Financial Fragility, Systemic Risk

and Financial Systems

By

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Certification

This thesis by publication is submitted in fulfilment of the requirements of the degree of PhD, in the Faculty of Business and Economics, Macquarie University. This represents the original work and contribution of the author, except as acknowledged by general and specific references.

I hereby certify that this has not been submitted for a higher degree to any other university or institution.

Amir Armanious

Dedication

To my little beloved Sister,

God rest her Soul

To my loving and caring father, mother and brother

Acknowledgement

To be at this point, where writing acknowledgments is necessary, is a very exciting, yet humbling moment. I am excited because this signals that I have persevered through the most challenging undertaking of my life. At the same time, it is humbling because I could not have gotten here without the guidance and support of many special people.

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Abstract

One of the significant catalysts for the 2007 Global Financial Crisis (GFC) events has been systemic risk within financial institutions. Subsequently, systemic risk measurement and management have turned into a more extensively researched area. Currently, researchers have yet to agree on the definition of systemic risk but instead a series of systemic risk definitions have developed.

This PhD thesis seeks to offer a new framework for measurement and management of systemic risk. This is achieved by combining the approach and methodology of various dimensions of systemic risk and different econometric techniques. This thesis is a collection of three chapters, which are presented in chapters two, three and four. All three chapters can be read in conjunction with each other as they share the same scope.

The main objective of this thesis is to quantify systemic risk within the Eurozone using various models and techniques. The sample is constant across all the three chapters which is the entire Eurozone financial system (4 sectors, 17 member states and 315 financial institutions) and the time framework covers the period 2000-2016, that starts by the inception of Euro and covers three major systemic events of 2001 dotcom bubble, 2007 global financial crisis and 2009 European sovereign debt crisis. We divide the entire sample period into three sub-periods (pre-crisis, crisis and post-crisis periods) in order to grasp the various facets of systemic risk within Eurozone financial system. We measure systemic risk within the 17 member states of the Eurozone on the union level, sector level and country level; (1) on the union level, we quantify systemic risk contribution of each financial sector and member state, (2) on the sector level, we measure systemic risk contribution of each member state within each sector, and (3) on the country level, we compute systemic risk contribution of each financial institution, the so-called Systemically Important Financial Institutions ($SIFIs$), within each member state.

In order to measure systemic risk and volatility linkages in the Eurozone financial system, we apply copula-based $\Delta CoVaR$ and stochastic volatility estimations using Generalised Method of Moments (GMM) (Hansen, 1982; Hansen *et al.*, 1996) in the second chapter, while we use $GARCH\text{-}DCC$ $\Delta CoVaR$ and other systemic risk measures (GCN, MES and $SRISK$) in the third chapter and finally we use quantile $\Delta CoVaR$ in the fourth chapter. The second and third chapters are estimated via indices' daily returns while the fourth chapter is estimated using

daily market value of assets (MVA) because MVA is strongly tied to the real economy's credit supply that measures risk spillover to the real economy.

In the second chapter, we measure dependence structure across the EU index and four Eurozone financial sectors' indices in absolute and tail-dependence over time via indices' daily returns. We implement six copula models to investigate tail co-movements across chosen indices. In order to assess the implications of our copula results in terms of the risk spillover between the EU-sector pairs, we quantify VaR, $CoVaR$ and $\Delta CoVaR$ risk measures for the EU and the four financial sectors based on different copulas. Furthermore, we estimate how information creates cross-sector linkages using GMM (Fleming *et al.*, 1998; Kodres and Pritsker, 2002). As a robustness check, we apply the bootstrap Komogorov-Smirnov significance test and stochastic dominance test by Abadie (2002) to check if a certain sector significantly contributes to system-wide risk and if a certain sector has higher systemic risk contribution (exposure) compared to another sector. Finally, we apply Kendall rank-order correlation coefficient (Kendall, 1955) to check if copula $\Delta CoVaR$ gives the similar ranking for each sector over time during the sample period. This chapter concludes the existence of a moderate to strong asymmetric time-varying dependence among all financial sectors that differs in bearish and bullish markets. It is noted that downside dependence is stronger compared to upside dependence, consequently, there is significant spillover effects on the EU index from the extreme downward movements in the different financial sectors. Furthermore, there is strong volatility linkages among banking, financial service, insurance and real-estate sectors as evidenced by GMM stochastic volatility estimation.

In the third chapter, we quantify Too-Systemic-To-Fail ($TSTF$) paradigm in the Eurozone, through three primary dimensions; Too-Big-To-Fail ($TBTF$), Too-Interconnected-To-Fail ($TITF$) and Too-Many-To-Fail ($TMTF$). We apply four widely-used systemic risk measures that are based on public data which are Granger-causality network (GCN), Delta Conditional Value-at-Risk ($\Delta CoVaR$), Marginal Expected Shortfall (MES) and Systemic Risk Index ($SRISK$). We measure financial interconnectedness and systemic risk exposure within the 17-member states of the Eurozone on two levels (union and sector). Further, we link macro-prudential measures ($GCN, \Delta CoVaR, MES$ and $SRISK$) with micro-prudential measures (systematic risk, tail risk, correlation, as well as firm characteristics such as leverage and market capitalization). Thus, some systemic risk measures could be expressed as transformations of market risk measures. Overall, our approach is likely to be highly relevant to regulators, policy makers and academicians as it addresses the multi-facets of systemic risk.

The empirical results indicate that Eurozone financial institutions became increasingly interconnected during the crisis period based on dynamic causality index and Granger causal relations which make them more susceptible to systemic risk. By applying $\Delta CoVaR$, MES and $SRISK$, we discover that systemic risk exposure increases during the crisis period due to higher interconnectedness. Since, each systemic risk method measures a certain dimension of systemic risk so each systemic risk measure gives different ranking for each financial sector and member state, that's why it is important to apply different risk measures to determine the various facets of systemic risk. Moreover, macro-prudential risk measures could be explained by micro-prudential risk measures on both time-series and cross-sectional dimensions.

In the last chapter, we estimate $\Delta CoVaR$ using quantile regression and daily changes in market value of assets (MVA) as we want to capture all forms of risk, including not only the risk of adverse asset price movements, but also funding liquidity risk. We estimate Contribution $\Delta CoVaR$, Exposure $\Delta CoVaR$ and Network $\Delta CoVaR$ on the three levels of analysis during full, pre-crisis, crisis and post-crisis periods in order to grasp the various facets of systemic risk within Eurozone financial system. In addition, we measure unconditional $\Delta CoVaR$ and conditional $\Delta CoVaR$ by analysing lagged systematic state variables that act as controlling variables to remove variations in tail risk which are not directly connected to financial system risk exposure. The empirical analysis concludes that $\Delta CoVaR$ is directional which means systemic risk contribution, exposure and network $\Delta CoVaR$ give different ranking consequently the spillover from the system to a certain institution is different than the spillover from this institution to the system and other institutions. Time-variant (conditional) $\Delta CoVaR$ is more robust compared to time-invariant (unconditional) $\Delta CoVaR$ as it incorporates lagged systematic state variables that capture the evolution of tail risk dependence over-time.

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List of Abbreviations

AIC	Akaike criteria
ARCH	Autoregressive Conditional Heteroscedasticity
ARCH-LM test	Autoregressive Conditional Heteroscedasticity Lagrange Multiplier test
ARMA	Autoregressive Moving Average
β	Beta
BA	Book Value of Assets
BE	Book Value of Equity
BGLM	Breusch-Godfrey Serial Correlation LM
C	Clayton Copula
CAViaR	Conditional Autoregressive Value at Risk
CDF	Cumulative Distribution Function
CDS	Credit Default Swap
CoVaR	Conditional Value at Risk
ΔCoVaR	Delta Conditional Value at Risk
CS	Capital Shortfall
DCC	Dynamic Conditional Correlation
DCI	Dynamic Causality Index
DFinancials	Diversified Financials
DIP	Distress Insurance Premium
ECB	European Central Bank
EMU	European Monetary Union
ES	Expected Shortfall
EVT	Extreme Value Theory
EZ	Eurozone
FDIC	Federal Deposit Insurance Corporation
FSAB	Financial Sector Assessment Program
G	Gumbel Copula
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GAS	Generalised Autoregressive Score
GC	Granger Causality
GCN	Granger Causality Network

GDP	Gross Domestic Product
GFC	Global Financial Crisis
GICS	Global Industry Classification Standard
GJR GARCH	Glosten-Jagannathan-Runkle GARCH
G-SIBs	Global Systemically Important Banks
GMM	Generalised Method of Moments
i.i.d	Independent and Identically Distributed
IFM	Inference Functions for the Margins
IMF	International Monetary Fund
JB	Jarque-Bera test
JC	Joe-Clayton Copula
KS Test	Kolmogorov-Smirnov Test
LEV	Assets-To-Book Equity Ratio
LMI	Liquidity Mismatch Index
LRMES	Long-run Marginal Expected Shortfall
$\mathcal{LL}$	Log-likelihood
LTQ	Liability
LVG	Leverage
ME	Market Value of Equity or Market Capitalisation
MES	Marginal Expected Shortfall
MLE	Maximum Likelihood Estimation
MVA	Market Value of Assets
N	Normal or Gaussian Copula
OLS	Ordinary Least Squares
PCA	Principal Components Analysis
PIIGS	Portugal, Ireland, Italy, Greece and Spain
PIT	Probability Integral Transformation
ρ	Correlation
RG	Rotated Gumbel Copula
S&P 500	Standard & Poor’s 500
SGARCH	Structural GARCH
SGP	Stability and Growth Pact
SIFI	Systemically Important Financial Institutions

SJC	Symmetrized Joe-Clayton Copula
SRISK	Systemic Risk Index
STD	Standard Deviation
SV	Stochastic Volatility
SVAR	State-dependent Sensitivity VaR
sys	System
T	Student-t Copula
τ	Tau
TBTF	Too-Big-To-Fail institutions
TITF	Too-Interconnected-To-Fail
TMTF	Too-Many-To-Fail
TSTF	Too-Systemic-To-Fail
TVP	Time-varying Parameter
VaR	Value at Risk

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Chapter 1
Introduction

The Global Financial Crisis (GFC) of 2007 has shed the light on the importance of the soundness of the entire financial system rather than the soundness of a single financial institution. Although the capital exposure and liquidity of a certain financial institution is healthy, this does not ensure the stability of the financial system as externalities and spill-over effects are building up over time. Therefore, there is a need to analyse macro-prudential regulations in addition to micro-prudential regulations. Yellen (2009) has described it as analysing the entire forest (economy) rather than focusing on a certain tree (institution).

Since the eruption of the GFC, there have been many attempts to unify the definition of systemic risk but it did not work as systemic risk is a complex phenomenon and each definition only describes one facet of its multiple facets. Consequently, different systemic risk measures are applied to measure different dimensions of systemic risk and there is no supremacy of one measure over another, unless a researcher is targeting a specific dimension of systemic risk.

In the absence of an exact definition, as the research field is currently in development, there are various dimensions that are embedded in different definitions. It is important to incorporate more than one definition to comprehend the breadth of systemic risk. Interestingly, how can systemic risk be determined? When various starting points for systemic shocks occur, particular methods in identifying and measuring systemic risks are crucial. (Abdymomunov, 2013). Daníelsson (2002) discovers an increasing amount of evidence that reveals the restrictions associated with imperfect regulatory structures and risk-modelling technology; these models do not operate as a scientific method of averting crashes but rather as placebos. According to this author, statistical analysis conducted under conditions of stability would not be meaningful in crisis periods as market data are endogenous to market behaviour.

There are two general approaches to measure systemic risk contribution of a given financial institution to the entire system. The first approach relies on information about risk exposures and positions, in which financial institutions transfer this classified information to the regulator. The second approach count on public market data solely like option prices, stock returns or credit default swap (CDS) spreads. The second approach is stated to represent all publicly traded financial institutions' information. The initial subset of measures concerns the second approach (market data) that is formed by two indicator types: firstly; indicators of slow-moving low-frequency built on balance sheet aggregates or macroeconomic data and secondly; indicators of high-frequency built on market prices and rates. Though, not much is understood in terms of the various measures' relative quality.

This thesis enhances our understanding on measuring and evaluating each financial institution's (financial sector, member state financial system) systemic importance from their inclusion of accounting and market information. This thesis depends upon the second subset of measures that are based on market data. We apply the commonly used systemic risk measures in literature, due to their vital economic interpretations, availability of public data, and real-time analysis enabled by these market-based systemic risk measures. Our purpose is then to analyse if these contemporary systemic risk measures are effective at determining how much a certain financial institution contributes to system-wide risk.

This thesis consists of three research papers that display the measurement of systemic risk in capturing the different facets of systemic risk definition which is essential to regulators and policy makers. The main objective of the thesis is to measure systemic risk in the Eurozone so we have the same sample across the three chapters which is the entire Eurozone financial system for the period 2000-2016, that reflects the major systemic events of 2001 dotcom bubble, 2007 global financial crisis and 2009 European sovereign debt crisis. We divide the entire sample period into three sub-periods (before-crisis, crisis and after-crisis periods). Each chapter is based on estimating $\Delta CoVaR$ systemic risk measure using different modelling techniques in addition to other measures. $\Delta CoVaR$ is a statistical tail-dependence technique that measures the degree to which a tail event in a financial sector (country or institution) spills over, cause or worsen a tail event in another sector (country or institution).

In the second chapter, we measure absolute and tail dependence structure across EU index and four Eurozone financial sector's indices using Delta $CoVaR$ copula-based approach. To investigate tail co-movements across chosen indices, Copula models including, Gaussian, Gumbel, Rotated Gumbel, Clayton, Symmetrized Joe-Clayton and Student-t copulas, are implemented. In order to assess the implications of our copula results in terms of the risk spillover between the EU-sector pairs, we quantify Value at Risk (VaR), Conditional Value at Risk ($CoVaR$) and Delta Conditional Value at Risk ($\Delta CoVaR$) risk measures for the EU and each financial sector based on different copula. In addition, we use stochastic volatility (SV) model as an alternative to $GARCH$ models in order to simulate time-varying volatility. The parameters of the stochastic volatility model (θ) has been estimated by applying generalized methods of moments (GMM) proposed by Hansen (1982) and Hansen *et al.* (1996).

Then, we use the estimated parameters to estimate the latent volatilities (σ_t) by running a Kalman filter model (Harvey, 1989). We follow Newey and West (1987, 1994) to define the Heteroskedasticity and Auto-correlation Consistent (HAC) matrix and Andrews (1991) for the selected bandwidth using the Quadratic Spectral kernel. GMM approach is used to impose the moment restrictions of our stochastic volatility model so that we estimate the correlation of the log information flows among the four Eurozone financial sectors following Fleming *et al.*, (1998), Kodres and Pritsker (2002). Furthermore, to check the robustness of our results, we apply the bootstrap Komogorov-Smirnov significance and stochastic dominance tests (Abadie, 2002). The significance test assesses whether a given financial sector contributes significantly to systemic risk while the dominance test evaluates whether or not a certain financial sector contributes more to systemic risk compared to another sector. Finally, we apply Kendall rank-order correlation coefficient to measure the ranking consistency of each systemic risk measure for a given sector through time (Kendall, 1955).

The empirical analysis of the second chapter concludes a significant asymmetric dynamic tail dependence between EU and the four Eurozone financial sectors. There is asymmetric magnitude of downside and upside risk measures ($VaRs$, $CoVaRs$ and $\Delta CoVaRs$), the downside risk measures are greater than the upside measures for all financial sectors during the three sub-periods. In addition, the spillover from each financial sector to the EU (contribution $\Delta CoVaR$) is significantly higher than the spillover from the EU to each financial sector (exposure $\Delta CoVaR$). GMM results reveal strong volatility linkages among Eurozone financial sectors which is expressed in the correlations between the log information flows among the six EU-Sector pairs. The banking/ financial sector pair has the highest estimated correlation of

85.72% while the insurance/ real-estate pair has the highest estimated correlation of 58.25%. Each financial sector has a significant systemic risk contribution (exposure) as evidenced by applying bootstrap KS significance test while the bootstrap KS dominance test shows the ranking consistency of each financial sector. The banking sector has a higher systematic risk contribution than the insurance sector, which in turn has a higher systematic risk contribution than the financial sector, which in turn has a higher systematic risk contribution than the real-estate sector. Additionally, Copula $\Delta CoVaR$ systemic risk measure delivers a consistent ranking for each financial sector through time which is an important characteristic for regulators as they cannot classify a certain sector as $SIFI$ in on day and then non-$SIFI$ on the next. Volatility linkages and systemic risk spillover should be at the heart of regulatory and policy makers to maintain financial stability.

In the third chapter, we quantify Too-Systemic-To-Fail ($TSTF$) paradigm in the Eurozone through three primary sources; Too-Big-To-Fail ($TBTF$) that is based on the size of each financial institution, Too-Interconnected-To-Fail ($TITF$) which is related to risk spillover and externalities among financial institution, and Too-Many-To-Fail ($TMTF$) that refers to numerous institutions share the same position and structure that act as part of a herd. This is done by applying the major prominent systemic risk measures which are Granger-causality network (GCN) of Billio, *et al.*, (2010), $GARCH\text{-}DCC$ Delta $CoVaR$ ($\Delta CoVaR$) of Adrian and Brunnermeier (2011) and Girardi and Ergun (2013), Marginal Expected Shortfall (MES) of Acharya, *et al.* (2017) and Systemic Risk Index ($SRISK$) of Acharya, Engle and Richardson (2012) and Brownlees and Engle (2012).

GCN estimates the direction and interconnectedness of financial institutions along with all of the financial system's systemic risk, a greater dynamic causality index (DCI) value means a highly interconnected system. Exposure $\Delta CoVaR$ links a given sector's VaR contingent on financial system being impacted by a systemic event. The sector's systemic risk exposure ($\Delta CoVaR$) is the change between the financial system's $CoVaR$ when it is under financial distress and its median state. Greater $\Delta CoVaR$ (in absolute values) means higher systemic risk exposure. MES measures expected equity loss by a sector when market falls under a given threshold in a certain time period, specifically a 2% drop within the market in one day for short-run MES and a 40% drop in the market in six-month for the long-run MES ($LRMES$). Generally, a sector with higher MES (in absolute values) contributes the most to market decline. $SRISK$ quantifies a sector's expected capital shortfall, under the circumstance of a financial crisis happening. Consequently, a sector with the biggest shortfall of capital specifically during a systemic crisis is believed to be the most systemically risky. Finally, we link macro-prudential measures ($GCN, \Delta CoVaR$, MES and $SRISK$) with micro-prudential measures (beta, tail risk, correlation, leverage and market capitalization).

The empirical results show that Eurozone financial institutions become highly interconnected during systemic shocks measured by DCI which reached its peak in late 2008 with the collapse of Lehman Brothers and the beginning of the subprime crisis as well as mid-2009 with the eruption of Eurozone sovereign debt crisis. GCN, which is as a proxy for how shocks could spillover within the system, became extremely interconnected during the crisis period. Higher interconnectedness triggers higher systemic risk spillover which was examined by systemic risk measures ($\Delta CoVaR$, MES, $LRMES$ and $SRISK$) that shows significant systemic risk exposure during the crisis period in comparison to the pre-crisis and post-crisis periods. It is worth noting that different systemic risk measures provide different ranking for each financial sector/ member state and these rankings differ from one period to another, the divergence of systemic risk ranking generated by each measure is not due to instability of a specific measure but rather due to their fundamental differences. Systemic risk measures ($\Delta CoVaR$, MES, $LRMES$, $SRISK$) could be expressed in terms of standard financial risk measures (systematic risk, tail risk, correlation), a certain standard financial risk measure could explain a certain systemic risk measure for time analysis but not in cross-sectional analysis and vice versa.

In the last chapter, we quantity systemic risk in the Eurozone financial system by applying the original $\Delta CoVaR$ using quantile regression (Adrian and Brunnermeier 2011). We measure Contribution $\Delta CoVaR$, Exposure $\Delta CoVaR$ and Network $\Delta CoVaR$. Contribution $\Delta CoVaR$ ($\Delta CoVaR_q^{sys|i}$) captures how much risk a certain institution (sector or country) adds to the overall systemic risk, Exposure $\Delta CoVaR$ ($\Delta CoVaR_q^{i|sys}$) investigates which institution (sector or country) is highly exposed to systemic risk in the case of a systemic financial crisis, while Network $\Delta CoVaR$ ($\Delta CoVaR_q^{j|i} and\ \Delta CoVaR_q^{i|j}$) captures how much risk a certain institution (sector or country) adds to another institution (sector or country) and vice versa. It is worth noting that $\Delta CoVaR$ is directional which means $\Delta CoVaR_q^{j|i}$ of institution j conditional on institution i being in crisis is not equivalent to $\Delta CoVaR_q^{i|j}$ of institution i conditional on institution j being in distress. In addition, we differentiate between Unconditional $CoVaR$ and Conditional $CoVaR$. Unconditional $CoVaR$ is time-invariant that is static in nature and gives a constant value over time, therefore, there is a need to estimate Conditional $CoVaR$ (time-variant $CoVaR$) that is dynamic in nature, by incorporating lagged systematic state variables that act as controlling variables to remove variations in tail risk which are not directly connected to financial system risk exposure. Finally, we estimate $\Delta CoVaR$ based on different quantiles (1% or 5%, … etc.) and frequencies (daily, weekly, … etc.) which results in different risk rankings, that's due to conditional $\Delta CoVaR$ is a high-frequency measure of tail-risk and the use of VaR ignores extreme loss above VaR levels and disregards the risk of fat-tails.

The fourth chapter concludes that there is a loose relationship between VaR and $\Delta CoVaR$, consequently, regulating financial institution's risk individually, through institution's VaR, may not be the best alternative to safeguard against financial fragility. Insurance sector has the highest systemic risk contribution while banking sector is the most exposed to systemic risk during financial turmoil at $q = 5\%$ and $q = 1\%$ based on time-variant $\Delta CoVaR$ analysis, while time-invariant $\Delta CoVaR$ analysis gives a different ranking as it is static in nature, therefore it is less vigorous. When we use a higher quantile (i.e. 1%, 5%, … etc.) and a higher frequency (i.e. daily, weekly, … etc.), the ranking changes for the same institution due to conditional $\Delta CoVaR$ is a high-frequency measure of tail risk.

On the union level, diversified financial sector has the highest systemic risk contribution during pre-crisis period while insurance sector contributes the most to systemic risk during both crisis and post-crisis periods $q = 5\%$. This is an important finding as the ranking of each sector differs during time span. The risk spillover from the insurance sector to banking sector is 2.88% while the risk spillover from the banking sector to insurance sector is 1.28% only. Ireland has the highest systemic risk contribution during the pre-crisis period while Italy and Austria contribute the most during the crisis and post-crisis periods respectively.

On the sector level, for the banking sector, Irish banking sector has the highest systemic risk contribution during the pre-crisis period while Spanish banking sector and Italian banking sector has the highest contribution in the crisis and post-crisis periods respectively. This is aligned with the PIIGS debt crisis. For the diversified financial sector, French diversified financial sector has the highest systemic risk contribution in the pre-crisis and crisis periods while Belgian diversified financial sector has the highest contribution in the post-crisis period. For the insurance sector, Italian insurance sector has the highest systemic risk contribution in the pre-crisis and crisis periods while German insurance sector has the highest contribution in the post-crisis period. For the real-estate sector, Dutch real-estate sector has the highest systemic risk contribution in the pre-crisis and crisis periods while French real-estate sector has the highest contribution in the post-crisis period. On the country level, a German diversified financial institution has the greatest systemic risk contribution during the pre-crisis period while a Dutch bank and a German insurance institution have the highest risk contribution during the crisis and post-crisis periods respectively.

As a robustness check, we discovered that the copula $\Delta CoVaR$ models (Gaussian, Student-t, Gumbel, Rotated Gumbel, Clayton, Rotated Clayton, Symmetrized Joe-Clayton, Plackett and Frank) give the same ranking for Eurozone financial sectors while QR-$\Delta CoVaR$, $GARCH$-DCC $\Delta CoVaR$ and OLS $\Delta CoVaR$ give the same ranking for financial sectors but different ranking from the nine copula models. All the twelve $\Delta CoVaR$ models give different ranking on the country level. the differences of systemic risk ranking generated by each model is not due to instability of a specific model but rather due to their fundamental differences and econometric specifications in capturing tail-dependence and systemic risk.

2

Chapter 2
Financial Dependence, Fragility and Interconnectedness among Eurozone Financial Sectors: Evidence from Copulas

Amir Armanious (Contribution 60%), Tom Smith (Contribution 30%)
and Geoffrey Loudon (Contribution 10%)

This chapter measures the absolute and tail dependence structure across EU index and four Eurozone financial sectors' indices, namely banking, financial services, insurance and real-estate, during bear, normal and bull markets under various time horizons. We estimate static and time-varying symmetric and asymmetric copula models, namely Gaussian, Gumbel, Rotated Gumbel, Clayton, Symmetrized Joe-Clayton and Student-t copulas, using Generalised Autoregressive Score (GAS) model of Creal, *et al.* (2013) to investigate tail comovements across chosen sectors. In order to assess the implications of our copula results in terms of the downside and upside risk spillover between the EU-sector pairs, we quantify the value at risk (VaR), conditional VaR ($CoVaR$) and the delta $CoVaR$ ($\Delta CoVaR$) systemic risk measures for the EU and sectors based on different copulas. In addition, we estimate stochastic volatility linkages using Generalised Method of Moments (GMM) approach following Fleming *et al.* (1998). The innovative $\Delta CoVaR$ method was modified to contain the Komogorov-Smirnov significance test and stochastic dominance test via bootstrapping developed by Abadie (2002) and was utilized to measure the significance of systemic risk contribution to real economy in distress periods and form a formal ranking of financial sectors in regards of their systemic risk spillover. The results show that there is a tail dependence and strong volatility linkages between all EU-sector pairs during different time horizons. Furthermore, we conclude strong evidence of downside and upside risk asymmetric spillover from financial sectors to EU and vice versa during pre-crisis, crisis and post-crisis periods.

2.1 Introduction

The 2007 global financial crisis (GFC) has brought to the public's attention the fragility of the financial system and its ever-growing systemic risk. The recent crisis highlights the importance of measuring and managing systemic risk to safe-guard financial stability. In distress periods, interdependence across financial institutions is exclusively significant as losses naturally extend among institutions which exposes the whole financial system to vulnerability. Furthermore, contagion episodes across institutions are not unusual, specifically in distress time and must be taken into consideration to assess the whole financial system's stability levels; meaning if a certain financial institution has significant systemic risk externalities, failure to include all risk spillover sources would signify significant information loss and consequently develop an inadequate risk measure.

European Central Bank (2009) defines systemic risk as "a risk of financial instability so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially", in relation to this Kaufman and Scott (2003) describe systemic risk as the likelihood or risk of a whole system breaking down, compared to breakdowns in individual components or parts and is cascaded by comovements (correlation) in most or all parts.

The harsh encounter of 2007 GFC with the incredibly gradual and difficult subsequent recovery has positioned systemic risk at the hub of global economic discourses. An important trait of the late financial crisis is the degree to where assets having presently moved mainly independently have unexpectedly move in unison which led to joint losses within the leading markets. This forms the basis to reveal the substantial contribution to systemic risk of each Eurozone financial sector.

This new transition from concentrating from an individual isolated institution risk (micro-prudential approach) to concentrating on the risk spillover made by an institution to a system-wide scale (macro-prudential approach) is the Basel III regulatory framework's core (see Borio and Lowe, 2002; Borio and Drehmann, 2009; Gauthier, *et al.*, 2012). Majority of systemic risk related issues are mentioned by the Basel III agreement, which forms a suitable framework to supervise and regulate financial markets on the basis of recent experience. This is highly valuable to financial regulators and central banks, for they can quantify risks of potential threat to the financial system at a national, regional and global levels. Preceding research in this area had suggested different financial fragility measures that are applicable at both individual and aggregate levels (Lehar 2005, Goodhart, *et al.* 2005, 2006, and Goodhart 2006). With the aim of raising measures' effectiveness to encourage financial system soundness in the member countries, the Financial Sector Assessment Program ($FSAP$) was established[1]. This view has immensely influenced policy deliberations across bank regulators, legislative committees and academic researchers. According to the Financial Stability Board's June 2010 interim report, financial institutions should be accountable for requirements that correspond with the risks they potentially impose upon the financial system[2].

With this background, a major concern for regulators is identifying the so-called Systemically Important Financial Institutions (*SIFIs*). *SIFIs* are defined by the Financial Stability Board (2010) as financial institutions with complexity, size and systemic interconnectedness that could cause substantial instability to economic activity and the wider financial system, in the event of disorderly failure. Under the Basel III agreements, $SIFIs$ should have capital surcharged based on the negative externalities they create, like their input to the financial system's overall risk.

The copula was first presented by Sklar (1959). However, copula modelling was not applied in the financial field until 1987 to 1991 (Mackenzie and Spears, 2014). Copula based measures were utilised to empirically determine the systemic risk level within the banking sector against other 11 industry sectors in the United States via stock market data gathered from 1990 to 2008 (Buhler and Prokopczuk, 2010). Compared to other sectors including non-banking financial sectors, the banking sector was discovered to have greater systemic risk contribution than other sectors, particularly under periods of market downturns.

Copula modelling was noticed by Fermanian and Scaillet (2005) to becoming increasingly prevalent in academics and the industry as it is famous for its returns of financial assets' dependence structures being non-Gaussian and showcase strong nonlinearities[3]. Copulas were initially used for credit risk analysis by Li (2000), while Rodriguez (2007) used copulas on financial contagion via a switch-parameter copula model. In their paper, the authors demonstrate proof of altering dependence in the time period of the global financial markets. Descriptions and applications of copulas were introduced by Cherubini, *et al.* (2004) in mathematical finance and risk management. Contagion-based distortion measures were

[1] This is a joint IMF and World Bank initiative.
[2] There is a rapid growing literature on macro-prudential regulations (see Crocket, 2000; Borio, 2003; Padoa-Schioppa, 2003; Allen and Wood, 2006; Brunnermeier, et al., 2009; Borio and Drehmann, 2009).
[3] A detailed research into copulas was conducted by Joe (1997) and Nelsen (1999).

designed by Cherubini and Mulinacci (2014) to possibly recover proper distortion measures via a set of possible copula functions. These models were utilised on European countries.

Our empirical approach makes several contributions in this chapter by applying copula $\Delta CoVaR$ methodology. Firstly, this is the first paper to apply $\Delta CoVaR$ as a systemic risk measure within an economic union. We estimate downside and upside systemic risk contribution and exposure of each financial sector of the Eurozone namely, banking, financial services, insurance and real-estate. In consistency with the systemic risk definition by the European Central Bank (2009), the system is not defined as the banking sector or financial sector only, as common in the literature, but is expressed as the real economy. Secondly, we apply various static and time-varying copula models in order to measure the dependence structure between EU index and each financial sector index. Consequently, we measure risk spillover between different financial sectors to and from EU index (contribution vs exposure $\Delta CoVaR$). Thirdly, we measure volatility linkages across the four financial sectors based on the relation between volatility and information flow using GMM approach (Fleming *et al.*, 1998). Finally, we propose bootstrap Kolmogorov-Smirnov significance and stochastic dominance tests to check the robustness of $\Delta CoVaR$ systemic risk measure. Significance test evaluates if a certain financial sector has a significant contribution to systemic risk while dominance test assesses if a certain sector has a higher systemic risk contribution compared to another sector. Furthermore, we propose a formal test of systemic-risk ranking consistency for a given sector over time. We apply Kendall (1955) rank-order correlation coefficient in order to measure if these systemic risk measures provide consistent raking through time so a certain sector would be regularly classified as $SIFI$, consequently require tighter supervision. Therefore, our analysis is essential for regulators, academicians and policy makers.

The remainder of the chapter is organized as follows. Section 2 provides a review of literature of systemic risk measure using various modelling techniques. Section 3 proposes a methodological analysis of VaR, $CoVaR$ and $\Delta CoVaR$ measures using copula as well as GMM approach for estimating stochastic volatility. In Section 4, we describe the data and summary statistics. Section 5 presents the main empirical findings of the marginal contribution and exposure of financial sectors to systemic risk and the volatility linkages among financial sectors. Section 6 reports the results of robustness check using bootstrap Komogorov-Smirnov significance test and stochastic dominance test. Section 7 summarizes and concludes for policy implications.

2.2 Review of Literature

The recent financial crisis has brought to society's attention the financial system's vulnerability and systemic risk. Value at Risk (VaR) is the most commonly used micro-prudential measure by regulators which detects the appropriate capital levels set by financial institutions to protect themselves from market risk. VaR only determines a single institution's risk in isolation and it is inappropriate to use an institution's VaR to determine the financial system's risk. With the VaR's flaws, alternative risk measures have recently received great attention to compensate for the VaR's failure at capturing financial distress and the potential contribution to systemic risk by each institution.

Conditional Value-at-Risk ($CoVaR$) is a new form of risk measurement that intends to incorporate the fact that losses generally spread across financial institutions during a financial crisis. Adrian and Brunnermeier (2011) designed $CoVaR$ as a systemic risk measure to quantify the level of financial institutions' risk externalities. It is the financial institution's (sector or system) VaR conditional on another institution's (or sector or system) VaR. This means if $CoVaR$ increases compared to VaR (in absolute value), there exists externalities risk and greater interconnection across institutions.

$CoVaR$ measures the degree to which a tail event in a financial institution spills over, causes or worsens a tail event in another institution (sector or system). Contribution $CoVaR_q^{sys|i}$ measures institution (sector) i marginal contribution of systemic risk to the overall financial system. Contribution $CoVaR_q^{sys|i}$ is calculated as the $VaR_{q,t}^{sys}$ of the entire financial system conditional on institution (sector) i, $VaR_{q,t}^{i}$, being in distress. It captures how much risk a certain institution adds to the overall systemic risk. While exposure $CoVaR_q^{i|sys}$ investigates which institutions (sectors) are highly exposed to systemic risk in the case of a systemic financial crisis. We condition each institution's (sector) $VaR_{q,t}^{i}$ on the event that the entire financial system is in distress, $VaR_{q,t}^{sys}$. It measures institution (sector) i's increase in VaR in the case of a market downturn or the extent to which an individual institution (sector) is affected by systemic events. The financial system's systemic risk contribution ($\Delta CoVaR$) is the change between the financial institution's $CoVaR$ when it is under financial distress and its median state.

An intricate literature on determining systemic risk has transformed since the GFC and many efforts have been made to utilize the various systemic risk measures. The first copula $CoVaR$

model was designed by Hakwa, *et al.* (2015). Various copula families were examined by Bernardi, *et al.* (2017) via weakening the typical joint distribution function assumptions of the involved random variables. Two alternative extensions were suggested by Di Bernardino, *et al.* (2015) for the classic univariate $CoVaR$ in a multivariate setting. A copula fitting procedure under a semiparametric multivariate setting for $CoVaR$ and MES was designed by Lourme and Maurer (2017) and Mainik and Schaanning (2012).

Copula $CoVaR$ was used by Reboredo and Ugolini (2015a) on sovereign bond benchmark prices for Germany, France, The Netherlands and $PIIGS$ markets[4] and the EMU's long-term sovereign bond price index between the period January 2000 and October 2012. Karimalis and Nomikos (2017) applied copula $CoVaR$ and conditional expected shortfall on a group of 42 largest European banks from April 2002 to December 2012 and analysed the presence of common market elements causing episodes of systemic risk. Analysis was conducted to the length where bank-specific factors like size, leverage and equity beta are linked with systemic risk contribution made by institutions and emphasise the significance of liquidity risk at the abrupt of the financial crisis. Smart and Panchenko (2013) apply copula $CoVaR$ within the Australian banking sector. Zhang, *et al.* (2015) conclude that $PIIGS$ sovereign debt markets were highly correlated with system and within each other before crisis, while they decoupled with system after the crisis using copula $CoVaR$.

Oh and Patton (2018) estimate a variety of systemic risk measures using copula-based dynamic models for high-dimensional conditional distributions of daily CDS spreads on 100 U.S. institutions over the period 2006-2012. They conclude that systemic risk, as measured by the joint probability of distress, is substantially higher nowadays than in the pre-crisis period, however, it is significantly reduced since the 2007 GFC. The foreign exchange markets' dynamic cross correlation structure was examined by Wang, *et al.* (2014) from a time-varying copula approach along with the minimum spanning tree method. Copula $CoVaR$ is used to model systemic risk and dependence structure between oil and stock markets (Mensi, *et al.*, 2017; Reboredo and Ugolini, 2016; Mensah and Alagidede, 2016; Aloui, *et al.*, 2013; Reboredo, 2011). Other studies applied copula to measure dependence patterns across stock indices (Mensah and Premaratne, 2017; Basher, *et al.*, 2014; Bhatti and Nguyen, 2012).

The negative systemic impacts of sovereign Greek debt distress were resolved by Reboredo and Ugolini (2015b) to be restrained to a minor group of countries, particularly Belgium, Italy,

[4] $PIIGS$ markets refer to countries of Portugal, Ireland, Italy, Greece and Spain.

the Netherlands and Portugal via a vine-copula $CoVaR$. From estimating daily vine-Copula $\Delta CoVaR$ and vine-Copula $\Delta CoES$ from January 1995 to July 2013. Chen and Khashanah (2015) were able to examine the transformation of dependence structure and systemic risk in ten $S\&P$ 500 sector indices. Clemente measures the marginal contribution to systemic risk by implementing $CoVaR$-based model on Copula Functions and EVT to a sample of 25 European Banks and STOXX Europe 600 Banks Index.

Some studies have suggested some modifications to $CoVaR$ definition and estimate in order to better capture systemic risk contribution. The $CoVaR$ model was altered by Girardi and Ergün (2013) by modifying the meaning of an institution's financial distress being precisely at its VaR to being at most at its VaR, it identifies how severe distress events occur in fat tails. Time-varying $CoVaR$ estimates are gathered from applying a procedure of three steps derived from a bivariate $GARCH\text{-}DCC$ model and an econometric procedure to capture the conditional quantile of four financial industry groups. There are benefits of modifying the definition of $CoVaR$. Firstly, it accounts more severe distress events for institution i further in the loss distribution tail (below its VaR level), which opposes the extremely selective and over-optimistic scenario (being exactly at its VaR). Furthermore, the adjusted versions of the standard Kupiec (1995) and Christoffersen (1998) methods can test the statistical accuracy and independence of $CoVaR$ estimates respectively. Most significant of all, Mainik and Schaanning (2012) was shown to have great dependence modelling benefits by the modification of conditioning on an institution being at most at its VaR.

Systemic risk contributions are the institution's VaR time-varying marginal effect on the whole financial system's VaR (Hautsch, *et al.*, 2011). Unlike the original $CoVaR$ measure's time-invariant systemic risk beta, a significant characteristic of their model is the supposed systemic risk beta coefficient is time-varying. Likewise, spillover effects from an institution's VaR and the market's use of vector auto-regressive extension to quantile models have been investigated by Manganelli, *et al.* (2010). Additionally, an analytical formula has been suggested to determine $CoVaR$ by disintegrating $CoVaR$ into a function of mean, correlation, volatility and a normal distribution's quantile.

An increasing amount of studies has suggested a variety of substitutes to $CoVaR$ quantitative measures of systemic risk with other approaches and variables. For example, a systemic risk indicator was suggested by Huang, *et al.* (2009) to be defined as insurance price compared to systemic financial distress derived on ex-ante measures of default chances of each bank and equity return correlation forecasts. The systemic importance of financial institutions was assessed by Zhou (2010) via a multivariate Extreme Value Theory (EVT) framework and proposes two systemic risk measures; the Systemic Impact Index (SII) which calculates the systemic impact size if a bank fails and the Vulnerability Index (VI) which calculates the effect on a certain institution when other areas of the system are under financial distress. Likewise, the EVT framework was used to assess contagion amongst markets (Gray and Jobst, 2010). It gives a dependence measure for tail events which is dependent on the occurrence of several market conditions. While investigating financial institution risk spillover, Adams, *et al.* (2010) utilised a State-Dependent Sensitivity Value-at-Risk ($SDSVaR$) approach. This approach is based on a two-stage quantile regression framework.

In order to check the robustness of the $CoVaR$ results, significance tests of $\Delta CoVaR$ were designed by Castro and Ferrari (2014) to decide if a financial institution could be categorised as a $SIFI$ and a dominance test to determine if a single financial institution has greater systemic importance compared to another based on estimated $\Delta CoVaR$. Benoit *et al.* (2013) use Kendall rank-order correlation coefficient to measure the ranking consistency of each systemic risk measure for a given sector through time.

Fleming *et al.* (1998) develop a speculative model to estimate volatility linkages among stock, bonds and money markets using generalized method of moments (GMM) approach. Li and Xiu (2016) and Bollerslev and Zhou (2004) use GMM approach to estimate stochastic volatility of high frequency intraday data while Chacko and Viceira (2003) estimate continuous time stochastic volatility models using GMM and jump diffusion models. Andersen and Sorensen (1996) and Jacquier *et al.* (1994) examine different alternative GMM procedures to estimate stochastic autoregressive volatility model while Chausse and Xu (2018) estimate stochastic volatility models using alternative GMM estimation procedures with realized volatility measures. Broto and Ruiz (2004) and Nilsson and Jochumzen (2016) compare different models to estimate stochastic volatility including GMM, Monte Carlo Markov Chain ($MCMC$) and quasi-maximum likelihood (QML) approaches.

2.3 Estimating Methodology

2.3.1 The Marginal Distribution Model

Before we fit the bivariate copula models, the suitable models must first be fitted for the conditional marginal distributions. Well-known characteristics are shown in financial time series, including long-memory, fat-tails, and conditional heteroscedasticity. Therefore, it is adequate to apply autoregressive-moving average ($ARMA(p,q)$) models to the conditional means (where p is the order of the autoregressive part and q is the order to the moving average part) as well as generalised autoregressive conditional heteroscedasticity ($GARCH(p,q)$) models to the conditional variances (where p and q are the order of the $GARCH$ and $ARCH$ terms respectively) as highlighted by Joe and Xu (1996):

$$Y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (1)$$

$$\varepsilon_t = \sigma_t z_t, z_t \sim NIID(0,1) \quad (2)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, \sigma_{t-i}^2 \quad (3)$$

where Y_t is the log-difference of stock market price at time t; c is the mean equation's constant term; ε_t is time t's real-valued discrete time stochastic process; Z_t is an unobservable random variable of the $i.i.d.$ process; σ_t^2 is the ε_t's conditional variance; ω, α_i and β_i are the constant, $ARCH$ parameter, and $GARCH$ parameters respectively.

z_{it} is presumed to have the skewed-t distribution of Hansen (1994) when approximating the marginal models. Two "shape parameters" arrive as the skewed-t distribution: the degree of freedom parameter $v \, \epsilon (2, \infty)$, which identifies the tail thickness; and a skewness parameter $\xi \, \epsilon (-1,1)$, which captures the distribution's degree of asymmetry. As $v \rightarrow \infty$, it becomes a skewed normal distribution. It is the standard Student's t distribution when $\xi = 0$. Therefore, when $v \rightarrow \infty$ and $\xi = 0$, it is $N(0,1)$ (Patton, 2012b).

In regards to the $GARCH$ (1,1) model, the following inequality restrictions must be meet to guarantee that the model is correctly specified: (i) $\omega \geq 0$, (ii) $\alpha_1 \geq 0$, (iii) $\beta_1 \geq 0$ and (iv) $\alpha_1 + \beta_1 < 1$. Bollerslev (1986) states that when $\alpha_1 + \beta_1 = 1$ then the conditional variance will not converge on a constant unconditional variance in the long-term. $GARCH$ models are calculated by the maximum likelihood.

2.3.2 Copula Approach

The copula concept was formed as an n-dimensional joint distribution, which can be separated into its n univariate marginal distributions and an n-dimensional copula: $X = (X_1, \ldots, X_n)$ signifies a random vector with distribution function F and with marginal functions $F_i, X_i \sim F_i, 1 \leq I \leq n$ (Sklar, 1959). A distributional function C also known as the variable X's copula, outlines $[0,1]^n$ in $[0,1]$ to the point where

$$F(x_1, \ldots, x_n) = C[F_1(x_1), \ldots, F_n(x_n)] \quad (4)$$

Therefore, the variable X's Copula (C) is a function that graphs the univariate marginal distributions F_i to the joint distribution F. On the other hand, Patton (2012a) states the probability integral transformation (PIT), $U_i = F_i(X_i)$ can be used to comprehend the copula function. Since F_i is continuous, it is demonstrated that the variable U_i will have the $Unif$ distribution of (0,1) regardless of the original distribution F_i:

$$U_i = F_i(X_i) \sim \text{Unif}\,(0,1), \text{i} = 1, \dots, \text{n} \tag{5}$$

Thus, we are able to comprehend the variable X's copula (C) as the joint distribution of the PIT's vectors, $U_i = [U_1, \dots, U_n]'$, and therefore, it is a joint function with the margins of $Unif$ $(0,1)$. While discerning the previous representation in regards to all its arguments, we result with the joint probability density function as discussed by Patton (2012a):

$$f(X_1, \dots, X_n) = c\big(F_1(x_1), \dots, F_n(x_\text{n})\big) \times \prod_{i=1}^{n} f_i(x_\text{i}) \tag{6}$$

where $C(U_1, \dots, U_n) = \frac{\partial^n C(U_1, \dots, U_n)}{\partial U_1, \dots, \partial U_n}$

Estimating the joint cumulative distribution function F requires two steps: first, the marginal distributions must be determined and calculated, second the copula function must be estimated and computed. The ease of distinguishing the copula and marginal distributions means that a varying set of distributions can be combined and will be valid. For instance, a valid joint distribution will be made by a skewed distribution variable combined with a symmetrically distributed variable via t-copula despite being unusual. Therefore, numerous studies on modelling univariate distributions become significant to academicians and professionals and only the task of dependence structure modelling remains (Patton, 2012a)[5].

Patton's (2006a) work is essential for time-series applications as it adds conditional distributions to Sklar's theorem. Since the marginal distribution of financial series returns display time-varying mean and volatility, the conditional copula becomes a significant instrument in determining the dependence of that regard. Let $X_t = (X_{1\text{t}}, \dots, X_{nt})$ denote a stochastic process and $\digamma_t$ denote an information set available at time t, and let the conditional distribution of $(X_{1\text{t}}, \dots, X_{nt})||\digamma_{t-1}$ be F_t. Then:

$$\text{F}_t(x_{1\text{t}}, \dots, x_{nt}|\digamma_{t-1}) = C_t[\text{F}_{1t}(x_{1\text{t}}|\digamma_{t-1}), \dots, \text{F}_{nt}(x_{\text{nt}}|\digamma_{t-1})] \tag{7}$$

[5] See Cherubini, et al. (2004), Nelsen (1999) and Heinen and Valdesogo (2012) for more studies of unconditional copulas.

A significant process essential in utilising Sklar's Theorem to conditional distribution is to guarantee that the formation's conditioning is constant for all marginal distributions and the copula. The general method is to believe that marginal models are only reliant on their respective past information while the copula has the option of being conditioned on all series' previous information. Fermanian and Wegkamp (2012) have demonstrated a scenario where various sets of information can be utilised.

The copula distribution for n number of assets is outlined in Eq. (4). This chapter only takes into consideration bivariate copulas as this is the scope of measuring systemic risk. Therefore, the bivariate distribution F with margins F_1, F_2 can be shown as:

$$F(x_1, x_2) = C[\mathrm{F}_1(x_1), \mathrm{F}_2(x_2)] \tag{8}$$

The joint distribution function's copula for a random vector $\mathrm{X} = (\mathrm{X}_1, \mathrm{X}_2)$ can be shown as

$$C(u, \mathrm{v}) = F[F_1^{-1}(u), F_2^{-1}(v)] \tag{9}$$

where the margin's quantile functions are $\mathrm{F}^{-1}(\mathrm{u}) = \inf\{\mathrm{x}: \mathrm{F}(\mathrm{x}) \geq \mathrm{u}\}, \mathrm{u} \in [0,1]$.

From Eq. (8), it is observed that the joint distribution is separated into marginal segments and the dependence structure (C) without missing any information as visited prior, the marginal parts F_1 and F_2, do not need to be from the same distribution family.

Copula models have the advantage of obtaining tail dependence, for many forms, which determines the likelihood that the two random variables being in their lower (upper) joint tails. Captured in the tail dependence is the random variables' behaviour during extreme events. For instance, given two stock market returns, X_1 and X_2, tail dependence captures the probability that an extremely large drop (increase) will be observed of stock market X_1 under the circumstances of the stock market X_2 having experienced an extreme drop (increase). Whether the two markets crash or boom together is determined by the tail dependence, therefore investors which hold long portfolios are primarily worried with the downward movement, while investors holding short positions are primarily worried with large upward movement risk. The lower and upper tail dependence between X_1 and X_2 can be defined as:

$$\tau^L = \lim_{u \to 0} Pr\{F(X_1) \leq u | F(X_2) \leq u\} = \lim_{u \to 0} Pr \frac{\mathrm{C}(u,u)}{u} \tag{10}$$

$$\tau^U = \lim_{u \to 1} Pr\{F(X_1) \geq u | F(X_2) \geq u\} = \lim_{u \to 1} \frac{1-2u+\mathrm{C}(u,u)}{1-u} \tag{11}$$

where τ^{L} and $\tau^{\mathrm{U}} \in (0,1)$. If the above limits exist and if τ^{L} and $\tau^{\mathrm{U}} > 0$, X_1 and X_2 tend to be left (lower) or right (upper) tail dependent.

To determine the various patterns of tail dependence, we have calculated Eq. (8) for six different copula specifications displayed in Table 2.1. The Gaussian (N), Gumbel (G), Rotated Gumbel (RG), Clayton (C), Symmetrized Joe-Clayton (SJC) and Student's t (T) copulas are the functional forms involved. The convenient properties of the Gaussian copula are the reason for it being the most commonly used in finance. Despite this, it cannot determine tail dependence. However, the Student-t copula makes the assumption that there is symmetric dependence of the joint distribution of the lower and upper tails. The rotated Gumbel copula is only handy in investigating dependence during market crashes; on the other hand, the Gumbel copula is valuable in capturing only the upper tail dependence, therefore it is significant in market boom periods. The SJC copula was presented by Patton (2006a) for its parameterized upper and lower tail dependence coefficients and highlighted a "conditional copula" as a multivariate distribution of variables that are distributed as a conditional uniform distribution.

Table 2.1: Copula model specifications

Copula	Distribution	Parameter space	Independ-ence	Lower tail depended	Upper tail depended
Gaussian	$C_N(u,v;\rho)=\Phi_\rho\left(\Phi^{-1}(u),\Phi^{-1}(v)\right)$	$\rho\in(-1,1)$	$\rho=0$	$\lambda_L=0$	$\lambda_U=0$
Gumbel	$C_G(u,v;\delta)=exp\left\{-\left[\left(-ln(u)\right)^\delta+\left(-ln(v)\right)^\delta\right]^{1/\delta}\right\}$	$\delta\in(1,\infty)$	$\delta=1$	0	$2-2^{1/\delta}$
Rotated Gumbel	$C_{RG}(u,v;\delta)=u+v-1+C_G(1-u,1-v,\delta)$	$\delta\in(1,\infty)$	$\delta=1$	$2-2^{1/\delta}$	0
Clayton	$C_C(u,v;\theta)=\left(u^{-\theta}+v^{-\theta}-1\right)^{-1/\theta}$	$(0,\infty)$	0	$2^{-1/\theta}$	0
SJC	$C_{SJC}(u,v;\lambda_U,\lambda_L)=0.5\big(C_{JC}(u,v;\lambda_U,\lambda_L)$ $+C_{JC}(1-u,1-v;\lambda_U,\lambda_L)+u+v-1\big)$	$\lambda_L\in(0,1)$, $\lambda_U\in(0,1)$	λ_L,λ_U $=(0,0)$	λ_L	λ_U
Student-t	$C_S(u,v;\rho,d)=T_{d,\rho}\left(T_d^{-1}(u),T_d^{-1}(v)\right)$	$\rho\in(-1,1)$, $d\in(2,\infty)$	ρ,d $=(0,\infty)$	$\vartheta T(\rho,d)$	$\vartheta T(\rho,d)$

Notes: The column titled "Independence" shows the parameter values that lead to independence copula. u and v denotes the cumulative density functions of the standardized residuals from the marginal models and $0\le u,v\le 1$. Φ_ρ is the bivariate cumulative distribution of the standard normal with correlation coefficient ρ and Φ^{-1} is the inverse function of the univariate normal distribution. $T_{d,\rho}$ is the bivariate student-t distribution with correlation coefficient ρ and degree of d, which captures the extent of symmetric extreme dependence; t^{-1} is the inverse function of the univariate Student-t distribution. k denotes the parameters for the Gumbel and rotated Gumbel copulas. SJC copula is based on Joe Clayton (JC) copula where $k={}^{1}/_{log_2}(2-\lambda_U),\gamma={}^{-1}/_{log_2}(\lambda_L)$.

Specifications of six various copulas are used to determine various features of dependence as below:

First of all, being the most frequently used distribution in the study of finance, the bivariate Gaussian is signified as by $C_N(u,v;\rho)=\Phi(\Phi^{-1}(u),\Phi^{-1}(v))$, whereas the bivariate standard normal CDF with correlation ρ across X and Y is represented by Φ and where the standard normal quantile functions are represented by $\Phi^{-1}(u)$ and $\Phi^{-1}(v)$. No tail dependence exists.

Secondly, while displaying the upper tail dependence and lower tail independence, the Gumbel copula is asymmetric. It is based on $C_G(u, v; \delta) = exp(-((-\log u)^{\delta} + (-\log v)^{\delta})^{1/\delta}$. Remember when $\delta = 1$, the two variables become independent.

Thirdly, represented as $C_{RG}(u, v; \delta) = u + v - 1 + C_G(1 - u, 1 - v; \delta)$, the 180-degree rotated Gumbel copula displays upper tail independence and lower tail dependence. The Gumbel (Rotated Gumbel) represents upper (lower) tail dependence structure between the markets. As the implied tail dependence is denoted as $2 - 2^{1/\delta}$, we can say that a higher upper (lower) tail dependence between the stock markets is suggested by a larger value of δ from the Gumbel (Rotated Gumbel).

Fourthly, Clayton copula allows modelling non-linear dependence structure in addition to its lower tail dependence. The upper tail dependence' coefficient of Clayton copula is set to zero while the lower tail dependence' coefficient is $\lambda^L(u, v) = 2^{-1/\theta}$.

Fifthly, SJC allows the tail dependence measures to determine the presence or absence of asymmetry. SJC becomes symmetric only when $\lambda_U = \lambda_L$. However, its specification does not force symmetric dependence on the variables.

Last of all, the Student-t is significant for realising systemic tail dependence. Based on $C_S(u, v; \rho, d) = T_{d,\rho}\left(T_d^{-1}(u), T_d^{-1}(v)\right)$, where the bivariate Student-t CDF with degree-of-freedom parameter d and correlation ρ is represented by T and where quantile functions of the univariate Student-t distribution with degree-of-freedom parameter d are represented by $T_d^{-1}(u)$ and $T_d^{-1}(v)$.

2.3.3 Generalised Autoregressive Score (GAS) Model

The copula parameters can be determined via two alternative frameworks: Maximum Likelihood Estimation (MLE) method and the Inference Functions for the Margins (IFM). Estimates of the copulas in this chapter are conducted with the IFM method because of its advantages over the MLE method. The advantages of IFM over the MLE includes, (1) the IFM requiring only a few computations; (2) it is very efficient; (3) the margins' goodness can be determined separately from the copula; and (4) the series of random variables are not needed to be equal in length (Bhatti and Nguyen, 2012).

Estimates of the time-varying copulas was based on the Generalised Autoregressive Score (GAS) model of Creal, *et al.* (2013). The assumption was made that the copula parameter transforms as a function of its own lagged value and a "forcing variable" connected to the copula log-likelihood's scaled score. To ensure that the parameters remain within a certain range ($\rho \in (-1,1)$), the approach uses strictly increasing transformation (log) to copula parameters. Based on Patton's work (2012a), the transformed parameter's evolution is represented by:

$$f_t = h(\delta_t) \Leftrightarrow \delta_t = h^{-1}(f_t) \tag{12}$$

where

$$f_{t+1} = \theta + \beta f_t + \alpha h I_t^{-1/2} S_t \tag{13}$$

$$S_t \equiv \frac{\partial}{\partial \rho} \log C(u_t, v_t; \delta_t) \tag{14}$$

$$I_t \equiv E_{t-1}[S_t S_t'] \tag{15}$$

With the use of these expressions, the copula parameter's future value is dependent upon a constant, the present value, and the score of the copula log-likelihood $\mathrm{I}_t^{-1/2}\mathrm{s}_t$. The GAS model was applied to the time-varying Gaussian, Gumbel and rotated Gumbel copulas. To guarantee the Gaussian copula parameter remains within (-1, 1) we utilise $\delta_t = \frac{(1-exp\{-f_t\})}{(1+exp\{f_t\})}$. To ensure that the Gumbel and rotated copular parameter is greater than one, the function $\delta_t = 1 + exp\{f_t\}$ was used.

Furthermore, we involve potential time-varying parameter (TVP) dependence by enabling parameters of certain copulas to change based on specific evolution equation. With the Student-t, Clayton and SJC copulas, we state the linear dependence parameter ρ_t as it transforms based on a model with 1 autoregressive term and q moving-average terms, as an $ARMA\ (1, q)$ type process (Patton, 2006a):

$$\rho_t = \Lambda_1 \left(\boldsymbol{\Psi_0} + \boldsymbol{\Psi_1} \rho_{t-1} + \boldsymbol{\Psi_2} \frac{1}{q} \sum_{j=1}^{q} \left[t_v^{-1}(u_{t-j}) t_v^{-1}(v_{t-j}) \right] \right) \tag{16}$$

The altered logistic transformation that holds the ρ_t value in (-1,1) is denoted as $\Lambda_1 = (1 - e^{-x})(1 + e^{-x})^{-1}$. A constant ($\Psi_0$), an autoregressive term (Ψ_1) and the average product over the last q observations of the transformed variables (Ψ_2), all explain the dependence parameter together. $\Phi^{-1}(x)$ is replaced by $t_v^{-1}(x)$ for the Student-t copula.

2.3.4 Copula ΔCoVaR Risk Measures

We identify $CoVaR$ systemic risk measure as suggested by Adrian and Brunnermeier (2011) and modify the econometric technique to be based on copulas. The copula's partial derivatives were tied to $CoVaR$ by Hakwa, *et al.* (2015) via their conditional probability interpretation. Their calculation of $CoVaR$ is offered by a closed formula. It demonstrates that $CoVaR$ relies on the financial system's marginal return distribution and the copula amongst the financial institution and the financial system.

Using copulas to determine $CoVaR$ has two main benefits. First of all, they provide great flexibility in modelling marginals as copulas enable separate modelling of the dependence structure and marginal. This flexibility is essential to calculate VaR and model the dependence structures with various tail dependence characteristics, like the tail independence and symmetric or asymmetric tail dependence that is particularly necessary for calculating the measure of $CoVaR$. When the linear correlation coefficient is inadequate for the traditional dependence measure to identify dependence structure or when the joint distribution functions is not elliptical, the copulas become important (Embrechts, *et al.*, 2003). This is particularly essential when bivariate Gaussian or Student-t distributions (both which are frequently used in multivariate $GARCH$) fail to sufficiently depict the data's joint distribution function. Lastly, rather than acquiring the $CoVaR$ via the method applied by Girardi and Ergün (2013), using copulas to calculate the $CoVaR$ provides greater computational tractability as the equation needs numerical resolution of a VaR computation and double integral for a market under financial distress. It is worth noting that characterising $CoVaR$ with copulas requires only information on the VaR's cumulative probability and not the value of VaR itself.

By giving information on a market's VaR, $CoVaR$ can determine the potential risk spillover across indices, depending upon whether another index is under financial distress. In a two-step procedure, the market's $CoVaR$ value can be obtained using copulas. With the cumulative probability of a financially distressed index's VaR and the $CoVaR$'s confidence level, we can use a copula function to calculate the $CoVaR$'s cumulative likelihood. In terms of computation, this method has greater tractability compared to other parametric methods as it is more flexible since copula functions are giving a measure of both average dependence, upper and lower tail dependence (joint extreme movements), in addition, it ensures that each stochastic variables' dependence structure is to be described in a comprehensive sense. This information is fundamental to finding a variable's VaR based on the condition that another variable accepts values lower or equal to its own VaR. Interestingly, a copula function's lower tail dependence provides this information but at its limit.

The EU index's $CoVaR$ is the VaR of the European market as an entirety conditional on a certain financial sector is in distress. The EU index return as a whole can be denoted as R_t^{sys} and the return of the financial sector, j, can be denoted as R_t^j. The $CoVaR$ is formally denoted as of the R_t^{sys}'s conditional distribution of α-quantile as follows:

$$Pr\left(R_t^{sys} \leq CoVaR_{q,t}^{sys|j} | R_t^j \leq VaR_{\alpha,t}^j\right) = q \tag{17}$$

where the financial sector j's VaR is denoted as $VaR_{\alpha,t}^j$ determines the maximum loss that sector j may incur for a confidence level 1-α and a specific time horizon, which is the sector j's α-quantile of the return distribution: $\Pr\left(R_t^j \leq VaR_{\alpha,t}^j\right) = \alpha$. This means calculating the $CoVaR$ requires confirming a conditional distribution's quantile or alternatively of an unconditional bivariate distribution if we characterise Eq. (17) as:

$$\frac{\left(R_t^{sys} \leq CoVaR_{q,t}^{sys|j} | R_t^j \leq VaR_{\alpha,t}^j\right)}{R_t^j \leq VaR_{\alpha,t}^j} = \alpha \tag{18}$$

Based on $\Pr\left(R_t^j \leq VaR_{\alpha,t}^j\right) = \alpha$, the $CoVaR$ in Eq. (18) can be defined as:

$$Pr\left(R_t^{sys} \leq CoVaR_{q,t}^{sys|j} | R_t^j \leq VaR_{\alpha,t}^j\right) = \alpha q \tag{19}$$

The $CoVaR$ in Eq. (19) was suggested to be numerically solved by a double integral as discussed by Girardi and Ergün (2013).

$$\int_{-\infty}^{CoVaR_{q,t}^{sys|j}} \int_{-\infty}^{VaR_{\alpha,t}^j} f_t\left(R_t^{sys}, R_t^j\right) dR_t^{sys} dR_t^j = \alpha q \tag{20}$$

Based on certain levels of α, q and $VaR_{\alpha,t}^j$ and where the bivariate density of R_t^{sys} and R_t^j is denoted as $f_t(R_t^{sys}, R_t^j)$.

In this chapter, we suggest to calculate $CoVaR$ via copulas. A summary of copula applications in finance can be revealed in Cherubini, *et al.* (2004) while the first $CoVaR$ representations in the forms of copula was given by Mainik and Schaanning (2012). Remember that Eq. (19) can be defined in the form of the joint distribution function of R_t^{sys} and R_t^j, $F_{R_t^{sys}, R_t^j}$, as:

$$F_{R_t^{sys},R_t^j}\left(CoVaR_{q,t}^{sys|\mathrm{j}}, VaR_{\alpha,t}^j\right) = \alpha q \tag{21}$$

and that, based on Sklar's (1959) theorem, two continuous variable's joint distribution function can be defined in a copula function form. Therefore, Eq. (20) can be expressed as:

$$C(u,v) = \alpha q \tag{22}$$

where copula function is denoted as $C(.,.)$, $u = F_{R_t^{sys}}(CoVaR_{\beta,t}^{sys|j})$ and $v = F_{R_t^j}(VaR_{\alpha,t}^j)$ and where the marginal distribution functions of R_t^{sys} and R_t^j are respectively defined as $F_{R_t^{sys}}$ and $F_{R_t^j}$. Based on the copula form in Eq. (22), using copulas in a two-step procedure can calculate the $CoVaR$.

Initially, we acquire the value of $u = F_{R_t^d}(CoVaR_{q,t}^{sys|j})$. As $C(u,v) = \alpha q$, where α, q and v are given (note that $v = \alpha$), from clarifying the copula function specification to attain the value of u.

Secondly, with u, we can acquire the $CoVaR$ value as the R_t^{sys}'s quantile of the distribution, with a cumulative likelihood squatted to u, by inverting the marginal distribution function of R_t^{sys}: $CoVaR_{q,t}^{sys|j} = F_{R_t^{sys}}^{-1}(u)$.

The systemic risk contributed by a certain sector j was expressed by Adrian and Brunnermeier (2011) and Girardi and Ergün (2013) as the delta $CoVaR$ ($\Delta CoVaR$), which is the difference amongst EU index's VaR as an entirety situational on the sector j's distressed condition ($R_t^j \leq VaR_{\alpha,t}^j$) and the EU index's VaR as a entirety based on the sector j's benchmark state, considering it as sector, j's return distribution median or on the other hand, the VaR for $\alpha = 0.5$. The sector j's systemic risk contribution is therefore expressed as:

$$\Delta CoVaR_t^{sys|j} = CoVaR_{q,t}^{sys|j} - CoVaR_{q,t}^{sys|j,\alpha=0.5} \tag{23}$$

Therefore, $\Delta CoVaR$ becomes significant as it attains sector j's marginal contribution to the aggregate systemic risk.

2.3.5 Stochastic Volatility Model using Generalised Method of Moments

Volatility linkages across financial sectors are based on the relation between volatility and information flow (Ross, 1989). Fleming *et al.* (1998) estimate how information creates cross-sector linkages using generalised method of moments (GMM). Stronger volatility linkages occur when we have high levels of common information and information spillover. The GMM approach is characterised by incorporating the stochastic volatility specification inside a rational expectations framework (Kodres and Pritsker, 2002). Information flow in each financial sector is unobservable, but their applied model implies empirical specifications where daily information flow is proportionate to variance of daily returns (Ross, 1989; Andersen, 1996). The degree of volatility persistence is estimated by modelling information flow as an $AR(1)$ process.

The major advantages of GMM approach in comparison to other approaches (such as $GARCH$) is that it is direct to implement, in addition to, its ability to generates a direct estimate of the desired correlation among sectors. Furthermore, GMM approach assumes volatilities are stochastic which is consistent with information flows analysis[6] (Hall, 2005; Deo, 2002).

Fleming *et al.* (1998) approach assume that daily returns are generated by the joint stochastic process as follows:

$$R_{k,t} = \mu_{k,t} + \sigma_{\varepsilon,k} I_{k,t}^{1/2} z_{k,t} \tag{24}$$

$$R_{k,t} = \mu_{k,t} + exp\left(\frac{1}{2} h_{k,t}\right) z_{k,t} \tag{25}$$

$$h_{k,t} = \gamma_{h,k} + \phi_{h,k} h_{k,t-1} + u_{k,t} \tag{26}$$

where $\mu_{k,t}$ is the conditional expected value of $R_{k,t}$; $I_{k,t}$ denotes the number of information events that impact sector k on day t; $z_{k,t} \equiv 1/I_{k,t}^{1/2} \sum_{i=1}^{I_{k,t}} \left(\varepsilon_{ik,t}/\sigma_{\varepsilon,k}\right)$; $\varepsilon_{ik,t}$ is the incremental return produced by event i which is assumed to be $i.i.d.$; $\sigma_{\varepsilon,k}$ is standard deviation of $\varepsilon_{ik,t}$; $u_{k,t}$ and $z_{k,t}$ are independent, $z_{k,t}$ ~ $i.i.d.\ N\,(0,1)$; and $u_{k,t}$ is $i.i.d.$, with mean zero and variance $\sigma_{u,k}^2$. The unpredicted component of returns is defined as $r_{k,t} = R_{k,t} - \mu_{k,t}$; $h_{k,t}$ is the natural logarithm of the daily variance. The autocorrelation of $r_{k,t}$ is zero at all lags, but there can be a substantial degree of high order serial dependence. Therefore:

$$\ln r_{k,t}^2 = h_{k,t} + \ln z_{k,t}^2 \tag{27}$$

[6] Since $GARCH$ models assume information flow is known and conditional on past prices which lacks stochastic volatilities assumption, therefore, they less likely capture the salient features of the return generating process (Chan *et al.*, 1991).

As $z_{k,t}$ is normally distributed with mean zero and variance one, consequently, the mean and variance of $\ln z_{k,t}^2$ are –1.27 and 4.93 (Abramowitz and Stegun, 1970). If $y_{k,t} = \ln r_{k,t}^2 - E\left[\ln z_{k,t}^2\right]$ is identified, the transformed model can be obtained as:

$$y_{k,t} = h_{k,t} + \xi_{k,t} \tag{28}$$

$$h_{k,t} = \gamma_{h,k} + \theta_{h,k} h_{k,t-1} + u_{k,t} \tag{29}$$

where $\xi_{k,t} \equiv \ln z_{k,t}^2 - E\left[\ln z_{k,t}^2\right]$ is mean zero and variance 4.93, and independent of $h_{k,t}$. Since $y_{k,t}$ is the sum of an $AR(1)$ component and a noise process, its autocovariance function should be identical to that of an $ARMA(1,1)$ specification. Consequently, we could form the moment restrictions on $y_{k,t}$ that form the basis of our GMM model estimation as follows:

$$E\left[y_{k,t}\right] = E\left[h_{k,t}\right] \tag{30}$$

$$var\left(y_{k,t}\right) = var\left(h_{k,t}\right) + var\left(\xi_{k,t}\right) \tag{31}$$

$$cov\left(y_{k,t}, y_{k,t+\tau}\right) = \left(\phi_{h,k}\right)^{\tau} var\left(h_{k,t}\right) \tag{32}$$

These above-mentioned formulas create the moment conditions of univariate estimation in a certain financial sector. The moment conditions of bivariate estimation could be derived the same way. We can state the bivariate estimation moment conditions as follows:

$$e_t(\theta) = \begin{bmatrix} y_{i,t} - \mu_{h,i} \\ \left(y_{i,t} - \mu_{h,i}\right)^2 - \sigma_{h,i}^2 - \sigma_{\xi}^2 \\ \left(y_{i,t} - \mu_{h,i}\right)\left(y_{i,t+\tau} - \mu_{h,i}\right) - \left(\phi_{h,i}\right)^{\tau}\left[\left(y_{i,t} - \mu_{h,i}\right)^2 - \sigma_{\xi}^2\right] \\ y_{j,t} - \mu_{h,j} \\ \left(y_{j,t} - \mu_{h,j}\right)^2 - \sigma_{h,j}^2 - \sigma_{\xi}^2 \\ \left(y_{j,t} - \mu_{h,j}\right)\left(y_{j,t+\tau} - \mu_{h,j}\right) - \left(\phi_{h,j}\right)^{\tau}\left[\left(y_{j,t} - \mu_{h,j}\right)^2 - \sigma_{\xi}^2\right] \\ \left(y_{i,t} - \mu_{h,i}\right)\left(y_{j,t} - \mu_{h,j}\right) - \rho_{h,ij}\sigma_{h,i}\sigma_{h,j} - \rho_{\xi,ij}\sigma_{\xi}^2 \\ \left(y_{i,t} - \mu_{h,i}\right)\left(y_{j,t+\tau} - \mu_{h,j}\right) - \left(\phi_{h,j}\right)^{\tau}\left[\left(y_{i,t} - \mu_{h,i}\right)\left(y_{j,t} - \mu_{h,j}\right) - \rho_{\xi,ij}\sigma_{\xi}^2\right] \\ \left(y_{i,t+\tau} - \mu_{h,i}\right)\left(y_{j,t} - \mu_{h,j}\right) - \left(\phi_{h,i}\right)^{\tau}\left[\left(y_{i,t} - \mu_{h,i}\right)\left(y_{j,t} - \mu_{h,j}\right) - \rho_{\xi,ij}\sigma_{\xi}^2\right] \end{bmatrix} \tag{33}$$

where $\tau = 1,2,3, \ldots, l$, is the number of autocorrelation restrictions which are applied in the estimation, and $\sigma_{\xi}^2 = 4.93$. To obtain the GMM parameter estimates, $g_T(\theta)'\hat{S}^{-1}g_T(\theta)$ has to be minimised, where $g_T(\theta) = [1/(T-l)\sum_{t=1}^{T-l} e_T(\theta)]$, and $\hat{S}$ is a consistent estimate of the GMM covariance matrix. We use Parzens weights as well as bandwidth selection method for the choice of the covariance matrix as proposed by Andrews (1991) and Newey and West (1987, 1994) in order to adjust $\hat{S}$ for conditional heteroscedacity and autocorrelation.

We estimate the cross-sector correlations six times by fitting the above-mentioned bivariate GMM moment conditions. In the equation model above, i and j subscripts denote the pairings of banking/ financial sectors, banking/ insurance sectors, banking/ real-estate sectors, financial/ insurance sectors, financial/ real-estate sectors, and insurance/ real-estate sectors, respectively. The first six moment conditions refer to univariate estimation of the two sectors in the selected pair. The last two moment conditions are for bivariate correlation estimation among the two sectors in each pair. $\rho_{h,ij}$ is the correlation between $h_{i,t}$ and $h_{j,t}$; and $\rho_{\xi,ij}$ is the correlation between $\xi_{i,t}$ and $\xi_{j,t}$. There are $2(l + 2)$ equations and a total of six unknown variables; three unknowns for each sector, $\theta = \left[\mu_{h,k}, \sigma^2_{h,k}, \phi_{h,k}\right]'$, for sectors, $k = i, j$. We have $2l + 1$ cross-sector equations with two unknowns in the remaining moment conditions, which results in $4l + 5$ equations with eight unknowns in the joint model. We determine the GMM moment conditions, then we apply GMM estimation procedures in order to obtain cross-sector volatility correlations among banking, financial, insurance and real-estate sectors.

The GMM technique generates a specification error test in terms of an over-identifying test statistic, J-statistics (Hansen, 1982; Hansen *et al.*, 1996). When we choose a suitable value for l in GMM estimation, it involves contradictory considerations. Daily volatility of returns is highly persistent based on empirical studies which require a large value of l, but in the meantime, in order to lessen the bias of parameter estimates and reduce the possibility of obtaining an ill-conditioned weighting matrix, we need to use a small number of moment conditions. Therefore, we estimate the model specification for l equal to 1, 10, 20, 30 and 40. In general, the empirical results are insensitive to the selection of l. We report the results of 40-lag scenario following Fleming *et al.* (1998) and Wang (2009).

2.4 Data

The indices of EU and financial sectors dependence structures draw tremendous consideration from researchers, practitioners, regulators and policy makers, in light of the September of 2008's collapse of Lehman Brothers. Interestingly, despite possessing significant influence over the different financial sectors, EU index effects vary in bear and bull markets and with various timespans. Particularly during and after the 2007 GFC and 2009 Eurozone sovereign debt crisis, they possess diverse upside and downside risk spillover. Ultimately, comprehending these multidimensional properties is significant for portfolio allocation and risk management.

