Spillover Effects & Early Warnings in European Markets using GVAR

Philosophy Doctor Thesis

Author: Filippo Umberto Andrini
Supervisor: Prof. Giovanni Urga
Co-Supervisor: Prof. Annamaria Bianchi

Dipartimento di Scienze Aziendali, Economiche e Metodi Quantitativi
University of Bergamo

26th January 2020

Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, in whole or in part, in any previous application for a degree. Except where states otherwise by reference or acknowledgement, the work presented is entirely my own.

Filippo Umberto Andrini

Bergamo, Italy 26.01.2020

Acknowledgement

I wish to express gratitude to my supervisors Giovanni Urga and Annamaria Bianchi for their helpful suggestions to this work. Thanks for letting me spend a great year at Cass Business School. In London, I had the opportunity to discuss with Cass PhD colleagues, researchers and professors and I thank everyone for making my experience amazing. I gratefully acknowledge the Department of Management, Economics and Quantitative Methods of the University of Bergamo for the scholarship that made possible these studies. Thanks also go to my PhD colleagues, in particular the XXXII Cycle guys and the Office 206 colleagues for making my years at the University of Bergamo an enjoyable experience. I wish to express gratitude to my friends and also to my colleagues in Compliance and Audit areas at UBI Banca that pushed me to achieve this extraordinary goal. Finally, I heartily thank my parents, my brother and Benedetta, whose love, encouragement and patience have supported me throughout these years.

Contents

List of Figures

List of Tables

Introduction

The great financial crisis of August 2007/September 2008 and its repercussions in Europe, including the sovereign debt and the various banking crises, have highlighted how the interconnections between economic and financial systems can be rapidly transformed into channels of contagion between the different entities. It is not a coincidence that many banking crises occurred during these years of turbulence for public finance. The close ties between the banking system and the dynamics of sovereign debt have exacerbated vulnerable situations. The difficulties of some European economies, as well as some financial events (such as the $7.2 bln trading loss at Société Générale in 2008 and the Deutsche Bank $7.3 bln loss in 2016 because of sanctions for fixing benchmark interest rate), have pushed both policy makers and researchers to focus more on assessing interconnections in financial markets. The aim of this thesis is to investigate the interconnections role among several entities in order to analyse both "systemicity" and "idiosyncraticism". We aim to investigate which shocks propagate to the connected entities and which, instead, have no effect outside. To reach these objectives we first analyse both spillover effects and interconnections among European countries. Then, we make use of an Early Warning System able to predict a crisis on the basis of both, financial and economic variables. This framework allows us to analyse the probability of being in a vulnerable period following a shock. In particular, we consider a negative shock on long time interest rate. Moving to the banking sector, we consider the operational risk topic. We analyse both main drivers and large operational losses effects on bank's returns.

In Chapter 1, we focus on the European monetary union, and we propose a robust empirical analysis about the contagion channels over last years with respect to European countries. We aim to assess the effects of contagion within the main Eurozone countries, with particular interest in the equity markets, the sovereign debt dynamics and the real economy. To this purpose, we divide the Eurozone into three regions: Core (the main entity is France), Periphery (the main entity is Italy) and Germany which, according to Kempa and Khan (2017), we consider as

benchmark economy. We use the Global Vector Auto-Regression (GVAR) methodology, able to overcome the "curse of dimensionality" typical of simple Vector Autoregression (VAR) techniques, and to capture bilateral connections through the presence of both foreign and global (common) variables. To investigate the shocks effects we use the Global Impulse Response Functions (GIRFs) that identify the channels and levels of interdependence between the different countries, while the Global Forecast Error Variance Decomposition (GFEVD) allows us not only to understand the weight that single or compounded economies have in the disturbance of the variables under examination, but also how themselves influence each other.

In Chapter 2 we test the change of being in a vulnerable state after a decline in European treasury bonds yields. To reach this aim, first we create a "crisis" variable following Laeven and Valencia (2012) able to capture the periods of pre-crisis, crisis and recover. Second, we set an Early Warning System (EWS) that exploits a Multinomial Logit technique able to overcome the so called "post-crisis" bias and then we evaluate the probability to move in a period of turbulence. Third, we apply a GVAR model and we introduce GIRFs that capture the reactions after a negative shock on 10 years Treasury bills yields. Finally, we compute the probability of being in a crisis period using these "new" observations. This allows to check if this probability changes or not.

Finally, in Chapter 3 we deal with another type of risk, namely the operational risk in banking sector. Firstly, we aim to investigate what are the main drivers that affect operational losses distribution for both frequency and severity. Second, we evaluate the large operational losses effects on bank's returns and finally, we investigate the idiosyncratic nature of operational losses. For this purpose we collected a dataset of all operational losses related to a significant supervised European bank. To define the main drivers we follow Chernobai et al. (2011) considering frequency and severity separately, and using Poisson and OLS regressions respectively. As regards operational losses effects, we follow Cummins et al. (2006), particularly we evaluate a three-factor model that considers, in addition to the bank's returns, also the stock index of the European banking sector (Stoxx 600) and the main national index in which the bank is listed. Finally, we identify the most significant operational losses, we compute abnormal and cumulative abnormal returns for both, the bank and the market in order to observe the large operational losses effect on the bank's returns.

Chapter 1

Spillover effects in the Euro-Area, a Global VAR analysis

1.1 Introduction

The Great Recession (starting from August 2007) as well as the European Sovereign Debt Crisis (erupted since 2011) has highlighted how the interconnections between the various economies have the power become channels of crisis transmission in particular periods of stress. In this paper we focus on the European monetary union, and we try to give a robust empirical analysis about the detection of contagion channels that have distinguished these last years. In particular we investigate if European countries, with different economic and financial characteristics, have sensitivities and different answers regarding the channels of interdependence. In this work we aim to assess the effects of contagion within the main Eurozone countries, with particular interest in the equity markets, the debt owed and the real economy. For this purpose, we have divided the Eurozone into three regions: Core (whose main entity is France), Periphery (whose main entity is Italy) and Germany, which we consider to be a broad economy, as proposed by Kempa and Khan (2017).

For our analysis we use the Global Vector Auto-Regression (GVAR) method, introduced by M. Pesaran et al. (2004). In particular, GVAR has three main advantages. First,it provide direct estimates of the transmission of shocks during normal and crisis times, enabling a complete understanding of the direction and the magnitude of contagion. Second, GVAR models have the advantage to overcome the so-called "curse of dimensionality" typical of simple Vector Autoregression (VAR). Third, using GVAR, it is possible to capture bilateral connections

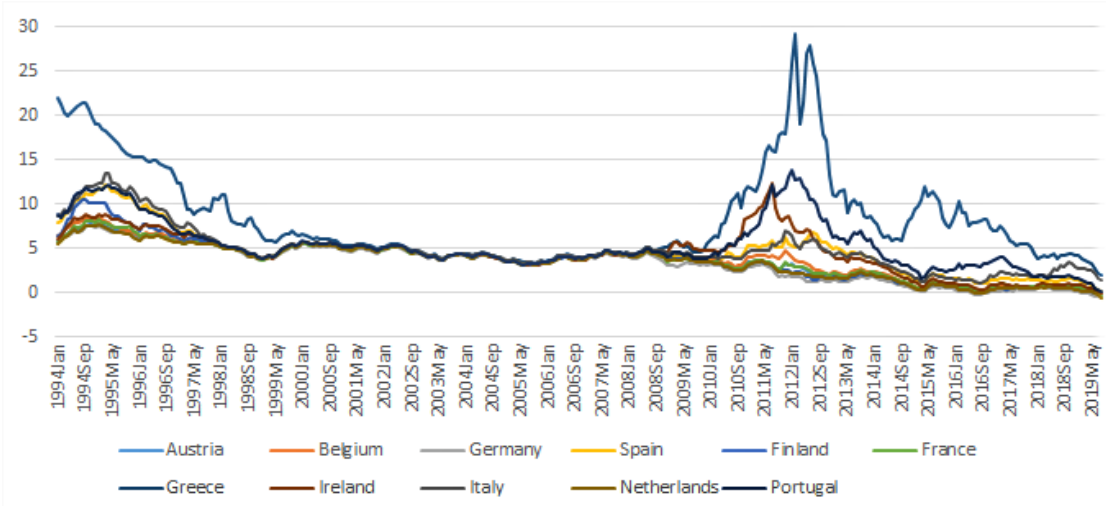

Figure 1.1: Long Term Interest Rates in the Eurozone (ECB)

through the presence of foreign variables, while the presence of global variables allows considering transmission channels of additional shocks and (also it allows) interdependence across individual variables within and across units. The use of the Global Impulse Response Functions (GIRFs) allow us to identify the channels and levels of interdependence between the different countries, while the Global Forecast Error Variance Decomposition (GFEVD) allows us not only to understand the weight that single or compounded economies have in the disturbance of the variables under examination, but also how they influence each other.

To set the focus of the discussion, it is useful to look at Figure 1.1 that shows the long-term interest rate from January 1994 to December 2017. The left hand side of the graph clearly shows how the introduction of the euro (established in 1999 and effectively adopted by 1st January 2001) has brought a convergent push to the European countries. This same trend can be found in other fundamentals of the economy, for example the inflation as in Sander and Kleimeier (2004). The early years of monetary union have been characterised by a strong convergence in Treasury bills yields, both in terms of their levels and their responsiveness to new information Ehrmann, Fratzscher, Gürkaynak and Swanson (2011), while the shock of Lehman Brother has certainly impacted on this convergence. In fact, in this respect, the spread between German (benchmark) and the Greeks interest rate (the highest) moves from 0.67 in August 2008 to 1.53 in the following November, until reaching the value of 2.85 in March 2009. This period of turbulence has eased until the end of 2009, re-positioning the differential around 1.30-1.40. From December 2009 to February 2012, a continuous growth of the differential was

observed up to the record value of 27.39. This trend, albeit with extremely low values, has been common to several economies, in particular those later called Periphery (namely Greece, Ireland, Portugal, Spain and Italy), but also core countries such as Belgium and France. It is only with the famous "whatever it takes" of 26 July 2012 that the tension seems to be attenuating up to the current 4% difference between Germany and Greece. While on the one hand the monetary union has promoted a convergence of European economies, on the other, Lane (2012) suggests how this convergence has been artificial and that the crisis that Europe has faced is a direct consequence of the unique monetary system construction that did not consider the heterogeneity between countries and no structures were set up with the aim of protecting the increasingly interconnected (and consequently subject to tensions) economic system.

