeness Centrality - Bonds - 2nd highest

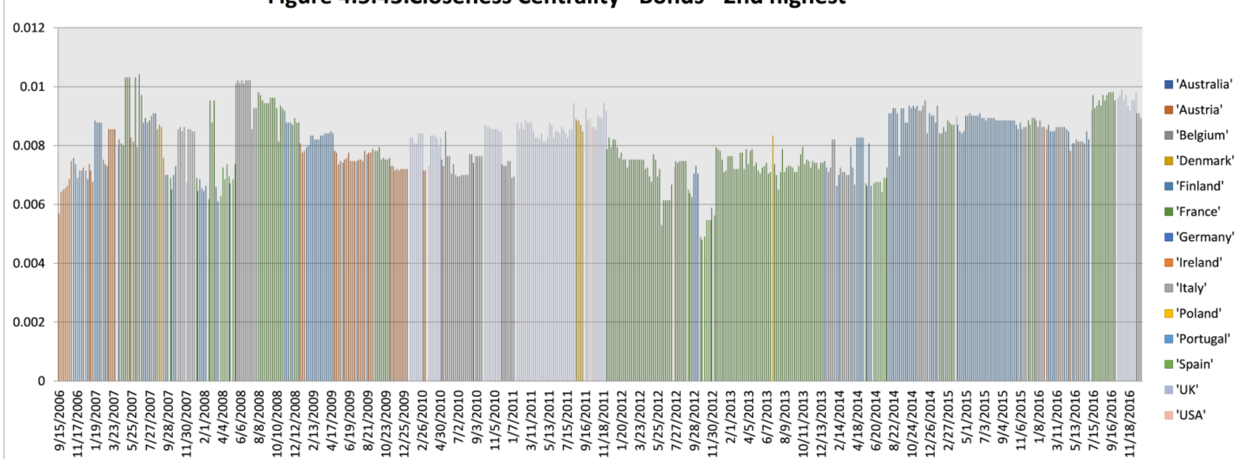


Figure 4.5.44.Closeness Centrality - Bonds - 2nd highest - Frequency

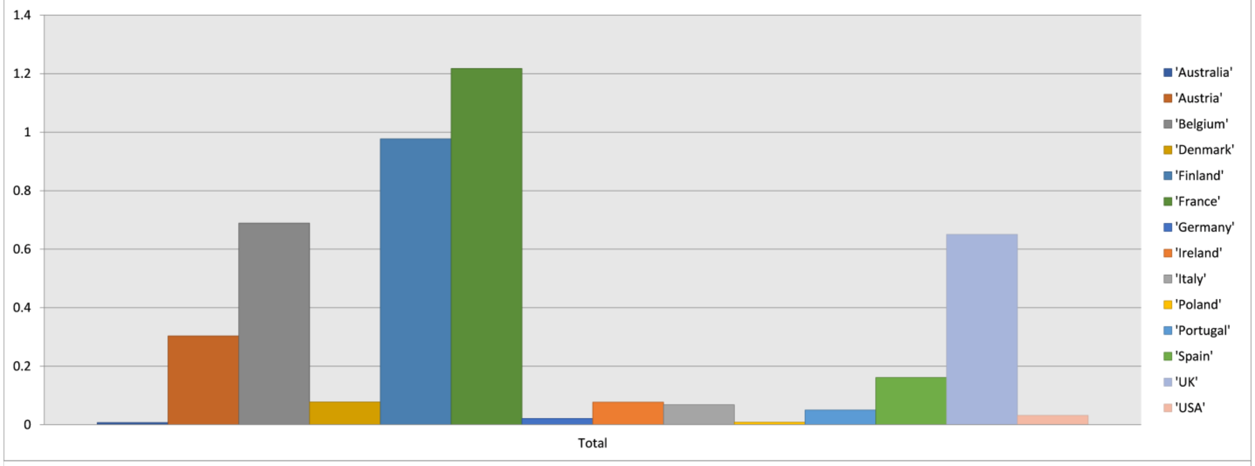


Figure 4.5.45.Degree Centrality - Bonds - 2nd highest

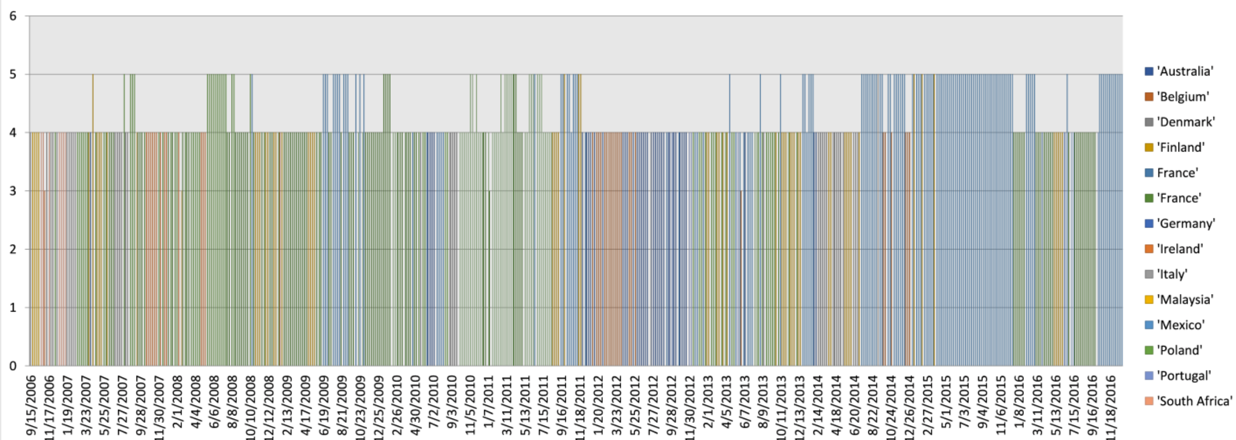


Figure 4.5.46.Degree Centrality - Bonds - 2nd highest - Frequency

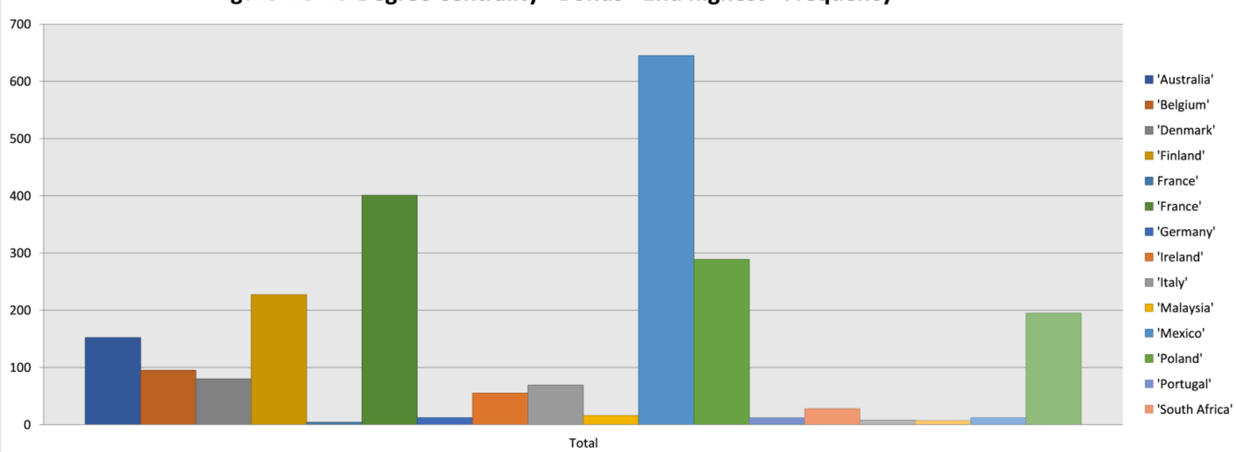


Figure 4.5.47.Eigenvector Centrality - Bonds - 2nd highest

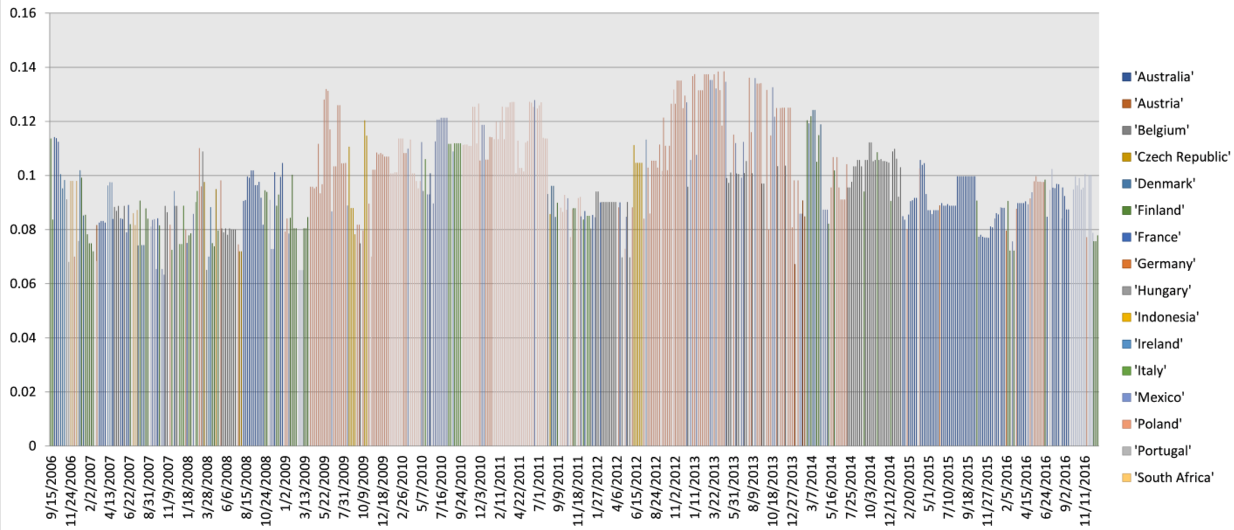


Figure 4.5.48.Eigenvector Centrality - Bonds - 2nd highest - Frequency

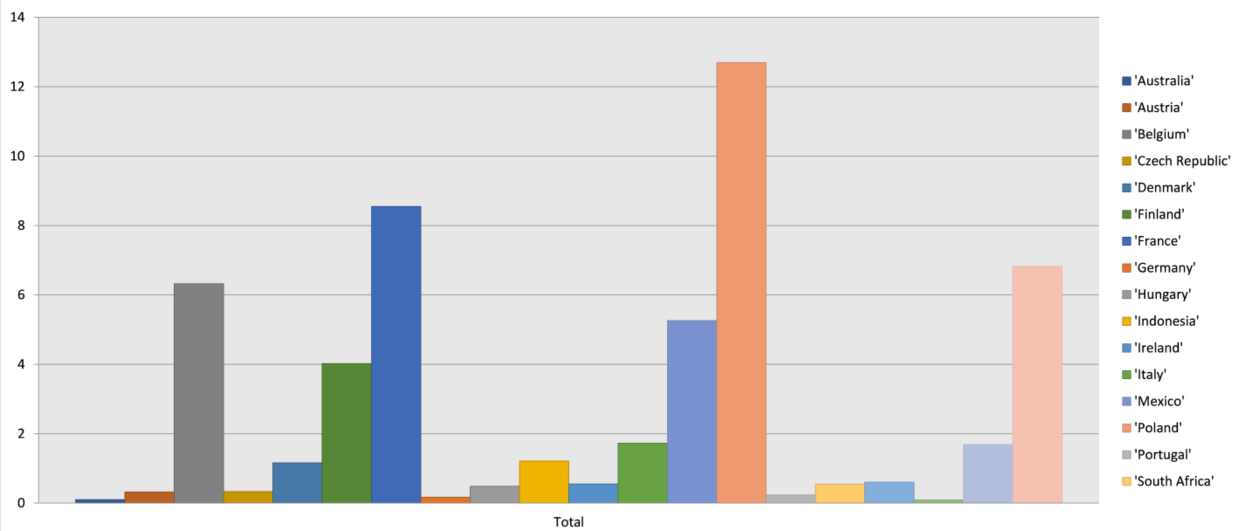


Figure 4.5.49. Betweenness Centrality - Bonds - 3rd highest