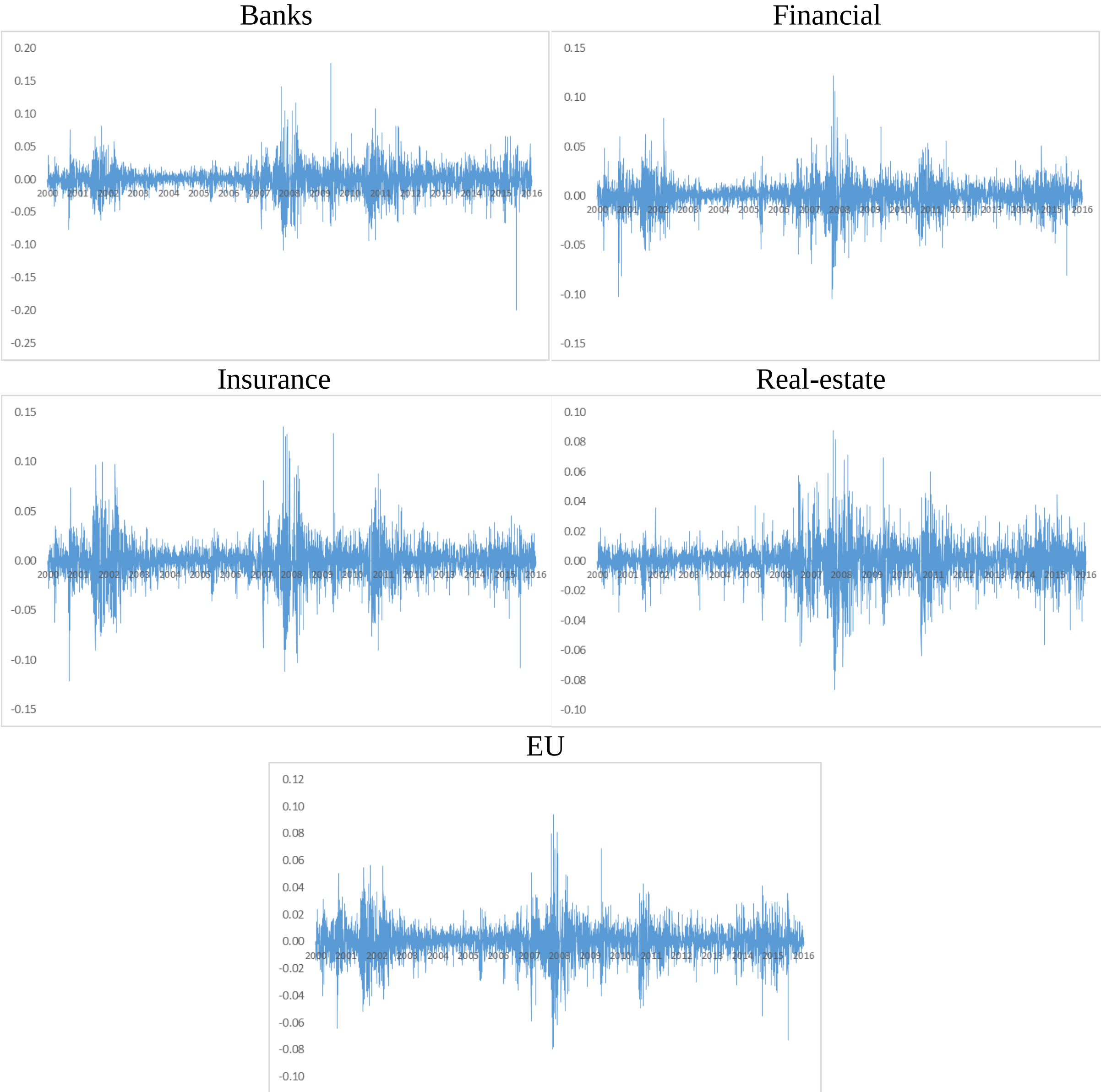


Figure 2.1: EU index and the four financial sectors return series

Notes: This figure displays the return series of EU and sectors indices. The continuously compounded daily returns are calculated by taking the difference in the logarithm of two consecutive prices.

The analysis presented here is based on daily equity adjusted prices to account for capital operations (i.e., splits, dividends etc.) for *EU* index (STOXX 600), which is a regional benchmark for European stock market, the four Eurozone financial sectors, namely, banks (SX7E Index), financial service (SXFE Index), insurance (SXIE Index) and real-estate (SX86E Index). The study period is from 1 January 2001 to 30 December 2016 and the data is sourced from Bloomberg. The sample period includes several important financial events including the

2001 dotcom recession, 2007 subprime crisis and the 2009 European sovereign debt crisis. A higher volatility of these indices also characterises this period.

Figure 2.1 shows the return series and their evolution dynamics as it displays the stylised facts (e.g. volatility clustering) for the EU index and four major financial sectors return series. The figure shows a stable retune for the period 2003-06 and there was a noticeable rise in the indices return in 2007-08, while it displays a significant decline in the subsequent period 2009-10.

Table 2.2 is a representation of descriptive statistics of the indices returns of EU and four Eurozone financial sectors between January 2001 to December 2016. In all cases, the mean percentage returns are near zero in all indices and are small in comparison to the standard deviation which suggests that in all sectors there exists high volatility. A comparison of the means reveals that real-estate sector is the highest, with financial services sector and EU index have average return of zero, while during the sample period the banking and insurance sectors display negative performance. All the series show a common negative value for skewness with the exception of insurance sector and all sectors show excess kurtosis, which indicates there is a higher chance of extreme negative returns in comparison to having extreme positive returns.

Table 2.2: Descriptive Statistics of EU and Eurozone Financial Sectors (2001-2016)

	Mean	STD	Min	Max	Skewness	Kurtosis	JB	Q(2)	Q2(2)	ARCH(2)
Banks	-0.02	2.00	-19.87	17.76	-0.05	7.51	9,818	12.24[a]	166.54[a]	144.81[a]
Financial	0.00	1.51	-10.39	12.25	-0.21	6.05	6,415	12.27[a]	402.44[a]	335.37[a]
Insurance	-0.02	1.93	-12.11	13.58	0.06	6.41	7,168	6.513[b]	387.17[a]	321.66[a]
Real-estate	0.02	1.29	-8.64	8.78	-0.20	5.38	5,078	9.868[a]	756.77[a]	583.84[a]
EU	0.00	1.25	-7.93	9.41	-0.17	5.43	5,158	5.378[c]	563.64[a]	462.09[a]

Notes: The table displays the summary statistics for daily stock returns of Eurozone financial sectors and EU index from January 2001 to December 2016. STD denotes the standard deviation; mean, STD, min and max are expressed in percentage. JB refers to the Jarque-Bera test for normality. The Jarque-Bera statistics are statistically significant at 1%. Ljung-Box-Q-statistics and Ljung-Box-Q2-statistics for serial correlation of order 2 in returns and squared returns are denoted by $Q(2)$ and $Q^2(2)$. $ARCH(2)$ is the Lagrange multiplier test for autoregressive conditional heteroscedasticity of order 2. [a], [b] and [c] denote statistical significance at 1%, 5% and 10%, respectively.

The null of the Gaussian distribution is rejected by the Jarque-Bera test for all series (Jarque and Bera, 1980, 1981). The highest Sharpe ratio is displayed by the real-estate sector, this indicates that this sector is more rewarding, while the lowest ratio is seen by insurance sector and therefore being the least rewarding. The expected return per unit of risk offered by financial services sector and EU return indices are similar. Stationary tests and the unit root provide indication that all indices are stationary. It is indicated by the Ljung-Box statistic, which is used for autocorrelation and squared autocorrelation up to the 2nd order, that there is temporal dependence in returns present. Evidence is provided by the Lagrange multiplier test for conditional heteroscedasticity of the $ARCH$ effect in each of the series (Engle, 1982), therefore it is appropriate to use $GARCH$ techniques to model the return distributions.

Table 2.3: Correlation between EU and Financial Sectors

	EU	Banks	Financial	Insurance	Real-estate
EU	1.000				
Banks	0.8521	1.000			
Financial	0.8665	0.8049	1.000		
Insurance	0.8863	0.8739	0.8311	1.000	
Real-estate	0.6848	0.6392	0.6918	0.0642	1.000

Notes: the table reports the linear correlation among EU index and four financial sectors indices.

Table 2.3 shows the unconditional correlation results, which shows a significant and positive correlation between EU and the four financial sectors indices, therefore, the EU and four sectors are more integrated. Unsurprisingly, the EU-insurance pair displays the highest correlation while the lowest correlation can be seen in the EU-realestate pair. There is a correlation between the four financial sectors, which indicates a high level of integration among the four financial sectors themselves. As a linear measure, correlation is still flawed as it fails to determine nonlinear dependence within indices and would require a stronger copular technique.

Embrechts, *et al.* (2002) states that the convenient characteristics of linear correlation allow it to canonically calculate the link between stock returns. With belief of constant correlation, previous studies used models that price stock returns jointly (Agmon, 1972; Solnik, 1974). Following research substantiates that comovement in stock returns change over time (Brooks and DelNegro, 2004; Forbes and Rigobon, 2002; Kizys and Pierdzioch, 2009). Due to linear correlation deficiencies, modelling time-varying stock dependence using multivariate $GARCH$ models is becoming more popular contemporarily in finance area (Syllignakis and Kouretas, 2011; Gjika and Horvath, 2013; Baumöhl and Lyócsa, 2014; Kundu and Sarkar, 2016). However, the multivariate $GARCH$ method is restricted by the assumption of symmetric multivariate normal or student-t distribution determining the innovations of returns (Patton, 2006b; Garcia and Tsafack, 2011). Therefore, this assumption conflicts with empirics as the distribution of financial returns contains heavy tails compared to the ones characterised as normally distributed and the dependence amongst stock returns are typically asymmetric and nonlinear.

2.5 Empirical Analysis and Results

2.5.1 Marginal Model Results

Before calculating the copula models, we have applied an $ARMA$ filtration on the index return series to guarantee that the residuals are autocorrelation free and have an expected return of zero. After using the $ARCH\text{-}LM$ test to determine the fitted series for $ARCH$-effects, the results show that heteroscedasticity is prevalent in each individual series. Therefore, we must choose for each univariate $GARCH$'s optimal lag length and fit a variety of specifications to the second moments. The estimates of the $ARMA\text{-}GARCH$ models for index returns is shown in Table 2.4. $ARMA(1,1)\text{-}GJR\text{-}GARCH$ $(1,1)$ is applied for all financial sectors and EU indices. Table 2.4 also shows that the estimated conditional variance is influenced by past squared shocks along with past conditional variance (around 0.1194 to 0.1865). The empirical distribution function must be used to change the standardised $i.i.d.$ residuals homogenous margins after the marginal specifications, thus enabling our model to become semiparametric. Against fully parametric models, semiparametric models possess a more empirical appeal (Patton, 2012a).

Table 2.4: Estimates of the marginal models

	Banks	Financial	Insurance	Real-estate	EU
Panel A: Conditional mean					
μ	0.0001	0.0005[a]	0.0000	0.0005[a]	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
φ	0.0251	0.0348[b]	0.0357	0.0447[a]	-0.0137
	(0.1169)	(0.0136)	(0.0250)	(0.0164)	(0.0152)
Panel B: Conditional variance					
ω	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.0104	0.0272[a]	0.0000	0.0613[a]	0.0000
	(0.0096)	(0.0098)	(0.0129)	(0.0126)	(0.0113)
β_1	0.9174[a]	0.8847[a]	0.9021[a]	0.8717[a]	0.8906[a]
	(0.0162)	(0.0133)	(0.0138)	(0.0174)	(0.0126)
γ	0.1409[a]	0.1495[a]	0.1715[a]	0.1194[a]	0.1865[a]
	(0.0269)	(0.0220)	(0.0222)	(0.0249)	(0.0230)
$\alpha_1 + \beta_1$	0.9278	0.9119	0.9021	0.9330	0.8906
Panel C: Distributional parameters					
υ	8.4918[a]	8.0926[a]	9.3844[a]	6.2651[a]	10.9136[a]
	(1.1703)	(0.9340)	(1.2464)	(0.5910)	(2.6341)
ξ	-0.0651	-0.0745[a]	-0.0806[a]	-0.0613[a]	-0.1173[a]
	(0.0561)	(0.0198)	(0.0215)	(0.0208)	(0.0203)
$\mathcal{LL}$	11,498.85	12,621.06	11,709.78	13,306.15	13,328.04
AIC	-22,981.71	-25,226.11	-23,403.57	-26,596.29	-26,640.07

Notes: The table reports the marginal model estimates for each index returns over the period January 2001 to December 2016. Panel A contains the parameter estimates for the conditional mean, modelled using an $AR(1)$ model; Panel B contains parameter estimates from $GJR\text{-}GARCH$ $(1,1)$ models of the conditional variance; and Panel C contains the parameter estimates for skewed-t models of the distribution of the standardized residuals. $\mathcal{LL}$ is the value of the log-likelihood function at the optimum. AIC corresponds to the Akaike criteria. Values in parenthesis are the standard errors. [a] and [b] indicate statistical significance at 1% and 5%, respectively.

The goodness-of-fit test is then assessed on the marginal models through the application of the Breusch-Godfrey serial correlation LM ($BGLM$) test (Breusch, 1978; Godfrey, 1978) to each underlying error terms' $PITs$ via the $ARMA(p,q)$-$GARCH(p,q)$ processes. The $BGLM$ test is conducted for the first four moments of the $PITs$ (u and v) of the marginal models' standardised residuals; therefore, $(\mathrm{u}-\bar{\mathrm{u}})^{\mathrm{k}}$ and $(\mathrm{v}-\bar{\mathrm{v}})^{\mathrm{k}}$ is regressed on 10 lags of both variables lags for $k = 1, 2, 3, 4$. In Table 2.5, the p-values have provided no sign of serial correlation, which then explains the marginal model's suitability.

Table 2.5: Breusch-Godfrey serial correlation LM test

Sector	First moment	Second moment	Third moment	Fourth moment
Banks	0.7954	0.4474	0.2575	0.2141
Financial	0.6214	0.4821	0.2606	0.1945
Insurance	0.6845	0.3446	0.1626	0.1262
Real-estate	0.7018	0.7010	0.7123	0.7612
EU	0.1124	0.0045	0.0005	0.0004

Notes: The table presents the goodness of fit test by reporting the p-values for the test for serial correlations in the standardized residuals of each index returns, based on Breusch-Godfrey serial correlation LM at 10 lags. The test was carried out for four moments.

2.5.2 Estimation Results of Copula Functions

The dependence structure estimated outcomes are prepared via the static and dynamic copulas for each EU-Sector return pair as shown in Tables 2.6 and 2.7. AIC adjusted is used for the small-sample bias to identify the best copula functions. While looking at the differences of various copula specifications, the results of these tables show firm proof that time-varying parameter (TVP) copulas provide the best fit for all pairs. These tables reveal that Student-t copula is the best fit for all EU-Sector pairs for both static and time-varying copulas. These results indicate that the dynamic copulas disclose temporal variations in the dependence structure of the concerned sectors. The parameters of all copulas are significant. Student-t copula' degrees of freedom are relatively low (between 5 to 6), indicating that tail dependence and comovement of all EU-Sector pairs are non-normal. The static Student-t parameter ρ holds statistical significance for all EU related pairs. Student-t copula' results show that the symmetric tail dependence between EU-Insurance pair is greater than the dependence of EU-Realestate pair. Therefore, we can conclude that all financial sectors are typically responsive to the EU index.

Figure 2.2 demonstrates the temporal evolution of the time-varying copula specification between EU and each financial sector. It is evident that there is moderate connection in the temporal evolution of dependence for the bivariate relationships of the Student-t copula GAS specification. EU-banks, financial and insurance sectors display peaks which are significant that correspond to the 2009-2010 Euro debt crises. All EU-sector pairs present mild clustering whereas there is an upward trend that can be seen for the EU-real-estate pair. This suggests that all financial sectors react consistently to occurring EU systemic events.

Table 2.6: Bivariate time-invariant copula estimates of EU index with EU financial sectors indices

Copula	Banks	Financial	Insurance	Real-estate
Gaussian Copula				
ρ	0.8535 *	0.8011*	0.8632*	0.6172*
	(0.0044)	(0.0057)	(0.0041)	(0.0101)
$\mathcal{LL}$	2,720.76	2,142.70	2,853.50	1,001.10
AIC	-5,437.52	-4,283.40	-5,705.10	-2,000.30
Gumbel Copula				
γ	2.7134 *	2.3172*	2.8184*	1.6716*
	(0.0342)	(0.0297)	(0.036)	(0.0217)
$\mathcal{LL}$	2,570.70	-4,002.80	2,719.90	931.56
AIC	-5,139.30	2,002.40	-5,437.80	-1,861.10
Rotated Gumbel Copula				
γ	2.8048 *	2.3949*	2.8923*	1.7133*
	(0.0552)	(0.0416)	(0.0573)	(0.0252)
$\mathcal{LL}$	2,717.09	2,150.80	2,839.95	1,031.27
AIC	-5,430.18	-4,297.61	-5,675.89	-2,058.53
Clayton Copula				
θ	2.5633*	2.0367*	2.6792*	1.1012*
	(0.0506)	(0.0433)	(0.0525)	(0.0223)
$\mathcal{LL}$	2,279.10	1,825.60	2,386.10	879.07
AIC	-4,556.10	-3,649.20	-4,770.20	-1,756.10
Symmetrised Joe-Clayton (SJC) Copula				
λ_U	0.6449 *	0.5699*	0.6731*	0.3702*
	(0.0089)	(0.0098)	(0.0494)	(0.0181)
λ_L	0.7120 *	0.658*	0.7206*	0.4747*
	(0.0013)	(0.0065)	(0.0292)	(0.0137)
$\mathcal{LL}$	2,659.90	2,131.10	2,817.40	1,045.60
AIC	-5,315.70	-4,258.30	-5,630.80	-2,087.30
Student-t Copula				
ρ	0.8599 *	0.8072*	0.868*	0.6235*
	(0.0032)	(0.0051)	(0.0036)	(0.0082)
v^{-1}	5.7389 *	5.9983*	5.4339*	5.5389*
	(0.1778)	(0.568)	(0.1795)	(0.8842)
$\mathcal{LL}$	2,818.00	2,220.40	2,952.70	1,069.40
AIC	**-5,632.00**	**-4,436.70**	**-5,901.50**	**-2,134.80**

Notes: the table shows the maximum likelihood estimates for the different dynamic bivariate copulas. The standard error values are given in parenthesis. The asterisk indicates statistical significance at 5% level. The bold values indicate the best copula.

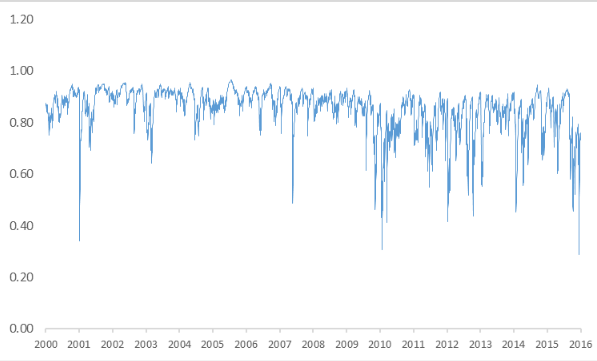
Table 2.7: Bivariate time-varying copula estimates of EU index with EU financial sectors indices

Copula	Banks	Financial	Insurance	Real-estate
TVP-Gaussian Copula				
$\boldsymbol{\Psi_0}$	2.6404*	2.2306*	2.6597*	1.3726*
	(0.0742)	(0.0535)	(0.0506)	(0.1392)
Ψ_1	0.0811*	0.0719*	0.0607*	0.0437*
	(0.0081)	(0.009)	(0.0073)	(0.0061)
Ψ_2	0.9626*	0.9403*	0.9486*	0.9893*
	(0.0076)	(0.0139)	(0.0116)	(0.004)
$\mathcal{LL}$	2,967.30	2,262.30	2,971.95	1,195.70
AIC	-5,930.60	-4,520.60	-5,939.90	-2,387.40
TVP-Gumbel Copula				
ω	0.0222*	0.0123*	0.0332*	-0.0065*
	(0.0025)	(0.0020)	(0.0026)	(0.0015)
α	0.1457*	0.1253*	0.1144*	0.1100*
	(0.0098)	(0.0165)	(0.0206)	(0.0179)
β	0.9594*	0.9563*	0.9452*	0.9870*
	(0.0002)	(0.0003)	(0.0156)	(0.0153)
$\mathcal{LL}$	2,570.66	2,002.39	2,719.92	931.56
AIC	-5,137.32	-4,000.77	-5,435.84	-1,859.12
TVP-Rotated Gumbel Copula				
ω_L	0.0247*	0.0308*	0.0486*	-0.0051*
	(0.0129)	(0.0064)	(0.0058)	(0.0016)
α_L	0.1540*	0.1526*	0.1241*	0.0985*
	(0.0744)	(0.0192)	(0.0267)	(0.0184)
β_L	0.9593*	0.9073*	0.9272*	0.9894*
	(0.0324)	(0.0167)	(0.0075)	(0.0029)
$\mathcal{LL}$	2,717.09	2,150.81	2,839.95	1,031.27
AIC	-5,430.18	-4,297.61	-5,675.89	-2,058.53
TVP-Clayton Copula				
ω	0.3040*	0.2657*	0.2731*	0.1160*
	(0.0740)	(0.0511)	(0.0586)	(0.0226)
α	-1.6321*	-1.1909*	-1.2923*	-0.6336*
	(0.3577)	(0.2160)	(0.2550)	(0.1239)
β	0.9063*	0.8644*	0.8980*	0.9464*
	(0.0266)	(0.0307)	(0.0246)	(0.0116)
$\mathcal{LL}$	2,482.68	1,910.25	2,484.87	1,025.93
AIC	-4,959.37	-3,814.49	-4,963.73	-2,045.85
TVP-Symmetrised Joe-Clayton (SJC) Copula				
ω_U	1.9420*	0.9808*	0.1320*	-1.7157*
	(0.0008)	(0.0054)	(0.0000)	(0.0229)
α_U	-8.5843*	-7.9933*	-4.4356*	-1.4174*
	(0.0018)	(0.0291)	(0.0009)	(0.0097)
β_U	-0.5501*	0.6091*	1.6654*	3.8224*
	(0.0010)	(0.0055)	(0.0002)	(0.0477)
ω_L	1.7820*	2.6173*	1.3945*	0.7290*
	(0.0008)	(0.0058)	(0.0002)	(0.0044)
α_L	-8.6323*	-4.8254*	-2.5540*	-6.6898*
	(0.0173)	(0.0406)	(0.0002)	(0.1501)
β_L	0.2038*	-1.9401*	-0.2517*	0.8737*
	(0.0002)	(0.0051)	(0.0000)	(0.0010)
$\mathcal{LL}$	2,828.02	2,204.88	2,875.97	1,180.00
AIC	-5,652.03	-4,405.77	-5,747.94	-2,355.99
TVP-Student-t Copula				
θ	10.2315*	8.0000*	7.0938*	9.2262*
	(1.4870)	(0.9527)	(0.7739)	(1.4076)
α	0.0603*	0.0560*	0.0425*	0.0449*
	(0.0076)	(0.0076)	(0.0053)	(0.0065)
β	0.9280*	0.9191*	0.9358*	0.9443*
	(0.0102)	(0.0122)	(0.0082)	(0.0087)
$\mathcal{LL}$	3,006.52	2,337.58	3,033.39	1,241.55
AIC	**-6,009.04**	**-4,671.15**	**-6,062.78**	**-2,479.09**

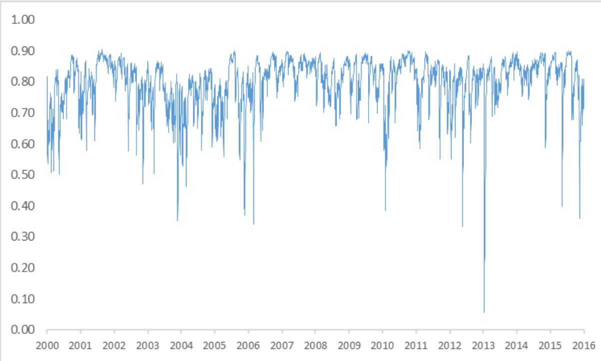
Notes: see notes in table 2.6.

Panel (A): Gaussian Copula

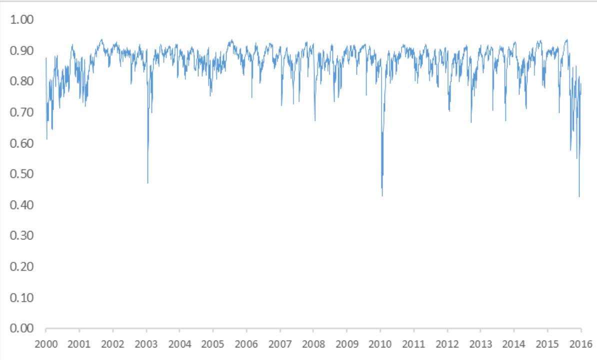
Banks



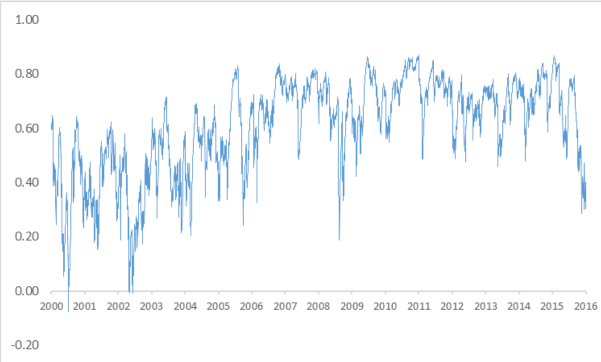
Financial



Insurance

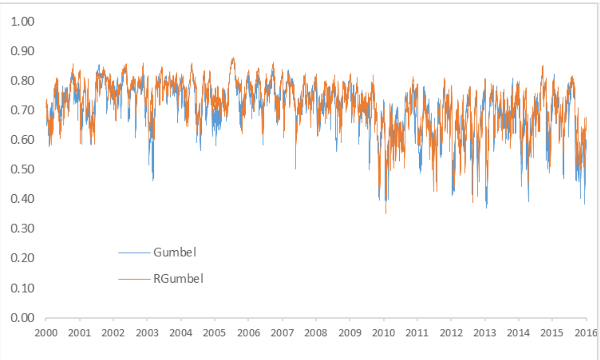


Real-estate



Panel (B): Gumbel and Rotated Gumbel Copulas

Banks



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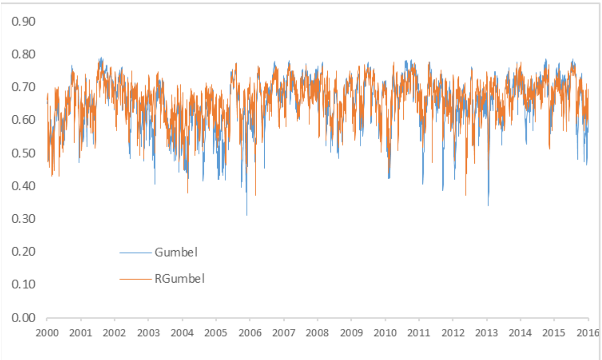

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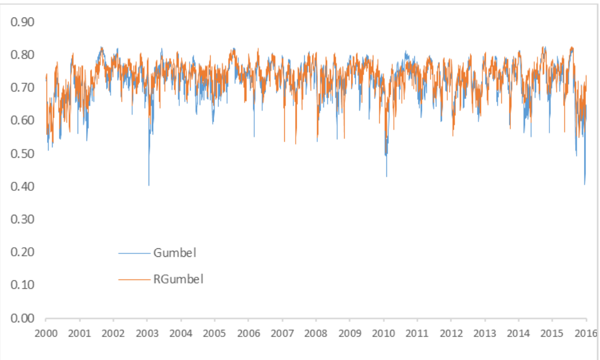
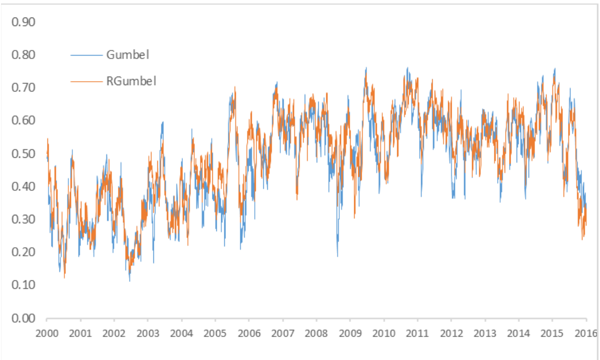
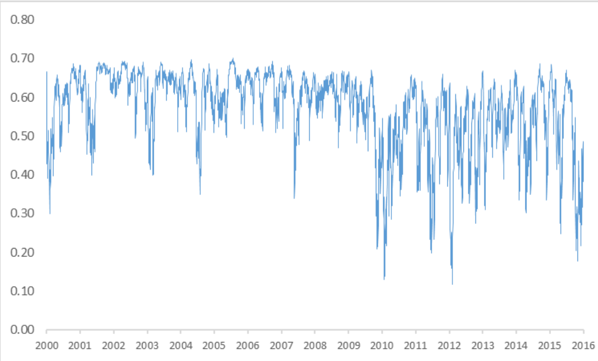


Real-estate

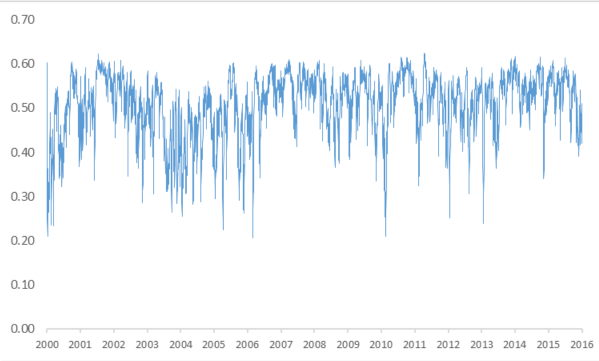


Panel (C): Clayton Copula

Banks



Financial



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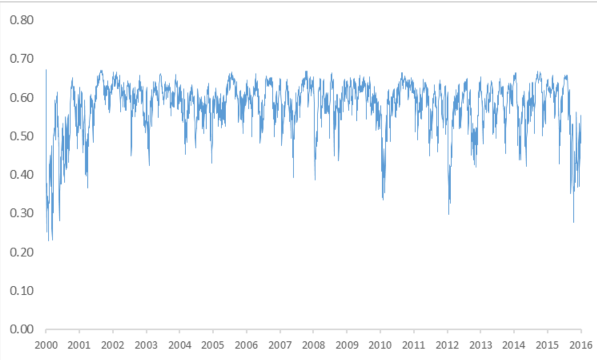
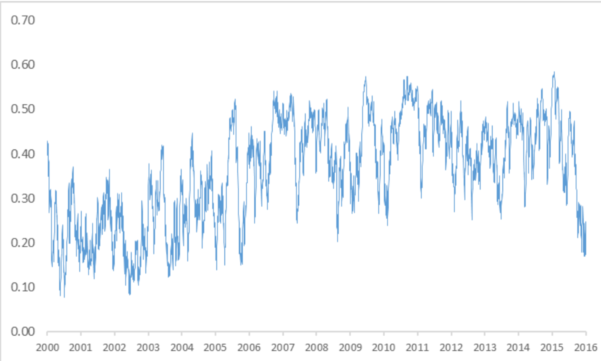
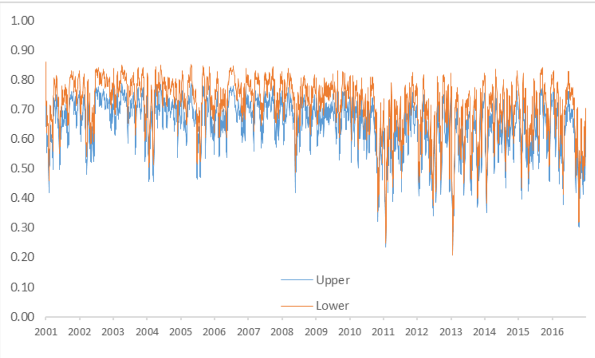


Real-estate

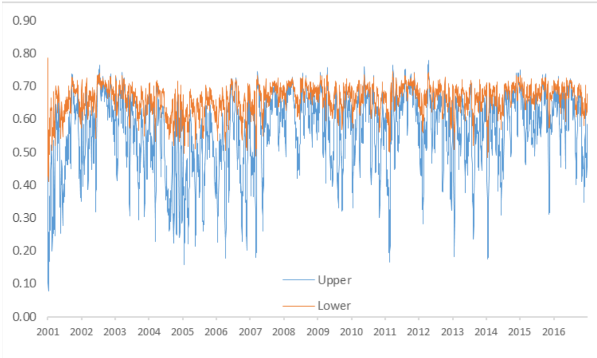


Panel (D): SJC Copula

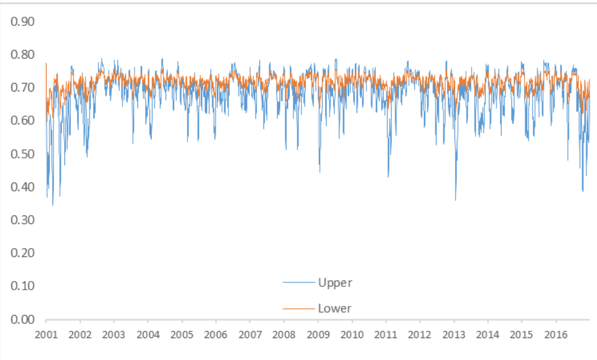
Banks



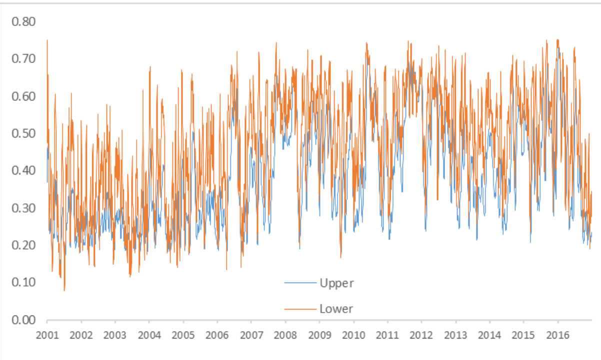
Financial



Insurance

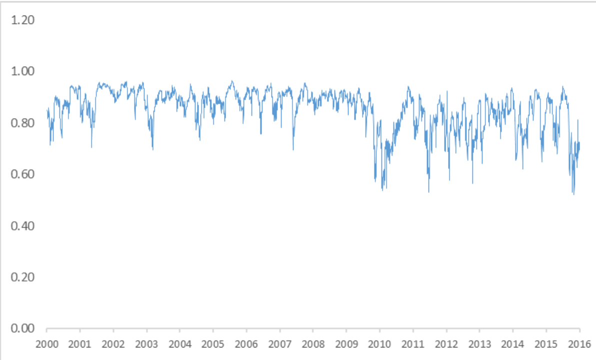


Real-estate

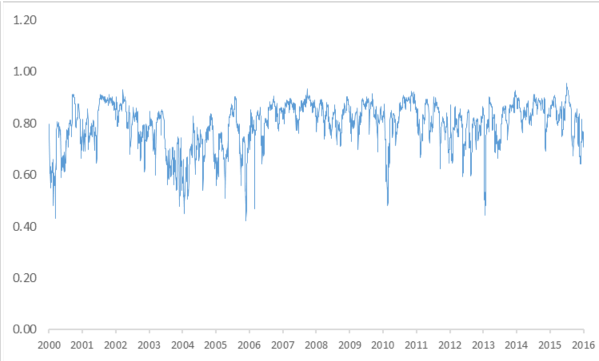


Panel (E): Student-t Copula

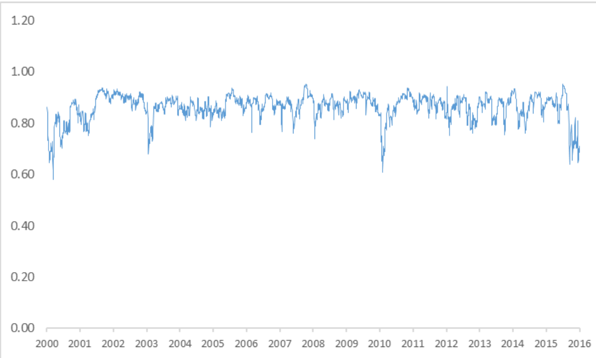
Banks



Financial



Insurance



Real-estate

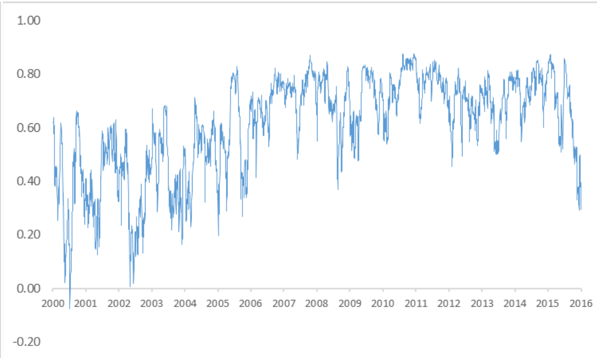


Figure 2.2: Time-varying copula dependence between EU and each financial sector

Notes: This figure displays the time-varying dependence structure between EU and four financial sectors pairs for six copula models during the full period (2001-2016). Lower tail dependence is higher than upper tail dependence.

2.5.3 Copula ΔCoVaR Estimates

The VaR, $CoVaR$ and $\Delta CoVaR$ risk measures for the EU and four financial sectors are computed in order to investigate the effects of the copula findings in relation to the risk spillover across the EU-sector pairs. Table 2.8 reports the downside $\Delta CoVaR$ for each financial sector using five different copulas during the full sample period. The ranking of systemic risk contribution is consistent among all copula models. Banking sector has the highest systemic risk contribution while the real-estate sector has the lowest contribution. Table 2.9 reports the downside and upside $\Delta CoVaR$ based on student-t copula for each financial sector during four periods of analysis (full, pre-crisis, crisis and post-crisis). Interestingly, systemic risk ranking of each financial sector differs from one period to another. For example, banking sector is the most systemically important financial sector during the crisis, post crisis and full periods while it has the third rank during the pre-crisis period.

The downside $\Delta CoVaR$ in the crisis period is higher than the downside $\Delta CoVaR$ in the post-crisis and pre-crisis periods respectively for all financial sectors. The results for the upside

$\Delta CoVaR$ are shown to be similar as well. The results obtained from quantifying the $CoVaR$ spillover from EU to financial sectors has nearly the same effect for all sectors but differs in magnitude during different time horizons. It is worth noting that downside $\Delta CoVaR$ is always higher than the upside $\Delta CoVaR$ for all financial sectors during different time horizons.

Table 2.8: Average Copula ΔCoVaR for each financial sector

Sector		Copula $\Delta CoVaR$											
		Gaussian		Gumbel		RGumbel		Clayton		SJC		Student-t	
		Rank	%	Rank	%	Rank	%	Rank	%	Rank	%	Rank	%
Banks	Mean	1	-3.88	1	-3.74	1	-3.89	1	-3.91	1	-1.48	1	-3.89
	STD		2.10		2.02		2.11		2.12		0.80		2.10
Financial	Mean	3	-2.95	3	-2.79	3	-2.98	3	-3.01	3	-1.11	3	-2.97
	STD		1.60		1.51		1.62		1.63		0.60		1.61
Insurance	Mean	2	-3.66	2	-3.54	2	-3.67	2	-3.69	2	-1.40	2	-3.67
	STD		2.05		1.98		2.06		2.07		0.78		2.05
Real-estate	Mean	4	-2.48	4	-2.25	4	-2.64	4	-2.70	4	-0.89	4	-2.58
	STD		1.33		1.21		1.42		1.29		0.48		1.39

Notes: The table ranks the average contribution to systemic risk measures according to $\Delta CoVaR$ of each financial sector in the Eurozone. Simple averages and standard deviations are computed within the overall period (2001-2016). Standard deviations and average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ risk measures are generated under the assumption of $q = 5\%$ level.

Table 2.9: Average Copula ΔCoVaR for each financial sector during different periods

Sector		**Full Period**		**Pre-crisis Period**		**Crisis Period**		**Post-crisis Period**	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**%**
Panel (A): Downside $\Delta CoVaR$									
Banks	Mean	1	-3.89	3	-1.705	1	-5.51	1	-4.94
	STD		2.10		0.36		2.67		1.40
Financial	Mean	3	-2.97	4	-1.65	4	-4.36	3	-2.89
	STD		1.61		0.65		1.96		0.97
Insurance	Mean	2	-3.67	1	-2.04	2	-5.17	2	-3.83
	STD		2.05		0.38		2.88		1.37
Real-estate	Mean	4	-2.58	2	-1.707	3	-4.40	4	-2.74
	STD		1.39		0.51		1.83		0.88
Panel (B): Upside $\Delta CoVaR$									
Banks	Mean	1	3.57	3	1.59	1	5.12	1	4.53
	STD		1.93		0.33		2.48		1.28
Financial	Mean	3	2.70	4	1.48	4	4.06	3	2.64
	STD		1.46		0.58		1.83		0.88
Insurance	Mean	2	3.37	1	1.89	2	4.77	2	3.53
	STD		1.89		0.35		2.65		1.26
Real-estate	Mean	4	2.24	2	1.49	3	3.98	4	2.48
	STD		1.21		0.44		1.65		0.80

Notes: The table ranks the average contribution to systemic risk measures according to Student-t Copula $\Delta CoVaR$ of each financial sector in the Eurozone. Panel (A) uses 5% downside $\Delta CoVaR$ while Panel (B) uses 95% upside $\Delta CoVaR$. Simple averages and standard deviations are computed within four periods; full period (2001-2016), pre-crisis period (Q3 2004-Q2 2007), crisis period (Q3 2007-Q2 2010) and post-crisis period (Q3 2010- Q2 2013). Standard deviations and average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ risk measures are generated under the assumption of $q = 5\%$ level.

Table 2.10 reports descriptive statistics of the downside and upside $VaRs$, contribution and exposure $\Delta CoVaRs$ in terms of EU and financial sectors returns. The VaR values' mean and standard deviation of the EU index are greater than their financial sectors' counterparts. It is also shown that the average and standard deviation of the downside $\Delta CoVaR$ are higher than their upside counterpart. These results are essential to control and observe market risk.

Table 2.10: Descriptive Statistics of VaR and Copula ΔCoVaR

Sector		$VaR_{5\%}$	$VaR_{95\%}$	$CoVaR_{5\%}$	$CoVaR_{50\%}$	$CoVaR_{95\%}$	$\Delta CoVaR_{5\%}$	$\Delta CoVaR_{95\%}$
Panel (A): Contribution $CoVaR$ and VaR of Financial Sectors								
Banks	Mean	-3.03	2.81	-4.97	-1.08	2.49	-3.89	3.57
	STD	1.69	1.57	2.72	0.61	1.32	2.10	1.93
Financial	Mean	-2.24	2.18	-3.70	-0.73	1.97	-2.97	2.70
	STD	1.23	1.20	2.05	0.44	1.02	1.61	1.46
Insurance	Mean	-2.75	2.64	-4.69	-1.02	2.35	-3.67	3.37
	STD	1.59	1.52	2.66	0.60	1.29	2.05	1.89
Real-estate	Mean	-1.93	1.79	-3.05	-0.48	1.76	-2.58	2.24
	STD	1.05	0.98	1.68	0.30	0.91	1.39	1.21
Panel (B): Exposure $CoVaR$ and VaR of Eurozone Index								
Banks	Mean	-1.93	1.79	-3.11	-0.66	1.59	-2.45	2.25
	STD	1.04	0.97	1.57	0.35	0.76	1.21	1.11
Financial	Mean	-1.93	1.79	-3.09	-0.63	1.62	-2.47	2.24
	STD	1.04	0.97	1.56	0.34	0.78	1.22	1.11
Insurance	Mean	-1.93	1.79	-3.11	-0.66	1.59	-2.44	2.25
	STD	1.04	0.97	1.57	0.36	0.76	1.11	1.11
Real-estate	Mean	-1.93	1.79	-3.01	-0.49	1.71	-2.53	2.20
	STD	1.04	0.97	1.52	0.27	0.82	1.25	1.09

Notes: The table presents the upside and downside VaR, $CoVaR$ and $\Delta CoVaR$ of EU index and each financial sector. Simple averages and standard deviations are computed within the full period (2001-2016). Standard deviations and average $\Delta CoVaR$ figures are expressed as a percentage. Contribution $CoVaR$ measures $CoVaR$ from financial sector to EU while Exposure $CoVaR$ measures $CoVaR$ from EU to financial sector.

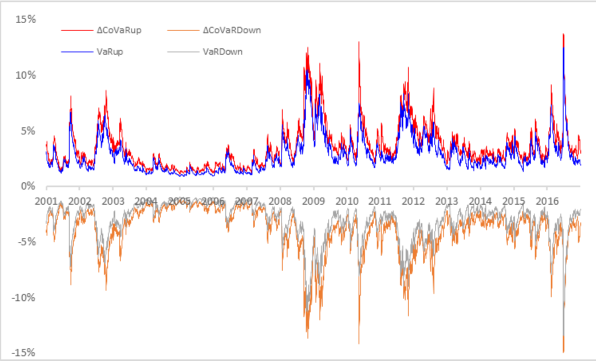
Figure 2.3 shows a depiction of the estimates of the time-varying VaR and $\Delta CoVaR$ to measure the spillover from financial sectors the EU (Panel A) and vice versa (Panel B). The downside and upside $VaRs$ for the EU index (Panel B) are demonstrated on the graphical plots to be systematically lower than those for the financial sectors (Panel A), suggesting that in comparison to those of four financial indices in both the bearish and bullish market conditions, the EU index is less risky. Graphical analysis of the upside and downside $CoVaRs$ also show that different trajectory during all subperiods with substantial differences in magnitude. The impact of the GFC and Euro crisis on subperiods risk spillover for the short and long positions is apparent in all the sectors. Through analysis of the downside and upside risk, it can be seen that there is a larger systemic influence on the EU index by financial sectors indices during the crisis than otherwise. This is an indication that with an increase in the VaR of financial sectors, an increase in the conditional VaR of the EU index would follow. More interestingly, there is greater importance in the crisis period than post-crisis and pre-crisis periods for both risk spillover to the EU and financial sectors. Results for the upside risk spillover are also similar.

Interestingly, the upside and downside VaR and $\Delta CoVaR$ trajectories are observed to showcase a comparable movement for all the circumstances with significant changes in scale across the sectors. It is observed that the effect of the 2007 GFC and 2009 Euro crisis on the EU index and financial sectors indices is obviously clear as substantial sudden variations were discovered during the 2008-2009 period. The banking sector index is seen to be highly systemic contributor to EU systemic risk during the GFC and Euro crisis against all other financial sectors when considering risk spillover from financial sectors to EU. Whereas the least important to EU systemic risk contribution is the real-estate sector as shown in Panel (A). VaR and $\Delta CoVaR$ risk measures vary where the downside $\Delta CoVaR$ suddenly drops or the upside $\Delta CoVaR$ raises considerably more than the downside and upside $VaRs$ for all the sectors during the same time horizon. This suggests that each sector has systemic influence on the other sector. Holistically, substantial bidirectional risk spillover across the EU and financial sectors are implied by these findings. These graphical proofs align with the descriptive statistics reported in Table 2.10.

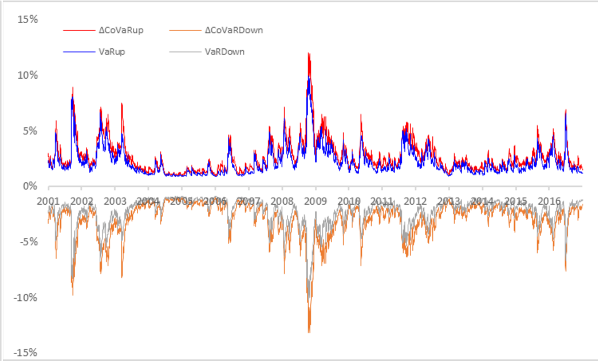
Typically, the reported evidence has significant impacts on market participants and policy makers in a variety of matters. Firstly, the existence of strong dependence across the financial sectors and EU index leads to the possibility of potential risk spillover and the inclination to boom or crash together that enhances systemic risk. Furthermore, the results may be significant for policymakers who are aiming to develop macro-prudential regulation to assess systemic risk contribution and maintain financial stability. While considering the stock market volatilities with the related spread of contagious shocks from financial sectors to EU index as well as with general macroeconomic effects, our research may be significant for policy makers and regulators, particularly for ECB and Eurozone member states, in the designing and implementing the correct intervention policies.

Panel (A): Contribution ΔCoVaR and VaR

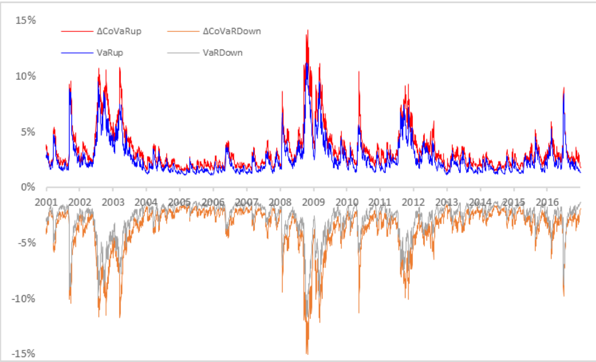
Banks



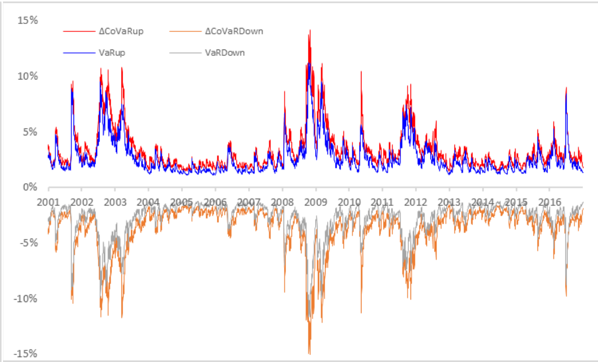
Financial



Insurance

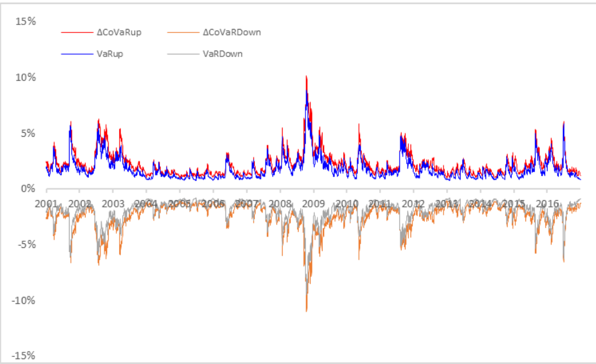


Real-estate

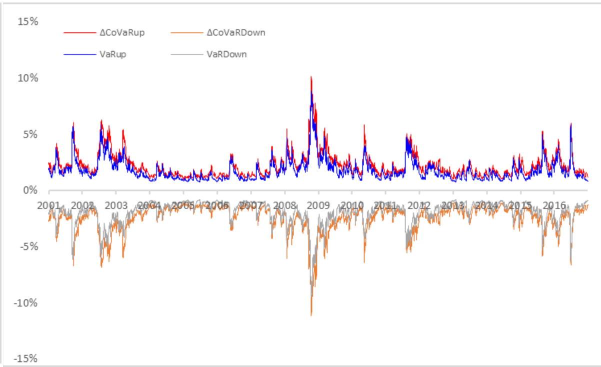


Panel (B): Exposure ΔCoVaR and VaR

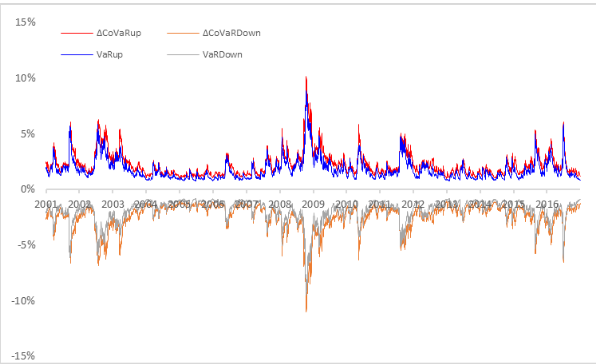
Banks



Financial



Insurance



Real-estate

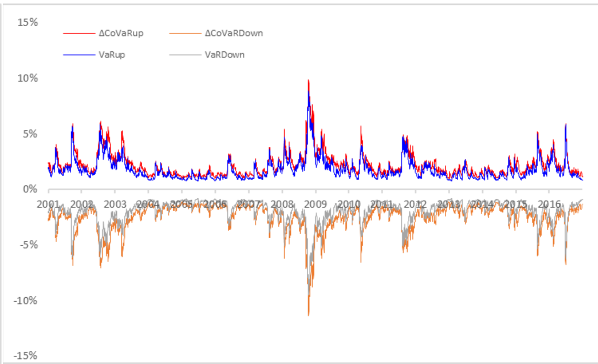


Figure 2.3: Downside and Upside Copula ΔCoVaR between EU and each financial sector.

Notes: The time-varying dependence structure is based on the best fitted copulas (Student-*t* Copula). Panel (A) represents the systemic risk contribution from each financial sector to *EU* index and the *VaR* of each sector while Panel (B) represents the systemic risk exposure from EU index to each financial sector and the VaR of EU.

2.5.4 Estimating Volatility Linkages using GMM Approach

We estimate the correlation of the log information flows among four financial sectors by applying GMM approach to impose the moment restrictions of our stochastic volatility model. In order to construct the data ($y_{k,t}$) required for GMM estimation, we remove both return and volatility seasonal patterns. Firstly, we remove return seasonality by regressing a financial sector return on a set of six dummy variables; one dummy for each weekday and the final dummy is holiday dummy which is the day following a market holiday in order to obtain the residuals ($r_{k,t}$). Secondly, we remove volatility seasonality by regressing $\ln r_{k,t}^2$ on a constant and two dummy variables; one dummy variable for Monday and the other dummy variable is holiday dummy. Finally, we obtain $y_{k,t}$ series by subtracting $E\left[\ln z_{k,t}^2\right]$ (or –1.27) from the sum of the intercept and residuals attained of the estimated regression in the second step. The three-step procedure applied are illustrated in Eqs. 34-36:

$$R_{k,t} = \sum_{i=1}^{6} a_i D_i + r_{k,t} \tag{34}$$

$$\ln r_{k,t}^2 = a_0 + \alpha_1 D_1 + \alpha_2 D_6 + \epsilon_{k,t} \tag{35}$$

$$y_{k,t} = a_0 + \epsilon_{k,t} + 1.27 \tag{36}$$

where D_i stands for dummy variables, D_1-D_5 are dummies of each weekday and D_6 is holiday dummy.

Table 2.11 reports the results from the GMM bivariate estimation for $l = 40$. The mean of natural logarithm of daily variance ($h_{k,t}$) is largest for the banking sector at 0.630 and smallest for the real-estate sector at -0.183. This ranking indicates that banking sector returns are more volatile compared to insurance sector returns, which in turn are more volatile compared to financial sector returns and real-estate sector returns respectively. Nevertheless, it is obvious that the largest variance of $h_{k,t}$ is for banking sector at 1.183 while the smallest variance is for the financial sector at 1.079[7].

[7] This analysis might seem counterintuitive but remember that $\sigma_{h,k}^2$ is the variance of the information flow, $\ln\left(I_{k,t}\right)$. Consequently, if we have a very small mean of $I_{k,t}$, the log transformation yields a highly variable $h_{k,t}$ series. In reality, if $h_{k,t}$ is assumed to be normally distributed and its moment generating function are used to calculate the variance of $I_{k,t}$ implied by each of these estimates, the variance is largest for the banking sector followed insurance, financial and realestate sectors respectively.

Table 2.11: Stochastic volatility Estimation Results using GMM Model

Parameter	Banks (i)/ Financial (j)		Banks (i)/ Insurance (j)		Banks (i)/ Real-estate (j)		Financial (i)/ Insurance (j)		Financial (i)/ Real-estate (j)		Insurance (i)/ Real-estate (j)	
	Coefficient Estimates	Standard Error	Coefficient Estimates	Standard Error	Coefficient Estimates	Standard Error	Coefficient Estimates	Standard Error	Coefficient Estimates	Standard Error	Coefficient Estimates	Standard Error
$\mu_{h,i}$	0.63062	0.04599	0.72209	0.03757	0.59374	0.04191	0.24474	0.04099	0.26505	0.04246	0.65227	0.03877
$\sigma^2_{h,i}$	1.18268	0.03959	1.11850	0.03875	1.14723	0.03806	1.07859	0.04061	1.05454	0.04194	1.07303	0.03802
$\phi_{h,i}$	0.96678	0.00203	0.96489	0.00181	0.97126	0.00179	0.96907	0.00217	0.97574	0.00175	0.97724	0.00188
$\mu_{h,j}$	0.26310	0.04088	0.58710	0.04030	-0.18308	0.03930	0.56007	0.04320	-0.22410	0.04483	-0.18726	0.04006
$\sigma^2_{h,j}$	1.07921	0.04180	1.11875	0.04053	1.11913	0.03584	1.13463	0.04326	1.13838	0.03849	1.11777	0.03603
$\phi_{h,j}$	0.96772	0.00213	0.97365	0.00194	0.97697	0.00169	0.97394	0.00216	0.97899	0.00170	0.97892	0.00160
$\rho_{h,ij}$	0.85719	0.02822	0.84406	0.02390	0.67235	0.03538	0.86855	0.02490	0.74534	0.03026	0.58251	0.03934
$\rho_{\xi,ij}$	0.43818	0.01558	0.53829	0.01202	0.21907	0.01449	0.44520	0.01384	0.33757	0.01321	0.28017	0.01371
J-statistic	156.1207		174.5565		187.3196		192.8849		143.6953		177.5762	
p-value	0.50482		0.16021		0.04957		0.02709		0.76897		0.12477	

Notes: The table displays the parameter estimates of generalized method of moments and over-identifying test statistics (J-statistic) for bivariate models of the log volatility ($h_{k,t}$) in four financial sectors namely banking, financial service, insurance and real-estate. The estimation procedure uses the moment conditions implied by the model for seasonally adjusted, log squared returns ($y_{k,t}$) to estimate the mean ($\mu_{h,k}$), variance ($\sigma^2_{h,k}$) and $AR(1)$ parameter ($\phi_{h,k}$) of the log volatility processes. The bivariate estimation also provides the estimates of the correlations between the volatilities ($\rho_{h,ij}$) and between the disturbance terms ($\rho_{\xi,ij}$) in market i and j. This table reports the coefficients estimates and standard errors for each model based on the lag length of 40, as well as the J-statistics which, under the model, are distributed x^2_{4l-3}; the full sample period is from 3 January 2001 to 31 December 2016 (4174 daily observations).

The GMM estimated parameter that is of greatest importance in the bivariate analysis is the correlation of the log volatility between sectors, $\rho_{h,ij}$, which reflects the linkages between financial sector information flow. The estimated correlation of the log information flows for the banking/ financial sectors pair is 85.72%, with standard error 0.02822, the estimates for banking/ insurance, banking/ real-estate, financial/ insurance, financial/ real-estate, and insurance/ real-estate pairs are 84.41%, 67.24%, 86.86%, 74.53% and 58.25% respectively. Since all the associated standard errors are small (less than 0.03), the estimated correlations are relatively precise and consequently, the volatility linkages among the four financial sectors are strong.

The over-identifying test statistics (J-test) reveals little evidence of misspecification for four GMM bivariate pair estimations (banking/ financial, banking/ insurance, financial/ real-estate and insurance/ real-estate) but the p-value is on the border for banking/ real-estate pair and is not significant for financial/ insurance sectors pair.

2.6 Robustness Check

We conducted detailed checks to investigate the main conclusions' robustness in relation to the previous subsection. To preserve space, quickly discussed below are these checks mentioned and the outcomes, but a complete analysis is ready from the authors upon request.

2.6.1 Kolmogorov–Smirnov (KS) test

An important restraint of the original $\Delta CoVaR$ systemic risk measure, i.e. the lack of a formal test to equate each individual financial institution or financial sector's relative systemic risk contribution. Significantly, this limitation was overcome by applying the Kolmogorov–Smirnov (KS) test designed by Abadie (2002), as it is applied using bootstrapping techniques.

We suggest a formal significance test of the $\Delta CoVaR$ built on the KS test to figure if a certain financial sector significantly adds on systemic risk. A dominance test is also applied, with the objective of determining if a certain financial sector contributes more to systemic risk in comparison to another.

The objective of the significance test is to highlight if a financial sector is considered to be systemically risky. We study the copula $\Delta CoVaR$ conditional on a certain financial sector to determine if it is statistically equivalent to 0 (meaning that specific financial sector is not systemically risky) or statistically different from 0. A test was carried out to determine if there was a difference between the $CDFs$ of the copula $CoVaRs$ at a quantile of 5% and 50%. The copula $\Delta CoVaR$'s stochastic dominance was assessed to order in accordance of the concerned financial sectors in terms of their systemic risk contributions. The bootstrap KS test developed by Abadie (2002) was used to do this.

The two-sample KS statistic for the significance test is identified as below:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x|F_m(x) - G_m(x)| \tag{37}$$

where $F_m(x)$ and $G_m(x)$ are the CDFs of the $CoVaRs$ related to the 5% and 50% quantiles, respectively, and m and n represent the size of the two samples. The null hypothesis is the equality of the $CDFs$ of the $CoVaRs$ related to the 5% and 50% quantiles:

$$H_0: copula\ \Delta CoVaR_q^{sys|sector_i} = copula\ CoVaR_{5\%}^{sys|sector_i} - copula\ CoVaR_{50\%}^{sys|sector_i} = 0 \tag{38}$$

The dominance test's objective is to test the significance of the ranking gathered from the $\Delta CoVaRs$ to determine if a given financial sector i does really attribute greater systemic risk in comparison to financial sector j. For a second time, we depend on Abadie's bootstrap KS test (2002) to compare the $\Delta CoVaRs$' $CDFs$ relative to the two financial sectors. The two-sample KS test statistic for the dominance test is identified as below:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x|A_m(x) - B_n(x)| \tag{39}$$

where $A_m(x)$ and $B_n(x)$ signify the $\Delta CoVaRs$' $CDFs$ related to two financial sectors; m and n are the size of the two samples. The null hypothesis is identified as below:

$$H_0: \left|copula\ \Delta CoVaR_q^{sys|sector_i}\right| > \left|copula\ \Delta CoVaR_q^{sys|sector_j}\right| \tag{40}$$

Provided that the estimated $\Delta CoVaRs$ are negative, in order to generate a simpler debate, interpreting the null hypothesis and comparing the bootstrap KS tests' results will be based upon the $\Delta CoVaR$ absolute values.

In relation to the significance test, the KS statistics and the related bootstrap p-values under Table 2.12 reveal the null hypothesis of no difference between the $CoVaR$ under a stress period (i.e. a 5% quantile) and the normal time $CoVaR$ (i.e. a 50% quantile), i.e. $\Delta CoVaR = 0$. At a 1% significance level, the null hypothesis was rejected for different financial sector of concern within the Eurozone, demonstrating there is a significant effect by each financial sector when the real economy is experiencing a distress period. Therefore, there is a significant contribution in the Eurozone's systemic risk by the four financial sectors of interest.

In relation to the dominance test, the objective of the bootstrap KS test was to run a comparison of the $CDFs$ of the copula $\Delta CoVaRs$ which are tied to two different financial sectors. Table 2.13 provides the results. We assess if the risk for the financial sector is equal to (or less than) the real-estate industry for the system. The p-value communicates that at a 1% significance level the null hypothesis is rejected, therefore showing that financial sector is systematically of higher risk than real-estate sector.

We can settle that the Eurozone's real-estate sector has lower systematic risk than its financial sector. Results about the five following comparisons, i.e. $Insurance \leq Financial$, $Insurance \leq Realestate$, $Banks \leq Insurance$, $Banks \leq Financial$ and $Banks \leq Realestate$, are more direct. In each case at a 1% significance level the null hypothesis is rejected, therefore providing confirmation that the banking sector has a higher systematic risk than the insurance sector, financial sector and the real-estate sector, respectively. The dominance test outcome also reveals for each comparison pair, there is a statistical difference between the contributions of each financial sector to systemic risk.

The different subperiods $\Delta CoVaR$ asymmetries are investigated for the financial sectors and the outcome is revealed in Table 2.14-2.15. Ultimately, a significant difference is discovered across the downside $\Delta CoVaR$ and the upside $\Delta CoVaR$ for all three subperiods. This finding suggests risk spillover possess an asymmetric behaviour in time horizons. These tables show asymmetric downside and upside $\Delta CoVaRs$ for the three-time horizons (sector's spillover to EU).

Investors engaged in the market become more susceptible to the downside risk than the upside risk and more in the crisis period than in the pre-crisis and post-crisis periods in the sector-to-EU direction. The financial sectors' information set (extreme movements) has an incredible predictive power for the EU index as revealed by the outcome. Variations in real cashflows and expected returns can support the EU's reaction to financial sectors shocks. Along with market fundamentals, other reasonable grounds for the risk spillover include the contagion, interconnectedness, investor reaction to news and investor sentiments. It is noted that the $\Delta CoVaR$ results (Tables 2.8-2.10) align with the sector indices' conditional VaR (Tables 2.12-2.15).

Table 2.12: Kolmogorov-Smirnov Significance Test for Eurozone Financial Sectors

	Copula $\Delta CoVaR$											
	Gaussian		Gumbel		RGumbel		Clayton		SJC		Student-t	
	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue
H_0: $Copula\ \Delta CoVaR\ Banks = 0$	0.8661	0.001	0.8685	0.001	0.8666	0.001	0.8726	0.001	0.9780	0.001	0.8692	0.001
H_0: $Copula\ \Delta CoVaR\ Financial = 0$	0.9032	0.001	0.9049	0.001	0.9044	0.001	0.9131	0.001	0.9825	0.001	0.9073	0.001
H_0: $Copula\ \Delta CoVaR\ Insurance = 0$	0.9176	0.001	0.9193	0.001	0.9181	0.001	0.9219	0.001	0.9947	0.001	0.9205	0.001
H_0: $Copula\ \Delta CoVaR\ Realestate = 0$	0.9564	0.001	0.9564	0.001	0.9619	0.001	0.9725	0.001	0.9880	0.001	0.9617	0.001

Notes: The objective of bootstrap KS test is to assess if the copula $CoVaRs$' $CDFs$ at a 5% and a 50% quantile are dissimilar to each other during the full period. The equality of the $CDFs$ of the copula $CoVaRs$ related to the 5% and 50% quantiles is the null hypothesis. The null hypothesis is rejected at a 1% significance level.

Table 2.13: Kolmogorov-Smirnov Stochastic Dominance Test for Eurozone Financial Sectors

	Copula $\Delta CoVaR$											
	Gaussian		Gumbel		RGumbel		Clayton		SJC		Student-t	
	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue
H_0: $Financial \leq Realestate$	0.1713	0.001	0.2060	0.001	0.1265	0.001	0.1159	0.001	0.2060	0.001	0.1449	0.001
H_0: $Insurance \leq Financial$	0.2122	0.001	0.2299	0.001	0.2062	0.001	0.2029	0.001	0.2285	0.001	0.2093	0.001
H_0: $Insurance \leq Realestate$	0.3811	0.001	0.4328	0.001	0.3250	0.001	0.3099	0.001	0.4319	0.001	0.3480	0.001
H_0: $Banks \leq Insurance$	0.1214	0.001	0.1174	0.001	0.1217	0.001	0.1219	0.001	0.9998	0.001	0.1214	0.001
H_0: $Banks \leq Financial$	0.2640	0.001	0.2759	0.001	0.2575	0.001	0.2556	0.001	0.9998	0.001	0.2601	0.001
H_0: $Banks \leq Realestate$	0.3837	0.001	0.4199	0.001	0.3401	0.001	0.3293	0.001	0.9998	0.001	0.3574	0.001

Notes: The null hypothesis "$Financial \leq Realestate$" signifies that the copula $\Delta CoVaR$ connected to the financial sector is lower (or equal to), in absolute value, than the copula $\Delta CoVaR$ tied to the real-estate sector during the full period. Ultimately, the null hypothesis means that the financial sector is less or equally systemically risky than the real-estate sector. The null hypothesis is rejected at a 1% significance level.

Table 2.14: Kolmogorov-Smirnov Significance Test of Equalities and Time Differences

	Panel (A) $H_0: CoVaR_D = VaR_D$ $H_1: CoVaR_D \neq VaR_D$		Panel (B) $H_0: CoVaR_U = VaR_U$ $H_1: CoVaR_U \neq VaR_U$		Panel (C) $H_0: \Delta CoVaR_D = \Delta CoVaR_U$ $H_1: \Delta CoVaR_D \neq \Delta CoVaR_U$		Panel (D) $H_0: \Delta CoVaR_{crisis} = \Delta CoVaR_{pre-crisis}$ $H_1: \Delta CoVaR_{crisis} \neq \Delta CoVaR_{pre-crisis}$		Panel (E) $H_0: \Delta CoVaR_{crisis} = \Delta CoVaR_{post-crisis}$ $H_1: \Delta CoVaR_{crisis} \neq \Delta CoVaR_{post-crisis}$	
	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue
Banks	0.3957	0.001	0.1020	0.001	0.9998	0.001	0.9361	0.001	0.1253	0.001
Financial	0.4213	0.001	0.0865	0.001	1.0000	0.001	0.8427	0.001	0.4182	0.001
Insurance	0.5250	0.001	0.1078	0.001	1.0000	0.001	0.8402	0.001	0.2724	0.001
Real-estate	0.3887	0.001	0.0199	0.001	1.0000	0.001	0.8069	0.001	0.4834	0.001

Notes: This table summarises the results of KS test. KS tests the hypothesis of no downside and upside systemic impact between EU and financial sectors (CoVaR vs VaR) in Panel (A and B). KS tests the hypothesis of ΔCoVaR asymmetry between downside and upside in Panel (C). KS tests the hypothesis of downside ΔCoVaR asymmetry among different time horizons in Panel (D and E). The analysis covers the full period in Panel (A, B and C). The null hypothesis is rejected at a 1% significance level.

Table 2.15: Kolmogorov-Smirnov Significance Test for Eurozone Financial Sectors During Subperiods

	Student-t Copula $\Delta CoVaR$							
	Full Period		Pre-crisis Period		Crisis Period		Post-crisis Period	
	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue
$H_0: Copula\ \Delta CoVaR\ Banks = 0$	0.8692	0.001	1.0000	0.001	0.9234	0.001	1.0000	0.001
$H_0: Copula\ \Delta CoVaR\ Financial = 0$	0.9073	0.001	0.9974	0.001	0.9540	0.001	1.0000	0.001
$H_0: Copula\ \Delta CoVaR\ Insurance = 0$	0.9205	0.001	1.0000	0.001	0.8800	0.001	1.0000	0.001
$H_0: Copula\ \Delta CoVaR\ Realestate = 0$	0.9617	0.001	1.0000	0.001	0.9694	0.001	1.0000	0.001

Notes: The objective of bootstrap KS test is to assess if the student-t copula $CoVaRs$' $CDFs$ at a 5% and a 50% quantile are dissimilar to each other during four periods; full period (2001-2016), pre-crisis period (Q3 2004-Q2 2007), crisis period (Q3 2007-Q2 2010) and post-crisis period (Q3 2010- Q2 2013). The equality of the $CDFs$ of the copula $CoVaRs$ related to the 5% and 50% quantiles is the null hypothesis. The null hypothesis is rejected at a 1% significance level.

2.6.2 Kendall Rank-order Correlation Coefficient

The Kendall Tau correlation coefficient assesses the degree of similarity between two groups of ranks given to a same group of objects. This Tau depends upon the number of inversions of pairs of objects which would be needed to transform one rank order into the other. With the purpose of comparing two ordered groups (on the same group of objects), Kendall approach is to count the number of different pairs between these two ordered groups. This coefficient gives a distance between groups called the symmetric difference distance (which is a group operation that associates to two groups the group of elements that belong to only one groups). Kendall rank order correlation coefficient is attained by normalizing the symmetric difference such that it will take values between −1 and +1.

Kendall Tau (τ) rank-order correlation coefficient is applied to measure the similarity of the orderings for different periods. Let $\left(x_1(t), x_1(t')\right), \left(x_2(t), x_2(t')\right), \ldots, \left(x_n(t), x_n(t')\right)$ be a set of rankings of the variables X for different periods t and t' respectively. Any pair of observations $\left(x_i(t), x_i(t')\right)$ and $\left(x_j(t), x_j(t')\right)$ are said to be concordant if both $x_i(t) > x_j(t)$ and $x_i(t') < x_j(t')$ or if both $x_i(t) < x_j(t)$. Otherwise, they are said to be discordant.

Noting that the maximum number of pairs which can differ between two groups with $\frac{1}{2}n(n-1)$ elements is equal to $n(n-1)$, the Kendall Tau (τ) coefficient is defined as:

$$\tau = \frac{number\ of\ concordant\ pairs - number\ of\ disconcordant\ pairs}{\frac{1}{2}n(n-1)} \tag{41}$$

where if two rankings are the same, $\tau = 1$, if two rankings are independent, $\tau = 0$, and if two rankings are discordant, $\tau = -1$.

Table 2.16: Kendall Rank-order Correlation Coefficient for Eurozone Financial Sectors

Financial Sector	Copula $\Delta CoVaR$	
	Tau	p-vlaue
$H_0: Banks\ Tau = 0$	92.60	0.001
$H_0: Financial\ Tau = 0$	91.28	0.001
$H_0: Insurance\ Tau = 0$	89.68	0.001
$H_0: Realestate\ Tau = 0$	90.94	0.001

Notes: The table displays the Kendal Tau and their p-vlaue for four Eurozone financial sectors within the full period (2001-2016). Regarding banking sector, the Kendall Tau has been calculated for $\Delta CoVaR$ obtained at time t and *t-1*. Kendal Tau figures are expressed as a percentage.

We compute the Kendall rank-order correlation coefficient between the systemic risk ranking produced by different risk measures obtained at time t and the one obtained at time $t-1$. Results indicate that the null hypothesis is rejected at the 1% significance level in each scenario, emphasizing that Copula $\Delta CoVaR$ systemic risk measure delivers a consistent ranking for a given financial sector through time. For example, the average correlations coefficient in the Eurozone banking sector during the full period is 92.60% as highlighted in table 2.16. These results show that the rankings produced by this measure is stable over time. This enhances the reliability of each systemic risk measure as it regularly classifies a sector (member state or institution) as $SIFI$[8].

2.7 Conclusion

This chapter explores the dependence structure of each Eurozone financial sector with EU index from the use of copulas and daily index prices from January 2001 to December 2016. Results reveal that all financial sectors possess dependence of a time-varying and strong to moderate nature. Additionally, proof was discovered for asymmetric dependence, which indicates that the index return comovement is different in bearish and bullish markets. In comparison to the other financial sectors, the results suggest a generally strong downside dependence compared to upside dependence. Furthermore, there is significant spillover effects on the EU index from the extreme downward movements in the different financial sectors.