In this paper, we analyse the countries that first adopted the Euro (with the exception of Luxembourg) from 2004 to December 2017. The variables of interest on which we focus are: the price of sovereign CDS, the price of the main equity index, the effective exchange rate and the interest rates on 10-year treasury bills. These variable aims to capture both financial and macroeconomics dynamics. Particularly, the price of sovereign CDS is among the most common derivative contracts for the credit risk transfer, in this case we consider the sovereign debt CDSs. Equity Prices are defined as the principal stock index for each country. The Effective Exchange Rate (EER) variable measures the value of a specific currency in relation to an average group of others major currencies. EER takes into account the relative price changes, thus defining the effective purchasing power of the currency of a single economy. Finally, Long Term Interest Rate represents the interest rates for 10 years government bonds in Euro for each country.

We evaluate the GIRF with reference to Italy (the most important country of the European Periphery region) and France (the most important country in the Core area of Europe), while Germany is used as a key country in the European system. The results can be summarised as follows: first, it is observed that only in 36 cases out of 88 a shock on French or Italian variables has no effects on European countries, more precisely 15 times for France and 21 for Italy. Secondly, it is observed that the propagation force of the shocks differs with regard to the country and variable combination. For France the propagation of the shock is less effective where it affects real variables (in particular the long-run interest rate and effective exchange rate), for Italy the financial variables that obtain less effects on other European countries when the price of CDS and the value of the main equity index are hit by a shock. Regarding the analysis of the GFEDV, conducted both

for the effective exchange rate and for the value of the equity index, it is interesting to note that the dynamics are similar for both countries analysed, in particular for the stock index. It is the Periphery that plays a decisive role, while the Core countries have a major impact on the disturbance of the effective exchange rate.

The paper is structured as follows, Section 1.2 presents the strands of literature we refer to within this work. The formulation of the GVAR methodology is proposed in Section 1.3. Section 1.4 presents the data and the empirical results, while Section 1.6 concludes.

1.2 An Overview on Contagion Literature

In this section, we present a review of the literature. In particular, we consider the European financial and sovereign debt crisis (Section 1.2.1), the analysis of the transmission of shocks from one entity to another (Section 1.2.2) and an overview of the methodologies most commonly used for studying spillover effects in the literature (Section 1.2.3).

1.2.1 European Financial and Sovereign Debt Crisis

Many authors have contributed in this field, analysing the most diverse facets of such a complex subject. A more general and institutional analysis is proposed by Cipollini et al. (2015), where the authors show how the overcoming of exchange rate risk plays a crucial role in the convergence of yields on treasury bills, while from 2010 the imbalances within the monetary union have made the market fragmented and unstable. Furthermore, Blundell-Wignall (2012) studies the policies adopted to deal with the financial crisis and the sovereign debt crisis, showing that the high heterogeneity between different countries of the monetary union has not been taken into account by policy makers. In particular, idiosyncratic characteristics such as competitiveness, growth strategies, public and private debt have not been considered by the regulator. The document analyses the role of banks that, having reached global dimensions, are exposed to infection. In support of these results, Baldi and Staehr (2016) deal with the issue of fiscal divergences between periods of quiet and crisis. The authors find that during crises there is much more feedback from the debt stock. These results should be valid at the same time for countries affected by the economic crisis to a different extent. Among others, Barrios et al. (2009) and Antonini et al. (2013) study the spread on treasury yields and the historical series of public debt in Europe, respectively. Particularly,

Barrios et al. (2009) find that the "general risk" plays a fundamental role in the dynamics of the differences in returns, while internal factors, such as sovereign risk and liquidity, have a secondary role which however grows in the periods of greatest crisis. Antonini et al. (2013), on the one hand, show a profound interconnection between the dynamics of European sovereign debts, while on the other one, a strong permanence of the effects produced by fiscal or economic cycle shocks.

An important part of the literature on the European sovereign debt crisis investigates the role of banks, in particular the effects that financial institutions have suffered from the holding of sovereign debt in various European countries. In this debate, Chan-Lau et al. (2015) show how European banks have experienced negative equity performances due to the large amounts of public debt of the various European governments in detention. To overcome this problem, the regulator invited the banks themselves to strengthen the capital and this seems to have brought positive results. Again, Becker and Ivashina (2018) show how the increase in public debt in European countries, held by banks, was the most important channel with which to exert financial repression. Again with reference to bank performances, Ejsing and Lemke (2011) focus on CDS role, while Tamakoshi and Hamori (2013) deal with equity performance. Ejsing and Lemke (2011) consider sovereign CDS premiums and show that those of banks that rescue packages for financial institutions have reduced the tension on bank derivatives while few effects have been seen sovereign market. As sovereign CDS are mostly held by banks, banks have also started to suffer from growing tension. Tamakoshi and Hamori (2013) demonstrate the presence of contagion by observing the trend of correlations of share returns from various European financial institutions that hold, largely, the Greek public debt. Furthermore, in relation to the concept of contagion and spillover effects, Broto and Perez-Quiros (2015) break down the CDSs into three sections: a common factor, a respective idiosyncratic factor for each country, and a last part subject to the European sovereign debt crisis. They show that this last one plays an important role especially according to the interdependence relationship among European countries. The key role of the peripheral countries is highlighted by Ehrmann and Fratzscher (2017) and Samarakoon (2017) which, respectively, analyse the effects of spillover and contagion between European countries and between high-debt European and emerging countries. Whereas Gorea and Radev (2014) study the channels of shock transmission between core and peripheral European countries, Gorea and Radev (2014) find that in the peripheral countries the key transmission channel is given by the financial markets, while the transfer of the shock from peripheral countries to the

core ones is based on real channels such as international trade.

1.2.2 Shocks Transmission

The second strand of literature is about the shocks transmission within the financial markets, especially during the sovereign debt crisis in Europe. This topic was early faced, among others, by Hamao et al. (1990) and Engle et al. (1988), that stressed spillover dynamics on equity markets between USA, Japan and UK. Recently, Diebold and Yilmaz (2009) present a "measure for interdependence" based on the formulation of two different types of indicators, return and volatility spillovers. Returns shows an increasing trend for the survey period (1990-2009), while the volatility spillovers are not characterised by trends but present explosions in times of crisis. Ehrmann, Fratzscher and Rigobon (2011) highlighted the shock transmission on financial markets not only among asset classes but also across asset internationally. Brutti and Saure (2015), using a VAR model of daily sovereign CDS to estimate shocks, find that Greek sovereign debt and debt of Greek banks constitute the most important transmission channels. Cetorelli and Goldberg (2011) show how international banks are, together with financial markets, the main channels for the transmission of shocks during 2008 crisis.

1.2.3 Spillover Effects and Related Methodologies

Contagion definition and main methodologies of investigation

The last strand of literature we investigate is about contagion and spillover effects and the most used methodologies to evaluates these phenomena. Rigobon (2016) proposes an overview of the definitions of contagion and spillover effects, where, in addition to proposing a general definition of contagion ("the phenomenon in which a shock from one country is sent to another"), the author analyses different methods used for the identification of diameters and channels of contagion between economies.

The autoregressive conditional heteroskedasticity (ARCH) and generalised autoregressive conditional heteroskedasticity (GARCH) models have been used, among others, by Hamao et al. (1990), Bekaert and Harvey (2003) and Baele (2005). Hamao et al. (1990) observe that the daily stock returns for the US, UK and Japanese markets can be described by a GARCH-M (1,1) model that shows the presence of spillover effects from the US and the UK stock markets to the Japanese one. Bekaert and Harvey (2003) focus on the crisis in South-east Asia and

Mexico, both of which occurred in the 90s of the twentieth century. The authors develop a two-factor model for three regions, namely Europe, South-east Asia and Latin America, while the two factors are the US equity market and the equity regional portfolio returns. Also in this case volatility is described by an asymmetric GARCH model. According to the authors the evidence of the presence of contagion is to be found in an increase in correlations in times of crisis, particularly during the South-east Asia crisis. Asymmetric GARCH models were also used by Baele (2005) to describe the volatility of the equity markets of 13 European countries and the United States. The author shows that with the increase in commercial traffic and interconnections between economies, the effects of spillovers are becoming stronger over time. As seen above, the correlation between economies is seen as the manifestation of contagion. In this context, Sander and Kleimeier (2003), exploiting the concepts of cointegration and of Granger Causality, analyse the Asian and Russian crises using daily data between the end of 1996 and March 2000. They find that the impacts of the Asian (before) and the Russian (later) crisis have changed the causality patterns. The cointegration methodology is also used by Yunus (2013), that evaluates the links between the stock markets of the major world economies (North America, Europe, Asia and Latin America) using the recursive cointegration technique, in particular concentrating on how the links between the economies change in the period 1993-2008.

Among the most considered methodologies used to evaluate spillover effects we have the Vector Autoregression (VAR). Differently from the previous ones, it has the advantage of providing direct estimates of the transmission of shocks during normal and crisis times, enabling a complete understanding of the direction and the magnitude of contagion. Particularly, we consider Eun and Shim (1989), where the authors investigate contagion reports in nine time series of stock returns on daily data from the end of 1979 to the end of 1985. Cuadro-Sáez et al. (2009) show through VAR models how the emerging economies have achieved an important role in the global financial market, while Samarakoon (2017) observes the effects of interdependence between high-debt and emerging European economies. Despite, VAR technique has many advantages, but the so-called "curse of dimensionality" is an important drawback that does not allow analysis with a large amount of data. With the main aim of overcoming this problem, M. Pesaran et al. (2004) introduce the GVAR methodology. The success of the GVAR methodology derives from the fact that it combines individual error-correcting models for a set of countries and estimates them in a single model through the assumption of weak exogeneity for foreign variables. Foreign variables are calculated through

weighted averages, generally based on commercial relationships. Several models have been developed in the literature to handle large datasets, in particular models using common factors, large Bayesyan VARs, Panel Vars and Global Var. In general we can see factor models as data narrowing procedures, where a large set of variables is restricted to a smaller set of factors. The estimated factors can be used with the vector of home variables to create a model called factor augmented VAR (FAVAR). Dees, Holly et al. (2007) suggest that FAVAR does not allow to precisely identify unobserved factors. Moreover, the number of estimated factors used in FAVAR is different for different countries and it is not clear how they relate to each other globally. In fact, Kapetanios et al. (2011) argue that GVAR estimators perform better than the corresponding ones based on principal components. Bayesian VARs large-scale and VAR panels have very similar characteristics. The differences between the two are that, while the large Bayesian VARs treat each variable symmetrically, the VAR panels take into account the structure of the variables, considering different sizes cross-section. Finally, according to Niehof (2014), there are many advantages of using a GVAR analysis: firstly, we do not need to rely on components being persistent processes, secondly, since foreign variables enter the estimation by a weighted matrix, the bilateral connections are also captured. Thirdly, GVAR allows for interdependencies across individual variables within and across units, as well as the reduced-form errors to be cross-sectional dependent. Furthermore, exploiting the common variable, we can investigate another influence and linkage channel between entities.