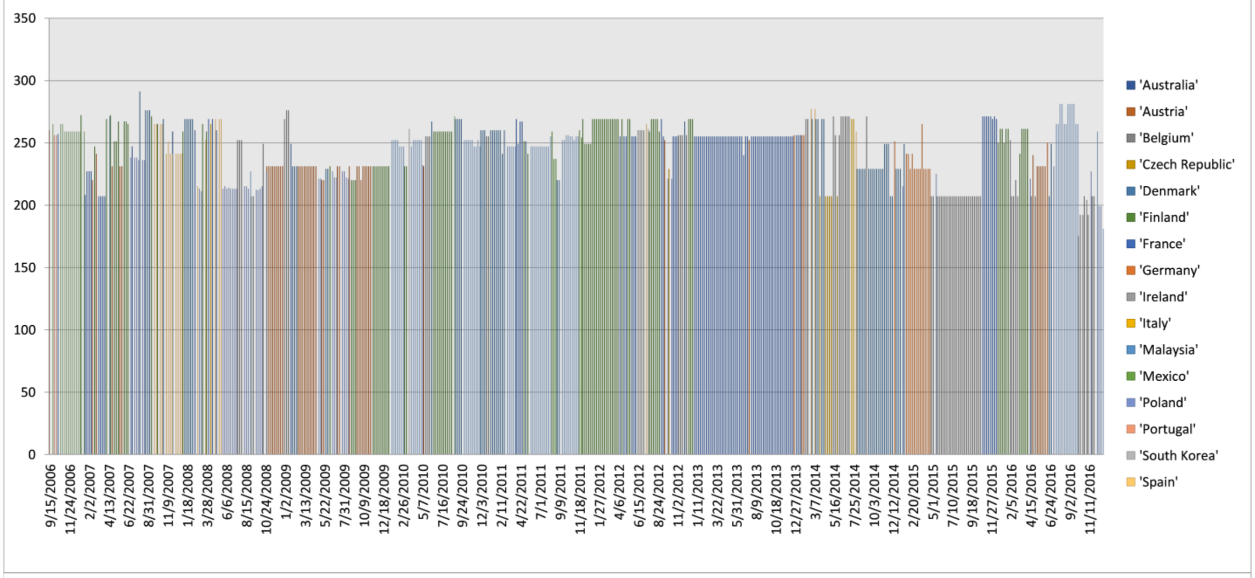
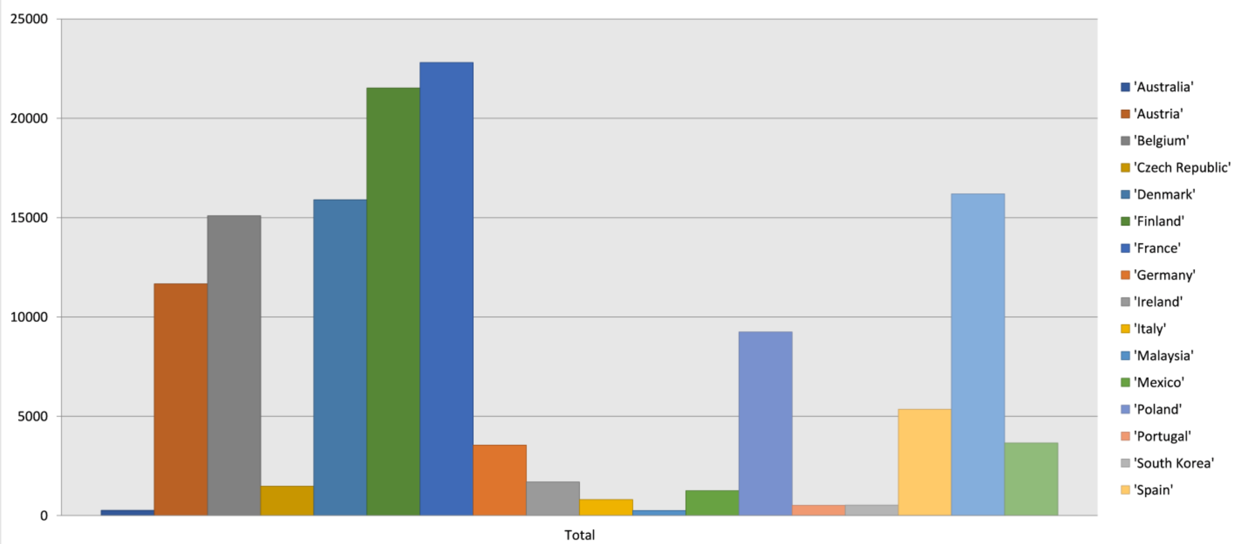


Figure 4.5.50. Betweenness Centrality - Bonds - 3rd highest - Frequency



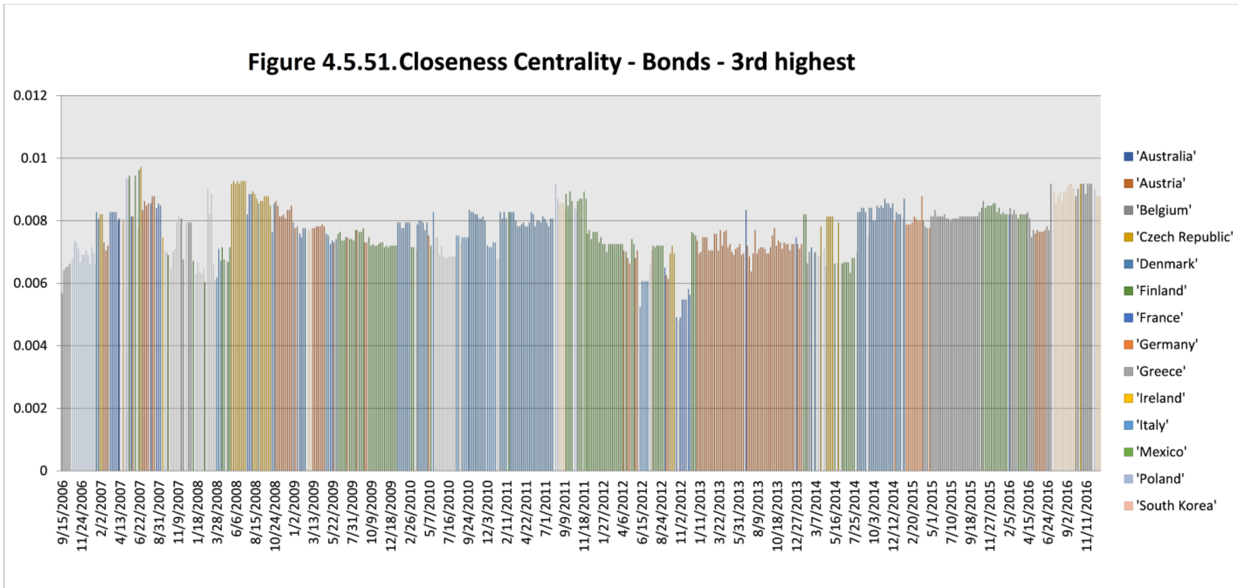


Figure 4.5.51.Closeness Centrality - Bonds - 3rd highest
'Australia'
'Austria'
'Belgium'
'Czech Republic'
'Denmark'
'Finland'
'France'
'Germany'
'Greece'
'Ireland'
'Italy'
'Mexico'
'Poland'
'South Korea'

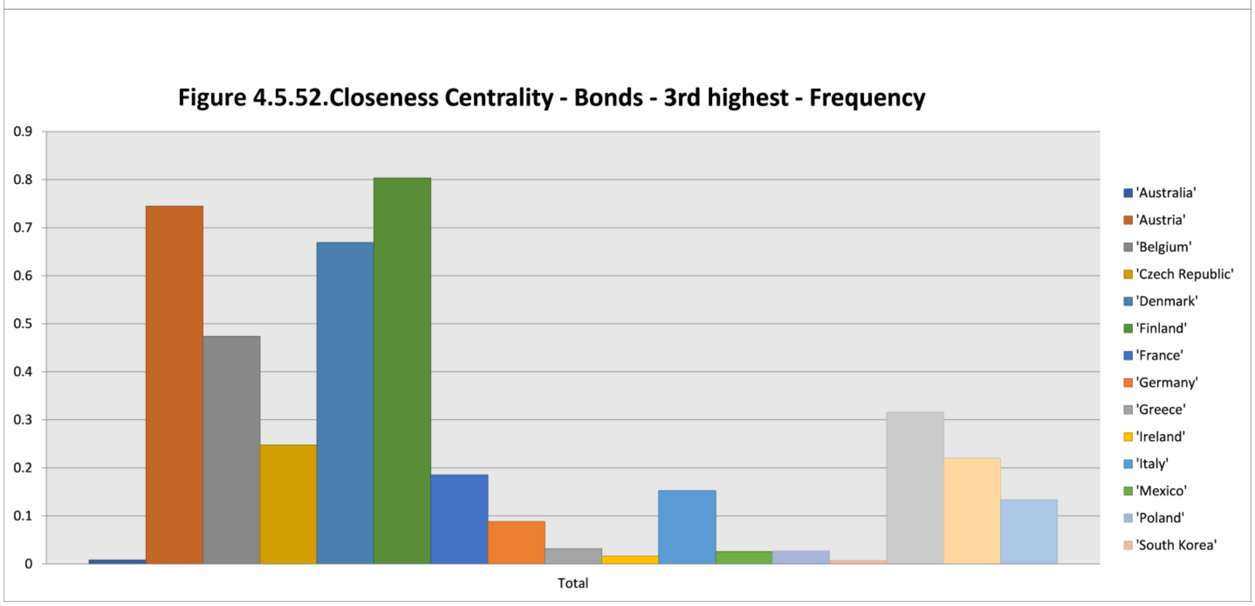


Figure 4.5.52.Closeness Centrality - Bonds - 3rd highest - Frequency
Total
'Australia'
'Austria'
'Belgium'
'Czech Republic'
'Denmark'
'Finland'
'France'
'Germany'
'Greece'
'Ireland'
'Italy'
'Mexico'
'Poland'
'South Korea'