We investigate the mean and extreme dependence from four Eurozone financial sectors to the EU (contribution $CoVaR$) and vice versa (exposure $CoVaR$), the upside and downside systemic risk spillover during different time horizons are also measured. For this reason, a cluster of copula functions is applied to measure the marginal model's residuals for three subperiods to deepen our understanding of systemic risk contribution (exposure) and portfolio risk management. We determine the risk spillover by calculating the downside and upside $VaRs$, $CoVaRs$ and $\Delta CoVaRs$ risk measures. Dynamic tail dependence between EU and four financial sectors is supported by the strong evidence provided in the results. In the pre-crisis period, there is an average dependence between EU-sector pairs. However, the crisis and post-crisis periods show a tail dependence for all EU-sector pairs. Through the use of $\Delta CoVaR$ risk measure, observations can be made that the downside $\Delta CoVaR$ is greater than the upside $\Delta CoVaR$ for all financial sectors. Taking into consideration different time horizons, it is shown that the pre-crisis period downside $\Delta CoVaR$ is lower than the post-crisis and crisis downside

[8] Regulators would be unsettled if systemic risk measures determine one institution as $SIFI$ in on day and then non-$SIFI$ on the next.

$\Delta CoVaR$ respectively. Furthermore, for all subperiods, asymmetric downside and upside $\Delta CoVaR$ can be found.

Observations made through graphical analysis of the downside and upside $VaRs$, communicate that in the bullish and bearish market conditions, the EU index is less risky than financial sectors indices. Comparison of systemic risk measures of the upside and downside $VaRs$ and $\Delta CoVaRs$ for EU and financial sectors return series, show that a similar pattern of both systemic risk measures for all sectors is present, with significant differences in magnitude across all sectors. Although, the influence on the $VaRs$ and $CoVaRs$ risk measures by the GFC and Euro crisis for the EU-sector pairs, is apparent as we find significant abrupt variations during the crisis period in 2007-2009. The GFC and Euro Crisis have increased significantly the VaR and $\Delta CoVaR$ for the EU index as well as for the financial sectors' indices, particularly for the banking sector. Furthermore, in all cases there is significant bidirectional risk spillover shown by the EU and financial sectors, specifically during the erupt of the 2007 GFC and 2009 European sovereign debt crisis. Furthermore, we applied a dominance and significance test for the empirical results by utilizing Abadie's proposed bootstrap Kolmogorov-Smirnov test (2002). The copula $\Delta CoVaRs$, shown in the significance test, are significantly different from zero, which means that each Eurozone financial sector significantly contributes to EU systemic risk spillover. Proof is given by the dominance test, that there is significance to the order, concluding that the banking sector has a higher systematic risk compared to the insurance sector, financial sector and the real-estate sector, respectively. This provides further confirmation that the qualitative conclusions related to the various concerned financial sectors and their contribution to systemic risk.

Furthermore, through the use of KS test, it is shown that there are significant differences between the downside and upside $VaRs$ and $CoVaRs$ during different time horizons. In addition, there is evidence found which show the behaviour of the upside and downside risk spillover to the EU and financial sectors to be asymmetric. Moreover, we calculate Kendall rank-order correlation coefficient for each systemic risk measure at time t and t-1. Results confirm that $\Delta CoVaR$ systemic risk measure delivers a consistent ranking for a given sector through time. This is an essential property for regulators as systemic risk measure regularly classifies a sector as $SIFI$.

Finally, following Wang (2009), Kodres and Pritsker (2002), Fleming *et al.* (1998), Andersen (1996), and Lamoureux and Lastrapes (1994), we develop a volatility linkages model between

Eurozone financial sectors by assuming that log volatility follows an $AR(1)$ process. We use Hansen's (1982) and Hansen's *et al.* (1996) generalized method of moments approach (GMM) to impose restrictions on the unconditional moments of daily returns and consequently extract the concurrent correlation between the log information flows in these sectors which is the estimate of the strength of volatility linkages among sectors. The GMM model indicates that informational linkages are reflected mainly in the correlation of volatilities instead of the correlation of returns.

We estimate GMM bivariate specifications to measure the correlations between the log information flows of four Eurozone financial sectors during the full sample period. The empirical results indicate that the model fits the data reasonably well for all six pairs and bivariate tests reveal little evidence of misspecification with the exception of banking/ real-estate and financial/ insurance sectors pair. The estimated correlation of the log information flows for the banking/ financial sectors pair is 85.72%, the estimates for banking/ insurance, banking/ real-estate, financial/ insurance, financial/ real-estate, and insurance/ real-estate pairs are 84.41%, 67.24%, 86.86%, 74.53% and 58.25% respectively. The empirical analysis indicates strong volatility linkages among banking, financial service, insurance and real-estate sectors. Since all the associated standard errors are small (less than 0.03), the estimated correlations are relatively precise and consequently, the volatility linkages among the four sectors are strong. This is an important result given the increasing popularity of systemic risk measurements that attempt to exploit predictable variations in return and volatility.

For regulators, policy makers and market participants, these findings present several important implications. Policymakers should be attentive of the impacts on the stock markets by the extreme movements of the price of different sectors and apply adequate macro-prudential regulation when required, to allow the operation of the stock markets to remain stable and become less systemic risky, having the wider objective of systemic financial stability in mind. Freixas, *et al.* (2015) and Haldane and May (2011) suggest a regulatory context to apply a macro-prudential regulatory approach rather than a micro-prudential regulatory approach for financial regulation. Volatility linkages as well as systemic risk measures should also be considered in setting regulatory policy, given their influence on investment and risk management decisions. Investors should all be aware of the bidirectional risk spillover between the EU and financial sectors. Time horizons should also be taken into consideration when market participants are managing their portfolios. Portfolio managers should hedge and change their positions accordingly while considering investment horizons.

3

Chapter 3
Too-Systemic-to-Fail: Empirical Comparison of Systemic Risk Measures in the Eurozone Financial System

Amir Armanious (Contribution 80%), Tom Smith (Contribution 10%)
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We quantify Too-Systemic-To-Fail ($TSTF$) paradigm in the Eurozone since the introduction of the Euro through three primary dimensions; Too-Big-To-Fail ($TBTF$), Too-Interconnected-To-Fail ($TITF$) and Too-Many-To-Fail ($TMTF$). We apply the major prominent systemic risk measures that are based on public data which are Granger-causality network (GCN) of Billio, *et al.*, (2010), Delta Conditional Value-at-Risk ($\Delta CoVaR$) of Adrian and Brunnermeier (2011), Marginal Expected Shortfall (MES) of Acharya, *et al.* (2017) and Systemic Risk Index ($SRISK$) of Acharya, Engle and Richardson (2012) and Brownlees and Engle (2012). We measure financial interconnectedness and systemic risk exposure within the 17-member states of the Eurozone on two levels: (i) identify which financial sectors, namely, the banking, diversified financials, insurance and real estate, are exposed the most to the entire systemic risk in the Eurozone on the union level; and (ii) identify which member state is exposed mostly to systemic risk within each financial sector on the country level. We extend the original $\Delta CoVaR$, MES and $SRISK$ models to include the bootstrap Kolmogorov–Smirnov stochastic dominance test to provide a formal ranking of sector/ country with respect to their exposure to systemic risk (Abadie, 2002).

3.1 Introduction

Measurements and management of systemic risk are in the limelight of academic research and supervisory policy agenda due to the recent global financial crisis. Specifically, the Basel Committee and the Financial Stability Board's continuous efforts aim to establish new regulatory requirements as Systemically Important Financial Institutions ($SIFI$) need a reachable agreement on which specific factors make a certain financial institution more susceptible to being adversely affected by system-wide shocks (systemic resilience or participation) compared to others or spreading to other institutions aforesaid shocks and magnifying the general effect (systemic contribution).

Two systemic risk dimensions were analysed by Furfine (2003); first of all, a group of markets or institutions inefficiently functioning simultaneously due to a financial shock, and second of all, the risk of a single or several institutions downfalls could spread to others due to all institutions being substantially linked. There are several reasons for systemic risk to exist in the financial system as; (1) due to different derivative contracts, financial institutions become more highly interconnected from interest rate or transferring exchange rate risk, (2) due to the high level capital structure, investing correlated assets by financial institutions that are vulnerable to risk above the required optimal level (Acharya, 2009), and (3) asymmetric information specifically at periods of confidence loss can magnify the distress of an institution and result in an illiquidity crisis.

The Financial Stability Board (2011) thus defines $SIFI$ as "financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause a significant disruption to the wider financial system and economic activity". If the whole financial system breaks down from a single institution's distress and subsequently affects the real economy via cascading, chain-reaction and contagion effects, then systemic risk is prominent. This chapter's primary focus is based on the entire financial sector or the financial institution of interest. Derived from the above definitions, systemic risk can be examined under the Too-Systemic-To-Fail ($TSTF$) paradigm, where the imminent failure, incompetence to operate and disorganised wind-down of certain institutions can disrupt the financial system and adversely affect the real economy (Thomson, 2009). $TSTF$ is examinable in three primary dimensions: first of all, Too-Big-To-Fail ($TBTF$)[9], is measured based on the relative size of an

[9] Initially utilised in a 1984 U.S. congressional hearing, the issue "Too-Big-To-Fail" explained the decision for Continental Illinois National Bank to be bailed out (by a $1.1 billion expense to the Federal Deposit Insurance

institution to the whole market. Second of all, Too-Interconnected-To-Fail ($TITF$), is measured via the chances of negative externalities generated by an institution's failure affecting the entire economy. Last of all, Too-Many-To-Fail ($TMTF$)[10], is measured via the chances of effects of negative externalities generated by financial institutions that gather ex-ante to take more risk and raising bailout chances in the event of systemic crisis.

A classical explanation of how small shocks can lead to systemic events is that financial institutions are inherently fragile, due to coordination problems between their creditors (Freixas and Rochet, 2008). Risk-sharing and propagation risks differs depending on the interlinkages formed by financial institutions. Freixas, *et al.* (2000) show that a circular chain of banks is less robust than a complete network in the framework of a general matrix of interbank exposures. They discuss the formation of interbank links (in particular the issue of coordination failures). Similarly, Allen, *et al.* (2012) show that having separate clusters of banks reduces contagion compared to a complete network but also decreases incentives to roll-over short-term debt.

During distress periods, interdependence across financial institutions becomes substantially significant as losses naturally extend to different institutions and makes the entire financial system vulnerable. Regarding this, systemic risk is the various large institutions simultaneously defaulting. The entire economy and society could face significant costs and repercussions if a systemic crisis erupts due to financial instability. Financial institutions frequently face contagion episodes in financial crisis periods and this must be accounted by regulators when evaluating the financial system's health. As central banks are accounting for increasing the domestic economy's financial stability, an essential element of their activities is to analyse and follow systemic risk. While promoting greater systemic analysis, the 2007 financial crisis has also pushed for improvements in system risk indicators that can be utilised as a monitoring instrument by central banks and other regulatory authorities. An essential component of assessing the financial system's stability is measuring the financial system's systemic risk.

Corporation - FDIC) along to 10 other large U.S. banks that would of required saving in the scenario of failure (Carrington, 1984).

[10] Mitchell (1997) has been the first to define the "too-many-to-fail" paradigm corresponding to a situation where it is less costly to rescue banks than to close large numbers of banks. Brown and Dinc (2014) have empirically illustrated this problem in emerging market countries whereas Acharya and Yorulmazer (2007) are the first to argue that this phenomenon gives banks incentives to herd and increases the risk that many banks may fail together. Adrian and Brunnermeier (2011) justified the phrase "Too-Many-To-Fail" as "systemic as part of a herd" whereas a collective of various institutions that behaved similar to each other can be precarious and dangerous to the system as a huge merged identify.

Our empirical approach in this chapter makes several contributions to academic literature on financial interconnectedness and systemic risk in four principal ways. First, this is the first attempt to apply systemic risk measures within an economic union. Our empirical analysis measures which sectors (member states) displays higher degree of interconnectedness during stress periods, in addition to measuring systemic risk exposure within the 17-member states of the Eurozone on the union level and sector level. On the union level, we identify which Eurozone financial sector and member state is exposed the most to the entire systemic risk in the Eurozone. On the sector level, we detect which member state is exposed to systemic events when a certain sector is in distress. Thus, we compare the exposure of the main components of the financial system, namely, the banking, diversified financials (DFinancials), insurance and real-estate sectors, systemic risk rather than focusing on the exposure of individual financial institutions only to systemic risk.

Second, we provide an assessment of the robustness of four prominent systemic risk measures of Granger-causality network (GCN) of Billio, *et al.*, (2010), Delta Conditional Value-at-Risk ($\Delta CoVaR$) by Adrian and Brunnermeier (2011), Marginal Expected Shortfall (MES) by Acharya, *et al.* (2017) and Systemic Risk Index ($SRISK$) by Acharya, *et al.* (2012) and Brownlees and Engle (2012). These measures are widely used because they are based on public data. These measures have been developed within different frameworks, consequently, we unify the theoretical framework of Brownlees and Engle (2012) in order to avoid discrepancies due to different estimation strategies.

Third, we extend the original $\Delta CoVaR$, MES and $SRISK$ models to include bootstrap Kolmogorov–Smirnov dominance test developed by Abadie (2002), in order to provide a formal ranking of the financial sectors (member states) with respect to their exposure to systemic risk.

Finally, we link macro-prudential measures ($\Delta CoVaR$, MES and $SRISK$) with micro-prudential measures (systematic risk, tail risk, and correlation, as well as firm characteristics such as leverage and market capitalization). Thus, some systemic risk measures could be expressed as transformations of market risk measures. Overall, our approach is likely to be highly relevant to regulators, policy makers and academicians.

The remainder of the chapter is organized as follows. Section 2 provides a review of literature of interconnectedness and systemic risk measures. Section 3 proposes a methodological analysis of Granger Causality Network, MES, $SRISK$, and $\Delta CoVaR$ measures and presents the common framework used for the comparison. In Section 4, we describe the data and summary statistics. Section 5 presents the main empirical findings of interconnectedness and systemic risk exposure on the union level and sector level during the sub-periods of analysis (before, during and after the crisis). Section 6 reports the results of robustness check. Section 7 summarizes and concludes for policy implications.

3.2 Literature Review on Systemic Risk Measures

Several systemic risk indices were shown by Billio, *et al.* (2012) to determine financial institution connectedness from Granger-causality networks and Principal Components Analysis (PCA) while using them on financial institution monthly returns from a variety of sectors. The Gonzalo and Granger metric and three Granger Causality test measures were used by Rodriguez-Moreno and Pena (2013) as well as the systemic events index correlating with the policy actions of two groups with high-frequency market-based systemic risk measure between 2004 to 2009 via U.S. and EU interbank rates data, stock prices and credit derivatives at both individual bank and aggregate market levels. Cai *et al.* (2018) find a positive correlation between interconnectedness and systemic risk at the bank level.

The three-recent notable systemic risk measure derived from public data are Acharya, *et al.*'s (2017) Marginal Expected Shortfall (MES), the Systemic Risk Index ($SRISK$) of Acharya, *et al.* (2012) and Brownlees and Engle (2012), and the Delta Conditional Value-at-Risk ($\Delta CoVaR$) by Adrian and Brunnermeier (2011)[11]. The above measures are conveniently well-known concepts that develop on popular methods of Value-at-Risk (VaR) and Expected Shortfall (ES). Systemic risk measures involved in this chapter have substantial economic interpretations. Expected equity loss by a financial institution equates to MES when market falls under a given threshold in a certain time period, specifically a 2% drop within the market in one day for short-run MES and a 40% drop in the market in six-month for the long-run MES ($LRMES$). Generally, financial institutions with higher MES (in absolute values) contribute more to market declines; therefore, these financial institutions are greater systemic risk drivers. An institution's expected capital shortfall, under the circumstance of a financial crisis happening is measured by $SRISK$. The understanding is that financial institutions with the biggest shortfall of capital specifically during a system crisis is believed to be most

[11] The New York University's Volatility Lab is formulating the common systemic risk measures for numerous international financial institutions. The outcomes are renewed weekly via http://vlab.stern.nyu.edu/.

systemically risky. $CoVaR$ links to the financial system's VaR contingent on a given financial institution being impacted by a certain event. The financial system's systemic risk ($\Delta CoVaR$) contributions is the change between the financial institution's $CoVaR$ when it is under financial distress and its median state. Greater $\Delta CoVaR$ (in absolute values) means high systemic risk contributions (or exposures)[12].

More studies have proposed a variety of alternate methods to deal with the presence of systemic interrelations via various variables and procedures (Adams, *et al.*, 2010; Drehmann and Tarashev, 2011; Cao, 2013; Singh, *et al.*, 2013; Lopez-Espinosa, *et al.*, 2013; Allen, *et al.*, 2016)[13]. Two commonly-cited measures of systemic risk, MES and $SRISK$, were compared with $\Delta CoVaR$ by Benoit *et al.* (2013) under the usually empirical and theoretical framework while utilising the same sample gathered from Acharya, *et al.* (2017) and Brownlees and Engle (2012). They settled that measures of market risk (like ES, VaR, Beta) can in terms represent measures of systemic risk within specific conditions. Both of the market's ES (market tail risk) and the institution beta (institution systemic risk) products coincide with MES. Additionally, a product of the institution's VaR (firm tail risk) along with the linear projection coefficient of the market return on the institution return both coincide with $\Delta CoVaR$.

Zhang, *et al.* (2015) analyse the efficiency of four different market-based systemic risk measures (including $\Delta CoVaR$ and $SRISK$) operating in three financial crises, specifically the 2007-2009 financial crisis, the 1997 Asian crisis and the 1998 Ruble crisis. The four market-based measures of concern were inspected to determine if they provide early warning signs on top of the signals acquired by traditional drivers of risk. To forecast various realised systemic risk measures (like realised capital shortfall and realised covariance risk), the $\Delta CoVaR$ was discovered to be the best measure of market-based systemic risk during the 2007 financial crisis. However, during the late 1990's Asian and Ruble crisis, the $\Delta CoVaR$ did not constantly predict realised systemic risk. It has been purposed that $SRISK$ is capable of predicting capital shortfalls in long periods of crises (Zhang, *et al.*, 2015, Acharya, *et al.*, 2014; Brownlees and Engle, 2012; Boucher, *et al.* 2014). This insinuates that SRISK is a meaningful measure used by regulators to observe the financial sector's vulnerability.

[12] Note that ES, MES, VaR_q^i, CoVaR and ΔCoVaR are typically negative numbers, in practice, the sign is often switched, which is followed in this chapter. While $SRISK$ is typically a positive number.

[13] A thorough research of the main systemic risk measures and analytical frameworks formed over the previous couple years is held in Bisias, *et al.* (2012).

The $SRISK$ was enhanced by the application of Structural $GARCH$, $SGARCH$, (see Engle and Siriwardane, 2015; Dungey, *et al.*, 2010). Due to the capital structure of financial institutions changing, this enhancement enables the fluctuation in the equity volatility occurring to be accurately modelled. The $SGARCH$ model computing $SRISK$ seems to give earlier signs in terms of capitalisation changes, despite differences related to normal $SRISK$ are quite small. Additionally, a multifactor model was announced by Engle, *et al.* (2015) to justify the financial institution's return dynamics. With this environment, introducing sub-markets like one of the European banks would be intriguing. This could result in the potential of separating specific shocks (like to European banks) from more typical shocks ($PIIGS$ growth prospects [14]).

Modelling the joint distribution of the market's and each financial institution's returns while considering each return's nonlinear dependence is a crucial component of $\Delta CoVaR$ and MES calculation. Under financial contagion, markets could be more dependent when they are moving adversely downward compared to facing upward movements (King and Wadhwani, 1990; Forbes and Rigobon, 2001; Forbes and Rigobon, 2002; Bekaert and Harvey, 2003; Roesch and Scheule, 2014). Research that expands upon the $\Delta CoVaR$ and MES suggest various methods of estimation to consider any potential nonlinear dependence return structures in order to include this quality of stock returns. This means the relation of institutions and returns from the market under extreme situations must be modelled most precisely to attain an accurate measure the amount of systemic risk contributed by the financial institution. These methods typically require almost sophisticated estimation procedures. For instance, quantile regression was used to model tail dependence by Adrian and Brunnermeier (2011), nonparametric tail estimators were implemented by Brownlees and Engle (2012) and Student-t copula was utilised by Engle, *et al.* (2012). The $\Delta CoVaR$, the MES and the $SRISK$ were proposed by Chuanliang (2012) to be more precisely measured by different copula functions while the extreme value theory was suggested by Straetmans and Chaudhry (2013) and Balla, *et al.* (2014) to assess systemic risk. However, the main issue is whether these endeavours are substantiated given the purpose.

[14] $PIIGS$ countries refer to countries of Portugal, Ireland, Italy, Greece and Spain.

3.3 Estimation Methodology

We consider N financial institutions and denote r_{it} the return of financial institution i at time t. Similarly, $r_{m,t}$ is the market return (union return or financial sector return) which is the value-weighted average of all financial institutions return as expressed in eq. (1).

$$r_{m,t} = \sum_{i=1}^{N} w_{i,t}\, r_{i,t} \quad (1)$$

where w_{it} denotes the relative market capitalization of financial institution i which is given by $w_{i,t} = \frac{ME_{i,t-1}}{\sum_i^N ME_{i,t-1}}$ and $ME_{i,t-1}$ denotes the market capitalization of institution i. Note that, by construction, index weights are time-varying and known given the information set at time $t = 1$. A market log-return is typically greater than the value-weighted firm log-return, particularly when extreme returns (far away from zero) need to be handled due to the Jensen Inequality.

This chapter contains various systemic risk measures which have been created via various frameworks. An example is Brownlees and Engle (2012) modelling time-varying linear dependencies while utilising a multivariate Generalised Autoregressive Conditional Heteroscedasticity, Dynamic Conditional Correlation ($GARCH$-DCC) model to assess the MES. Interestingly, tail dependence was allowed for Adrian and Brunnermeier (2011) as they utilised a quantile regression approach to determine the $\Delta CoVaR$. Therefore, a direct comparison is not straightforward as a few empirical differences could potentially be caused by the estimation strategies. Thus, we speculate that all these risk measures under a unified theoretical framework to supply a common platform. After Brownlees and Engle (2012), we contemplate a bivariate $GARCH$ process for the demeaned returns:

$$r_t = H_t^{1/2} v_t \quad (2)$$

where $r_t' = (r_{m,t}\; r_{i,t})$ denotes the vector of market and financial institution returns and the random vector $v_t' = (\varepsilon_{m,t}\;\; \xi_{i,t})$ is serially independent and identically distributed ($i.i.d.$) over time and has the following first moments: $\mathbb{E}(v_t) = 0$ and $\mathbb{E}(v_t v_t') = I_2$, a two-by-two identity matrix. The H_t matrix denotes the conditional variance-covariance matrix:

$$H_t = \begin{pmatrix} \sigma_{m,t}^2 & \sigma_{i,t}\,\sigma_{m,t}\,\rho_{i,t} \\ \sigma_{i,t}\,\sigma_{m,t}\,\rho_{i,t} & \sigma_{i,t}^2 \end{pmatrix} \quad (3)$$

where $\sigma_{i,t}$ and $\sigma_{m,t}$ denote the conditional volatilities and $\rho_{i,t}$ the conditional correlation. No particular assumptions are made about the bivariate distribution of the standardized innovations v_t, which is assumed to be unknown. It is assumed that the time-varying conditional correlations $\rho_{i,t}$ fully captures the dependence between the financial institution and market returns. Formally, this assumption implies that the standardized innovations $\varepsilon_{m,t}$ and $\xi_{i,t}$ are independently distributed at time t[15].

3.3.1 Granger Causality Network

To estimate the interconnectedness of financial institutions along with all of the financial system's systemic risk, statistics from granger-causality tests as well as other techniques have been proposed (Billio, *et al.*, 2010). Derived from the monthly return indices by hedge funds, broker/dealers, insurance companies and banks, these measures reveal granger-causality networks to be really active and are highly interconnected at times before systemic shocks. Granger-causality tests were customised to determine the direction and interconnectedness in the bonds of financial institutions within the financial system. If past X values possess information that is useful in anticipating Y above the information solely inherent in past Y values, then Y is Granger-caused by X. This granger-causality equation is expressed as:

$$X_t = \sum_{j=1}^{m} a_j\, x_{t-j} + \sum_{j=1}^{m} b_j\, x_{t-j} + \epsilon_t \tag{4}$$

$$Y_t = \sum_{j=1}^{m} c_j\, x_{t-j} + \sum_{j=1}^{m} d_j\, x_{t-j} + \omega_t \tag{5}$$

The max lag length being m. Two uncorrelated white noise processes being ϵ_t and ω_t. If b_j is not equal to zero, then Y affects X. Likewise, when c_j is different from zero then Y is caused by X on the condition that the p-value is below 5%. When both conditions are held true, then the two time-series forms a feedback connection.

Analytically, the experiment is conducted on the indices of monthly returns by the banks, hedge funds, broker/ dealers and insurance companies. Insight from this chapter is based on the Eurozone's financial institutions' return indices. Similarly, we have estimated a collection of Eurozone financial sectors indices, namely banking, diversified financials, insurance and real-estate, from the past 36 monthly returns in a quarterly basis from 2000 to 2015. The dynamic causality index (DCI) is calculated for each interval where:

$$DCI_t = \frac{number\ of\ casual\ relationships\ in\ window}{total\ possible\ number\ of\ casual\ relatinships} \tag{6}$$

[15] See Benoit *et al.* (2017) for detailed description of the unified framework for estimating MES, $SRISK$ and $\Delta CoVaR$.

The DCI degree precisely correlates to the financial system's level of interconnectedness. Therefore, a financial system being more interconnected would have a greater DCI value. Furthermore, a single institution Granger-causes at 5% was used to estimate the connections of several financial institutions within each sector. We use a sample of 315 publicly listed financial institutions in the Eurozone.

On a daily interval with the past returns of 36 months, the relationship's direction and interconnectedness amongst banks within the Eurozone financial system have been determined by Granger-causality tests. Since the extent of the dynamic causality index reveals the financial system's interconnectedness, the DCI can be calculated for each interval. Therefore, a greater DCI value means a highly interconnected system.

3.3.2 Marginal Expected Shortfall (MES)

To gather estimates of MES, many strategies can be utilised. In this chapter, we have structured the multi stage modelling approach to be comparable to Engle and Brownlees (2012). Inspired by the Dynamic Conditional Correlation (DCC) Framework by Engle (2002, 2009), this approach reveals how using univariate $GARCH$ models can determine the volatilities and standardised residuals for each series. These standardised residuals can be used to determine the conditional correlations via the DCC framework. Also, nonparametric estimators are used to determine the MES's tail dependence, which are formulated from the standardise residuals from the $GARCH$-DCC residuals[16].

Let us consider the Cholesky decomposition of the variance-covariance matrix H_t:

$$H_t^{1/2} = \begin{pmatrix} \sigma_{m,t} & 0 \\ \sigma_{i,t}\,\rho_{i,t} & \sigma_{i,t}\sqrt{1-\rho_{i,t}^2} \end{pmatrix} \tag{7}$$

Given Eq. (2),

Let $r_{i,t}$ and $r_{m,t}$ denote financial institution (sector or country) i's return and the market return on day t respectively. The following specification of the bivariate process of financial institution and market returns can be expressed as:

$$r_{m,t} = \sigma_{m,t}\,\varepsilon_{m,t} \tag{8}$$

[16] While simple and flexible, the modelling paradigm is appealing for a wide spectrum of univariate volatility models that exist, models for estimators of tail dependence as well as correlations.

$$r_{i,t} = \sigma_{i,t}\,\rho_{i,t}\,\varepsilon_{m,t} + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}\,\xi_{i,t} \qquad (9)$$

$$(\varepsilon_{m,t}\,, \xi_{i,t}) \sim F$$

where σ and ρ depict the series' conditional volatility and correlation of the return respectively. While assumed to be serially independent, the shocks $\varepsilon_{m,t}$ and $\xi_{i,t}$ are identically distributed over time with zero mean, unit variance and zero covariance. It is necessary to remember that they are not assumed to be independent random variables. This dependence assumptions were approved by Brownlees and Engle (2012) due the extreme figures of these disruptions could happen simultaneously for *SIFIs*. With a potential threat of defaults, the financial institutions disruptions may be further in the tail when the market is in the tail.

The stochastic setup can be described as the two conditional standard deviations and the conditional correlation. The asymmetric $GARCH$ models determine the volatilities and the DCC models determine the correlations. While remained unspecified, the joint distribution F from where $\varepsilon_{m,t}$ and $\xi_{i,t}$ are derived and straightforward nonparametric approaches are utilised for interference on tail dependence.

MES signifies the marginal contribution of institution i to systemic risk, as determined by the system's ES. MES was initially suggested by Acharya, *et al.* (2017) to be recently extended to a conditional version of Brownlees and Engle's (2012). In theory, the q% level of the ES's expected returns in the worst q% of cases, but it can be prolonged to the typical case where returns are greater than a certain threshold (C). Properly, the system's conditional ES is denoted as:

$$ES_{mt}(C) = \mathbb{E}_{t-1}(r_{mt}|r_{mt} < C) = \sum_{i=1}^{N} w_{it}\mathbb{E}_{t-1}(r_{it}|r_{mt} < C) \qquad (10)$$

where C is some negative constant. A realization of the condition $r_{mt} < C$ is called a systemic event. Note that we define ES as the negative tail expectation. Correspondingly, a higher ES value indicates a larger expected loss.

Then, MES corresponds to the partial derivative of the system ES with respect to the weight of firm *i* in the economy (Scaillet, 2004).

Then, MES correlated to the system ES's partial derivative in regards to the institution *i* 's weight in the economy:

$$MES_{it}(C) = \frac{\partial ES_{mt}(C)}{\partial w_{it}} = \mathbb{E}_{t-1}(r_{it}|r_{mt} < C) \qquad (11)$$

The MES can be seen as a natural enhancement to the marginal VaR concept suggested by Jorion (2007) to the ES, a coherent risk measure (Artzner, *et al.*, 1999). It determines the rise in system risk (calculated by ES) generated by a marginal increase in the institution i's weight in the system. The greater the institution's MES, the greater the individual contribution of the institution to financial system risk. MES can be portrayed as a signal of how much the share price of a particular financial institution will descend within a day when the market is undergoing a systemic event with equity fall by at least amount C. Therefore, the expected capital loss a financial institution would experience in a systemic crisis can be determined by MES. While sensitive to the aggregates market's performance, financial institutions will typically have a high MES as they experience distress periods during systemic events. Ultimately, they are important candidates to be systemically risky.

For any conditioning event C, we can decompose MES in Eq. (11) as a function of volatility, correlation, and tail expectations of the standardized innovations distribution:

$$MES_{i,t}(C) = \mathbb{E}_{t-1}(r_{it}|r_{mt} < C) \tag{12}$$

$$MES_{i,t}(C) = \sigma_{i,t}\,\rho_{i,t}\mathbb{E}_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}\,\mathbb{E}_{t-1}\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) \tag{13}$$

Couple notable features from the specification are worth mentioning with the assumption that there is a positive dependence between the financial institution and the market. Initially, more volatile financial institutions will cross-sectionally appear riskier as MES is an increasing function of individual institutions. As opposed to traditional risk measures, ES also relies on the correlation between the financial institution's return and the market. As $SIFIs$ are seen as a combination of volatility, correlation and tail dependence, this focuses on the risk measure's systemic nature. Based on being either a high or low correlation, the MES formula provides more substance to the tail expectation, either to the standardised market residual tail expectation or the standardised idiosyncratic financial institution residual tail expectation. The term $\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right)$ in Eq. (13) comes as the dependence assumption between $\varepsilon_{m,t}$ and $\xi_{i,t}$ would become zero if dependence was determined completely by correlation[17].

If we assume that $\xi_{i,t}$ and $\varepsilon_{m,t}$ are independent, we have:

$$MES_{i,t}(C) = \sigma_{i,t}\,\rho_{i,t}\mathbb{E}_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) \tag{14}$$

[17] If $\varepsilon_{m,t}$ and $\xi_{i,t}$ are independent, the conditioning event becomes irrelevant and by assumption $\mathbb{E}_{t-1}\,\xi_{i,t} = 0$.

or equivalently:

$$MES_{i,t}(C) = \sigma_{i,t}\, \rho_{i,t} \mathbb{E}_{t-1}\left(\varepsilon_{m,t} | r_{m,t} < C\right) \tag{15}$$

Let $\beta_{i,t} = \frac{cov(r_{i,t}, r_{m,t})}{var(r_{m,t})} = \frac{\sigma_{i,t}\, \rho_{i,t}}{\sigma_{m,t}}$ denotes the time-varying beta of financial institution i. Combining $\beta_{i,t}$ it with Eq. (15), we obtain:

$$MES_{i,t}(C) = \beta_{i,t}\, \sigma_{m,t}\, \mathbb{E}_{t-1}\left(\varepsilon_{m,t} | r_{m,t} < C\right) \tag{16}$$

$$MES_{i,t}(C) = \beta_{i,t}\, \mathbb{E}_{t-1}\left(r_{m,t} | r_{m,t} < C\right) \tag{17}$$

The MES is portrayed as the commodity between the market return's truncated expectation for a certain threshold C and the time varying beta. In theory, the market return's expected shortfall $ES_{m,t}(q)$ equates to the market return's truncated expectation for a given threshold equivalent to the conditional VaR (Jorion, 2007), $C = VaR_{m,t}(q)$:

$$ES_{m,t}(q) = \mathbb{E}_{t-1}\left(r_{m,t} | r_{m,t} < VaR_{m,t}(q)\right) \tag{18}$$

Then, the MES defined for the specific event $C = VaR_{m,t}$, denoted $MES_{i,t}(q)$, is simply expressed as the product of time-varying financial institution beta and expected shortfall of the market return:

$$MES_{i,t}(q) = \beta_{i,t}\, ES_{m,t}(q) \tag{19}$$

3.3.3 Systemic Risk Index (SRISK)

As suggested by Acharya, *et al.* (2012) and Brownlees and Engle (2012), the $SRISK$ measure broadens the MES to account both the financial institution's liabilities and size. The $SRISK$ responses to a given financial institutions' expected capital shortfall depending on whether a crisis influencing the whole financial system. From this point of view, financial institutions having the largest capital shortfall are assumed to be the biggest contributors to the crisis and are considered to be most systemically risky.

The function of $SRISK$ is to determine the financial institution's expected capital shortfall when experiencing a crisis. Therefore, $SRISK$ endeavours to compute both balance sheets and equity markets. A crisis is estimated with a typical stock market collapse. $SRISK$ can be utilised as a market-based replacement to the traditional regulatory stress tests.

$SRISK$ for institution i at time t is defined by:

$$SRISK_{i,t} = E_t\left(CS_{i,t+h} | Crisis_{t:t+h}\right) \quad (20)$$

As 'Capital Shortfall' is abbreviated as CS and the future point in time at which the crisis occurs is signified as $t+h$. The financial institution's vulnerability in the light of a system-wide shock is captured by $SRISK$. After Brownlees and Engle (2012), the capital shortfall for institution i at time t is signified by:

$$CS_{i,t} = \mathrm{k}\, A_{i,t} - MV_{i,t} \quad (21)$$

$$CS_{i,t} = \mathrm{k}\left(D_{i,t} + MV_{i,t}\right) - MV_{i,t} \quad (22)$$

where the market value of equity is signified as $MV_{i,t}$, the book values of debt is shown as $D_{i,t}$ and $A_{i,t} = D_{i,t} + MV_{i,t}$ is the quasi assets for institution i at time t (Brownlees and Engle, 2012). Being assessed on the institution's assets via the equity market, the quasi assets can be seen as the market values of outstanding shares used instead of the book value of equity. Last of all, k is the efficient capital fraction, e.g. minimum amount of quasi assets institution i is meant to fund via equity[18].

The crisis in $SRISK$ is defined to be a general stock market crash over the next h days of at least C percent:

$$Crisis_{t:t+h} = \left\{R_{M,t:t+h} \leq C\right\} \quad (23)$$

where $R_{M,t:t+h}$ being the cumulative market return over the next h days.

Using the definition of $SRISK$ from Eq. (20) along with the definitions of capital shortfall and a crisis, the following expression for $SRISK$ can be written:

$$SRISK_{i,t} = E_t\left(5.5\%.\left(D_{i,t+132} + MV_{i,t+132}\right) - MV_{i,t+132} | R_{M,t:t+132} \leq -40\%\right) \quad (24)$$

$SRISK$ determines the capital shortfall in relation to a capital requirement of 5.5 percent of total assets in six months provided that the stock market has fell by 40%. What is left is to depict the hypothetical share market crash into the asset values or rather how to model a hypothetical stock market crash would influence the values of debt and the market value of the firm. With the simple assumption that the expected value of debt is unaffected by the crisis (Brownlees and Engle, 2012):

[18] While a leverage ratio of three percent ($k = 3$) is the current proposal from the Basel Committee of Banking Supervision, Brownlees and Engle (2012) uses a slightly stricter percentage ($k = 5.5$) for European Financial Institutions and k=8 for American financial institutions. This chapter utilises a higher k of 5.5 percent for the Eurozone systemic risk analysis.

$$E_t\left(D_{i,t+132} \middle| R_{M,t:t+132} \leq -40\%\right) = D_{i,t} \tag{25}$$

In practice, the assumption may not hold due to the use of hybrid debt for example resolution regimes with bail-in. These features could both suggest a minimal value of debt will be reduced when a financial institution is in difficulty, resulting to lower capital shortfall.

To ascertain an approximation on the expectation of the financial institution's market value conditional on a general stock market crash, it must be divided into two parts. One demonstrating what the market value is nowadays and the second relating the expectation of the percentage the market value will fall based on a general stock market crash. Brownlees and Engle (2012) denote the latter, the $LRMES$.

$$E_t\left(MV_{i,t+132} | R_{M,t:t+132} \leq -40\%\right) = MV_{i,t}\ (1 + LRMES_{i,t}) \tag{26}$$

where

$$LRMES_{i,t} = E_t\left(MV_{i,t+132} | R_{M,t:t+132} \leq -40\%\right) \tag{27}$$

To compute the time-varying dependence between a particular financial institution and the stock market, the DCC was proposed by Brownlees and Engle (2012). Modelling the univariate return series' time varying variances, the $GARCH$-models were suggested. The joint model is identified as the $GARCH$-DCC model. Highlighting the use of dynamic models is fundamental when determining $SRISK$[19]. The variances are computed via univariate $GARCH$-models and a multivariate DCC-model is used for the correlations.

The estimation of $SRISK$ is based on the same framework as that of MES. According to Engle, *et al.* (2012) the capital shortfall of a given financial institution i is defined as:

$$CS_{i,t} = \mathrm{k}\, D_{i,t} - (1-k)\left(1 - LRMES_{i,t}\right)W_{i,t} \tag{28}$$

where $D_{i,t}$ and $W_{i,t}$ denote the value of the book value of total liabilities and equity of institution i and k is a prudential capital ratio of equity to assets, and $LRMES$ is given by the following equation:

$$LRMES_{i,t} = LRMES_{i,t:t+T} = -\mathbb{E}_{t-1}(R_{i,t:t+T} | R_{m,t:t+T} \leq -40\%) \tag{29}$$

where $R_{i,t:t+T}$ and $R_{m,t:t+T}$ are cumulative returns defined as:

[19] While using various models for determining $LRMES$, Brownlees and Engle (2012) compared SRISK outcomes. They discovered that $SRISK$ estimates gather via the dynamic $GARCH$-DCC model Granger-causes $SRISK$-estimates using both static and other dynamic models. In the end, the $GARCH$-DCC model is the most appropriate for $LRMES$ and $SRISK$ modelling as it ensures the most accurate signal.

$$R_{i,t:t+T} = \exp\left(\sum_{j=1}^{T} r_{i,t+j}\right) - 1 \text{ and } R_{m,t:t+T} = \exp\left(\sum_{j=1}^{T} r_{m,t+j}\right) - 1 \tag{30}$$

$LRMES$ is estimated at a time horizon of six-month and T sets at 126 trading days (6 months). Then, the $LRMES$ is approximated without simulation by:

$$LRMES_{i,t} = -\left(\exp\left(18 * MES_{i.t}(q)\right) - 1\right) = 1 - \exp\left(18 * MES_{i.t}(q)\right) \tag{31}$$

Finally, the $SRIS$K contribution of a given institution to the risk of the system following Acharya, *et al.* (2012) is given by:

$$SRISK_{i,t} = \max(0; CS_{i,t}) \tag{32}$$

$$SRISK_{i,t} = \max(0; required\ capital - available\ capital) \tag{33}$$

$$SRISK_{i,t} = \max\left(0; k\left(D_{i,t} + \left(1 - LRMES_{i,t}\right)W_{i,t}\right) - \left(1 - LRMES_{i,t}\right)W_{i,t}\right) \tag{34}$$

where k is the prudential capital ratio and $D_{i,t}$ is the book value of total liabilities. It is worth noting that if we define the leverage as $L_{i,t}$ = $(D_{i,t} + W_{i,t})/W_{i,t}$; $SRISK$ becomes:

$$SRISK_{i,t} = \max\left(0; (kL_{i,t} - 1 + \left(1 - k\right)LRMES_{i,t}\right)W_{i,t}\right) \tag{35}$$

We discovered that $SRISK$ rises with leverage. The $SRISK$ also acknowledges the relationship of a financial institution with the system via $LRMES$. The latter coincides the expected fall in a financial institution's equity value will experiment if the market fell more than a given threshold within the next six months. Acharya, *et al.* (2012) suggest to estimate it via the daily MES (determined by a threshold C equal to 2%) as $LRMES_{i,t} \approx 1 - \exp(18 * \ MES_{it})$. This estimation equates to the institution's expected losses over a six-month period, obtained on the condition of the market dropping more than 40% over the course of the next six months. Since $SRISK$ is a function of MES, considered in the calculation of nonlinear MES as given in Eq. (13) is the potential nonlinear dependence in returns. Therefore, the linear version of $SRISK$ can be determined by MES is shown in Eq. (19), in the definition of $SRISK$.

As a function of both the equity markets expected shortfall, an institution's time varying β (systematic risk) and the institution's joint tail risk with the market, $LRMES$ has a tendency to crash if the market crashes. Both effects can vary over time from the use of dynamic econometric models.

The parameters can be approximated with two techniques. The time consuming one step approach, where full likelihood is maxed out. On the other hand, it can be done in two steps, by calculating the standardised residuals for estimating the DCC-model's parameters. The two-step approach is seen by Engle (2009) to be stable and at majority of times, close to the one step approach. Since the two-step approach is less time constricting, it shall be used within this chapter.

Brownlees and Engle (2012) suggest calculating $SRISK$ for the entire financial sector as:

$$SRISK_t = \sum_{i=1}^{N} \max\left(0; SRISK_{i,t}\right) \tag{36}$$

where N stands for the number of financial institutions within the financial sector under study. Eq. (36) revolves around the notion that financial institutions with capital surpluses do not take over institutions with capital shortfalls during a crisis. This means capital surpluses cannot cover for capital shortfalls. The purpose behind this is that possible capital shortfalls happen in a crisis, i.e. when the entire system is undercapitalized.

3.3.4 Delta Conditional Value-at-Risk (ΔCoVaR)

Between the conditioning event and the direction between MES and $\Delta CoVaR$, there is a distinction. When the financial system is under distress and experiencing losses, MES investigates an institution's returns, whereas the original $CoVaR$ (contribution $CoVaR_q^{sys|i}$) acts in reverse and investigates the financial system's returns when an institution is under financial distress. It is not due to the two measures' few intrinsic properties that the difference exists, but is rather tied to the usage that has been done for each. In this chapter, we use exposure $CoVaR$ ($CoVaR_q^{i|sys}$) only that is constructed with the same conditioning logic as MES.

$CoVaR$ measures the degree to which a tail event in a financial institution spills over and cause or worsen a tail event in another institution (sector or country). $CoVaR_q^{i|sys}$ can be defined as a conditional VaR, that is, $VaR_{q,t}^{i}$ of financial institution, i, conditional on the event that the financial system, sys, is under stress ($r^{sys} = VaR_{q,t}^{sys}$). In other words, we can implicitly define $CoVaR_{q,t}^{i|sys}$ by the q-quantile of the conditional probability:

$$\Pr\left(r_t^i \le CoVaR_{q,t}^{i|sys} | r_t^{sys} = VaR_{q,t}^{sys}\right) = q \tag{37}$$

where r_t^i refers to asset return of financial institution, i. More simply, Eq. (37) avers that when the return of financial system, sys, falls below a threshold value, the probability that losses of the financial institution, i, exceeds $CoVaR$ equal to q.

VaR of each institution, i, is computed by estimating the following univariate model

$$r_t^i = \mu_t^i + \varepsilon_{i,t} \tag{38}$$

where $\mu_t^i = q_0 + q_1 r_{t-1}^i$; $\varepsilon_{i,t} = z_{i,t}\,\sigma_{i,t}$ where $z_{i,t}$ is $i.i.d.$ with zero mean and unit variance; and the conditional variance has the standard $GARCH(1,1)$ specification

$$\sigma_{i,t}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t-1}^2 + \beta_2^i \sigma_{i,t-1}^2 \tag{39}$$

Given a distributional assumption for z and, hence, the q-quantile of the estimated conditional distribution, we can compute for each time period the VaR of each institution i[20].

Then, for each institution i, we estimate a bivariate $GARCH$ model with Engle's (2002) DCC specification for returns of institution and the financial system. Let $r_t = (r_t^{sys}, r_t^i)'$, whose joint dynamics is given by:

$$r_t = \mu_t + \varepsilon_t \tag{40}$$

$$\varepsilon_t = \Sigma_t^{1/2} z_t \tag{41}$$

where Σ_t the (2x2) conditional covariance matrix of the error term ε_t and μ_t is the (2x1) vector of conditional means. The standardized innovation vector $z_t = \Sigma_t^{-1/2}(r_t - \mu_t)$ is $i.i.d.$ with $E(z_t) = 0$ and $Var(z_t) = I_2$. We define D_t to be the $(2x2)$ diagonal matrix with the conditional variances $\sigma_{x,t}^2$ and $\sigma_{y,t}^2$ along the diagonal so that $\{D_{xx}\}_t = \{\Sigma_{xx}\}_t, \{D_{yy}\}_t = \{\Sigma_{yy}\}_t$ and $\{D_{xy}\}_t = 0$ for $x, y = s, i$. The conditional variances are modelled as $GARCH(1,1)$:

$$\sigma_{x,t}^2 = \theta_0^x + \theta_1^x \varepsilon_{x,t}^2 + \theta_2^x \sigma_{x,t-1}^2 \tag{42}$$

$$\sigma_{y,t}^2 = \theta_0^y + \theta_1^y \varepsilon_{y,t}^2 + \theta_2^y \sigma_{y,t-1}^2 \tag{43}$$

and the conditional covariance $\sigma_{xy,t}$ is:

$$\sigma_{xy,t} = \rho_{xy,t}\sqrt{\sigma_{x,t}^2\,\sigma_{y,t}^2} \tag{44}$$

Let $C_t = D_t^{-1/2}\Sigma_t D_t^{-1/2} = \{\rho_{xy}\}_t$ be the $(2x2)$ matrix of conditional correlations of ε_t. Following Engle (2002) we specify the conditional correlation matrix as follows:

$$C_t = diag(Q_t)^{-1/2}\, x\, Q_t\, x\, diag(Q_t)^{-1/2} \tag{45}$$

[20] For VaR calculations via univariate $GARCH$ models, refer to Duffie and Pan (1997) and Giot and Laurent (2003).

$$Q_t = (1 - \delta_1 - \delta_2)\bar{Q} + \delta_1(u_{t-1}u'_{t-1}) + \delta_2 Q_{t-1} \quad (46)$$

where $\bar{Q}$ is the unconditional covariance matrix of $u_t = \{\varepsilon_{x,t}/\sigma_{x,t}\}_{x=s,i}$ and $diag(Q_t)$ is the $(2x2)$ matrix with the diagonal of Q_t on the diagonal and zeros off-diagonal.

Once we estimate the bivariate density $pdf_t(r_t^{sys}, r_t^i)$ for each $r_t = (r_t^{sys}, r_t^i)'$ pair in the above steps, we proceed to obtain our $CoVaR_{q,t}^{i|sys}$ measure for each financial institution i and time period *t*. Given the definition of $CoVaR$ in Eq. (37) it follows that:

$$\Pr(r_t^i \leq CoVaR_{q,t}^{i|sys} | r_t^{sys} = VaR_{q,t}^{sys}) = q \quad (47)$$

$$\frac{\Pr(r_t^i \leq CoVaR_{q,t}^{i|sys} | r_t^{sys} = VaR_{q,t}^{sys})}{\Pr(r_t^{sys} = VaR_{q,t}^{sys})} = q \quad (48)$$

By definition of $VaR_{q,t}^{sys}$, $\Pr(r_t^{sys} = VaR_{q,t}^{sys}) = q$ so:

$$\Pr(r_t^i \leq CoVaR_{q,t}^{i|sys}, r_t^{sys} = VaR_{q,t}^{sys}) = q^2 \quad (49)$$

If we let $x, y = i, sys$, given the $VaR_{q,t}^{sys}$ estimates, we can numerically solve the following double integral for $CoVaR_{q,t}^{i|sys}$

$$\int_{-\infty}^{CoVaR_{q,t}^{i|sys}} \int_{-\infty}^{VaR_{q,t}^{sys}} pdf_t(x,y)dydx = q^2 \quad (50)$$

It is worth noting that the time-varying correlation between r_t^{sys} and r_t^i ensures that the $CoVaR_{q,t}^{i|sys}$ of a given financial institution has a time-varying exposure to its $VaR_{q,t}^i$.

3.4 Data

The sample employed in this chapter comprises of publicly listed financial institutions selected from the 17 Eurozone member states, namely Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia and Spain. The sample is formed by a total of 315 European financial institutions representing four main sectors, namely banks, diversified financials, insurance and real-estate[21]. See appendix (A) for the number of financial institutions within each sector in all Eurozone member states.

[21] This broad classification by sector is categorised according to Bloomberg GICS Industry Group Name.

Contrary to previous researches (see Beltratti and Stulz, 2012; Acharya, *et al.*, 2017; Brownlees and Engle, 2012), the sample is not restricted to financial institutions with total assets in excess of \$10 billion, but rather, smaller financial institutions are included. Most studies on systemic risk tend to focus only on large financial institutions, so-called '$TBTF$' (see Acharya, *et al.*, 2017; Adrian and Brunnermeier, 2011; Engle, *et al.*, 2014). However, as noted by Allen, Bali and Tang (2012), smaller financial institutions with more interconnections could have significant systemic risk potential due to common risk factors. Moreover, Kashyap and Stein (2000) point out that when financial institutions are distributed according to size, those found at bottom ninety-fifth percentile (that is, smaller financial institutions) who are facing liquidity challenges, are the main drivers of aggregate declines in loan supply. Thus, we do not only focus on the largest financial institutions since excluding the smaller financial institutions may not give the true nature of the potential systemic risk. Consequently, $TITF$ and $TMTF$ could contribute to systemic risk even more than $TBTF$.

The sample covers the period from 3 January 2000 to 31 December 2015. This time period provides a good platform to assess the level of exposure to systemic risk of the systemically important financial institutions in Eurozone since it includes a number of significant events (e.g. the U.S. subprime mortgage crisis, the Lehman Brothers collapse, the European sovereign debt crisis etc.). We assign the Q1 2000 – Q2 2007 as a pre-crisis period, the Q3 2007 – Q4 2010 as crisis period because the majority of U.S. and Eurozone systemic events occurred during this time window, and the Q1 2011 – Q4 2015 as a post-crisis period.

For our sample period, we obtain daily equity adjusted prices to account for capital operations (i.e., splits, dividends etc.), value-weighted market index returns, number of shares outstanding, and book values of total liabilities from the Bloomberg database. There are 4173 daily returns for the majority of financial institution in our sample. See appendix (B) for list of these institutions and their sectors classification within each member state.

For each financial institution, a weighted average of the returns of the remaining financial institutions in the sample is used as a proxy for financial system (sector or country). In this way, the resulting system return portfolios can be considered as representative of Eurozone financial system allowing the study of possible spillover effects between a stressed institution (sector or country) and financial system. Moreover, this approach rules out any spurious correlation that may be induced due to sizeable disparity in the composition of financial system proxy.

Table 3.1 presents the summary statistics of the Eurozone financial index returns and Eurozone member state financial sector returns for the entire period. The returns span -76%to 45% with a daily average of -0.02% across all member states. Four-member states show average positive returns while the remaining thirteen-member states register average negative returns or average zero returns. Overall, the evidence shows that returns have been low for member states during the crisis period. Table 3.1 indicates that the standard deviation spans 1.06% to 3.94% with the average estimated to be 1.99%, which is higher than the average daily returns. As the standard deviation is a crude measure of risk, the finding indicates that investors are likely to face large losses at a given return.

Table 3.1: Summary Statistics on Returns

	Mean	STD	Min.	Max.	Skewness	Kurtosis	JB	5%-VaR	5%-ES
Panel A: Eurozone Financial Sectors (2000-2015)									
Banks	-0.03	1.84	-10.31	17.23	0.09	6.63	7,670	2.72	4.33
DFinancials	-0.01	1.45	-9.46	10.20	-0.19	4.87	4,160	2.26	3.17
Insurance	-0.01	1.72	-12.49	10.92	-0.08	5.56	5,387	2.56	3.48
Real-estate	0.00	0.87	-6.05	6.62	-0.75	7.73	10,807	1.21	2.36
Panel B: Member States and Eurozone Financial Index (2000-2015)									
Austria	0.00	1.48	-11.29	12.53	-0.44	8.99	14,206	2.09	4.89
Belgium	0.00	1.63	-14.38	14.47	-0.38	9.75	16,648	2.29	3.80
Cyprus	-0.11	2.23	-12.69	16.09	0.02	4.51	3,545	3.19	9.46
Estonia	0.01	1.24	-34.46	13.49	-5.33	172.38	5,191,400	0.54	7.70
Finland	0.06	1.60	-16.00	11.01	-0.04	6.53	7,436	2.42	3.93
France	0.00	1.90	-11.14	15.71	0.13	6.59	7,571	2.76	4.30
Germany	-0.02	1.74	-13.08	14.39	-0.12	6.72	7,882	2.58	4.51
Greece	-0.15	3.35	-34.48	24.17	-0.68	12.39	27,045	4.48	13.43
Ireland	-0.12	3.94	-76.00	27.62	-1.96	42.91	323,140	4.74	14.35
Italy	-0.02	1.81	-9.99	14.94	-0.10	4.77	3,961	2.78	5.23
Luxembourg	0.00	1.06	-9.95	7.29	-0.32	6.79	8,090	1.72	13.69
Malta	0.02	1.10	-13.79	23.78	2.48	76.50	1,022,900	1.41	8.84
Netherlands	-0.02	2.37	-18.23	18.44	-0.07	8.85	13,637	3.20	14.16
Portugal	-0.07	1.87	-14.05	16.09	-0.06	6.84	8,142	2.68	7.44
Slovakia	0.08	2.50	-27.57	18.04	-0.79	15.13	39,733	3.65	15.82
Slovenia	-0.03	2.90	-47.61	44.93	-0.21	82.16	937,000	3.06	15.19
Spain	-0.01	1.87	-11.38	18.78	0.26	5.85	6,016	2.87	4.60
PIIGS	-0.04	1.68	-9.90	16.29	0.03	6.05	6,368	2.57	4.16
Eurozone	-0.02	1.62	-9.64	13.45	-0.01	5.92	6,105	2.39	3.67

Notes: The table displays the summary statistics for daily index returns of Eurozone financial sectors and each member state financial index from January 2000 to December 2015 (Overall Period). STD denotes the standard deviation. JB refers to the Jarque-Bera test for normality. The Jarque-Bera statistics are statistically significant at 1%. ES and VaR are estimated under the assumption of $q = 5\%$ level.

The evidence in Table 3.1 indicates that the return distributions are leptokurtic, with average kurtosis of 25.77 and average skewness of -0.40. For asset allocation, option pricing, other financial market activities and risk management, the skewness and kurtosis have significant effects. Stocks characterised with low negative skewness and low kurtosis (Kim and White, 2004) are typically sought out by investors. Causes for high negative skewness involve generally high turnover and infrequent high returns over prior periods. The Jarque-Bera statistic firmly rejects the null hypothesis of normality in the return distributions which proves the massive losses during stress periods. The rank of member states based on the highest ES is not exactly the same as the one produced by VaR and this is due to estimation procedure of each one.

3.5 Empirical Analysis and Results

3.5.1 Granger Causality Connections

Over the whole sample period of 2000-2015, this section uses the Granger causality test outlined in Eqs. 4 to 6. Displayed in Figure 3.1 the 36-month rolling window estimate, is positioned at around 0.2134-0.0522 in the entire sample period. Valuable information on the Eurozone financial institutions' interconnectedness is given by the dynamic causality index. It demonstrates that the level of connectedness of the financial institutions in the Eurozone is fluctuating reasonably over time. In instances of systemic shocks, the institutions become highly interconnected. For example, the start of the sample reveals a weak upward trend for the DCI, with a minimum at 0.0522 in the third quarter of 2000 and increases to approximately 0.1448 in the second quarter of 2004 when the government of Greece declared that the national statistics are unreliable and the budget deficit is above 3% which was set by Maastricht treaty (Cline and Wolff, 2012)[22].

The DCI carries on with local peaks and troughs, it sky-rocks in the fourth quarter of 2008 with 0.2124 DCI (following the collapse of Lehman Brothers and the beginning of the subprime crisis) which disturbs the interbank payment system and generating difficulties in payment instructions for financial institutions. It remains high in the first quarter of 2009 then reaches a higher peak in second quarter of 2009 with 0.2126 DCI (the eruption of Eurozone sovereign

[22] Maastricht Treaty was signed in 1992 among 12 European Union members to attain Economic and Monetary Union (EMU). Stability and Growth Pact (SGP) was agreed in 1997 and went into force with Euro introduction in 1999. It harmonises the fiscal policy and unify the monetary policy. All Eurozone members need to maintain low inflation, low interest rates and a maximum of 60% public debt and 3% budget deficit.

debt crisis and Eurozone commands a decrease in budget deficit of France, Spain, Greece and Ireland), followed by the highest peak in third quarter of 2009 with 0.2134 DCI (Bailout and austerity measures are applied by PIIGS countries). Despite the DCI displaying a falling trend in the post European debt crisis, it irregularly reveals local peaks that correlate with key financial events (Weiß *et al.*, 2014).

Additionally, a network diagram of estimated linear Granger causality relationships with the daily returns of the 315 Eurozone financial institutions; these are statistically significant at the 5% level. The $GARCH$ process helps attune the Granger causality relationships for autocorrelation and heteroskedasticity. The Granger causality relationships are signified by the curved lines connecting the institutions; that is, the financial institution at date t that Granger causes the returns of another institution at date $t + 1$. The three subsamples in Figures 3.2-3.4 present the results. These periods correlate to both periods of tranquillity and crisis in the sample.

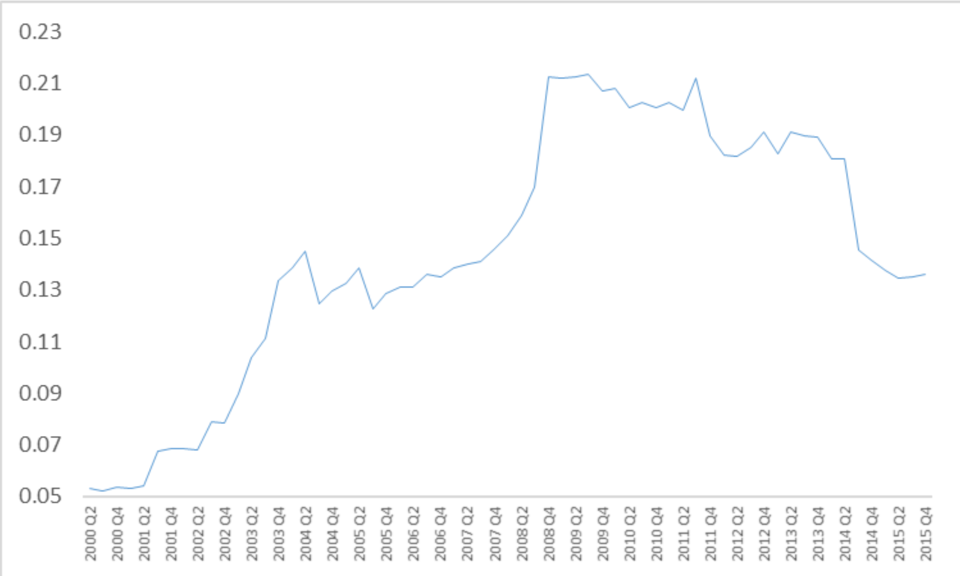

Figure 3.1: Eurozone Financial Sector Dynamic Causality Index

Notes: The graph displays the DCI interconnectedness among the 315 financial institutions in the Eurozone on a quarterly basis from Q2 2000 to Q4 2015. We estimate DCI for sub-samples in an overlapping form by using returns from a widow of the previous 12 quarters. The level of interconnectedness in the financial system is measured by the magnitude of DCI, so, a highly connected financial system is captured by higher value of DCI and vice versa.

These figures show the granger causality network within the Eurozone financial system's institutions. They can be seen as a proxy for how shocks could spillover within the system. It demonstrates the system's interconnections. In Figures 3.2-3.4, the network diagrams displayed show that there has been an increasing number of causal relations (i.e., significant granger causality relationships) among the financial institutions since 2004. For example, during the pre-crisis period (Q3 2004-Q2 2007), there were 13,836 links among the financial institutions. Though, this raised to 19,821 in crisis period of 2007 GFC and 2009 Eurozone crisis (Q3 2007-Q2 2010), and then falling slightly to 18,905 in the aftermaths of the crisis which is the post-crisis period (Q3 2010- Q2 2013).

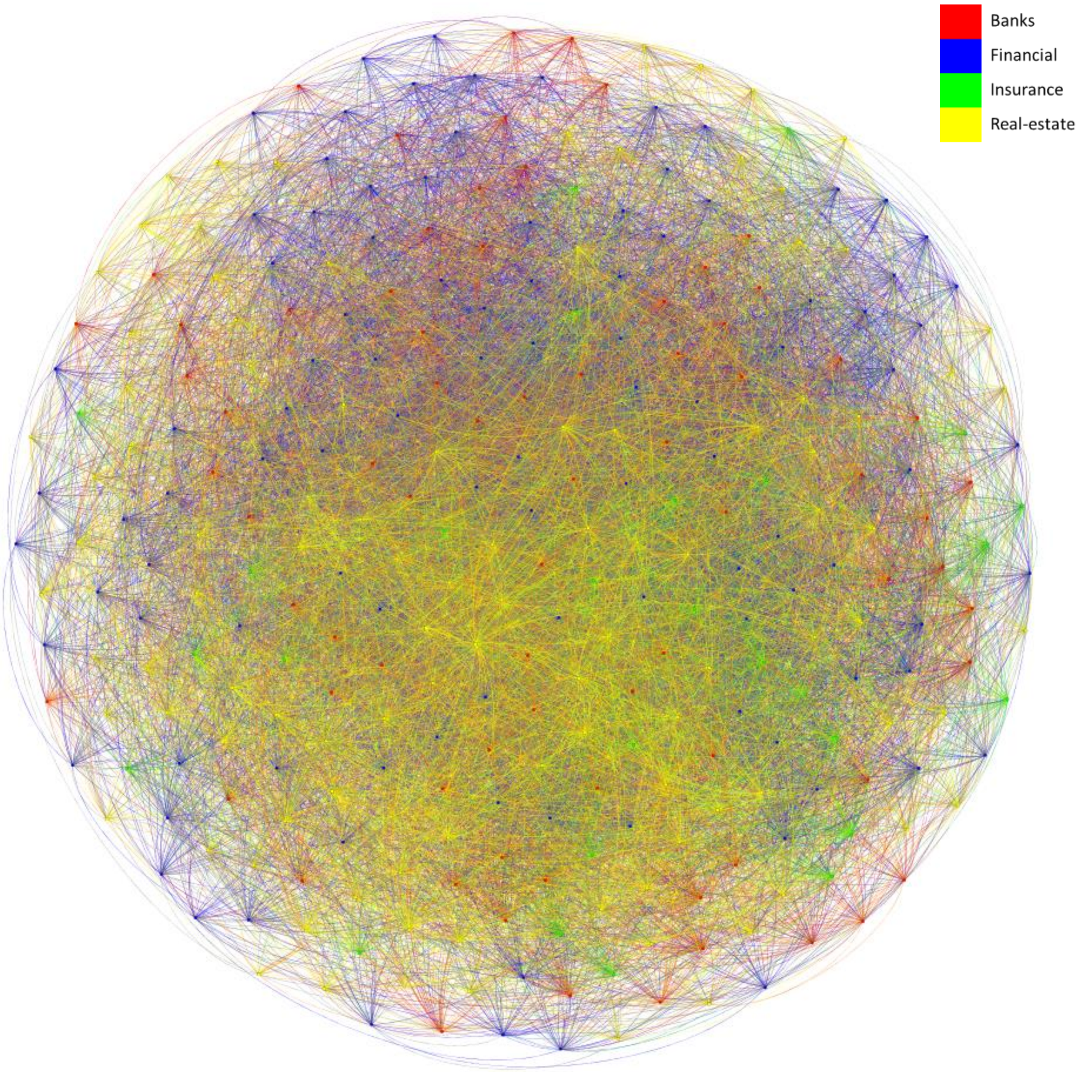

Figure 3.2: Granger Causality Network for Eurozone Financial Sector (pre-crisis period)

Notes: Linear granger causal relationships are displayed in a network diagram among the daily returns of 315 financial institutions in the Eurozone. Total number of 13,836 significant granger causality relationships are present at 5% level within the pre-crisis sample (Q3 2004-Q2 2007). See Appendix (C) for the full list of financial institutions within each sector.

The Eurozone financial system is also suggested by the figures that it becomes much more densely linked during financial crises when compared with more periods of tranquillity. For example, amongst the financial institutions in the pre-crisis period, the total number of causal relationships was 13,836 but these institutions became extremely interconnected during the crisis period of 19,821 links with an approximate increase of 43%.

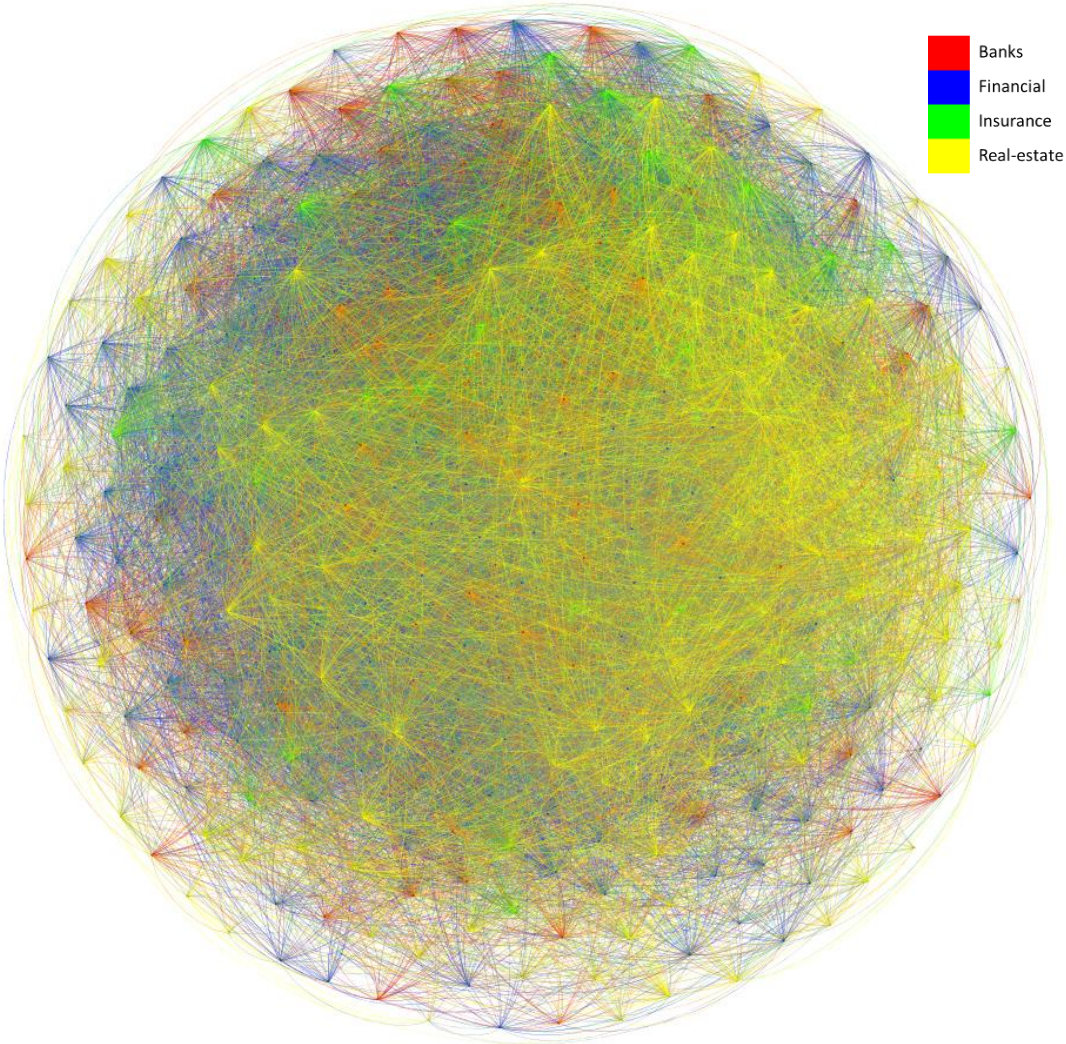

Figure 3.3: Granger Causality Network for Eurozone Financial Sector (crisis period)

Notes: Linear granger causal relationships are displayed in a network diagram among the daily returns of 315 financial institutions in the Eurozone. Total number of 19,821 significant granger causality relationships are present at 5% level within the crisis sample (Q3 2007-Q2 2010). See Appendix (D) for the full list of financial institutions within each sector.

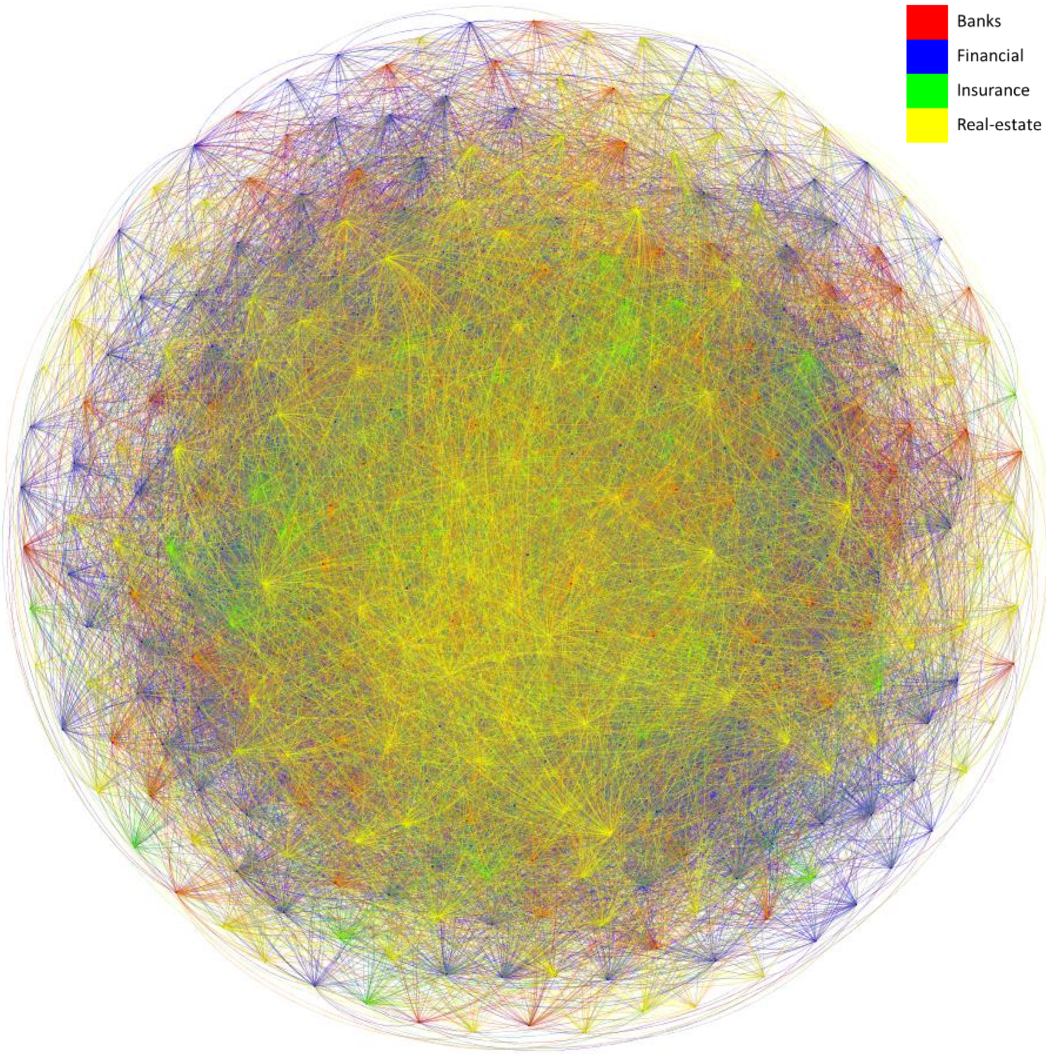

Figure 3.4: Granger Causality Network for Eurozone Financial Sector (post-crisis period)

Notes: Linear granger causal relationships are displayed in a network diagram among the daily returns of 315 financial institutions in the Eurozone. Total number of 18,905 significant granger causality relationships are present at 5% level within the post-crisis sample (Q3 2010- Q2 2013). See Appendix (E) for the full list of financial institutions within each sector.

The entire amount of significant Granger causal relations of singular financial sector in the three subperiods is demonstrated in Table 3.2. We discovered that the connection rankings altered during each subperiod, both pre-crisis and post-crisis periods have the same connections rankings. For instance, real-estate sector has the highest number of connections followed by diversified financials and banking sectors respectively while insurance sector is the least connected during the pre-crisis and post-crisis periods. On the contrary, during the crisis period interconnectedness ranking changes so that banking sector is the most connected followed by diversified financials, real-estate and insurance sectors respectively. It is worth noting that insurance sector is the lease connected and the financial sector is the second most connected in all subperiods (pre-crisis, crisis and post-crisis).

Although the number of connections change from one sample to another, the percentage of connections of each financial sector varies slightly across all subperiods. For example, banking sector connections of the total connections ranges from 27.52% to 32.09% during all subperiods. The banking sector has the third rank in both pre-crisis and post crisis periods with 3,807 and 5,314 significant connections respectively which signifies 27.52% and 28.11% of the total connections in these subperiods. However, the banking sector becomes the most connected sector during the crisis period with 6,361 significant Granger causal relations that represents 32.09% of the total Granger causality relations.