GVAR Methodology and empirical literature

Chudik and Pesaran (2016) have recently proposed a rich overview of the GVAR methodology that analyses both the methodological contributions and the empirical ones, showing how the GVAR methodology is applicable to a wide set of economic studies. As we anticipated earlier, the GVAR literature bases its roots in the contribution of M. Pesaran et al. (2004), in which the authors introduce the Global VAR technique and consider relations of interdependence between countries and regions. In particular, the authors analyse the economic effects of a shock on a portfolio that includes investments in over 100 companies located in 20 countries (11 regions). The authors demonstrate the feasibility of the GVAR approach to analyse interconnection relationships between economies.

The GVAR technique is based on the aggregation of several single vector error-correcting regional models into a single global system through an aggregation

matrix, where each single model includes both domestic and foreign variables. These foreign variables are the weighted average of the home variables of the other regions. This methodology, as well as the VAR models, allow generating forecasts, but in the GVAR case these can be done simultaneously for each model variable. M. Pesaran et al. (2004) do not theoretically justify the GVAR methodology. Dees, Mauro et al. (2007) and subsequently Chudik and Pesaran (2011) show how the GVAR technique can be derived from the approximation of a global factorial model and a factor augmented stationary high dimensional VAR, respectively.

Moving to the empirical literature, Chudik and Pesaran (2016) propose a rich selection of works that exploit GVAR methodology for numerous topics. In this section, we just analyse some of the contributions that are most closely related to our work, given that the aim of our research is to evaluate the interdependence and spillover effects of a single economy (France or Italy) in relation to the whole European system reorganised in three regions, namely Core (composed of Austria, Belgium, Finland, France and the Netherlands), Periphery (consisting of Greece, Ireland, Italy, Portugal and Spain) and Germany (which plays the role of large economy).

The impacts of a country on the economic system The impact of an economy on an entire economic system is the object of study of the contributions of Cesa-Bianchi et al. (2012) and Dreger and Zhang (2013). In both works the GVAR methodology, through the Global Impulse Response Functions (GIRFs), is used to analyse the role of China in relation to Latin America and the developed economies, respectively. Cesa-Bianchi et al. (2012) analyse how shocks on the Chinese GDP (and US) are reflected in the business cycle of countries that include Latin America. The authors note that the role of China is stronger and stronger over time. The contribution of Dreger and Zhang (2013) has the merit of comparing the results that a shock on the Chinese GDP has on GDP and inflation of the main world economies (US, Euro Area, Japan and China itself) using the GVAR methodology and the National Institute Global Econometric Model (NiGEM). The results of the two models are extremely similar. The NiGEM methodology has an important weakness: it is based on a large number of equations to estimate (from 60 to 90) with 30 key behavioural relations. On the contrary, the GVAR technique requires a lower number of parameters to be estimated.

As anticipated in the Introduction, our work considers, in addition to financial variables, also the economic relations between the different entities (both countries and regions). To capture the economic dynamics, in addition to the long-term

interest rate, we also use the effective exchange rate which, as a measure of competitiveness, captures the business cycle dynamics of the various components of the Eurozone, both individually and aggregated at regional level.

The role of the effective exchange rate has been studied, among others, by Bussiere et al. (2013). The authors exploit the infinite-dimensional VAR (IVAR) methodology (Chudik and Pesaran (2011) show how the GVAR methodology is the approximation of a Factor Augmented Stationary High-dimensional VAR model). Their results suggest a divergence among European countries based on the different degrees of competitiveness of the core and peripheral countries of the Monetary Union.

Business cycle dynamics The study of business cycle dynamics is the basis of the contribution of Xu (2012), in which the author observes how the role of credit is fundamental in the performance of GDP and the business cycle. The model presents the interactions between 26 economies, in particular it observes the effects of a fall in internal credit in the US on the other economies, mainly the Eurozone, Japan and the United Kingdom. The effects of a tightening on US credit are serious in many regions, especially in real terms, and these negative effects on the real level, in turn, have a cross-sectional effect. Konstantakis and Michaelides (2014) complete, in some way, the work of Xu (2012) considering the channels and the direction that the effects of contagion have followed with reference precisely to the sovereign debt crisis. In particular, the authors show that the effects of shocks on the US economy have greater effects on the Eurozone than vice-versa. Moreover, even in this case the role of internal credit is shown to be a determining factor.

Channels and intensity of contagion The economic literature has exploited the GVAR methodology to evaluate intensity and channels of contagion between different economies in the event of a crisis. Among the most interesting contributions is that of Dovern and van Roye (2014) which focuses on the main 20 world economies for the period 1970-2012. The key variable of the work is the Financial Stress Index. The authors, through a dynamic approximate factor model, extract from the stress index the set of variables (stock market volatility, exchange rate volatility, volatility bond volatility, banking sector volatility, etc.) for each country. Dovern and van Roye (2014) show that the opening of the markets increases the probability that the stress will spread on the markets and that the comovements increase in the event of a crisis (confirming the definition of contagion).

The GVAR technique makes it possible to evaluate how spillover effects generally go from developed to emerging countries (and not vice-versa) and how the US position is decisive: a US financial stress shock propagates very quickly to other economies. Unlike the previously analysed work, Beirne and Gieck (2014) evaluate the differences between interdependence and contagion relationships. The discriminant is given by a dummy variable in the GVAR model, which is 0 in quiet moments, while it is 1 in crisis periods (when the Global Financial Stress index, GFS, ≤ 25). Authors estimate both interdependence and contagion among different assets (bonds, stocks and currencies) in the same equation. They show that the effects of infection are strong in Latin America and in Emerging Asia equities. During the crisis period, the role of the US is dominant with respect to the equity markets, while the Eurozone is important in the bond market.

As we have seen up to here, the GVAR methodology allows to evaluate different economies and assets simultaneously but always using a single cross-section dimension. Gross and Kok (2013) contribution allows to take a step forward. The GVAR Mixed Cross-Section (MCS-GVAR) allows combining two (or more) cross-sections related to different markets. The authors propose to evaluate simultaneously both the national economic systems (with reference to the sovereign debt market) and the different banking systems, creating two GVAR models joined together by a link matrix. This methodology allows to observe endogenous feedback within and across cross-section. On the one hand, the authors show that the channels of contagion between banks and sovereign debt strength intensified during the crisis, on the other they explain that the GVAR (or MCS-GVAR) technique is suitable to the regulator to carry out analyses and estimates in a way to adopt policies to overcome moments of crisis, thanks also to the forecast nature of the GVAR model. In this spirit, Echevarria-Icaza and Sosvilla Rivero (2017), analyse the transmission of unconventional monetary policy adopted by Mario Draghi to face the sovereign debt crisis in Europe through a "classical" methodology GVAR. Also in this case, the authors show how the bond market (and in particular yields) have a role to find in explaining the relationships and spillover channels between the different Eurozone countries.

Forecast using GVAR Although not directly linked to empirical research, a large strand of literature focus on the use of the GVAR methodology in the forecast field. Among others, we cite the contribution of M. H. Pesaran et al. (2009a) and M. H. Pesaran et al. (2009b). In these works, the authors use Dees, Mauro et al. (2007) results in order to predict the trend of both financial and economic

variables. The authors show that simple averaging across model specifications and estimation windows can make a significant difference. In particular, the double-averaged GVAR forecasts (across windows and models) perform better than the typical univariate benchmark competitors, especially for output, inflation and real equity prices. The good forecasting capabilities of GVAR models were also assessed by De Waal et al. (2013), Garratt et al. (2016), Bussière et al. (2009) and Greenwood-Nimmo et al. (2012). De Waal et al. (2013) and Garratt et al. (2016) compare the forecast performances of the GVAR methodology with a VECM model (with reference to the South African economy) and random walk, AR and VAR models (analysing the growth of the output), respectively. In both cases the GVAR methodology is preferable, especially if we consider forecasts with a longer time horizon. Bussiere et al. (2013) and Greenwood-Nimmo et al. (2012) conclude that GVAR models are particularly suited to forecast in the institutional political sphere. Bussiere et al. (2013) focus on the trend of international trade (in particular the collapse of 2008-2009) by observing how macroeconomic variables are able to predict their performance. Greenwood-Nimmo et al. (2012), however, study the growth of the output, inflation and trade imbalances for thirty-three countries. Chudik et al. (2016) deals with GVAR's performances in the field of very short-term forecasting. In particular, the authors increase the GVAR model with equations that approximate the common non-observable factors. Doing so, they get an augmented GVAR model (AugGVAR) that uniformly converges in probability to the infeasible optimal forecasts obtained from a factor-augmented high-dimensional VAR model. Empirically they analyse the value of the information content of Purchasing Managers Indices (PMIs) for forecasting in 48 countries. The results of the analysis are compared to other forecasting models such as Lasso, Ridge, partial least squares and factor-based methods. It turns out that the AugGVAR methodology has similar performances to other short-term estimators and better in the long run. Favero (2013) uses a GVAR model to predict the performance of the bond market in the euro area.

1.3 GVAR Methodology

The economies and financial markets are linked by different channels. Although some of these can be investigated quite simply, others need models able to assess the interdependencies deriving from unobservable spillover effects, which can not be taken into account using the classic channels of interaction. The Global VAR (GVAR) approach, originally proposed by M. Pesaran et al. (2004), provides a

model that allows to overcome the so-called curse of dimensionality in a theoretically coherent and statistically consistent way. The GVAR was originally designed as a tool for the analysis of credit risk, with particular attention to the Asian financial crisis of the late nineties, but the use of this methodology has spread in many applications. The GVAR model combines individual country vector error correcting models, in which domestic variables are related to country-specific foreign variables in a consistent manner. The foreign variables are constructed from the domestic variables so as to match the international trade, or financial relationship, where the foreign variables serve as a proxy for common unobserved factors. The GVAR model allows for complex interactions/interdependencies at national and international levels. It allows for long-run relationships consistent with the theory and short-run relationships that are consistent with the data.

The GVAR is a two-step procedure. In the first step, small-scale country-specific models are estimated conditional on the rest of the world. These models are represented as augmented VAR models, denoted $VARX^*$ and feature domestic variables and weighted cross-section averages of foreign variables, also commonly referred to as "star variables" which are treated as weakly exogenous. In the second step, individual country $VARX^*$ models are stacked and solved simultaneously as a one large global VAR model. The solution can be used for shock scenario analysis and forecasting as usually done with standard VAR models. In this presentation of the GVAR methodology we rely on two main texts, Di Mauro and Pesaran (2013) and M. H. Pesaran (2015).