Figure 4.5.53.Degree Centrality - Bonds - 3rd highest

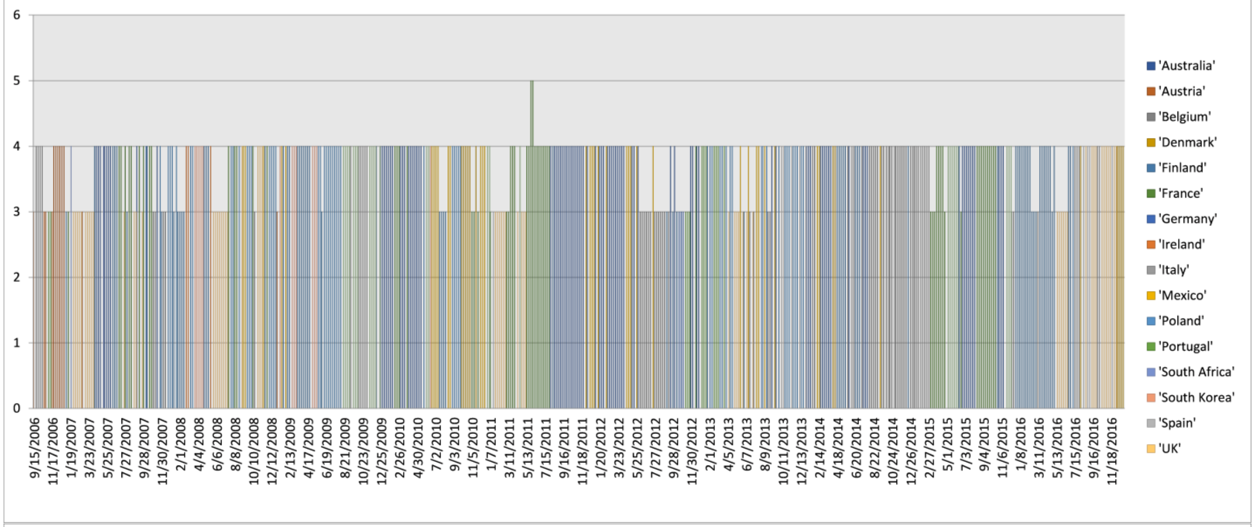


Figure 4.5.54.Degree Centrality - Bonds - 3rd highest - Frequency

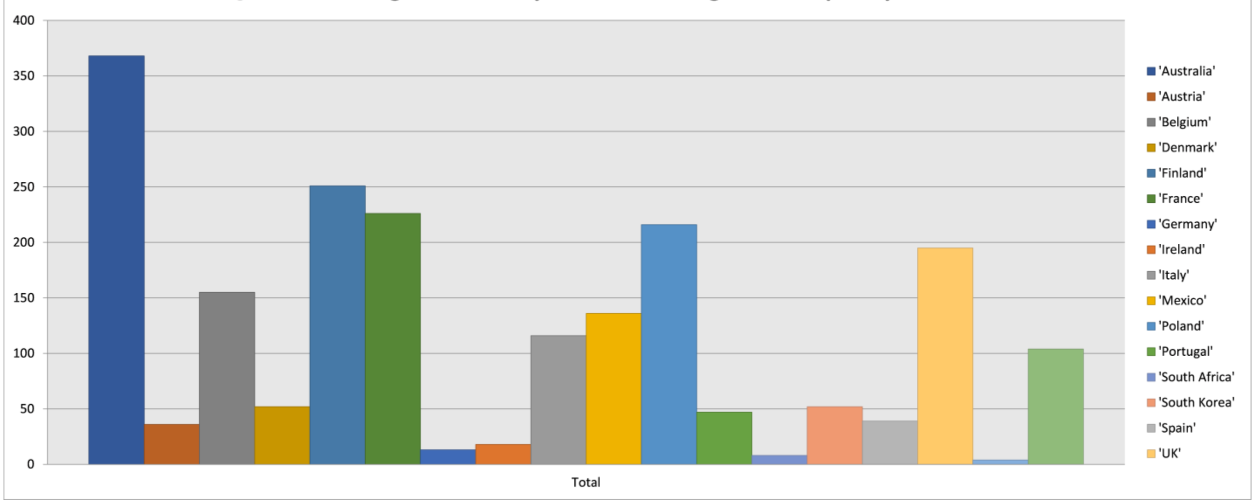


Figure 4.5.55.Eigenvector Centrality - Bonds - 3rd highest

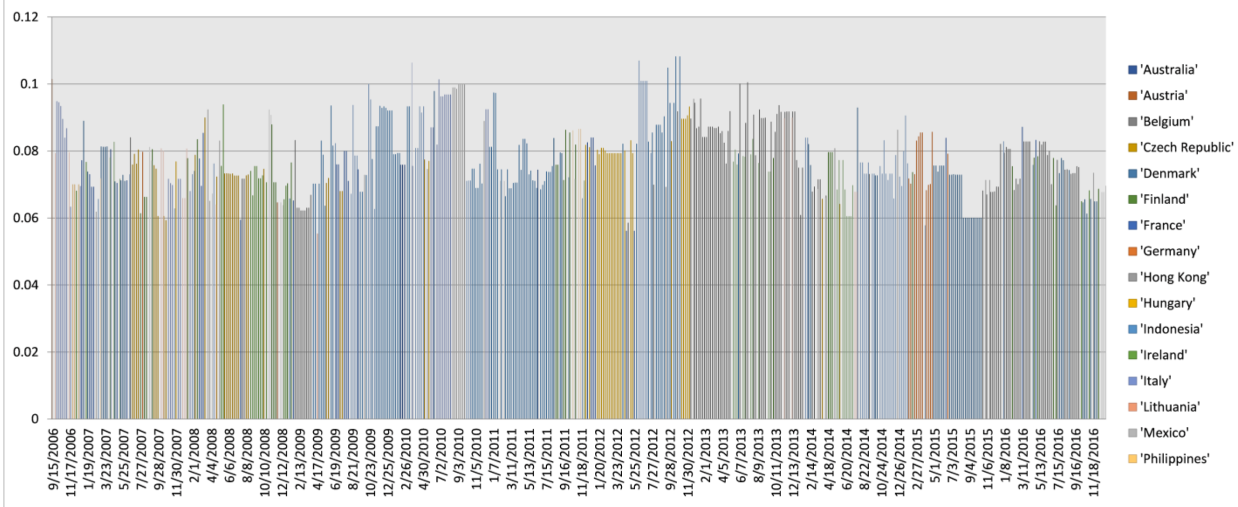


Figure 4.5.56.Eigenvector Centrality - Bonds - 3rd highest - Frequency

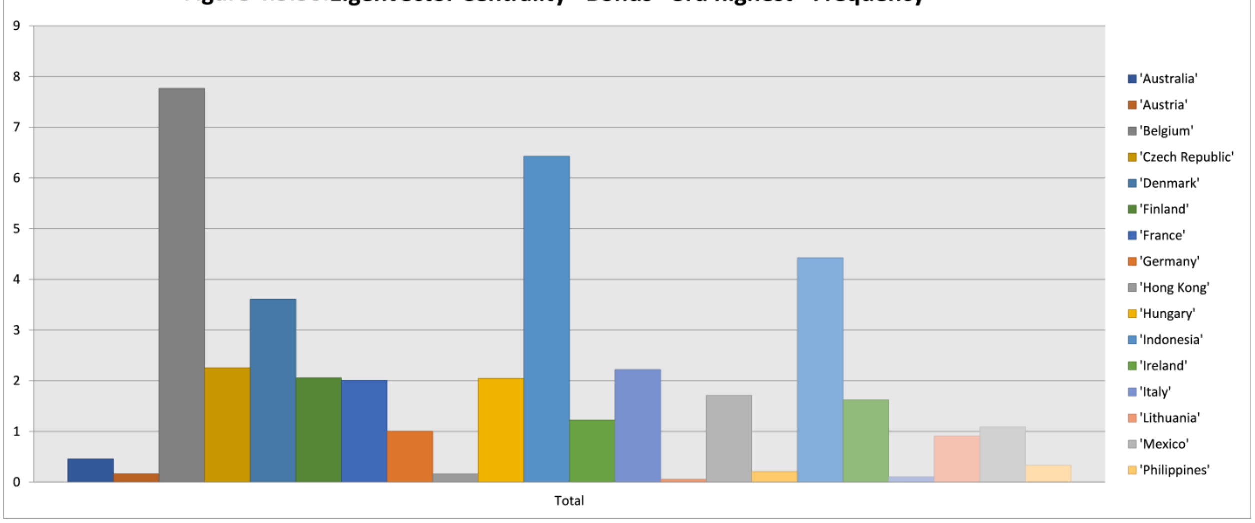


Figure 4.5.57.Betweenness Centrality - CDS - 1st highest

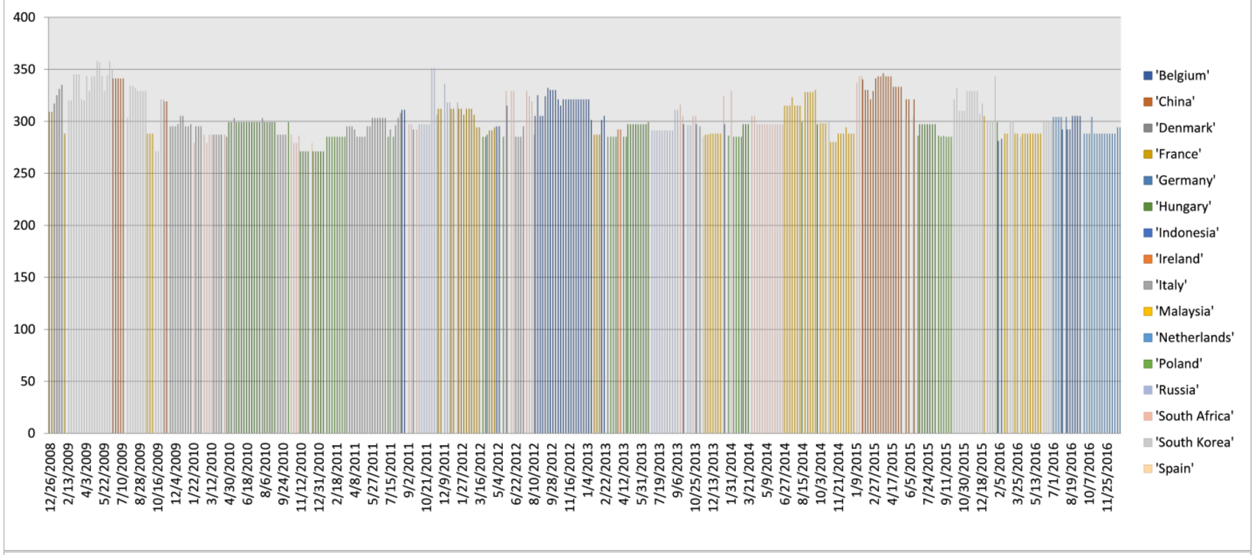


Figure 4.5.58.Betweenness Centrality - CDS - 1st highest - Frequency

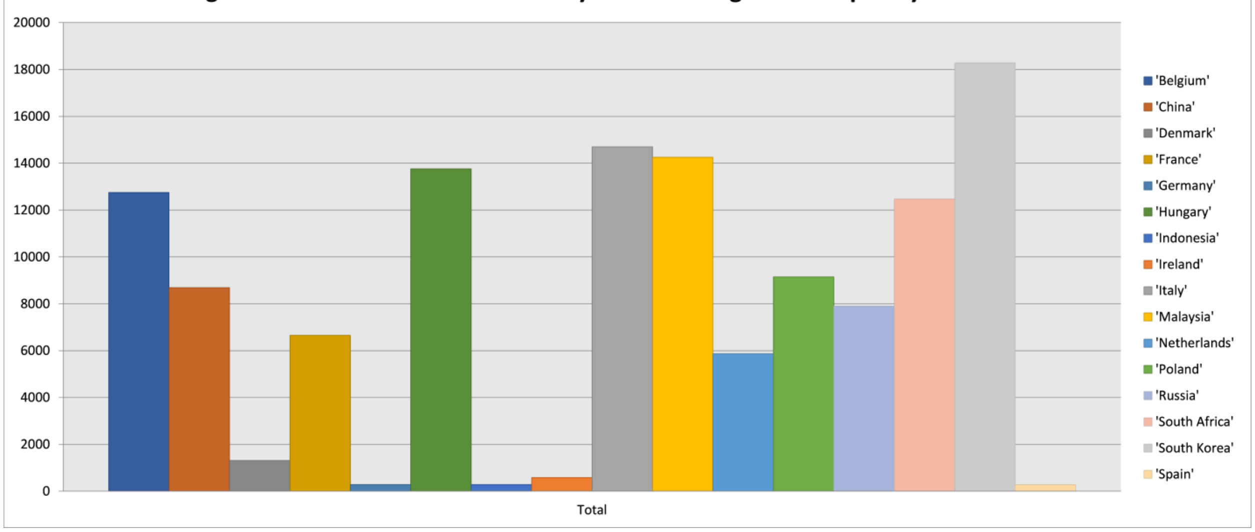


Figure 4.5.59.Closeness Centrality - CDS - 1st highest