Though, the Granger causal relations results indicate that the Eurozone financial institutions became increasingly connected during the crisis. The amount of Granger causal relations stayed high in comparison with the pre-subprime crisis period, despite falling slightly after the GFC and Euro crisis. The financial institutions' high interconnection is suggestive of the Eurozone possibly susceptible to systemic risk.

Table 3.2: Linear Granger Causality Connections

Financial Sector	Pre-crisis Period			Crisis Period			Post-crisis Period		
	Rank	links	% of Total	Rank	links	% of Total	Rank	links	% of Total
Banks	3	3,807	27.52%	1	6,361	32.09%	3	5,314	28.11%
Financial	2	4,051	29.28%	2	5,949	30.01%	2	5,329	28.19%
Insurance	4	1,511	10.92%	4	2,261	11.41%	4	2,418	12.79%
Real-estate	1	4,467	32.29%	3	5,250	26.49%	1	5,844	30.91%
Total		**13,836**			**19,821**			**18,905**	

Notes: This table reports the number of linear granger causality connections among the daily returns of the four Eurozone financial sectors for three equal sub-periods of three years; pre-crisis period (Q3 2004-Q2 2007), crisis period (Q3 2007-Q2 2010) and post-crisis period (Q3 2010- Q2 2013). The linear granger causal relationships are statistically significant at 5%.

3.5.2 Systemic Risk Measures

The Eurozone financial sectors' high interconnectedness is proven by the Granger-causality network. The next concern is which financial sectors are exposed the most to European systemic event. With the systemic risk measures discussed in Section 3.3.2-4, the concern is followed up. The systemic risk exposure of each financial sector within the Eurozone is measured by $\Delta CoVaR$, MES and $SRISK$ models and enables these financial sectors to be positioned in order of importance.

Following Brownlees and Engle (2012), we estimate the MES and $SRISK$ using an $GARCH$-DCC model. The coverage rate is fixed at 5%, and the threshold C is fixed at 2% market drop over one-day for the short-run MES, and a 40% market drop over six-month for the $LRMES$ in our sample. The $\Delta CoVaR$ is estimated using the same theoretical framework ($GARCH$-DCC model) in order to be able to compare between the various risk measures.

The main objective of any systemic risk analysis is to rank financial institutions (sectors or countries) according to their systemic risk exposure (contribution) and, in turn, identify the $SIFIs$. The results discussed in this section need to be treated with caution for two reasons. First, using the average of the systemic risk measures ($MES, SRISK\ and\ \Delta CoVaR$) figures do not allow the conclusion that a member state (or sector or institution) is systemically riskier than another over the whole sample. Second, the following analysis relies exclusively on daily estimated values of the systemic risk measures. It is therefore possible that once there is a high confidence interval estimation for $MES, SRISK\ and\ \Delta CoVaR$ or high minimal prudential capital requirements for $SRISK$, a member state (or sector or institution) displaying lower risk will turn into a significant exposure of risk to the system.

We measure systemic risk exposure within the 17-member states of the Eurozone on two levels: (i) identify which financial sector and member state is exposed the most to the entire systemic risk in the Eurozone on the union level, (ii) identify which member state has the highest exposure to systemic risk within each financial sector, namely, the banking, diversified financials, insurance and real-estate.

Table 3.3 provides descriptive statistics of systemic risk measures for each financial sector in the Eurozone. MES and $LRMES$ have the same ranking within each period while $\Delta CoVaR$, MES and $SRISK$ provide different ranking in each period and these rankings differ from one period to another. The $\Delta CoVaR$, MES and $LRMES$ mean of insurance sector has the highest systemic risk exposure, in absolute terms, while the banking sector is the highest according to $SRISK$ during crisis period. Insurance sector is the second most exposed sector to systemic risk for all risk measures during crisis period while real-estate sector is the least exposed sector for all risk measures during pre-crisis period.

Table 3.3: Eurozone Financial Sectors Average Systemic Risk Measures

Financial Sector		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (A): Overall Period									
Banks	Mean	3	1.94	3	2.12	3	30.18	1	290,107
	STD		1.16		1.27		12.99		183,698
DFinancials	Mean	1	2.21	1	2.42	1	33.35	2	46,715
	STD		1.34		1.48		14.47		41,679
Insurance	Mean	2	2.10	2	2.32	2	32.13	3	41,186
	STD		1.33		1.46		14.58		46,369
Real-estate	Mean	4	1.45	4	1.74	4	25.04	4	-22,804
	STD		1.09		1.32		14.63		14,513
Panel (B): Pre-crisis Period									
Banks	Mean	3	1.07	2	1.44	2	22.59	1	140,599
	STD		0.35		0.46		5.71		35,245
DFinancials	Mean	1	1.12	1	1.45	1	22.81	3	7,251
	STD		0.34		0.44		5.62		11,108
Insurance	Mean	2	1.09	3	1.39	3	21.82	2	34,846
	STD		0.37		0.46		5.92		18,093
Real-estate	Mean	4	0.56	4	0.93	4	15.17	4	-27,916
	STD		0.34		0.46		6.47		11,274
Panel (C): Crisis Period									
Banks	Mean	4	2.77	3	3.04	3	40.18	1	455,973
	STD		1.40		1.56		13.39		150,984
DFinancials	Mean	2	3.37	2	3.53	2	44.76	2	85,319
	STD		1.65		1.77		13.89		26,001
Insurance	Mean	1	3.72	1	3.60	1	45.45	3	77,729
	STD		1.77		1.75		13.47		27,769
Real-estate	Mean	3	2.81	4	2.98	4	39.48	4	-18,105
	STD		1.44		1.58		13.72		9,199
Panel (D): Post-crisis Period									
Banks	Mean	4	1.97	4	2.24	4	32.42	1	519,293
	STD		0.77		0.88		9.61		56,410
DFinancials	Mean	1	2.82	2	2.95	2	40.14	2	97,647
	STD		1.03		1.08		10.35		21,386
Insurance	Mean	2	2.68	1	3.01	1	40.72	3	76,117
	STD		1.01		1.15		10.92		22,252
Real-estate	Mean	3	2.25	3	2.50	3	35.27	4	-22,936
	STD		0.85		0.98		10.41		6,530

Notes: The table ranks the average exposure of systemic risk measures according to $\Delta CoVaR, MES, LRMES$ and $SRISK$ of each Eurozone financial sector. Simple averages and standard deviations are computed within the four periods; overall period (2000-2015), pre-crisis period (Q3 2004-Q2 2007), crisis period (Q3 2007-Q2 2010) and post-crisis period (Q3 2010- Q2 2013). Standard deviations and average $MES, LRMES$ and $\Delta CoVaR$ figures are expressed as a percentage while $SRISK$ figures are expressed in terms of million Euros. All risk measures are generated under the assumption of $q = 5\%$ level.

According to Table 3.4, the highly exposed member states to stress events in the Eurozone are PIIGS, Spain, Italy and France for all systemic risk measures but each risk measure gives different ranking for these countries which is consistent with $TBTF$ paradigm.

Table 3.4: Eurozone Member States Average Systemic Risk Measures

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Austria	Mean	8	2.88	8	3.04	8	40.20	10	3,257
	STD		1.41		1.53		13.35		5,711
Belgium	Mean	6	3.14	9	2.93	9	39.19	7	29,295
	STD		1.52		1.48		13.17		16,210
Cyprus	Mean	13	1.99	12	2.49	12	34.51	15	-574
	STD		1.07		1.35		13.00		1,765
Estonia	Mean	16	0.13	15	0.43	15	7.36	17	-1,525
	STD		0.09		0.27		4.31		72
Finland	Mean	9	2.60	6	3.26	6	42.42	18	-3,187
	STD		1.26		1.59		13.35		1,519
France	Mean	4	3.24	4	3.50	4	44.54	1	254,553
	STD		1.60		1.75		13.59		49,190
Germany	Mean	5	3.16	5	3.38	5	43.46	2	160,127
	STD		1.51		1.66		13.53		29,816
Greece	Mean	10	2.32	10	2.81	10	38.01	14	-508
	STD		1.15		1.42		12.96		13,085
Ireland	Mean	12	2.07	13	2.00	13	28.90	8	12,117
	STD		1.11		1.16		12.67		6,679
Italy	Mean	3	3.41	2	3.63	3	45.61	4	64,306
	STD		1.67		1.82		13.79		36,683
Luxembourg	Mean	15	0.14	18	0.11	18	2.03	16	-1,024
	STD		0.07		0.06		0.98		64
Malta	Mean	17	0.08	17	0.14	17	2.50	13	-207
	STD		0.09		0.13		2.23		205
Netherlands	Mean	7	2.98	7	3.23	7	42.13	6	40,904
	STD		1.42		1.57		13.21		31,495
Portugal	Mean	11	2.28	11	2.63	11	35.62	9	5,361
	STD		1.35		1.54		14.13		3,791
Slovakia	Mean	18	0.05	16	0.26	16	4.62	11	277
	STD		0.03		0.13		2.17		76
Slovenia	Mean	14	0.38	14	0.48	14	7.65	12	-153
	STD		0.52		0.67		9.60		57
Spain	Mean	2	3.51	3	3.62	2	45.63	5	45,765
	STD		1.70		1.78		13.67		23,305
PIIGS	Mean	1	3.64	1	3.81	1	47.07	3	135,522
	STD		1.83		1.95		14.09		78,259

Notes: The table ranks the average exposure to systemic risk measures according to $\Delta CoVaR, MES, LRMES\ and\ SRISK$ of each member state in the Eurozone. Simple averages and standard deviations are computed within the crisis period (Q3 2007-Q2 2010). Standard deviations and average $MES, LRMES\ and\ \Delta CoVaR$ figures are expressed as a percentage while $SRISK$ figures are expressed in terms of million Euros. All risk measures are generated under the assumption of $q = 5\%$ level. See panel (A), (B) and (C) in appendix (F) for systemic risk exposure values during overall period (2000-2015), pre-crisis period (Q3 2004-Q2 2007) and post-crisis period (Q3 2010- Q2 2013) respectively.

Table 3.5 proves that each systemic risk measure gives different ranking of financial sectors within each member state. The divergence of systemic risk ranking produced by each measure is not due to instability of a specific measure but rather due to their fundamental differences. Consequently, we cannot generalise the outcome of a particular measure but instead there is a need to integrate these systemic risk measures into a larger framework to capture the multiple dimensions of systemic risk.

Table 3.5: Average Systemic Risk Measures of Each Financial Sector within Member States

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (A): Banks									
Austria	Mean STD	5	3.84 1.52	5	4.28 1.72	4	51.75 12.09	9	6,549 2,720
Belgium	Mean STD	2	4.71 2.86	2	5.16 3.19	2	55.69 16.26	6	38,315 10,571
Cyprus	Mean STD	11	2.82 0.94	10	3.42 1.12	9	44.92 9.98	12	112 1,398
Finland	Mean STD	13	0.11 0.02	14	0.40 0.07	14	6.99 1.14	13	30 20
France	Mean STD	3	4.45 1.96	4	4.73 2.13	3	54.58 13.93	1	242,833 33,829
Germany	Mean STD	10	3.06 1.48	11	3.27 1.60	11	42.70 11.85	5	38,906 9,842
Greece	Mean STD	8	3.47 1.38	8	3.73 1.51	8	47.14 12.53	15	-1,010 11,787
Ireland	Mean STD	1	5.83 4.16	1	6.34 4.46	1	61.45 17.20	8	14,869 4,825
Italy	Mean STD	7	3.50 1.71	6	4.03 2.01	5	48.98 13.91	3	59,535 27,400
Malta	Mean STD	15	0.04 0.05	15	0.18 0.11	15	3.12 1.77	14	-189 199
Netherlands	Mean STD	4	4.05 3.89	3	4.98 4.68	7	48.19 27.20	7	36,787 29,796
Portugal	Mean STD	12	2.20 0.77	12	2.38 0.85	12	34.09 9.00	10	5,407 3,369
Slovakia	Mean STD	14	0.08 0.03	13	0.56 0.21	13	9.56 3.35	11	288 77
Spain	Mean STD	6	3.54 1.83	7	4.03 2.12	6	48.57 15.16	4	51,771 21,292
PIIGS	Mean STD	9	3.15 1.45	9	3.52 1.65	10	44.89 13.31	2	123,147 67,774

Table 3.5: Average Systemic Risk Measures of Each Financial Sector within Member States (continued)

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (B): Diversified Financial									
Austria	Mean	12	0.26	12	0.53	12	9.06	5	-50
	STD		0.12		0.20		3.11		15
Belgium	Mean	4	2.17	4	2.27	4	31.84	14	-4,886
	STD		1.28		1.39		12.76		4,562
Cyprus	Mean	9	1.50	6	2.01	6	29.69	7	-107
	STD		0.64		0.80		8.70		67
Finland	Mean	11	0.96	11	1.21	11	19.36	8	-194
	STD		0.34		0.45		5.93		49
France	Mean	3	2.38	3	2.63	3	36.63	13	-3,578
	STD		0.97		1.09		10.39		2,380
Germany	Mean	1	3.38	1	3.62	1	45.51	1	92,880
	STD		1.68		1.86		13.56		16,656
Greece	Mean	8	1.69	9	1.83	9	27.53	2	2,887
	STD		0.63		0.69		7.47		1,390
Ireland	Mean	10	1.23	10	1.53	10	23.71	6	-56
	STD		0.46		0.53		6.94		26
Italy	Mean	6	1.97	7	2.00	7	29.67	11	-2,098
	STD		0.70		0.74		8.47		2,100
Luxembourg	Mean	13	0.09	13	0.23	13	4.11	9	-1,001
	STD		0.03		0.07		1.20		66
Netherlands	Mean	7	1.85	5	2.16	5	31.18	12	-2,160
	STD		0.84		1.01		10.43		824
Slovenia	Mean	14	0.00	14	0.00	14	0.03	4	-2
	STD		0.00		0.00		0.04		0
Spain	Mean	5	2.01	8	1.96	8	29.08	10	-1,456
	STD		0.76		0.77		8.94		361
PIIGS	Mean	2	2.99	2	3.16	2	41.54	3	554
	STD		1.40		1.52		13.16		3,864

Table 3.5: Average Systemic Risk Measures of Each Financial Sector within Member States (continued)

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (C): Insurance									
Austria	Mean	8	2.18	8	2.32	8	33.00	10	-538
	STD		1.04		1.12		11.14		1,065
Cyprus	Mean	11	0.73	11	1.08	11	17.52	7	-33
	STD		0.28		0.30		4.26		7
Finland	Mean	5	2.78	6	2.66	6	36.86	12	-3,070
	STD		1.16		1.14		11.24		1,151
France	Mean	2	4.15	2	3.83	2	46.86	1	30,837
	STD		2.19		2.05		15.45		8,672
Germany	Mean	6	2.74	4	3.02	4	39.30	2	28,856
	STD		1.67		1.84		15.13		14,278
Greece	Mean	10	1.38	9	1.89	9	28.07	6	-12
	STD		0.71		0.81		9.67		16
Ireland	Mean	9	1.54	10	1.70	10	25.65	9	-188
	STD		0.77		0.84		9.51		148
Italy	Mean	7	2.46	7	2.64	7	36.65	5	6,447
	STD		1.08		1.13		11.52		7,122
Netherlands	Mean	1	5.70	1	5.80	1	57.94	3	11,294
	STD		3.84		3.96		19.27		2,945
Slovenia	Mean	12	0.42	12	0.94	12	15.06	8	-137
	STD		0.46		0.63		8.41		51
Spain	Mean	4	2.96	5	2.87	5	39.18	11	-1,418
	STD		1.17		1.16		11.04		1,114
PIIGS	Mean	3	3.31	3	3.28	3	42.67	4	6,774
	STD		1.54		1.55		13.13		8,037

Table 3.5: Average Systemic Risk Measures of Each Financial Sector within Member States (continued)

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (D): Real-estate									
Austria	Mean	2	3.20	1	3.93	2	46.49	6	-1,518
	STD		2.20		2.72		16.25		1,418
Belgium	Mean	8	1.41	8	1.65	8	24.84	8	-1,735
	STD		0.75		0.90		10.04		402
Cyprus	Mean	10	0.96	9	1.44	9	22.56	2	-177
	STD		0.43		0.50		6.41		107
Estonia	Mean	12	0.00	13	0.00	13	0.01	7	-1,646
	STD		0.00		0.00		0.02		5
Finland	Mean	1	3.22	2	3.86	1	48.85	3	-335
	STD		1.05		1.28		10.17		215
France	Mean	7	2.46	6	2.39	6	33.86	13	-6,871
	STD		1.06		1.07		11.28		2,934
Germany	Mean	3	3.16	10	1.26	10	19.92	10	-2,408
	STD		1.51		0.58		7.10		518
Greece	Mean	9	1.25	7	2.10	7	30.98	4	-342
	STD		0.46		0.74		7.34		153
Italy	Mean	6	2.62	3	2.96	4	39.44	5	-746
	STD		1.31		1.51		13.55		572
Malta	Mean	13	0.00	12	0.01	12	0.19	1	-12
	STD		0.00		0.00		0.00		1
Netherlands	Mean	5	2.67	5	2.89	3	39.44	9	-2,350
	STD		0.98		1.11		10.78		785
Spain	Mean	11	0.66	11	0.79	11	13.02	11	-2,977
	STD		0.42		0.44		6.93		2,477
PIIGS	Mean	4	2.67	4	2.95	5	39.29	12	-3,066
	STD		1.34		1.52		13.56		2,879

Notes: The table ranks the average exposure to systemic risk measures according to $\Delta CoVaR, MES, LRMES\ and\ SRISK$ of each member state in the Eurozone. Simple averages and standard deviations are computed within the crisis period (Q3 2007-Q2 2010). Standard deviations and average $MES\ and\ \Delta CoVaR$ figures are expressed as a percentage while $SRISK$ figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $\alpha = 5\%$ level. See appendix (G), (H) and (I) for systemic risk exposure values during overall period (2000-2015), pre-crisis period (Q3 2004-Q2 2007) and post-crisis period (Q3 2010- Q2 2013) respectively.

Figure 3.5 clearly reveals how the tail risk measures dynamics provide a relatively poor fit for PIIGS countries during the crisis period with several large ES and VaR exceptions in the end of 2009 as well as the start of 2011 and 2012. From the figure, market VaR reaches its most extreme levels around October 2009 where Greece, Portugal and Spain launched austerity measures and the whole financial market stumbled. However, $PIIGS$ countries experienced its most severe period during the end of 2008 and end of 2012 but because the financial market as a whole was slightly recovering during this period, the VaR estimates for $PIIGS$ member states took on less extreme values here.

$PIIGS$ Return vs Tail Risk Measures　　　Market Return vs Tail Risk Measures

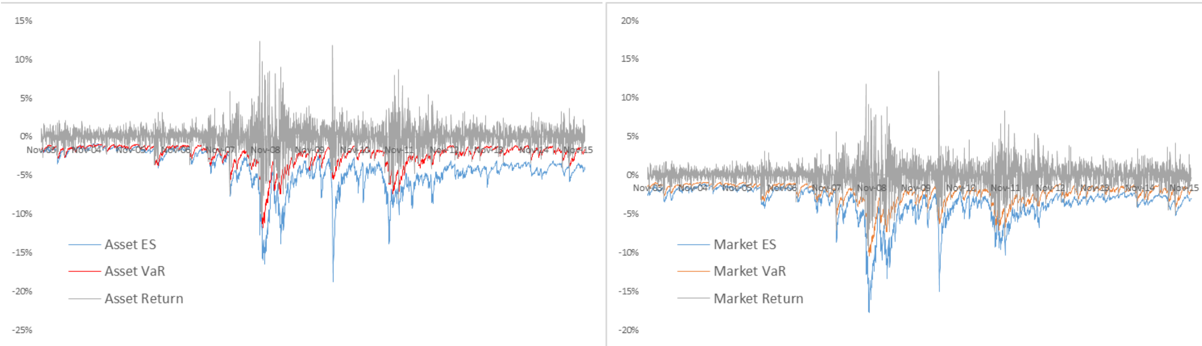

Figure 3.5: Return vs Tail Risk Measures (VaR and ES)

Notes: The left-side graph displays the asset return, VaR and ES of $PIIGS$ countries while the right-side graph displays the market return, VaR and ES. The analysis covers the overall period (2000-2015). Tail risk measures are generated under the assumption of $q = 5\%$ level. Return, VaR and ES figures are expressed as a percentage.

Figure 3.6 displays the average daily conditional volatility series of $PIIGS$ member states and Eurozone financial index for the period 2000-2015. The early 2000's are characterized by high levels of volatility which can be associated with the dot-com recession of 2001. This is followed by a protracted period of low volatility until spiked again early 2008 as the economy was experiencing a significant bubble before the crash. Volatility reached three peaks in 2009, 2010 and 2011 when the European sovereign debt crisis occurred and different bailout plans went into effect where volatility started to slowly decay but is still higher compared to the period before the crisis. The correlation between $PIIGS$ member states and the market is relatively low but it spikes in distress times as it is observed in 2002, 2003, 2009 and 2012.

Conditional Volatility of $PIIGS$ Returns	Conditional Volatility of Market Returns	Correlation between $PIIGS$ and Market Returns

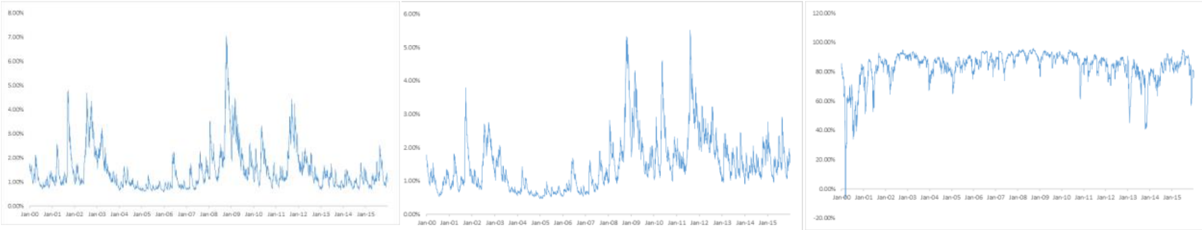

Figure 3.6: Conditional Volatility and Correlation

Notes: The right-side graph displays the conditional volatility of the $PIIGS$ returns, the middle graph displays the conditional volatility of the market returns, and the right-side graph displays the correlation between $PIIGS$ returns and the market returns. The analysis covers the overall period (2000-2015). Conditional volatility and correlation is expressed as a percentage.

Figure 3.7 displays the evolution of the three main systemic risk measures for $PIIGS$ between 2000 and 2015. It is obvious that that all risk measures raise around end of 2008 and that $SRISK$ increases much more, in relative terms, than the other measures. It is obvious that $MES\ and\ \Delta CoVaR$ follow nearly the same pattern compared to $SRISK$. $MES\ and\ \Delta CoVaR$ reached their maximum on October 2008 while spiked on March 2009 and August 2011.

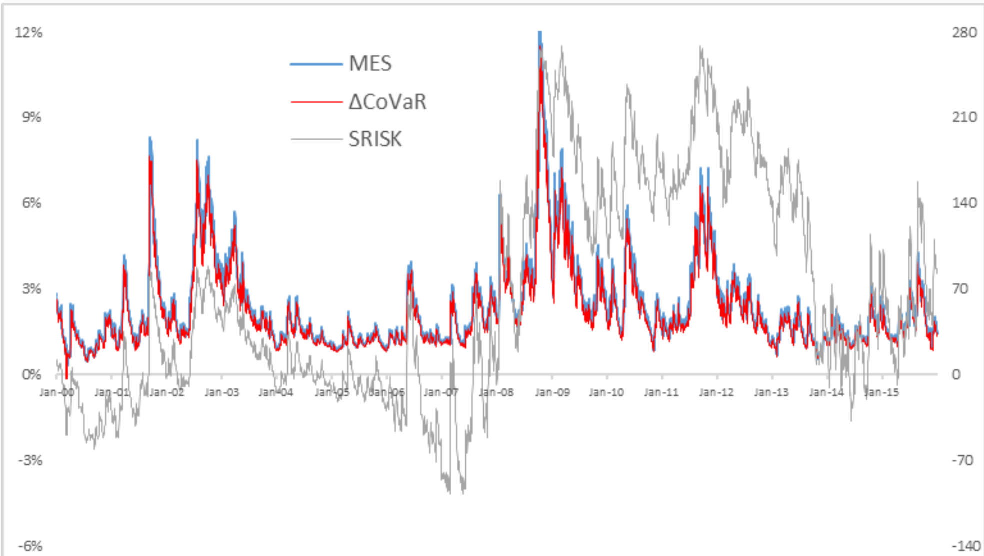

Figure 3.7: Time Series Evolution of Systemic Risk Measures for PIIGS Member States

Notes: The graph displays the $\Delta CoVaR\ and\ MES$ (left axis) and the $SRISK$ (right axis) of $PIIGS$ countries within the overall period (2000-2015). Average $MES\ and\ \Delta CoVaR$ figures are expressed as a percentage while average $SRISK$ are expressed in terms of Billion Euros. All risk measures are generated under the assumption of $q = 5\%$ level.

Figure 3.8 shows a strong relationship between average $\Delta CoVaR$ and MES while there is a weak association between $SRISK$ with $\Delta CoVaR$ and MES. This could be explained by the

$TITF$ paradigm that is related to MES and $\Delta CoVaR$ while $SRISK$ is explained by $TBTF$ paradigm (through the liabilities) and $TITF$ paradigm (through the beta).

MES vs $SRISK$ MES vs $\Delta CoVaR$ $SRISK$ vs $\Delta CoVaR$

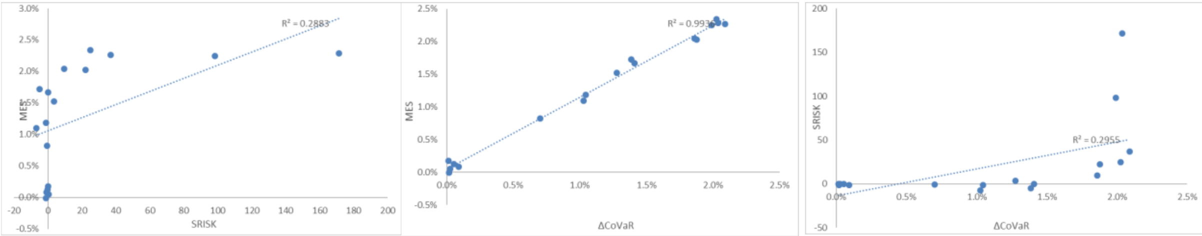

Figure 3.8: Cross-Section Evolution of Systemic Risk Measures for Eurozone Member States

Notes: Each point represents a member state of the Eurozone. Averages are calculated for the overall period (2000-2015). The right-side graph displays the relationship between average MES (y-axis) and $SRISK$ (x-axis), the middle graph displays the relationship between average MES (y-axis) and $\Delta CoVaR$ (x-axis), and the right-side graph displays the relationship between average $SRISK$ (y-axis) and $\Delta CoVaR$ (x-axis). Average MES and $\Delta CoVaR$ figures are expressed as a percentage while average $SRISK$ figures are expressed in terms of Billion Euros. All risk measures are generated under the assumption of $q = 5\%$ level.

Figure 3.9 plots the time-series average of PIIGS member states' standard financial risk measures (systematic risk, tail risk, correlation) and its exposure to systemic risk ($\Delta CoVaR$, MES and $SRISK$) over time. MES could be explained by VaR and ES in the time series dimension while beta shows similar spikes but does not reflect the same pattern of MES over time. It is evident that $\Delta CoVaR$ and VaR measures have a strong relationship in the time series analysis. Similar findings are also reported in Adrian and Brunnermeier (2011), Benoit, *et al.* (2013), Andreev, *et al.* (2005) and Boucher, *et al.* (2014)[23]. Conditional volatility shows similar pattern of $\Delta CoVaR$ while conditional correlation poorly reflects the changes in $\Delta CoVaR$ over time. ES and $LRMES$ displays similar pattern as $SRISK$ while leverage reflects the same pattern mainly during the crisis period. There is an opposite direction between market capitalization and beta with $SRISK$ when market value of equity (beta) falls, $SRISK$ rises and vice versa. Liability weakly reflects $SRISK$.

[23] An inferior relationship between $\Delta CoVaR$ and VaR was demonstrated in Girardi and Ergün's (2013) time series analysis, due to the alternative meanings of $\Delta CoVaR$ used by Girardi and Ergün and not from the alternative $CoVaR$ meanings.

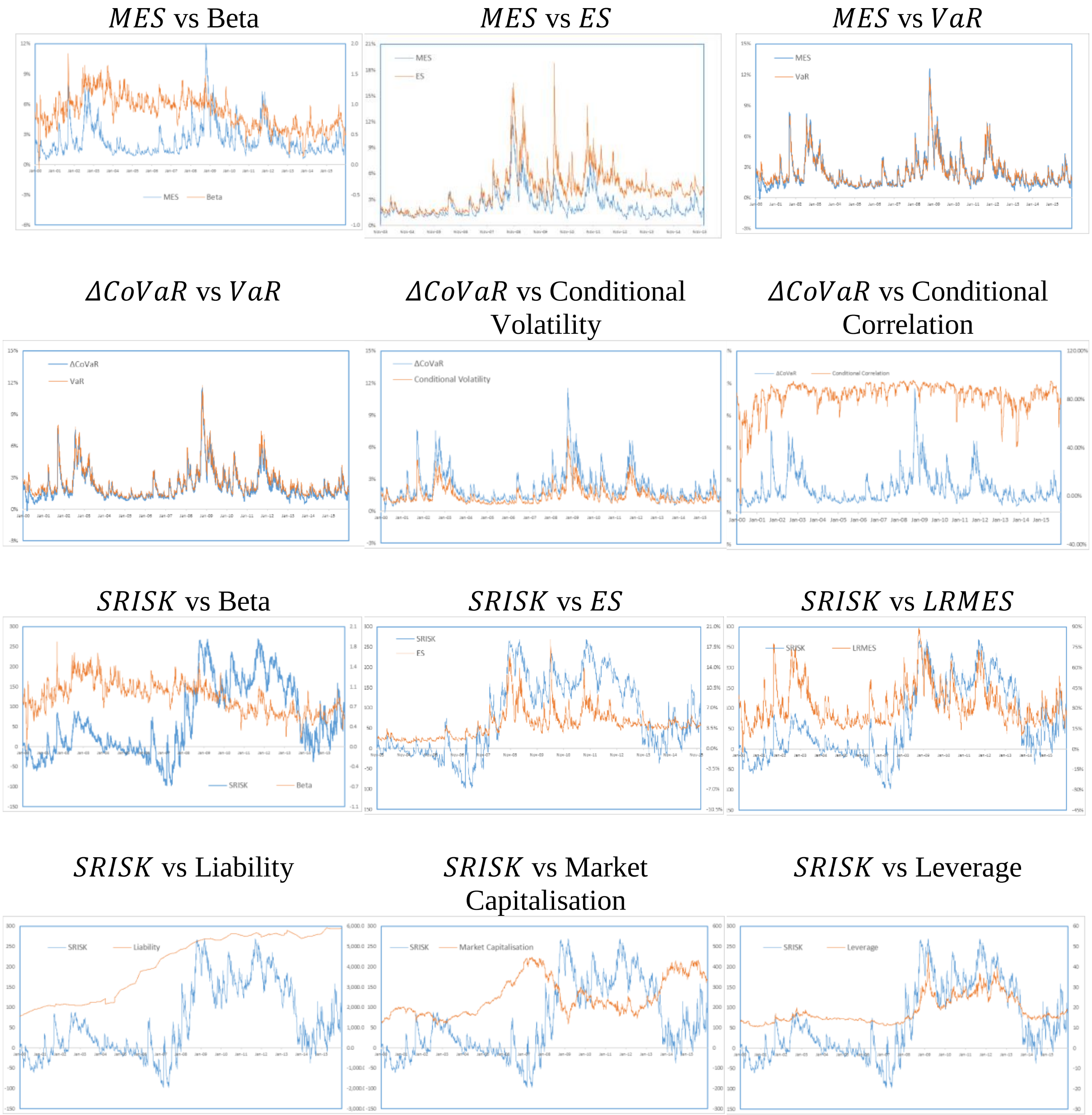

Figure 3.9: Time-Series Analysis of Macro-prudential and Micro-prudential Measures

Notes: This figure shows the time-series average of daily systemic risk measures and standard financial risk measures. The estimation covers the period from 03 January 2000 to 31 December 2015. All risk measures are generated under the assumption of $q = 5\%$ level. MES, $LRMES$, ES, $\Delta CoVaR$, VaR, conditional volatility and conditional correlation figures are expressed as a percentage while $SRISK$, liability and market capitalisation figures are expressed in terms of Billion Euros.

Figure 3.10 displays a cross-section plot of member state's average standard financial risk measures (systematic risk, tail risk, correlation) and its exposure to systemic risk ($\Delta CoVaR$, MES, $LRMES$ and $SRISK$). We report a strong positive relationship between MES and firm beta. There is strong cross-sectional link ($R^2 = 0.8506$) between the time-series average of the MES at 5% estimated for each member state of the Eurozone and its time-varying beta. This implies that systemic risk rankings of member states based on MES mirror rankings obtained by sorting member states on betas. There is a weak relationship between MES and tail risk measures (ES and VaR). There is a weak relationship between a member state's risk in isolation, measured by its VaR, and its exposure to system risk, measured by its $\Delta CoVaR$ in the cross-section analysis. Similar findings are also reported in Adrian and Brunnermeier (2011), Girardi and Ergün (2013), Benoit, *et al.* (2013), Andreev, *et al.* (2005) and Boucher, *et al.* (2014). In addition, conditional volatility is weakly related to $\Delta CoVaR$. However, 99.6% of the variance of the $\Delta CoVaR$ of the member states is explained by conditional correlation. The scatter plots of $SRISK$ in figure 3.10 displays that it is highly correlated to firm characteristics of liabilities and market capitalisation rather than standard financial risk measures of systematic risk and tail risk. This concludes that regulating the risk of financial institutions (sectors, countries) in isolation, through institutions' ES or VaR, might not be the optimal policy for protecting the financial sector against systemic risk.

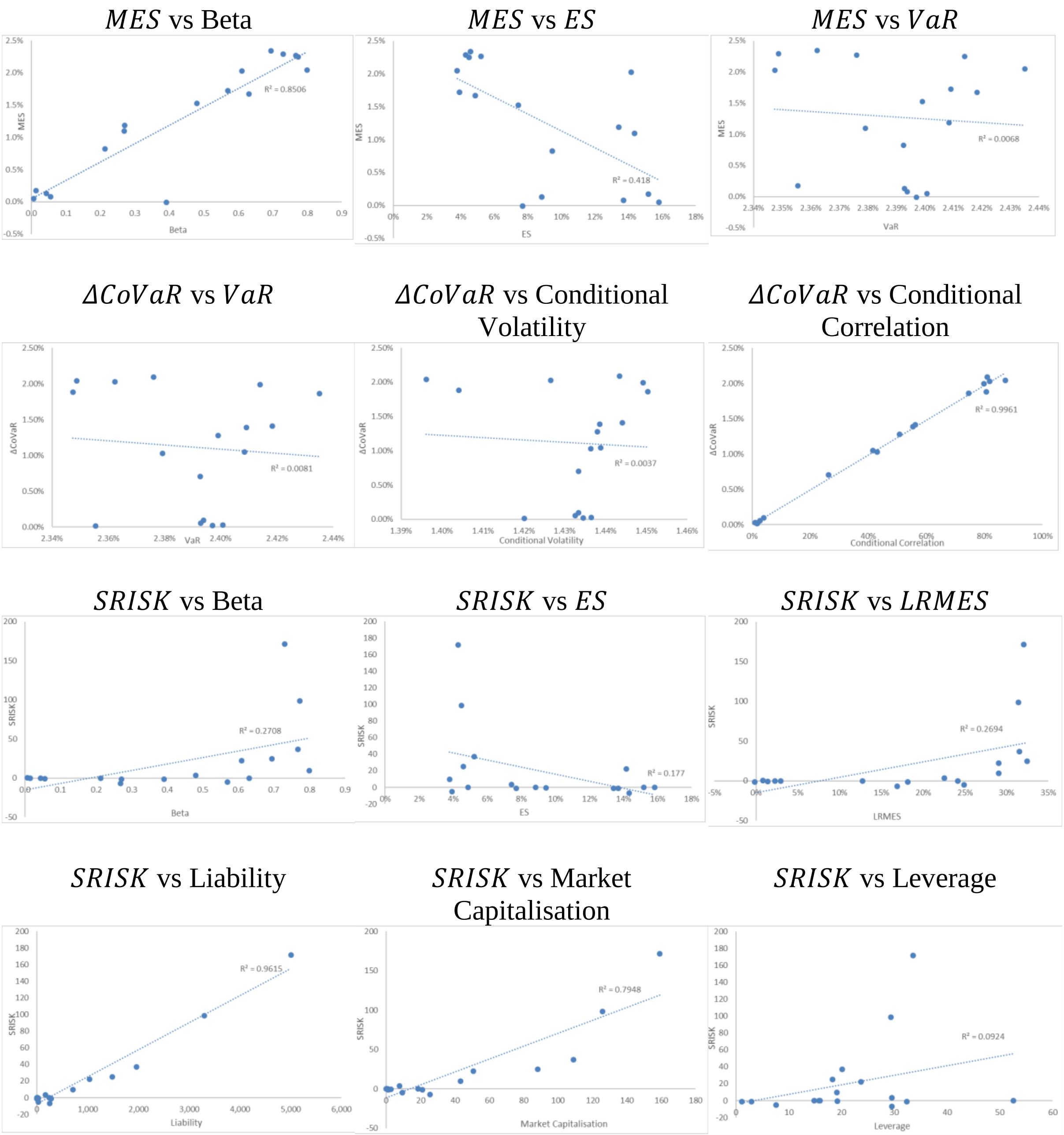

Figure 3.10: Cross-Sectional Analysis of Macro-prudential and Micro-prudential Measures

Notes: The scatter plot shows the cross-sectional link between the time-series average of Eurozone member state's risk in isolation, measured by ES and VaR, firm characteristics, measured by leverage and market capitalisation, and the time-series average exposure to systemic risk, measured by MES, $SRISK$ and $\Delta CoVaR$. All risk measures are generated under the assumption of $q = 5\%$ level. Each point represents a member state of the Eurozone. Averages are calculated for the overall period (2000-2015). Average MES, $LRMES$, ES, $\Delta CoVaR$, VaR, conditional volatility and conditional correlation figures are expressed as a percentage while Average $SRISK$, liability and market capitalisation figures are expressed in terms of Billion Euros.

Table 3.6: Systemic Risk Measures and Firm Characteristics Values and Ranking

Member	MES	$SRISK$	$\Delta CoVaR$	ES	VaR	β	MV	LTQ	LVG	ρ
Panel (A): Values										
Austria	1.40	-4.20	1.18	2.82	1.91	0.78	28.16	299.90	11.65	63.74
Belgium	1.64	-13.98	1.50	2.48	1.95	1.07	63.80	562.49	9.82	77.71
Cyprus	0.23	-0.15	0.21	11.15	1.88	0.07	1.90	28.46	16.01	11.68
Estonia	-0.01	-0.11	0.02	10.15	1.88	0.01	0.12	0.05	1.37	1.87
Finland	1.66	-19.46	1.35	2.90	1.90	0.75	30.42	33.96	2.12	73.66
France	1.91	186.66	1.70	2.97	1.92	0.89	275.34	6,749.93	25.51	90.55
Germany	1.66	56.28	1.45	2.97	1.97	0.77	202.08	3,599.23	18.81	73.12
Greece	0.55	15.16	0.45	29.05	1.89	0.05	12.65	472.43	38.35	25.30
Ireland	0.04	-15.90	0.08	11.66	1.80	0.01	29.48	213.78	8.25	5.68
Italy	1.78	42.99	1.65	3.89	1.87	0.74	147.21	2,616.31	18.77	83.72
Luxembourg	0.06	-1.47	0.07	6.78	1.88	0.05	1.85	4.63	3.50	3.91
Malta	0.09	-0.77	0.03	3.08	1.88	0.03	1.79	16.15	10.04	2.14
Netherlands	1.69	8.28	1.57	3.19	1.90	0.85	84.46	1,221.08	15.46	85.58
Portugal	1.07	6.61	0.90	9.60	1.88	0.27	4.71	186.83	40.71	48.41
Slovakia	0.04	0.03	0.02	12.77	1.89	0.00	0.56	10.18	19.08	1.09
Slovenia	0.15	-0.02	0.02	14.00	1.91	0.01	0.03	0.14	6.05	3.08
Spain	1.62	35.45	1.39	4.76	1.73	0.41	136.96	2,403.41	18.55	78.16
PIIGS	1.44	82.68	1.32	3.99	1.65	0.49	331.01	5,892.76	18.80	76.43
Panel (B): Rank										
Austria	9	15	9	17	4	4	10	9	11	9
Belgium	6	16	4	18	2	1	7	7	13	5
Cyprus	12	12	12	5	12	11	13	13	9	12
Estonia	18	11	18	6	13	17	17	18	18	17
Finland	4	18	7	16	7	6	8	12	17	7
France	1	1	1	14	3	2	2	1	3	1
Germany	5	3	5	15	1	5	3	3	5	8
Greece	11	6	11	1	8	13	11	8	2	11
Ireland	16	17	13	4	16	15	9	10	14	13
Italy	2	4	2	11	15	7	4	4	7	3
Luxembourg	15	14	14	8	11	12	14	16	16	14
Malta	14	13	15	13	10	14	15	14	12	16
Netherlands	3	7	3	12	6	3	6	6	10	2
Portugal	10	8	10	7	14	10	12	11	1	10
Slovakia	17	9	17	3	9	18	16	15	4	18
Slovenia	13	10	16	2	5	16	18	17	15	15
Spain	7	5	6	9	17	9	5	5	8	4
PIIGS	8	2	8	10	18	8	1	2	6	6
Panel (C): Concordant Pairs										
	MES	$SRISK$	$\Delta CoVaR$	ES	VaR	β	MV	LTQ	LVG	ρ
MES										
$SRISK$	2									
$\Delta CoVaR$	11	3								
ES	0	1	0							
VaR	2	2	2	0						
β	4	0	5	1	1					
MV	1	4	3	0	1	2				
LTQ	4	5	3	0	2	1	6			
LVG	2	0	2	0	1	2	0	2		
ρ	5	3	8	0	2	3	3	2	2	

Notes: In the upper panel, we report the values of systematic risk measures and firm characteristics for each member state in the Eurozone on December 31, 2015. Marginal expected shortfall (MES), delta conditional value at risk ($\Delta CoVaR$), expected shortfall (ES), value at risk (VaR) and conditional correlation (ρ) are expressed as percentage while systemic risk index ($SRISK$), market capitalisation (MV) and liabilities (LTQ) are expressed in billion Euros. conditional beta (β) and leverage (LVG) are expressed in units. In the middle panel, we rank each Eurozone member state based on MES, $SRISK$, $\Delta CoVaR$, ES, VaR, β, MV, LTQ, LVG, and ρ respectively. In the lower panel, we report the number of concordant pairs between two macro-prudential risk measures or micro-prudential risk measures. $MES, \Delta CoVaR, ES, VaR$ and ρ figures are expressed as a percentage while $SRISK, MV$ and LTQ figures are expressed in terms of billion Euros and β and LVG are times. All risk measures are generated under the assumption of $q = 5\%$ level.

Table 3.6 displays the ranking of systemic risk measures, standard financial risk measures and firm characteristics as of December 31, 2015. MES-based ranking and rakings produced by conditional correlation, beta and liabilities tend to identify the same $SIFIs$, five, four and four out of the eighteen-member states (including $PIIGS$) has equal ranking with MES and correlation, beta and liabilities on that day respectively. Surprisingly, the $\Delta CoVaR$-based ranking is not determined mainly by its VaR but rather correlation which implies that systemic risk rankings of eight-member states based on $\Delta CoVaR$ mirror rankings obtained by sorting member states based on correlation. $SRISK$-based ranking is highly sensitive to liability and market capitalisation rather than leverage.

According to Figure 3.11, we can observe that the highest value of $SRISK$ in the Eurozone member states is for France (€186.66 b), followed by PIIGS (€82.68b), Germany (€56.28b) and Italy (€42.99b) respectively while the lowest value of SRISK is for € Finland (€-19.46b), Ireland (€-15.90b) and Belgium (€-13.98b). Based on $SRISK$ values, we conclude that $SRISK$ depends on economy size, the bigger the economy, the higher the $SRISK$ (relatively). Consequently, in order to allow for a comparison across countries, we may express $SRISK$ as a percentage of current GDP (market value of equity) to reflect the size of the economy. Greece (8.63%) has the highest value of $SRISK/$ GDP followed by France (8.51%) and Portugal (3.68%) respectively which means the measure is not manipulated by the size of the economy. When it comes to stock market, Portugal (140.44%) has the highest value of $SRISK/$ market capitalisation followed by Greece (119.85%), France (67.79%) and Italy (29.20%) respectively. It is obvious that $PIIGS$ member states are highly sensitive to systemic events.

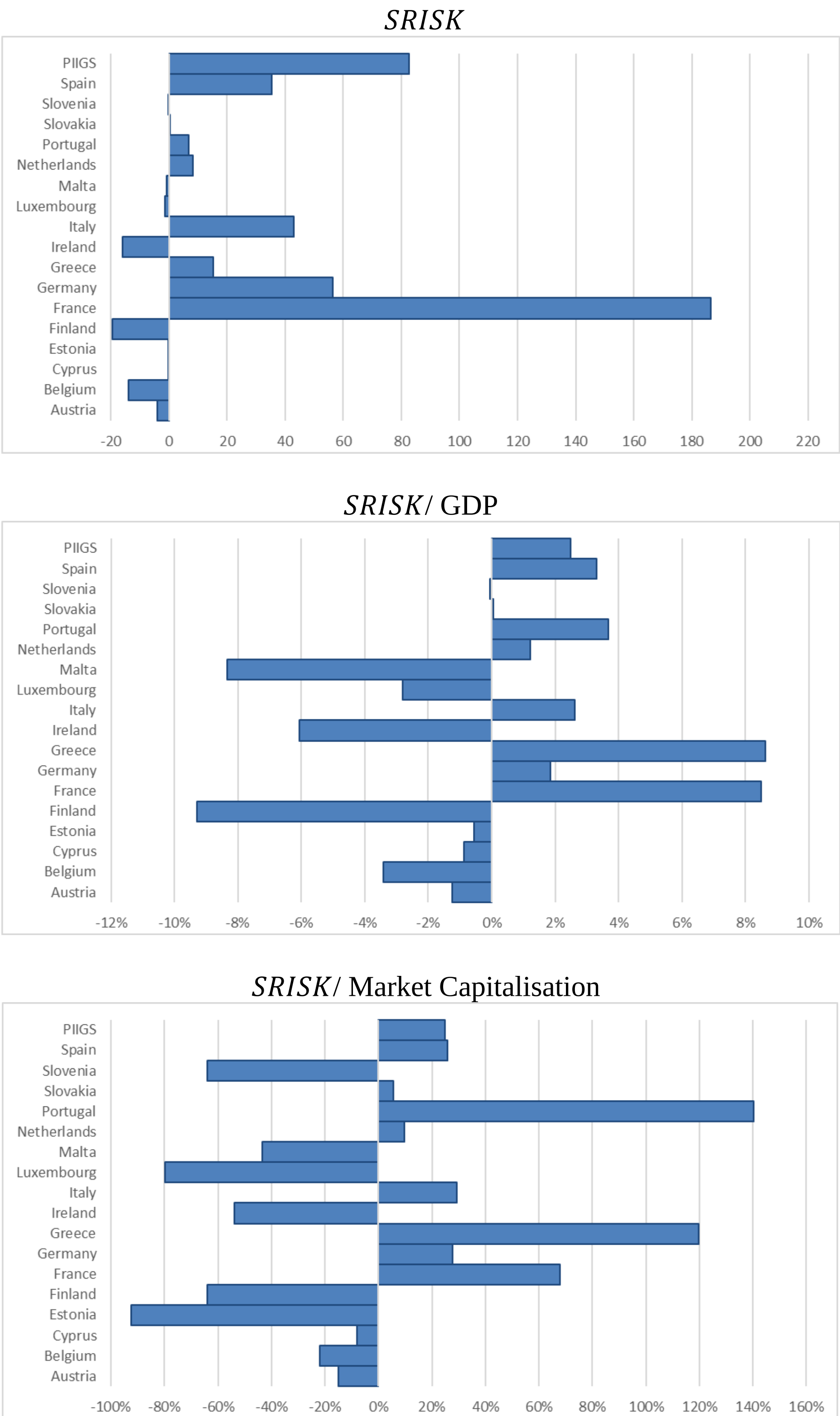

Figure 3.11: SRISK of Eurozone Member States as of December 31, 2015

Notes: $SRISK$ is expressed in terms of Billion Euros while $SRISK/$ nominal GDP and $SRISK/$ Market Capitalisation are expressed as percentage.

Table 3.7: Too-Systemic-To-Fail Measures

	MV	LTQ	GCC	# Institutions	β	ΔCoVaR	MES	LRMES	SRISK
Panel (A): Too-Systemic-To-Fail Measures Values									
Banks	410,825	12,650,023	6,361	75	0.68	2.77	3.04	40.18	455,973
DFinancials	86,708	2,405,030	5,949	105	1.03	3.37	3.53	44.76	85,319
Insurance	150,680	2,869,298	2,261	27	1.05	3.72	3.60	45.45	77,729
Real-estate	39,923	98,239	5,250	108	1.23	2.81	2.98	39.48	-18,105
Panel (B): Too-Systemic-To-Fail Measures Rank									
Banks	1	1	1	3	4	4	3	3	1
DFinancials	3	3	2	2	3	2	2	2	2
Insurance	2	2	4	4	2	1	1	1	3
Real-estate	4	4	3	1	1	3	4	4	4

Notes: In the upper panel, we report the values of too-systemic-to-fail and systematic risk measures for each Eurozone financial sector during the crisis period (Q3 2007-Q2 2010). MV and LTQ stands for market capitalisation and liabilities (expressed in million Euros) which is a measure of too-big-to-fail, GCC and β stands for Granger-causality connections (expressed as number of connections) and beta which is a measure of too-interconnected-to-fail, # Institutions is the number of institutions within each sector which is a measure of too-many-to-fail, $\Delta CoVaR$, MES and $LRMES$ are expressed as percentages while $SRISK$ is expressed in million Euros. In the lower panel, we rank each Eurozone sector based on these measures. All risk measures are generated under the assumption of $q = 5\%$ level.

Table 3.7 shows that $\Delta CoVaR$, MES and $LRMES$ have a tendency to typically allured by number of institutions which is too-many-to-fail paradigm and interconnected institutions via beta which is too-interconnected-to-fail paradigm, these results are aligned with Markose, *et al.* (2010). Based on $SRISK$ definition, $SRISK$ can be regarded as a compromise between the too-big-to-fail paradigm (via liabilities and market capitalisation) and the too-interconnected-to-fail paradigm (via Granger-causality connections) which includes that large institutions and highly interconnected institutions raise systemic risk scores.

3.6 Robustness Check

The dominance test aims to test the significance of the ranking obtained from different systemic risk measures ($MES, SRISK\ and\ \Delta CoVaR$) in order to check whether a given financial sector (country or institution) i contributes more to systemic risk than another financial sector (country or institution) j. The standard KS test was not utilized due to the estimation procedure providing an "estimated" cumulative distribution functions ($CDFs$) for the systemic risk measures ($\Delta CoVaR, MES\ and\ SRISK$), which may result in producing to a nuisance parameter to the null hypothesis that is known as the Durbin problem identified in Durbin (1973) which can threaten the standard KS test's distribution-free nature. To overcome the Durbin issue that happens during the application of the KS test when two $CDFs$ are not distribution-free, Abadie's (2002) bootstrapping strategy was applied.

The concern was handled by depending on Abadie's proposed resampling method (2002). Therefore, the bootstrap KS test used is suitable for two main reasons. Firstly, the test runs a comparison of the entire $CDFs$ rather than concentrating on the mean values that are sensitive to outliers since false conclusions may be reached from statistical tests which are based on mean values. Second of all is the KS test's non-parametric nature, which is asymptotically distribution-free. Therefore, assumptions about the underlying distribution is not required as opposed to the statistical tests which are based on mean values (e.g. student-t tests or two-sample z test), the use of these tests may have higher risk of errors if the datasets are highly not normally distributed.

We apply the two-sample bootstrap KS test to compare the $CDFs$ of the MES (or $SRISK$ or $\Delta CoVaR$) in relation to two financial sectors (or countries or institutions). The two-sample KS test statistic for the dominance test is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x |A_m(x) - B_n(x)| \tag{51}$$

where $A_m(x)$ and $B_n(x)$ represent the CDFs of the MES $(or\ SRISK\ or\ \Delta CoVaR)$ related to two financial sectors (or countries or institutions) and m and n are the size of the two samples. For example, the null hypothesis for MES is defined as follows:

$$H_0: |MES^{Banks}| > |MES^{Insurance}| \tag{52}$$

The interpretation of the null hypothesis and the comparison of the results of the bootstrap KS stochastic dominance tests will rely on the absolute values of $MES\ and\ \Delta CoVaR$, while $SRISK$ figures are positive already.

The bootstrap KS dominance test aims to compare the $CDFs$ of the systemic risk measures ($MES, SRISK\ and\ \Delta CoVaR$) related to two different financial sectors (banks, diversified financial, insurance and real-estate). Results are given in Table 3.8. We test whether the diversified financial sector is less or equally risky for the system than the real-estate sector. The p-value shows that the null hypothesis is rejected at the 1% significance level, meaning that diversified financial sector is systemically riskier than real-estate sector. In other words, we can conclude that the diversified financial sector represents a greater systemic risk than the real-estate sector within the Eurozone. Results concerning the two following comparisons, i.e. $Insurance \leq DFinancial$ and $Insurance \leq Realestate$, are more straightforward. The null hypothesis is rejected at the 1% significance level in each case, confirming that the insurance sector is systemically riskier than the diversified financial sector and than the real-estate sector, respectively.

Regarding the comparison between banking sector and other three sectors, i.e. $Banks \leq Insurance$, $Banks \leq Financial$ and $Banks \leq Realestate$. Results indicate that the null hypothesis is rejected at the 1% significance level in each scenario, emphasizing that the banking sector is systemically riskier than the insurance sector and than diversified financial sector and than the real-estate sector, respectively. Results of the dominance tests also mean that, for each comparison pair, the contributions of each financial sector to systemic risk are statistically different from each other[24].

The bootstrap KS dominance test confirms the ranks generated by each systemic risk measure. Based on MES and $\Delta CoVaR$, diversified financial sector are systemically risky than insurance sector which is risker than banks and the least $SIFI$ is real-estate sector. While based on $SRISK$, banking sector has the highest systemic risk exposure followed by diversified financials, insurance and real-estate respectively.

[24] Due to limited space, KS dominance test for Eurozone Financial Sectors (pre-crisis, crisis and post-crisis), member states (overall, pre-crisis, crisis and post-crisis), and member states within each financial sector (overall, pre-crisis, crisis and post-crisis) are available upon request.

Table 3.8: KS Dominance Test for Eurozone Financial Sectors (Overall Period)

	Panel A: $\Delta CoVaR$		Panel B: MES		Panel C: LRMES	
	Stat	p-vlaue	Stat	p-vlaue	Stat	p-vlaue
H_0: $Banks \leq Realestate$	0.331	0.001	0.296	0.001	0.296	0.001
H_0: $Insurance \leq Banks$	0.090	0.001	0.098	0.001	0.098	0.001
H_0: $Insurance \leq Realestate$	0.289	0.001	0.260	0.001	0.260	0.001
H_0: $DFinancial \leq Insurance$	0.067	0.001	0.060	0.001	0.060	0.001
H_0: $DFinancial \leq Banks$	0.123	0.001	0.126	0.001	0.126	0.001
H_0: $DFinancial \leq Realestate$	0.332	0.001	0.301	0.001	0.301	0.001

	Panel D: $SRISK$	
	Stat	p-vlaue
H_0: $Insurance \leq Realestate$	0.856	0.001
H_0: $DFinancial \leq Insurance$	0.111	0.001
H_0: $DFinancial \leq Realestate$	0.920	0.001
H_0: $Banks \leq DFinancial$	0.751	0.001
H_0: $Banks \leq Insurance$	0.806	0.001
H_0: $Banks \leq Realestate$	0.998	0.001

Notes: The null hypothesis "$Banks \leq Realestate$" means that the systemic risk measures ($MES, SRISK$ and $\Delta CoVaR$) related to the banking sector are lower (or equal to), in absolute value, than the systemic risk measures ($MES, SRISK$ and $\Delta CoVaR$) related to the real-estate sector. Therefore, the null hypothesis signifies that the banking sector is less or equally systemically risky than the real-estate sector.

3.7 Conclusion and Policy Recommendations

Lacking a generally approved academic meaning, a typical systemic risk definition would be a disturbance in the operations of financial services, generated by the weakening of all or parts of the financial system by providing a negative impact on the real economy. Logically, a huge amount of various definitions would cause a correspondingly huge amount of various systemic risk measures. While different definitions focus on dissimilar systemic risk features, the measures of systemic risk were built upon various components of the phenomenon. Therefore, there is an immense need to apply various systemic risk measures simultaneously in order to measure the different facets of systemic risk.

Durations of typical turmoil in the financial system can have multiple causes based on Rodríguez-Moreno and Pena's work (2013). This mean relying on one systemic risk measure could be inappropriate or undesirable. Ellis, *et al.* (2014a) followed accordingly; for they believed the financial system's diversity also substantiates the notion that it is improbable for a single systemic risk measure or a single financial stability policy instrument to be generally applicable.

This chapter assesses interconnectedness and systemic risk exposure in the Eurozone financial sector by applying four prominent systemic risk measures of Ganger-causality Network by Billio, *et al.*, (2010), Marginal Expected Shortfall (MES) by Acharya, *et al.* (2017), Systemic Risk Index ($SRISK$) by Acharya, *et al.* (2012) and Brownlees and Engle (2012) and Delta Conditional Value-at-Risk ($\Delta CoVaR$) by Adrian and Brunnermeier (2011). We measure systemic risk exposure on the union level and the financial sector level (namely, the banking, diversified financials, insurance and real-estate). We unify the theoretical framework of the three measures in order to be able to compare them. The sample period ranging from 2000 to 2015 and is divided into three sub-periods (pre-crisis, crisis, post-crisis).

By calculating Granger causality network connections for each financial institution within each financial sector in the Eurozone, we discover that the Eurozone financial sectors have become more interrelated in the last sixteen years, raising the risk for systemic events. This finding is not a complete surprise as the abundance of evidence that correlation among financial markets has become more globally significant; though, it does give the incentive to form mitigating controls. While considering market capitalisation and liabilities in the $SRISK$ definition, it inclines to raise large institutions' systemic risk scores. This outcome ties with the $TBTF$ paradigm, while the MES has a tendency to typically allured by interconnected institutions (via the beta), and $\Delta CoVaR$ is connected by interconnected institutions (via the VaR), which is more connected with the $TITF$ paradigm (Markose, *et al.*, 2010). Therefore, $SRISK$ can be regarded as a compromise between the $TBTF$ paradigm (via the liabilities) and the $TITF$ paradigm (via the beta).

By applying the major systemic risk measures on the Eurozone financial institutions, the empirical analysis concludes that various systemic risk measures ($\Delta CoVaR$, MES and $SRISK$) give different rankings of $SIFIs$ (sector or country) which indicates that a single systemic risk measure is incapable of capturing the numerous dimensions of systemic risk. Thus, the divergence of the systemic risk rankings is not due to the instability of a particular measure but instead to their fundamental differences. Therefore, we cannot generalize the outcome of a single systemic risk measure but rather there is a need to integrate several systemic risk measures in a bigger framework to capture the multiple facets of systemic risk.

$SIFIs$ rankings of macro-prudential measures ($\Delta CoVaR$, MES and $SRISK$) reflect similar rankings of some micro-prudential measures (ES and VaR) and market risk measures (beta, liability and market capitalisation). Consequently, the majority of systemic risk estimates' variability could be explained by the one-factor linear model, which shows that systemic risk measures fall short in determining the systemic risk's multiple facets.

In the time-series dimension, there is a strong relationship between MES with VaR and ES. Time-varying beta tend to increase during economic downturns, which makes MES procyclical. The empirical $\Delta CoVaR$ of a member state (sector) is strongly correlated with its VaR and conditional volatility. Consequently, if a certain member state (sector) wants to minimise its systemic risk score, given the fact that the key driver of the country's MES or $\Delta CoVaR$ is the ES or VaR of its index return, the country has to make its index return distribution less leptokurtic and/or skewed. $SRISK$ is highly related to leverage especially during relatively distress period and negatively related to market capitalisation. The spikes in ES and $LRMES$ are consistent with the spikes in $SRISK$.

In the cross-sectional domain, a strong positive relationship exists between MES and institution beta. This signifies that financial institutions' systemic risk rankings based on MES mirror rankings gathered by assigning institution on betas. A comparable result for $SRISK$ with liabilities and market capitalisation was discovered as well. The same goes for $\Delta CoVaR$ and conditional correlation.

We develop a dominance test for the empirical results using the bootstrap Kolmogorov–Smirnov test proposed by Abadie (2002). The bootstrap KS stochastic dominance test provides evidence that the ranking of systemic risk exposure is significant, confirming that a certain sector (country) has a higher systemic risk exposure compared to another sector (country). The results are consistent for the three systemic risk measures ($\Delta CoVaR$, MES and $SRISK$) on the two levels (union and sector) for all sub-periods (overall, pre-crisis, crisis and post-crisis).

Freixas and Rochet (2013) propose a regulatory framework to manage $TBTF$ $SIFIs$. The optimal regulation in such a case is complex, as it involves a systemic risk authority empowered with special resolution authorities, a regulatory systemic risk tax, and controls on bank managers' compensation packages.

4

Chapter 4
Measuring Systemic Risk and Financial Linkage in the Eurozone Financial System: European CoVaR Approach

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The aim of this chapter is to measure systemic risk in the Eurozone financial sector since the introduction of the Euro by applying Adrian and Brunnermeier's (2011) Conditional Value-at-Risk ($CoVaR$) which is the VaR of the financial system conditional on an institution being in financial distress. We quantify systemic risk within seventeen members of the Eurozone on three levels: (i) the union level by identifying which sector and member state contributes the most to the Eurozone systemic risk, (ii) the sector level by detecting which member contributes significantly to each Eurozone financial sector systemic risk, and (iii) the country level by recognizing which financial institution, the so-called Systemically Important Financial Institutions ($SIFIs$), contributes mostly to the member's financial system risk. Further, we estimate Contribution $\Delta CoVaR$, Exposure $\Delta CoVaR$ and Network $\Delta CoVaR$ on the three levels of analysis during pre-crisis, crisis and post-crisis periods in order to grasp the various facets of systemic risk within Eurozone financial system. In addition, we measure time-invariant $\Delta CoVaR$ and time-variant $\Delta CoVaR$ at different quantiles by analysing lagged systematic state variables that act as controlling variables to remove variations in tail risk which are not directly connected to financial system risk exposure. To check robustness, we estimate $\Delta CoVaR$ using $GARCH\text{-}DCC$ model (Engle 2002, 2009; Girardi and Ergün, 2013) and various copula models namely, Gaussian, Student-t, Gumbel, Rotated Gumbel, Clayton, Rotated Clayton, Symmetrized Joe-Clayton, Plackett and Frank (Patton 2012a and b).

4.1 Introduction

Including the European Union, the Global Financial Crisis (GFC) of 2007 had extended to the majority of the developed economies. However, nearly the entire EU jurisdictions were deficient in proper crisis resolutions mechanisms, particularly in regards to the cross-border aspects of a global crisis, regardless of the decades of work to construct a single financial market. This resulted to potential danger of widespread financial institutions failures within each EU member state and the close collapse of their financial systems. Investors and regulators are becoming increasingly concerned about the financial system's stability and EU's risk contagion due to the European debt crisis. As the crisis and concerns are still ongoing, the demand of supplementary risk management tools other than micro-prudential measure is aroused.

The Bank for International Settlements (1994) defines systemic risk as the hazard of institution's failure to satisfy their contractual obligations that may result in other institutions defaulting with a chain reaction raising greater financial instability. Systemic risk is the jeopardy of the whole financial system or market crashing, when an individual financial institution, or group institutions falls into distress. Therefore, systemic risk can be represented as "financial system instability, possibly destructive, created or worsen by idiosyncratic events or circumstances in financial intermediaries" (Kaufman and Scott, 2003). Market's interconnections and interdependencies exacerbates risk, where an individual or group of entities can initiate a cascading failure and possibly bankrupt or break down the whole market or system (Schwarcz, 2008).

Systemic risk within the EU's financial system has been the main concern of research lately in the aftermath of the GFC. Though, few efforts have been made to determine contributions of systemic risk to the European Monetary Union's (EMU) financial system. Additionally, the spectacle of numerous institutions concurrently being in financial distress has been provided little focus. Despite the shared failure of collective financial institutions being not only a theoretic construction but having happened in practice, research on this occasion is very narrow.

The global crisis exposed the micro-prudential regulatory framework to be insufficient in avoiding global contagion due to bank failures initiated in the U.S., with EU and the world following on. Designed by the Basel I and II agreements' provisions, the micro-prudential regulatory framework enforces minimum capital requirements on banks as a precautionary control to avoid unexpected losses (Pillar I). The Basel II agreement in the framework initiated internal system upgrades to measure market risk and this regulation inspected each individual financial institution's soundness. Despite this, factors like leverage degree, size and the remaining system's interrelationships are ignored since provisions are designed on capital adequacy. The financial reform's overarching goal was debated by Stein (2010) to reinforce a large set of institutions while lowering the vulnerability of our entire credit system.

Spillover effects or systemic risk should not be simplified as risk specific to the financial system as debated by other scholars. For example, systemic risk was perceived by Hellström (2003, 2007, 2009) under a technological perspective whereas Bartle and laperrouza (2009) analysed the systemic risk amongst financial industries and network industries to determine the importance of systemic risk in network industries. Systemic risk was also analysed in the energy sector by Kerste, *et al.* (2015) and Reboredo (2011). In terms of economics, the financial system is seen to be contagious and susceptible to a systemic event compared to other of the economy's sectors.

This chapter makes several contributions to academic literature on systemic risk. Firstly, this is the first attempt to apply $CoVaR$ as a systemic risk measure within an economic union. Our empirical analysis measure systemic risk contribution on the union level, sector level and country level; (1) on the union level, we quantify systemic risk contribution of each financial sector and member state, (2) on the sector level, we measure systemic risk contribution of each member state within each sector, and (3) on the country level, we compute systemic risk contribution of each financial institution within each member state. Secondly, we estimate three types of $CoVaR$, namely contribution, exposure and network $CoVaR$. Contribution $CoVaR$ measures systemic risk contribution of each member state (sector, institution) to the entire Eurozone financial system when this member state is in distress, exposure $CoVaR$ measures the exposure to systemic risk of each member state when the entire Eurozone financial system is in distress and network $CoVaR$ measures systemic risk contribution of each member state on each other. Thirdly, we estimate unconditional $\Delta CoVaR$ and conditional $\Delta CoVaR$ that captures the time-variation in the joint distribution of a sector (member state or institution) and system growth in market value of assets. Since $\Delta CoVaR$ is a high frequency measure of tail risk, we estimate $\Delta CoVaR$ using various quantiles (1% and 5%) at different periods; pre-crisis, crisis and post-crisis. Finally, to check the robustness of $\Delta CoVaR$ systemic risk measure, we apply various modelling techniques including $GARCH\text{-}DCC$ model (Engle 2002, 2009; Girardi and Ergün, 2013) and copula models (Patton 2012a and b).

The remainder of the chapter is organized as follows. Section 2 provides a review of literature of $CoVaR$ systemic risk measures. Section 3 proposes a methodological analysis of the contribution, exposure and network $\Delta CoVaR$ measures in addition to time-variant and unconditional $\Delta CoVaR$. In Section 4, we describe the data and summary statistics. Section 5 presents the main empirical findings of systemic risk contribution, exposure and network on the union level, sector level and institution level during the sub-periods of analysis (overall, pre-crisis, crisis and post-crisis). Section 6 reports the results of robustness check using various econometric models to compute $\Delta CoVaR$. Section 7 summarizes and concludes for policy implications.

4.2 Literature Review on Systemic Risk Determinants

Value at Risk (VaR) is the most commonly utilised measure of risk to quantify the maximum loss of a financial institution based on a specified time horizon and confidence level. However, VaR is based on an institution's individual risk and ignores the possible spillover effects that defaulting will have on other institutions. The Conditional Value-at-Risk ($CoVaR$) was created by Adrian and Brunnermeier (2011) as a systemic risk measure. $CoVaR$ determines a financial institution's contribution of systemic risk to the entire financial system along with other financial institutions. This signifies the financial institution i's VaR, given that financial institution j is under distress. With the ability to catch alternative risk sources that influence institution i despite they are not created by it, the $CoVaR$ was argued to be a more holistic risk measure. If we portray the entire financial system as institution i, $\Delta CoVaR$ is interpreted as the difference of $CoVaR$ and unconditional VaR as it catches a particular institutions marginal non-causal contribution to systemic risk overall.

Thus, academic research on macro-prudential policy has concentrated on determining each individual financial institution's contribution to the risk of other institutions or to the financial system as an entirety and designed a variety of tools to determine systemic risk (see Bisias, *et al.*, 2012; Bernal, *et al.*, 2014; Huang, *et al.*, 2009; Segoviano and Goodhart, 2009; Acharya, *et al.*, 2017; Allen, *et al.*, 2010; Zhou, 2010; Adrian and Brunnermeier, 2011; Brownlees and Engle, 2012; Billio, *et al.*, 2012; Girardi and Ergün, 2013; Gravelle and Li, 2013).

An increasing amount of research expands upon $\Delta CoVaR$ as a measure to assess interdependencies and measure systemic importance across financial institutions. For instance, the $CoVaR$ approach was utilised by Lopez-Espinoza, *et al.* (2013) to examine the systemic factors within a global framework. Across 18 countries, 54 large international financial institutions from the period of 2001 to 2009 were accounted. $CoVaR$ was derived from Girardi and Ergün (2013) by characterising financial distress as a financial institution's return being optimal at its VaR level compared to being precisely at its VaR level. Further analysis of adverse distress conditions and using standard tests to backtest the calculated $CoVaR$ measure was enabled by the changes. The meaning of $\Delta CoVaR$ was altered by Sedunov (2013) as the financial institutions' VaR changes to prepare for a financial crisis. While also known as the adapted exposure $\Delta CoVaR$, it is a measure that determines a single institution's systemic risk exposures. Under the high-frequency market-based systemic risk measures, two separate groups were estimated by Rodriguez-Moreno and Pena (2013) and involves $\Delta CoVaR$ for a composition of banks from the U.S. and Europe region. With the Gonzalo and Franger metric and the Granger causality test, the best performing measures were more deeply analysing in each composition.

Several studies have lately enhanced the $CoVaR$ methodology and employed it on various developed financial sectors. For instance, to separate financial institution spillover from interdependence, Agrippino (2009) suggested to apply the $CoVaR$ analysis on five U.S. commercial banks. Compared to traditional VaR model's estimate, the analysis proves $CoVaR$ to be a first-rate risk measure, specifically in instances of financial instability as negative effects extend across institutions. Systemic risk exposures for the Canadian banking system were estimated by Gauthier, *et al.* (2012) while setting macro-prudential capital requirements to equate the institution's input to systemic risk by using $\Delta CoVaR$ as a dynamic to allocate risk. $CoVaR$ was also applied to examine circumstances at levels of significantly low probability (Van Oordt and Zhou, 2014). The analysis was conducted on 46 equally weighted industry portfolios involving NYSE, AMEX and NASDAQ institutions. $CoVaR$ was utilised by Bjarnadottir (2012) to capture four big Swedish banks contributions to the Swedish financial system's systemic risk. Between January 2002 and March 2014, Krygier (2014) investigated how 36 institutions from the Nordic stock market had contributed to systemic risk. Bernal, *et al.* (2014) distinguished themselves from the above researchers as they examine systemic risk from assessing how each financial sector contributes to systemic risk. Thus, they inspect the presence of interrelationships between the financial sector and the entire economy, instead of analysing the interdependence among financial institutions.

Another strand of researches has used the $CoVaR$ technique on several emerging financial sectors like panel data from six huge Thailand banks employed by Roengpitya and

Rungcharoenkitkul (2011) to investigate how financial institutions are affected by risk spillover. Arias, *et al.* (2010) determined the whole Colombian financial sector's systemic risk by examining $CoVaR$ on six pension funds, sixteen commercial banks and all the credit institutions along with non-banking financial institutions and for the financial system as a whole. Other papers used the $CoVaR$ technique on copula correlation (Hakwa, *et al.*, 2015; Reboredo and Ugolini, 2015; Karimalis and Nomikos, 2017).

An indicator of systemic risk was designed for systemic financial distress based on the price of credit default swaps (CDS) (Huang, *et al.*, 2009). Based on CDS data, a banking stability index was built to examine interank dependence for tail events (Segoviano and Goodhart, 2009). There exists proof of CDS data's suitability to calculate systemic risk (Rodriguez-Moreno and Pena, 2013). To determine downside risk and how financial institutions contribute to risk, indicators such as systemic expected shortfall and marginal expected shortfall were developed by Acharya, *et al.* (2017). A systemic risk measure known as $SRISK$ was introduced by Brownless and Engle (2012) which signified the quantity of capital necessary to ensure a minimal capital requirement. An aggregate systemic risk measure known as $CATFIN$ was suggested by Allen, *et al.* (2012) to anticipate drops in overall bank lending activity six months beforehand. Five systemic risk measures were introduced by Billio, *et al.* (2012) to determine contagion and exposure in the connections amongst financial institutions. The Conditional Autoregressive Value at Risk ($CAViaR$) model was made by Engle and Manganelli (2004) to determine each return's tail behaviour via quantile regression.

With Shapley values, system-wide risk across financial institutions was disintregrated by Cao (2013) in a $CoVaR$ setting. Based on CDS prices to evaluate risk dependencies across financial institutions, a co-risk method was suggested by the International Monetary Fund (2009). A state-dependent sensitivity VaR ($SVAR$) was determined by Adams, *et al.* (2010) to calculate the spillover effects across $SIFIs$ while considering how the degree of risk spillover is impacted by various market states.