1.3.1 Factor-augmented high-dimensional VAR models

Firstly we consider a large set of variables endogenously determined in a factor-augmented high-dimensional VAR model. This kind of model allows for very general patterns of interlinkages among variables, but it cannot be estimated consistently due to the curse of dimensionality, when the cross-section dimension, N, is large. To introduce the GVAR methodology, it is useful to consider the so called large-scale VAR. Consider a panel of N $(i = 1, ..., N)$ cross-sectional units. For each unit, k_i variables are observed at time $t = 1, 2, ..., T$, x_{it} denotes the $k_i \times 1$ vector of all the panel variables and $x_t = (x'_{1t}, x'_{2t}, ..., x'_{Nt})$ is the $k \times N$ vector of all variables in the panel, where $k = \sum_{i=1}^{N} k_i$. Now, suppose that x_t is generated by the following factor augmented VAR model:

$$\Theta(L, p)x_t = \Gamma_f(L, s_f)f_t + \Gamma_\omega(L, s_\omega)\omega_t + u_t \tag{1.1}$$

where L is the lag operator, $\Theta(L,p) = I_k - \sum_{\ell=1}^{p} \Theta_\ell L^\ell$ is a matrix lag polynomial in L, Θ_ℓ for $\ell = 1, 2, ..., p$ are the $k \times k$ matrices of unknown coefficients, $\Gamma_a(L, s_a) = \sum_{\ell=1}^{s_a} \Gamma_{a\ell} L^\ell$, for $\ell = 1, 2, ..., s_a$ and $a = f, \omega$ are $k \times m_a$ matrices of factor loadings, f_t is the $m_f \times 1$ vector of unobserved common factors, ω_t is the $m_\omega \times 1$ vector of observed common effects, finally, u_t is a $k \times 1$ vector of reduced form errors with zero means, and $k \times k$ covariance matrix, $\Sigma_u = \mathrm{E}(u_t u_t')$. VAR models provide a rather general description of linear dynamic systems, but the number of unknown parameters to be estimated grows at a quadratic rate in the dimension of the model k. Finally, the GVAR approach solves the dimensionality issue by decomposing the underlying large dimensional VARs into a smaller number of conditional models, linked together by cross-sectional averages, in this case no restrictions are imposed on the dynamics of each sub-model.

1.3.2 GVAR Derivation

We now present the GVAR methodology. We follow the approach proposed originally by M. Pesaran et al. (2004), and we present the changes introduced by the subsequent literature. Consider a panel of N $(i = 1, ...N)$ cross-sectional countries, where k_i country-specific variables are observed at time $t = 1, 2, ..., T$. By x_{it} denote the $k_i \times 1$ vector of the country-specific variables and by $x_t = (x_{1t}', x_{2t}', ..., x_{Nt}')$ the $k \times N$ vector of all the variables where $k = \sum_{i=1}^{N} k_i$. The GVAR methodology allows all the small-scale country specific conditional models to be estimated separately, we denote by x_{it}^*, $k^* \times 1$ the vector, collecting the cross-sectional average of the foreign variables according to the rule:

$$x_{it}^* = \tilde{W}_i' x_t \tag{1.2}$$

for $i = 1, 2, ..., N$, where $\tilde{W}_i'$ is the $k_i \times k_i^*$ matrix of country specific weights. These are generally predetermined (based on trade relationships), and can be fixed or variable over time.

In general k_i and k^* are assumed to be small. x_{it} is modelled as a VAR augmented by the vector of foreign variables x_{it}^* and their lagged values:

$$x_{it} = \sum_{\ell=1}^{p_i} \Phi_{i\ell} x_{i,t-\ell} + \sum_{\ell=0}^{q_i} \Lambda_{i\ell} x_{i,t-\ell}^* + \epsilon_{it} \tag{1.3}$$

for $i = 1, 2, ..., N$, where $\Phi_{i\ell}$, for $\ell = 1, 2, ...p_i$, $\Lambda_{i\ell}$ for $\ell = 0, 1, 2, ..., q_i$ are the $k_i \times k_i$ and $k_i \times k^*$ matrices of unknown parameters, respectively, and ϵ_{it} are $k_i \times 1$ country-specific error vectors. The "star variables" are treated as

weakly exogenous for the purpose of estimating the unknown coefficients of the conditional country models.[1] Let now consider $z_{it} = (x_{it}^{'}, x_{it}^{*'})'$ be the $k_i + k^*$ dimensional vector of domestic and country specific foreign variables included in the country i sub-model. We can express Equation (1.3) as:

$$A_{i0} z_{it} = \sum_{\ell=1}^{p} A_{i\ell} z_{it-\ell} + \epsilon_{it}, \tag{1.4}$$

where $A_{i0} = (I_{k_i} - \Lambda_{i0})$, $A_{i\ell} = (\Phi_{i\ell}, \Lambda_{i\ell})$ for $\ell = 1, 2, ..., p$, $p = max(p_i, q_i)$ and $\Phi_{i\ell} = 0$ for $\ell > p_i$ and similarly $\Lambda_{i\ell} = 0$ for $\ell > q_i$. The individual country models (Equation (1.3)) can be reformulated as:

$$\Delta x_{it} = \Lambda_{i0} \Delta x_{it}^* - \Pi_i z_{i,t-1} + \sum_{\ell=1}^{p} H_{i\ell} \Delta z_{i,t-1} + \epsilon_{it}, \tag{1.5}$$

where Δ is the usual first difference operator and

$$\Pi_i = A_{i0} - \sum_{\ell=1}^{p} A_{i\ell}, \quad and \quad H_{i\ell} = -(A_{i,\ell+1}, A_{i,\ell+2}, ..., A_{i,\ell+p}).$$

Furthermore, taking into account the possibility of cointegration both within x_{it} and across x_{it} and x_{it}^*, the following decomposition holds: $\Pi_i = \alpha_i \beta_i'$, where α_i is the speed of adjustment and β_i are the coefficients of the cointegrating vectors $((k_i + k^*) \times r_i)$ obtained for each country model. The estimation of country models (which allows for cointegration within and across countries) is the first step of the GVAR procedure.

The second step consists of stacking the estimated country models to form one large Global VAR, using the $(k_i + k^*) \times k$ dimensional link matrices $W_i = (E_i', \tilde{W'}_i)$ where E_i is the $k \times k_i$ dimensional selection matrix that selects x_{it}, namely $x_{it} = E_i' x_t$ and $\tilde{W'}_i$ is the weight matrix introduced above to define the "star" variables. We have that

$$z_{it} = (x_{it}^{'}, x_{it}^{*'})' = W_i x_t. \tag{1.6}$$

Replacing Equation (1.6) in (1.4), we obtain:

[1] Weak exogeneity is defined as $\mathrm{E}[u_{i,t}|z_{i,s}] = 0$ for $s \leq t$, specifically, the error terms are assumed to be independent of all lagged values of the instruments and to have mean zero conditional on information at time t.

$$A_{i0}W_i x_t = \sum_{\ell=1}^{p} A_{i\ell}W_i x_{t-\ell} + \epsilon_{it} \tag{1.7}$$

and stacking the models for $i = 1, 2, ..., N$ we obtain:

$$G_0 x_t = \sum_{\ell=1}^{p} G_\ell x_{t-\ell} + \epsilon_t, \tag{1.8}$$

where $\epsilon_t = (\epsilon'_{1t}, \epsilon'_{2t}, ..., \epsilon'_{Nt})$ and $G_\ell = (A_{1,\ell}W_1, A_{2,\ell}W_2, ..., A_{N,\ell}W_N)'$ for $\ell = 0, 1, 2, ..., p$, If matrix G_0 is invertible we have:

$$x_t = \sum_{\ell=1}^{p} F_\ell x_{t-\ell} + G_0^{-1}\epsilon_t \tag{1.9}$$

where $F_\ell = G_0^{-1}G_\ell$ for $\ell = 1, 2, ..., p$. Equation (1.8) may be solved recursively forward to obtain the future value of x_t.

1.3.3 Common Variables

Chudik and Pesaran (2011) argue about the possibility to add common variables in the country models. Recalling the factor-augmented high-dimensional VAR model considered at the beginning of this section, Equation (1.1), $m_\omega > 0$, so the conditional country models need to be augmented by ω_t and its lagged values, according to the formulation:

$$x_{it} = \sum_{\ell=1}^{p_i} \Phi_{i\ell} x_{i,t-\ell} + \sum_{\ell=0}^{q_i} \Lambda_{i\ell} x^*_{i,t-\ell} + \sum_{\ell=0}^{s_i} D_{i\ell}\omega_{t-\ell} + \epsilon_{it}. \tag{1.10}$$

As before, also in this case we can treat common variables as weakly exogenous. Now, we follow the previously adopted procedure, in particular (in case of no feedback effects by x_{it}) we have the following marginal model:

$$\omega_t = \sum_{\ell=1}^{p_\omega} \Phi_{\omega\ell}\omega_{t-\ell} + \eta_{\omega t}, \tag{1.11}$$

which in ECM terms corresponds to:

$$\Delta\omega_t = -\alpha_\omega\beta'_\omega\omega_{t-1} + \sum_{\ell=1}^{p_\omega-1} H_{\omega\ell}\Delta\omega_{t-\ell} + \eta_{\omega t}, \tag{1.12}$$

where $\alpha_\omega\beta'_\omega = \sum_{\ell=1}^{p_\omega}\Phi_{\omega\ell}$, $H_{\omega\ell} = (\Phi_{\omega,\ell+1} + \Phi_{\omega,\ell+2} + ... + \Phi_{\omega,\ell+p_\omega-1})$, for $\ell = 1, 2, ..., p_\omega - 1$. In presence of unit roots, this representation allows for cointeg-

rating relationship, so we have to augment the marginal model by the lags of $x^*_{\omega t} = \tilde{W}_\omega x_t$ where $\tilde{W}_\omega$ is a $k^* \times k$ dimensional weight matrix defining k^* global cross section averages:

$$\omega_t = \sum_{\ell=1}^{p_\omega} \Phi_{\omega\ell}\omega_{i,t-\ell} + \sum_{\ell=1}^{q_\omega} \Lambda_{\omega\ell} x^*_{i,t-\ell} + \eta_{\omega t}. \tag{1.13}$$