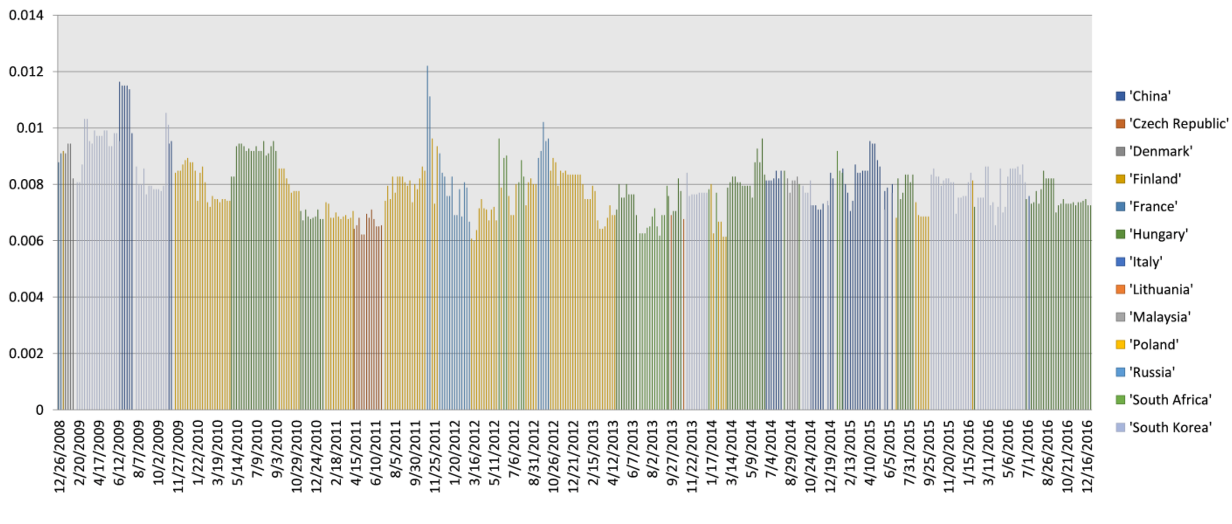


Figure 4.5.60.Closeness Centrality - CDS - 1st highest - Frequency

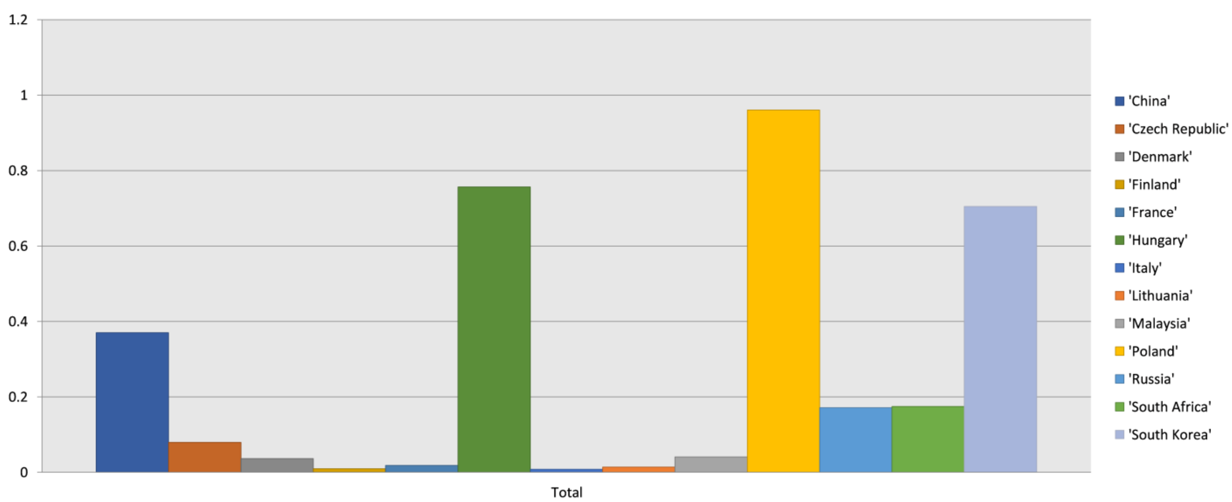


Figure 4.5.61.Degree Centrality - CDS - 1st highest

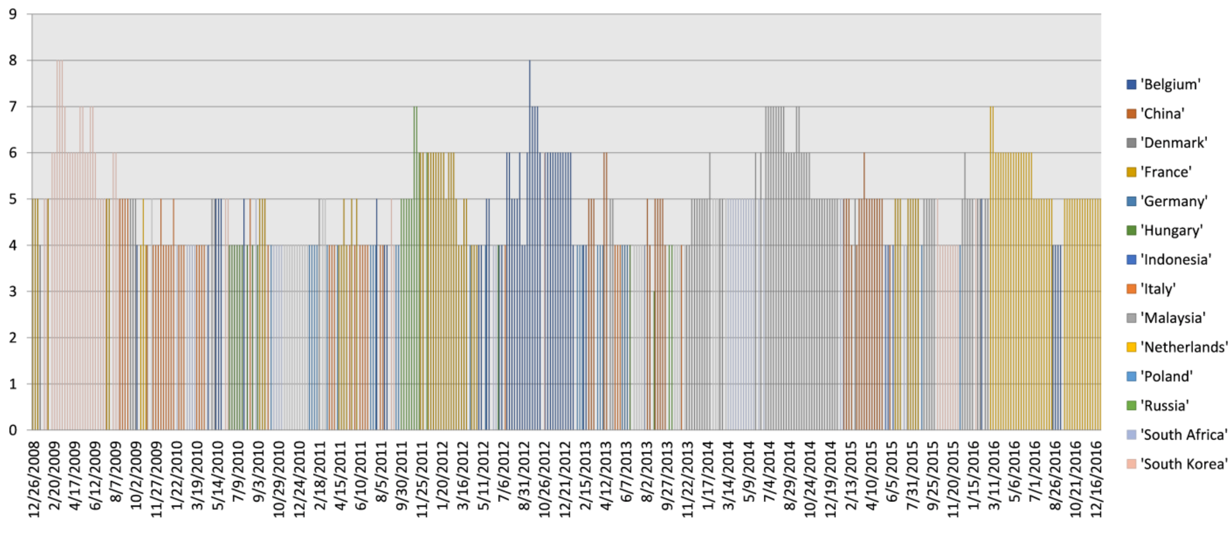


Figure 4.5.62.Degree Centrality - CDS - 1st highest Frequency

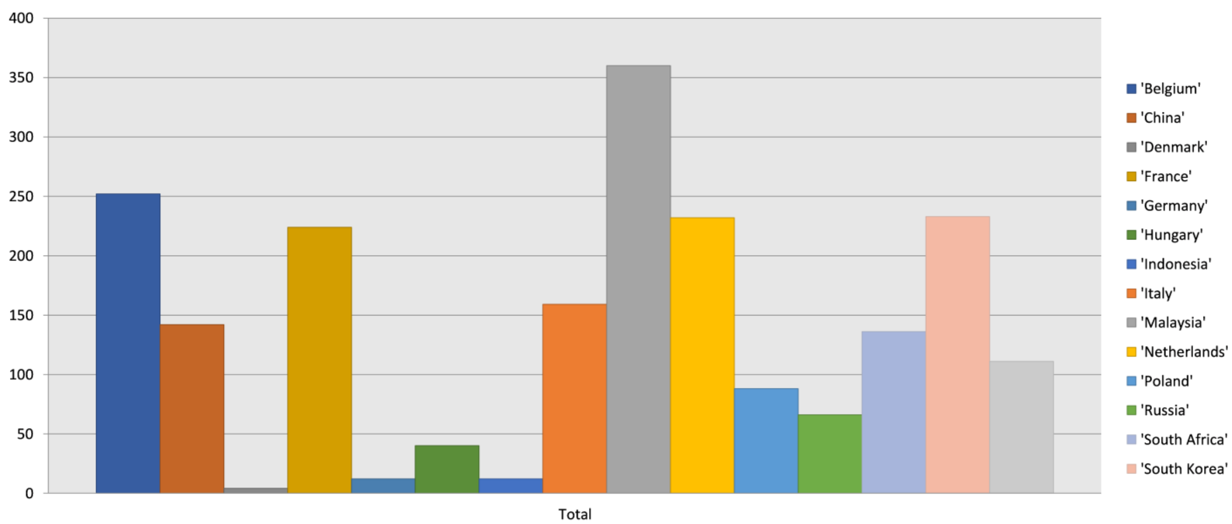


Figure 4.5.63.Eigenvector Centrality - CDS - 1st highest

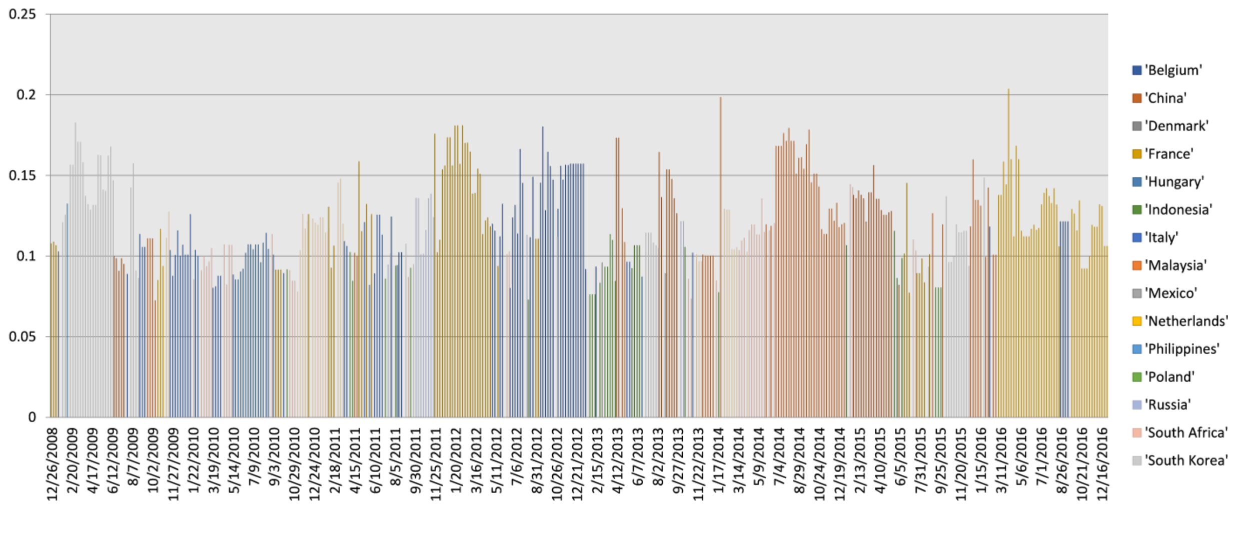


Figure 4.5.64.Eigenvector Centrality - CDS - 1st highest - Frequency

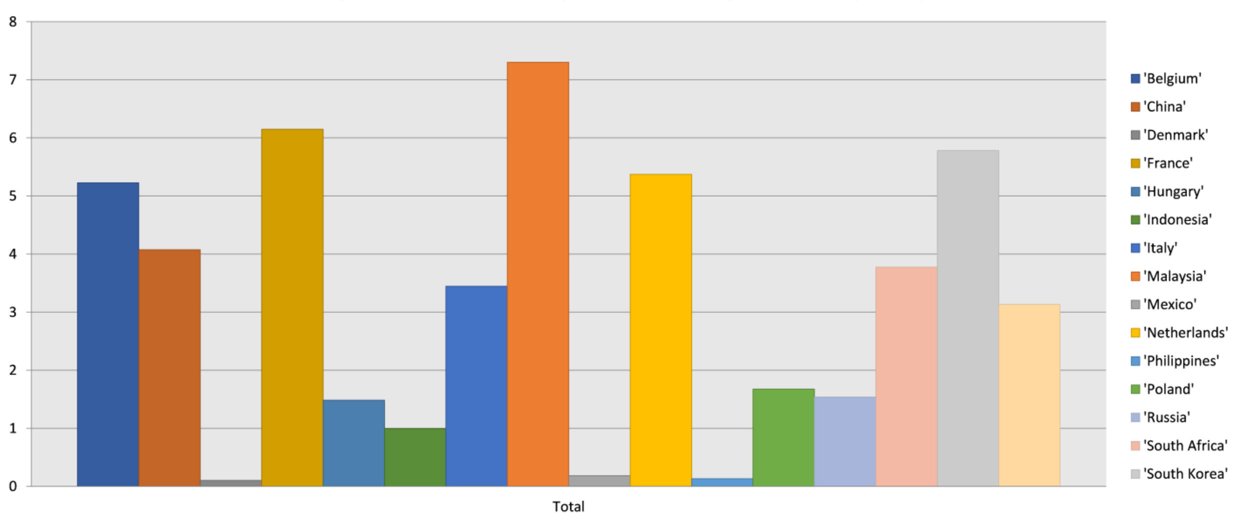


Figure 4.5.65.Betweenness Centrality - CDS - 2nd highest

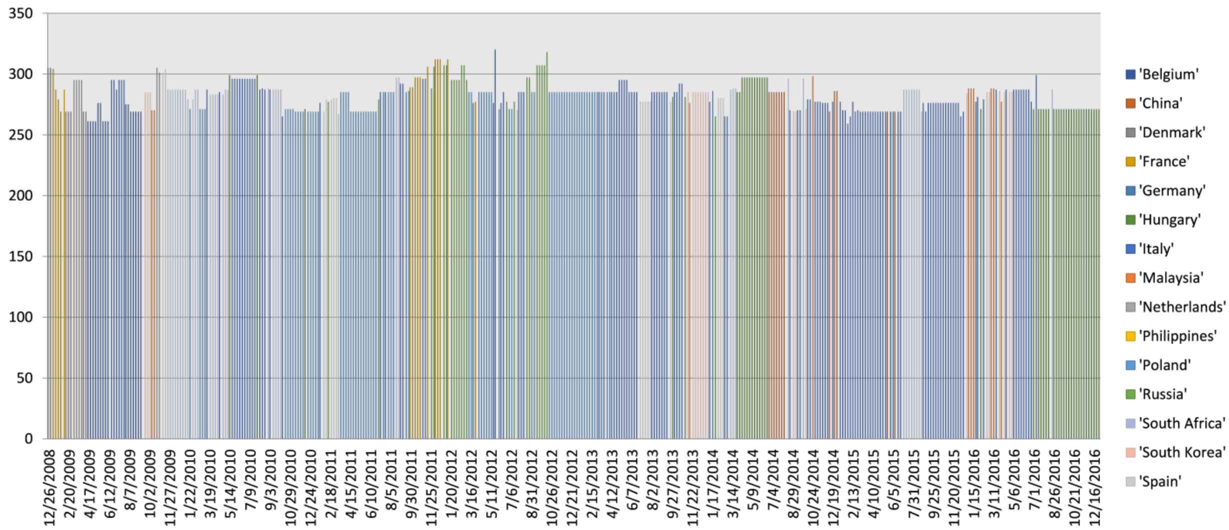


Figure 4.5.66.Betweenness Centrality - CDS - 2nd highest - Frequency