The preference of the $CoVaR$ method as an instrument to define systemic risk in this study is encouraged by three factors. Firstly, this method is attractive as it enables us to define contagion under balance sheet deleveraging which is the prime regulatory concern and an essential force in this study. On the other hand, most substitute measures exclude balance sheet data since they are generally meant for default-related data with/without stock market return data, as previously surveyed. Secondly, the $CoVaR$ is substantially informative about the mechanisms of an individual institution's systemic contribution to the system and enables us to categorise the different observable variables effects on the time-series mechanisms of this inherent process. Furthermore, $CoVaR$ can smoothly govern related data features like an institution recapitalisation or a crisis incident and enables us to use historical-based and forward-looking state variables to advance downside risk forecasts. Lastly, this setting can be discerned simply to account non-linear patterns and other related effects that probably characterise large financial institutions contribution to the global system which has yet to be debated.

4.3 CoVaR Methodology

The most commonly used measure of systematic risk is the Value-at-Risk (VaR) which calculates the monetary loss an institution may experience within a given confidence level (see Kupiec, 2002; Jorion, 2007)[25]. VaR does not provide information on how bad the loss of the portfolio (sector, system) may be if a sharp adverse movement were to occur under these normal market conditions. VaR is only valid under normal market conditions and a series of theoretical assumptions. During normal times, the comovement of financial institutions' assets and liabilities is driven by fundamentals; in these circumstances VaR provides a valid risk measure. However, in the time of market turmoil such as the recent financial crisis when the comovement between the market and financial institutions' asset increased significantly, VaR was unable to reflect such systemic risk properly, this is because VaR focuses on the risk of an individual institution in isolation. Such increases of comovement give rise to systemic risk, the risk that institutional distress spreads widely and distorts the supply of credit and capital to the real economy. A single institution's risk measured by micro-prudential measures does not necessarily reflect systemic risk measured by macro-prudential measures.

Conditional Value at Risk ($CoVaR$) measure proposed by Adrian and Brunnermeier (2011) uses quantile regression to estimate the lower tail quantile of financial system returns conditional on the VaR loss of an institution at a specific probability quantile. By estimating the difference between the $CoVaR$ conditional on the median state of the institution and the $CoVaR$ conditional on the institution's distress state, we come up with a measure of the institution's marginal contribution to overall systemic risk, which is termed as $\Delta CoVaR$.

[25] Note that VaR_q^i is typically a negative number, consequently $CoVaR$ and $\Delta CoVaR$ are typically negative numbers. In practice, the sign is often switched, which is followed in this chapter.

$CoVaR$ measures the degree to which a tail event in a financial institution spills over and cause or worsen a tail event in another institution[26]. $CoVaR_q^{j|i}$ can be defined as a conditional VaR, that is, VaR_q^j of institution, j, conditional on the event that institution i is under stress ($X^i = VaR_q^i$). In other words, we can implicitly define $CoVaR_q^{j|i}$ by the q-quantile of the conditional probability:

$$\Pr\,(X^j \le CoVaR_q^{j|i} | X^i = VaR_q^j) = q \tag{1}$$

where X^i refers to asset return of financial institution i. More simply, Eq. (1) avers that when the return of institution i falls below a threshold value, the probability that losses of the institution, j, exceeds $CoVaR$ equal to q. The marginal contribution of an individual institution to VaR of j is denoted by:

$$\Delta CoVaR_q^{j|i} = \begin{pmatrix} CoVaR\ of\ institution\ j\ conditional\ on \\ institution\ i\ being\ at\ its\ VaR\ q\ level \end{pmatrix} - \begin{pmatrix} CoVaR\ of\ institution\ j\ conditional\ on \\ institution\ i\ being\ at\ its\ VaR\ median\ level \end{pmatrix} \tag{2}$$

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{50\%}^i} \tag{3}$$

Eq. (3) estimates the i^{th} institution contribution to the risk of institution, j, by taking the difference between the $CoVaR$ conditional on the distress state of the institution and the $CoVaR$ conditional on the normal state of the institution. Suppose we assume that j in Eq. (3) stands for the entire financial system and then marginal contribution of the individual financial institution can be expressed as[27]:

$$\Delta CoVaR_q^{sys|i} = CoVaR_q^{sys|X^i=VaR_q^i} - CoVaR_q^{sys|X^i=VaR_{50\%}^i} \tag{4}$$

Apart from measuring the marginal contribution of individual institution to systemic risk, the $\Delta CoVaR$ can also measure the exposure of individual institutions to systemic risk and measure spillover from one institution or sector to the other. This makes it much useful tool for financial supervisory authorities whose duty is ensuring the soundness of the financial system.

There are three types of $CoVaR$ namely contribution $CoVaR_q^{sys|i}$, exposure $CoVaR_q^{i|sys}$ and network $CoVaR$ ($CoVaR_q^{j|i}$ and $CoVaR_q^{i|j}$). Contribution $CoVaR_q^{sys|i}$ measures institution i marginal contribution of systemic risk to the overall financial system. We calculate the VaR of

[26] It could be another institution or a portfolio of institutions or a sector or an entire financial system of a country or an economic union.

[27] Superscript "sys" refers to financial system.

the entire financial system conditional on institution i being in distress. It captures how much risk a certain institution adds to the overall systemic risk. This measure can capture externalities that arise because an institution is 'too-big-to-fail', 'too-interconnected-to-fail' or 'too-many-to-fail'.

Exposure $CoVaR_q^{i|sys}$ investigates which institutions are highly exposed to systemic risk in the case of a financial crisis. We condition each institution's VaR on the event that the the entire financial system is in distress. It measures institution i's increase in VaR in the case of a market downturn or the extent to which an individual institution is affected by systemic financial events. This is in the same spirit as the stress test framework used to assess the resilience of financial institutions to a new financial crisis.

$CoVaR$ is directional, so that $CoVaR_q^{j|i}$ is not necessarily equal to $CoVaR_q^{i|j}$. This raises the possibility of mapping the magnitude of spillover, as different institutions go into financial distress which is called Network $CoVaR$. $CoVaR_q^{j|i}$ measures financial institution i marginal contribution of systemic risk to institution j. We calculate the VaR of institution j conditional on institution i being in distress. Then calculate $CoVaR_q^{i|j}$ which measures financial institution j marginal contribution of systemic risk to institution i. We calculate the VaR of institution i conditional on institution j being in distress. Network $CoVaR$ captures how much risk a certain institution adds to another institution and vice versa.

In addition, we compute unconditional and conditional $CoVaR$. Unconditional $CoVaR$ is also called time-invariant $CoVaR$ as it does not capture the time variation therefore it is static in nature (constant over a given period of time) while conditional $CoVaR$ which is also called time-variant $CoVaR$ as it captures the time variation consequently it is dynamic in nature (variable over a given period of time). Both unconditional and conditional $CoVaR$ are called contemporaneous $CoVaR$ because they are procyclical.

4.3.1 Unconditional CoVaR and ΔCoVaR Estimation

In this chapter, we primarily use quantile regression approach originally proposed by Koenker and Bassett (1978) to estimate the coefficients of $CoVaR$ and $\Delta CoVaR$[28]. Quantile regression is appealing for their simplicity and efficient use of data. This approach makes it possible to

[28] There are several methods to estimate $CoVaR$ including quantile regression, $GARCH$, copula approach, bootstrap, extreme value theory, … etc.

model the loss distribution of the dependent variable on a set of conditioning variables at different quantiles. The approach is more robust as strong distributional assumptions are not required. Since we want to capture all forms of risk, including not only the risk of adverse asset price movements, but also funding liquidity risk, our estimates of $\Delta CoVaR$ are based on daily changes in market value of assets (MVA) of all publicly traded financial institutions in the Eurozone. We denote the expected value of a quantile regression of the financial system on the q^{th} quantile of a given institution i as follows:

$$\hat{X}_q^{sys,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \tag{5}$$

where $\hat{X}_q^{sys,i}$ refers to growth in MVA of the financial system on a given quantile (q) conditional on institution i. The expected value from the quantile regression of the system on financial institution i is equivalent to VaR of the system conditional on X^i (i.e. $VaR_q^{sys}|X^i = \hat{X}_q^{sys,i}$). Therefore, given the conditioning event ($X^i = VaR_q^i$), we obtain $CoVaR_q^i$ as follows:

$$CoVaR_q^{sys|X^i=VaR_q^i} = VaR_q^{sys}|VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{6}$$

The marginal contribution of individual institution to systemic risk, $\Delta CoVaR_q^i$ is given by

$$\Delta CoVaR_q^{sys|i} = CoVaR_q^{sys|X^i=VaR_q^i} - CoVaR_q^{sys|X^i=VaR_{50\%}^i} \tag{7}$$

$$\Delta CoVaR_q^{sys|i} = \left(\hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i\right) - \left(\hat{\alpha}_q^i + \hat{\beta}_q^i VaR_{50\%}^i\right) \tag{8}$$

$$\Delta CoVaR_q^{sys|i} = \hat{\beta}_q^i \left(VaR_q^i - VaR_{50\%}^i\right) \tag{9}$$

where $\Delta CoVaR_q^{sys|i}$ quantifies how much the entire financial system's VaR increases when an institution, i, goes from a normal state (median) to a distress state ($q = 5\%$) as represented by its VaR_q^i level. To interpret, a larger $\Delta CoVaR_q^{sys|i}$ (in absolute values) means that institution i imposes a larger negative externality on the entire financial system when it gets into distress.

4.3.2 Time-Variant ΔCoVaR

$\Delta CoVaR$ measure explained in the previous section does not capture the time-variation in the joint distribution of X^i and X^{sys} but rather produces a value that is constant over a given sample period. In order to capture the time-variation in the joint distribution, we estimate the following quantile regressions with subscript t denoting the time-variation:

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \quad (10)$$

$$X_t^{sys} = \alpha^{sys|i} + \beta^{sys|i} X_t^i + \gamma^{sys|i} M_{t-1} + \varepsilon_t^{sys|i} \quad (11)$$

where X^i is the change in MVA of institution i, X^{sys} is the change in MVA of the financial system, and M_{t-1} denotes a set of lagged systematic state variables. The respective predicted values from Eqs. (10) and (11) are denoted as

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \quad (12)$$

$$CoVaR_t^i(q) = \hat{\alpha}_q^{sys|i} + \hat{\beta}_q^{sys|i} VaR_q^i + \hat{\gamma}_q^{sys|i} M_{t-1} \quad (13)$$

We then estimate the $\Delta CoVaR_t^i$ to measure institution i's contribution to systemic risk

$$\Delta CoVaR_{q,t}^i = CoVaR_{q,t}^i - CoVaR_{50\%,t}^i \quad (14)$$

$$\Delta CoVaR_{q,t}^i = \hat{\beta}_q^{sys|i} \left(VaR_{q,t}^i - VaR_{50\%,t}^i\right) \quad (15)$$

A set of lagged systematic state variables (M_{t-1}) were employed to estimate the above-mentioned equations. These state variables act as controlling variables to remove variations in tail risk not directly connected to the financial system risk exposure. Selection of these variables is guided by economic theory and evidence from previous studies on conditional mean predictability (Adrian and Brunnermeier, 2011). The variables used are sourced from $bloomberg$ and $datastream$, they are sampled daily. The relevant state variables used in quantile regressions are displayed as follows:

(i) $Volatility\ Index$, which is a proxy for the European implied volatility index (V2X).

(ii) $T\text{-}Bill\ Spread\ Variation$, which is the first difference of the three-month Euro treasury bill rate.

(iii) $Yield\ Spread\ Change$, which is measured by the spread between the 10-year Euro bond rate and the 3-month Euro bond rate.

(iv) $Change\ Credit\ Spread$, which is the change in the $IBOXX$ Corporate Index and the 10-year Euro bond rate.

(v) $TED\ Spread$, which is the difference between the UK 3-month $LIBOR$ rate and the 3-month UK treasury bill rate.

(vi) $Equity\ Return$, which is measured by the $STOXX$ Europe 600 Index.

(vii) $Sovereign\,Spread$, which is the change in the spread between the 10-year benchmark government bond for each member state and the 10-year Euro bond rate. It captures the sovereign risk following the eruption of Eurozone sovereign debt crisis[29].

In addition to state variables of Adrian and Brunnermeier (2011), we add another state variable called 'Sovereign Spread' in order to capture sovereign risk in the union subsequent to eruption of 2009 European sovereign debt crisis.

4.4 Data

The systemic risk of seventeen Eurozone member states, namely, Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia and Spain, has been accessed with special reference to $PIIGS$ countries (Portugal, Ireland, Italy, Greece and Spain) that faced severe debt crisis in the aftermath of 2007 global financial crisis. 315 Eurozone publicly listed financial institutions in our sample are used to portray four main financial sectors specifically banks, diversified financials (DFinancials), insurance and real-estate. The analysis timeframe covers the period 3 January 2000 to 31 December 2015. It is an acceptable foundation to determine the amount of systemic risk added to the $SIFIs$ in the Eurozone as it accounts for the three financial crises (2000 dotcom crisis, 2007 subprime crisis and 2009 Eurozone sovereign debt crisis). We have separated the period into three subperiods: pre-crisis period (3 January 2000 – 31 June 2007), crisis period[30] (2 July 2007 – 31 December 2010) and post-crisis period (3 January 2011 - 31 December 2015). See appendix (A) for the number of financial institutions within each sector in all Eurozone member states.

From the Bloomberg database, daily equity adjusted prices were acquired to cover for capital operations (i.e., splits, dividends etc.). Based on the sample, each institution has an average of 4173 daily returns. See appendix (B) for list of these institutions and their sectors classification within each member state. From these financial institutions' quarterly balance sheets, leverage data is extracted and transformed in daily series via linear interpolation, this is based on the assumption that the leverage ratio stays roughly consistent through consecutive days within any quarter (period), ultimately the low-frequency data available in the period will reach the

[29] 10-year treasury bond was not available for Cyprus, Estonia, Luxembourg, Malta, and Slovenia.

[30] July 2007 – December 2010 was designated as crisis period since this timeframe includes the majority of systemic events of global financial crisis and European sovereign debt crisis.

unobservable daily value[31]. Based on the daily frequency, total asset market valuations are then calculated so the daily time-series of growth rates of market value of assets X_t^i and X_t^{sys} can be generated accordingly. In order to obtain a series of market value of assets, we use daily values of market capitalization and quarterly balance sheet data of book value of assets and equity.

Table 4.1: Summary Statistics of Growth in Market Value of Assets (Overall Period)

	Mean	STD	Min.	Max.	Skewness	Kurtosis	JB	VaR
Panel (A): Eurozone Financial Sectors								
Banks	0.05	2.98	-42.75	39.74	-0.17	66.07	759,640	3.08
DFinancials	0.03	1.97	-11.35	22.01	0.75	10.40	19,222	2.88
Insurance	0.02	1.82	-16.34	18.97	0.27	9.87	17,005	2.56
Real-estate	0.06	0.98	-10.49	13.12	1.02	24.97	109,260	1.31
Panel (B): Eurozone Member States								
Austria	0.05	1.77	-14.41	17.26	0.46	19.23	64,485	2.25
Belgium	0.05	1.69	-12.70	24.15	0.93	18.98	63,314	2.25
Cyprus	0.00	2.84	-12.47	62.29	6.77	134.43	3,176,600	3.50
Estonia	0.04	1.74	-29.12	59.57	16.06	587.50	60,237,000	0.93
Finland	0.07	1.84	-14.57	57.43	7.35	227.04	9,006,700	2.53
France	0.04	1.94	-10.41	20.15	0.71	9.76	16,917	2.75
Germany	0.04	1.86	-13.72	15.79	0.33	8.55	12,813	2.64
Greece	0.07	3.81	-29.21	64.36	1.98	32.55	187,110	4.80
Ireland	-0.03	3.85	-51.43	31.87	-0.01	18.50	59,585	4.73
Italy	0.04	1.93	-10.46	16.75	0.70	8.54	13,034	2.81
Luxembourg	0.03	1.09	-8.74	15.64	0.73	15.57	42,570	1.68
Malta	0.02	1.76	-38.63	64.13	8.69	522.19	47,499,000	1.46
Netherlands	0.09	4.32	-64.08	67.86	1.59	83.38	1,211,400	3.91
Portugal	0.00	2.27	-13.40	62.53	6.51	156.44	4,287,900	2.79
Slovakia	0.05	3.02	-81.07	19.00	-7.12	169.49	4,966,500	3.80
Slovenia	0.03	3.01	-36.98	59.27	3.75	103.11	1,483,500	2.92
Spain	0.05	1.95	-12.45	20.81	0.84	10.29	18934	2.81
PIIGS	0.03	1.79	-16.34	18.52	0.31	9.27	15,014	2.58
Eurozone	0.06	2.39	-26.82	47.18	3.11	84.64	1,253,500	2.83

Notes: The table displays the summary statistics for daily growth in market value of assets of Eurozone financial sectors and each member state financial index from January 2000 to December 2015. STD denotes the standard deviation. JB refers to the Jarque-Bera test for normality. The Jarque-Bera statistics are statistically significant at 1%. VaR is estimated under the assumption of $q = 5\%$ level.

[31] To avert from the seasonal discontinuities that this method may generate, Cubic spline interpolation could be utilised. In applied finance and other disciplines, it is a famous method (e.g., it is regularly utilised to generate the term structure). The final outcomes are not responsive to this factor, therefore linear interpolation is used as the main approach.

Descriptive statistics of alterations in MVA for Eurozone financial sectors and Eurozone member states over the sample period are demonstrated in Table 4.1. The average daily growth in MVA is approximately near zero while being positively skewed with the exception of banking sectors, Ireland and Slovakia. This is substantiated by Table 4.1 as it demonstrates MVA distributions growth is leptokurtic with an average kurtosis of 27.83 in the financial sectors and 116.81 in member states. Interestingly, non-normal distributions are present under the Jarque–Bera (Jarque and Bera, 1980, 1981) test for all series. Each Eurozone member states and financial sector possesses different standard deviations. Remarkably, the highest values among member states belong to the Netherlands, Ireland and Greece while banking sector followed by diversified financials are the uppermost of the financial sector as this is established by the series' maximum and minimum values analysed.

Table 4.2: EU Market Variables Summary Statistics

	Mean	STD	Min.	Max.	Skewness	Kurtosis
Panel (A): EU Market variables						
Volatility Index	24.95	9.65	11.60	87.51	1.64	3.49
T-Bill spread variation	-0.08	4.10	-117.70	85.50	-1.84	258.91
Yield spread change	135.38	75.24	-31.00	313.70	0.22	-0.64
Change credit spread	29.99	33.23	-2.00	277.43	3.45	14.75
TED Spread	0.01	10.78	-134.48	237.31	3.13	151.66
Equity return	0.00	1.25	-7.93	9.41	-0.17	5.24
Panel (B): EU Sovereign Spread						
Austria	-0.07	11.76	-160.48	262.19	2.91	157.68
Belgium	-0.06	11.26	-146.91	263.61	3.05	164.92
Finland	-0.12	14.05	-247.51	277.49	0.82	156.17
France	-0.06	11.21	-142.50	258.91	3.11	163.59
Germany	0.00	0.45	-16.87	13.29	-7.30	940.97
Greece	-0.02	11.08	-134.59	238.03	2.82	137.36
Ireland	-0.06	10.78	-135.15	252.84	3.43	163.59
Italy	-0.05	10.79	-133.14	242.08	3.29	155.98
Netherlands	0.00	14.42	-264.55	296.11	3.24	184.54
Portugal	-0.03	10.88	-135.63	240.03	3.14	149.88
Slovakia	-0.08	11.61	-132.52	245.15	3.18	137.80
Spain	-0.05	10.86	-135.27	243.82	3.17	154.78

Notes: Panel (A) displays the EU market variables. The spread and spread changes are expressed in basis points and the returns and volatility are expressed as a percentage. Panel (B) shows EU sovereign spread, for example the sovereign spread for Austria is calculated as the spread between 10-year Austrian government bond and the 10-year Euro bond rate.

The daily market variables' summary statistics are depicted in Table 4.2. Stress periods are when nearly all extreme values of those variables arise. The variables' distributions are demonstrated to be highly skewed. As revealed in Table 4.2, the market volatility index ($V2X$) has a positive and relevant coefficient which positively influences the expected VaR size. Thus, higher levels of volatility trigger higher VaR values. Since greater spreads generate higher risk levels, variating credit spreads and liquidity levels have generally been positive and are extensively connected to a day-ahead VaR. On the other hand, the $T\text{-}bill$ rate shifts and the $STOXX$ Europe 600's market return have heterogeneously impacted the financial institution's VaR. It is not typically considerably different from zero individually, despite having various signs. Last of all, VaR generally being reduced by a greater positive slope's yield curve demonstrates that lower levels of risk can be portrayed through higher prospects of growth.

4.5 Analysis and Results

Calculating the VaR of individual institution (sector or country) and the system in our sample is required for the $CoVaR$ methodology. We utilise the quantile regression methodology similar to Adrian and Brunnermeier (2011) and Lòpez-Espinosa, *et al.* (2013). The concentration on the 1% or 5% quantile produces a standard market risk measure utilised via financial institutions and regulatory authorities in formulating capital requirements.

Consider a random variable r_t^i that represents the returns of financial institution i at time t ($i = 1, \ldots, N$; $t = 1, \ldots, T$). VaR of the random variable r_t^i at the confidence level $q \in (0,1)$, $VAR_{q,t}^i$ is defined as the q-quantile of the return distribution as follows:

$$VaR_{q,t}^i = F_{i,t}^{-1}(q) \qquad (16)$$

Where $F_{i,t}^{-1}$ is the generalised inverse distribution function of the return distribution $F_{i,t}$, which is $F_{i,t}^{-1}(q) \coloneqq inf\{r_{i,t} \in \mathbb{R} : F_{i,t}(r_{i,t}) \geq q\}$[32].

The daily returns of a portfolio constructed by the $MVAs$ of each financial institution are accounted for. For this specific portfolio, our concern is completely driven from a regulatory perspective as financial sector instability could be prompted by negative spillover as they are tied with balance sheet contraction. Data captured from all financial institutions involves total assets, total liabilities, ordinary shareholders' equity and market capitalization. By calculating

[32] Eq. (16) can be rewritten as Eq. (1).

the asset's market value growth rates' VaR and $CoVaR$, we apply a similar methodology of Adrian and Brunnermeier (2011). The reason is the asset's market value is strongly tied to the real economy's credit supply. The growth rate of market value of assets X_t^i for financial institution i at time t is defined by:

$$X_t^i = \frac{BA_t^i\left(\frac{ME_t^i}{BE_t^i}\right) - BA_{t-1}^i\left(\frac{ME_{t-1}^i}{BE_{t-1}^i}\right)}{BA_{t-1}^i\left(\frac{ME_{t-1}^i}{BE_{t-1}^i}\right)} = \frac{LEV_t^i\, ME_t^i - LEV_{t-1}^i\, ME_{t-1}^i}{LEV_{t-1}^i\, ME_{t-1}^i} = \frac{MA_t^i - MA_{t-1}^i}{MA_{t-1}^i} \tag{17}$$

where $\mathrm{BA_t^i}$, $\mathrm{BE_t^i}$, $\mathrm{ME_t^i}$, $\mathrm{LEV_t^i}$ and $\mathrm{MA_t^i}$ are the book value of assets, book value of equity, market value of equity, the ratio of assets-to-book equity and market value of assets of institution i at time t. To acquire the $MVAs$, the Price-to-Book equity value is used to convert book value of assets.

For each member state's financial system (or sector), a distinct regional financial system portfolio is constructed from a cross-sectional summation of $n-1$ weighted assets of the remaining financial institutions. In this scenario, the assets are the growth rate of market value of all financial institutions' assets, except the member state's financial institutions under analysis. For the contribution of the member state's financial institutions we want to quantify, we must exempt them to avert any spurious correlation. As a result, 17 different financial system portfolios, each relating to one of the 17-member states is designed. Consequently, the representative Eurozone financial system portfolio returns for each member state's financial system i are characterized according to:

$$X_t^{sys,i} = \sum_{j=1, j\neq i}^{n} \omega_{j,t} X_t^j, \omega_{j,t} = \omega_t^j \left(\sum_{j=1, j\neq i}^{n} \omega_t^j\right)^{-1} \tag{18}$$

where X_t^j is the simple returns of the jth country (or sector) and ω_t^j is some (strictly positive) variable utilised in the weighting scheme so that the resultant weights are within the restriction $0 \leq \omega_t^j \leq 1$.

Portfolios of the Eurozone's financial system are generated after exempting the country (or sector) under analysis. This method secures an adjustment to the small-sample which avoids a mechanical correlation effect (i.e. a spurious interdependence) amongst country (or sector) and the system, for the occasion when the total amount of countries (or sectors) n in the sample is not relatively large as well as when a single country (or sector) has a considerable weight in comparison to the entire system n is reasonably large. Since the country (or sector) being analysed is excluded, the further analysis of this country (or sector) and the resulting system's tail comovements is more burdensome. This eliminates the potential of spurious interrelations arising via simultaneous existences of the same country (or sector) in both portfolios.

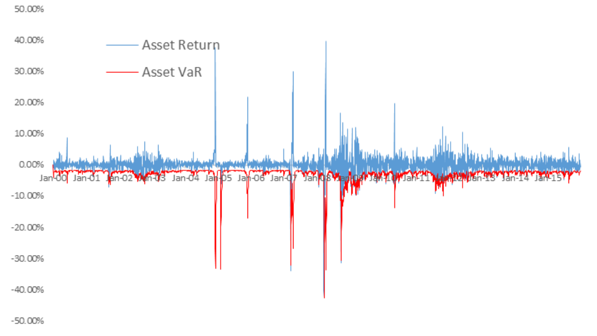
To determine the portfolios of the Eurozone financial system portfolios, the weighted variable used is the lagged value of market capitalisation which portrays the asset-liability mismatch inherent within the systemic risk. Adrian and Brunnermeier (2011) employ total assets variable's lagged value as typically larger financial institutions form greater shocks on the credit supply, whereas Lòpez-Espinosa, *et al.* (2013) use the institution's liabilities' lagged book value to determine the interconnectedness level amongst financial institutions under certain circumstances.

Figure 4.1 shows the temporal dynamics of change in market value of assets for all Eurozone financial sectors and member states under analysis along with their related standard $VaRs$. It shows differences in the size and timing of MVA movements in different sectors and member states while sharing high volatility episodes around the inception of the subprime crisis and Eurozone crisis. The size and dynamics of MVA volatility differs significantly as well across members.

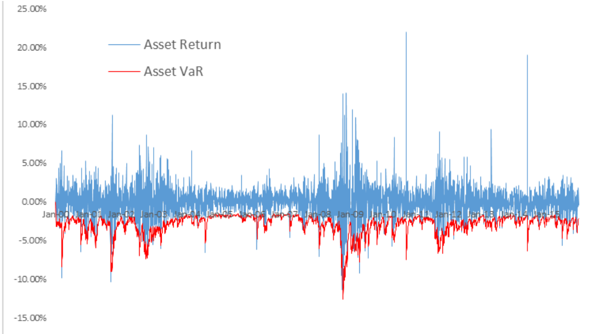
Individual returns depict various structural volatilities. It is evident that for example, more volatile daily returns are typically experienced by Ireland then by Greece. This is substantiated by Ireland's VaR being generally lower than that of Greece. The unconditional $VaRs$ alone have been emphasised to be insufficient in developing policy implications. Countries with generally low volatilities in their returns could possibly attribute greater risk to the overall system.

$VaRs$ are positively correlated, which is evident in the common underlying trend of $VaRs$. Over the periods surrounding, all the $PIIGS$ countries' $VaRs$ were generally lower between the period of the 2007 global financial crisis and 2009 European sovereign debt crisis. However, all $VaRs$ trended up together due the economy experiencing recovery in the following periods. $VaRs$ have typically been stimulated by the stock market's overall condition after the 2007 crisis era, as well as the recent risk aversion episode during the subprime and debt crises. Ultimately, different $PIIGS$ countries react uniquely to typical shocks while some are more resistant compared to others.

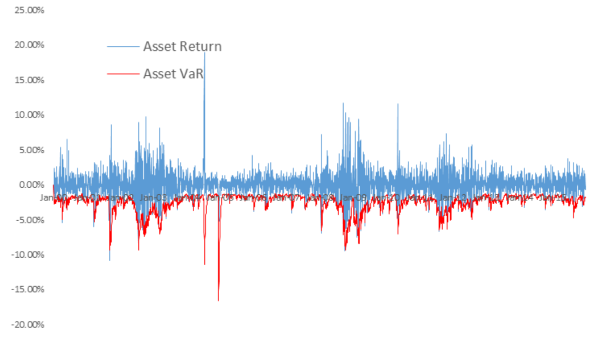
Banks



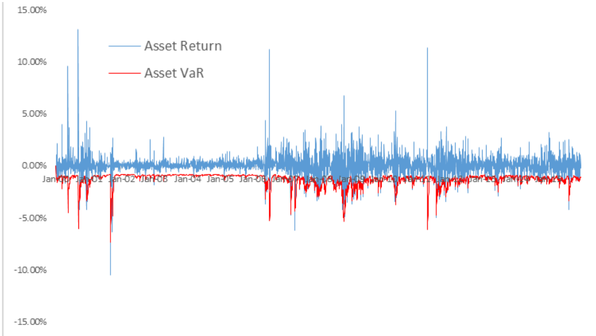
Diversified Financials



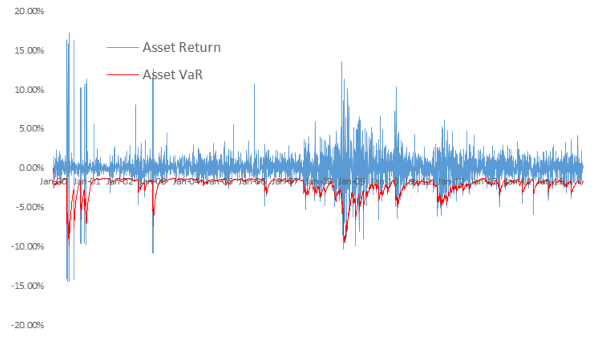
Insurance



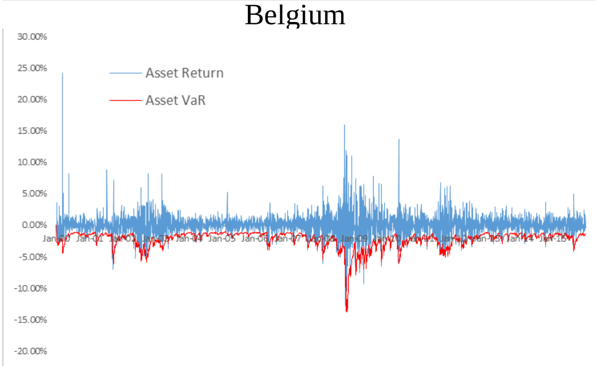
Realestate



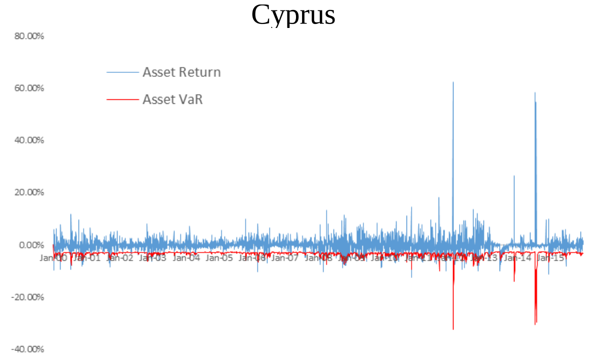
Austria



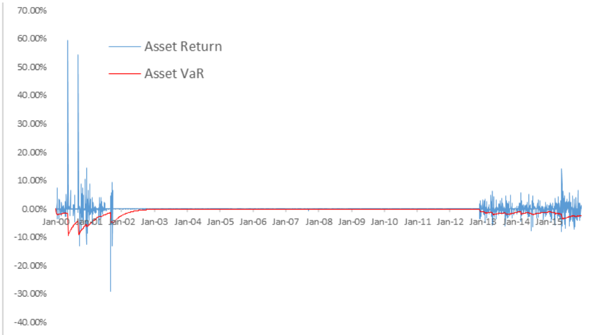
Belgium



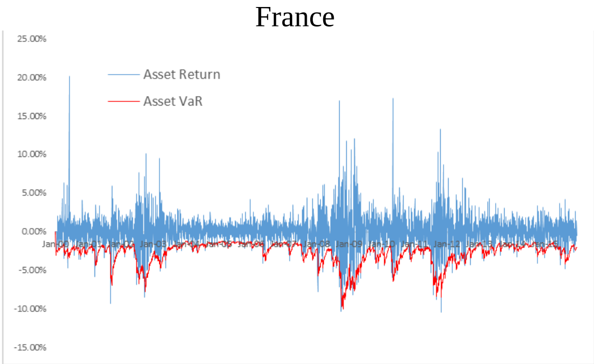
Cyprus

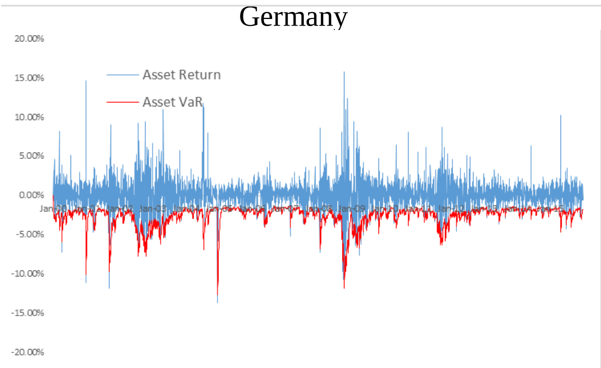


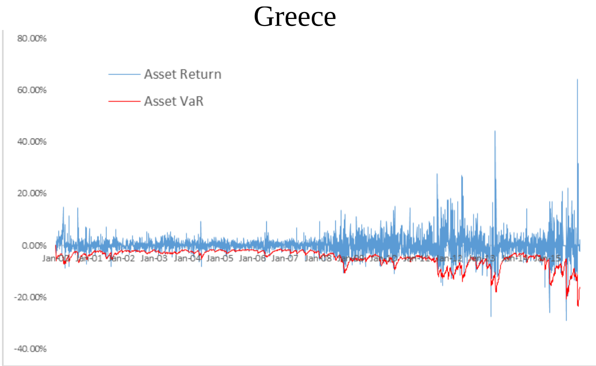
Estonia

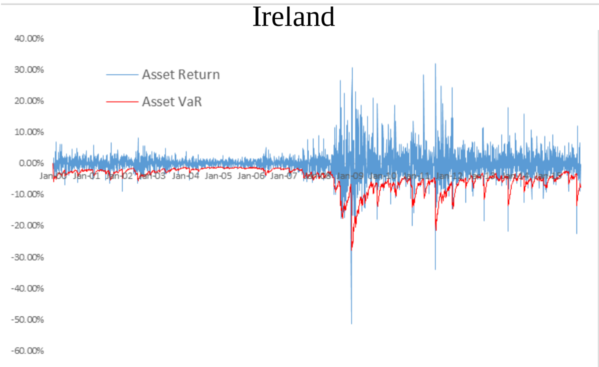


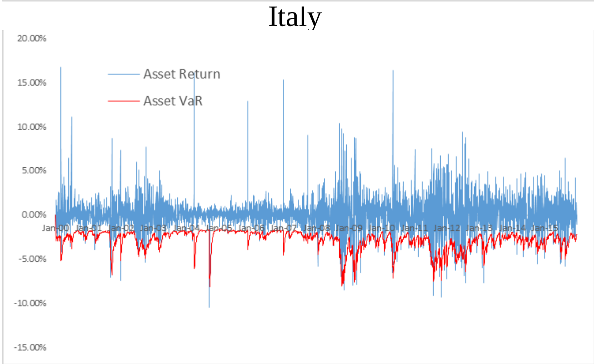

Finland
Asset Return
Asset VaR

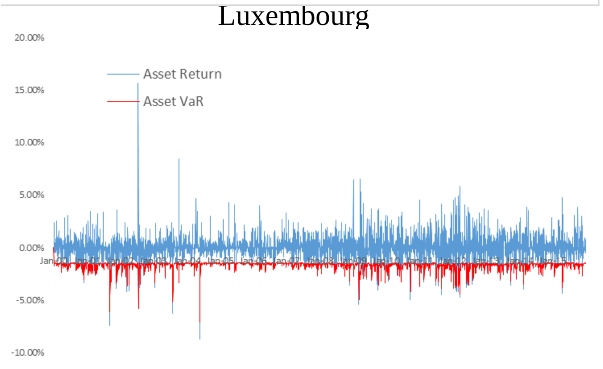

France
Asset Return
Asset VaR

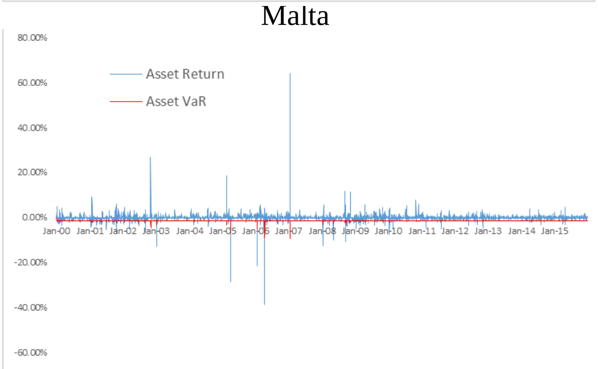

Germany
Asset Return
Asset VaR

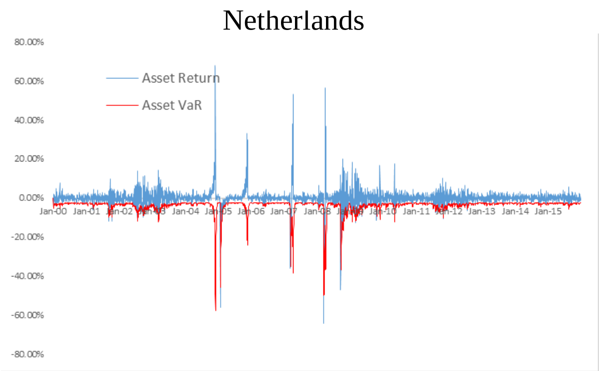

Greece
Asset Return
Asset VaR

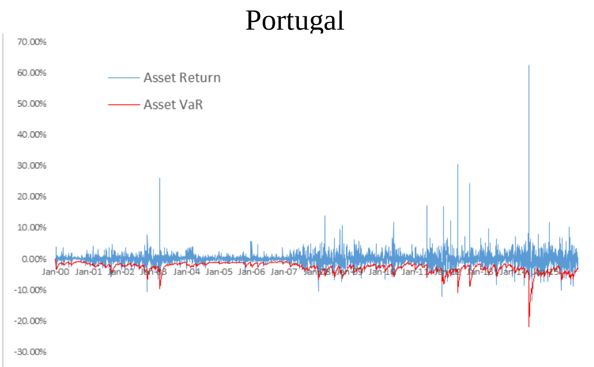

Ireland
Asset Return
Asset VaR


Italy
Asset Return
Asset VaR


Luxembourg
Asset Return
Asset VaR


Malta
Asset Return
Asset VaR


Netherlands
Asset Return
Asset VaR


Portugal
Asset Return
Asset VaR

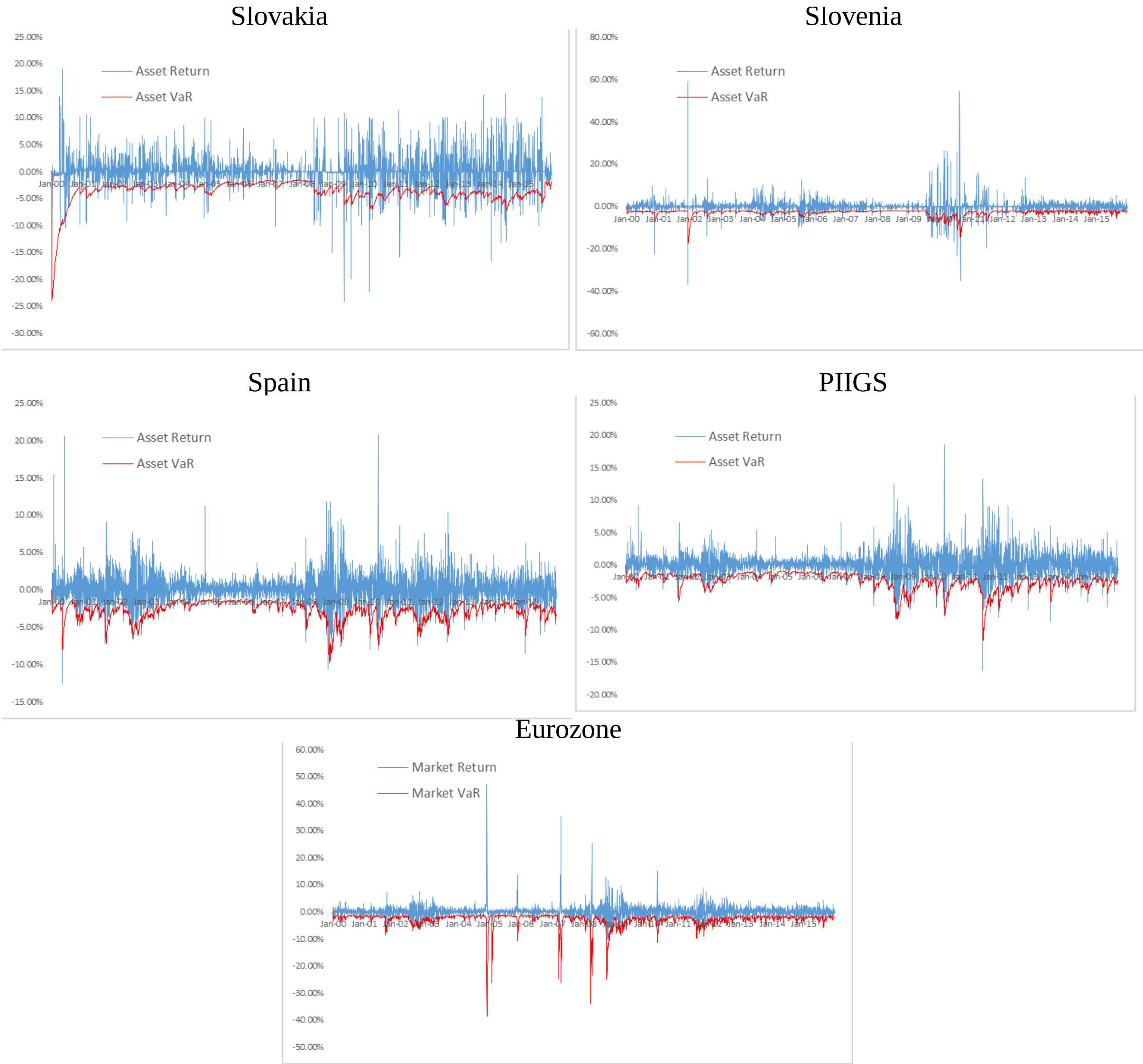


Figure 4.1: Time series plots for daily growth in MVA and VaR (Overall Period)

Notes: This figure shows Eurozone financial sectors, member states and the entire financial system's daily market value of asset returns. VaR is estimated at $q = 5\%$ level.

A cross-section plot of country's 5% unconditional $VaRs$ averages and its input towards systemic risk is determined by average $\Delta CoVaRs$ at 5%, is depicted on Figure 4.2. Evidently, the cross-section demonstrates a weak connection between country's VaR and $\Delta CoVaR$. Keep in mind that Italy, France, Spain and Germany, the greatest contributor to systemic risk (i.e. the one with largest $\Delta CoVaR$), have the lowest values in terms of unconditional VaR. However, Greece, Ireland. the Netherlands and Slovakia possess the largest unconditional VaR being definitely the riskiest, is at the simultaneously imposing the lowest system risk. These infer that powerful externalities possibly do exist, and the idea of systemic risk should be made aware to regulators and policy makers. A financial sector (country or institution) could potentially appear to conduct in a prudent manner and be exposed to a limited amount of risk. However, simultaneously it is crucial for the system's financial viability. Similar results are identified by Adrian and Brunnermeier (2011) and Girardi and Ergün (2013) which supports the case that regulating financial institution's risk individually, through institution's VaR, may not be the best alternative to safeguard the financial sector against systemic risk.

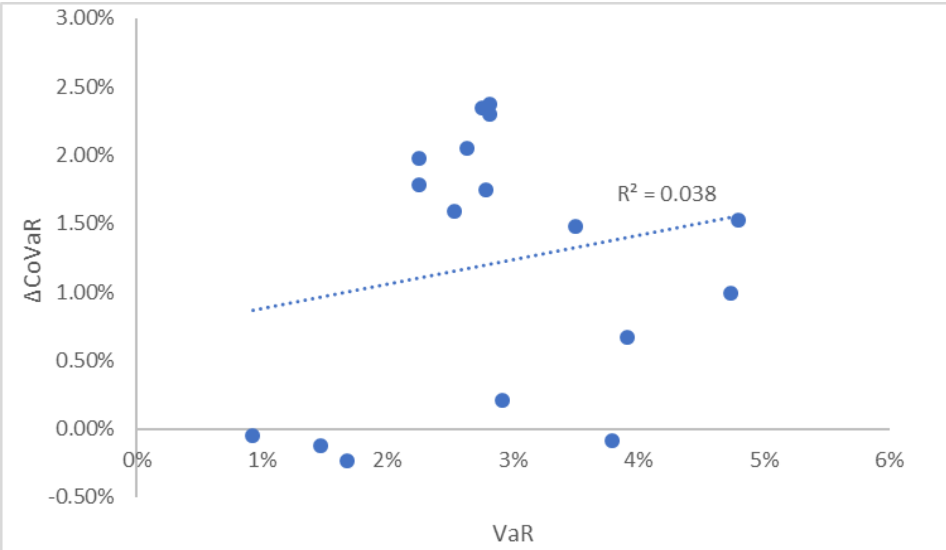


Figure 4.2: Cross Section Average VaR and Delta CoVaR during the crisis period

Notes: The scatter plot shows the cross-sectional link between VaR and $\Delta CoVaR$. All risk measures are generated under the assumption of $q = 5\%$ level. Each point represents a member state of the Eurozone. Averages are calculated for the crisis period (2000-2015). Average VaR and $\Delta CoVaR$ figures are expressed as a percentage.

Table 4.3: Contribution and Exposure Time-invariant 5%-ΔCoVaR vs Time-variant 5%-ΔCoVaR

Sector/ Member State	Time-invariant $\Delta CoVaR_{5\%}$				Time-variant $\Delta CoVaR_{5\%}$			
	Contribution		Exposure		Contribution		Exposure	
	Rank	%	Rank	%	Rank	%	Rank	%
Panel (A): Eurozone Financial Sectors 5%-$\Delta CoVaR$								
Banks	4	2.37	1	3.52	4	1.32	1	2.51
DFinancials	2	2.78	3	2.32	2	1.94	2	1.43
Insurance	1	3.39	2	2.46	1	2.29	3	1.28
Real-estate	3	2.54	4	1.23	3	1.35	4	0.54
Panel (B): Eurozone Member States 5%-$\Delta CoVaR$								
Austria	6	2.70	5	2.44	7	1.79	4	1.50
Belgium	5	2.86	7	2.38	6	1.98	5	1.49
Cyprus	10	2.30	13	0.96	11	1.48	13	0.61
Estonia	17	0.26	18	0.00	15	-0.05	16	0.00
Finland	8	2.43	11	1.44	9	1.59	9	0.99
France	3	2.97	3	2.92	3	2.35	2	1.87
Germany	7	2.68	8	2.18	5	2.05	8	1.34
Greece	11	1.93	10	1.68	10	1.52	11	0.85
Ireland	12	1.61	9	1.80	12	0.99	10	0.96
Italy	2	3.20	6	2.40	1	2.38	6	1.43
Luxembourg	16	0.48	17	0.01	18	-0.23	18	-0.03
Malta	18	-0.06	16	0.08	17	-0.12	17	-0.02
Netherlands	13	1.53	1	4.66	13	0.67	1	3.16
Portugal	9	2.42	12	1.12	8	1.74	12	0.84
Slovakia	15	0.52	15	0.50	16	-0.09	15	0.08
Slovenia	14	1.03	14	0.50	14	0.21	14	0.29
Spain	4	2.87	2	2.92	4	2.30	3	1.67
PIIGS	1	3.44	4	2.73	2	2.35	7	1.38

Notes: The table compares between contribution $\Delta CoVaR$ and exposure $\Delta CoVaR$ within the time-invariant $\Delta CoVaR$ and time-variant $\Delta CoVaR$ for each Eurozone financial sector and member state in the union. Simple averages are computed within the crisis period. Average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ is estimated using quantile regression of $q = 5\%$ level.

Table 4.4: Contribution and Exposure Time-invariant 1%-ΔCoVaR vs Time-variant 1%-ΔCoVaR

Sector/ Member State	Time-invariant $\Delta CoVaR_{1\%}$				Time-variant $\Delta CoVaR_{1\%}$			
	Contribution		Exposure		Contribution		Exposure	
	Rank	%	Rank	%	Rank	%	Rank	%
Panel (A): Eurozone Financial Sectors 1%-$\Delta CoVaR$								
Banks	4	1.36	1	2.47	4	1.00	1	2.46
DFinancials	3	1.75	3	1.28	3	1.77	3	0.79
Insurance	1	4.84	2	1.44	1	3.69	2	0.85
Real-estate	2	4.44	4	0.95	2	3.56	4	0.37
Panel (B): Eurozone Member States 1%-$\Delta CoVaR$								
Austria	2	5.27	4	1.92	11	2.46	7	1.00
Belgium	3	5.23	3	2.03	6	2.76	4	1.66
Cyprus	11	3.03	11	1.36	9	2.65	8	0.98
Estonia	14	2.35	17	-0.01	10	2.47	16	0.00
Finland	13	2.75	7	1.56	3	4.16	6	1.27
France	6	4.73	10	1.40	5	3.98	10	0.83
Germany	10	3.45	5	1.77	7	2.74	5	1.38
Greece	9	3.61	13	1.14	13	2.20	9	0.89
Ireland	12	2.96	2	3.88	12	2.30	2	1.71
Italy	5	4.88	8	1.50	2	4.21	12	0.62
Luxembourg	17	0.10	18	-0.86	17	-0.44	17	-0.50
Malta	16	0.34	15	0.76	16	0.20	15	0.10
Netherlands	15	1.70	1	13.46	15	0.77	1	6.83
Portugal	4	5.09	6	1.75	8	2.70	3	1.67
Slovakia	18	-1.20	16	0.20	18	-1.77	18	-0.84
Slovenia	8	3.70	14	1.04	14	1.26	14	0.54
Spain	7	3.85	9	1.48	4	4.06	11	0.69
PIIGS	1	6.35	12	1.35	1	4.55	13	0.60

Notes: The table compares between contribution $\Delta CoVaR$ and exposure $\Delta CoVaR$ within the time-invariant $\Delta CoVaR$ and time-variant $\Delta CoVaR$ for each Eurozone financial sector and member state in the union. Simple averages are computed within the crisis period. Average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ is estimated using quantile regression of $q = 1\%$ level.

We estimate contribution $\Delta CoVaR$ corresponding to each financial sector and member state's financial sector in the Eurozone conditional on any financial sector and member state is under distress in table 4.3 and 4.4. We reversed the condition by calculating exposure $\Delta CoVaR$ corresponding to each financial sector and member state conditional on the Eurozone financial system is under stress. Furthermore, we assess time-variant $\Delta CoVaR$ which is different than time-invariant $\Delta CoVaR$ by adding to the model lagged systematic state variables that allows us to estimate the dynamic values of $\Delta CoVaR$ over-time and it assists in avoiding the omitted variable bias that arises from failure to differentiate between systemic risk and macro risk. Further, we computed $\Delta CoVaR$ at different quantiles of 5% and 1%. The systemic risk rankings of contribution $\Delta CoVaR$ differs from exposure $\Delta CoVaR$ which means that sectors (countries or institutions) that contributes the most to systemic risk are not necessarily the sectors (countries or institutions) that are highly exposed to systemic risk when the entire Eurozone financial system crashes. This is an important remark for regulators, policy makers, and portfolio managers. In addition, systemic risk ranking of conditional $\Delta CoVaR$ diverse from the rankings of unconditional $\Delta CoVaR$ which reflects the importance of lagged systematic state variables that capture the evolution of tail risk dependence over-time. While only determining the distribution quantile, the consistency of systemic risk ranking based on different quantiles of 5%-$\Delta CoVaR$ and 1%-$\Delta CoVaR$ is not sustainable for both contribution $\Delta CoVaR$ and exposure $\Delta CoVaR$ which indicates that VaR ignores extreme loss above VaR levels that does not take into account the risk of indices with fat-tailed characteristics.

Average systemic risk conditional contribution of different financial sectors and member states to the Eurozone financial index is computed for four periods (overall, pre-crisis, crisis and post-crisis periods) in table 4.5. The results of this table need to be interpreted with caution as return, VaR, $CoVaR$ and $\Delta CoVaR$ are calculated on daily frequency. Greater frequencies (i.e. weekly, monthly, quarterly, etc.), would result in greater changes, consequently, ranking of sectors (countries or institutions) would differ and it is possible that a certain sector (country or institution) with a high positive $\Delta CoVaR$ at a certain interval, would be insignificant source of systemic risk at another interval. In addition, we use average values of $\Delta CoVaR$ so a single sector (country or institution) with a high systemic risk in a single day or period (pre-crisis, crisis or post-crisis), does not necessarily means this sector (country or institution) is systemically riskier than another over the whole period. For example, France has the highest systemic risk contribution to the Eurozone financial index during the overall period while Ireland, Italy and Austria have the maximum systemic risk contribution during the pre-crisis, crisis and post-crisis periods respectively.

Table 4.5: Average Conditional Contribution ΔCoVaR of Financial Sectors and Member States in the Union

Member State	**Overall**		**Pre-Crisis**		**Crisis**		**Post-Crisis**	
	Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**%**
Panel (A): Eurozone Financial Sectors								
Banks	4	0.71	4	0.10	4	1.32	3	1.67
DFinancials	1	1.59	1	1.24	2	1.94	2	1.94
Insurance	2	1.58	2	0.53	1	2.29	1	2.28
Real-estate	3	0.88	3	0.27	3	1.35	4	1.52
Panel (B): Eurozone Member States								
Austria	8	0.92	12	0.14	7	1.79	1	1.97
Belgium	5	1.35	7	0.45	6	1.98	3	1.88
Cyprus	13	0.23	9	0.34	11	1.48	14	0.08
Estonia	14	0.00	18	-0.05	15	-0.05	13	0.21
Finland	7	0.97	8	0.43	9	1.59	4	1.88
France	1	1.64	2	0.88	3	2.35	2	1.92
Germany	4	1.37	6	0.51	5	2.05	8	1.77
Greece	11	0.48	5	0.55	10	1.52	12	0.32
Ireland	10	0.52	1	0.93	12	0.99	11	0.47
Italy	3	1.42	11	0.26	1	2.38	7	1.80
Luxembourg	16	-0.04	17	-0.04	18	-0.23	16	0.04
Malta	17	-0.05	14	0.02	17	-0.12	17	-0.03
Netherlands	12	0.25	13	0.04	13	0.67	5	1.86
Portugal	9	0.81	10	0.30	8	1.74	10	0.52
Slovakia	18	-0.09	16	-0.03	16	-0.09	18	-0.04
Slovenia	15	-0.01	15	0.00	14	0.21	15	0.07
Spain	2	1.48	3	0.84	4	2.30	6	1.83
PIIGS	6	1.28	4	0.75	2	2.35	9	1.21

Notes: The table ranks the average time-varying contribution to systemic risk measures according to $\Delta CoVaR_q^{sys|i}$ of each Eurozone financial sector and member state. Simple averages are computed within the periods; overall period, pre-crisis period, crisis period and post-crisis period. Average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ is estimated using quantile regression of $q = 5\%$ level.

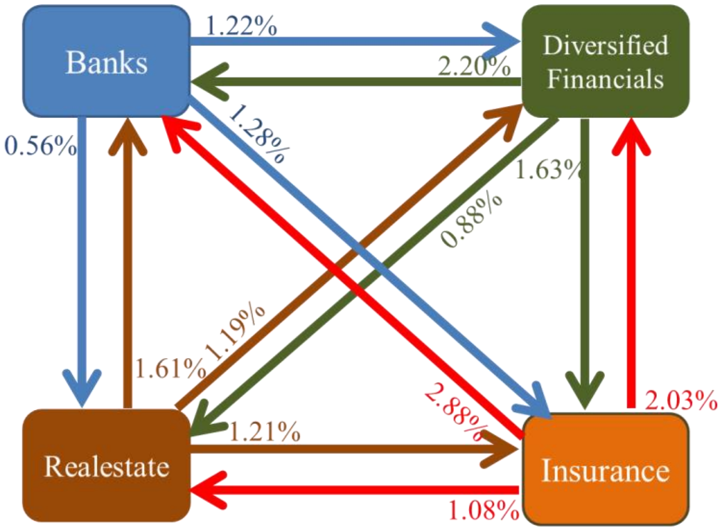


Figure 4.3: Network Time-variant ΔCoVaR of Eurozone Financial Sectors

Notes: The figure shows the network time-variant $\Delta CoVaR$ for each financial sector in the union. Simple averages are computed within the crisis period. Average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ is estimated using quantile regression of $q = 5\%$ level.

Delta $CoVaR$ model introduced by Adrian and Brunnermeier (2011) can be applied to estimate the financial linkages between financial sectors (countries or institutions) which is called Network $\Delta CoVaR$. Figure 4.3 and table 4.5 show the change in VaR of a single sector (or country) when another sector (or country) becomes financially stressed. Banking sector has the highest systemic exposure from insurance and diversified financial sectors. The VaR of the banking sector changes by 2.88% and 2.20% when insurance and diversified financial sectors are in distress respectively. On the contrary, real-estate sector has the lowest systemic exposure of banking and diversified financial sectors with $\Delta CoVaR$ of 0.56% and 0.88% respectively. This is an interesting finding as banking sector has the lowest systemic risk contribution and the highest systemic risk exposure at the same time which proves that sectors (countries or institutions) that contribute the most to systemic risk are not the ones that are severely affected by systemic events. Similar findings are revealed on the union level where $PIIGS$ and Spain have the highest systemic risk contribution to Ireland (5.04% and 4.48%) while Ireland's contribution to $PIIGS$' and Spain's systemic risk is low at 1.16% and 1.04% respectively.

Table 4.6: Network Time-variant ΔCoVaR of Eurozone Member States

i \ j	Austria	Belgium	Cyprus	Estonia	Finland	France	Germany	Greece	Ireland	Italy	Luxembourg	Malta	Netherlands	Portugal	Slovakia	Slovenia	Spain	PIIGS
Austria		2.01	1.61	0.00	1.21	1.83	1.64	1.74	2.81	1.70	0.12	0.01	2.19	1.17	0.37	0.23	1.76	1.67
Belgium	1.74		1.20	0.00	1.46	2.05	1.66	1.65	3.44	1.85	0.01	0.00	2.19	1.25	0.39	0.50	2.09	1.92
Cyprus	1.22	1.00		0.00	0.86	1.41	1.31	2.73	1.85	1.32	0.07	-0.02	1.41	0.99	-0.45	0.07	1.56	1.53
Estonia	0.07	0.12	0.06		0.08	0.03	-0.04	-0.03	0.04	0.02	0.05	-0.02	-0.08	-0.03	0.14	0.17	0.02	0.01
Finland	1.26	1.40	1.23	0.00		1.48	1.26	1.33	2.38	1.32	0.09	-0.02	2.06	1.04	0.39	0.28	1.34	1.37
France	1.99	2.45	1.51	0.00	1.48		1.83	2.22	4.24	2.17	-0.10	-0.03	2.90	1.34	0.21	0.28	2.30	2.25
Germany	1.73	1.92	1.00	0.00	1.20	1.87		1.41	2.63	1.65	-0.06	-0.02	2.39	1.10	0.36	0.18	1.89	1.74
Greece	1.58	1.73	3.01	0.00	0.99	1.54	1.39		3.07	1.42	-0.06	0.16	1.58	1.36	-0.22	0.03	2.16	2.08
Ireland	1.08	1.11	1.05	0.00	0.82	1.00	0.85	1.40		0.91	-0.03	-0.08	1.25	0.74	-0.01	0.34	1.04	1.16
Italy	2.16	2.34	1.46	0.00	1.43	2.55	2.04	2.01	3.90		-0.07	-0.05	2.57	1.25	0.14	0.27	2.28	2.46
Luxembourg	-0.16	0.16	0.56	0.00	0.41	-0.03	-0.02	0.44	0.37	-0.45		0.62	-0.36	0.39	-0.39	0.54	-0.14	-0.46
Malta	-0.02	-0.15	-0.09	0.00	-0.30	-0.12	-0.29	-0.12	0.12	-0.21	0.01		0.16	0.05	0.26	-0.14	-0.05	-0.08
Netherlands	0.29	0.64	0.32	0.00	0.35	0.44	0.59	0.37	0.48	0.37	0.00	0.00		0.42	0.05	0.03	0.32	0.56
Portugal	1.60	1.70	1.55	0.00	1.08	1.57	1.30	1.34	2.18	1.31	-0.02	-0.03	1.75		0.12	0.21	1.73	1.69
Slovakia	0.30	0.43	-0.60	0.00	0.02	0.03	0.17	-0.21	0.58	0.03	-0.17	-0.10	-0.27	0.30		0.09	0.12	-0.03
Slovenia	0.41	0.38	0.50	0.00	0.21	0.21	0.04	0.34	0.56	0.22	-0.22	-0.26	0.14	0.29	0.15		-0.03	0.24
Spain	2.33	2.61	1.50	0.00	1.60	2.64	1.98	2.39	4.48	2.44	-0.13	0.06	2.88	1.67	0.22	0.36		2.85
PIIGS	2.33	2.68	2.01	0.00	1.79	2.79	2.19	2.47	5.04	2.59	-0.07	-0.01	2.94	1.83	0.21	0.39	2.96	

Notes: The table states the network time-variant $\Delta CoVaR$ for each member state in the union. The first column for example $CoVaR_q^{Austria|i}$ measures member state i marginal contribution of systemic risk to Austria. Simple averages are computed within the crisis period. Average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ is estimated using quantile regression of $q = 5\%$ level.

Table 4.7: Average Conditional Contribution ΔCoVaR of Member States within Each Eurozone Financial Sector

Member State	Overall Period		Pre-crisis Period		Crisis Period		Post-crisis Period	
	Rank	%	Rank	%	Rank	%	Rank	%
Panel (A): Banks								
Austria	7	1.11	7	0.38	5	2.00	5	1.93
Belgium	5	1.19	8	0.35	6	1.90	7	1.43
Cyprus	12	0.13	10	0.24	8	1.60	12	0.10
Finland	14	-0.03	11	0.20	13	0.16	14	-0.26
France	2	1.75	3	0.76	3	2.72	4	2.04
Germany	8	1.07	4	0.76	9	1.56	9	0.76
Greece	10	0.51	6	0.49	10	1.49	11	0.46
Ireland	9	0.51	1	0.96	11	0.94	10	0.67
Italy	4	1.40	12	0.15	4	2.48	1	2.15
Malta	13	0.02	14	0.02	15	-0.06	13	-0.20
Netherlands	11	0.21	13	0.04	12	0.50	3	2.08
Portugal	6	1.12	9	0.30	7	1.84	8	0.99
Slovakia	15	-0.11	15	-0.02	14	0.05	15	-0.29
Spain	1	1.76	2	0.86	2	2.75	2	2.14
PIIGS	3	1.47	5	0.75	1	3.20	6	1.50
Panel (B): Diversified Financials								
Austria	13	0.09	11	0.09	12	0.02	13	0.08
Belgium	1	1.35	6	0.70	3	1.86	1	1.90
Cyprus	9	0.48	8	0.45	7	1.12	12	0.09
Finland	8	0.55	7	0.59	10	0.86	8	0.64
France	2	1.26	1	0.94	2	2.23	2	1.75
Germany	6	0.87	5	0.77	9	0.90	5	1.01
Greece	10	0.45	10	0.31	8	1.02	9	0.62
Ireland	11	0.15	13	0.06	11	0.17	10	0.16
Italy	4	1.16	3	0.88	4	1.75	4	1.30
Luxembourg	12	0.09	12	0.07	13	0.01	11	0.10
Netherlands	7	0.79	9	0.37	6	1.19	6	0.86
Slovenia	14	0.00	14	0.00	14	0.00	14	0.00
Spain	5	1.03	4	0.84	5	1.39	7	0.81
PIIGS	3	1.24	2	0.91	1	2.24	3	1.36

Table 4.7: Average Conditional Contribution ΔCoVaR of Member States within Each Eurozone Financial Sector (continued)

Member State	Overall Period		Pre-crisis Period		Crisis Period		Post-crisis Period	
	Rank	%	Rank	%	Rank	%	Rank	%
Panel (C): Insurance								
Austria	8	0.58	12	-0.05	7	1.18	8	1.28
Cyprus	11	0.18	10	0.12	11	0.33	12	-0.06
Finland	7	0.78	8	0.24	6	1.19	3	1.72
France	1	1.73	3	0.88	3	1.80	2	1.83
Germany	4	1.23	7	0.25	5	1.45	1	2.15
Greece	10	0.31	6	0.28	10	0.35	11	-0.02
Ireland	9	0.38	9	0.15	9	0.45	9	0.65
Italy	3	1.65	2	0.89	2	2.17	5	1.59
Netherlands	5	1.20	4	0.68	8	1.09	6	1.47
Slovenia	12	-0.03	11	-0.01	12	0.10	10	-0.02
Spain	6	0.82	5	0.29	4	1.48	7	1.40
PIIGS	2	1.67	1	1.04	1	2.36	4	1.69
Panel (D): Real-estate								
Austria	8	0.32	12	0.02	9	0.44	3	0.93
Belgium	3	0.56	3	0.19	4	0.77	4	0.89
Cyprus	10	0.18	4	0.17	10	0.36	10	0.16
Estonia	12	0.03	11	0.02	13	-0.01	11	0.02
Finland	4	0.56	2	0.33	3	0.78	5	0.80
France	2	0.61	6	0.12	5	0.71	1	0.99
Germany	5	0.44	5	0.16	6	0.69	6	0.79
Greece	11	0.15	8	0.11	2	0.82	13	-0.01
Italy	7	0.36	7	0.12	7	0.59	7	0.45
Malta	13	0.00	13	0.00	12	0.00	12	0.00
Netherlands	1	0.70	1	0.35	1	0.88	2	0.93
Spain	9	0.19	10	0.05	11	0.07	9	0.29
PIIGS	6	0.41	9	0.11	8	0.58	8	0.41

Notes: The table ranks the average time-varying contribution to systemic risk measures according to $\Delta CoVaR_q^{sys|i}$ of each member state within each Eurozone financial sector. Simple averages are computed within the four periods; overall period, pre-crisis period, crisis period and post-crisis period. Average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ is estimated using quantile regression of $q = 5\%$ level.

Table 4.8: Average Conditional Contribution ΔCoVaR of Top 30 SIFIs in the Eurozone

Rank	Panel (A): Overall Period				Panel (B): Pre-crisis Period			
	Institution	Sector	Country	ΔCoVaR	Institution	Sector	Country	ΔCoVaR
1	INGA NA Equity	Banks	Netherlands	2.17	DBK GR Equity	DFinancials	Germany	1.45
2	BNP FP Equity	Banks	France	1.93	GLE FP Equity	Banks	France	1.23
3	CS FP Equity	Insurance	France	1.90	ALB SM Equity	DFinancials	Spain	1.21
4	DBK GR Equity	DFinancials	Germany	1.90	SAN SM Equity	Banks	Spain	1.21
5	SAN SM Equity	Banks	Spain	1.85	BKT SM Equity	Banks	Spain	1.19
6	GLE FP Equity	Banks	France	1.84	BNP FP Equity	Banks	France	1.12
7	MUV2 GR Equity	Insurance	Germany	1.83	BKIR ID Equity	Banks	Ireland	1.01
8	G IM Equity	Insurance	Italy	1.76	DRN GR Equity	DFinancials	Germany	1.00
9	ALV GR Equity	Insurance	Germany	1.68	G IM Equity	Insurance	Italy	0.94
10	AGN NA Equity	Insurance	Netherlands	1.64	KN FP Equity	Banks	France	0.90
11	BBVA SM Equity	Banks	Spain	1.64	MUV2 GR Equity	Insurance	Germany	0.84
12	ACA FP Equity	Banks	France	1.45	INGA NA Equity	Banks	Netherlands	0.81
13	MB IM Equity	DFinancials	Italy	1.40	ALBK ID Equity	Banks	Ireland	0.79
14	GBLB BB Equity	DFinancials	Belgium	1.33	CS FP Equity	Insurance	France	0.79
15	BKT SM Equity	Banks	Spain	1.31	COM GR Equity	Banks	Germany	0.78
16	FFP FP Equity	DFinancials	France	1.31	FFP FP Equity	DFinancials	France	0.76
17	ALB SM Equity	DFinancials	Spain	1.30	BMPS IM Equity	Banks	Italy	0.75
18	RF FP Equity	DFinancials	France	1.28	AGN NA Equity	Insurance	Netherlands	0.74
19	UCG IM Equity	Banks	Italy	1.21	POP SM Equity	Banks	Spain	0.72
20	CE IM Equity	Banks	Italy	1.19	CNP FP Equity	Insurance	France	0.72
21	HNR1 GR Equity	Insurance	Germany	1.18	KBC BB Equity	Banks	Belgium	0.71
22	CNP FP Equity	Insurance	France	1.17	BBVA SM Equity	Banks	Spain	0.70

23	ACKB BB Equity	DFinancials	Belgium	1.17	ICP GR Equity	DFinancials	Germany	0.69
24	COM GR Equity	Banks	Germany	1.15	ALV GR Equity	Insurance	Germany	0.66
25	POP SM Equity	Banks	Spain	1.12	CBK GR Equity	Banks	Germany	0.65
26	MF FP Equity	DFinancials	France	1.07	RF FP Equity	DFinancials	France	0.64
27	SOF BB Equity	DFinancials	Belgium	1.07	BNS IM Equity	Real-estate	Italy	0.63
28	EBS AV Equity	Banks	Austria	1.03	MB IM Equity	DFinancials	Italy	0.61
29	UBI IM Equity	Banks	Italy	1.03	KA NA Equity	DFinancials	Netherlands	0.60
30	BNS IM Equity	Real-estate	Italy	1.02	NR IM Equity	Real-estate	Italy	0.59

Rank	Panel (C): Crisis Period				Panel (D): Post-crisis Period			
	Institution	Sector	Country	ΔCoVaR	Institution	Sector	Country	ΔCoVaR
1	INGA NA Equity	Banks	Netherlands	3.54	ALV GR Equity	Insurance	Germany	2.56
2	BNP FP Equity	Banks	France	2.77	GBLB BB Equity	DFinancials	Belgium	2.41
3	BBVA SM Equity	Banks	Spain	2.70	CS FP Equity	Insurance	France	2.34
4	G IM Equity	Insurance	Italy	2.68	INGA NA Equity	Banks	Netherlands	2.24
5	SAN SM Equity	Banks	Spain	2.58	BBVA SM Equity	Banks	Spain	2.23
6	UBI IM Equity	Banks	Italy	2.58	ISP IM Equity	Banks	Italy	2.19
7	ACA FP Equity	Banks	France	2.50	SAN SM Equity	Banks	Spain	2.13
8	ISP IM Equity	Banks	Italy	2.44	BNP FP Equity	Banks	France	2.11
9	SAB SM Equity	Banks	Spain	2.43	SAMAS FH Equity	Insurance	Finland	2.10
10	PMI IM Equity	Banks	Italy	2.41	G IM Equity	Insurance	Italy	2.09
11	BKT SM Equity	Banks	Spain	2.16	RF FP Equity	DFinancials	France	2.06
12	CS FP Equity	Insurance	France	2.14	GLE FP Equity	Banks	France	2.05
13	ARL GR Equity	Banks	Germany	2.11	MUV2 GR Equity	Insurance	Germany	2.04
14	GLE FP Equity	Banks	France	2.08	MF FP Equity	DFinancials	France	2.02

15	MB IM Equity	DFinancials	Italy	2.06	AGN NA Equity	Insurance	Netherlands	1.99
16	MAP SM Equity	Insurance	Spain	2.04	DBK GR Equity	DFinancials	Germany	1.98
17	DBK GR Equity	DFinancials	Germany	2.03	SOF BB Equity	DFinancials	Belgium	1.90
18	BPE IM Equity	Banks	Italy	1.97	KN FP Equity	Banks	France	1.87
19	ALB SM Equity	DFinancials	Spain	1.97	UCG IM Equity	Banks	Italy	1.87
20	MF FP Equity	DFinancials	France	1.95	GFC FP Equity	Real-estate	France	1.86
21	FFP FP Equity	DFinancials	France	1.91	ACKB BB Equity	DFinancials	Belgium	1.83
22	RF FP Equity	DFinancials	France	1.90	ACA FP Equity	Banks	France	1.82
23	UCG IM Equity	Banks	Italy	1.90	CORA NA Equity	Real-estate	Netherlands	1.80
24	AGN NA Equity	Insurance	Netherlands	1.87	SDA1V FH Equity	Real-estate	Finland	1.79
25	BPI PL Equity	Banks	Portugal	1.85	CNP FP Equity	Insurance	France	1.78
26	BCP PL Equity	Banks	Portugal	1.85	HNR1 GR Equity	Insurance	Germany	1.77
27	GBLB BB Equity	DFinancials	Belgium	1.83	MAP SM Equity	Insurance	Spain	1.74
28	POP SM Equity	Banks	Spain	1.82	SCR FP Equity	Insurance	France	1.70
29	CNP FP Equity	Insurance	France	1.79	EBS AV Equity	Banks	Austria	1.70
30	EBS AV Equity	Banks	Austria	1.75	UBI IM Equity	Banks	Italy	1.68

Notes: The table ranks the average time-varying contribution to systemic risk measure according to $\Delta CoVaR_q^{sys|i}$ of Top 30 systemically important financial institution ($SIFIs$) in the Eurozone which represents around 10% of total number of financial institutions. We rank the 315 institutions based on their systemic risk contribution from the highest to the lowest within the four periods; overall period, pre-crisis period, crisis period and post-crisis period. Average $\Delta CoVaR$ figures are expressed as a percentage. $\Delta CoVaR$ is estimated using quantile regression of $q = 5\%$ level. See Appendix (J), (K), (L), and (M) for the full list of financial institutions within each member state during overall period, pre-crisis period, crisis period and post-crisis period respectively.

Table 4.7 shows average conditional contribution $\Delta CoVaR$ of each member state within each Eurozone financial sector during the overall, pre-crisis, crisis and post-crisis periods. It is obvious that systemic risk ranking within each financial sector differs from one period to another as well as the member state that contributes the most to systemic risk in one sector could have the lowest systemic risk contribution in another financial sector. For example, during the overall period, Spain, Belgium, France and the Netherlands have the highest contribution $\Delta CoVaR$ for banking, diversified financial, insurance and real-estate sectors respectively while during the pre-crisis period, Ireland, France $PIIGS$, and the Netherlands have the most contribution to systemic risk for the respective sectors. During the crisis period, $PIIGS$ has the extreme systemic risk contribution in the banking, diversified financial and insurance sectors and the Netherlands has the highest risk contribution in the real-estate sector while during the post-crisis period, Italy, Belgium, Germany and France have the highest risk contribution for banking, diversified financial, insurance and real-estate sectors respectively. It is obvious that the majority of member states that contributes to systemic risk are the biggest economies with large market capitalisation which is consistent with the too-big-to-fail paradigm.