Now, assuming no cointegrations among common variables and the cross section averages, we can rewrite the former equation as:

$$\Delta\omega_t = -\alpha_\omega \beta'_\omega \omega_{t-1} + \sum_{\ell=1}^{p_\omega - 1} H_{\omega\ell}\Delta\omega_{t-\ell} + \sum_{\ell=1}^{q_\omega - 1} B_{\omega\ell}\Delta x^*_{\omega,t-\ell} + \eta_{\omega t}, \tag{1.14}$$

where $B_{\omega\ell} = -(\Lambda_{\omega,\ell+1} + \Lambda_{\omega,\ell+2} + ... + \Lambda_{\omega,\ell+q_\omega-1})$. Following the same procedure described above we combine Equations (1.10) and (1.14) solving the system as a GVAR. Particularly, we let $y_t = (\omega'_t, x'_t)'$ be the $(k+m_\omega)\times 1$ vector of all observable variables and, recalling that $z_{it} = (x'_{it}, x^{*'}_{it})' = W_i x_t$, we stack the country specific conditional models together:

$$G_{y,0} y_t = \sum_{\ell=1}^{p} G_{y,\ell} y_{t-\ell} + \epsilon_{yt}, \tag{1.15}$$

where $\epsilon_{yt} = (\epsilon'_t, \eta'_{\omega t})'$, $G_{y,0} = \begin{pmatrix} I_{m_\omega} & 0_{m_\omega \times k} \\ D_0 & G_0 \end{pmatrix}$, $G_{y,\ell} = \begin{pmatrix} \Phi_{\omega\ell} & \Lambda_{\omega\ell}\tilde{W}_\omega \\ D_\ell & G_\ell \end{pmatrix}$ for $\ell = 1, 2, ..., p$, $D_\ell = (D'_{1\ell}, D'_{2\ell}, ..., D'_{N\ell})'$ for $\ell = 0, 1, 2, ..., p$, $p = max_i p_i, q_i, s_i, p_\omega, q_\omega$, and $D_{i\ell} = 0$ for $\ell > s_i$, $\Phi_{\omega\ell} = 0$ for $\ell > p_\omega$ and $\Lambda_{\omega\ell} = 0$ for $\ell > q_\omega$. Matrix $G_{y,0}$ is invertible if and only if G_0 is invertible. So, assuming that G_0^{-1} exists, the inverse of $G_{y,0}$ is:

$$G_{y,0}^{-1} = \begin{pmatrix} I_{m_\omega} & 0_{m_\omega \times k} \\ -G_0^{-1} D_0 & G_0^{-1} \end{pmatrix},$$

which is a block lower triangular matrix, showing the long run causal nature of the common variables ω_t. As seen before, considering $G_{y,0}^{-1}$, we obtain the final formulation of our GVAR for y_t:

$$y_t = \sum_{\ell=1}^{p} F_\ell y_{t-\ell} + G_{y,0}^{-1}\epsilon_{y,t}, \tag{1.16}$$

where $F_\ell = G_{y,0}^{-1} G_{y,\ell}$ for $\ell = 1, 2, ..., p$.

1.3.4 Impulse Response Analysis

The purpose of the impulse response analysis is to study the dynamic properties of the global model and to assess the time profile of the effects of variable-specific shocks across economies. An impulse response function measures the time profile of the effect of shocks at a given point in time on the expected future values of the variables. The easiest way to consider an impulse response function is to view it as the outcome of a conceptual experiment, whereby interest is on the effect of shock hitting the economy at time t on the future state of the economy at time $t+n$, given the history of the economy. In this subsection we discuss two main topics, namely the Generalised IRF and the Generalised Forecast Error Variance Decomposition.

GVAR methodology, as all the structural VAR models, provides a powerful framework for policy analysis. Through IRF we can track the impact of any variable on others in the system.

Considering the classical IRF, we set x_t as a $k-$dimensional vector generated by the following data generating process:

$$x_t = A_1 x_{t-1} + ... + A_p Y_{t-p} + u_t = \Phi(B) u_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{1.17}$$

and

$$I = (I - A_1 B - A_2 B - ... - A_p B^p)\Phi(B) \tag{1.18}$$

where $cov(u_t) = \Sigma$, Φ is the MA coefficients that measure the impulse response. Generally, $\Phi_{jk,i}$ is the response of variable j to a unit impulse in variable k occurring $i-$th periods before. Usually, Σ is not diagonal, so to shock one variable with the other we need to exploit Cholesky decomposition. Let P be a lower triangular matrix such that $\Sigma = PP'$, so Equation (1.17) can be rewritten as:

$$x_t = \sum_{i=0}^{\infty} \Theta_i \omega_{t-i}, \tag{1.19}$$

where $\Theta_i = \Phi_i P$, $\omega_t = P^{-1} u_t$ and $E[\omega_t \omega_t'] = I$. Considering, now, D a diagonal matrix with same diagonals with P and $W = PD^{-1}$, $\Lambda = DD'$. Setting $B_0 = I_k - W^{-1}$, $W = PD_{-1}$ and $B_i = W^{-1} A_i$ we obtain that:

$$x_t = B_0 x_t + B_1 x_{t-1} + ... + B_p x_{t-p} + v_t \tag{1.20}$$

B_0 is a lower triangular matrix with 0 diagonals. Cholesky decomposition imposes a recursive causal structure from the top to the bottom variables but not the other way around. The use of IRFs is criticised, among others, by Swanson and Granger (1997) and M. Pesaran and Shin (1998) because this methodology is sensitive to the order in which the variables are considered and, in the case of omitted variables, would lead to distortions that would make the IRF results worthless. To overcome these weaknesses M. Pesaran and Shin (1998) introduce the so called GIRF. Let

$$x_t = \sum_{i=1}^{p} A_i x_{t-i} + u_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{1.21}$$

where

$$\Phi_i = A_1\Phi_{i-1} + A_2\Phi_{i-2} + ... + A_p\Phi_{i-p} \quad with \quad 1 = 1, 2, ... \tag{1.22}$$

and $E[u_t u_t'] = \Sigma$. Considering that $\Sigma = PP'$ we have:

$$x_t = \sum_{i=0}^{\infty} (A_i P)(P^{-1} u_{t-i}), \tag{1.23}$$

so the IRF is defined as:

$$\Psi_j^o(n) = \Phi_n P e_j \quad n = 0, 1, 2, ... \tag{1.24}$$

where e_j is the $m \times 1$ selection vector with unity as its $j-$th element and zeros elsewhere. We can finally define the GIRF formulation as:

$$GIRF_x(n, \delta_j, \mathcal{I}_{t-1}) = E[x_{t+n}|u_{jt} = \delta_j, \mathcal{I}_{t-1}] - E[x_{t+n}|\mathcal{I}_{t-1}] \tag{1.25}$$

where $\delta_j = E[u_{jt}^2]$ is the size of the shock, and $\mathcal{I}_t = (X_t, x_{t-1}, ...)$ is the information set consisting of all available information at time t. Assuming normal distribution for u_t we can set:

$$E[u_t|u_{jt} = \delta_j] = (\sigma_{1j}, \sigma_{2j}, ..., \sigma_{mj})'\sigma_{jj}'\delta_j = \sum u_j e_j \sigma_{jj}^{-1}\delta_j, \tag{1.26}$$

where $\sigma_{jj} = e_j'\Sigma e_j$. We can also differentiate among Scaled and Unscaled GIRF. The latter is defined as:

$$\frac{\Phi_n \Sigma e_j}{\sqrt{\sigma_{jj}}} \frac{\delta_j}{\sigma_{jj}}, \quad with \quad n = 0, 1, 2, ..., \tag{1.27}$$

while, for the Scaled we need to define $\delta_j = \sqrt{\sigma_{jj}}$, so:

$$\Psi_j^g(n) = \sigma_{jj}^{-1/2}\Psi_n \Sigma u_j, \quad with \quad n = 0, 1, 2, ... \tag{1.28}$$

Differently from IRF, GIRF sets non-linear impulse response function and compute the mean impulse response function. When one variable is shocked, other variables also vary as implied by the covariance. GIRF computes the mean by integrating out all other shocks. Finally, in the case of diagonal Σ, GIRF and IRF are equivalent.

The second topic of this subsection concerns the Generalised Forecast Error Variance Decomposition ($GFEVD$). This topic is closely related to the impulse response analysis and the relative contributions of the shocks to reducing the mean square error of forecasts of individual endogenous variables at a given horizon. Forecast error variance decomposition is the proportion of the n-step ahead forecast error variance of variable i which is accounted for by the innovations in variable j in the VAR. In the case of orthogonalised shocks we define the Orthogonalised Forecast Error Variance Decomposition, θ_{ij}^o, as:

$$\theta_{ij}^o(n) = \frac{\sum_{\ell=0}^n (e_i' A_\ell P e_j)^2}{\sum_{\ell=0}^n e_i' A_\ell \Sigma A_\ell' e_i}, \tag{1.29}$$

for $n = 0, 1, 2, ...$ and $i, j = 1, ..., m$. We can notice, by construction, taht $\sum_{j=1}^m \theta_{ij}^o(n) = 1$.

In the case of Generalised Forecast Error Variance Decomposition, θ_{ij}^g, we have:

$$\theta_{ij}^g(n) = \frac{\sum_{\ell=0}^n (e_i' A_\ell \Sigma e_j)^2}{\sum_{\ell=0}^n e_i' A_\ell \Sigma A_\ell' e_i}. \tag{1.30}$$

In this case, since the covariance between shocks may be different from 0, $\sum_{j=1}^m \theta_{ij}^g(n) \neq 1$.

1.3.5 Forecasting using GVAR

Although not the purpose of this work, the GVAR methodology is also indicated for forecasting. The main characteristic of the GVAR method in this area is the use of panel structures, where each cross-section unit is characterised by a limited number of variables.