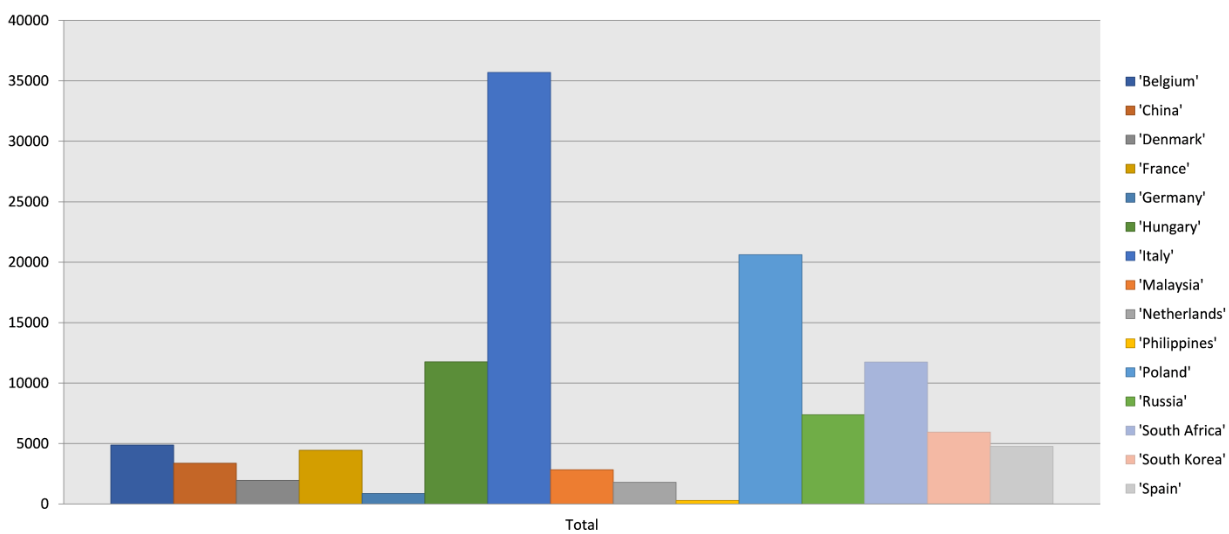


Figure 4.5.67.Closeness Centrality - CDS - 2nd highest

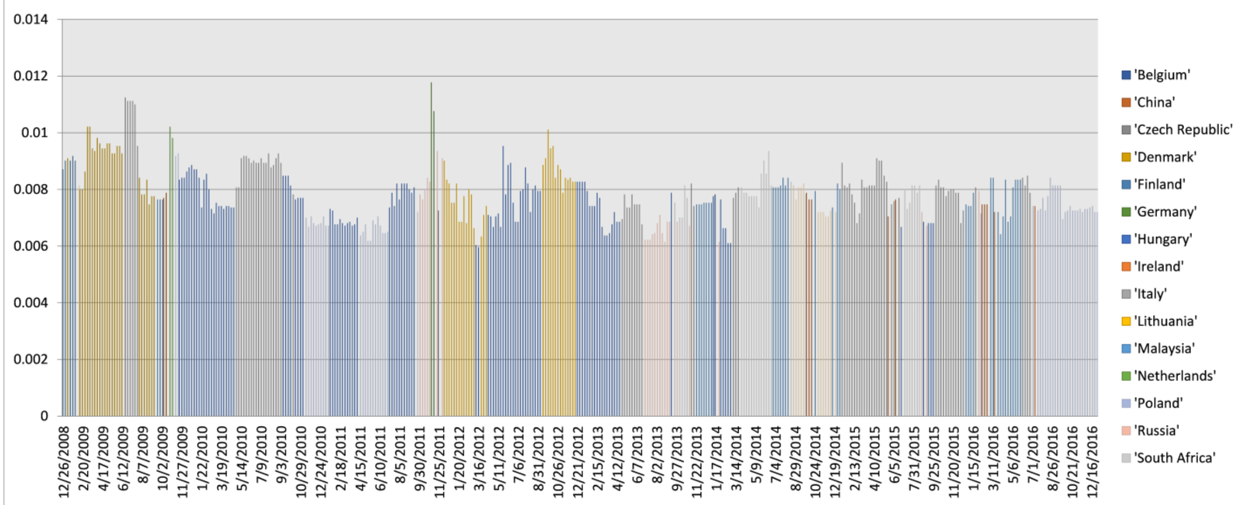


Figure 4.5.68.Closeness Centrality - CDS - 2nd highest - Frequency

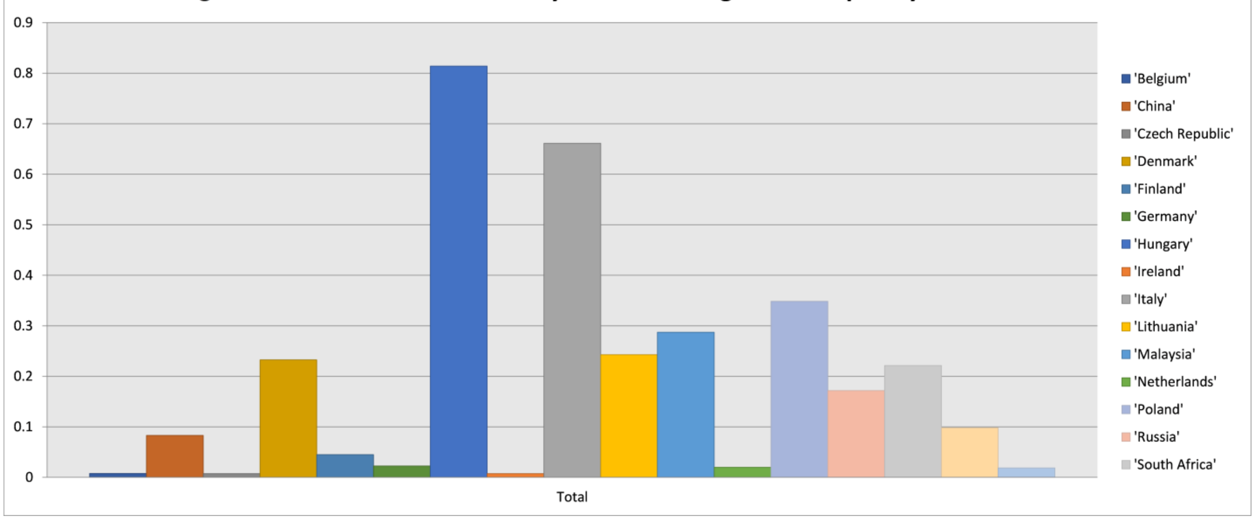


Figure 4.5.69.Degree Centrality - CDS - 2nd highest

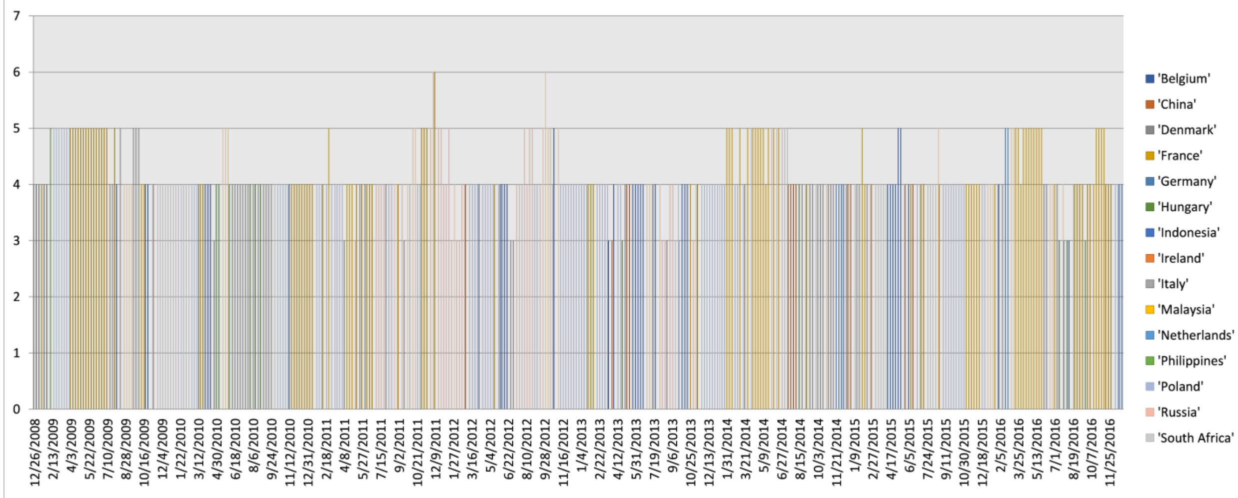


Figure 4.5.70.Degree Centrality - CDS - 2nd highest - Frequency

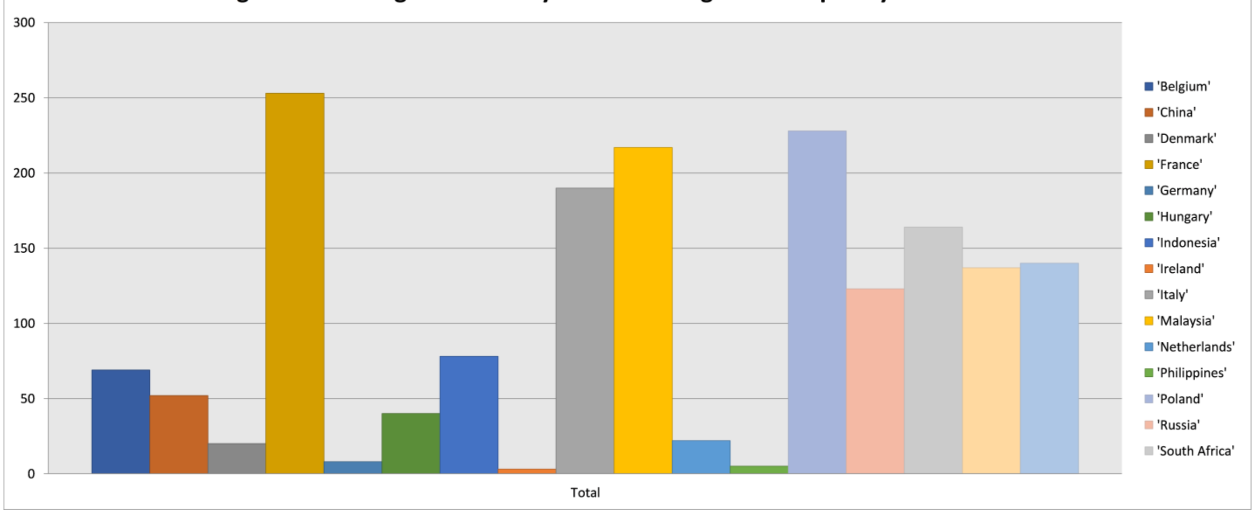


Figure 4.5.71.Eigenvector Centrality - CDS - 2nd highest

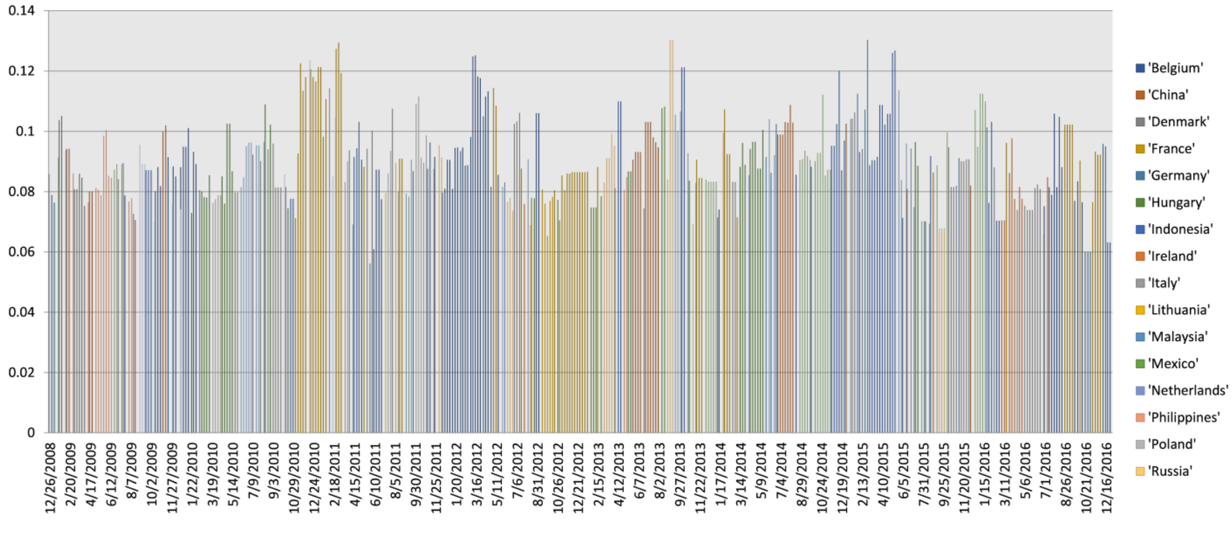


Figure 4.5.72.Eigenvector Centrality - CDS - 2nd highest - Frequency

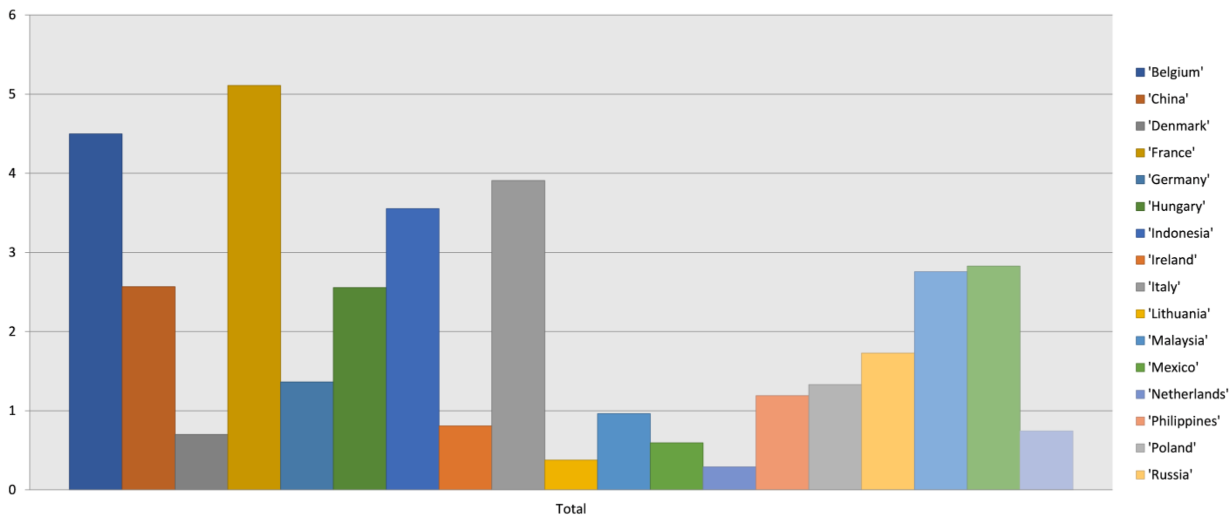