Table 4.8 displays contribution $\Delta CoVaR$ of financial institutions within each member state. We can conclude that banks in the Netherlands are the most systemic institutions during the overall period, followed by French banks, French insurance firms, German diversified financial institution and Spanish banks respectively. It is noted that too-big-to-fail paradigm prevails as large member states (France, Germany, Spain and Italy) contributes the most to systemic risk compared to small member states (Austria, Belgium, Cyprus and Malta).

4.6 Robustness Check

In the previous section, we applied quantile regression approach to characterize and estimate the dynamics of $\Delta CoVaR$ of Eurozone financial sectors, member states and financial institutions. In order to check the robustness of our analysis, we consider alternative estimation procedures to estimate contribution $\Delta CoVaR$ using Generalised Autoregressive Conditional Heteroscedasticity, Dynamic Conditional Correlation, $GARCH$ (1,1)-DCC, (Engle 2002, 2009; Girardi and Ergün, 2013), Ordinary Least Square, OLS, and different copula models including Gaussian, Student-t, Gumbel (1960), Rotated Gumbel, Clayton (1978), Rotated Clayton, Symmetrized Joe-Clayton (SJC), Plackett and Frank (1979) copulas (Patton 2012a and b).

Quantile repression is more appealing than OLS because standard OLS regression estimates the mean of the distribution of the dependent variable X^j, given the explanatory variables X^i while quantile regression estimates the q^{th} percentile of the distribution of X^j, given X^i.

Time-varying $CoVaR$ estimates could be attained from the implementation of a three-step procedure derived from a bivariate $GARCH\text{-}DCC$ model (Girardi and Ergün, 2013) and a conditional quantile solved by a numerical procedure. Contributions of systemic risk are characterised by Hautsch, *et al.* (2011) as a financial institution's VaR having a time-varying marginal effect on the whole financial system's VaR, thus enabling the supposed systemic risk beta coefficient to become time-varying.

Copulas rationally explain the dependence structure across random variables across a range of variation, such as dependence being categorised as extreme or tail, linear or non-linear and symmetric and asymmetric. Furthermore, copula functions are constant to non-linear ever-growing data transformations and differ to traditional dependence methods like linear correlation (Embrechts et al. 2002). Table 4.9 display the copula specifications to determine various patterns of tail dependence.

Table 4.10 shows $\Delta CoVaR$ systemic risk contribution values and ranks using quantile regression, $GARCH\text{-}DCC$, OLS and nine copula models for each Eurozone financial sector and member state. Quantile regression, $GARCH\text{-}DCC$ and OLS $\Delta CoVaR$ provide similar rankings for Eurozone financial sectors where insurance sector has the highest systemic risk contribution followed by diversified financials, real-estate and banking sectors respectively. While copula-based $\Delta CoVaR$ give different rankings compare to QR, $GARCH\text{-}DCC$ and OLS $\Delta CoVaR$ but the nine copula-based $\Delta CoVaR$ have consistent rankings where banking sector contributes the most to systemic risk followed by diversified financials, insurance and real-estate sectors respectively. Surprisingly, the results based on these models are remarkably different to those obtained under the quantile regression approach for each member state[33].

[33] In order to save space, these copula results are briefly discussed, but a complete analysis of marginal models and copula estimates are available from the authors upon request.

Table 4.9: Copula Model Characteristics

Copula	Distribution	Parameter(s)	Parameter Space	Independence	Lower tail dependence	Upper tail dependence
Gaussian	$C_N(u,v;\rho)=\Phi_\rho\left(\Phi^{-1}(u),\Phi^{-1}(v)\right)$	ρ	$(-1,1)$	0	0	0
Student-t	$C_T(u,v;\rho,d)=T_{d,\rho}\left(t_d^{-1}(u),t_d^{-1}(v)\right)$	ρ,d	$(-1,1)x(2,\infty)$	$(0,\infty)$	$g_T(\rho,d)$	$g_T(\rho,d)$
Gumbel	$C_G(u,v;k)=exp\left\{-\left[\left(-ln(u)\right)^k+\left(-ln(v)\right)^k\right]^{1/k}\right\}$	k	$(1,\infty)$	1	0	$2-2^{1/k}$
Rotated Gumbel	$C_{RG}(u,v;k)=u+v-1+C_G(1-u,1-v,k)$	k	$(1,\infty)$	1	$2-2^{1/k}$	0
Clayton	$C_C(u,v;\theta)=\left(u^{-\theta}+v^{-\theta}-1\right)^{-1/\theta}$	θ	$(0,\infty)$	0	$2^{-1/\theta}$	0
Rotated Clayton	$C_{RC}(u,v;\theta)=u+v-1+\left[(1-u)^{-\theta}+(1-v)^{-\theta}-1\right]^{-1/\theta}$	θ	$(0,\infty)$	0	0	$2^{-1/\theta}$
SJC	$C_{SJC}(u,v;\lambda_U,\lambda_L)=$ $0.5\left(C_{JC}(u,v;\lambda_U,\lambda_L)+C_{JC}(1-u,1-v;\lambda_U,\lambda_L)+u+v-1\right)$	λ_L,λ_U	$(0,1)x(0,1)$	$(0,0)$	λ_L	λ_U
Plackett	$C_P(u,v;\theta)=\frac{1}{2(\theta-1)}\left(1+(\theta-1)(u+v)\right) - \sqrt{\left(1+(\theta-1)(u+v)\right)^2-4\theta(\theta-1)uv}$	θ	$(0,\infty)$	1	0	0
Frank	$C_F(u,v;\theta)=-\frac{1}{\theta}log\left(1+\left[\left(e^{-\theta u}-1\right)\left(e^{-\theta v}-1\right)/\left(e^{-\theta}-1\right)\right]\right)$	θ	$(-\infty,\infty)$	0	0	0

Notes: the most common copula models are presented in this table. Parameter spaces and analytical forms of dependence measures is presented for each copula. The column titled "Independence" shows the parameter values that lead to independence copula. u and v denotes the cumulative density functions of the standardized residuals from the marginal models and $0 \leq u,v \leq 1$. Φ_ρ is the bivariate cumulative distribution of the standard normal with correlation coefficient ρ, and Φ^{-1} is the inverse function of the univariate normal distribution. $T_{d,\rho}$, is the bivariate student's t distribution with correlation coefficient ρ and degree of d, which captures the extent of symmetric extreme dependence; t^{-1} is the inverse function of the univariate Student's t distribution. k denotes the parameters for the Gumbel and rotated Gumbel copulas. SJC copula is based on Joe Clayton (JC) copula where $k={}^{1}/_{log_2}(2-\lambda_U), \gamma={}^{-1}/_{log_2}(\lambda_L)$. Both Clayton and rotated Clayton copulas tolerate for negative dependence for $\theta\epsilon(-1,0)$, though this method of dependence is unlike positive dependence situation ($\theta>0$) and is not commonly applied in empirical work.

Table 4.10: ΔCoVaR Systemic Risk Contribution Using Various Models

Sector/ State	QR	GARHC-DCC	OLS	Copula								
				Gaussian	**Student-*t***	**Gumbel**	**RGumbel**	**Clayton**	**RClayton**	**SJC**	**Plackett**	**Frank**
Panel (A): Eurozone Financial Sectors 5%-$\Delta CoVaR$ Rank												
Banks	4	4	4	1	1	1	1	1	1	1	1	1
DFinancial	2	2	2	2	2	2	2	2	2	2	2	2
Insurance	1	1	1	3	3	3	3	3	3	3	3	3
Real-estate	3	3	3	4	4	4	4	4	4	4	4	4
Panel (B): Eurozone Financial Sectors 5%-$\Delta CoVaR$ Value												
Banks	2.37	2.33	1.51	6.89	6.91	6.61	6.93	6.98	5.10	2.61	6.40	5.81
	2.23	1.13	1.42	6.08	6.10	5.83	6.11	6.16	4.49	2.30	5.65	5.12
DFinancial	2.78	2.70	2.66	5.44	5.48	5.16	5.51	5.56	3.99	2.04	4.97	4.51
	1.22	2.29	1.17	2.85	2.87	2.70	2.88	2.91	2.09	1.07	2.60	2.36
Insurance	3.39	3.43	3.29	4.23	4.24	4.07	4.24	4.26	3.14	1.61	3.95	3.58
	1.73	2.42	1.68	2.21	2.22	2.13	2.22	2.23	1.64	0.84	2.07	1.87
Real-estate	2.54	2.47	2.63	2.59	2.67	2.38	2.74	2.80	1.91	0.94	2.28	2.10
	0.99	1.72	1.02	0.98	1.01	0.90	1.04	1.06	0.72	0.36	0.86	0.79
Panel (C): Eurozone Member States 5%-$\Delta CoVaR$ Rank												
Austria	6	7	7	7	8	8	7	6	9	8	8	9
Belgium	5	5	4	6	6	7	8	7	8	7	7	7
Cyprus	10	12	11	4	4	5	4	4	4	5	5	4
Estonia	17	15	16	16	18	18	18	18	18	18	18	18
Finland	8	8	8	11	14	14	15	12	15	14	14	14
France	3	4	5	5	5	4	6	5	6	4	4	5
Germany	7	6	6	10	13	12	14	13	14	11	12	12
Greece	11	10	10	3	3	3	3	3	3	3	3	3
Ireland	12	11	12	1	1	1	1	1	1	1	1	1
Italy	2	3	2	8	11	10	12	11	11	10	10	11
Luxembourg	16	16	15	15	17	17	17	17	17	17	17	17
Malta	18	18	18	14	16	16	16	16	16	16	16	16
Netherlands	13	13	13	2	2	2	2	2	2	2	2	2
Portugal	9	9	9	9	10	13	10	9	12	12	13	13
Slovakia	15	17	17	12	12	11	5	14	5	13	11	8
Slovenia	14	14	14	13	15	15	13	15	13	15	15	15
Spain	4	2	3	17	7	6	9	8	7	6	6	6
PIIGS	1	1	1	18	9	9	11	10	10	9	9	10

Panel (D): Eurozone Member States 5%-$\Delta CoVaR$ Value													
Austria	Mean	2.70	2.74	2.87	4.97	5.03	4.65	5.09	5.17	3.63	1.83	4.46	4.07
	STD	1.30	2.08	1.38	2.29	2.31	2.14	2.34	2.38	1.67	0.84	2.05	1.87
Belgium	Mean	2.86	3.09	3.03	5.05	5.08	4.83	5.08	5.12	3.72	1.91	4.67	4.24
	STD	1.52	2.34	1.61	2.76	2.77	2.64	2.78	2.80	2.03	1.04	2.56	2.32
Cyprus	Mean	2.30	1.79	2.07	5.78	6.18	5.23	6.44	6.61	4.36	2.07	5.01	4.72
	STD	0.48	1.50	0.43	1.18	1.26	1.07	1.31	1.35	0.89	0.42	1.02	0.96
Estonia	Mean	0.26	0.10	0.07	0.08	0.08	0.08	0.11	0.08	0.08	0.03	0.08	0.08
	STD	0.42	0.22	0.11	0.04	0.04	0.04	0.05	0.04	0.04	0.02	0.04	0.04
Finland	Mean	2.43	2.60	2.58	4.15	4.24	3.85	4.31	4.39	3.04	1.52	3.67	3.36
	STD	1.11	1.99	1.18	1.80	1.84	1.67	1.87	1.90	1.32	0.66	1.59	1.46
France	Mean	2.97	3.12	3.00	5.35	5.36	5.24	5.35	5.38	4.07	2.07	5.11	4.69
	STD	1.35	2.43	1.36	2.50	2.50	2.45	2.50	2.51	1.90	0.97	2.38	2.19
Germany	Mean	2.68	2.97	2.89	4.31	4.33	4.12	4.34	4.38	3.18	1.63	3.97	3.61
	STD	1.42	2.31	1.52	2.33	2.34	2.22	2.35	2.37	1.72	0.88	2.14	1.95
Greece	Mean	1.93	2.06	2.11	6.78	7.07	6.16	7.34	7.53	5.02	2.44	5.88	5.48
	STD	0.63	1.64	0.69	2.20	2.29	2.00	2.38	2.44	1.63	0.79	1.91	1.78
Ireland	Mean	1.61	1.94	1.67	11.39	12.00	10.36	12.43	12.75	8.49	4.09	9.94	9.24
	STD	0.95	1.53	0.99	6.61	6.96	6.01	7.20	7.39	4.92	2.37	5.76	5.36
Italy	Mean	3.20	3.19	3.25	4.53	4.54	4.39	4.54	4.56	3.39	1.74	4.26	3.89
	STD	1.24	2.30	1.26	1.72	1.72	1.67	1.72	1.73	1.29	0.66	1.62	1.47
Luxembourg	Mean	0.48	0.10	0.18	1.93	2.08	1.88	2.54	2.03	1.85	0.71	1.88	1.88
	STD	0.14	0.10	0.05	0.66	0.72	0.65	0.88	0.70	0.64	0.25	0.65	0.65
Malta	Mean	-0.31	-0.06	-0.01	2.29	2.41	2.31	3.16	2.31	2.31	0.88	2.31	2.31
	STD	0.09	0.05	0.00	0.86	0.91	0.87	1.19	0.87	0.87	0.33	0.87	0.87
Netherlands	Mean	1.53	1.46	0.98	9.07	9.11	8.72	9.13	9.20	6.72	3.44	8.44	7.67
	STD	1.42	0.84	0.91	8.15	8.18	7.84	8.20	8.27	6.04	3.09	7.58	6.89
Portugal	Mean	2.42	2.16	2.47	4.44	4.58	4.06	4.72	4.83	3.26	1.61	3.86	3.58
	STD	0.73	1.49	0.75	1.48	1.52	1.35	1.57	1.61	1.09	0.53	1.29	1.19
Slovakia	Mean	0.52	0.00	0.03	4.14	4.34	4.19	5.74	4.29	4.19	1.59	4.15	4.15
	STD	0.12	0.00	0.01	0.92	0.96	0.93	1.28	0.95	0.93	0.35	0.92	0.92
Slovenia	Mean	1.03	0.25	0.61	3.12	3.61	3.29	4.44	3.62	3.23	1.25	3.27	3.21
	STD	0.45	0.37	0.27	1.44	1.67	1.52	2.05	1.67	1.49	0.57	1.51	1.48
Spain	Mean	2.87	3.25	3.12	-0.26	5.05	4.84	5.05	5.08	3.74	1.92	4.68	4.25
	STD	1.36	2.47	1.48	0.13	2.51	2.41	2.51	2.53	1.86	0.95	2.33	2.11
PIIGS	Mean	3.44	3.45	3.43	-0.57	4.65	4.54	4.64	4.67	3.51	1.79	4.41	4.04
	STD	1.43	2.79	1.42	0.25	2.02	1.97	2.02	2.03	1.53	0.78	1.92	1.76

Notes: Simple averages and standard deviations of $\Delta CoVaR$ figures are expressed as a percentage and estimated within the crisis period.

4.7 Conclusion and Regulatory Policy Implications

In this chapter, we examine systemic risk in a European Framework. We focus on systemic risk contribution, exposure and network $\Delta CoVaR$ on three levels; union, sector and country, by estimating which financial sector, member state and institution has the highest contribution or exposure to systemic events. By applying $\Delta CoVaR$ methodology, we conclude interesting results for financial regulators, policy makers, portfolio and risk managers. Firstly, there is a loose relationship between sector's (countries or institutions) VaR and its $\Delta CoVaR$, this is proved by empirical analysis. Sector (country or institution) with the highest VaR, is not necessarily the one with the highest systemic risk spillover, consequently there is a need for macro-prudential measures ($\Delta CoVaR$) in addition to micro-prudential measures (VaR).

Secondly, it is important to estimate contribution and exposure $\Delta CoVaR$, the analysis results in sectors (countries or institutions) with the highest contribution to systemic risk have low exposure to systemic risk when the financial sector collapses which emphasizes the need for stress tests and macro-prudential regulations. It is also noted that sectors (countries or institutions) have different risk spillover among themselves by estimating network $\Delta CoVaR$.

Thirdly, systemic risk ranking differs between unconditional and conditional $\Delta CoVaR$. Time-invariant $\Delta CoVaR$ (unconditional $\Delta CoVaR$) is static in nature which gives a constant value over time, therefore, there is a need to estimate time-variant $\Delta CoVaR$ (conditional $\Delta CoVaR$)that is dynamic in nature, by incorporating lagged systematic state variables that capture the evolution of tail risk dependence over-time.

Fourthly, conditional $\Delta CoVaR$ is a high-frequency measure of tail risk, therefore, the same sector (country or institution) has different systemic rankings based on the frequency (i.e. daily, weekly, … etc.). In addition, $\Delta CoVaR$ can be estimated at various quantiles (1% or 5%) which results in different systemic risk rankings for contribution, exposure and network $\Delta CoVaR$, that's due to the use of VaR that ignores extreme loss above VaR levels and disregards the risk of fat-tails. During the crisis period, diversified financials and insurance sectors has the highest systemic risk contribution to the union level while Italy, France and Spain are the member states with the highest contribution to systemic risk which is aligned to the too-big-to fail paradigm. Spain, France, Italy and Netherlands contribute the most to systemic risk in banking, diversified financials, insurances and real-estate sectors respectively.

Fifthly, the results reported in this chapter need to be treated with caution as using the average of systemic risk measure ($\Delta CoVaR$) figures do not allow the conclusion that a certain sector (country or institution) is always systemically riskier than another. By changing the sample period, ranking change consequently, this proved by our empirical analysis as each sector (country or institution) ranking differ during overall, pre-crisis, crisis and post-crisis periods.

Lastly, the main objective of any systemic risk analysis is to rank financial institutions (sectors or countries) according to their systemic risk contribution (exposure) and, in turn, identify the $SIFIs$. By applying different econometric techniques (quantile, $GARCH\text{-}DCC$, OLS and nine copulas) to estimate $\Delta CoVaR$, they resulted in different systemic risk ranking for the same country. Therefore, a direct comparison is not straightforward as few empirical differences could potentially be caused by the estimation strategies.

5

Chapter 5
Conclusion

According to Banulescu and Dumitrescu (2014), Systemically Important Financial Institutions ($SIFIs$) can be identified as institutions whose chaotic failure caused by their complexity, interconnectivity and size would extravagantly disturb the financial system and damage economic activities. Regardless of increased concern for systemic risk, a succinct definition is still ambiguous (Billio, *et al.*, 2012; Bisias, *et al.*, 2012). The idea of systemic risk is typically tied with the effect of financial distress of an asset or a financial institution on other assets or on the entire financial system since it is firmly connected to failures generated from a single asset or institution to another or to the entire system.

Systemic risk is a phenomenon which is intricate and displays several different characteristics and has an impact on the financial system as a whole which produces adverse results for the financial system and the real economy through spillover effects. The complexity of phenomenon is shown through the numerous systemic risk definitions and a single definition of systemic risk may never be agreed upon. Given that there are numerous but incomplete possible mechanisms affecting systemic risk, it appears safe to postulate that a greater number than just one risk measure is required to encompass its complex nature. Particularly, policymakers, who are responsible for confirming financial stability, should depend on systemic risk measures from a broad range

In relation to the Eurozone financial crisis, the EU is at a critical crossroad. A decision needs to be made if the path to recovery is going to be achieved through a closer integration of financial policies and of financial sector supervision and resolution, or by fragment with a steady return to controlled protectionism in the course of narrow national interest. However, the latter option brings about danger for the single market. Ultimately, the policy concerns confronting the EU and contemporary institution building within the Eurozone show a significant glimpse in the future of financial integration at a global and regional level.

The second chapter explores the dependence structure of four Eurozone financial sectors, namely banking, financial services, insurance and real-estate, with EU index from the use of six copulas (Gaussian, Gumbel, Rotated Gumbel, Clayton, Symmetrized Joe-Clayton and Student-t) and daily index prices from January 2001 to December 2016. Results reveal that all financial sectors possess strong to moderate dependence of a time-varying nature. Time-varying Student-t copula is the best fit for all EU-Sector pairs based on AIC criteria. Additionally, proof was discovered for asymmetric dependence, which indicates that index return comovement is different in bearish and bullish markets. In comparison to other financial sectors indices, the results suggest a generally strong downside dependence compared to upside dependence. Furthermore, there is significant spillover effects on the EU index from the extreme downward movements in each financial sector.

We determine the risk spillover by calculating the downside and upside $VaRs$, $CoVaRs$ and $\Delta CoVaRs$ risk measures. In the pre-crisis period, there is an average dependence between EU-sector pairs. However, the crisis and post-crisis periods show a tail dependence for all EU-sector pairs. The VaR of EU index is less risky than the $VaRs$ of financial sectors indices. Comparison of systemic risk measures of the upside and downside $VaRs$ and $\Delta CoVaRs$ for EU and financial sectors return series, shows that a similar pattern of both systemic risks for all sectors is present, with significant differences in magnitude across all sectors. Although, the influence on the $VaRs$ and $CoVaRs$ risk measures by the GFC and Euro crisis for the EU-sector pairs, is apparent as we find significant abrupt variations during the crisis period in 2007-2010. The GFC and Euro Crisis have increased significantly the VaR and $\Delta CoVaR$ for the EU index as well as for the financial sectors indices, particularly for the banking sector. Furthermore, in all cases there is significant bidirectional risk spillover shown by the EU and financial sectors, specifically during the outbreak of the 2007 GFC and 2009 European sovereign debt crisis. More interestingly, there is greater importance in the crisis period than post-crisis and pre-crisis periods for both risk spillover to the EU and financial sectors. Results for the upside risk spillover are also similar. Through the use of $\Delta CoVaR$ risk measure, observations can be made that the downside $\Delta CoVaR$ is greater than the upside $\Delta CoVaR$ for all financial sectors. Taking into consideration different time horizons, it is shown that the pre-crisis period down-side

$\Delta CoVaR$ is lower than the post-crisis and crisis down-side $\Delta CoVaR$ respectively. Furthermore, at all subperiods, asymmetric downside and upside $\Delta CoVaR$ can be found.

In addition, we develop a volatility linkages model between Eurozone financial sectors by assuming that log volatility follows an $AR(1)$ process (Kodres and Pritsker (2002); Fleming *et al.*, 1998; Andersen, 1996). We use Hansen's (1982) and Hansen *et al.* (1996) generalized method of moments approach (GMM) approach to impose restrictions on the unconditional moments of daily returns, in which we remove both return and volatility seasonal patterns. Consequently, we extract the concurrent correlation between the log information flows in these sectors which is the estimate of the strength of volatility linkages among sectors. The empirical results indicate that the model fits the data reasonably well for all six pairs and bivariate tests reveal little evidence of misspecification with the exception of banking/ real-estate sector pair and financial/ insurance pair. The empirical analysis indicates strong volatility linkages among banking, financial service, insurance and real-estate sectors. Since all the associated standard errors are small (less than 0.03), the estimated correlations are relatively precise and consequently, the volatility linkages among the four financial sectors are strong.

Finally, we have estimated a dominance test and significance test for the empirical results by utilizing Abadie's proposed bootstrap Kolmogorov-Smirnov test (2002). The copula $\Delta CoVaRs$, shown in the significance test, are significantly different from zero, meaning each financial sector is systemically risky and have significant systemic risk contribution (exposure) to the Eurozone financial system. Dominance test proves that banking sector is systemically riskier than insurance sectors which is riskier than financial services sector that is riskier than real-estate sector. Through use of the KS test, it is shown that there are significant differences between the downside and upside $VaRs$ and $CoVaRs$ during different time horizons which emphasizes the need of systemic risk measures in addition to idiosyncratic risk measures. Furthermore, there is evidence that the behaviour of the upside and downside risk spillover to the EU and financial sectors to be asymmetric. Finally, results confirm that copula $\Delta CoVaR$ systemic risk measure delivers a consistent ranking for a given sector through time, by applying Kendall rank-order correlation coefficient for each copula $\Delta CoVaRs$ at time t and t-1. This is an essential property for regulators as a systemic risk measure regularly classifies a certain sector as $SIFI$.

Typically, the evidence reported has significant impacts on market participants and policymakers in a variety of matters. Firstly, the existence of strong/ moderate dependence across the financial sectors and EU index leads to the possibility of potential risk spillover and the inclination to boom or crash together that enhances systemic risk. Furthermore, the results may be significant for regulators, particularly for ECB, that are aiming to develop macro-prudential regulation to assess systemic risk contribution to maintain financial stability and designing and implementing the correct intervention policies. In conclusion, volatility linkages as well as systemic risk measures should also be considered in setting regulatory policy, given their influence on investment and risk management decisions.

The third chapter assesses interconnectedness and systemic risk exposure in the Eurozone financial sector by applying four prominent systemic risk measures of Ganger-causality Network (GCN) by Billio, *et al.*, (2010), $GARCH\text{-}DCC$ Delta $CoVaR$ ($\Delta CoVaR$) of Adrian and Brunnermeier (2011) and Girardi and Ergun (2013), Marginal Expected Shortfall (MES) of Acharya, *et al.* (2017) and Systemic Risk Index ($SRISK$) of Acharya, Engle and Richardson (2012) and Brownlees and Engle (2012). We measure systemic risk exposure on the union level and the financial sector level by identifying which (i) financial sector and member states are exposed the most to Eurozone systemic events, and (ii) which member state has higher exposure to Eurozone financial crisis within each sector. The sample period ranges from 2000 to 2015 and is divided into three sub-periods (pre-crisis, crisis, post-crisis). Since various systemic risk measures are developed under different frameworks so in order to have a meaningful comparison, there was a need to unify the theoretical framework of $\Delta CoVaR$, MES and $SRISK$.

There are several interesting findings from our empirical analysis: firstly, by calculating Granger causality network connections for each financial institution within each financial sector in the Eurozone, we discover that the Eurozone financial sectors have become more interrelated in the last sixteen years, that is suggestive of the Eurozone possibly susceptible to systemic risk. During the crisis period, banking sector has the highest number of significant connections followed by financial services, real-estate and insurance sectors respectively. The number of significant Granger causal relations of each financial sector differ in the three subperiods.

Secondly, $\Delta CoVaR$, MES and $SRISK$ measures give different ranking of each $SIFI$ (member state or financial sector) exposure to systemic risk which indicates that a single systemic risk measure is incapable of capturing the numerous dimensions of systemic risk. Thus, the divergence of the systemic risk rankings is not due to the instability of a particular measure but instead to their fundamental differences. Therefore, we cannot generalize the outcome of a single systemic risk measure but rather there is a need to integrate several systemic risk measures in a bigger framework to capture the multiple facets of systemic risk.

Thirdly, $\Delta CoVaR$ and MES have a tendency to be typically allured by 'number of institutions' which is aligned to too-many-to-fail paradigm and 'interconnected institutions' via beta (for MES) and VaR (for $\Delta CoVaR$) which is aligned to too-interconnected-to-fail paradigm, these results are aligned with Markose, *et al.* (2010). $SRISK$ can be regarded as a compromise between the too-big-to-fail paradigm (via liabilities and market capitalisation) and the too-interconnected-to-fail paradigm (via Granger-causality connections) which indicates that large institutions and highly interconnected institutions raise systemic risk scores.

Fourthly, $SIFIs$ rankings of macro-prudential measures ($\Delta CoVaR$, MES and $SRISK$) reflect similar rankings of some micro-prudential measures (ES and VaR) and market risk measures (beta, liability and market capitalisation). Consequently, the majority of systemic risk estimates' variability could be partially explained by a one-factor linear model, which shows that systemic risk measures fall short in determining the systemic risk's multiple facets.

Fifthly, in the time-series dimension, there is a strong relationship between MES with VaR and ES. Time-varying beta tend to increase during economic downturns, which makes MES procyclical. The empirical $\Delta CoVaR$ of a member state (sector) is strongly correlated with its VaR and conditional volatility. Consequently, if a certain member state (sector) wants to minimise its systemic risk score, given the fact that the key driver of the country's MES or $\Delta CoVaR$ is the ES or VaR of its index return, the state has to make its index return distribution less leptokurtic and/or skewed. $SRISK$ is highly related to leverage especially during relatively distress period and negatively related to market capitalisation. The spikes in ES and $LRMES$ are consistent with the spikes in $SRISK$.

Sixthly, in the cross-sectional domain, a strong positive relationship exists between MES and member state's beta. This signifies that member states' systemic risk rankings based on MES mirror rankings gathered by assigning member state on betas. A comparable result for $SRISK$ with liabilities and market capitalisation was discovered as well. The same goes for $\Delta CoVaR$ and conditional correlation.

Finally, the bootstrap KS stochastic dominance test provides evidence that the ranking of systemic risk exposure is significant, confirming that a certain sector (country) has a higher systemic risk exposure compared to another sector (country). The results are consistent for the three systemic risk measures ($\Delta CoVaR$, MES and $SRISK$) on the union and sector levels for all sub-periods (overall, pre-crisis, crisis and post-crisis).

The fourth chapter applies quantile $\Delta CoVaR$ methodology to estimate systemic risk contribution, exposure and network $\Delta CoVaR$ on three levels; union, sector and member state, by estimating which financial sector, member state and institution has the highest contribution or exposure to systemic events. Unlike the previous two chapters that uses copula $\Delta CoVaR$ and $GARCH\text{-}DCC$ $\Delta CoVaR$ (and other measures), this chapter uses quantile $\Delta CoVaR$, quantile regression is appealing for their simplicity and efficient use of data. This approach makes it possible to model the loss distribution of the dependent variable on a set of conditioning variables at different quantiles. The approach is more robust as strong distributional assumptions are not required. Since we want to capture all forms of risk, including not only the risk of adverse asset price movements, but also funding liquidity risk, our estimates of $\Delta CoVaR$ are based on daily changes in market value of assets (MVA) of all publicly traded financial institutions in the Eurozone.

By applying quantile $\Delta CoVaR$ methodology, we conclude interesting results for financial regulators, policy makers, portfolio and risk managers. Firstly, it is important to estimate contribution and exposure $\Delta CoVaR$, the analysis results in sectors (countries or institutions) with the highest contribution to systemic risk could have low exposure to systemic risk when the financial sector collapses which emphasizes the need for stress tests and macro-prudential regulations. It is also noted that sectors (countries or institutions) have different risk spillover among themselves, therefore we need to estimate network $\Delta CoVaR$.

Secondly, systemic risk rankings differ between unconditional and conditional $\Delta CoVaR$. Time-invariant $\Delta CoVaR$ is static in nature and gives a constant value over time, consequently, there is a need to estimate time-variant $\Delta CoVaR$ that is dynamic in nature, by incorporating lagged systematic state variables that capture the evolution of tail risk dependence over-time.

Thirdly, conditional $\Delta CoVaR$ is a high-frequency measure of tail risk, therefore, the same sector (country or institution) has different systemic rankings based on the frequency (daily, weekly, … etc.). In addition, $\Delta CoVaR$ can be estimated at various quantiles (1% or 5%) which results in different systemic risk rankings for both contribution and exposure $\Delta CoVaR$, that's due to the use of VaR that ignores extreme loss above VaR levels and disregards the risk of fat-tails.

Fourthly, there is a loose relationship between sector's (country or institution) VaR and its $\Delta CoVaR$, this is proved by empirical analysis. Sector (country or institution) with the highest VaR, is not necessarily the one with the highest systemic risk, consequently there is a need for macro-prudential measures ($\Delta CoVaR$) in addition to micro-prudential measures (VaR).

Fifthly, the results reported in this chapter need to be treated with caution as using the average of systemic risk measure ($\Delta CoVaR$) figures do not allow the conclusion that a certain sector (country or institution) is always systemically riskier than another. By changing the sample period, rankings change consequently, each sector (country or institution) ranking differ during full, pre-crisis, crisis and post-crisis periods.

Finally, systemic risk measurement has multi facets due to interconnectedness, spillover, complexity, size, leverage, liquidity and substitutability. Therefore, there is a need to incorporate various measures of systemic risk contribution/ exposure to reflect the different facets of financial fragility. Risk managers, regulators and policy makers should not rely on a single measure for their decision but rather a set of tools to monitor, measure and manage the dynamic evolving nature of systemic risk spillover.

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Appendix A:

Financial Institutions within Each Financial Sector in Eurozone Members

Country	Code	Banks	DFinancials	Insurance	Real-estate	Total
Austria	AT	5	2	2	7	**16**
Belgium	BE	2	11	0	15	**28**
Cyprus	CY	3	6	3	4	**16**
Estonia	EE	0	0	0	2	**2**
Finland	FI	1	4	1	4	**10**
France	FR	20	19	5	24	**68**
Germany	DE	9	40	6	24	**79**
Greece	EL	5	2	1	4	**12**
Ireland	IE	2	1	1	0	**4**
Italy	IT	13	6	4	6	**29**
Luxembourg	LU	0	4	0	0	**4**
Malta	MT	4	0	0	1	**5**
Netherlands	NL	2	5	1	7	**15**
Portugal	PT	3	0	0	0	**3**
Slovakia	SK	1	0	0	0	**1**
Slovenia	SI	0	1	1	0	**2**
Spain	ES	5	4	2	10	**21**
Total		**75**	**105**	**27**	**108**	**315**

Notes: Data is extracted from Bloomberg. This broad classification by sector is categorised according to Bloomberg GICS Industry Group Name.

Appendix B:

Dataset Tickers and Company Names of Eurozone Member States

#	Country	Ticker	Short Name	GICS SubInd Name	GICS Ind Grp Name
1	Austria	ATRS AV Equity	ATRIUM EUROPEAN	Real Estate Operating Companies	Real Estate
2	Austria	BKUS AV Equity	BKS BANK AG	Diversified Banks	Banks
3	Austria	BTUV AV Equity	BANK FUER TIROL	Diversified Banks	Banks
4	Austria	CAI AV Equity	CA IMMOBILIEN AN	Real Estate Operating Companies	Real Estate
5	Austria	CWI AV Equity	CONWERT IMMOBILI	Real Estate Development	Real Estate
6	Austria	EBS AV Equity	ERSTE GROUP BANK	Diversified Banks	Banks
7	Austria	IIA AV Equity	IMMOFINANZ AG	Real Estate Operating Companies	Real Estate
8	Austria	OBS AV Equity	OBERBANK AG	Diversified Banks	Banks
9	Austria	SPI AV Equity	S IMMO AG	Real Estate Operating Companies	Real Estate
10	Austria	STM AV Equity	STADLAUER MALZFA	Real Estate Operating Companies	Real Estate
11	Austria	UBS AV Equity	UBM REALITAETEN	Diversified Real Estate Activities	Real Estate
12	Austria	UIV AV Equity	UNTERNEHMENS INV	Asset Management & Custody Banks	Diversified Financials
13	Austria	UQA AV Equity	UNIQA INSURANCE	Multi-line Insurance	Insurance
14	Austria	VIG AV Equity	VIENNA INSURANCE	Multi-line Insurance	Insurance
15	Austria	VVPS AV Equity	VOLKSBANK VORARL	Diversified Banks	Banks
16	Austria	WPB AV Equity	WIENER PRIVATBAN	Investment Banking & Brokerage	Diversified Financials
17	Belgium	ACKB BB Equity	ACKERMANS & VAN	Multi-Sector Holdings	Diversified Financials
18	Belgium	ATEB BB Equity	ATENOR GROUP	Real Estate Operating Companies	Real Estate
19	Belgium	BEFB BB Equity	BEFIMMO	Office REITs	Real Estate
20	Belgium	BELR BB Equity	BELRECA	Diversified Real Estate Activities	Real Estate
21	Belgium	BELU BB Equity	BELUGA	Asset Management & Custody Banks	Diversified Financials
22	Belgium	BNB BB Equity	BANQ NATL BELGIQ	Specialized Finance	Diversified Financials
23	Belgium	BREB BB Equity	BREDERODE	Asset Management & Custody Banks	Diversified Financials
24	Belgium	COFB BB Equity	COFINIMMO	Diversified REITs	Real Estate
25	Belgium	COMB BB Equity	CIE BOIS SAUVAGE	Multi-Sector Holdings	Diversified Financials
26	Belgium	CPINV BB Equity	CARE PROPERTY IN	Residential REITs	Real Estate
27	Belgium	DEXB BB Equity	DEXIA SA	Diversified Banks	Banks
28	Belgium	GBLB BB Equity	GROUPE BRUX LAMB	Multi-Sector Holdings	Diversified Financials
29	Belgium	GIMB BB Equity	GIMV NV	Asset Management & Custody Banks	Diversified Financials
30	Belgium	HOMI BB Equity	HOME INVEST BELG	Residential REITs	Real Estate
31	Belgium	IMMO BB Equity	IMMOBEL	Real Estate Development	Real Estate
32	Belgium	INTO BB Equity	INTERVEST OFFICE	Office REITs	Real Estate
33	Belgium	KBC BB Equity	KBC GROEP	Diversified Banks	Banks
34	Belgium	KBCA BB Equity	KBC ANCORA	Other Diversified Financial Services	Diversified Financials
35	Belgium	LEAS BB Equity	LEASINVEST	Office REITs	Real Estate
36	Belgium	QFG BB Equity	QUESTFOR GR-PRIC	Asset Management & Custody Banks	Diversified Financials
37	Belgium	RET BB Equity	RETAIL ESTATES	Retail REITs	Real Estate
38	Belgium	SOF BB Equity	SOFINA	Multi-Sector Holdings	Diversified Financials
39	Belgium	SOFT BB Equity	SOFTIMAT	Real Estate Operating Companies	Real Estate
40	Belgium	TUB BB Equity	FINANCIERE DE TU	Asset Management & Custody Banks	Diversified Financials
41	Belgium	VASTB BB Equity	VASTNED RETAIL B	Retail REITs	Real Estate
42	Belgium	WDP BB Equity	WAREHOUSES DE PA	Industrial REITs	Real Estate
43	Belgium	WEB BB Equity	WEB SCA	Diversified REITs	Real Estate
44	Belgium	WEHB BB Equity	WERELDHAVE BELGM	Retail REITs	Real Estate
45	Cyprus	AIAS CY Equity	AIANTAS INVESTME	Asset Management & Custody Banks	Diversified Financials
46	Cyprus	ATL CY Equity	ATLANTIC INSURAN	Multi-line Insurance	Insurance

47	Cyprus	BOCY CY Equity	BANK OF CYPRUS	Diversified Banks	Banks
48	Cyprus	DEM CY Equity	DEMETRA INVESTME	Asset Management & Custody Banks	Diversified Financials
49	Cyprus	ELF CY Equity	ELLINAS FINANCE	Specialized Finance	Diversified Financials
50	Cyprus	EXE CY Equity	CYVENTURE CAPITA	Asset Management & Custody Banks	Diversified Financials
51	Cyprus	FWW CY Equity	WOOLWORTH CYPRUS	Diversified Real Estate Activities	Real Estate
52	Cyprus	HB CY Equity	HELLENIC BANK PU	Diversified Banks	Banks
53	Cyprus	KG CY Equity	K+G COMPLEX PCL	Diversified Real Estate Activities	Real Estate
54	Cyprus	LI CY Equity	LAIKI CAPITAL PC	Investment Banking & Brokerage	Diversified Financials
55	Cyprus	LIB CY Equity	LIBERTY LIFE INS	Multi-line Insurance	Insurance
56	Cyprus	MINE CY Equity	MINERVA INSURANC	Multi-line Insurance	Insurance
57	Cyprus	PES CY Equity	PHILOKTIMATIKI	Diversified Real Estate Activities	Real Estate
58	Cyprus	PND CY Equity	PANDORA INVE LTD	Real Estate Development	Real Estate
59	Cyprus	SFS CY Equity	SFS GROUP	Investment Banking & Brokerage	Diversified Financials
60	Cyprus	USB CY Equity	USB BANK PLC	Regional Banks	Banks
61	Estonia	PKG1T ET Equity	PRO KAPITAL GRUP	Real Estate Development	Real Estate
62	Estonia	TPD1T ET Equity	AS TRIGON PROPER	Real Estate Operating Companies	Real Estate
63	Finland	ALBAV FH Equity	ALANDSBANKEN-A	Diversified Banks	Banks
64	Finland	CPMBV FH Equity	CAPMAN OYJ-B SHS	Asset Management & Custody Banks	Diversified Financials
65	Finland	CTY1S FH Equity	CITYCON OYJ	Real Estate Operating Companies	Real Estate
66	Finland	EQV1V FH Equity	EQ OYJ	Asset Management & Custody Banks	Diversified Financials
67	Finland	NORVE FH Equity	NORVESTIA OYJ-B	Asset Management & Custody Banks	Diversified Financials
68	Finland	SAMAS FH Equity	SAMPO OYJ-A SHS	Multi-line Insurance	Insurance
69	Finland	SCI1V FH Equity	SIEVI CAPITAL PL	Asset Management & Custody Banks	Diversified Financials
70	Finland	SDA1V FH Equity	SPONDA OYJ	Real Estate Operating Companies	Real Estate
71	Finland	INVEST FH Equity	SUOMEN SAASTAJIE	Real Estate Operating Companies	Real Estate
72	Finland	TPS1V FH Equity	TECHNOPOLIS OYJ	Real Estate Operating Companies	Real Estate
73	France	ABCA FP Equity	ABC ARBITRAGE	Specialized Finance	Diversified Financials
74	France	ACA FP Equity	CREDIT AGRICOLE	Diversified Banks	Banks
75	France	ALGIS FP Equity	GLOBAL INVESTMEN	Asset Management & Custody Banks	Diversified Financials
76	France	ALIDS FP Equity	IDSUD	Asset Management & Custody Banks	Diversified Financials
77	France	ALSAS FP Equity	STRADIM ESPACE	Real Estate Development	Real Estate
78	France	ALSIP FP Equity	SI PARTICIPATION	Asset Management & Custody Banks	Diversified Financials
79	France	ALTA FP Equity	ALTAREA	Retail REITs	Real Estate
80	France	APR FP Equity	APRIL	Insurance Brokers	Insurance
81	France	AREIT FP Equity	ALTAREIT	Diversified Real Estate Activities	Real Estate
82	France	ARTO FP Equity	ARTOIS (IND FIN)	Multi-Sector Holdings	Diversified Financials
83	France	BERR FP Equity	FIN ETANG BERRE	Diversified Real Estate Activities	Real Estate
84	France	BNP FP Equity	BNP PARIBAS	Diversified Banks	Banks
85	France	BQRE FP Equity	BANQUE REUNION	Regional Banks	Banks
86	France	CAF FP Equity	CR DE CA IDF	Regional Banks	Banks
87	France	CAT31 FP Equity	CREDIT AGRICOLE	Regional Banks	Banks
88	France	CC FP Equity	CIC	Diversified Banks	Banks
89	France	CCN FP Equity	CA NORMANDIE SEI	Regional Banks	Banks
90	France	CIV FP Equity	CA ILLE ET VILAI	Regional Banks	Banks
91	France	CMO FP Equity	CREDIT AGR MORBI	Regional Banks	Banks
92	France	CNF FP Equity	CA NORD DE FRANC	Regional Banks	Banks
93	France	CNP FP Equity	CNP ASSURANCES	Life & Health Insurance	Insurance
94	France	COUR FP Equity	COURTOIS-R	Real Estate Development	Real Estate
95	France	CRAP FP Equity	CA ALPES PROVENC	Regional Banks	Banks
96	France	CRAV FP Equity	CA ATLANTIQUE VE	Regional Banks	Banks

97	France	CRLO FP Equity	CA LOIRE-HAUTE-L	Regional Banks	Banks
98	France	CRSU FP Equity	CA SUD RHONE ALP	Regional Banks	Banks
99	France	CRTO FP Equity	CA TOURAINE POIT	Regional Banks	Banks
100	France	CS FP Equity	AXA	Multi-line Insurance	Insurance
101	France	DP FP Equity	IRD NORD CALAIS	Diversified Real Estate Activities	Real Estate
102	France	EEM FP Equity	ELEC & EAUX MADA	Real Estate Operating Companies	Real Estate
103	France	EIFF FP Equity	TOUR EIFFEL	Office REITs	Real Estate
104	France	ELE FP Equity	EULER HERMES GRO	Property & Casualty Insurance	Insurance
105	France	FDL FP Equity	FDL	Residential REITs	Real Estate
106	France	FDPA FP Equity	FONCIERE DE PARI	Real Estate Operating Companies	Real Estate
107	France	FDR FP Equity	FONCIERE DES REG	Diversified REITs	Real Estate
108	France	FFP FP Equity	FFP	Multi-Sector Holdings	Diversified Financials
109	France	FLY FP Equity	FONCIERE LYONN	Office REITs	Real Estate
110	France	FMU FP Equity	FONCIERE DES MUR	Hotel & Resort REITs	Real Estate
111	France	GFC FP Equity	GECINA SA	Diversified REITs	Real Estate
112	France	GLE FP Equity	SOC GENERALE SA	Diversified Banks	Banks
113	France	ICAD FP Equity	ICADE	Diversified REITs	Real Estate
114	France	IDIP FP Equity	IDI	Asset Management & Custody Banks	Diversified Financials
115	France	IMDA FP Equity	IMMOBIL DASSAULT	Diversified REITs	Real Estate
116	France	IML FP Equity	AFFINE	Diversified REITs	Real Estate
117	France	KN FP Equity	NATIXIS	Diversified Banks	Banks
118	France	LBON FP Equity	LEBON	Asset Management & Custody Banks	Diversified Financials
119	France	LD FP Equity	LOCINDUS	Thrifts & Mortgage Finance	Banks
120	France	LI FP Equity	KLEPIERRE	Retail REITs	Real Estate
121	France	LTA FP Equity	ALTAMIR	Asset Management & Custody Banks	Diversified Financials
122	France	MF FP Equity	WENDEL	Multi-Sector Holdings	Diversified Financials
123	France	MLCFM FP Equity	CFM	Diversified Banks	Banks
124	France	MLCVG FP Equity	TRAMWAYS VAR GAR	Asset Management & Custody Banks	Diversified Financials
125	France	MLFMM FP Equity	MARTIN MAUREL SA	Diversified Banks	Banks
126	France	MLMAB FP Equity	BAUD (ANTOINE)	Real Estate Operating Companies	Real Estate
127	France	MONC FP Equity	MONCEY FINANCIER	Multi-Sector Holdings	Diversified Financials
128	France	MRM FP Equity	M.R.M.	Diversified REITs	Real Estate
129	France	ORC FP Equity	ORCO PROPERTY GR	Diversified Real Estate Activities	Real Estate
130	France	ORIA FP Equity	FIDUCIAL REAL ES	Real Estate Operating Companies	Real Estate
131	France	PAOR FP Equity	PARIS ORLEANS	Diversified Capital Markets	Diversified Financials
132	France	RF FP Equity	EURAZEO	Multi-Sector Holdings	Diversified Financials
133	France	SCDU FP Equity	SCHAEFFER-DUFOUR	Asset Management & Custody Banks	Diversified Financials
134	France	SCR FP Equity	SCOR SE	Reinsurance	Insurance
135	France	SFBS FP Equity	SOFIBUS PATRIMOI	Real Estate Operating Companies	Real Estate
136	France	SOFR FP Equity	SOFRAGI	Asset Management & Custody Banks	Diversified Financials
137	France	SPEL FP Equity	FONCIERE VOLTA	Real Estate Operating Companies	Real Estate
138	France	SY FP Equity	SALVEPAR	Multi-Sector Holdings	Diversified Financials
139	France	UFF FP Equity	UNION FIN FRANCE	Asset Management & Custody Banks	Diversified Financials
140	France	VIL FP Equity	VIEL ET COMPAGNI	Investment Banking & Brokerage	Diversified Financials
141	Germany	AAA GR Equity	AAA-AG ALLGEM AN	Real Estate Operating Companies	Real Estate
142	Germany	ABHA GR Equity	HASEN-BRAEU AG	Real Estate Operating Companies	Real Estate
143	Germany	ADC GR Equity	ADCAPITAL AG	Asset Management & Custody Banks	Diversified Financials
144	Germany	ADL GR Equity	ADLER REAL EST	Real Estate Development	Real Estate
145	Germany	AGR GR Equity	AGROB IMMOBILIEN	Real Estate Operating Companies	Real Estate
146	Germany	ALG GR Equity	ALBIS LEAS. AG G	Specialized Finance	Diversified Financials

147	Germany	ALV GR Equity	ALLIANZ SE-VINK	Multi-line Insurance	Insurance
148	Germany	ARL GR Equity	AAREAL BANK AG	Thrifts & Mortgage Finance	Banks
149	Germany	ATW GR Equity	ALLERTHAL-WERKE	Asset Management & Custody Banks	Diversified Financials
150	Germany	BBH GR Equity	DEUTSCHE BALATON	Asset Management & Custody Banks	Diversified Financials
151	Germany	BBI GR Equity	BBI BUERGERLICHE	Real Estate Operating Companies	Real Estate
152	Germany	BBR GR Equity	BUERGER RAVENSB	Real Estate Operating Companies	Real Estate
153	Germany	BFK GR Equity	BASTFASERKONTOR	Real Estate Operating Companies	Real Estate
154	Germany	BFV GR Equity	BERLINER EFFEKTE	Investment Banking & Brokerage	Diversified Financials
155	Germany	BTBA GR Equity	BMP MEDIA INVEST	Asset Management & Custody Banks	Diversified Financials
156	Germany	BWB GR Equity	BAADER BANK	Investment Banking & Brokerage	Diversified Financials
157	Germany	CBK GR Equity	COMMERZBANK	Diversified Banks	Banks
158	Germany	CCB GR Equity	TIBERIUS HOLDING	Asset Management & Custody Banks	Diversified Financials
159	Germany	CMBT GR Equity	ATEVIA AG	Asset Management & Custody Banks	Diversified Financials
160	Germany	COM GR Equity	COMDIRECT BANK	Diversified Banks	Banks
161	Germany	DAL GR Equity	DAHLBUSCH AG	Real Estate Operating Companies	Real Estate
162	Germany	DB1 GR Equity	DEUTSCHE BOERSE	Specialized Finance	Diversified Financials
163	Germany	DBAN GR Equity	DEUTSCHE BETEILI	Asset Management & Custody Banks	Diversified Financials
164	Germany	DBK GR Equity	DEUTSCHE BANK-RG	Diversified Capital Markets	Diversified Financials
165	Germany	DEQ GR Equity	DEUTSCHE EUROSHO	Real Estate Operating Companies	Real Estate
166	Germany	DGR GR Equity	DEUTSCHE GRUNDST	Real Estate Services	Real Estate
167	Germany	DIC GR Equity	DIC ASSET AG	Diversified Real Estate Activities	Real Estate
168	Germany	DLB GR Equity	DLB ANLAGESERVIC	Asset Management & Custody Banks	Diversified Financials
169	Germany	DRN GR Equity	DAB BANK AG	Investment Banking & Brokerage	Diversified Financials
170	Germany	DVB GR Equity	DVB BANK SE	Diversified Banks	Banks
171	Germany	EFF GR Equity	DEUTSCHE EFFECTE	Asset Management & Custody Banks	Diversified Financials
172	Germany	EFS GR Equity	EFFECTEN-SPIEGEL	Asset Management & Custody Banks	Diversified Financials
173	Germany	EUX GR Equity	EUWAX AG	Investment Banking & Brokerage	Diversified Financials
174	Germany	FAK GR Equity	FALKENSTEIN	Asset Management & Custody Banks	Diversified Financials
175	Germany	FRS GR Equity	FORIS AG	Specialized Finance	Diversified Financials
176	Germany	GBQ GR Equity	GBK BETEILIGUNGE	Asset Management & Custody Banks	Diversified Financials
177	Germany	GLJ GR Equity	GRENKELEASING AG	Specialized Finance	Diversified Financials
178	Germany	GWK3 GR Equity	GAG IMMOBILIEN A	Real Estate Operating Companies	Real Estate
179	Germany	HAB GR Equity	HAMBORNER REIT	Diversified REITs	Real Estate
180	Germany	HGL GR Equity	HAMBURG GETREIDE	Asset Management & Custody Banks	Diversified Financials
181	Germany	HNR1 GR Equity	HANNOVER RUECK S	Reinsurance	Insurance
182	Germany	HRU GR Equity	HORUS AG	Asset Management & Custody Banks	Diversified Financials
183	Germany	IKB GR Equity	IKB DEUT INDBANK	Diversified Banks	Banks
184	Germany	IPO GR Equity	HEIDELBERGER BET	Specialized Finance	Diversified Financials
185	Germany	KBU GR Equity	COLONIA REAL EST	Real Estate Operating Companies	Real Estate
186	Germany	KSW GR Equity	KST BETEILIGUNGS	Asset Management & Custody Banks	Diversified Financials
187	Germany	LBN GR Equity	NYMPHENBURG IMM	Real Estate Operating Companies	Real Estate
188	Germany	LBR GR Equity	CUSTODIA HLDG	Real Estate Operating Companies	Real Estate
189	Germany	MBK GR Equity	MERKUR BANK KGAA	Diversified Banks	Banks
190	Germany	MLP GR Equity	MLP AG	Asset Management & Custody Banks	Diversified Financials
191	Germany	MPCK GR Equity	MPC CAPITAL AG	Asset Management & Custody Banks	Diversified Financials
192	Germany	MUK GR Equity	BAYERISCHE GEWER	Real Estate Operating Companies	Real Estate
193	Germany	MUV2 GR Equity	MUENCHENER RUE-R	Reinsurance	Insurance
194	Germany	MWB GR Equity	MWB FAIRTRADE	Investment Banking & Brokerage	Diversified Financials
195	Germany	NBG6 GR Equity	NUERNB BETEI 'B'	Multi-line Insurance	Insurance
196	Germany	OLB GR Equity	OLDENBURG LANDES	Regional Banks	Banks

197	Germany	ICP GR Equity	PANAMAX AG	Asset Management & Custody Banks	Diversified Financials
198	Germany	PEH GR Equity	PEH WERTPAPIER	Asset Management & Custody Banks	Diversified Financials
199	Germany	PPZ GR Equity	POMMER PROV ZUCK	Asset Management & Custody Banks	Diversified Financials
200	Germany	RLV GR Equity	RHEINLAND HLDG	Multi-line Insurance	Insurance
201	Germany	RMO GR Equity	RM RHEINER MANAG	Asset Management & Custody Banks	Diversified Financials
202	Germany	SGB GR Equity	SCHLOSSGARTENBAU	Real Estate Operating Companies	Real Estate
203	Germany	SIN GR Equity	SINNER AG	Real Estate Operating Companies	Real Estate
204	Germany	SMWN GR Equity	SM WIRTSCHAFTSBE	Real Estate Operating Companies	Real Estate
205	Germany	SPB GR Equity	SEDLMAYR GRUND	Real Estate Operating Companies	Real Estate
206	Germany	SPT6 GR Equity	SPARTA AG	Asset Management & Custody Banks	Diversified Financials
207	Germany	SPZI GR Equity	MISTRAL MEDI-REG	Asset Management & Custody Banks	Diversified Financials
208	Germany	STG GR Equity	STINAG STUTTGART	Real Estate Operating Companies	Real Estate
209	Germany	SVE GR Equity	SHAREHOLDER VALU	Asset Management & Custody Banks	Diversified Financials
210	Germany	TEG GR Equity	TAG IMMOBILIEN	Real Estate Development	Real Estate
211	Germany	TUB GR Equity	HSBC TRINKAUS &	Diversified Banks	Banks
212	Germany	UBK GR Equity	UMWELTBANK AG	Diversified Banks	Banks
213	Germany	UCA1 GR Equity	U.C.A. AG	Asset Management & Custody Banks	Diversified Financials
214	Germany	VEH GR Equity	VALORA EFFEKTEN	Investment Banking & Brokerage	Diversified Financials
215	Germany	VHO GR Equity	VALUE HOLDINGS	Asset Management & Custody Banks	Diversified Financials
216	Germany	VVV3 GR Equity	OKOWORLD AG	Other Diversified Financial Services	Diversified Financials
217	Germany	WEG1 GR Equity	WESTGRUND AG	Diversified Real Estate Activities	Real Estate
218	Germany	WLV GR Equity	WUERTTEMBERG LEB	Life & Health Insurance	Insurance
219	Germany	WUW GR Equity	WUESTENROT & WUE	Other Diversified Financial Services	Diversified Financials
220	Greece	ALPHA GA Equity	ALPHA BANK A.E.	Diversified Banks	Banks
221	Greece	ASTAK GA Equity	ALPHA ASTIKA AKI	Real Estate Services	Real Estate
222	Greece	ETE GA Equity	NATL BANK GREECE	Diversified Banks	Banks
223	Greece	EUPIC GA Equity	EUROPEAN RELIANC	Life & Health Insurance	Insurance
224	Greece	EUROB GA Equity	EUROBANK ERGASIA	Diversified Banks	Banks
225	Greece	EXAE GA Equity	HELLENIC EXCHANG	Specialized Finance	Diversified Financials
226	Greece	KAMP GA Equity	REDS SA	Diversified Real Estate Activities	Real Estate
227	Greece	KEKR GA Equity	KEKROPS	Real Estate Development	Real Estate
228	Greece	LAMDA GA Equity	LAMDA DEVELOPMEN	Diversified Real Estate Activities	Real Estate
229	Greece	TATT GA Equity	ATTICA BANK SA	Diversified Banks	Banks
230	Greece	TELL GA Equity	BANK GREECE	Specialized Finance	Diversified Financials
231	Greece	TPEIR GA Equity	PIRAEUS BANK	Diversified Banks	Banks
232	Ireland	ALBK ID Equity	ALLIED IRISH BK	Diversified Banks	Banks
233	Ireland	BKIR ID Equity	BANK IRELAND	Diversified Banks	Banks
234	Ireland	FBD ID Equity	FBD HOLDINGS PLC	Multi-line Insurance	Insurance
235	Ireland	IFP ID Equity	IFG GROUP PLC	Other Diversified Financial Services	Diversified Financials
236	Italy	AE IM Equity	AEDES SPA	Diversified Real Estate Activities	Real Estate
237	Italy	BDB IM Equity	BANCO DESIO	Diversified Banks	Banks
238	Italy	BIM IM Equity	BANCA INTERMOBIL	Investment Banking & Brokerage	Diversified Financials
239	Italy	BMPS IM Equity	BANCA MONTE DEI	Diversified Banks	Banks
240	Italy	BNS IM Equity	BENI STABILI SPA	Office REITs	Real Estate
241	Italy	BPE IM Equity	BANCA POP EMILIA	Diversified Banks	Banks
242	Italy	BPSO IM Equity	BANCA POP SONDRI	Diversified Banks	Banks
243	Italy	BRI IM Equity	BRIOSCHI	Diversified Real Estate Activities	Real Estate
244	Italy	BSRP IM Equity	BANCO SARDEG-RSP	Regional Banks	Banks
245	Italy	CASS IM Equity	CATTOLICA ASSIC	Life & Health Insurance	Insurance
246	Italy	CE IM Equity	CREDITO EMILIANO	Diversified Banks	Banks

247	Italy	CRG IM Equity	BANCA CARIGE	Diversified Banks	Banks
248	Italy	CVAL IM Equity	CREDITO VALTELLI	Regional Banks	Banks
249	Italy	DEA IM Equity	DEA CAPITAL SPA	Asset Management & Custody Banks	Diversified Financials
250	Italy	G IM Equity	GENERALI ASSIC	Multi-line Insurance	Insurance
251	Italy	GAB IM Equity	GABETTI PROPERTY	Diversified Real Estate Activities	Real Estate
252	Italy	IF IM Equity	BANCA IFIS SPA	Specialized Finance	Diversified Financials
253	Italy	ISP IM Equity	INTESA SANPAOLO	Diversified Banks	Banks
254	Italy	LVEN IM Equity	LVENTURE GROUP	Asset Management & Custody Banks	Diversified Financials
255	Italy	MB IM Equity	MEDIOBANCA	Investment Banking & Brokerage	Diversified Financials
256	Italy	NR IM Equity	NOVA RE	Diversified Real Estate Activities	Real Estate
257	Italy	PEL IM Equity	BANCA POP ETRURI	Regional Banks	Banks
258	Italy	PMI IM Equity	BANCA POP MILANO	Diversified Banks	Banks
259	Italy	PRO IM Equity	BANCA PROFILO	Investment Banking & Brokerage	Diversified Financials
260	Italy	RN IM Equity	RISANAMENTO SPA	Diversified Real Estate Activities	Real Estate
261	Italy	UBI IM Equity	UBI BANCA SCPA	Diversified Banks	Banks
262	Italy	UCG IM Equity	UNICREDIT SPA	Diversified Banks	Banks
263	Italy	UNI IM Equity	UNIPOL GRUPPO FI	Multi-line Insurance	Insurance
264	Italy	VAS IM Equity	VITTORIA ASSIC	Multi-line Insurance	Insurance
265	Luxembourg	COFI LX Equity	COFI	Asset Management & Custody Banks	Diversified Financials
266	Luxembourg	INSIN LX Equity	IDB HOLDINGS S.A	Investment Banking & Brokerage	Diversified Financials
267	Luxembourg	LXMP LX Equity	LUXEMPART SA	Asset Management & Custody Banks	Diversified Financials
268	Luxembourg	QUIL LX Equity	QUILVEST SA	Asset Management & Custody Banks	Diversified Financials
269	Malta	BOV MV Equity	BANK VALLETTA	Diversified Banks	Banks
270	Malta	FIM MV Equity	FIMBANK PLC	Diversified Banks	Banks
271	Malta	HSB MV Equity	HSBC BANK MALTA	Diversified Banks	Banks
272	Malta	LOM MV Equity	LOMBARD BANK MAL	Regional Banks	Banks
273	Malta	PZC MV Equity	PLAZA CENTERS	Real Estate Operating Companies	Real Estate
274	Netherlands	AGN NA Equity	AEGON NV	Life & Health Insurance	Insurance
275	Netherlands	BEVER NA Equity	BEVER HOLDING	Diversified Real Estate Activities	Real Estate
276	Netherlands	BINCK NA Equity	BINCKBANK NV	Investment Banking & Brokerage	Diversified Financials
277	Netherlands	CORA NA Equity	CORIO NV	Retail REITs	Real Estate
278	Netherlands	ECMPA NA Equity	EUROCOMMERCI-CVA	Retail REITs	Real Estate
279	Netherlands	GROHA NA Equity	GROOTHANDELS	Real Estate Operating Companies	Real Estate
280	Netherlands	HAL NA Equity	HAL TRUST	Multi-Sector Holdings	Diversified Financials
281	Netherlands	INGA NA Equity	ING GROEP NV	Diversified Banks	Banks
282	Netherlands	KA NA Equity	KAS BANK NV-CVA	Asset Management & Custody Banks	Diversified Financials
283	Netherlands	KARD NA Equity	KARDAN NV	Multi-Sector Holdings	Diversified Financials
284	Netherlands	LANS NA Equity	VAN LANSCHOT-CVA	Diversified Banks	Banks
285	Netherlands	NSI NA Equity	NSI NV	Diversified REITs	Real Estate
286	Netherlands	VALUE NA Equity	VALUE8 NV	Asset Management & Custody Banks	Diversified Financials
287	Netherlands	VASTN NA Equity	VASTNED RETAIL N	Retail REITs	Real Estate
288	Netherlands	WHA NA Equity	WERELDHAVE NV	Diversified REITs	Real Estate
289	Portugal	BCP PL Equity	BANCO COM PORT-R	Diversified Banks	Banks
290	Portugal	BPI PL Equity	BANCO BPI SA-REG	Diversified Banks	Banks
291	Portugal	ESF PL Equity	ESPIRITO SANTO	Diversified Banks	Banks
292	Slovakia	VUB SK Equity	VUB AS	Diversified Banks	Banks
293	Slovenia	KDHR SV Equity	KMECKA DRUZBA	Property & Casualty Insurance	Insurance
294	Slovenia	NIKN SV Equity	NIKA INVESTIRANJ	Other Diversified Financial Services	Diversified Financials
295	Spain	ALB SM Equity	ALBA	Multi-Sector Holdings	Diversified Financials
296	Spain	BBVA SM Equity	BBVA	Diversified Banks	Banks

297	Spain	BKT SM Equity	BANKINTER	Diversified Banks	Banks
298	Spain	CEV SM Equity	CEVASA SA-	Real Estate Operating Companies	Real Estate
299	Spain	CGI SM Equity	GEN DE INVERSION	Asset Management & Custody Banks	Diversified Financials
300	Spain	COL SM Equity	INMOBILIARIA COL	Real Estate Operating Companies	Real Estate
301	Spain	FICIS SM Equity	FINANZAS E INVER	Real Estate Operating Companies	Real Estate
302	Spain	GCO SM Equity	CATALANA OCC	Multi-line Insurance	Insurance
303	Spain	ILV SM Equity	INMOLEVANTE SA	Real Estate Development	Real Estate
304	Spain	LIB SM Equity	LIBERTAS SIETE	Real Estate Operating Companies	Real Estate
305	Spain	MAP SM Equity	MAPFRE SA	Multi-line Insurance	Insurance
306	Spain	MTB SM Equity	MONTEBALITO SA	Diversified Real Estate Activities	Real Estate
307	Spain	POP SM Equity	BANCO POPULAR	Diversified Banks	Banks
308	Spain	QBT SM Equity	QUABIT INMOBILIA	Diversified Real Estate Activities	Real Estate
309	Spain	REA SM Equity	CARTERA INDUSTRI	Asset Management & Custody Banks	Diversified Financials
310	Spain	SAB SM Equity	BANCO SABADELL	Diversified Banks	Banks
311	Spain	SAN SM Equity	BANCO SANTANDER	Diversified Banks	Banks
312	Spain	STG SM Equity	SOTOGRANDE	Diversified Real Estate Activities	Real Estate
313	Spain	TST SM Equity	TESTA INMUEBLES	Real Estate Operating Companies	Real Estate
314	Spain	UBS SM Equity	URBAS GRUPO FINA	Real Estate Development	Real Estate
315	Spain	UEI SM Equity	UNION EUROPEA IN	Asset Management & Custody Banks	Diversified Financials

Appendix C:

Number of Granger Causality Connections of Each Eurozone Financial Institution

(Pre-Crisis Period)

#	Ticker	Sector	Country	# of Connections
1	BKUS AV Equity	Banks	Austria	63
2	BTUV AV Equity	Banks	Austria	24
3	EBS AV Equity	Banks	Austria	42
4	OBS AV Equity	Banks	Austria	39
5	VVPS AV Equity	Banks	Austria	56
6	DEXB BB Equity	Banks	Belgium	55
7	KBC BB Equity	Banks	Belgium	73
8	BOCY CY Equity	Banks	Cyprus	114
9	HB CY Equity	Banks	Cyprus	92
10	USB CY Equity	Banks	Cyprus	16
11	ALBAV FH Equity	Banks	Finland	14
12	ACA FP Equity	Banks	France	66
13	BNP FP Equity	Banks	France	73
14	BQRE FP Equity	Banks	France	18
15	CAF FP Equity	Banks	France	16
16	CAT31 FP Equity	Banks	France	18
17	CC FP Equity	Banks	France	38
18	CCN FP Equity	Banks	France	26
19	CIV FP Equity	Banks	France	27
20	CMO FP Equity	Banks	France	22
21	CNF FP Equity	Banks	France	46
22	CRAP FP Equity	Banks	France	22
23	CRAV FP Equity	Banks	France	19
24	CRLO FP Equity	Banks	France	24
25	CRSU FP Equity	Banks	France	17
26	CRTO FP Equity	Banks	France	32
27	GLE FP Equity	Banks	France	87
28	KN FP Equity	Banks	France	78
29	LD FP Equity	Banks	France	29
30	MLCFM FP Equity	Banks	France	15
31	MLFMM FP Equity	Banks	France	23
32	ARL GR Equity	Banks	Germany	39
33	CBK GR Equity	Banks	Germany	116
34	COM GR Equity	Banks	Germany	77
35	DVB GR Equity	Banks	Germany	35
36	IKB GR Equity	Banks	Germany	72
37	MBK GR Equity	Banks	Germany	39
38	OLB GR Equity	Banks	Germany	66
39	TUB GR Equity	Banks	Germany	23
40	UBK GR Equity	Banks	Germany	39
41	ALPHA GA Equity	Banks	Greece	37
42	ETE GA Equity	Banks	Greece	51
43	EUROB GA Equity	Banks	Greece	50

44	TATT GA Equity	Banks	Greece	37
45	TPEIR GA Equity	Banks	Greece	60
46	ALBK ID Equity	Banks	Ireland	65
47	BKIR ID Equity	Banks	Ireland	68
48	BDB IM Equity	Banks	Italy	71
49	BMPS IM Equity	Banks	Italy	79
50	BPE IM Equity	Banks	Italy	36
51	BPSO IM Equity	Banks	Italy	40
52	BSRP IM Equity	Banks	Italy	53
53	CE IM Equity	Banks	Italy	58
54	CRG IM Equity	Banks	Italy	50
55	CVAL IM Equity	Banks	Italy	54
56	ISP IM Equity	Banks	Italy	65
57	PEL IM Equity	Banks	Italy	90
58	PMI IM Equity	Banks	Italy	37
59	UBI IM Equity	Banks	Italy	76
60	UCG IM Equity	Banks	Italy	49
61	BOV MV Equity	Banks	Malta	25
62	FIM MV Equity	Banks	Malta	35
63	HSB MV Equity	Banks	Malta	30
64	LOM MV Equity	Banks	Malta	37
65	INGA NA Equity	Banks	Netherlands	85
66	LANS NA Equity	Banks	Netherlands	44
67	BCP PL Equity	Banks	Portugal	57
68	BPI PL Equity	Banks	Portugal	58
69	ESF PL Equity	Banks	Portugal	37
70	VUB SK Equity	Banks	Slovakia	14
71	BBVA SM Equity	Banks	Spain	97
72	BKT SM Equity	Banks	Spain	80
73	POP SM Equity	Banks	Spain	125
74	SAB SM Equity	Banks	Spain	86
75	SAN SM Equity	Banks	Spain	81
76	UIV AV Equity	Financial	Austria	24
77	WPB AV Equity	Financial	Austria	39
78	ACKB BB Equity	Financial	Belgium	31
79	BELU BB Equity	Financial	Belgium	30
80	BNB BB Equity	Financial	Belgium	25
81	BREB BB Equity	Financial	Belgium	31
82	COMB BB Equity	Financial	Belgium	26
83	GBLB BB Equity	Financial	Belgium	99
84	GIMB BB Equity	Financial	Belgium	38
85	KBCA BB Equity	Financial	Belgium	50
86	QFG BB Equity	Financial	Belgium	26
87	SOF BB Equity	Financial	Belgium	52
88	TUB BB Equity	Financial	Belgium	29
89	AIAS CY Equity	Financial	Cyprus	30
90	DEM CY Equity	Financial	Cyprus	50
91	ELF CY Equity	Financial	Cyprus	24
92	EXE CY Equity	Financial	Cyprus	36
93	LI CY Equity	Financial	Cyprus	48

94	SFS CY Equity	Financial	Cyprus	58
95	CPMBV FH Equity	Financial	Finland	42
96	EQV1V FH Equity	Financial	Finland	41
97	NORVE FH Equity	Financial	Finland	34
98	SCI1V FH Equity	Financial	Finland	21
99	ABCA FP Equity	Financial	France	27
100	ALGIS FP Equity	Financial	France	22
101	ALIDS FP Equity	Financial	France	26
102	ALSIP FP Equity	Financial	France	50
103	ARTO FP Equity	Financial	France	27
104	FFP FP Equity	Financial	France	57
105	IDIP FP Equity	Financial	France	44
106	LBON FP Equity	Financial	France	18
107	LTA FP Equity	Financial	France	30
108	MF FP Equity	Financial	France	76
109	MLCVG FP Equity	Financial	France	21
110	MONC FP Equity	Financial	France	23
111	PAOR FP Equity	Financial	France	0
112	RF FP Equity	Financial	France	58
113	SCDU FP Equity	Financial	France	45
114	SOFR FP Equity	Financial	France	23
115	SY FP Equity	Financial	France	33
116	UFF FP Equity	Financial	France	42
117	VIL FP Equity	Financial	France	42
118	ADC GR Equity	Financial	Germany	17
119	ALG GR Equity	Financial	Germany	18
120	ATW GR Equity	Financial	Germany	20
121	BBH GR Equity	Financial	Germany	28
122	BFV GR Equity	Financial	Germany	16
123	BTBA GR Equity	Financial	Germany	26
124	BWB GR Equity	Financial	Germany	55
125	CCB GR Equity	Financial	Germany	41
126	CMBT GR Equity	Financial	Germany	39
127	DB1 GR Equity	Financial	Germany	84
128	DBAN GR Equity	Financial	Germany	51
129	DBK GR Equity	Financial	Germany	131
130	DLB GR Equity	Financial	Germany	62
131	DRN GR Equity	Financial	Germany	74
132	EFF GR Equity	Financial	Germany	26
133	EFS GR Equity	Financial	Germany	15
134	EUX GR Equity	Financial	Germany	39
135	FAK GR Equity	Financial	Germany	54
136	FRS GR Equity	Financial	Germany	31
137	GBQ GR Equity	Financial	Germany	17
138	GLJ GR Equity	Financial	Germany	16
139	HGL GR Equity	Financial	Germany	16
140	HRU GR Equity	Financial	Germany	15
141	IPO GR Equity	Financial	Germany	17
142	KSW GR Equity	Financial	Germany	49
143	MLP GR Equity	Financial	Germany	39

144	MPCK GR Equity	Financial	Germany	41
145	MWB GR Equity	Financial	Germany	49
146	ICP GR Equity	Financial	Germany	26
147	PEH GR Equity	Financial	Germany	49
148	PPZ GR Equity	Financial	Germany	27
149	RMO GR Equity	Financial	Germany	49
150	SPT6 GR Equity	Financial	Germany	43
151	SPZI GR Equity	Financial	Germany	18
152	SVE GR Equity	Financial	Germany	32
153	UCA1 GR Equity	Financial	Germany	36
154	VEH GR Equity	Financial	Germany	26
155	VHO GR Equity	Financial	Germany	22
156	VVV3 GR Equity	Financial	Germany	25
157	WUW GR Equity	Financial	Germany	31
158	EXAE GA Equity	Financial	Greece	65
159	TELL GA Equity	Financial	Greece	33
160	IFP ID Equity	Financial	Ireland	22
161	BIM IM Equity	Financial	Italy	45
162	DEA IM Equity	Financial	Italy	37
163	IF IM Equity	Financial	Italy	41
164	LVEN IM Equity	Financial	Italy	22
165	MB IM Equity	Financial	Italy	67
166	PRO IM Equity	Financial	Italy	41
167	COFI LX Equity	Financial	Luxembourg	78
168	INSIN LX Equity	Financial	Luxembourg	30
169	LXMP LX Equity	Financial	Luxembourg	18
170	QUIL LX Equity	Financial	Luxembourg	29
171	BINCK NA Equity	Financial	Netherlands	57
172	HAL NA Equity	Financial	Netherlands	52
173	KA NA Equity	Financial	Netherlands	73
174	KARD NA Equity	Financial	Netherlands	37
175	VALUE NA Equity	Financial	Netherlands	22
176	NIKN SV Equity	Financial	Slovenia	25
177	ALB SM Equity	Financial	Spain	69
178	CGI SM Equity	Financial	Spain	48
179	REA SM Equity	Financial	Spain	81
180	UEI SM Equity	Financial	Spain	41
181	UQA AV Equity	Insurance	Austria	68
182	VIG AV Equity	Insurance	Austria	48
183	ATL CY Equity	Insurance	Cyprus	40
184	LIB CY Equity	Insurance	Cyprus	19
185	MINE CY Equity	Insurance	Cyprus	45
186	SAMAS FH Equity	Insurance	Finland	76
187	APR FP Equity	Insurance	France	36
188	CNP FP Equity	Insurance	France	70
189	CS FP Equity	Insurance	France	69
190	ELE FP Equity	Insurance	France	41
191	SCR FP Equity	Insurance	France	62
192	ALV GR Equity	Insurance	Germany	90
193	HNR1 GR Equity	Insurance	Germany	72