Rigorously, considering Equation (1.9), we take the expectation for $t = t_0 + h$

conditional on the information set $\mathcal{I}_{t_0}$, so we have:

$$E(x_{t_0+h}|\mathcal{I}_{t_0}) = \sum_{\ell=1}^{p} F_\ell E(x_{t_0+h-\ell}|\mathcal{I}_{t_0}) + G_0^{-1} E(\epsilon_{t_0+h}|\mathcal{I}_{t_0}) \tag{1.31}$$

for any $h = 0, 1, 2, ...$ In general, $\mathcal{I}_{t_0}$ is the available information up to t_0, so $\mathcal{I}_{t_0} \equiv \{x_{t_0}, x_{t_0-1}, ...\}$, consequently we have:

$$E(\epsilon_{t_0+h}|\mathcal{I}_{t_0}) = 0 \qquad for \quad h > 0. \tag{1.32}$$

Standard forecasts $E(x_{t_0+h}|\mathcal{I}_{t_0})$ can be computed recursively from Equation (1.9) using F_ℓ and G_0^{-1}, Equation (1.32) and $E(x_{t'}|\mathcal{I}_{t_0}) = x_{t'}$ for all $t' \leq t$. More difficult is to generate conditional forecasts for non-standard conditioning information sets with unbalanced information in our panel. Following M. H. Pesaran (2015), we consider t' where the first k_a variables in the vector $x_{t'}$ belong to $\mathcal{I}_{t_0}$ and $k_b = k - k_a$ do not, let ϵ_t be equal to $(\epsilon'_{at}, \epsilon'_{bt})'$ and the variance covariance matrix $\Sigma = E(\epsilon_t \epsilon'_t)$ be defined as:

$$\Sigma = \begin{pmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{pmatrix}. \tag{1.33}$$

It follows that $E(\epsilon_{at'}|\mathcal{I}_{t_0}) = \epsilon_{at'}$, whereas $E(\epsilon_{bt'}|\mathcal{I}_{t_0}) = \Sigma_{ba}\Sigma_{aa}^{-1}\epsilon_{at'}$. Let $\hat{\Sigma}$ be an estimate of Σ. The estimate of $E(\epsilon_{t'}|\mathcal{I}_{mt_0})$ is computed as:

$$\hat{E}(\epsilon_{t'}|\mathcal{I}_{mt_0}) = \begin{pmatrix} \hat{\epsilon}_{at'} \\ \hat{\Sigma}_{ba}\hat{\Sigma}_{aa}^{-1}\hat{\epsilon}_{at'} \end{pmatrix} \tag{1.34}$$

for any given $t' \leq t_0 + h$. Using Equation (1.31), we can compute the conditional forecasts $E(x_{t_0+h}|\mathcal{I}_{t_0})$ recursively. Σ (and its sub-matrices) can have large dimension and $\hat{\Sigma}_{aa}$ invertibility is not guaranteed, but even if it was, not necessarily the variance-covariance matrix (that could have such a large size) does not guarantee good small sample properties when the number of variables is large. For these reasons, we need to implement a variance-covariance matrix with better small sample properties in the computation of conditional forecast. There are several estimators proposed in the literature for estimation of high-dimensional covariance matrices, including Ledoit and Wolf (2004), Bickel and Levina (2008), Fan et al. (2008), Friedman et al. (2008), the shrinkage estimator considered in Dees et al. (2014), and the multiple testing approach by Bailey et al. (2014).

As we have seen before, G_0 is assumed to be non singular. In this case, the system in Equation (1.9) must be augmented by additional equations, as

considered in Chudik et al. (2016), where the authors implement forecasting using the GVAR methodology in the case of $N, T \to \infty$ jointly and the data generating process is a factor-augmented infinite-dimensional VAR. Assume for simplicity $k_i = 1$ (one variable per country) and $m = 1$ (one unobservable common factor) generated as:

$$f_t = \rho f_{t-1} + \eta_{ft}, \tag{1.35}$$

where $|\rho| < 1$ and η_{ft}, the macro shock, serially uncorrelated and distributed with zero mean and variance σ_η^2. Let $\gamma = (\gamma_1, \gamma_2, ..., \gamma_N)'$ be the factor loadings, while $\tilde{W}_i' = (w_1, w_2, ..., w_N)'$ be the granular weights vector that defines $x_{it}^* = x_t^* = \tilde{W}_i' x_t$ cross section averages, we derive that:

$$x_{it} = \phi_{ii} x_{i,t-1} + \lambda_{i0} x_{wt}^* + \lambda_{i1} x_{w,t-1}^* + u_{it} + O_p(N^{-1/2}) \; for \; i = 1, 2, ..., N \tag{1.36}$$

where $\lambda_{i0} = \gamma_i / \gamma^*$, $\lambda_{i1} = -\phi_{ii}\gamma_i/\gamma^*$ and $\gamma^* = \tilde{W}'\gamma$ and O_p describes the function limiting behaviour when $N \to \infty$.

For forecasting purposes, we need to augment Equation (1.36) with the following marginal equation for cross section averages:

$$x_t^* = \rho x_{t-1}^* + \gamma \eta_{ft} + O_P(N^{-1/2}), \tag{1.37}$$

where x_t^* is treated as a proxy for the unobservable common factor. Combining Equations (1.36) and (1.37), and considering that $z_t = (x_t', x_t^*)'$, we obtain the following VAR model:

$$B_0 z_t = B_1 z_{t-1} + u_{zt} + O_P(N^{-1/2}), \tag{1.38}$$

where $u_{zt} = (u_t', \gamma\eta_{ft})'$, $B_0 = \begin{pmatrix} I_N & -\lambda_0 \\ 0' & 1 \end{pmatrix}$, $B_1 = \begin{pmatrix} \Phi & \lambda_1 \\ 0' & \rho \end{pmatrix}$ and Φ is an $N \times N$ diagonal matrix with elements ϕ_{ii} for $i = 1, 2, ..., N$ and B_0 is invertible by construction.

Considering the forecast of $x_{i,t+h}$ conditional on $\mathcal{I}_t = \{\mathbf{x}_t, \mathbf{x}_{t-1}, ...\}$, we have:

$$x_{i^{th}}^f = \tilde{e}_i B^\ell z_t \tag{1.39}$$

where $B = B_0^{-1} B_1$ and $\tilde{e}_i$ is the $N + 1$ dimensional selection vector that selects

the i-th element. Chudik et al. (2016) establish that

$$x^f_{i^{th}} = E(x_{i^{th}}|\mathcal{I}_t) + O_P(N^{-1/2}) \tag{1.40}$$

where the expectation operator is taken assuming that $\mathbf{x}_t$ is given by a factor augmented infinite-dimensional VAR model:

$$(\mathbf{x}_t - \Gamma f_t) = \Theta(\mathbf{x}_{t-1} - \Gamma f_{t-1}) + u_t, \tag{1.41}$$

where Γ is a $k \times m$ matrix of factor loadings and f_f is the $m \times 1$ covariance stationary process of unobserved common factors with one factor given by Equation (1.35). It follows that:

$$E(\mathbf{x}_{t+h}|\mathcal{I}_t) = \Theta^h \mathbf{t} + (\rho^h I^N - \Theta^\ell)\gamma f_t \tag{1.42}$$

This shows the large N optimality of forecast $x^f_{i^{th}}$ defined in Equation (1.39). With the aim of improving forecasting performance, it is possible to augment matrices G_0 with equations, even if this is invertible. Forecasts based on the augmented model avoid inversion of high-dimensional matrices.

1.4 Empirical Application

In this section, first we present the data in Section 1.4.1 then the model settings in Section 1.4.2 and preliminary results in Section 1.4.3. In the final two Sections 1.4.4 and 1.4.5 we discuss the generalised impulse response functions and the generalised forecast error variance decomposition.

1.4.1 Data

The dataset we made includes 11 European countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain. As regards variables, we consider equity prices, sovereign CDS prices, long run interest rates, effective exchange rates and VIX index at monthly frequency. Data belong from Bloomberg, ECB and Eurostat economy and finance database.

The dataset considers the period from January 2004 until December 2017. According to Figure 1.2 we notice that in this period we face at least two different regimes. From January 2004 until January 2007 the volatility index shows a decreasing pattern. These dynamics are in line with the ones in Figure 1.1. From

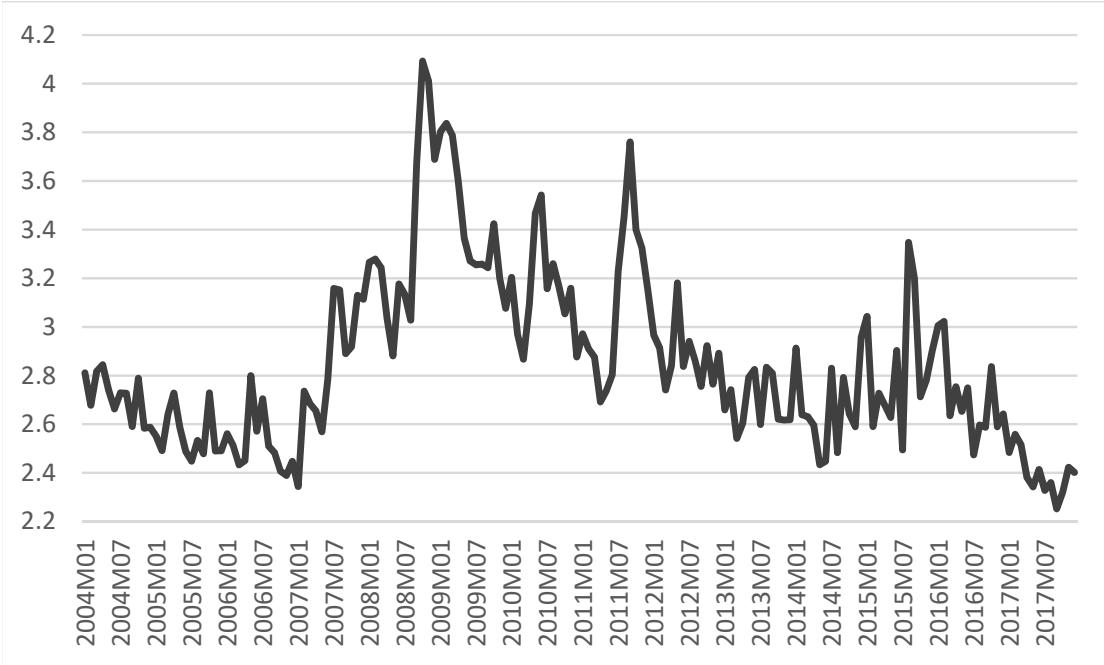

Figure 1.2: CBOE Volatility Index

the middle of 2007, VIX is characterised by a higher heterogeneity which flows into several peaks, namely August 2008, September 2011 and August 2015. Because of this, we use as a common variable (as define in Section 1.3) the CBOE Volatility Index (VIX), in fact the VIX is often used in jobs that consider periods of crisis. Among the works using VIX and the GVAR methodology, we cite Chudik and Fratzscher (2011) and Niehof (2014). The performance of the VIX index is shown in the Figure 1.2, where it can be noted that a negative trend (i.e. a drop in market volatility) characterises the first part of the series. Starting from mid-2007 until mid-2015 the situation is less clear, with peaks alternating more or less frequently. From mid-2015 to the end of the series (December 2017) the trend is again negative, re-positioning itself to pre-crisis values. The values of the VIX variable are derived from the Bloomberg database.