Figure 4.5.73.Betweenness Centrality - CDS - 3rd highest

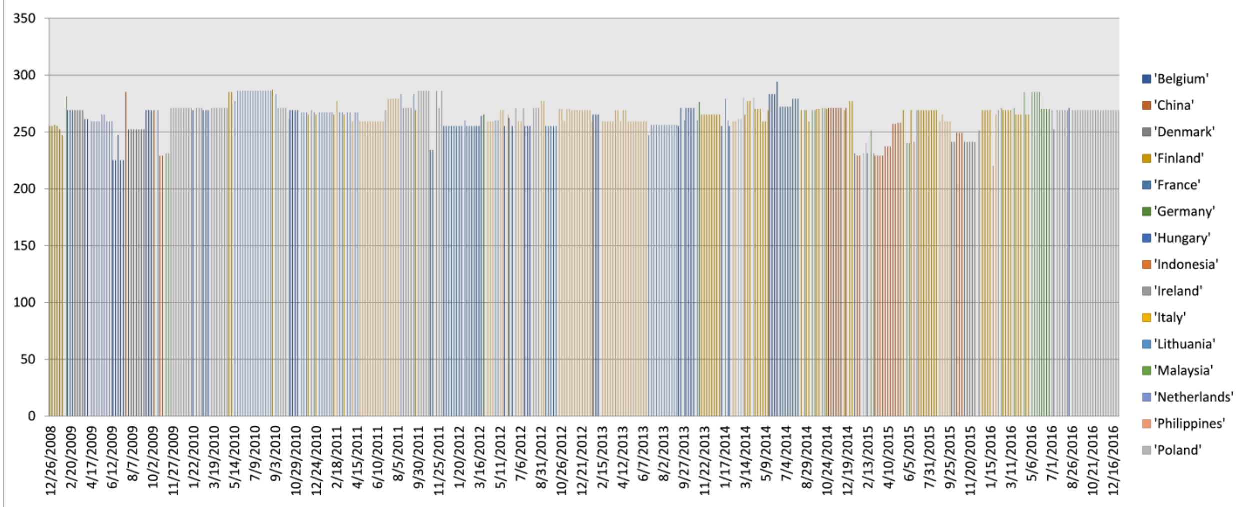


Figure 4.5.74.Betweenness Centrality - CDS - 3rd highest - Frequency

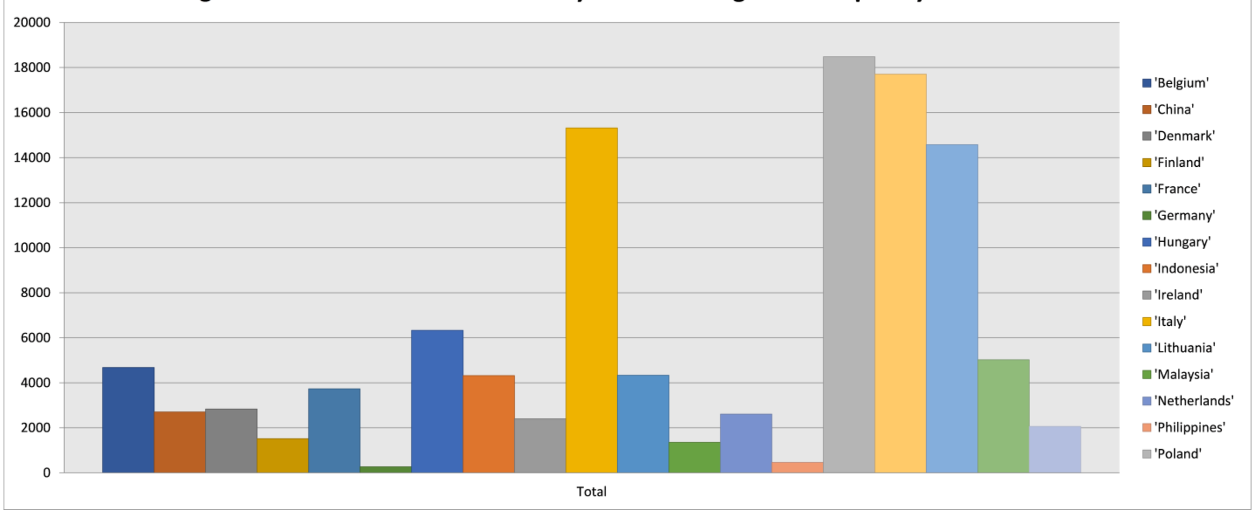


Figure 4.5.75.Closeness Centrality - CDS - 3rd highest

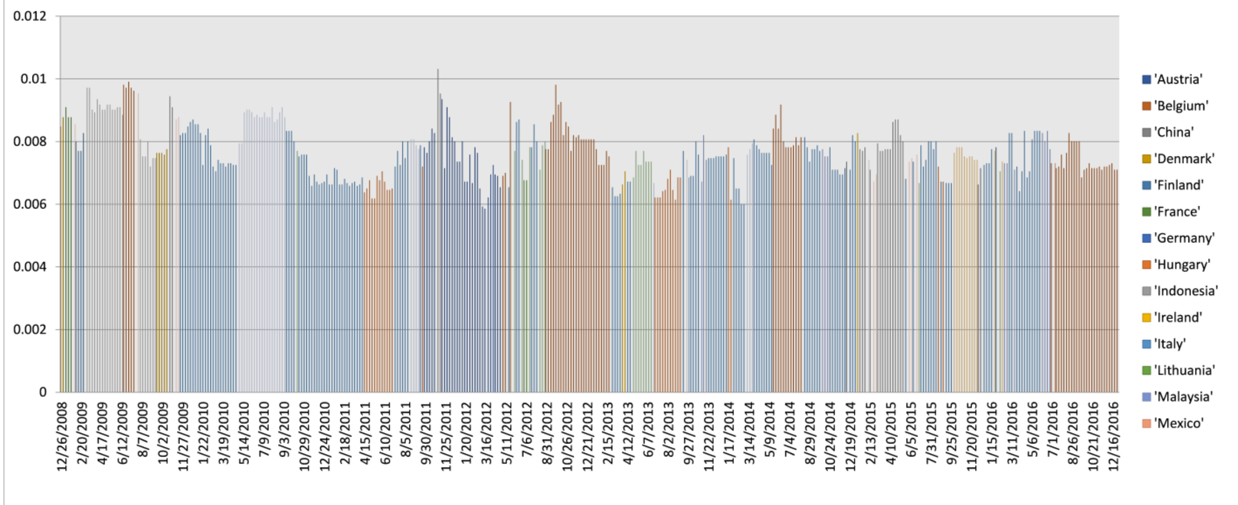


Figure 4.5.76.Closeness Centrality - CDS - 3rd highest- Frequency

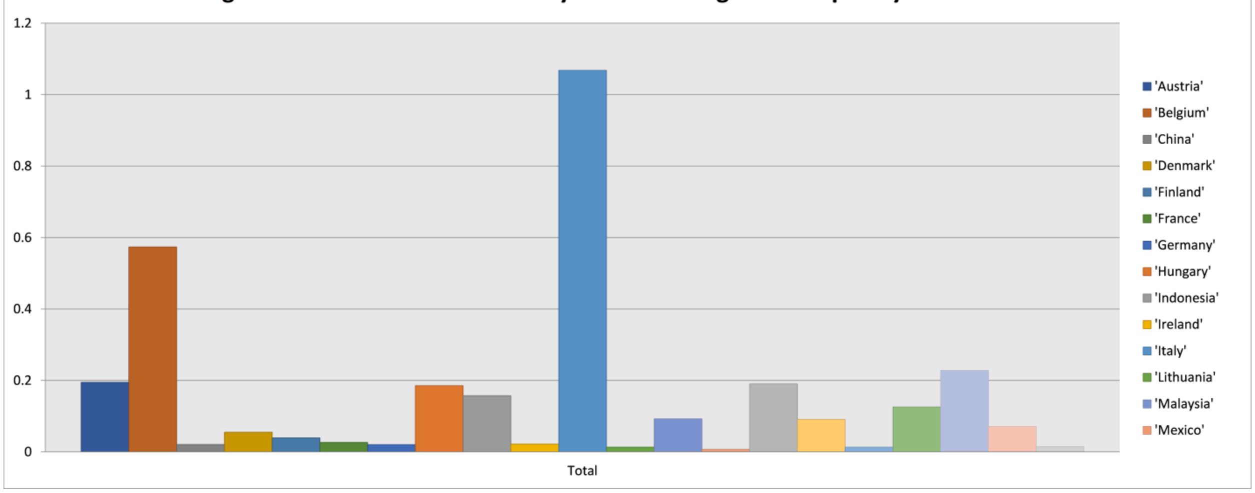


Figure 4.5.77.Degree Centrality - CDS - 3rd highest

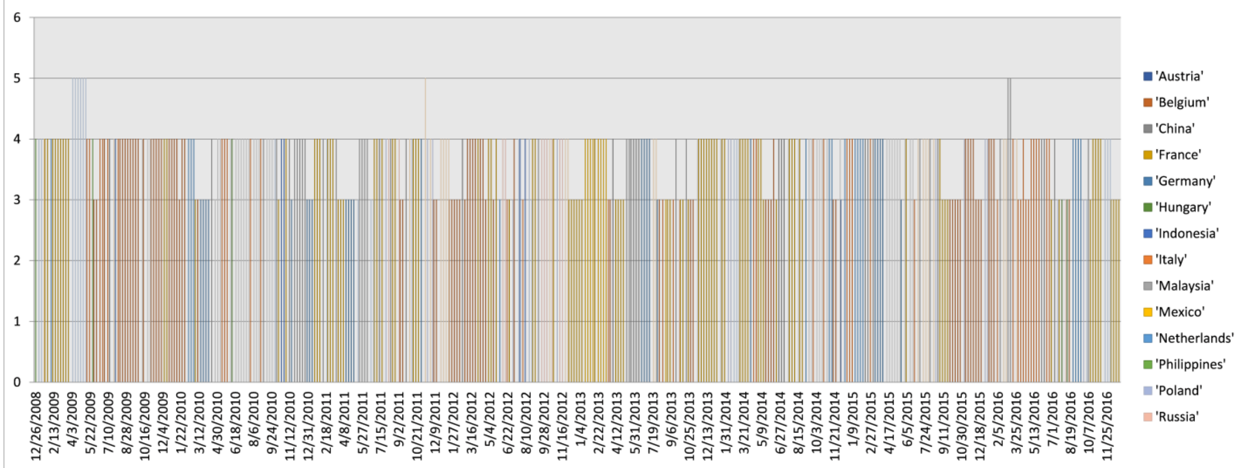


Figure 4.5.78.Degree Centrality - CDS - 3rd highest - Frequency

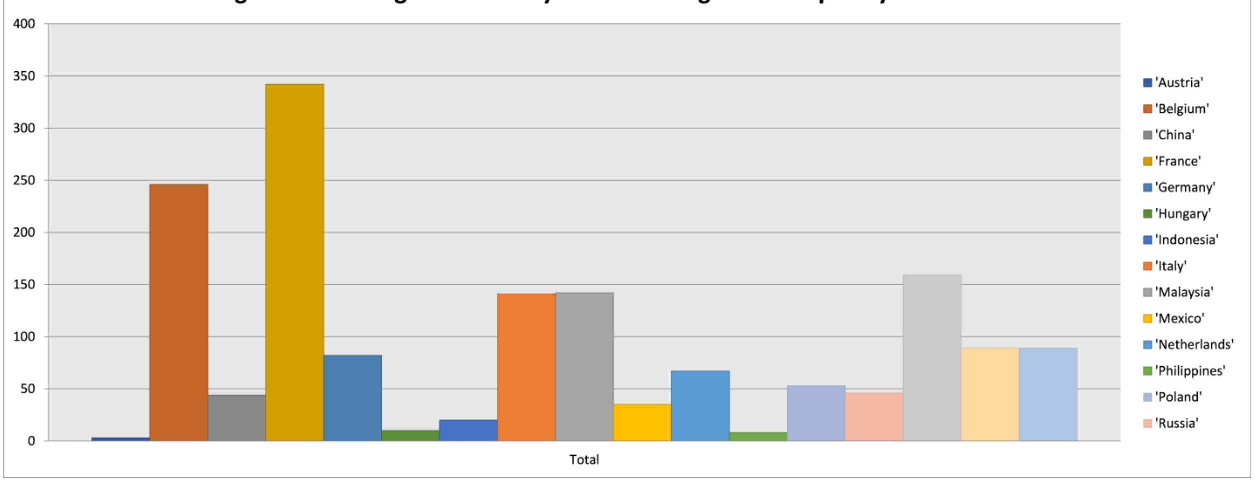


Figure 4.5.79.Eigenvector Centrality - CDS - 3rd highest

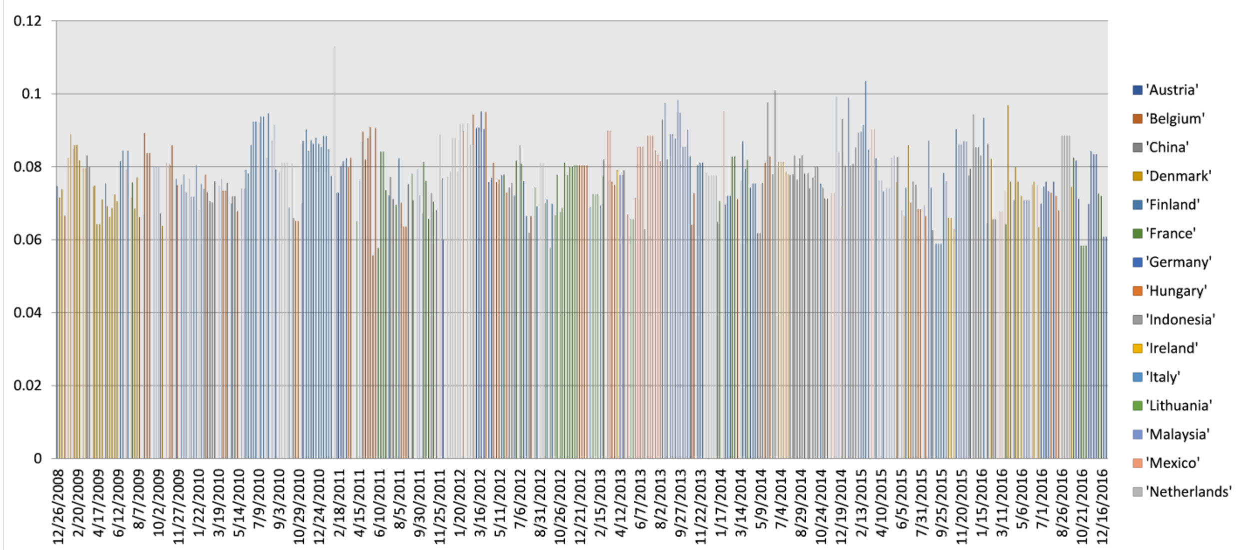