194	MUV2 GR Equity	Insurance	Germany	103
195	NBG6 GR Equity	Insurance	Germany	16
196	RLV GR Equity	Insurance	Germany	63
197	WLV GR Equity	Insurance	Germany	21
198	EUPIC GA Equity	Insurance	Greece	44
199	FBD ID Equity	Insurance	Ireland	34
200	CASS IM Equity	Insurance	Italy	66
201	G IM Equity	Insurance	Italy	46
202	UNI IM Equity	Insurance	Italy	61
203	VAS IM Equity	Insurance	Italy	54
204	AGN NA Equity	Insurance	Netherlands	71
205	KDHR SV Equity	Insurance	Slovenia	24
206	GCO SM Equity	Insurance	Spain	95
207	MAP SM Equity	Insurance	Spain	77
208	ATRS AV Equity	Real	Austria	48
209	CAI AV Equity	Real	Austria	49
210	CWI AV Equity	Real	Austria	49
211	IIA AV Equity	Real	Austria	62
212	SPI AV Equity	Real	Austria	85
213	STM AV Equity	Real	Austria	23
214	UBS AV Equity	Real	Austria	33
215	ATEB BB Equity	Real	Belgium	46
216	BEFB BB Equity	Real	Belgium	89
217	BELR BB Equity	Real	Belgium	34
218	COFB BB Equity	Real	Belgium	49
219	CPINV BB Equity	Real	Belgium	32
220	HOMI BB Equity	Real	Belgium	34
221	IMMO BB Equity	Real	Belgium	20
222	INTO BB Equity	Real	Belgium	43
223	LEAS BB Equity	Real	Belgium	21
224	RET BB Equity	Real	Belgium	30
225	SOFT BB Equity	Real	Belgium	15
226	VASTB BB Equity	Real	Belgium	23
227	WDP BB Equity	Real	Belgium	38
228	WEB BB Equity	Real	Belgium	48
229	WEHB BB Equity	Real	Belgium	57
230	FWW CY Equity	Real	Cyprus	38
231	KG CY Equity	Real	Cyprus	77
232	PES CY Equity	Real	Cyprus	16
233	PND CY Equity	Real	Cyprus	27
234	PKG1T ET Equity	Real	Estonia	0
235	TPD1T ET Equity	Real	Estonia	24
236	CTY1S FH Equity	Real	Finland	46
237	SDA1V FH Equity	Real	Finland	50
238	INVEST FH Equity	Real	Finland	19
239	TPS1V FH Equity	Real	Finland	37
240	ALSAS FP Equity	Real	France	41
241	ALTA FP Equity	Real	France	43
242	AREIT FP Equity	Real	France	64
243	BERR FP Equity	Real	France	20

244	COUR FP Equity	Real	France	17
245	DP FP Equity	Real	France	0
246	EEM FP Equity	Real	France	0
247	EIFF FP Equity	Real	France	74
248	FDL FP Equity	Real	France	35
249	FDPA FP Equity	Real	France	18
250	FDR FP Equity	Real	France	35
251	FLY FP Equity	Real	France	23
252	FMU FP Equity	Real	France	39
253	GFC FP Equity	Real	France	95
254	ICAD FP Equity	Real	France	17
255	IMDA FP Equity	Real	France	36
256	IML FP Equity	Real	France	30
257	LI FP Equity	Real	France	78
258	MLMAB FP Equity	Real	France	93
259	MRM FP Equity	Real	France	16
260	ORC FP Equity	Real	France	89
261	ORIA FP Equity	Real	France	20
262	SFBS FP Equity	Real	France	36
263	SPEL FP Equity	Real	France	11
264	AAA GR Equity	Real	Germany	30
265	ABHA GR Equity	Real	Germany	18
266	ADL GR Equity	Real	Germany	20
267	AGR GR Equity	Real	Germany	47
268	BBI GR Equity	Real	Germany	28
269	BBR GR Equity	Real	Germany	33
270	BFK GR Equity	Real	Germany	41
271	DAL GR Equity	Real	Germany	28
272	DEQ GR Equity	Real	Germany	67
273	DGR GR Equity	Real	Germany	30
274	DIC GR Equity	Real	Germany	49
275	GWK3 GR Equity	Real	Germany	37
276	HAB GR Equity	Real	Germany	57
277	KBU GR Equity	Real	Germany	44
278	LBN GR Equity	Real	Germany	27
279	LBR GR Equity	Real	Germany	41
280	MUK GR Equity	Real	Germany	49
281	SGB GR Equity	Real	Germany	48
282	SIN GR Equity	Real	Germany	21
283	SMWN GR Equity	Real	Germany	38
284	SPB GR Equity	Real	Germany	33
285	STG GR Equity	Real	Germany	42
286	TEG GR Equity	Real	Germany	50
287	WEG1 GR Equity	Real	Germany	17
288	ASTAK GA Equity	Real	Greece	43
289	KAMP GA Equity	Real	Greece	29
290	KEKR GA Equity	Real	Greece	38
291	LAMDA GA Equity	Real	Greece	40
292	AE IM Equity	Real	Italy	48
293	BNS IM Equity	Real	Italy	77

294	BRI IM Equity	Real	Italy	44
295	GAB IM Equity	Real	Italy	24
296	NR IM Equity	Real	Italy	15
297	RN IM Equity	Real	Italy	66
298	PZC MV Equity	Real	Malta	33
299	BEVER NA Equity	Real	Netherlands	10
300	CORA NA Equity	Real	Netherlands	57
301	ECMPA NA Equity	Real	Netherlands	75
302	GROHA NA Equity	Real	Netherlands	31
303	NSI NA Equity	Real	Netherlands	62
304	VASTN NA Equity	Real	Netherlands	34
305	WHA NA Equity	Real	Netherlands	93
306	CEV SM Equity	Real	Spain	114
307	COL SM Equity	Real	Spain	34
308	FICIS SM Equity	Real	Spain	82
309	ILV SM Equity	Real	Spain	44
310	LIB SM Equity	Real	Spain	17
311	MTB SM Equity	Real	Spain	54
312	QBT SM Equity	Real	Spain	125
313	STG SM Equity	Real	Spain	43
314	TST SM Equity	Real	Spain	27
315	UBS SM Equity	Real	Spain	21
Total				**13,836**

Appendix D:

Number of Granger Causality Connections of Each Eurozone Financial Institution

(Crisis Period)

#	Ticker	Sector	Country	# of Connections
1	BKUS AV Equity	Banks	Austria	41
2	BTUV AV Equity	Banks	Austria	12
3	EBS AV Equity	Banks	Austria	124
4	OBS AV Equity	Banks	Austria	81
5	VVPS AV Equity	Banks	Austria	44
6	DEXB BB Equity	Banks	Belgium	155
7	KBC BB Equity	Banks	Belgium	139
8	BOCY CY Equity	Banks	Cyprus	123
9	HB CY Equity	Banks	Cyprus	88
10	USB CY Equity	Banks	Cyprus	89
11	ALBAV FH Equity	Banks	Finland	27
12	ACA FP Equity	Banks	France	90
13	BNP FP Equity	Banks	France	74
14	BQRE FP Equity	Banks	France	50
15	CAF FP Equity	Banks	France	65
16	CAT31 FP Equity	Banks	France	58
17	CC FP Equity	Banks	France	73
18	CCN FP Equity	Banks	France	79
19	CIV FP Equity	Banks	France	82
20	CMO FP Equity	Banks	France	36
21	CNF FP Equity	Banks	France	43
22	CRAP FP Equity	Banks	France	53
23	CRAV FP Equity	Banks	France	53
24	CRLO FP Equity	Banks	France	44
25	CRSU FP Equity	Banks	France	69
26	CRTO FP Equity	Banks	France	40
27	GLE FP Equity	Banks	France	67
28	KN FP Equity	Banks	France	122
29	LD FP Equity	Banks	France	31
30	MLCFM FP Equity	Banks	France	13
31	MLFMM FP Equity	Banks	France	38
32	ARL GR Equity	Banks	Germany	143
33	CBK GR Equity	Banks	Germany	147
34	COM GR Equity	Banks	Germany	122
35	DVB GR Equity	Banks	Germany	36
36	IKB GR Equity	Banks	Germany	38
37	MBK GR Equity	Banks	Germany	15
38	OLB GR Equity	Banks	Germany	126
39	TUB GR Equity	Banks	Germany	66
40	UBK GR Equity	Banks	Germany	29
41	ALPHA GA Equity	Banks	Greece	102
42	ETE GA Equity	Banks	Greece	121
43	EUROB GA Equity	Banks	Greece	106

44	TATT GA Equity	Banks	Greece	93
45	TPEIR GA Equity	Banks	Greece	115
46	ALBK ID Equity	Banks	Ireland	126
47	BKIR ID Equity	Banks	Ireland	172
48	BDB IM Equity	Banks	Italy	68
49	BMPS IM Equity	Banks	Italy	136
50	BPE IM Equity	Banks	Italy	110
51	BPSO IM Equity	Banks	Italy	99
52	BSRP IM Equity	Banks	Italy	81
53	CE IM Equity	Banks	Italy	142
54	CRG IM Equity	Banks	Italy	104
55	CVAL IM Equity	Banks	Italy	105
56	ISP IM Equity	Banks	Italy	170
57	PEL IM Equity	Banks	Italy	147
58	PMI IM Equity	Banks	Italy	132
59	UBI IM Equity	Banks	Italy	104
60	UCG IM Equity	Banks	Italy	98
61	BOV MV Equity	Banks	Malta	18
62	FIM MV Equity	Banks	Malta	14
63	HSB MV Equity	Banks	Malta	15
64	LOM MV Equity	Banks	Malta	31
65	INGA NA Equity	Banks	Netherlands	141
66	LANS NA Equity	Banks	Netherlands	39
67	BCP PL Equity	Banks	Portugal	101
68	BPI PL Equity	Banks	Portugal	99
69	ESF PL Equity	Banks	Portugal	74
70	VUB SK Equity	Banks	Slovakia	7
71	BBVA SM Equity	Banks	Spain	132
72	BKT SM Equity	Banks	Spain	121
73	POP SM Equity	Banks	Spain	130
74	SAB SM Equity	Banks	Spain	149
75	SAN SM Equity	Banks	Spain	134
76	UIV AV Equity	Financial	Austria	25
77	WPB AV Equity	Financial	Austria	45
78	ACKB BB Equity	Financial	Belgium	126
79	BELU BB Equity	Financial	Belgium	26
80	BNB BB Equity	Financial	Belgium	59
81	BREB BB Equity	Financial	Belgium	122
82	COMB BB Equity	Financial	Belgium	59
83	GBLB BB Equity	Financial	Belgium	134
84	GIMB BB Equity	Financial	Belgium	69
85	KBCA BB Equity	Financial	Belgium	106
86	QFG BB Equity	Financial	Belgium	39
87	SOF BB Equity	Financial	Belgium	111
88	TUB BB Equity	Financial	Belgium	94
89	AIAS CY Equity	Financial	Cyprus	29
90	DEM CY Equity	Financial	Cyprus	39
91	ELF CY Equity	Financial	Cyprus	17
92	EXE CY Equity	Financial	Cyprus	30
93	LI CY Equity	Financial	Cyprus	30

94	SFS CY Equity	Financial	Cyprus	66
95	CPMBV FH Equity	Financial	Finland	28
96	EQV1V FH Equity	Financial	Finland	27
97	NORVE FH Equity	Financial	Finland	86
98	SCI1V FH Equity	Financial	Finland	48
99	ABCA FP Equity	Financial	France	68
100	ALGIS FP Equity	Financial	France	53
101	ALIDS FP Equity	Financial	France	17
102	ALSIP FP Equity	Financial	France	45
103	ARTO FP Equity	Financial	France	22
104	FFP FP Equity	Financial	France	161
105	IDIP FP Equity	Financial	France	93
106	LBON FP Equity	Financial	France	92
107	LTA FP Equity	Financial	France	44
108	MF FP Equity	Financial	France	85
109	MLCVG FP Equity	Financial	France	16
110	MONC FP Equity	Financial	France	50
111	PAOR FP Equity	Financial	France	0
112	RF FP Equity	Financial	France	112
113	SCDU FP Equity	Financial	France	13
114	SOFR FP Equity	Financial	France	51
115	SY FP Equity	Financial	France	60
116	UFF FP Equity	Financial	France	51
117	VIL FP Equity	Financial	France	37
118	ADC GR Equity	Financial	Germany	45
119	ALG GR Equity	Financial	Germany	23
120	ATW GR Equity	Financial	Germany	58
121	BBH GR Equity	Financial	Germany	30
122	BFV GR Equity	Financial	Germany	30
123	BTBA GR Equity	Financial	Germany	29
124	BWB GR Equity	Financial	Germany	59
125	CCB GR Equity	Financial	Germany	23
126	CMBT GR Equity	Financial	Germany	65
127	DB1 GR Equity	Financial	Germany	121
128	DBAN GR Equity	Financial	Germany	133
129	DBK GR Equity	Financial	Germany	169
130	DLB GR Equity	Financial	Germany	72
131	DRN GR Equity	Financial	Germany	74
132	EFF GR Equity	Financial	Germany	29
133	EFS GR Equity	Financial	Germany	52
134	EUX GR Equity	Financial	Germany	18
135	FAK GR Equity	Financial	Germany	31
136	FRS GR Equity	Financial	Germany	25
137	GBQ GR Equity	Financial	Germany	30
138	GLJ GR Equity	Financial	Germany	92
139	HGL GR Equity	Financial	Germany	16
140	HRU GR Equity	Financial	Germany	25
141	IPO GR Equity	Financial	Germany	21
142	KSW GR Equity	Financial	Germany	58
143	MLP GR Equity	Financial	Germany	88

144	MPCK GR Equity	Financial	Germany	101
145	MWB GR Equity	Financial	Germany	19
146	ICP GR Equity	Financial	Germany	28
147	PEH GR Equity	Financial	Germany	52
148	PPZ GR Equity	Financial	Germany	12
149	RMO GR Equity	Financial	Germany	15
150	SPT6 GR Equity	Financial	Germany	58
151	SPZI GR Equity	Financial	Germany	7
152	SVE GR Equity	Financial	Germany	37
153	UCA1 GR Equity	Financial	Germany	47
154	VEH GR Equity	Financial	Germany	61
155	VHO GR Equity	Financial	Germany	43
156	VVV3 GR Equity	Financial	Germany	27
157	WUW GR Equity	Financial	Germany	54
158	EXAE GA Equity	Financial	Greece	107
159	TELL GA Equity	Financial	Greece	127
160	IFP ID Equity	Financial	Ireland	133
161	BIM IM Equity	Financial	Italy	70
162	DEA IM Equity	Financial	Italy	50
163	IF IM Equity	Financial	Italy	90
164	LVEN IM Equity	Financial	Italy	53
165	MB IM Equity	Financial	Italy	81
166	PRO IM Equity	Financial	Italy	97
167	COFI LX Equity	Financial	Luxembourg	43
168	INSIN LX Equity	Financial	Luxembourg	37
169	LXMP LX Equity	Financial	Luxembourg	21
170	QUIL LX Equity	Financial	Luxembourg	18
171	BINCK NA Equity	Financial	Netherlands	108
172	HAL NA Equity	Financial	Netherlands	98
173	KA NA Equity	Financial	Netherlands	113
174	KARD NA Equity	Financial	Netherlands	46
175	VALUE NA Equity	Financial	Netherlands	14
176	NIKN SV Equity	Financial	Slovenia	19
177	ALB SM Equity	Financial	Spain	82
178	CGI SM Equity	Financial	Spain	25
179	REA SM Equity	Financial	Spain	28
180	UEI SM Equity	Financial	Spain	27
181	UQA AV Equity	Insurance	Austria	32
182	VIG AV Equity	Insurance	Austria	118
183	ATL CY Equity	Insurance	Cyprus	47
184	LIB CY Equity	Insurance	Cyprus	52
185	MINE CY Equity	Insurance	Cyprus	21
186	SAMAS FH Equity	Insurance	Finland	157
187	APR FP Equity	Insurance	France	100
188	CNP FP Equity	Insurance	France	66
189	CS FP Equity	Insurance	France	103
190	ELE FP Equity	Insurance	France	58
191	SCR FP Equity	Insurance	France	112
192	ALV GR Equity	Insurance	Germany	144
193	HNR1 GR Equity	Insurance	Germany	125

194	MUV2 GR Equity	Insurance	Germany	130
195	NBG6 GR Equity	Insurance	Germany	41
196	RLV GR Equity	Insurance	Germany	56
197	WLV GR Equity	Insurance	Germany	11
198	EUPIC GA Equity	Insurance	Greece	45
199	FBD ID Equity	Insurance	Ireland	46
200	CASS IM Equity	Insurance	Italy	115
201	G IM Equity	Insurance	Italy	112
202	UNI IM Equity	Insurance	Italy	133
203	VAS IM Equity	Insurance	Italy	65
204	AGN NA Equity	Insurance	Netherlands	101
205	KDHR SV Equity	Insurance	Slovenia	42
206	GCO SM Equity	Insurance	Spain	98
207	MAP SM Equity	Insurance	Spain	131
208	ATRS AV Equity	Real	Austria	49
209	CAI AV Equity	Real	Austria	68
210	CWI AV Equity	Real	Austria	131
211	IIA AV Equity	Real	Austria	116
212	SPI AV Equity	Real	Austria	79
213	STM AV Equity	Real	Austria	12
214	UBS AV Equity	Real	Austria	21
215	ATEB BB Equity	Real	Belgium	34
216	BEFB BB Equity	Real	Belgium	36
217	BELR BB Equity	Real	Belgium	29
218	COFB BB Equity	Real	Belgium	118
219	CPINV BB Equity	Real	Belgium	19
220	HOMI BB Equity	Real	Belgium	20
221	IMMO BB Equity	Real	Belgium	35
222	INTO BB Equity	Real	Belgium	78
223	LEAS BB Equity	Real	Belgium	74
224	RET BB Equity	Real	Belgium	33
225	SOFT BB Equity	Real	Belgium	40
226	VASTB BB Equity	Real	Belgium	76
227	WDP BB Equity	Real	Belgium	60
228	WEB BB Equity	Real	Belgium	16
229	WEHB BB Equity	Real	Belgium	44
230	FWW CY Equity	Real	Cyprus	56
231	KG CY Equity	Real	Cyprus	24
232	PES CY Equity	Real	Cyprus	12
233	PND CY Equity	Real	Cyprus	41
234	PKG1T ET Equity	Real	Estonia	0
235	TPD1T ET Equity	Real	Estonia	50
236	CTY1S FH Equity	Real	Finland	94
237	SDA1V FH Equity	Real	Finland	66
238	INVEST FH Equity	Real	Finland	31
239	TPS1V FH Equity	Real	Finland	63
240	ALSAS FP Equity	Real	France	32
241	ALTA FP Equity	Real	France	49
242	AREIT FP Equity	Real	France	13
243	BERR FP Equity	Real	France	20

244	COUR FP Equity	Real	France	27
245	DP FP Equity	Real	France	0
246	EEM FP Equity	Real	France	0
247	EIFF FP Equity	Real	France	72
248	FDL FP Equity	Real	France	22
249	FDPA FP Equity	Real	France	24
250	FDR FP Equity	Real	France	84
251	FLY FP Equity	Real	France	40
252	FMU FP Equity	Real	France	49
253	GFC FP Equity	Real	France	100
254	ICAD FP Equity	Real	France	107
255	IMDA FP Equity	Real	France	17
256	IML FP Equity	Real	France	39
257	LI FP Equity	Real	France	104
258	MLMAB FP Equity	Real	France	7
259	MRM FP Equity	Real	France	17
260	ORC FP Equity	Real	France	106
261	ORIA FP Equity	Real	France	40
262	SFBS FP Equity	Real	France	39
263	SPEL FP Equity	Real	France	17
264	AAA GR Equity	Real	Germany	43
265	ABHA GR Equity	Real	Germany	49
266	ADL GR Equity	Real	Germany	35
267	AGR GR Equity	Real	Germany	23
268	BBI GR Equity	Real	Germany	32
269	BBR GR Equity	Real	Germany	23
270	BFK GR Equity	Real	Germany	7
271	DAL GR Equity	Real	Germany	30
272	DEQ GR Equity	Real	Germany	117
273	DGR GR Equity	Real	Germany	33
274	DIC GR Equity	Real	Germany	98
275	GWK3 GR Equity	Real	Germany	25
276	HAB GR Equity	Real	Germany	164
277	KBU GR Equity	Real	Germany	116
278	LBN GR Equity	Real	Germany	32
279	LBR GR Equity	Real	Germany	30
280	MUK GR Equity	Real	Germany	17
281	SGB GR Equity	Real	Germany	24
282	SIN GR Equity	Real	Germany	1
283	SMWN GR Equity	Real	Germany	35
284	SPB GR Equity	Real	Germany	62
285	STG GR Equity	Real	Germany	22
286	TEG GR Equity	Real	Germany	50
287	WEG1 GR Equity	Real	Germany	37
288	ASTAK GA Equity	Real	Greece	64
289	KAMP GA Equity	Real	Greece	79
290	KEKR GA Equity	Real	Greece	30
291	LAMDA GA Equity	Real	Greece	43
292	AE IM Equity	Real	Italy	86
293	BNS IM Equity	Real	Italy	93

294	BRI IM Equity	Real	Italy	73
295	GAB IM Equity	Real	Italy	51
296	NR IM Equity	Real	Italy	13
297	RN IM Equity	Real	Italy	84
298	PZC MV Equity	Real	Malta	34
299	BEVER NA Equity	Real	Netherlands	18
300	CORA NA Equity	Real	Netherlands	121
301	ECMPA NA Equity	Real	Netherlands	93
302	GROHA NA Equity	Real	Netherlands	14
303	NSI NA Equity	Real	Netherlands	59
304	VASTN NA Equity	Real	Netherlands	102
305	WHA NA Equity	Real	Netherlands	130
306	CEV SM Equity	Real	Spain	30
307	COL SM Equity	Real	Spain	61
308	FICIS SM Equity	Real	Spain	14
309	ILV SM Equity	Real	Spain	20
310	LIB SM Equity	Real	Spain	24
311	MTB SM Equity	Real	Spain	26
312	QBT SM Equity	Real	Spain	36
313	STG SM Equity	Real	Spain	29
314	TST SM Equity	Real	Spain	11
315	UBS SM Equity	Real	Spain	57
Total				**1,981**

Appendix E:

Number of Granger Causality Connections of Each Eurozone Financial Institution

(Post-Crisis Period)

#	Ticker	Sector	Country	# of Connections
1	BKUS AV Equity	Banks	Austria	26
2	BTUV AV Equity	Banks	Austria	37
3	EBS AV Equity	Banks	Austria	168
4	OBS AV Equity	Banks	Austria	14
5	VVPS AV Equity	Banks	Austria	24
6	DEXB BB Equity	Banks	Belgium	60
7	KBC BB Equity	Banks	Belgium	143
8	BOCY CY Equity	Banks	Cyprus	63
9	HB CY Equity	Banks	Cyprus	38
10	USB CY Equity	Banks	Cyprus	17
11	ALBAV FH Equity	Banks	Finland	21
12	ACA FP Equity	Banks	France	134
13	BNP FP Equity	Banks	France	144
14	BQRE FP Equity	Banks	France	27
15	CAF FP Equity	Banks	France	59
16	CAT31 FP Equity	Banks	France	43
17	CC FP Equity	Banks	France	83
18	CCN FP Equity	Banks	France	70
19	CIV FP Equity	Banks	France	45
20	CMO FP Equity	Banks	France	35
21	CNF FP Equity	Banks	France	52
22	CRAP FP Equity	Banks	France	38
23	CRAV FP Equity	Banks	France	28
24	CRLO FP Equity	Banks	France	22
25	CRSU FP Equity	Banks	France	34
26	CRTO FP Equity	Banks	France	30
27	GLE FP Equity	Banks	France	144
28	KN FP Equity	Banks	France	108
29	LD FP Equity	Banks	France	28
30	MLCFM FP Equity	Banks	France	21
31	MLFMM FP Equity	Banks	France	0
32	ARL GR Equity	Banks	Germany	122
33	CBK GR Equity	Banks	Germany	128
34	COM GR Equity	Banks	Germany	78
35	DVB GR Equity	Banks	Germany	13
36	IKB GR Equity	Banks	Germany	14
37	MBK GR Equity	Banks	Germany	23
38	OLB GR Equity	Banks	Germany	43
39	TUB GR Equity	Banks	Germany	31
40	UBK GR Equity	Banks	Germany	74
41	ALPHA GA Equity	Banks	Greece	83
42	ETE GA Equity	Banks	Greece	77
43	EUROB GA Equity	Banks	Greece	52

44	TATT GA Equity	Banks	Greece	36
45	TPEIR GA Equity	Banks	Greece	90
46	ALBK ID Equity	Banks	Ireland	86
47	BKIR ID Equity	Banks	Ireland	121
48	BDB IM Equity	Banks	Italy	65
49	BMPS IM Equity	Banks	Italy	107
50	BPE IM Equity	Banks	Italy	83
51	BPSO IM Equity	Banks	Italy	71
52	BSRP IM Equity	Banks	Italy	109
53	CE IM Equity	Banks	Italy	86
54	CRG IM Equity	Banks	Italy	107
55	CVAL IM Equity	Banks	Italy	74
56	ISP IM Equity	Banks	Italy	135
57	PEL IM Equity	Banks	Italy	95
58	PMI IM Equity	Banks	Italy	102
59	UBI IM Equity	Banks	Italy	100
60	UCG IM Equity	Banks	Italy	164
61	BOV MV Equity	Banks	Malta	22
62	FIM MV Equity	Banks	Malta	11
63	HSB MV Equity	Banks	Malta	53
64	LOM MV Equity	Banks	Malta	38
65	INGA NA Equity	Banks	Netherlands	140
66	LANS NA Equity	Banks	Netherlands	50
67	BCP PL Equity	Banks	Portugal	68
68	BPI PL Equity	Banks	Portugal	89
69	ESF PL Equity	Banks	Portugal	43
70	VUB SK Equity	Banks	Slovakia	15
71	BBVA SM Equity	Banks	Spain	151
72	BKT SM Equity	Banks	Spain	126
73	POP SM Equity	Banks	Spain	115
74	SAB SM Equity	Banks	Spain	120
75	SAN SM Equity	Banks	Spain	148
76	UIV AV Equity	Financial	Austria	46
77	WPB AV Equity	Financial	Austria	25
78	ACKB BB Equity	Financial	Belgium	116
79	BELU BB Equity	Financial	Belgium	30
80	BNB BB Equity	Financial	Belgium	119
81	BREB BB Equity	Financial	Belgium	103
82	COMB BB Equity	Financial	Belgium	35
83	GBLB BB Equity	Financial	Belgium	133
84	GIMB BB Equity	Financial	Belgium	69
85	KBCA BB Equity	Financial	Belgium	127
86	QFG BB Equity	Financial	Belgium	44
87	SOF BB Equity	Financial	Belgium	127
88	TUB BB Equity	Financial	Belgium	65
89	AIAS CY Equity	Financial	Cyprus	7
90	DEM CY Equity	Financial	Cyprus	21
91	ELF CY Equity	Financial	Cyprus	23
92	EXE CY Equity	Financial	Cyprus	55
93	LI CY Equity	Financial	Cyprus	87

94	SFS CY Equity	Financial	Cyprus	26
95	CPMBV FH Equity	Financial	Finland	60
96	EQV1V FH Equity	Financial	Finland	60
97	NORVE FH Equity	Financial	Finland	59
98	SCI1V FH Equity	Financial	Finland	28
99	ABCA FP Equity	Financial	France	133
100	ALGIS FP Equity	Financial	France	32
101	ALIDS FP Equity	Financial	France	60
102	ALSIP FP Equity	Financial	France	47
103	ARTO FP Equity	Financial	France	14
104	FFP FP Equity	Financial	France	120
105	IDIP FP Equity	Financial	France	26
106	LBON FP Equity	Financial	France	46
107	LTA FP Equity	Financial	France	44
108	MF FP Equity	Financial	France	161
109	MLCVG FP Equity	Financial	France	12
110	MONC FP Equity	Financial	France	24
111	PAOR FP Equity	Financial	France	0
112	RF FP Equity	Financial	France	103
113	SCDU FP Equity	Financial	France	21
114	SOFR FP Equity	Financial	France	58
115	SY FP Equity	Financial	France	26
116	UFF FP Equity	Financial	France	46
117	VIL FP Equity	Financial	France	54
118	ADC GR Equity	Financial	Germany	22
119	ALG GR Equity	Financial	Germany	18
120	ATW GR Equity	Financial	Germany	31
121	BBH GR Equity	Financial	Germany	71
122	BFV GR Equity	Financial	Germany	27
123	BTBA GR Equity	Financial	Germany	15
124	BWB GR Equity	Financial	Germany	29
125	CCB GR Equity	Financial	Germany	30
126	CMBT GR Equity	Financial	Germany	38
127	DB1 GR Equity	Financial	Germany	94
128	DBAN GR Equity	Financial	Germany	37
129	DBK GR Equity	Financial	Germany	161
130	DLB GR Equity	Financial	Germany	44
131	DRN GR Equity	Financial	Germany	54
132	EFF GR Equity	Financial	Germany	53
133	EFS GR Equity	Financial	Germany	24
134	EUX GR Equity	Financial	Germany	31
135	FAK GR Equity	Financial	Germany	38
136	FRS GR Equity	Financial	Germany	29
137	GBQ GR Equity	Financial	Germany	25
138	GLJ GR Equity	Financial	Germany	64
139	HGL GR Equity	Financial	Germany	17
140	HRU GR Equity	Financial	Germany	21
141	IPO GR Equity	Financial	Germany	58
142	KSW GR Equity	Financial	Germany	13
143	MLP GR Equity	Financial	Germany	43

144	MPCK GR Equity	Financial	Germany	44
145	MWB GR Equity	Financial	Germany	28
146	ICP GR Equity	Financial	Germany	27
147	PEH GR Equity	Financial	Germany	66
148	PPZ GR Equity	Financial	Germany	87
149	RMO GR Equity	Financial	Germany	11
150	SPT6 GR Equity	Financial	Germany	31
151	SPZI GR Equity	Financial	Germany	39
152	SVE GR Equity	Financial	Germany	20
153	UCA1 GR Equity	Financial	Germany	34
154	VEH GR Equity	Financial	Germany	28
155	VHO GR Equity	Financial	Germany	19
156	VVV3 GR Equity	Financial	Germany	41
157	WUW GR Equity	Financial	Germany	51
158	EXAE GA Equity	Financial	Greece	53
159	TELL GA Equity	Financial	Greece	66
160	IFP ID Equity	Financial	Ireland	28
161	BIM IM Equity	Financial	Italy	45
162	DEA IM Equity	Financial	Italy	66
163	IF IM Equity	Financial	Italy	47
164	LVEN IM Equity	Financial	Italy	46
165	MB IM Equity	Financial	Italy	106
166	PRO IM Equity	Financial	Italy	134
167	COFI LX Equity	Financial	Luxembourg	43
168	INSIN LX Equity	Financial	Luxembourg	16
169	LXMP LX Equity	Financial	Luxembourg	17
170	QUIL LX Equity	Financial	Luxembourg	23
171	BINCK NA Equity	Financial	Netherlands	89
172	HAL NA Equity	Financial	Netherlands	107
173	KA NA Equity	Financial	Netherlands	64
174	KARD NA Equity	Financial	Netherlands	68
175	VALUE NA Equity	Financial	Netherlands	21
176	NIKN SV Equity	Financial	Slovenia	46
177	ALB SM Equity	Financial	Spain	82
178	CGI SM Equity	Financial	Spain	21
179	REA SM Equity	Financial	Spain	16
180	UEI SM Equity	Financial	Spain	20
181	UQA AV Equity	Insurance	Austria	88
182	VIG AV Equity	Insurance	Austria	136
183	ATL CY Equity	Insurance	Cyprus	17
184	LIB CY Equity	Insurance	Cyprus	14
185	MINE CY Equity	Insurance	Cyprus	32
186	SAMAS FH Equity	Insurance	Finland	146
187	APR FP Equity	Insurance	France	104
188	CNP FP Equity	Insurance	France	124
189	CS FP Equity	Insurance	France	157
190	ELE FP Equity	Insurance	France	98
191	SCR FP Equity	Insurance	France	126
192	ALV GR Equity	Insurance	Germany	171
193	HNR1 GR Equity	Insurance	Germany	151

194	MUV2 GR Equity	Insurance	Germany	141
195	NBG6 GR Equity	Insurance	Germany	30
196	RLV GR Equity	Insurance	Germany	19
197	WLV GR Equity	Insurance	Germany	41
198	EUPIC GA Equity	Insurance	Greece	20
199	FBD ID Equity	Insurance	Ireland	40
200	CASS IM Equity	Insurance	Italy	73
201	G IM Equity	Insurance	Italy	132
202	UNI IM Equity	Insurance	Italy	55
203	VAS IM Equity	Insurance	Italy	95
204	AGN NA Equity	Insurance	Netherlands	138
205	KDHR SV Equity	Insurance	Slovenia	61
206	GCO SM Equity	Insurance	Spain	122
207	MAP SM Equity	Insurance	Spain	87
208	ATRS AV Equity	Real	Austria	67
209	CAI AV Equity	Real	Austria	81
210	CWI AV Equity	Real	Austria	112
211	IIA AV Equity	Real	Austria	138
212	SPI AV Equity	Real	Austria	58
213	STM AV Equity	Real	Austria	23
214	UBS AV Equity	Real	Austria	18
215	ATEB BB Equity	Real	Belgium	85
216	BEFB BB Equity	Real	Belgium	75
217	BELR BB Equity	Real	Belgium	67
218	COFB BB Equity	Real	Belgium	111
219	CPINV BB Equity	Real	Belgium	42
220	HOMI BB Equity	Real	Belgium	27
221	IMMO BB Equity	Real	Belgium	49
222	INTO BB Equity	Real	Belgium	36
223	LEAS BB Equity	Real	Belgium	36
224	RET BB Equity	Real	Belgium	30
225	SOFT BB Equity	Real	Belgium	21
226	VASTB BB Equity	Real	Belgium	34
227	WDP BB Equity	Real	Belgium	69
228	WEB BB Equity	Real	Belgium	35
229	WEHB BB Equity	Real	Belgium	22
230	FWW CY Equity	Real	Cyprus	16
231	KG CY Equity	Real	Cyprus	22
232	PES CY Equity	Real	Cyprus	8
233	PND CY Equity	Real	Cyprus	39
234	PKG1T ET Equity	Real	Estonia	57
235	TPD1T ET Equity	Real	Estonia	81
236	CTY1S FH Equity	Real	Finland	106
237	SDA1V FH Equity	Real	Finland	138
238	INVEST FH Equity	Real	Finland	39
239	TPS1V FH Equity	Real	Finland	78
240	ALSAS FP Equity	Real	France	35
241	ALTA FP Equity	Real	France	60
242	AREIT FP Equity	Real	France	45
243	BERR FP Equity	Real	France	24

244	COUR FP Equity	Real	France	38
245	DP FP Equity	Real	France	0
246	EEM FP Equity	Real	France	0
247	EIFF FP Equity	Real	France	139
248	FDL FP Equity	Real	France	23
249	FDPA FP Equity	Real	France	20
250	FDR FP Equity	Real	France	108
251	FLY FP Equity	Real	France	49
252	FMU FP Equity	Real	France	60
253	GFC FP Equity	Real	France	122
254	ICAD FP Equity	Real	France	115
255	IMDA FP Equity	Real	France	28
256	IML FP Equity	Real	France	94
257	LI FP Equity	Real	France	129
258	MLMAB FP Equity	Real	France	73
259	MRM FP Equity	Real	France	40
260	ORC FP Equity	Real	France	61
261	ORIA FP Equity	Real	France	44
262	SFBS FP Equity	Real	France	12
263	SPEL FP Equity	Real	France	18
264	AAA GR Equity	Real	Germany	22
265	ABHA GR Equity	Real	Germany	33
266	ADL GR Equity	Real	Germany	49
267	AGR GR Equity	Real	Germany	26
268	BBI GR Equity	Real	Germany	44
269	BBR GR Equity	Real	Germany	22
270	BFK GR Equity	Real	Germany	30
271	DAL GR Equity	Real	Germany	66
272	DEQ GR Equity	Real	Germany	117
273	DGR GR Equity	Real	Germany	48
274	DIC GR Equity	Real	Germany	111
275	GWK3 GR Equity	Real	Germany	24
276	HAB GR Equity	Real	Germany	95
277	KBU GR Equity	Real	Germany	42
278	LBN GR Equity	Real	Germany	11
279	LBR GR Equity	Real	Germany	24
280	MUK GR Equity	Real	Germany	31
281	SGB GR Equity	Real	Germany	25
282	SIN GR Equity	Real	Germany	18
283	SMWN GR Equity	Real	Germany	18
284	SPB GR Equity	Real	Germany	17
285	STG GR Equity	Real	Germany	15
286	TEG GR Equity	Real	Germany	57
287	WEG1 GR Equity	Real	Germany	64
288	ASTAK GA Equity	Real	Greece	33
289	KAMP GA Equity	Real	Greece	44
290	KEKR GA Equity	Real	Greece	49
291	LAMDA GA Equity	Real	Greece	38
292	AE IM Equity	Real	Italy	36
293	BNS IM Equity	Real	Italy	133

294	BRI IM Equity	Real	Italy	98
295	GAB IM Equity	Real	Italy	72
296	NR IM Equity	Real	Italy	54
297	RN IM Equity	Real	Italy	116
298	PZC MV Equity	Real	Malta	59
299	BEVER NA Equity	Real	Netherlands	31
300	CORA NA Equity	Real	Netherlands	136
301	ECMPA NA Equity	Real	Netherlands	127
302	GROHA NA Equity	Real	Netherlands	8
303	NSI NA Equity	Real	Netherlands	77
304	VASTN NA Equity	Real	Netherlands	128
305	WHA NA Equity	Real	Netherlands	118
306	CEV SM Equity	Real	Spain	22
307	COL SM Equity	Real	Spain	98
308	FICIS SM Equity	Real	Spain	15
309	ILV SM Equity	Real	Spain	19
310	LIB SM Equity	Real	Spain	15
311	MTB SM Equity	Real	Spain	28
312	QBT SM Equity	Real	Spain	47
313	STG SM Equity	Real	Spain	12
314	TST SM Equity	Real	Spain	38
315	UBS SM Equity	Real	Spain	27
Total				**18,905**

Appendix F:

Eurozone Member States Average Systemic Risk Measures

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	%	Rank	%	Rank	Value	Rank	%
Panel (A): Overall Period									
Austria	Mean	8	1.41	9	1.67	9	24.15	11	5
	STD		1.14		1.32		14.87		5,461
Belgium	Mean	7	1.86	6	2.04	7	29.03	7	9,497
	STD		1.20		1.33		14.22		16,562
Cyprus	Mean	13	0.70	13	0.82	13	12.76	13	-451
	STD		0.75		0.90		11.72		1,642
Estonia	Mean	18	0.02	18	-0.01	18	-0.14	16	-1,309
	STD		0.01		0.00		0.08		619
Finland	Mean	9	1.39	8	1.72	8	24.92	17	-4,904
	STD		1.06		1.28		14.67		5,422
France	Mean	3	2.04	3	2.29	3	32.03	1	171,479
	STD		1.21		1.35		13.68		89,636
Germany	Mean	5	1.99	5	2.25	5	31.44	2	98,425
	STD		1.24		1.39		14.21		57,032
Greece	Mean	11	1.04	11	1.19	11	18.14	15	-1,177
	STD		0.86		0.97		11.72		13,249
Ireland	Mean	12	1.03	12	1.10	12	16.90	18	-7,043
	STD		0.82		0.94		11.61		17,651
Italy	Mean	2	2.09	4	2.27	4	31.52	4	36,888
	STD		1.33		1.45		14.53		44,566
Luxembourg	Mean	14	0.09	16	0.08	16	1.43	14	-962
	STD		0.05		0.04		0.79		238
Malta	Mean	15	0.05	15	0.13	15	2.25	12	-251
	STD		0.06		0.10		1.72		272
Netherlands	Mean	6	1.88	7	2.03	6	29.05	6	22,245
	STD		1.15		1.23		13.32		29,117
Portugal	Mean	10	1.28	10	1.52	10	22.57	8	3,361
	STD		0.94		1.14		13.03		4,532
Slovakia	Mean	16	0.04	17	0.06	17	1.07	9	318
	STD		0.10		0.12		1.98		734
Slovenia	Mean	17	0.03	14	0.16	14	2.74	10	93
	STD		0.14		0.24		3.79		771
Spain	Mean	4	2.03	2	2.34	2	32.45	5	24,790
	STD		1.26		1.44		14.17		28,774
PIIGS	Mean	1	2.21	1	2.39	1	32.80	3	64,887
	STD		1.43		1.56		14.87		88,757

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**Value**	**Rank**	**%**
Panel (B): Pre-crisis Period									
Austria	Mean	10	0.57	10	1.65	10	23.91	15	-1,647
	STD		0.25		1.30		14.48		6,251
Belgium	Mean	7	0.87	7	1.73	7	25.16	11	-650
	STD		0.34		1.26		13.82		5,934
Cyprus	Mean	13	0.22	13	1.59	13	22.96	10	-627
	STD		0.13		1.34		15.24		5,403
Estonia	Mean	14	0.09	14	1.56	14	22.56	12	-661
	STD		0.03		1.36		15.60		5,368
Finland	Mean	9	0.60	8	1.69	8	24.51	13	-903
	STD		0.27		1.28		14.12		5,490
France	Mean	4	1.00	4	1.75	4	25.41	1	19,054
	STD		0.34		1.26		13.71		41,635
Germany	Mean	2	1.10	5	1.75	5	25.41	2	13,333
	STD		0.35		1.26		13.70		30,202
Greece	Mean	11	0.55	12	1.64	12	23.78	17	-3,466
	STD		0.26		1.31		14.58		8,717
Ireland	Mean	8	0.72	9	1.67	9	24.31	14	-1,468
	STD		0.25		1.29		14.18		5,819
Italy	Mean	3	1.06	1	1.78	1	25.77	16	-1,727
	STD		0.38		1.25		13.67		8,118
Luxembourg	Mean	15	0.05	18	1.51	18	21.56	9	-522
	STD		0.08		1.42		16.79		5,353
Malta	Mean	17	0.02	17	1.52	17	21.75	7	-392
	STD		0.01		1.41		16.53		5,353
Netherlands	Mean	6	0.94	6	1.74	6	25.21	3	778
	STD		0.36		1.26		13.80		7,280
Portugal	Mean	12	0.41	11	1.65	11	23.86	8	-512
	STD		0.19		1.30		14.49		5,413
Slovakia	Mean	16	0.02	15	1.53	15	21.91	5	-347
	STD		0.03		1.40		16.34		5,356
Slovenia	Mean	18	-0.05	16	1.52	16	21.81	6	-362
	STD		0.03		1.40		16.46		5,355
Spain	Mean	5	0.98	3	1.75	3	25.44	4	201
	STD		0.34		1.26		13.73		7,394
PIIGS	Mean	1	1.19	2	1.78	2	25.76	18	-4,091
	STD		0.38		1.25		13.65		16,432

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	%	Rank	%	Rank	Value	Rank	%
Panel (C): Post-crisis Period									
Austria	Mean STD	7	2.27 0.83	9	2.31 0.86	9	33.31 9.44	10	2,615 4,009
Belgium	Mean STD	1	2.56 0.96	3	2.75 1.04	3	38.07 10.33	7	17,088 14,741
Cyprus	Mean STD	12	0.87 0.40	13	0.73 0.38	13	12.06 5.71	11	1,130 731
Estonia	Mean STD	16	0.00 0.00	17	-0.21 0.08	17	-3.81 1.42	16	-1,392 638
Finland	Mean STD	9	2.13 1.02	8	2.42 1.15	8	34.01 12.30	18	-6,312 2,671
France	Mean STD	3	2.54 0.88	7	2.60 0.90	7	36.58 9.34	1	273,207 30,666
Germany	Mean STD	2	2.56 0.94	2	2.79 1.03	2	38.52 10.17	3	151,181 24,947
Greece	Mean STD	13	0.85 0.39	12	0.79 0.42	12	12.98 6.27	8	14,243 4,285
Ireland	Mean STD	11	0.90 0.34	11	1.14 0.44	11	18.24 6.05	17	-4,432 15,185
Italy	Mean STD	4	2.52 0.95	5	2.69 1.03	5	37.42 10.27	4	94,313 16,654
Luxembourg	Mean STD	17	-0.04 0.02	18	-0.25 0.09	18	-4.52 1.69	15	-1,182 46
Malta	Mean STD	18	-0.15 0.09	16	0.10 0.12	16	1.74 2.05	14	-496 88
Netherlands	Mean STD	6	2.38 0.91	6	2.63 1.01	6	36.78 10.39	6	57,516 8,583
Portugal	Mean STD	10	1.67 0.68	10	1.92 0.79	10	28.53 9.03	9	8,860 1,049
Slovakia	Mean STD	15	0.03 0.14	14	0.31 0.23	14	5.40 3.89	12	339 26
Slovenia	Mean STD	14	0.08 0.12	15	0.27 0.17	15	4.63 2.90	13	-80 18
Spain	Mean STD	5	2.44 0.98	1	2.90 1.16	1	39.53 10.97	5	64,698 15,089
PIIGS	Mean STD	8	2.25 0.95	4	2.71 1.15	4	37.42 11.18	2	182,575 32,550

Notes: The table ranks the average exposure to systemic risk measures according to $MES, LRMES, SRISK\ and\ \Delta CoVaR$ of each member state in the Eurozone. Simple averages and standard deviations are computed within the overall period (2000-2015) in panel (A), pre-crisis period (Q3 2004-Q2 2007) in panel (B), and post-crisis period (Q3 2010- Q2 2013) in panel (C). Standard deviations and average $MES, LRMES\ and\ \Delta CoVaR$ figures are expressed as a percentage while $SRISK$ figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $q = 5\%$ level.

Appendix G:

Average Systemic Risk Measures of Each Financial Sector within Member States

(Overall Period)

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (A): Banks									
Austria	Mean	10	1.78	9	2.20	9	30.51	8	3,829
	STD		1.32		1.51		15.46		2,909
Belgium	Mean	3	2.70	2	3.11	3	38.65	7	19,689
	STD		2.10		2.40		19.14		13,389
Cyprus	Mean	12	1.07	12	1.32	12	19.65	12	-25
	STD		0.99		1.12		14.02		1,399
Finland	Mean	13	0.09	13	0.30	13	5.26	11	60
	STD		0.02		0.07		1.12		50
France	Mean	2	2.76	3	2.97	2	38.84	1	169,334
	STD		1.64		1.78		15.50		84,593
Germany	Mean	9	1.95	10	2.18	8	31.22	5	26,358
	STD		1.01		1.12		11.29		10,656
Greece	Mean	7	2.12	8	2.21	10	30.27	14	-2,557
	STD		1.51		1.60		17.01		10,981
Ireland	Mean	6	2.34	6	2.63	6	32.70	15	-3,178
	STD		2.47		2.74		19.55		14,225
Italy	Mean	5	2.45	4	2.70	5	35.76	3	38,474
	STD		1.59		1.75		16.75		35,993
Malta	Mean	15	0.04	14	0.11	14	1.93	13	-246
	STD		0.11		0.14		1.88		270
Netherlands	Mean	1	2.92	1	3.25	1	39.12	6	24,129
	STD		2.46		2.70		20.61		23,933
Portugal	Mean	11	1.53	11	1.92	11	27.64	9	3,717
	STD		1.00		1.20		13.76		4,526
Slovakia	Mean	14	0.05	15	0.07	15	1.02	10	332
	STD		0.28		0.36		4.80		861
Spain	Mean	4	2.46	5	2.67	4	36.41	4	32,074
	STD		1.30		1.42		13.72		27,830
PIIGS	Mean	8	2.09	7	2.27	7	31.75	2	64,485
	STD		1.23		1.33		14.17		78,881

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (B): Diversified Financial									
Austria	Mean	12	0.18	12	0.40	12	6.94	5	-58
	STD		0.11		0.19		2.94		24
Belgium	Mean	6	1.20	6	1.44	6	21.72	14	-7,757
	STD		0.89		1.03		11.58		4,704
Cyprus	Mean	9	0.73	11	0.90	11	14.45	7	-131
	STD		0.55		0.59		8.61		110
Finland	Mean	10	0.71	10	0.92	10	15.08	8	-187
	STD		0.36		0.44		6.35		81
France	Mean	5	1.31	4	1.59	4	23.74	13	-5,546
	STD		0.92		1.05		12.25		2,924
Germany	Mean	1	2.06	1	2.49	1	34.34	1	60,577
	STD		1.20		1.44		13.35		33,946
Greece	Mean	7	1.10	8	1.26	8	19.85	2	3,451
	STD		0.56		0.60		7.96		2,889
Ireland	Mean	11	0.59	9	1.15	9	18.10	6	-77
	STD		0.43		0.67		8.52		45
Italy	Mean	3	1.68	3	1.98	3	29.20	11	-2,202
	STD		0.77		0.88		10.22		2,600
Luxembourg	Mean	13	0.08	13	0.32	13	5.54	9	-917
	STD		0.02		0.08		1.37		227
Netherlands	Mean	8	0.90	7	1.36	7	20.96	12	-2,553
	STD		0.63		0.80		9.58		2,316
Slovenia	Mean	14	0.00	14	0.00	14	0.05	4	-4
	STD		0.00		0.00		0.05		2
Spain	Mean	4	1.34	5	1.51	5	23.28	10	-1,452
	STD		0.64		0.71		9.05		463
PIIGS	Mean	2	1.95	2	2.20	2	30.95	3	72
	STD		1.19		1.33		14.20		5,592

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (C): Insurance									
Austria	Mean	8	0.92	9	1.14	9	17.45	10	-879
	STD		0.84		0.97		12.40		1,078
Cyprus	Mean	12	0.34	11	0.73	11	12.19	7	-33
	STD		0.18		0.26		3.95		40
Finland	Mean	7	1.46	7	1.63	7	24.26	12	-4,250
	STD		0.92		1.01		12.40		4,855
France	Mean	2	2.65	2	2.98	2	39.13	1	22,918
	STD		1.51		1.70		14.66		11,003
Germany	Mean	3	2.08	3	2.47	3	33.68	2	15,673
	STD		1.37		1.61		14.63		24,558
Greece	Mean	9	0.88	8	1.50	8	23.25	9	-332
	STD		0.49		0.58		7.53		2,610
Ireland	Mean	10	0.53	10	0.93	10	14.88	8	-228
	STD		0.48		0.65		8.59		192
Italy	Mean	5	1.84	5	2.02	5	29.31	4	3,685
	STD		0.97		1.06		12.12		9,561
Netherlands	Mean	1	3.11	1	3.58	1	43.01	3	7,890
	STD		2.32		2.64		17.95		7,018
Slovenia	Mean	11	0.44	12	0.64	12	9.37	5	2,529
	STD		0.93		1.03		16.73		5,210
Spain	Mean	6	1.61	6	1.83	6	26.74	11	-1,447
	STD		1.00		1.09		13.02		1,608
PIIGS	Mean	4	1.94	4	2.09	4	29.58	6	2,141
	STD		1.23		1.32		14.23		9,969

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (D): Real-estate									
Austria	Mean	6	0.93	5	1.28	6	17.46	9	-2,732
	STD		1.30		1.78		18.20		1,989
Belgium	Mean	8	0.58	10	0.73	10	11.77	8	-2,273
	STD		0.53		0.66		9.34		1,472
Cyprus	Mean	12	0.44	9	0.85	9	14.01	1	-93
	STD		0.20		0.31		4.52		80
Estonia	Mean	13	0.01	13	0.13	13	2.24	6	-1,288
	STD		0.01		0.19		3.27		615
Finland	Mean	1	1.37	2	1.74	2	25.08	4	-645
	STD		1.07		1.33		15.22		554
France	Mean	5	1.02	6	1.27	5	19.19	13	-8,724
	STD		0.85		1.05		13.22		6,707
Germany	Mean	11	0.46	11	0.67	11	11.11	10	-2,962
	STD		0.34		0.44		6.45		1,603
Greece	Mean	7	0.66	7	1.06	7	17.06	3	-338
	STD		0.34		0.46		6.32		168
Italy	Mean	3	1.30	1	1.83	1	26.36	5	-963
	STD		1.00		1.29		14.32		717
Malta	Mean	10	0.46	12	0.61	12	8.82	2	-178
	STD		0.81		1.12		15.41		340
Netherlands	Mean	4	1.14	4	1.40	4	20.76	11	-2,988
	STD		0.92		1.14		14.26		1,678
Spain	Mean	9	0.50	8	0.87	8	14.19	7	-2,099
	STD		0.33		0.48		6.94		2,429
PIIGS	Mean	2	1.31	3	1.69	3	24.42	12	-3,213
	STD		1.05		1.32		15.13		3,341

Notes: The table ranks the average exposure to systemic risk measures according to $MES, SRISK\ and\ \Delta CoVaR$ of each member state in the Eurozone. Simple averages and standard deviations are computed within the overall period (2000-2015). Standard deviations and average $MES\ and\ \Delta CoVaR$ figures are expressed as a percentage while $SRISK$ figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $\alpha = 5\%$ level.

Appendix H:
Average Systemic Risk Measures of Each Financial Sector within Member States
(Pre-crisis Period)

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	%	Rank	%	Rank	%	Rank	Value
Panel (A): Banks									
Austria	Mean	9	0.87	9	1.33	7	21.22	7	358
	STD		0.23		0.29		4.00		1,664
Belgium	Mean	4	1.06	5	1.46	5	22.70	4	11,688
	STD		0.42		0.55		6.78		3,752
Cyprus	Mean	11	0.52	11	0.92	11	15.10	12	-884
	STD		0.28		0.42		6.04		1,232
Finland	Mean	13	0.05	13	0.48	13	8.24	9	22
	STD		0.01		0.05		0.87		8
France	Mean	1	1.34	2	1.73	2	26.54	1	112,008
	STD		0.31		0.39		4.88		19,421
Germany	Mean	3	1.15	1	1.79	1	27.31	2	18,988
	STD		0.31		0.43		5.13		3,154
Greece	Mean	10	0.85	8	1.33	9	21.12	15	-14,218
	STD		0.31		0.42		5.52		5,618
Ireland	Mean	7	0.92	4	1.48	4	23.09	13	-3,305
	STD		0.30		0.44		5.68		1,878
Italy	Mean	5	0.94	7	1.33	8	21.17	6	1,431
	STD		0.28		0.38		5.10		7,602
Malta	Mean	15	0.03	14	0.23	14	4.08	10	-92
	STD		0.02		0.14		2.25		138
Netherlands	Mean	8	0.92	6	1.45	6	22.52	5	8,146
	STD		0.52		0.62		8.86		9,273
Portugal	Mean	12	0.50	12	0.77	12	12.78	11	-749
	STD		0.21		0.30		4.35		1,827
Slovakia	Mean	14	0.04	15	0.12	15	2.12	8	119
	STD		0.10		0.14		2.51		36
Spain	Mean	2	1.15	3	1.61	3	24.96	3	13,113
	STD		0.28		0.37		4.69		6,247
PIIGS	Mean	6	0.92	10	1.32	10	20.92	14	-6,544
	STD		0.31		0.41		5.39		20,843

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (B): Diversified Financial									
Austria	Mean	12	0.15	12	0.15	12	2.74	4	-46
	STD		0.05		0.05		0.84		12
Belgium	Mean	8	0.71	9	1.10	9	17.62	14	-10,771
	STD		0.35		0.49		6.42		2,674
Cyprus	Mean	5	0.76	8	1.10	8	17.85	6	-125
	STD		0.27		0.34		4.91		56
Finland	Mean	11	0.50	11	0.99	11	16.20	7	-213
	STD		0.21		0.29		4.05		31
France	Mean	6	0.74	7	1.12	7	17.94	13	-7,812
	STD		0.38		0.50		6.50		1,972
Germany	Mean	1	1.05	2	1.48	2	23.16	1	33,403
	STD		0.35		0.48		6.08		12,600
Greece	Mean	9	0.65	10	1.01	10	16.54	2	775
	STD		0.25		0.34		4.79		148
Ireland	Mean	10	0.63	6	1.23	6	19.36	5	-53
	STD		0.52		0.66		8.73		21
Italy	Mean	2	1.02	1	1.55	1	24.28	11	-5,444
	STD		0.21		0.28		3.72		1,184
Luxembourg	Mean	13	0.05	13	0.11	13	1.89	8	-796
	STD		0.11		0.14		2.37		129
Netherlands	Mean	7	0.72	5	1.30	5	20.55	9	-1,589
	STD		0.36		0.53		6.38		822
Slovenia	Mean	14	0.00	14	0.00	14	0.03	3	-4
	STD		0.00		0.00		0.04		2
Spain	Mean	4	0.88	3	1.35	3	21.55	10	-1,669
	STD		0.19		0.25		3.47		494
PIIGS	Mean	3	0.96	4	1.32	4	20.95	12	-6,670
	STD		0.30		0.40		5.29		1,832

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (C): Insurance									
Austria	Mean	9	0.55	8	1.01	8	16.25	9	-1,800
	STD		0.38		0.51		6.86		1,009
Cyprus	Mean	10	0.42	11	0.59	11	10.13	6	-17
	STD		0.09		0.13		2.10		12
Finland	Mean	7	0.91	6	1.30	6	20.66	10	-1,832
	STD		0.28		0.32		4.58		1,511
France	Mean	1	1.76	1	2.05	1	30.65	2	16,048
	STD		0.32		0.38		4.38		3,341
Germany	Mean	3	1.30	3	1.71	3	26.39	1	27,386
	STD		0.28		0.36		4.48		11,292
Greece	Mean	8	0.55	9	0.93	9	14.29	5	-11
	STD		0.76		0.92		13.57		7
Ireland	Mean	11	0.28	10	0.63	10	10.68	7	-520
	STD		0.09		0.11		1.68		158
Italy	Mean	4	1.08	4	1.35	4	21.34	11	-2,566
	STD		0.34		0.40		5.46		2,332
Netherlands	Mean	2	1.64	2	1.98	2	29.72	3	5,350
	STD		0.38		0.45		5.35		1,361
Slovenia	Mean	12	-0.27	12	-1.21	12	-60.00	4	15
	STD		0.72		1.37		729.11		308
Spain	Mean	6	0.94	7	1.29	7	20.70	8	-1,268
	STD		0.17		0.23		3.11		1,118
PIIGS	Mean	5	1.00	5	1.30	5	20.60	12	-4,557
	STD		0.34		0.42		5.61		3,570

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (D): Real-estate									
Austria	Mean	11	0.12	11	0.21	11	3.68	11	-4,693
	STD		0.08		0.13		2.26		2,242
Belgium	Mean	8	0.28	10	0.49	10	8.35	6	-1,789
	STD		0.19		0.27		4.28		282
Cyprus	Mean	10	0.20	8	0.56	8	9.43	2	-103
	STD		0.19		0.26		4.16		56
Estonia	Mean	12	0.00	12	0.00	12	0.05	5	-1,650
	STD		0.00		0.00		0.03		3
Finland	Mean	1	0.82	1	1.41	1	21.74	4	-567
	STD		0.55		0.77		9.28		233
France	Mean	5	0.56	6	0.93	6	15.29	12	-7,234
	STD		0.23		0.34		4.94		2,473
Germany	Mean	9	0.27	9	0.50	9	8.45	8	-2,561
	STD		0.22		0.32		4.98		860
Greece	Mean	4	0.59	5	0.99	5	16.02	3	-382
	STD		0.40		0.53		7.40		160
Italy	Mean	2	0.73	2	1.35	2	21.05	7	-2,048
	STD		0.42		0.65		8.03		686
Malta	Mean	13	-0.01	13	-0.11	13	-2.03	1	-10
	STD		0.10		0.13		2.47		1
Netherlands	Mean	3	0.69	4	1.14	4	18.09	9	-3,057
	STD		0.39		0.58		7.65		626
Spain	Mean	6	0.56	3	1.16	3	18.19	10	-4,413
	STD		0.50		0.80		7.48		3,840
PIIGS	Mean	7	0.52	7	0.91	7	14.80	13	-7,238
	STD		0.31		0.42		6.01		4,752

Notes: The table ranks the average exposure to systemic risk measures according to $MES, SRISK\ and\ \Delta CoVaR$ of each member state in the Eurozone. Simple averages and standard deviations are computed within the pre-crisis period (Q3 2004-Q2 2007). Standard deviations and average $MES\ and\ \Delta CoVaR$ figures are expressed as a percentage while $SRISK$ figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $\alpha = 5\%$ level.

Appendix I:

Average Systemic Risk Measures of Each Financial Sector within Member States

(Post-crisis Period)

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (A): Banks									
Austria	Mean	9	2.49	6	2.97	6	40.68	10	6,192
	STD		0.76		0.92		8.85		2,345
Belgium	Mean	1	4.15	1	4.67	1	54.61	7	24,474
	STD		1.65		1.87		13.03		14,428
Cyprus	Mean	12	1.60	12	1.35	12	21.00	11	1,363
	STD		0.72		0.66		9.17		628
Finland	Mean	13	0.05	13	0.21	13	3.58	13	98
	STD		0.24		0.26		4.41		31
France	Mean	3	3.50	2	4.14	2	50.52	1	263,760
	STD		1.47		1.75		12.58		22,432
Germany	Mean	10	2.16	9	2.30	9	32.73	6	36,257
	STD		0.99		1.07		11.76		4,054
Greece	Mean	7	2.81	10	2.14	10	31.09	9	7,695
	STD		0.96		0.89		10.95		4,055
Ireland	Mean	8	2.55	11	2.11	11	30.77	15	-1,467
	STD		1.13		0.97		9.74		13,079
Italy	Mean	2	3.95	7	2.69	7	37.42	3	94,313
	STD		1.30		1.03		10.27		16,654
Malta	Mean	15	-0.10	15	-0.18	15	-3.27	14	-546
	STD		0.04		0.06		1.09		87
Netherlands	Mean	4	3.49	3	4.07	3	49.68	5	53,229
	STD		1.57		1.81		13.56		6,010
Portugal	Mean	11	1.97	8	2.34	8	33.48	8	9,067
	STD		0.82		0.97		10.15		922
Slovakia	Mean	14	0.01	14	-0.12	14	-2.29	12	323
	STD		0.25		0.27		4.99		28
Spain	Mean	5	2.99	4	3.08	4	41.92	4	69,582
	STD		0.78		0.82		8.11		11,984
PIIGS	Mean	6	2.94	5	3.02	5	41.24	2	169,209
	STD		0.82		0.85		8.39		22,905

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (B): Diversified Financial									
Austria	Mean	12	0.18	11	0.38	11	6.46	7	-62
	STD		0.15		0.24		3.88		21
Belgium	Mean	6	1.42	6	1.68	6	25.64	14	-5,757
	STD		0.52		0.60		7.44		2,564
Cyprus	Mean	10	0.41	12	0.32	12	5.67	6	-57
	STD		0.08		0.07		1.24		8
Finland	Mean	9	0.72	10	0.82	10	13.57	9	-193
	STD		0.32		0.36		5.33		27
France	Mean	4	1.86	4	2.21	4	31.62	13	-4,303
	STD		0.94		1.07		11.47		1,629
Germany	Mean	2	2.41	1	2.83	1	39.01	1	99,786
	STD		0.88		1.02		10.00		15,245
Greece	Mean	7	1.39	5	1.70	5	25.89	2	7,905
	STD		0.61		0.68		7.71		908
Ireland	Mean	11	0.22	9	0.83	9	13.88	8	-113
	STD		0.05		0.18		2.44		19
Italy	Mean	3	2.38	3	2.41	3	34.71	4	931
	STD		0.64		0.65		7.38		1,212
Luxembourg	Mean	14	-0.04	13	0.28	13	4.95	10	-1,061
	STD		0.02		0.10		1.67		48
Netherlands	Mean	8	0.98	8	1.31	8	20.64	12	-3,864
	STD		0.41		0.51		6.62		709
Slovenia	Mean	13	0.00	14	0.00	14	0.04	5	-3
	STD		0.00		0.00		0.04		1
Spain	Mean	5	1.60	7	1.66	7	25.27	11	-1,410
	STD		0.63		0.66		8.61		296
PIIGS	Mean	1	2.76	2	2.76	2	38.51	3	7,889
	STD		0.80		0.81		8.37		2,094

Member State		$\Delta CoVaR$		MES		$LRMES$		$SRISK$	
		Rank	**%**	**Rank**	**%**	**Rank**	**%**	**Rank**	**Value**
Panel (C): Insurance									
Austria	Mean	8	1.34	8	1.89	7	28.37	10	-449
	STD		0.49		0.66		7.85		778
Cyprus	Mean	12	0.04	11	0.20	11	3.47	7	-17
	STD		0.02		0.07		1.23		8
Finland	Mean	7	1.68	7	1.90	8	28.25	12	-6,041
	STD		0.68		0.78		9.33		2,131
France	Mean	2	2.97	2	3.38	2	44.08	1	36,258
	STD		1.22		1.37		11.69		5,786
Germany	Mean	6	2.04	6	2.47	6	34.66	2	14,871
	STD		0.96		1.15		11.50		9,298
Greece	Mean	10	0.46	10	0.69	10	11.51	6	-1
	STD		0.22		0.27		4.34		6
Ireland	Mean	9	0.67	9	1.06	9	17.32	9	-145
	STD		0.18		0.23		3.39		61
Italy	Mean	4	2.54	5	2.64	5	37.32	3	14,605
	STD		0.67		0.72		7.71		2,770
Netherlands	Mean	1	3.08	1	3.69	1	46.94	4	14,014
	STD		1.24		1.47		12.11		1,446
Slovenia	Mean	11	0.07	12	0.07	12	1.13	8	-81
	STD		0.21		0.23		3.92		21
Spain	Mean	5	2.47	3	2.87	3	39.95	11	-1,232
	STD		0.54		0.63		6.56		851
PIIGS	Mean	3	2.76	4	2.73	4	38.08	5	13,272
	STD		0.87		0.89		9.23		3,660

Member State		$\Delta CoVaR$ Rank	$\Delta CoVaR$ %	MES Rank	MES %	$LRMES$ Rank	$LRMES$ %	$SRISK$ Rank	$SRISK$ Value
Panel (D): Real-estate									
Austria	Mean	6	1.44	6	1.86	6	27.78	9	-2,848
	STD		0.60		0.75		8.65		771
Belgium	Mean	7	0.77	9	0.91	9	14.88	10	-2,932
	STD		0.32		0.38		5.19		438
Cyprus	Mean	10	0.54	10	0.89	10	14.77	2	-39
	STD		0.10		0.17		2.54		16
Estonia	Mean	13	-0.01	13	0.03	13	0.54	8	-1,335
	STD		0.02		0.05		0.95		613
Finland	Mean	3	1.94	3	2.29	3	33.06	5	-786
	STD		0.74		0.86		8.73		254
France	Mean	5	1.56	5	1.92	5	28.06	13	-10,956
	STD		0.84		1.02		11.53		3,279
Germany	Mean	9	0.61	11	0.82	11	13.57	12	-3,627
	STD		0.20		0.26		3.73		571
Greece	Mean	11	0.42	8	0.91	8	14.98	3	-202
	STD		0.14		0.30		4.48		44
Italy	Mean	2	2.10	1	2.88	1	39.24	4	-416
	STD		0.89		1.16		11.66		253
Malta	Mean	12	0.10	12	0.17	12	2.88	1	-10
	STD		0.16		0.18		3.26		4
Netherlands	Mean	4	1.81	4	2.13	4	30.82	11	-3,407
	STD		0.83		0.99		11.08		902
Spain	Mean	8	0.77	7	1.03	7	16.68	6	-1,001
	STD		0.37		0.45		6.51		711
PIIGS	Mean	1	2.23	2	2.42	2	34.77	7	-1,278
	STD		0.65		0.74		8.14		891

Notes: The table ranks the average exposure to systemic risk measures according to $MES, SRISK\ and\ \Delta CoVaR$ of each member state in the Eurozone. Simple averages and standard deviations are computed within the post-crisis period (Q3 2010- Q2 2013). Standard deviations and average $MES\ and\ \Delta CoVaR$ figures are expressed as a percentage while $SRISK$ figures are expressed in terms of billion Euros. All risk measures are generated under the assumption of $\alpha = 5\%$ level.