Now let us analyse the variables that characterise the VARX model. The descriptive statistics of all the variables are shown in Table 1.1. The table reports the main descriptive statistics (mean, median, maximum, minimum, standard deviation, skewness and kurtosis), and the Jarque-Bera test (J-B) for testing the hypothesis of normality. Although the hypothesis of normality is often rejected in the series under examination, we can observe that the values of the J-B test (and the related p-value) are close to the acceptance threshold, for instance, in the case of of the log-price of the equity indices and the effective exchange rate.

The first variable considered is the Equity Price (in logarithm). This variable, as described in Table 1.2, considers the financial markets with the greatest capitalisation of all the European countries considered. The data derive from the Thomson Reuters Eikon database, and show, that generally the maximum value is between May and December 2007, while the minimum is found between January and February 2009 for all the series, except for the Greek one, which continues to decline until February 2016. For methodological purposes, we used the natural logarithms of prices.

Secondly, we consider the Real Effective Exchange Rate (EER). This variable measures the value of a specific currency in relation to an average group of major currencies. EER takes into account any changes in relative prices and shows what can actually be purchased with a currency. This means that EER is normally weighted for commercial exchanges. EER is obtained by taking the effective nominal exchange rate of a country (NEER) and adjusting it to include price indices and other trends. The EER of a country is an important measure in assessing its commercial capabilities and the current import / export situation. This variable measures the equilibrium value of a country's currency, identify the underlying factors of a country's trade flow, examine any changes in international competition in terms of prices or costs and allocate incentives between the tradable and non-tradable sectors negotiable. A country can positively influence its EER through rapid productivity growth. When this happens, the country achieves lower costs and can reduce prices, thus making the EER more advantageous for the country. The economic significance of the real effective exchange rate is that an increase in EER corresponds to a decrease in the country's competitiveness. With reference to our series we can see how, generally, the variable has a growing trend until the end of 2009, followed by a sudden drop and then a period of stagnation which ends with another decline that occurs between the end of 2014 and the first half of 2015, finally, we can appreciate a generalised positive trend. This variable is the one that acts as a link of our GVAR model, in particular this variable is considered endogenous for our key economy (Germany) also in its foreign version. We chose EER as link variable for several reasons. First, this variable represents an index of competitiveness and it is clear that Germany is the most competitive country in the Eurozone. Second, since we use data on international trade to derive the weight matrix, EER indirectly captures the trade dynamics among countries. Data are provided by the Eurostat in the economy and finance database.

Third we consider the Sovereign Credit Default Swaps (CDS). These are among

the most common derivative contracts (swaps, i.e. exchange of cash flows) for the credit risk transfer. The data are obtained from Bloomberg. Series for the Netherlands and Ireland are characterised by some missing data in the initial part. In this case an average of the major banks CDSs has been made (ING and ABN AMRO for the Netherlands and Bank of Ireland Corp., Allied Irish Banks and Danske Bank for Ireland). Once the dynamic component was extracted, it was reported on the data of the sovereign CDS (relations between Sovereign and Banks CDSs are considered in Alter and Schüler (2012) and Black et al. (2016)). The CDSs behaviours are, at least until August 2011, consistent among European countries. In particular, after an initial phase of low volatility, since June 2007 we observe a growth that, with different speeds, persists until 2009, then there is a general decline that lasts until September 2009. Afterwards an increase characterises the period between the end of 2009 and the last quarter of 2011. From there a slow decline for all the countries, except Greece that presents a peak in June 2015 and then follows the trend of the rest of the sample, albeit with a significant gap.

Finally we consider the Long Term Interest Rate (Ltir). This variable represents the interest rates for long-term government bonds in Euro for the Eurozone. The dynamics that characterise the Ltir are presented in Figure 1.1. Substantially all the series behave in a similar way until June 2008, from there we can observe a constant crescendo until the beginning of 2012. From 2012, the series (excluding the Greek one) show a slow convergence that is reached in 2015. A bit of variability characterises the Portuguese and Greek series until the end of the analysed time window. Data are available on the ECB website.

In conclusion, for a country the increase in the price of its CDS denotes an increase in the risk that the government may encounter difficulties in repaying debts issued in the form of treasury bonds. An increase in the effective exchange rate has a negative connotation, a rise corresponding to a loss of commercial competitiveness on the international markets. An increase of the Stock Index means a higher confidence in the companies that are listed in the country and indirectly a growth in the trust for the country itself. The significance of the long-term interest rate is less trivial, on the one hand, it is obvious that an increase in the rate of interest implies less confidence in the solvency of the entity issuing debt securities, but, on the other hand, an improvement in economic conditions, substantially during economic growth, interest rates are used to rise.

1.4.2 Model set-up

The main aim of this work is to evaluate the effects of spillover between European countries, with particular reference to the sovereign debt crisis. To this purpose, we estimate a GVAR model for 11 European countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain for the period January 2004 - December 2017, using monthly data. Following Kempa and Khan (2017) setting, we divided the Eurozone into three regions: Core (consisting of Austria, Belgium, Finland, the Netherlands and France, which is the main economy of the region), Periphery (consisting of Greece, Ireland, Portugal, Spain and Italy, which represents the main economy of the region) and Germany, which is treated individually as a large entity. With the aim of analysing the interdependence between economies, the variables analysed are stock log-prices (equity), effective exchange rates (EER), log-prices of sovereign credit default swaps (CDS) and long-term interest rates treasure bonds (Ltir). In particular with reference to Equation (1.6), we have that $z = (equity, EER, CDS, Ltir, equity^*, EER^*, CDS^*, Ltir^*)$ where the "star" variables represent the foreign variables, i.e. those calculated from equation (1.2), as a weighted average of the variables of the other countries. The weight matrix, W, on the basis of trade flows (import and export) between countries The weights matrix is presented in Table 1.3 and is computed by averaging commercial relations (ratio between import and export) between countries over the period January 2004 - May 2017 (last available data) using the Eurostat database (international trade section). We use this type of data as it is by far the most exploited in the literature. Moreover the choice of fixed weights over time derives from the fact that the commercial relations between countries are not only quite fixed throughout the period of time under examination, but also because other works that focus on the Eurozone, including Caporale and Girardi (2013) and Vansteenkiste and Hiebert (2011) consider fixed relations. In particular, not only use a fixed weight matrix over time but although with different time windows, matrices show very high values similar to those calculated by us and reported in Table 1.3.

Finally, with reference to Equation (1.10), we set the VIX as the common variable, in order to capture the volatility of the financial markets. We set up the model using Germany as the large entity and the other ten countries as small open economies. Thus is justified by several reasons. First, since the German economy is the most important in the Eurozone. Second it represents the most important node of the European network according to the international trade.

Third, because the German bund is the benchmark in the government debt bond market.[2] We have decided to use fixed weights for two reasons, the first that they do not vary significantly over time and the second that also in Caporale and Girardi (2013), although data for a period are used different (2004-2006) and coming from different databases (OECD, while we have used Eurostat) the values are still almost unchanged.[3]

1.4.3 Preliminaries

With respect to Equation (1.10), we define a GVAR model with $p_i = 2$, $q_i = s_i = 1$. Moreover, from Section 1.3 we know that no assumptions about the order of integration of the variables is necessary. To investigate the variables integration order we perform the Augmented Dikey Fuller (ADF) test. Results show that all the variables investigated are characterised by the presence of a unitary root, I (1). As a further specification, we also performed the Weighted Symmetric (WS) test, which confirms the results of the ADF test except for the EER variable for Austria and Belgium, where the stationary hypothesis can not be rejected.

Through Equations (1.5) and (1.12) we investigate cointegration phenomena. In particular we observe that in our sample we observe two cointegration relations for Austria, Germany, Greece, the Netherlands and Portugal, one for Finland, France, Ireland, Italy and Spain while no cointegration relationship is observed for Belgium. Table 1.4 shows the results of the Quandt Likelihod Ratio (QLR)[4]

[2] Konstantakis et al. (2015) propose a way to evaluate a GVAR model using more than one large entity. Following their methodology we find that Europe can be lead by two countries (there are two eigenvalues with module higher than 0.4), according to the network theory, is easy to observe that the two main entities are Germany and France. We decided to do not perform their methodology because, firstly Germany is used as benchmark for, at least, the European economy (especially for the sovereign debt dynamics), secondly our aim is to shock the peripheral countries, not the core ones.

[3] Following Gross (2013) the weights matrix can be estimated directly using a GVAR by:

$$\min_{\Gamma_i, \omega_{i,j,k}} \sum_{t=1}^{T} u_{i,t}^2$$

s.t.:

$$\omega_{i,j,k} \geq 0 \quad j = 0, ..., N$$

$$\sum_{j=0}^{N} \omega_{i,j,k} = 1$$

where Γ_i comprises all local model coefficients contained in $\alpha_0, \alpha_{i,1}, \Phi_{i,p}, \Lambda_{i,q}, \Psi$ and g_t.

[4] The QLR test statistic is the maximum of all the Chow F-statistics, over a range of τ, $\tau_0 \leq \tau \leq \tau_1$ and so $QLR = max[F(\tau_0), F(\tau_0 + 1), ..., F(\tau_1 - 1), F(\tau_1)]$, where F represents the F-statistic.

performed to identify all possible break points. The QLR test is based on the Chow test and attempts to eliminate the need for picking a break point by computing the Chow test at all possible break points. The largest Chow test statistic across the grid of all potential break points is chosen as the Quandt statistic as it indicates the most likely break point. In particular, we can notice that for the Stock Index variable the structural disruptions for Austria, Belgium, Italy and the Netherlands are distributed over 2008 and at the beginning of 2009, while the break-up points for Germany, France, Spain and Ireland are distributed throughout 2010, Greece and Portugal show a break point towards the end of 2014 and 2015 respectively. Considering the EER variable, it is observed that for the Netherlands and Portugal the breaking points are in March 2009 and for Greece, Italy and Spain at the end of 2012, the remaining countries should wait until the end of 2014.

As for the variable Ltir, it seems that for Spain and Finland the break occurs in August 2010, for the other countries it takes place between the end of 2011 and the beginning of 2012.

Finally, observing the CDS variable, breaks for France and Finland are before the Great Recession, while for all the other countries this happens in the middle of the crisis (financial or sovereign debts).