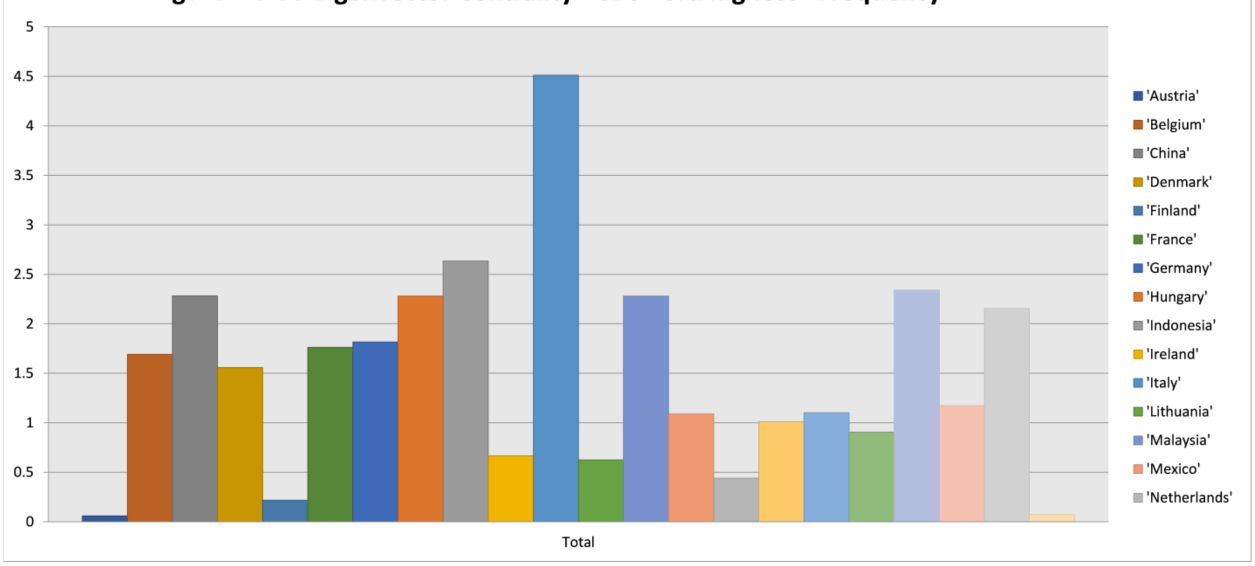


Figure 4.5.80.Eigenvector Centrality - CDS - 3rd highest - Frequency



GLOSSARY

ADF	Augmented Dickey–Fuller
AIC	Akaike information criterion
AIG	American International Group
ARMA	Autoregressive Moving Average Model
AUC	Area Under the Curve
BEKK	Baba, Engle, Kraft and Kroner
BIC	Bayesian information criterion
BRIC	Brazil, Russia, India and China
CBOE	Chicago Board Options Exchange
CCC	Constant Conditional Correlation
CDS	Credit Default Swap
CSI	China Securities Index
DCC	Dynamic Conditional Correlation
ECB	European Central Bank
EDC	Eurozone Debt Crisis
EEC	European Economic Community
EEZ	Exclusive Economic Zone
EFSF	European Financial Stability Facility
EMU	Economic and Monetary Union
EPU	Economic Policy Uncertainty index
ESM	European Stability Mechanism
EWS	Early Warning Systems
FIAPARCH	Fractionally Integrated Asymmetric Power ARCH
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
GDP	Gross Domestic Product

GFC	Global Financial Crisis
IMF	International Monetary Fund
LTCM	Long-Term Capital Management
ML	Machine Learning
MST	Minimum Spanning Tree
PIIGS	Portugal, Italy, Ireland, Greece and Spain
REER	Real Effective Exchange Rate
RGM	Regime-Switching Model
RNN	Recurrent Neural Networks
ROC	Receiver Operating Characteristic
SJC Copula	Symmetrized Joe-Clayton Copula
SVM	Support Vector Machine
VAR	Vector Autoregression

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