Appendix J:

Average Conditional Contribution ΔCoVaR of Financial Institutions (Overall Period)

Member State	Sector	Institution	$\Delta CoVaR_q^{sys\|i}$	Rank
Austria	BKUS AV Equity	Banks	-0.08	240
Austria	BTUV AV Equity	Banks	0.00	270
Austria	EBS AV Equity	Banks	-1.03	28
Austria	OBS AV Equity	Banks	0.00	283
Austria	VVPS AV Equity	Banks	0.00	279
Austria	UIV AV Equity	Diversified Financials	-0.10	229
Austria	WPB AV Equity	Diversified Financials	0.09	305
Austria	UQA AV Equity	Insurance	-0.24	166
Austria	VIG AV Equity	Insurance	-0.13	209
Austria	ATRS AV Equity	Real Estate	-0.05	256
Austria	CAI AV Equity	Real Estate	-0.43	101
Austria	CWI AV Equity	Real Estate	-0.13	216
Austria	IIA AV Equity	Real Estate	-0.29	141
Austria	SPI AV Equity	Real Estate	-0.37	113
Austria	STM AV Equity	Real Estate	-0.01	267
Austria	UBS AV Equity	Real Estate	-0.11	225
Belgium	DEXB BB Equity	Banks	-0.40	106
Belgium	KBC BB Equity	Banks	-0.98	33
Belgium	ACKB BB Equity	Diversified Financials	-1.17	23
Belgium	BELU BB Equity	Diversified Financials	-0.04	260
Belgium	BNB BB Equity	Diversified Financials	-0.53	86
Belgium	BREB BB Equity	Diversified Financials	-0.63	70
Belgium	COMB BB Equity	Diversified Financials	-0.53	83
Belgium	GBLB BB Equity	Diversified Financials	-1.33	14
Belgium	GIMB BB Equity	Diversified Financials	-0.77	55
Belgium	KBCA BB Equity	Diversified Financials	-0.82	47
Belgium	QFG BB Equity	Diversified Financials	-0.19	191
Belgium	SOF BB Equity	Diversified Financials	-1.07	27
Belgium	TUB BB Equity	Diversified Financials	-0.96	34
Belgium	ATEB BB Equity	Real Estate	-0.41	102
Belgium	BEFB BB Equity	Real Estate	-0.39	108
Belgium	BELR BB Equity	Real Estate	0.00	277
Belgium	COFB BB Equity	Real Estate	-0.51	88
Belgium	CPINV BB Equity	Real Estate	-0.04	259
Belgium	HOMI BB Equity	Real Estate	0.12	311
Belgium	IMMO BB Equity	Real Estate	-0.48	93
Belgium	INTO BB Equity	Real Estate	-0.09	234
Belgium	LEAS BB Equity	Real Estate	-0.23	170
Belgium	RET BB Equity	Real Estate	-0.14	206
Belgium	SOFT BB Equity	Real Estate	-0.28	142
Belgium	VASTB BB Equity	Real Estate	-0.30	137
Belgium	WDP BB Equity	Real Estate	-0.52	87
Belgium	WEB BB Equity	Real Estate	-0.22	176
Belgium	WEHB BB Equity	Real Estate	-0.33	129

Cyprus	BOCY CY Equity	Banks	-0.22	181
Cyprus	HB CY Equity	Banks	-0.25	163
Cyprus	USB CY Equity	Banks	-0.02	265
Cyprus	AIAS CY Equity	Diversified Financials	-0.09	232
Cyprus	DEM CY Equity	Diversified Financials	-0.44	99
Cyprus	ELF CY Equity	Diversified Financials	-0.23	168
Cyprus	EXE CY Equity	Diversified Financials	-0.05	257
Cyprus	LI CY Equity	Diversified Financials	-0.23	171
Cyprus	SFS CY Equity	Diversified Financials	-0.34	125
Cyprus	ATL CY Equity	Insurance	-0.18	192
Cyprus	LIB CY Equity	Insurance	-0.08	239
Cyprus	MINE CY Equity	Insurance	-0.09	237
Cyprus	FWW CY Equity	Real Estate	-0.25	159
Cyprus	KG CY Equity	Real Estate	-0.12	222
Cyprus	PES CY Equity	Real Estate	-0.12	220
Cyprus	PND CY Equity	Real Estate	-0.22	178
Estonia	PKG1T ET Equity	Real Estate	0.04	296
Estonia	TPD1T ET Equity	Real Estate	0.00	284
Finland	ALBAV FH Equity	Banks	-0.05	251
Finland	CPMBV FH Equity	Diversified Financials	-0.51	91
Finland	EQV1V FH Equity	Diversified Financials	-0.22	182
Finland	NORVE FH Equity	Diversified Financials	-0.21	185
Finland	SCI1V FH Equity	Diversified Financials	-0.44	100
Finland	SAMAS FH Equity	Insurance	-0.96	35
Finland	CTY1S FH Equity	Real Estate	-0.23	172
Finland	SDA1V FH Equity	Real Estate	-0.77	56
Finland	INVEST FH Equity	Real Estate	0.02	291
Finland	TPS1V FH Equity	Real Estate	-0.46	97
France	ACA FP Equity	Banks	-1.45	12
France	BNP FP Equity	Banks	-1.93	2
France	BQRE FP Equity	Banks	-0.26	153
France	CAF FP Equity	Banks	-0.47	95
France	CAT31 FP Equity	Banks	-0.36	117
France	CC FP Equity	Banks	-0.58	79
France	CCN FP Equity	Banks	-0.37	116
France	CIV FP Equity	Banks	-0.38	111
France	CMO FP Equity	Banks	-0.51	89
France	CNF FP Equity	Banks	-0.62	72
France	CRAP FP Equity	Banks	-0.26	154
France	CRAV FP Equity	Banks	-0.26	157
France	CRLO FP Equity	Banks	-0.25	158
France	CRSU FP Equity	Banks	-0.28	144
France	CRTO FP Equity	Banks	-0.14	205
France	GLE FP Equity	Banks	-1.84	6
France	KN FP Equity	Banks	-0.79	53
France	LD FP Equity	Banks	-0.28	148
France	MLCFM FP Equity	Banks	-0.12	219
France	MLFMM FP Equity	Banks	0.00	274
France	ABCA FP Equity	Diversified Financials	-0.56	81
France	ALGIS FP Equity	Diversified Financials	0.02	290

France	ALIDS FP Equity	Diversified Financials	-0.37	115
France	ALSIP FP Equity	Diversified Financials	-0.09	233
France	ARTO FP Equity	Diversified Financials	-0.23	173
France	FFP FP Equity	Diversified Financials	-1.31	16
France	IDIP FP Equity	Diversified Financials	-0.13	212
France	LBON FP Equity	Diversified Financials	-0.51	92
France	LTA FP Equity	Diversified Financials	-0.31	132
France	MF FP Equity	Diversified Financials	-1.07	26
France	MLCVG FP Equity	Diversified Financials	0.00	278
France	MONC FP Equity	Diversified Financials	-0.13	213
France	PAOR FP Equity	Diversified Financials	-0.01	268
France	RF FP Equity	Diversified Financials	-1.28	18
France	SCDU FP Equity	Diversified Financials	0.11	309
France	SOFR FP Equity	Diversified Financials	0.06	301
France	SY FP Equity	Diversified Financials	-0.11	226
France	UFF FP Equity	Diversified Financials	-0.73	62
France	VIL FP Equity	Diversified Financials	-0.28	145
France	APR FP Equity	Insurance	-0.85	44
France	CNP FP Equity	Insurance	-1.17	22
France	CS FP Equity	Insurance	-1.90	3
France	ELE FP Equity	Insurance	-0.87	42
France	SCR FP Equity	Insurance	-0.60	76
France	ALSAS FP Equity	Real Estate	-0.37	114
France	ALTA FP Equity	Real Estate	-0.05	252
France	AREIT FP Equity	Real Estate	0.00	281
France	BERR FP Equity	Real Estate	0.04	297
France	COUR FP Equity	Real Estate	-0.16	198
France	DP FP Equity	Real Estate	-0.03	261
France	EEM FP Equity	Real Estate	-0.27	151
France	EIFF FP Equity	Real Estate	-0.25	160
France	FDL FP Equity	Real Estate	0.01	287
France	FDPA FP Equity	Real Estate	-0.08	241
France	FDR FP Equity	Real Estate	-0.69	64
France	FLY FP Equity	Real Estate	-0.28	143
France	FMU FP Equity	Real Estate	-0.05	253
France	GFC FP Equity	Real Estate	-0.75	59
France	ICAD FP Equity	Real Estate	-0.25	161
France	IMDA FP Equity	Real Estate	-0.04	258
France	IML FP Equity	Real Estate	-0.61	74
France	LI FP Equity	Real Estate	-0.79	52
France	MLMAB FP Equity	Real Estate	0.00	276
France	MRM FP Equity	Real Estate	-0.06	246
France	ORC FP Equity	Real Estate	-0.29	138
France	ORIA FP Equity	Real Estate	-0.14	208
France	SFBS FP Equity	Real Estate	-0.01	269
France	SPEL FP Equity	Real Estate	0.03	294
Germany	ARL GR Equity	Banks	-0.21	184
Germany	CBK GR Equity	Banks	-1.00	32
Germany	COM GR Equity	Banks	-1.15	24
Germany	DVB GR Equity	Banks	-0.11	224

Germany	IKB GR Equity	Banks	-0.40	105
Germany	MBK GR Equity	Banks	-0.07	242
Germany	OLB GR Equity	Banks	-0.27	149
Germany	TUB GR Equity	Banks	0.24	315
Germany	UBK GR Equity	Banks	-0.14	203
Germany	ADC GR Equity	Diversified Financials	-0.07	244
Germany	ALG GR Equity	Diversified Financials	-0.34	126
Germany	ATW GR Equity	Diversified Financials	0.01	289
Germany	BBH GR Equity	Diversified Financials	-0.06	245
Germany	BFV GR Equity	Diversified Financials	-0.24	165
Germany	BTBA GR Equity	Diversified Financials	-0.22	175
Germany	BWB GR Equity	Diversified Financials	-0.66	68
Germany	CCB GR Equity	Diversified Financials	-0.06	248
Germany	CMBT GR Equity	Diversified Financials	-0.34	124
Germany	DB1 GR Equity	Diversified Financials	-0.62	73
Germany	DBAN GR Equity	Diversified Financials	-0.71	63
Germany	DBK GR Equity	Diversified Financials	-1.90	4
Germany	DLB GR Equity	Diversified Financials	-0.13	214
Germany	DRN GR Equity	Diversified Financials	-0.85	45
Germany	EFF GR Equity	Diversified Financials	-0.26	156
Germany	EFS GR Equity	Diversified Financials	-0.30	135
Germany	EUX GR Equity	Diversified Financials	-0.13	210
Germany	FAK GR Equity	Diversified Financials	-0.05	254
Germany	FRS GR Equity	Diversified Financials	-0.25	162
Germany	GBQ GR Equity	Diversified Financials	-0.05	255
Germany	GLJ GR Equity	Diversified Financials	-0.81	50
Germany	HGL GR Equity	Diversified Financials	0.12	310
Germany	HRU GR Equity	Diversified Financials	0.10	307
Germany	IPO GR Equity	Diversified Financials	-0.01	266
Germany	KSW GR Equity	Diversified Financials	-0.09	236
Germany	MLP GR Equity	Diversified Financials	-0.31	133
Germany	MPCK GR Equity	Diversified Financials	-0.20	186
Germany	MWB GR Equity	Diversified Financials	-0.38	110
Germany	ICP GR Equity	Diversified Financials	-0.12	217
Germany	PEH GR Equity	Diversified Financials	-0.47	96
Germany	PPZ GR Equity	Diversified Financials	-0.02	263
Germany	RMO GR Equity	Diversified Financials	0.04	295
Germany	SPT6 GR Equity	Diversified Financials	-0.18	193
Germany	SPZI GR Equity	Diversified Financials	0.00	285
Germany	SVE GR Equity	Diversified Financials	-0.15	202
Germany	UCA1 GR Equity	Diversified Financials	-0.35	121
Germany	VEH GR Equity	Diversified Financials	-0.15	201
Germany	VHO GR Equity	Diversified Financials	-0.22	177
Germany	VVV3 GR Equity	Diversified Financials	-0.31	134
Germany	WUW GR Equity	Diversified Financials	-0.09	235
Germany	ALV GR Equity	Insurance	-1.68	9
Germany	HNR1 GR Equity	Insurance	-1.18	21
Germany	MUV2 GR Equity	Insurance	-1.83	7
Germany	NBG6 GR Equity	Insurance	-0.28	146
Germany	RLV GR Equity	Insurance	-0.06	247

Germany	WLV GR Equity	Insurance	-0.09	238
Germany	AAA GR Equity	Real Estate	0.02	293
Germany	ABHA GR Equity	Real Estate	-0.03	262
Germany	ADL GR Equity	Real Estate	-0.11	227
Germany	AGR GR Equity	Real Estate	-0.12	223
Germany	BBI GR Equity	Real Estate	-0.12	218
Germany	BBR GR Equity	Real Estate	-0.07	243
Germany	BFK GR Equity	Real Estate	0.07	304
Germany	DAL GR Equity	Real Estate	0.05	299
Germany	DEQ GR Equity	Real Estate	-0.82	48
Germany	DGR GR Equity	Real Estate	-0.31	131
Germany	DIC GR Equity	Real Estate	-0.14	204
Germany	GWK3 GR Equity	Real Estate	-0.13	211
Germany	HAB GR Equity	Real Estate	-0.28	147
Germany	KBU GR Equity	Real Estate	-0.24	167
Germany	LBN GR Equity	Real Estate	-0.25	164
Germany	LBR GR Equity	Real Estate	-0.35	119
Germany	MUK GR Equity	Real Estate	-0.26	155
Germany	SGB GR Equity	Real Estate	0.10	308
Germany	SIN GR Equity	Real Estate	0.16	313
Germany	SMWN GR Equity	Real Estate	-0.34	122
Germany	SPB GR Equity	Real Estate	-0.06	250
Germany	STG GR Equity	Real Estate	-0.20	187
Germany	TEG GR Equity	Real Estate	-0.27	152
Germany	WEG1 GR Equity	Real Estate	-0.10	230
Greece	ALPHA GA Equity	Banks	-0.51	90
Greece	ETE GA Equity	Banks	-0.30	136
Greece	EUROB GA Equity	Banks	-0.27	150
Greece	TATT GA Equity	Banks	-0.29	140
Greece	TPEIR GA Equity	Banks	-0.20	189
Greece	EXAE GA Equity	Diversified Financials	-0.66	69
Greece	TELL GA Equity	Diversified Financials	-0.48	94
Greece	EUPIC GA Equity	Insurance	-0.38	112
Greece	ASTAK GA Equity	Real Estate	-0.23	174
Greece	KAMP GA Equity	Real Estate	-0.39	107
Greece	KEKR GA Equity	Real Estate	-0.35	120
Greece	LAMDA GA Equity	Real Estate	-0.22	180
Ireland	ALBK ID Equity	Banks	-0.53	84
Ireland	BKIR ID Equity	Banks	-0.40	104
Ireland	IFP ID Equity	Diversified Financials	-0.17	196
Ireland	FBD ID Equity	Insurance	-0.55	82
Italy	BDB IM Equity	Banks	-0.75	60
Italy	BMPS IM Equity	Banks	-0.68	65
Italy	BPE IM Equity	Banks	-0.88	41
Italy	BPSO IM Equity	Banks	-0.78	54
Italy	BSRP IM Equity	Banks	-0.61	75
Italy	CE IM Equity	Banks	-1.19	20
Italy	CRG IM Equity	Banks	-0.33	128
Italy	CVAL IM Equity	Banks	-0.58	80
Italy	ISP IM Equity	Banks	-0.89	40

Italy	PEL IM Equity	Banks	-0.17	195
Italy	PMI IM Equity	Banks	-0.91	39
Italy	UBI IM Equity	Banks	-1.03	29
Italy	UCG IM Equity	Banks	-1.21	19
Italy	BIM IM Equity	Diversified Financials	-0.39	109
Italy	DEA IM Equity	Diversified Financials	-0.67	67
Italy	IF IM Equity	Diversified Financials	-0.35	118
Italy	LVEN IM Equity	Diversified Financials	-0.22	183
Italy	MB IM Equity	Diversified Financials	-1.40	13
Italy	PRO IM Equity	Diversified Financials	-0.62	71
Italy	CASS IM Equity	Insurance	-0.86	43
Italy	G IM Equity	Insurance	-1.76	8
Italy	UNI IM Equity	Insurance	-0.15	200
Italy	VAS IM Equity	Insurance	-0.76	57
Italy	AE IM Equity	Real Estate	-0.23	169
Italy	BNS IM Equity	Real Estate	-1.02	30
Italy	BRI IM Equity	Real Estate	-0.45	98
Italy	GAB IM Equity	Real Estate	-0.20	188
Italy	NR IM Equity	Real Estate	-0.11	228
Italy	RN IM Equity	Real Estate	-0.12	221
Luxembourg	COFI LX Equity	Diversified Financials	0.00	271
Luxembourg	INSIN LX Equity	Diversified Financials	0.06	303
Luxembourg	LXMP LX Equity	Diversified Financials	-0.34	127
Luxembourg	QUIL LX Equity	Diversified Financials	0.13	312
Malta	BOV MV Equity	Banks	0.09	306
Malta	FIM MV Equity	Banks	0.06	302
Malta	HSB MV Equity	Banks	0.04	298
Malta	LOM MV Equity	Banks	-0.02	264
Malta	PZC MV Equity	Real Estate	0.00	273
Netherlands	INGA NA Equity	Banks	-2.17	1
Netherlands	LANS NA Equity	Banks	-0.33	130
Netherlands	BINCK NA Equity	Diversified Financials	-0.58	78
Netherlands	HAL NA Equity	Diversified Financials	-0.93	37
Netherlands	KA NA Equity	Diversified Financials	-0.68	66
Netherlands	KARD NA Equity	Diversified Financials	-0.53	85
Netherlands	VALUE NA Equity	Diversified Financials	-0.13	215
Netherlands	AGN NA Equity	Insurance	-1.64	10
Netherlands	BEVER NA Equity	Real Estate	-0.14	207
Netherlands	CORA NA Equity	Real Estate	-0.74	61
Netherlands	ECMPA NA Equity	Real Estate	-0.80	51
Netherlands	GROHA NA Equity	Real Estate	-0.18	194
Netherlands	NSI NA Equity	Real Estate	-0.40	103
Netherlands	VASTN NA Equity	Real Estate	-0.81	49
Netherlands	WHA NA Equity	Real Estate	-0.84	46
Portugal	BCP PL Equity	Banks	-0.59	77
Portugal	BPI PL Equity	Banks	-1.01	31
Portugal	ESF PL Equity	Banks	-0.06	249
Slovakia	VUB SK Equity	Banks	0.20	314
Slovenia	NIKN SV Equity	Diversified Financials	0.00	282
Slovenia	KDHR SV Equity	Insurance	0.02	292

Spain	BBVA SM Equity	Banks	-1.64	11
Spain	BKT SM Equity	Banks	-1.31	15
Spain	POP SM Equity	Banks	-1.12	25
Spain	SAB SM Equity	Banks	-0.75	58
Spain	SAN SM Equity	Banks	-1.85	5
Spain	ALB SM Equity	Diversified Financials	-1.30	17
Spain	CGI SM Equity	Diversified Financials	-0.16	199
Spain	REA SM Equity	Diversified Financials	0.05	300
Spain	UEI SM Equity	Diversified Financials	0.01	288
Spain	GCO SM Equity	Insurance	-0.92	38
Spain	MAP SM Equity	Insurance	-0.95	36
Spain	CEV SM Equity	Real Estate	0.00	275
Spain	COL SM Equity	Real Estate	-0.29	139
Spain	FICIS SM Equity	Real Estate	0.00	280
Spain	ILV SM Equity	Real Estate	0.00	272
Spain	LIB SM Equity	Real Estate	0.00	286
Spain	MTB SM Equity	Real Estate	-0.17	197
Spain	QBT SM Equity	Real Estate	-0.34	123
Spain	STG SM Equity	Real Estate	-0.22	179
Spain	TST SM Equity	Real Estate	-0.10	231
Spain	UBS SM Equity	Real Estate	-0.19	190

Appendix K:

Average Conditional Contribution ΔCoVaR of Financial Institutions (Pre-crisis Period)

Member State	Sector	Institution	$\Delta CoVaR_q^{sys\|i}$	Rank
Austria	BKUS AV Equity	Banks	-0.02	236
Austria	BTUV AV Equity	Banks	0.04	283
Austria	EBS AV Equity	Banks	-0.43	48
Austria	OBS AV Equity	Banks	0.07	292
Austria	VVPS AV Equity	Banks	0.01	273
Austria	UIV AV Equity	Diversified Financials	-0.09	185
Austria	WPB AV Equity	Diversified Financials	0.20	307
Austria	UQA AV Equity	Insurance	-0.29	89
Austria	VIG AV Equity	Insurance	0.00	259
Austria	ATRS AV Equity	Real Estate	0.00	265
Austria	CAI AV Equity	Real Estate	-0.01	248
Austria	CWI AV Equity	Real Estate	-0.02	235
Austria	IIA AV Equity	Real Estate	0.01	274
Austria	SPI AV Equity	Real Estate	-0.12	168
Austria	STM AV Equity	Real Estate	0.01	270
Austria	UBS AV Equity	Real Estate	0.09	297
Belgium	DEXB BB Equity	Banks	-0.22	115
Belgium	KBC BB Equity	Banks	-0.71	21
Belgium	ACKB BB Equity	Diversified Financials	-0.59	32
Belgium	BELU BB Equity	Diversified Financials	0.01	269
Belgium	BNB BB Equity	Diversified Financials	-0.19	127
Belgium	BREB BB Equity	Diversified Financials	-0.21	119
Belgium	COMB BB Equity	Diversified Financials	-0.37	67
Belgium	GBLB BB Equity	Diversified Financials	-0.50	40
Belgium	GIMB BB Equity	Diversified Financials	-0.41	56
Belgium	KBCA BB Equity	Diversified Financials	-0.25	100
Belgium	QFG BB Equity	Diversified Financials	-0.09	188
Belgium	SOF BB Equity	Diversified Financials	-0.38	61
Belgium	TUB BB Equity	Diversified Financials	-0.38	64
Belgium	ATEB BB Equity	Real Estate	-0.10	177
Belgium	BEFB BB Equity	Real Estate	-0.13	155
Belgium	BELR BB Equity	Real Estate	0.00	257
Belgium	COFB BB Equity	Real Estate	-0.46	45
Belgium	CPINV BB Equity	Real Estate	0.22	309
Belgium	HOMI BB Equity	Real Estate	0.21	308
Belgium	IMMO BB Equity	Real Estate	-0.46	46
Belgium	INTO BB Equity	Real Estate	0.27	311
Belgium	LEAS BB Equity	Real Estate	-0.01	245
Belgium	RET BB Equity	Real Estate	-0.11	173
Belgium	SOFT BB Equity	Real Estate	-0.19	130
Belgium	VASTB BB Equity	Real Estate	-0.18	133
Belgium	WDP BB Equity	Real Estate	-0.51	37
Belgium	WEB BB Equity	Real Estate	-0.22	116
Belgium	WEHB BB Equity	Real Estate	-0.29	87

Cyprus	BOCY CY Equity	Banks	-0.32	82
Cyprus	HB CY Equity	Banks	-0.36	69
Cyprus	USB CY Equity	Banks	-0.08	191
Cyprus	AIAS CY Equity	Diversified Financials	-0.06	209
Cyprus	DEM CY Equity	Diversified Financials	-0.07	206
Cyprus	ELF CY Equity	Diversified Financials	-0.14	148
Cyprus	EXE CY Equity	Diversified Financials	-0.38	62
Cyprus	LI CY Equity	Diversified Financials	-0.10	175
Cyprus	SFS CY Equity	Diversified Financials	-0.14	150
Cyprus	ATL CY Equity	Insurance	-0.12	167
Cyprus	LIB CY Equity	Insurance	0.02	278
Cyprus	MINE CY Equity	Insurance	-0.10	176
Cyprus	FWW CY Equity	Real Estate	-0.38	65
Cyprus	KG CY Equity	Real Estate	0.01	277
Cyprus	PES CY Equity	Real Estate	-0.20	124
Cyprus	PND CY Equity	Real Estate	-0.10	178
Estonia	PKG1T ET Equity	Real Estate	0.14	301
Estonia	TPD1T ET Equity	Real Estate	-0.09	187
Finland	ALBAV FH Equity	Banks	-0.22	117
Finland	CPMBV FH Equity	Diversified Financials	-0.02	238
Finland	EQV1V FH Equity	Diversified Financials	0.03	280
Finland	NORVE FH Equity	Diversified Financials	0.07	294
Finland	SCI1V FH Equity	Diversified Financials	-0.35	73
Finland	SAMAS FH Equity	Insurance	-0.41	55
Finland	CTY1S FH Equity	Real Estate	-0.30	86
Finland	SDA1V FH Equity	Real Estate	-0.16	141
Finland	INVEST FH Equity	Real Estate	0.01	272
Finland	TPS1V FH Equity	Real Estate	-0.21	120
France	ACA FP Equity	Banks	-0.36	72
France	BNP FP Equity	Banks	-1.12	6
France	BQRE FP Equity	Banks	-0.14	152
France	CAF FP Equity	Banks	-0.13	156
France	CAT31 FP Equity	Banks	-0.03	227
France	CC FP Equity	Banks	-0.13	159
France	CCN FP Equity	Banks	-0.03	226
France	CIV FP Equity	Banks	-0.26	99
France	CMO FP Equity	Banks	0.38	313
France	CNF FP Equity	Banks	-0.09	183
France	CRAP FP Equity	Banks	-0.07	205
France	CRAV FP Equity	Banks	0.04	285
France	CRLO FP Equity	Banks	0.04	286
France	CRSU FP Equity	Banks	-0.05	211
France	CRTO FP Equity	Banks	-0.08	197
France	GLE FP Equity	Banks	-1.23	2
France	KN FP Equity	Banks	-0.90	10
France	LD FP Equity	Banks	-0.17	135
France	MLCFM FP Equity	Banks	-0.13	158
France	MLFMM FP Equity	Banks	0.00	255
France	ABCA FP Equity	Diversified Financials	-0.42	52
France	ALGIS FP Equity	Diversified Financials	0.13	300

France	ALIDS FP Equity	Diversified Financials	-0.40	57
France	ALSIP FP Equity	Diversified Financials	-0.50	39
France	ARTO FP Equity	Diversified Financials	-0.13	162
France	FFP FP Equity	Diversified Financials	-0.76	16
France	IDIP FP Equity	Diversified Financials	-0.19	128
France	LBON FP Equity	Diversified Financials	-0.42	53
France	LTA FP Equity	Diversified Financials	-0.04	222
France	MF FP Equity	Diversified Financials	-0.31	85
France	MLCVG FP Equity	Diversified Financials	0.00	262
France	MONC FP Equity	Diversified Financials	0.39	314
France	PAOR FP Equity	Diversified Financials	0.05	288
France	RF FP Equity	Diversified Financials	-0.64	26
France	SCDU FP Equity	Diversified Financials	0.19	305
France	SOFR FP Equity	Diversified Financials	0.00	254
France	SY FP Equity	Diversified Financials	-0.21	121
France	UFF FP Equity	Diversified Financials	-0.28	92
France	VIL FP Equity	Diversified Financials	-0.36	70
France	APR FP Equity	Insurance	-0.43	50
France	CNP FP Equity	Insurance	-0.72	20
France	CS FP Equity	Insurance	-0.79	14
France	ELE FP Equity	Insurance	-0.43	51
France	SCR FP Equity	Insurance	-0.17	137
France	ALSAS FP Equity	Real Estate	-0.03	232
France	ALTA FP Equity	Real Estate	-0.02	239
France	AREIT FP Equity	Real Estate	0.07	291
France	BERR FP Equity	Real Estate	0.46	315
France	COUR FP Equity	Real Estate	-0.05	219
France	DP FP Equity	Real Estate	-0.05	212
France	EEM FP Equity	Real Estate	-0.39	60
France	EIFF FP Equity	Real Estate	-0.16	139
France	FDL FP Equity	Real Estate	0.03	281
France	FDPA FP Equity	Real Estate	0.05	287
France	FDR FP Equity	Real Estate	0.00	261
France	FLY FP Equity	Real Estate	-0.12	166
France	FMU FP Equity	Real Estate	-0.01	247
France	GFC FP Equity	Real Estate	0.10	298
France	ICAD FP Equity	Real Estate	0.15	302
France	IMDA FP Equity	Real Estate	-0.05	218
France	IML FP Equity	Real Estate	-0.34	78
France	LI FP Equity	Real Estate	-0.43	49
France	MLMAB FP Equity	Real Estate	0.00	258
France	MRM FP Equity	Real Estate	-0.01	242
France	ORC FP Equity	Real Estate	-0.08	194
France	ORIA FP Equity	Real Estate	0.09	296
France	SFBS FP Equity	Real Estate	0.00	256
France	SPEL FP Equity	Real Estate	0.20	306
Germany	ARL GR Equity	Banks	0.00	252
Germany	CBK GR Equity	Banks	-0.65	25
Germany	COM GR Equity	Banks	-0.78	15
Germany	DVB GR Equity	Banks	-0.05	213

Germany	IKB GR Equity	Banks	-0.59	31
Germany	MBK GR Equity	Banks	-0.13	160
Germany	OLB GR Equity	Banks	-0.07	202
Germany	TUB GR Equity	Banks	0.25	310
Germany	UBK GR Equity	Banks	-0.04	224
Germany	ADC GR Equity	Diversified Financials	-0.02	241
Germany	ALG GR Equity	Diversified Financials	-0.13	161
Germany	ATW GR Equity	Diversified Financials	0.04	284
Germany	BBH GR Equity	Diversified Financials	-0.32	84
Germany	BFV GR Equity	Diversified Financials	-0.23	109
Germany	BTBA GR Equity	Diversified Financials	-0.20	122
Germany	BWB GR Equity	Diversified Financials	-0.37	66
Germany	CCB GR Equity	Diversified Financials	-0.18	132
Germany	CMBT GR Equity	Diversified Financials	-0.38	63
Germany	DB1 GR Equity	Diversified Financials	-0.09	186
Germany	DBAN GR Equity	Diversified Financials	-0.35	75
Germany	DBK GR Equity	Diversified Financials	-1.45	1
Germany	DLB GR Equity	Diversified Financials	-0.06	210
Germany	DRN GR Equity	Diversified Financials	-1.00	8
Germany	EFF GR Equity	Diversified Financials	-0.07	203
Germany	EFS GR Equity	Diversified Financials	-0.14	153
Germany	EUX GR Equity	Diversified Financials	-0.17	136
Germany	FAK GR Equity	Diversified Financials	0.02	279
Germany	FRS GR Equity	Diversified Financials	-0.03	228
Germany	GBQ GR Equity	Diversified Financials	0.07	290
Germany	GLJ GR Equity	Diversified Financials	-0.47	44
Germany	HGL GR Equity	Diversified Financials	0.00	266
Germany	HRU GR Equity	Diversified Financials	0.06	289
Germany	IPO GR Equity	Diversified Financials	-0.10	180
Germany	KSW GR Equity	Diversified Financials	-0.01	246
Germany	MLP GR Equity	Diversified Financials	-0.11	169
Germany	MPCK GR Equity	Diversified Financials	-0.42	54
Germany	MWB GR Equity	Diversified Financials	-0.36	68
Germany	ICP GR Equity	Diversified Financials	-0.69	23
Germany	PEH GR Equity	Diversified Financials	-0.36	71
Germany	PPZ GR Equity	Diversified Financials	-0.03	233
Germany	RMO GR Equity	Diversified Financials	0.01	271
Germany	SPT6 GR Equity	Diversified Financials	-0.15	145
Germany	SPZI GR Equity	Diversified Financials	-0.13	157
Germany	SVE GR Equity	Diversified Financials	-0.01	249
Germany	UCA1 GR Equity	Diversified Financials	-0.47	43
Germany	VEH GR Equity	Diversified Financials	-0.08	196
Germany	VHO GR Equity	Diversified Financials	-0.27	93
Germany	VVV3 GR Equity	Diversified Financials	-0.05	217
Germany	WUW GR Equity	Diversified Financials	-0.08	198
Germany	ALV GR Equity	Insurance	-0.66	24
Germany	HNR1 GR Equity	Insurance	-0.39	59
Germany	MUV2 GR Equity	Insurance	-0.84	11
Germany	NBG6 GR Equity	Insurance	-0.19	126
Germany	RLV GR Equity	Insurance	-0.03	234

Germany	WLV GR Equity	Insurance	-0.23	108
Germany	AAA GR Equity	Real Estate	0.17	303
Germany	ABHA GR Equity	Real Estate	-0.06	207
Germany	ADL GR Equity	Real Estate	-0.04	221
Germany	AGR GR Equity	Real Estate	-0.15	143
Germany	BBI GR Equity	Real Estate	0.01	276
Germany	BBR GR Equity	Real Estate	-0.26	98
Germany	BFK GR Equity	Real Estate	-0.18	131
Germany	DAL GR Equity	Real Estate	0.01	275
Germany	DEQ GR Equity	Real Estate	-0.28	90
Germany	DGR GR Equity	Real Estate	-0.05	216
Germany	DIC GR Equity	Real Estate	-0.01	243
Germany	GWK3 GR Equity	Real Estate	-0.06	208
Germany	HAB GR Equity	Real Estate	-0.22	113
Germany	KBU GR Equity	Real Estate	-0.03	230
Germany	LBN GR Equity	Real Estate	-0.11	174
Germany	LBR GR Equity	Real Estate	-0.13	165
Germany	MUK GR Equity	Real Estate	-0.16	142
Germany	SGB GR Equity	Real Estate	0.12	299
Germany	SIN GR Equity	Real Estate	0.37	312
Germany	SMWN GR Equity	Real Estate	-0.33	80
Germany	SPB GR Equity	Real Estate	-0.10	181
Germany	STG GR Equity	Real Estate	-0.28	91
Germany	TEG GR Equity	Real Estate	-0.01	244
Germany	WEG1 GR Equity	Real Estate	-0.02	237
Greece	ALPHA GA Equity	Banks	-0.27	95
Greece	ETE GA Equity	Banks	-0.24	105
Greece	EUROB GA Equity	Banks	-0.11	171
Greece	TATT GA Equity	Banks	-0.14	146
Greece	TPEIR GA Equity	Banks	-0.34	77
Greece	EXAE GA Equity	Diversified Financials	-0.22	114
Greece	TELL GA Equity	Diversified Financials	-0.16	140
Greece	EUPIC GA Equity	Insurance	-0.24	106
Greece	ASTAK GA Equity	Real Estate	-0.52	35
Greece	KAMP GA Equity	Real Estate	-0.49	42
Greece	KEKR GA Equity	Real Estate	-0.46	47
Greece	LAMDA GA Equity	Real Estate	-0.23	110
Ireland	ALBK ID Equity	Banks	-0.79	13
Ireland	BKIR ID Equity	Banks	-1.01	7
Ireland	IFP ID Equity	Diversified Financials	-0.04	223
Ireland	FBD ID Equity	Insurance	-0.29	88
Italy	BDB IM Equity	Banks	-0.35	76
Italy	BMPS IM Equity	Banks	-0.75	17
Italy	BPE IM Equity	Banks	-0.08	192
Italy	BPSO IM Equity	Banks	-0.09	184
Italy	BSRP IM Equity	Banks	-0.50	41
Italy	CE IM Equity	Banks	-0.56	33
Italy	CRG IM Equity	Banks	-0.07	200
Italy	CVAL IM Equity	Banks	-0.11	172
Italy	ISP IM Equity	Banks	-0.14	147

Italy	PEL IM Equity	Banks	-0.11	170
Italy	PMI IM Equity	Banks	-0.54	34
Italy	UBI IM Equity	Banks	-0.27	94
Italy	UCG IM Equity	Banks	-0.33	79
Italy	BIM IM Equity	Diversified Financials	-0.40	58
Italy	DEA IM Equity	Diversified Financials	-0.15	144
Italy	IF IM Equity	Diversified Financials	-0.32	83
Italy	LVEN IM Equity	Diversified Financials	-0.23	111
Italy	MB IM Equity	Diversified Financials	-0.61	28
Italy	PRO IM Equity	Diversified Financials	-0.51	38
Italy	CASS IM Equity	Insurance	-0.25	101
Italy	G IM Equity	Insurance	-0.94	9
Italy	UNI IM Equity	Insurance	-0.07	201
Italy	VAS IM Equity	Insurance	-0.51	36
Italy	AE IM Equity	Real Estate	-0.14	154
Italy	BNS IM Equity	Real Estate	-0.63	27
Italy	BRI IM Equity	Real Estate	-0.17	138
Italy	GAB IM Equity	Real Estate	-0.18	134
Italy	NR IM Equity	Real Estate	-0.59	30
Italy	RN IM Equity	Real Estate	-0.13	163
Luxembourg	COFI LX Equity	Diversified Financials	0.00	253
Luxembourg	INSIN LX Equity	Diversified Financials	0.18	304
Luxembourg	LXMP LX Equity	Diversified Financials	-0.20	125
Luxembourg	QUIL LX Equity	Diversified Financials	0.07	293
Malta	BOV MV Equity	Banks	-0.03	225
Malta	FIM MV Equity	Banks	-0.03	229
Malta	HSB MV Equity	Banks	0.04	282
Malta	LOM MV Equity	Banks	-0.03	231
Malta	PZC MV Equity	Real Estate	0.00	263
Netherlands	INGA NA Equity	Banks	-0.81	12
Netherlands	LANS NA Equity	Banks	-0.09	189
Netherlands	BINCK NA Equity	Diversified Financials	-0.27	96
Netherlands	HAL NA Equity	Diversified Financials	-0.32	81
Netherlands	KA NA Equity	Diversified Financials	-0.60	29
Netherlands	KARD NA Equity	Diversified Financials	-0.08	190
Netherlands	VALUE NA Equity	Diversified Financials	-0.08	199
Netherlands	AGN NA Equity	Insurance	-0.74	18
Netherlands	BEVER NA Equity	Real Estate	-0.21	118
Netherlands	CORA NA Equity	Real Estate	-0.14	151
Netherlands	ECMPA NA Equity	Real Estate	-0.25	103
Netherlands	GROHA NA Equity	Real Estate	-0.07	204
Netherlands	NSI NA Equity	Real Estate	-0.10	182
Netherlands	VASTN NA Equity	Real Estate	-0.20	123
Netherlands	WHA NA Equity	Real Estate	-0.23	112
Portugal	BCP PL Equity	Banks	-0.10	179
Portugal	BPI PL Equity	Banks	-0.35	74
Portugal	ESF PL Equity	Banks	0.00	267
Slovakia	VUB SK Equity	Banks	0.08	295
Slovenia	NIKN SV Equity	Diversified Financials	0.00	264
Slovenia	KDHR SV Equity	Insurance	0.00	268

Spain	BBVA SM Equity	Banks	-0.70	22
Spain	BKT SM Equity	Banks	-1.19	5
Spain	POP SM Equity	Banks	-0.72	19
Spain	SAB SM Equity	Banks	-0.24	107
Spain	SAN SM Equity	Banks	-1.21	4
Spain	ALB SM Equity	Diversified Financials	-1.21	3
Spain	CGI SM Equity	Diversified Financials	-0.19	129
Spain	REA SM Equity	Diversified Financials	-0.05	214
Spain	UEI SM Equity	Diversified Financials	-0.04	220
Spain	GCO SM Equity	Insurance	-0.26	97
Spain	MAP SM Equity	Insurance	-0.25	104
Spain	CEV SM Equity	Real Estate	0.00	260
Spain	COL SM Equity	Real Estate	-0.13	164
Spain	FICIS SM Equity	Real Estate	-0.02	240
Spain	ILV SM Equity	Real Estate	0.00	251
Spain	LIB SM Equity	Real Estate	0.00	250
Spain	MTB SM Equity	Real Estate	-0.14	149
Spain	QBT SM Equity	Real Estate	-0.08	193
Spain	STG SM Equity	Real Estate	-0.25	102
Spain	TST SM Equity	Real Estate	-0.08	195
Spain	UBS SM Equity	Real Estate	-0.05	215

Appendix L:

Average Conditional Contribution ΔCoVaR of Financial Institutions (Crisis Period)

Member State	Sector	Institution	$\Delta CoVaR_q^{sys\|i}$	Rank
Austria	BKUS AV Equity	Banks	-0.09	236
Austria	BTUV AV Equity	Banks	-0.02	283
Austria	EBS AV Equity	Banks	-1.75	48
Austria	OBS AV Equity	Banks	-0.22	292
Austria	VVPS AV Equity	Banks	0.02	273
Austria	UIV AV Equity	Diversified Financials	0.02	185
Austria	WPB AV Equity	Diversified Financials	0.50	307
Austria	UQA AV Equity	Insurance	-0.55	89
Austria	VIG AV Equity	Insurance	-1.66	259
Austria	ATRS AV Equity	Real Estate	-0.23	265
Austria	CAI AV Equity	Real Estate	-1.36	248
Austria	CWI AV Equity	Real Estate	-1.44	235
Austria	IIA AV Equity	Real Estate	-0.60	274
Austria	SPI AV Equity	Real Estate	-0.64	168
Austria	STM AV Equity	Real Estate	0.15	270
Austria	UBS AV Equity	Real Estate	-0.30	297
Belgium	DEXB BB Equity	Banks	-1.42	115
Belgium	KBC BB Equity	Banks	-1.32	21
Belgium	ACKB BB Equity	Diversified Financials	-1.75	32
Belgium	BELU BB Equity	Diversified Financials	0.09	269
Belgium	BNB BB Equity	Diversified Financials	-0.67	127
Belgium	BREB BB Equity	Diversified Financials	-1.54	119
Belgium	COMB BB Equity	Diversified Financials	-1.18	67
Belgium	GBLB BB Equity	Diversified Financials	-1.83	40
Belgium	GIMB BB Equity	Diversified Financials	-1.43	56
Belgium	KBCA BB Equity	Diversified Financials	-1.23	100
Belgium	QFG BB Equity	Diversified Financials	-0.91	188
Belgium	SOF BB Equity	Diversified Financials	-1.58	61
Belgium	TUB BB Equity	Diversified Financials	-1.20	64
Belgium	ATEB BB Equity	Real Estate	-0.98	177
Belgium	BEFB BB Equity	Real Estate	-1.35	155
Belgium	BELR BB Equity	Real Estate	0.00	257
Belgium	COFB BB Equity	Real Estate	-0.75	45
Belgium	CPINV BB Equity	Real Estate	-0.32	309
Belgium	HOMI BB Equity	Real Estate	0.44	308
Belgium	IMMO BB Equity	Real Estate	-0.82	46
Belgium	INTO BB Equity	Real Estate	-1.27	311
Belgium	LEAS BB Equity	Real Estate	-1.10	245
Belgium	RET BB Equity	Real Estate	-0.93	173
Belgium	SOFT BB Equity	Real Estate	0.01	130
Belgium	VASTB BB Equity	Real Estate	-0.68	133
Belgium	WDP BB Equity	Real Estate	-0.89	37
Belgium	WEB BB Equity	Real Estate	-0.27	116
Belgium	WEHB BB Equity	Real Estate	-0.78	87

Cyprus	BOCY CY Equity	Banks	-1.66	82
Cyprus	HB CY Equity	Banks	-0.90	69
Cyprus	USB CY Equity	Banks	0.29	191
Cyprus	AIAS CY Equity	Diversified Financials	0.15	209
Cyprus	DEM CY Equity	Diversified Financials	-1.31	206
Cyprus	ELF CY Equity	Diversified Financials	-0.26	148
Cyprus	EXE CY Equity	Diversified Financials	0.00	62
Cyprus	LI CY Equity	Diversified Financials	-1.12	175
Cyprus	SFS CY Equity	Diversified Financials	-1.05	150
Cyprus	ATL CY Equity	Insurance	-0.20	167
Cyprus	LIB CY Equity	Insurance	-0.26	278
Cyprus	MINE CY Equity	Insurance	-0.03	176
Cyprus	FWW CY Equity	Real Estate	-0.23	65
Cyprus	KG CY Equity	Real Estate	-0.57	277
Cyprus	PES CY Equity	Real Estate	0.03	124
Cyprus	PND CY Equity	Real Estate	-0.37	178
Estonia	PKG1T ET Equity	Real Estate	0.00	301
Estonia	TPD1T ET Equity	Real Estate	-0.02	187
Finland	ALBAV FH Equity	Banks	-0.10	117
Finland	CPMBV FH Equity	Diversified Financials	-0.56	238
Finland	EQV1V FH Equity	Diversified Financials	-0.38	280
Finland	NORVE FH Equity	Diversified Financials	-0.82	294
Finland	SCI1V FH Equity	Diversified Financials	-0.86	73
Finland	SAMAS FH Equity	Insurance	-1.53	55
Finland	CTY1S FH Equity	Real Estate	-1.04	86
Finland	SDA1V FH Equity	Real Estate	-0.95	141
Finland	INVEST FH Equity	Real Estate	-0.18	272
Finland	TPS1V FH Equity	Real Estate	-0.89	120
France	ACA FP Equity	Banks	-2.50	72
France	BNP FP Equity	Banks	-2.77	6
France	BQRE FP Equity	Banks	-1.11	152
France	CAF FP Equity	Banks	-0.81	156
France	CAT31 FP Equity	Banks	-1.19	227
France	CC FP Equity	Banks	-0.91	159
France	CCN FP Equity	Banks	-0.75	226
France	CIV FP Equity	Banks	-0.59	99
France	CMO FP Equity	Banks	-0.90	313
France	CNF FP Equity	Banks	-1.15	183
France	CRAP FP Equity	Banks	-0.94	205
France	CRAV FP Equity	Banks	-1.06	285
France	CRLO FP Equity	Banks	-0.02	286
France	CRSU FP Equity	Banks	-0.74	211
France	CRTO FP Equity	Banks	-0.43	197
France	GLE FP Equity	Banks	-2.08	2
France	KN FP Equity	Banks	-1.07	10
France	LD FP Equity	Banks	-0.43	135
France	MLCFM FP Equity	Banks	-0.32	158
France	MLFMM FP Equity	Banks	0.04	255
France	ABCA FP Equity	Diversified Financials	-0.79	52
France	ALGIS FP Equity	Diversified Financials	-0.08	300

France	ALIDS FP Equity	Diversified Financials	-0.83	57
France	ALSIP FP Equity	Diversified Financials	-0.18	39
France	ARTO FP Equity	Diversified Financials	-0.69	162
France	FFP FP Equity	Diversified Financials	-1.91	16
France	IDIP FP Equity	Diversified Financials	-0.44	128
France	LBON FP Equity	Diversified Financials	-0.25	53
France	LTA FP Equity	Diversified Financials	-0.91	222
France	MF FP Equity	Diversified Financials	-1.95	85
France	MLCVG FP Equity	Diversified Financials	0.00	262
France	MONC FP Equity	Diversified Financials	-0.18	314
France	PAOR FP Equity	Diversified Financials	-0.43	288
France	RF FP Equity	Diversified Financials	-1.90	26
France	SCDU FP Equity	Diversified Financials	0.35	305
France	SOFR FP Equity	Diversified Financials	-0.20	254
France	SY FP Equity	Diversified Financials	-0.60	121
France	UFF FP Equity	Diversified Financials	-0.62	92
France	VIL FP Equity	Diversified Financials	-0.71	70
France	APR FP Equity	Insurance	-1.43	50
France	CNP FP Equity	Insurance	-1.79	20
France	CS FP Equity	Insurance	-2.14	14
France	ELE FP Equity	Insurance	-1.59	51
France	SCR FP Equity	Insurance	-1.00	137
France	ALSAS FP Equity	Real Estate	-1.02	232
France	ALTA FP Equity	Real Estate	-0.30	239
France	AREIT FP Equity	Real Estate	0.00	291
France	BERR FP Equity	Real Estate	-0.31	315
France	COUR FP Equity	Real Estate	-0.61	219
France	DP FP Equity	Real Estate	0.01	212
France	EEM FP Equity	Real Estate	-0.49	60
France	EIFF FP Equity	Real Estate	-1.21	139
France	FDL FP Equity	Real Estate	-0.03	281
France	FDPA FP Equity	Real Estate	0.13	287
France	FDR FP Equity	Real Estate	-0.95	261
France	FLY FP Equity	Real Estate	-0.73	166
France	FMU FP Equity	Real Estate	-0.48	247
France	GFC FP Equity	Real Estate	-1.52	298
France	ICAD FP Equity	Real Estate	-0.50	302
France	IMDA FP Equity	Real Estate	0.06	218
France	IML FP Equity	Real Estate	-0.70	78
France	LI FP Equity	Real Estate	-1.15	49
France	MLMAB FP Equity	Real Estate	0.00	258
France	MRM FP Equity	Real Estate	-0.02	242
France	ORC FP Equity	Real Estate	-1.08	194
France	ORIA FP Equity	Real Estate	-0.02	296
France	SFBS FP Equity	Real Estate	-0.01	256
France	SPEL FP Equity	Real Estate	-0.08	306
Germany	ARL GR Equity	Banks	-2.11	252
Germany	CBK GR Equity	Banks	-1.34	25
Germany	COM GR Equity	Banks	-1.55	15
Germany	DVB GR Equity	Banks	-0.35	213

Germany	IKB GR Equity	Banks	-0.52	31
Germany	MBK GR Equity	Banks	0.14	160
Germany	OLB GR Equity	Banks	-0.55	202
Germany	TUB GR Equity	Banks	0.18	310
Germany	UBK GR Equity	Banks	-0.30	224
Germany	ADC GR Equity	Diversified Financials	-0.02	241
Germany	ALG GR Equity	Diversified Financials	-1.18	161
Germany	ATW GR Equity	Diversified Financials	-0.35	284
Germany	BBH GR Equity	Diversified Financials	0.35	84
Germany	BFV GR Equity	Diversified Financials	-0.29	109
Germany	BTBA GR Equity	Diversified Financials	-0.39	122
Germany	BWB GR Equity	Diversified Financials	-0.99	66
Germany	CCB GR Equity	Diversified Financials	-0.04	132
Germany	CMBT GR Equity	Diversified Financials	-0.82	63
Germany	DB1 GR Equity	Diversified Financials	-1.64	186
Germany	DBAN GR Equity	Diversified Financials	-1.03	75
Germany	DBK GR Equity	Diversified Financials	-2.03	1
Germany	DLB GR Equity	Diversified Financials	-0.31	210
Germany	DRN GR Equity	Diversified Financials	-0.77	8
Germany	EFF GR Equity	Diversified Financials	-0.69	203
Germany	EFS GR Equity	Diversified Financials	-0.64	153
Germany	EUX GR Equity	Diversified Financials	-0.69	136
Germany	FAK GR Equity	Diversified Financials	-0.30	279
Germany	FRS GR Equity	Diversified Financials	-0.58	228
Germany	GBQ GR Equity	Diversified Financials	-0.31	290
Germany	GLJ GR Equity	Diversified Financials	-1.08	44
Germany	HGL GR Equity	Diversified Financials	0.07	266
Germany	HRU GR Equity	Diversified Financials	0.14	289
Germany	IPO GR Equity	Diversified Financials	-0.07	180
Germany	KSW GR Equity	Diversified Financials	-0.90	246
Germany	MLP GR Equity	Diversified Financials	-1.65	169
Germany	MPCK GR Equity	Diversified Financials	-0.20	54
Germany	MWB GR Equity	Diversified Financials	-0.33	68
Germany	ICP GR Equity	Diversified Financials	0.01	23
Germany	PEH GR Equity	Diversified Financials	-0.52	71
Germany	PPZ GR Equity	Diversified Financials	-0.20	233
Germany	RMO GR Equity	Diversified Financials	-0.26	271
Germany	SPT6 GR Equity	Diversified Financials	-0.11	145
Germany	SPZI GR Equity	Diversified Financials	-0.03	157
Germany	SVE GR Equity	Diversified Financials	-0.65	249
Germany	UCA1 GR Equity	Diversified Financials	0.04	43
Germany	VEH GR Equity	Diversified Financials	-0.30	196
Germany	VHO GR Equity	Diversified Financials	-0.44	93
Germany	VVV3 GR Equity	Diversified Financials	-0.34	217
Germany	WUW GR Equity	Diversified Financials	-0.47	198
Germany	ALV GR Equity	Insurance	-1.74	24
Germany	HNR1 GR Equity	Insurance	-1.25	59
Germany	MUV2 GR Equity	Insurance	-1.34	11
Germany	NBG6 GR Equity	Insurance	-0.30	126
Germany	RLV GR Equity	Insurance	0.14	234

Germany	WLV GR Equity	Insurance	-0.25	108
Germany	AAA GR Equity	Real Estate	-0.02	303
Germany	ABHA GR Equity	Real Estate	-0.07	207
Germany	ADL GR Equity	Real Estate	-0.35	221
Germany	AGR GR Equity	Real Estate	-0.02	143
Germany	BBI GR Equity	Real Estate	0.45	276
Germany	BBR GR Equity	Real Estate	0.01	98
Germany	BFK GR Equity	Real Estate	0.06	131
Germany	DAL GR Equity	Real Estate	0.10	275
Germany	DEQ GR Equity	Real Estate	-0.75	90
Germany	DGR GR Equity	Real Estate	-0.66	216
Germany	DIC GR Equity	Real Estate	-1.38	243
Germany	GWK3 GR Equity	Real Estate	-0.18	208
Germany	HAB GR Equity	Real Estate	-0.09	113
Germany	KBU GR Equity	Real Estate	-1.37	230
Germany	LBN GR Equity	Real Estate	-0.33	174
Germany	LBR GR Equity	Real Estate	-0.29	165
Germany	MUK GR Equity	Real Estate	-0.41	142
Germany	SGB GR Equity	Real Estate	0.01	299
Germany	SIN GR Equity	Real Estate	0.07	312
Germany	SMWN GR Equity	Real Estate	-0.69	80
Germany	SPB GR Equity	Real Estate	-0.23	181
Germany	STG GR Equity	Real Estate	-0.01	91
Germany	TEG GR Equity	Real Estate	-0.81	244
Germany	WEG1 GR Equity	Real Estate	-0.19	237
Greece	ALPHA GA Equity	Banks	-1.31	95
Greece	ETE GA Equity	Banks	-1.56	105
Greece	EUROB GA Equity	Banks	-1.66	171
Greece	TATT GA Equity	Banks	-0.35	146
Greece	TPEIR GA Equity	Banks	-1.23	77
Greece	EXAE GA Equity	Diversified Financials	-1.49	114
Greece	TELL GA Equity	Diversified Financials	-1.38	140
Greece	EUPIC GA Equity	Insurance	-0.71	106
Greece	ASTAK GA Equity	Real Estate	-0.10	35
Greece	KAMP GA Equity	Real Estate	-0.51	42
Greece	KEKR GA Equity	Real Estate	-0.99	47
Greece	LAMDA GA Equity	Real Estate	-0.99	110
Ireland	ALBK ID Equity	Banks	-0.75	13
Ireland	BKIR ID Equity	Banks	-0.58	7
Ireland	IFP ID Equity	Diversified Financials	0.08	223
Ireland	FBD ID Equity	Insurance	-0.78	88
Italy	BDB IM Equity	Banks	-1.37	76
Italy	BMPS IM Equity	Banks	-1.26	17
Italy	BPE IM Equity	Banks	-1.97	192
Italy	BPSO IM Equity	Banks	-1.61	184
Italy	BSRP IM Equity	Banks	-1.14	41
Italy	CE IM Equity	Banks	-1.48	33
Italy	CRG IM Equity	Banks	-1.15	200
Italy	CVAL IM Equity	Banks	-1.14	172
Italy	ISP IM Equity	Banks	-2.44	147

Italy	PEL IM Equity	Banks	-0.84	170
Italy	PMI IM Equity	Banks	-2.41	34
Italy	UBI IM Equity	Banks	-2.58	94
Italy	UCG IM Equity	Banks	-1.90	79
Italy	BIM IM Equity	Diversified Financials	-0.60	58
Italy	DEA IM Equity	Diversified Financials	-1.61	144
Italy	IF IM Equity	Diversified Financials	-0.99	83
Italy	LVEN IM Equity	Diversified Financials	-0.70	111
Italy	MB IM Equity	Diversified Financials	-2.06	28
Italy	PRO IM Equity	Diversified Financials	-0.79	38
Italy	CASS IM Equity	Insurance	-1.60	101
Italy	G IM Equity	Insurance	-2.68	9
Italy	UNI IM Equity	Insurance	-1.52	201
Italy	VAS IM Equity	Insurance	-0.89	36
Italy	AE IM Equity	Real Estate	-0.34	154
Italy	BNS IM Equity	Real Estate	-0.97	27
Italy	BRI IM Equity	Real Estate	-0.62	138
Italy	GAB IM Equity	Real Estate	-0.32	134
Italy	NR IM Equity	Real Estate	-0.03	30
Italy	RN IM Equity	Real Estate	-0.09	163
Luxembourg	COFI LX Equity	Diversified Financials	0.07	253
Luxembourg	INSIN LX Equity	Diversified Financials	0.02	304
Luxembourg	LXMP LX Equity	Diversified Financials	-0.86	125
Luxembourg	QUIL LX Equity	Diversified Financials	0.82	293
Malta	BOV MV Equity	Banks	-0.03	225
Malta	FIM MV Equity	Banks	0.22	229
Malta	HSB MV Equity	Banks	-0.09	282
Malta	LOM MV Equity	Banks	-0.09	231
Malta	PZC MV Equity	Real Estate	0.00	263
Netherlands	INGA NA Equity	Banks	-3.54	12
Netherlands	LANS NA Equity	Banks	-0.32	189
Netherlands	BINCK NA Equity	Diversified Financials	-0.85	96
Netherlands	HAL NA Equity	Diversified Financials	-1.08	81
Netherlands	KA NA Equity	Diversified Financials	-1.12	29
Netherlands	KARD NA Equity	Diversified Financials	-0.66	190
Netherlands	VALUE NA Equity	Diversified Financials	-0.57	199
Netherlands	AGN NA Equity	Insurance	-1.87	18
Netherlands	BEVER NA Equity	Real Estate	0.07	118
Netherlands	CORA NA Equity	Real Estate	-1.13	151
Netherlands	ECMPA NA Equity	Real Estate	-1.43	103
Netherlands	GROHA NA Equity	Real Estate	-0.49	204
Netherlands	NSI NA Equity	Real Estate	-0.99	182
Netherlands	VASTN NA Equity	Real Estate	-1.07	123
Netherlands	WHA NA Equity	Real Estate	-1.50	112
Portugal	BCP PL Equity	Banks	-1.85	179
Portugal	BPI PL Equity	Banks	-1.85	74
Portugal	ESF PL Equity	Banks	-0.35	267
Slovakia	VUB SK Equity	Banks	0.34	295
Slovenia	NIKN SV Equity	Diversified Financials	0.00	264
Slovenia	KDHR SV Equity	Insurance	-0.18	268

Spain	BBVA SM Equity	Banks	-2.70	22
Spain	BKT SM Equity	Banks	-2.16	5
Spain	POP SM Equity	Banks	-1.82	19
Spain	SAB SM Equity	Banks	-2.43	107
Spain	SAN SM Equity	Banks	-2.58	4
Spain	ALB SM Equity	Diversified Financials	-1.97	3
Spain	CGI SM Equity	Diversified Financials	-0.05	129
Spain	REA SM Equity	Diversified Financials	0.03	214
Spain	UEI SM Equity	Diversified Financials	0.43	220
Spain	GCO SM Equity	Insurance	-1.52	97
Spain	MAP SM Equity	Insurance	-2.04	104
Spain	CEV SM Equity	Real Estate	0.00	260
Spain	COL SM Equity	Real Estate	-0.34	164
Spain	FICIS SM Equity	Real Estate	0.00	240
Spain	ILV SM Equity	Real Estate	0.02	251
Spain	LIB SM Equity	Real Estate	0.03	250
Spain	MTB SM Equity	Real Estate	-0.94	149
Spain	QBT SM Equity	Real Estate	-0.29	193
Spain	STG SM Equity	Real Estate	-0.64	102
Spain	TST SM Equity	Real Estate	0.02	195
Spain	UBS SM Equity	Real Estate	-0.15	215

Appendix M:

Average Conditional Contribution ΔCoVaR of Financial Institutions

(Post-crisis Period)

Member State	Sector	Institution	$\Delta CoVaR_q^{sys\|i}$	Rank
Austria	BKUS AV Equity	Banks	-0.12	236
Austria	BTUV AV Equity	Banks	-0.08	283
Austria	EBS AV Equity	Banks	-1.70	48
Austria	OBS AV Equity	Banks	-0.11	292
Austria	VVPS AV Equity	Banks	-0.01	273
Austria	UIV AV Equity	Diversified Financials	-0.01	185
Austria	WPB AV Equity	Diversified Financials	-0.08	307
Austria	UQA AV Equity	Insurance	-0.16	89
Austria	VIG AV Equity	Insurance	-1.53	259
Austria	ATRS AV Equity	Real Estate	-0.82	265
Austria	CAI AV Equity	Real Estate	-1.15	248
Austria	CWI AV Equity	Real Estate	-0.89	235
Austria	IIA AV Equity	Real Estate	-1.46	274
Austria	SPI AV Equity	Real Estate	-0.77	168
Austria	STM AV Equity	Real Estate	-0.08	270
Austria	UBS AV Equity	Real Estate	0.07	297
Belgium	DEXB BB Equity	Banks	-0.12	115
Belgium	KBC BB Equity	Banks	-1.49	21
Belgium	ACKB BB Equity	Diversified Financials	-1.83	32
Belgium	BELU BB Equity	Diversified Financials	-0.11	269
Belgium	BNB BB Equity	Diversified Financials	-0.68	127
Belgium	BREB BB Equity	Diversified Financials	-0.53	119
Belgium	COMB BB Equity	Diversified Financials	-0.53	67
Belgium	GBLB BB Equity	Diversified Financials	-2.41	40
Belgium	GIMB BB Equity	Diversified Financials	-0.90	56
Belgium	KBCA BB Equity	Diversified Financials	-1.40	100
Belgium	QFG BB Equity	Diversified Financials	-0.28	188
Belgium	SOF BB Equity	Diversified Financials	-1.90	61
Belgium	TUB BB Equity	Diversified Financials	-1.21	64
Belgium	ATEB BB Equity	Real Estate	-0.52	177
Belgium	BEFB BB Equity	Real Estate	-0.87	155
Belgium	BELR BB Equity	Real Estate	0.00	257
Belgium	COFB BB Equity	Real Estate	-0.79	45
Belgium	CPINV BB Equity	Real Estate	0.07	309
Belgium	HOMI BB Equity	Real Estate	-0.19	308
Belgium	IMMO BB Equity	Real Estate	-0.58	46
Belgium	INTO BB Equity	Real Estate	0.29	311
Belgium	LEAS BB Equity	Real Estate	-0.15	245
Belgium	RET BB Equity	Real Estate	-0.12	173
Belgium	SOFT BB Equity	Real Estate	-0.23	130
Belgium	VASTB BB Equity	Real Estate	-0.09	133
Belgium	WDP BB Equity	Real Estate	-0.56	37
Belgium	WEB BB Equity	Real Estate	-0.35	116
Belgium	WEHB BB Equity	Real Estate	-0.06	87

Cyprus	BOCY CY Equity	Banks	-0.13	82
Cyprus	HB CY Equity	Banks	-0.08	69
Cyprus	USB CY Equity	Banks	-0.01	191
Cyprus	AIAS CY Equity	Diversified Financials	0.00	209
Cyprus	DEM CY Equity	Diversified Financials	0.03	206
Cyprus	ELF CY Equity	Diversified Financials	0.00	148
Cyprus	EXE CY Equity	Diversified Financials	-0.01	62
Cyprus	LI CY Equity	Diversified Financials	0.10	175
Cyprus	SFS CY Equity	Diversified Financials	-0.10	150
Cyprus	ATL CY Equity	Insurance	0.25	167
Cyprus	LIB CY Equity	Insurance	-0.06	278
Cyprus	MINE CY Equity	Insurance	-0.04	176
Cyprus	FWW CY Equity	Real Estate	-0.43	65
Cyprus	KG CY Equity	Real Estate	-0.03	277
Cyprus	PES CY Equity	Real Estate	0.00	124
Cyprus	PND CY Equity	Real Estate	-0.81	178
Estonia	PKG1T ET Equity	Real Estate	0.16	301
Estonia	TPD1T ET Equity	Real Estate	0.11	187
Finland	ALBAV FH Equity	Banks	0.12	117
Finland	CPMBV FH Equity	Diversified Financials	-0.60	238
Finland	EQV1V FH Equity	Diversified Financials	-0.44	280
Finland	NORVE FH Equity	Diversified Financials	-0.77	294
Finland	SCI1V FH Equity	Diversified Financials	-0.19	73
Finland	SAMAS FH Equity	Insurance	-2.10	55
Finland	CTY1S FH Equity	Real Estate	-0.12	86
Finland	SDA1V FH Equity	Real Estate	-1.79	141
Finland	INVEST FH Equity	Real Estate	-0.05	272
Finland	TPS1V FH Equity	Real Estate	-0.57	120
France	ACA FP Equity	Banks	-1.82	72
France	BNP FP Equity	Banks	-2.11	6
France	BQRE FP Equity	Banks	-0.18	152
France	CAF FP Equity	Banks	-0.46	156
France	CAT31 FP Equity	Banks	-0.49	227
France	CC FP Equity	Banks	-0.83	159
France	CCN FP Equity	Banks	-0.67	226
France	CIV FP Equity	Banks	-0.79	99
France	CMO FP Equity	Banks	-0.98	313
France	CNF FP Equity	Banks	-0.54	183
France	CRAP FP Equity	Banks	-0.53	205
France	CRAV FP Equity	Banks	-0.37	285
France	CRLO FP Equity	Banks	-0.44	286
France	CRSU FP Equity	Banks	-0.52	211
France	CRTO FP Equity	Banks	-0.46	197
France	GLE FP Equity	Banks	-2.05	2
France	KN FP Equity	Banks	-1.87	10
France	LD FP Equity	Banks	-0.36	135
France	MLCFM FP Equity	Banks	-0.02	158
France	MLFMM FP Equity	Banks	0.00	255
France	ABCA FP Equity	Diversified Financials	-0.95	52
France	ALGIS FP Equity	Diversified Financials	0.02	300

France	ALIDS FP Equity	Diversified Financials	-0.14	57
France	ALSIP FP Equity	Diversified Financials	-0.07	39
France	ARTO FP Equity	Diversified Financials	-0.07	162
France	FFP FP Equity	Diversified Financials	-1.61	16
France	IDIP FP Equity	Diversified Financials	-0.07	128
France	LBON FP Equity	Diversified Financials	-0.25	53
France	LTA FP Equity	Diversified Financials	-0.98	222
France	MF FP Equity	Diversified Financials	-2.02	85
France	MLCVG FP Equity	Diversified Financials	0.00	262
France	MONC FP Equity	Diversified Financials	-0.32	314
France	PAOR FP Equity	Diversified Financials	0.05	288
France	RF FP Equity	Diversified Financials	-2.06	26
France	SCDU FP Equity	Diversified Financials	0.00	305
France	SOFR FP Equity	Diversified Financials	0.05	254
France	SY FP Equity	Diversified Financials	-0.08	121
France	UFF FP Equity	Diversified Financials	-0.75	92
France	VIL FP Equity	Diversified Financials	-0.49	70
France	APR FP Equity	Insurance	-0.97	50
France	CNP FP Equity	Insurance	-1.78	20
France	CS FP Equity	Insurance	-2.34	14
France	ELE FP Equity	Insurance	-0.95	51
France	SCR FP Equity	Insurance	-1.70	137
France	ALSAS FP Equity	Real Estate	-0.18	232
France	ALTA FP Equity	Real Estate	-0.34	239
France	AREIT FP Equity	Real Estate	0.00	291
France	BERR FP Equity	Real Estate	-0.32	315
France	COUR FP Equity	Real Estate	-0.26	219
France	DP FP Equity	Real Estate	-0.16	212
France	EEM FP Equity	Real Estate	-0.07	60
France	EIFF FP Equity	Real Estate	-0.31	139
France	FDL FP Equity	Real Estate	0.04	281
France	FDPA FP Equity	Real Estate	-0.06	287
France	FDR FP Equity	Real Estate	-1.46	261
France	FLY FP Equity	Real Estate	-0.21	166
France	FMU FP Equity	Real Estate	-0.60	247
France	GFC FP Equity	Real Estate	-1.86	298
France	ICAD FP Equity	Real Estate	-1.08	302
France	IMDA FP Equity	Real Estate	-0.22	218
France	IML FP Equity	Real Estate	-0.82	78
France	LI FP Equity	Real Estate	-1.09	49
France	MLMAB FP Equity	Real Estate	0.00	258
France	MRM FP Equity	Real Estate	-0.04	242
France	ORC FP Equity	Real Estate	-0.15	194
France	ORIA FP Equity	Real Estate	-0.23	296
France	SFBS FP Equity	Real Estate	0.02	256
France	SPEL FP Equity	Real Estate	0.08	306
Germany	ARL GR Equity	Banks	-0.19	252
Germany	CBK GR Equity	Banks	-0.57	25
Germany	COM GR Equity	Banks	-0.91	15
Germany	DVB GR Equity	Banks	-0.02	213

Germany	IKB GR Equity	Banks	-0.34	31
Germany	MBK GR Equity	Banks	-0.20	160
Germany	OLB GR Equity	Banks	-0.24	202
Germany	TUB GR Equity	Banks	0.29	310
Germany	UBK GR Equity	Banks	-0.29	224
Germany	ADC GR Equity	Diversified Financials	-0.21	241
Germany	ALG GR Equity	Diversified Financials	-0.26	161
Germany	ATW GR Equity	Diversified Financials	-0.09	284
Germany	BBH GR Equity	Diversified Financials	-0.16	84
Germany	BFV GR Equity	Diversified Financials	-0.33	109
Germany	BTBA GR Equity	Diversified Financials	-0.43	122
Germany	BWB GR Equity	Diversified Financials	-0.29	66
Germany	CCB GR Equity	Diversified Financials	-0.19	132
Germany	CMBT GR Equity	Diversified Financials	-0.04	63
Germany	DB1 GR Equity	Diversified Financials	-1.60	186
Germany	DBAN GR Equity	Diversified Financials	-1.15	75
Germany	DBK GR Equity	Diversified Financials	-1.98	1
Germany	DLB GR Equity	Diversified Financials	-0.13	210
Germany	DRN GR Equity	Diversified Financials	-0.18	8
Germany	EFF GR Equity	Diversified Financials	-0.42	203
Germany	EFS GR Equity	Diversified Financials	-0.54	153
Germany	EUX GR Equity	Diversified Financials	-0.31	136
Germany	FAK GR Equity	Diversified Financials	-0.01	279
Germany	FRS GR Equity	Diversified Financials	-0.18	228
Germany	GBQ GR Equity	Diversified Financials	0.24	290
Germany	GLJ GR Equity	Diversified Financials	-0.49	44
Germany	HGL GR Equity	Diversified Financials	0.20	266
Germany	HRU GR Equity	Diversified Financials	-0.06	289
Germany	IPO GR Equity	Diversified Financials	-0.04	180
Germany	KSW GR Equity	Diversified Financials	-0.36	246
Germany	MLP GR Equity	Diversified Financials	-0.52	169
Germany	MPCK GR Equity	Diversified Financials	-0.31	54
Germany	MWB GR Equity	Diversified Financials	0.05	68
Germany	ICP GR Equity	Diversified Financials	0.02	23
Germany	PEH GR Equity	Diversified Financials	-0.19	71
Germany	PPZ GR Equity	Diversified Financials	0.05	233
Germany	RMO GR Equity	Diversified Financials	-0.09	271
Germany	SPT6 GR Equity	Diversified Financials	-0.47	145
Germany	SPZI GR Equity	Diversified Financials	0.07	157
Germany	SVE GR Equity	Diversified Financials	-0.35	249
Germany	UCA1 GR Equity	Diversified Financials	-0.15	43
Germany	VEH GR Equity	Diversified Financials	-0.20	196
Germany	VHO GR Equity	Diversified Financials	0.18	93
Germany	VVV3 GR Equity	Diversified Financials	-0.41	217
Germany	WUW GR Equity	Diversified Financials	-0.10	198
Germany	ALV GR Equity	Insurance	-2.56	24
Germany	HNR1 GR Equity	Insurance	-1.77	59
Germany	MUV2 GR Equity	Insurance	-2.04	11
Germany	NBG6 GR Equity	Insurance	-0.38	126
Germany	RLV GR Equity	Insurance	-0.27	234

Germany	WLV GR Equity	Insurance	0.02	108
Germany	AAA GR Equity	Real Estate	0.09	303
Germany	ABHA GR Equity	Real Estate	-0.05	207
Germany	ADL GR Equity	Real Estate	-0.08	221
Germany	AGR GR Equity	Real Estate	-0.31	143
Germany	BBI GR Equity	Real Estate	-0.70	276
Germany	BBR GR Equity	Real Estate	-0.05	98
Germany	BFK GR Equity	Real Estate	0.02	131
Germany	DAL GR Equity	Real Estate	-0.08	275
Germany	DEQ GR Equity	Real Estate	-1.54	90
Germany	DGR GR Equity	Real Estate	-0.18	216
Germany	DIC GR Equity	Real Estate	-0.77	243
Germany	GWK3 GR Equity	Real Estate	-0.33	208
Germany	HAB GR Equity	Real Estate	-0.36	113
Germany	KBU GR Equity	Real Estate	-0.30	230
Germany	LBN GR Equity	Real Estate	-0.43	174
Germany	LBR GR Equity	Real Estate	-0.33	165
Germany	MUK GR Equity	Real Estate	-0.53	142
Germany	SGB GR Equity	Real Estate	0.12	299
Germany	SIN GR Equity	Real Estate	-0.02	312
Germany	SMWN GR Equity	Real Estate	-0.14	80
Germany	SPB GR Equity	Real Estate	-0.17	181
Germany	STG GR Equity	Real Estate	-0.17	91
Germany	TEG GR Equity	Real Estate	-0.38	244
Germany	WEG1 GR Equity	Real Estate	-0.09	237
Greece	ALPHA GA Equity	Banks	-0.26	95
Greece	ETE GA Equity	Banks	-0.39	105
Greece	EUROB GA Equity	Banks	-0.23	171
Greece	TATT GA Equity	Banks	-0.17	146
Greece	TPEIR GA Equity	Banks	-0.20	77
Greece	EXAE GA Equity	Diversified Financials	-0.79	114
Greece	TELL GA Equity	Diversified Financials	-0.62	140
Greece	EUPIC GA Equity	Insurance	-0.38	106
Greece	ASTAK GA Equity	Real Estate	-0.22	35
Greece	KAMP GA Equity	Real Estate	0.17	42
Greece	KEKR GA Equity	Real Estate	-0.17	47
Greece	LAMDA GA Equity	Real Estate	-0.07	110
Ireland	ALBK ID Equity	Banks	-0.56	13
Ireland	BKIR ID Equity	Banks	-0.64	7
Ireland	IFP ID Equity	Diversified Financials	-0.33	223
Ireland	FBD ID Equity	Insurance	-0.83	88
Italy	BDB IM Equity	Banks	-0.90	76
Italy	BMPS IM Equity	Banks	-0.37	17
Italy	BPE IM Equity	Banks	-1.35	192
Italy	BPSO IM Equity	Banks	-1.53	184
Italy	BSRP IM Equity	Banks	-0.51	41
Italy	CE IM Equity	Banks	-1.28	33
Italy	CRG IM Equity	Banks	-0.46	200
Italy	CVAL IM Equity	Banks	-0.75	172
Italy	ISP IM Equity	Banks	-2.19	147

Italy	PEL IM Equity	Banks	-0.09	170
Italy	PMI IM Equity	Banks	-1.02	34
Italy	UBI IM Equity	Banks	-1.68	94
Italy	UCG IM Equity	Banks	-1.87	79
Italy	BIM IM Equity	Diversified Financials	-0.18	58
Italy	DEA IM Equity	Diversified Financials	-0.67	144
Italy	IF IM Equity	Diversified Financials	-0.96	83
Italy	LVEN IM Equity	Diversified Financials	-0.06	111
Italy	MB IM Equity	Diversified Financials	-1.67	28
Italy	PRO IM Equity	Diversified Financials	-0.66	38
Italy	CASS IM Equity	Insurance	-0.68	101
Italy	G IM Equity	Insurance	-2.09	9
Italy	UNI IM Equity	Insurance	-0.45	201
Italy	VAS IM Equity	Insurance	-1.25	36
Italy	AE IM Equity	Real Estate	-0.41	154
Italy	BNS IM Equity	Real Estate	-1.66	27
Italy	BRI IM Equity	Real Estate	-0.68	138
Italy	GAB IM Equity	Real Estate	-0.19	134
Italy	NR IM Equity	Real Estate	-0.02	30
Italy	RN IM Equity	Real Estate	-0.07	163
Luxembourg	COFI LX Equity	Diversified Financials	0.00	253
Luxembourg	INSIN LX Equity	Diversified Financials	0.09	304
Luxembourg	LXMP LX Equity	Diversified Financials	-0.12	125
Luxembourg	QUIL LX Equity	Diversified Financials	-0.11	293
Malta	BOV MV Equity	Banks	0.29	225
Malta	FIM MV Equity	Banks	0.15	229
Malta	HSB MV Equity	Banks	0.32	282
Malta	LOM MV Equity	Banks	0.03	231
Malta	PZC MV Equity	Real Estate	0.00	263
Netherlands	INGA NA Equity	Banks	-2.24	12
Netherlands	LANS NA Equity	Banks	-0.64	189
Netherlands	BINCK NA Equity	Diversified Financials	-1.59	96
Netherlands	HAL NA Equity	Diversified Financials	-1.07	81
Netherlands	KA NA Equity	Diversified Financials	-0.74	29
Netherlands	KARD NA Equity	Diversified Financials	-0.40	190
Netherlands	VALUE NA Equity	Diversified Financials	-0.08	199
Netherlands	AGN NA Equity	Insurance	-1.99	18
Netherlands	BEVER NA Equity	Real Estate	-0.19	118
Netherlands	CORA NA Equity	Real Estate	-1.80	151
Netherlands	ECMPA NA Equity	Real Estate	-1.57	103
Netherlands	GROHA NA Equity	Real Estate	0.32	204
Netherlands	NSI NA Equity	Real Estate	-0.43	182
Netherlands	VASTN NA Equity	Real Estate	-1.57	123
Netherlands	WHA NA Equity	Real Estate	-0.90	112
Portugal	BCP PL Equity	Banks	-0.45	179
Portugal	BPI PL Equity	Banks	-1.11	74
Portugal	ESF PL Equity	Banks	-0.03	267
Slovakia	VUB SK Equity	Banks	0.14	295
Slovenia	NIKN SV Equity	Diversified Financials	-0.01	264
Slovenia	KDHR SV Equity	Insurance	-0.08	268

Spain	BBVA SM Equity	Banks	-2.23	22
Spain	BKT SM Equity	Banks	-1.57	5
Spain	POP SM Equity	Banks	-1.19	19
Spain	SAB SM Equity	Banks	-0.84	107
Spain	SAN SM Equity	Banks	-2.13	4
Spain	ALB SM Equity	Diversified Financials	-1.00	3
Spain	CGI SM Equity	Diversified Financials	0.03	129
Spain	REA SM Equity	Diversified Financials	0.08	214
Spain	UEI SM Equity	Diversified Financials	0.11	220
Spain	GCO SM Equity	Insurance	-1.28	97
Spain	MAP SM Equity	Insurance	-1.74	104
Spain	CEV SM Equity	Real Estate	0.00	260
Spain	COL SM Equity	Real Estate	-0.39	164
Spain	FICIS SM Equity	Real Estate	0.00	240
Spain	ILV SM Equity	Real Estate	0.00	251
Spain	LIB SM Equity	Real Estate	0.03	250
Spain	MTB SM Equity	Real Estate	-0.23	149
Spain	QBT SM Equity	Real Estate	-0.52	193
Spain	STG SM Equity	Real Estate	-0.16	102
Spain	TST SM Equity	Real Estate	-0.25	195
Spain	UBS SM Equity	Real Estate	-0.19	215