Table 1.5 shows the weights that the individual countries have towards the variables considered in the model. The weights derive from the trade flows between the Euro-zone countries. In particular, we can see that as many as 7 countries (Austria, Belgium, Finland, Greece, Ireland, the Netherlands and Portugal) have lower weights than 10%, Spain stands just under 12%, France and Italy have similar values at the turn of 20% (21 for France and 19 for Italy), while Germany alone is worth more than a quarter (27.5%) of the entire Eurozone. These conclusions are confirmed by Table 1.6, where we can see that France and Italy have an absolute majority weight in the respective region (60 and 51%, respectively).

To fully understand the results obtained through the GVAR model, it is useful to understand the economic meanings of the variables considered and their dynamics. We summarise the expectations we have regarding the effects that follow a shock on the variables considered. To a positive shock on a European equity index, we expect the other indices to respond positively. On the other hand we expect negative replies both on the price of the CDS and on the long-term interest rate. The relationship between equity indices and the effective exchange rate is less direct, in particular we expect EER to decrease for the country where the shock occurs while remaining unchanged in other countries. Following a positive shock on CDS, we expect an increase in the price of CDS for all European countries, and

in the long-term interest rate resulting from greater tension on the markets. We expect this tension also to have repercussions on equity markets, causing a general decline in European indices. Less clear is the impact on the effective exchange rate. On the one hand we expect that a worsening of the financial environment will worsen the position of the economy affected by the shock in international trade (therefore an increase of EER at least for the country subject to the shock), while on the other we believe that a single deterioration in competitiveness is reflected in an improvement (decrease in EER) for European competitors. A positive shock on the long-term interest rate for a country should also have a consistent effect on interest rates for the other Eurozone countries, as we expect an increase in sovereign CDS prices for all European countries. A different issue for equity indices, where we expect a widespread fall across the sample. While the issue is more complex for the effective exchange rate, on the one hand we expect an increase in EER for those experiencing the shock, on the other hand we expect feedback for the rest of the countries. Finally, we hypothesise the consequences of a shock on the effective exchange rate. As far as equity indices are concerned, we expect that an increase in EER will result in a decline in the value of equity indices and an increase in both the long-term interest rate and the price of CDS for the entire sample, while an increase in EER for a country should lead to a (perhaps slight) drop in the effective exchange rates for other European competitors. In order to make the results more concise and to observe the effects of spillover, we aggregate the Eurozone countries in order to design three regions, Germany, Core (Austria, Belgium, Finland, France and the Netherlands) and Periphery (Greece, Ireland, Italy, Portugal and Spain), the weights of the individual states in the formation of the respective region are presented in Table 1.6 and derive from trade flows in the euro area for the period 2004-2017. With division into regions we can see how a shock in a single state propagates in its own region but also in others.

1.4.4 Global Impulse Response Functions Analysis

According to Section 1.3.4 we performed several shocks with 1 standard error size for France, Italy, Germany and VIX, in order to identify the interconnection channels. Before going into the details of the results of the generalised impulse response functions, it is useful to consider the following. First of all, we note that for the 110 GIRFs considered (shown in Figures 1.4 to 1.11), 69 show the presence of spillover effects between individual countries (France, Germany, Italy) and the VIX index, compared to the three analysed regions, namely Germany,

Core and Periphery (following the Kempa and Khan (2017)). In particular, we studied 44 response functions for France, of which 15 did not show evidence of contagion among the economies, and 44 for Italy, of which 21 were sterile for our research. This fact already allows us to conclude that the role of France within the European economic system is more central (at least considering the variables studied) than the Italian one. Another conclusion that we can draw from the analysis of the GIRFs is that related to the transmission channels of the shocks, in fact, in partial agreement with Gorea and Radev (2014), we can see that as many as 17 shocks (out of the 22) concentrated on stock price and CDS variables, that capture financial dynamics, show significant contagion effects between the Eurozone regions. While only 9 response functions based in Italy (always focusing on stock prices and CDS) show clear spillover effects. On the other hand, if we consider the variables that capture real dynamics, such as the long-term interest rate and the effective exchange rate, only in 12 cases (out of 22) there are spillover effects, while for Italy they are 14. Concluding this first analysis, we can see how the shocks on the financial markets are more spread when they occur for the countries of the Core region or for Germany, where a shock on the stock index has a positive effect on all 11 reports considered. On the other hand, a shock on the real variables is more likely to propagate if it is located in the Periphery region. Very interesting are the responses to a positive shock on the VIX index (corresponding to an increase in the volatility of the financial markets), as reported in Figure 1.3. In particular, we observe that only financial variables respond (positive effects on the CDS market and negative on stock prices, which in both cases are reabsorbed over the long term), while the long-term interest rate and the effective exchange rate for the three areas do not show any kind of interdependence.

We consider the GIRFs results. In the event of a positive shock on the price of CDS for France or Italy, as presented in Figures 1.4 and 1.5, different answers are obtained. In particular, we note that if the shock comes from Italy there are spillover effects only in 3 cases out of the 11 analysed, or there is a significant (but not lasting) increase in the price of CDS for the Core and Periphery regions, while no significant dynamics is observed on the German CDS. There are no contagion effects on long-term interest rates or stock prices, while there is a negative effect on the effective exchange rate of the Core region (which denotes an improvement in competitiveness), but this effect is also not lasting. When shock occurs for French CDS, long-lasting spillover effects are generally observed. These spillover effects are positive on the CDS market (for all three regions analysed), while they

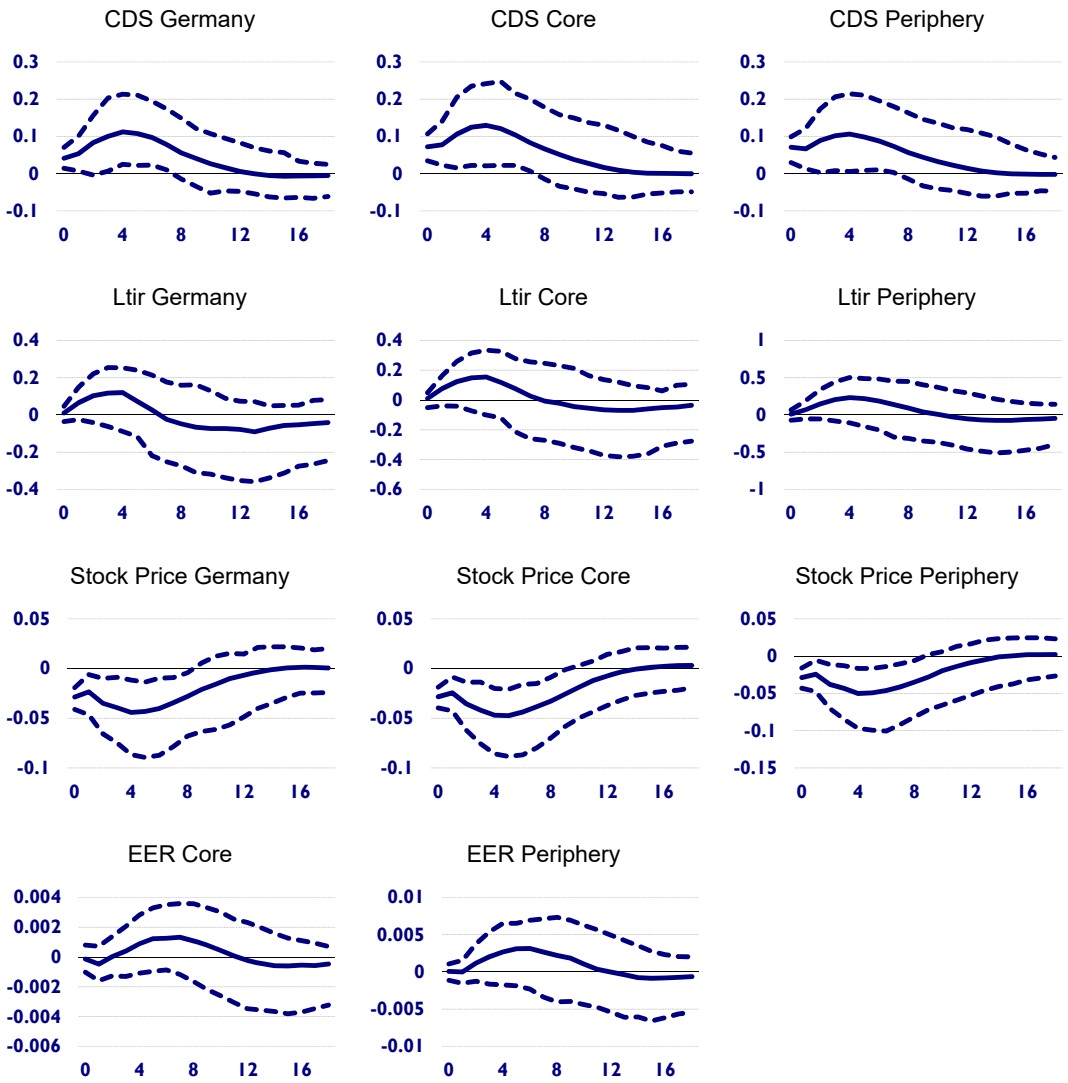

Figure 1.3: Eurozone Regions GIRF at 1 s.e. Positive Shock on VIX Index. The dashed lines indicate the 90% confidence interval.

are negative if we consider the long-term interest rate or the effective exchange rate. As far as stock prices are concerned, there is a widespread fall, which is reabsorbed in the medium / long term.

The shocks on the effective exchange rate are those with a lower degree of interdependence, as referred in Figures 1.6 and 1.7. Analysing the effects of a positive EER shock for France, we obtain spillover effects on the price of the equity indices, which respond positively to the three regions, and on the effective exchange rate, which responds positively to both the Core and the Periphery, but in this last case lasts. Both for the sovereign CDS market and for the interest rate on treasury bonds there are no significant dynamics. Otherwise, if we analyse the effects of an EER shock for Italy, we observe heterogeneous effects both between regions and between different variables. As far as the sovereign CDS market is concerned, we only see a (temporary) drop in the price of German CDS. We find the same dynamic on the Ltir variable for the Periphery region only. On the other hand, positive dynamics (even if not lasting) are observed for the Core region, with reference to the prices of the stock indices, and for the Core and Periphery for the effective exchange rate.

The dynamics that develop, along with a shock on long-term interest rates, for France and Italy, reported in Figures 1.8 and 1.9, are very interesting. Starting from the effects of a shock on Ltir for France, we find the absence of spillover effects with regard to the market and sovereign CDS. A shock on the Italian Ltir, correspond to an increase (after the shock) of the price of CDS which is then reabsorbed for the three regions. The effects on long-term interest rates are always positive and temporary regardless of the analysed region and the country where the shock occurred. The effects on stock index prices are generally negative and temporary, except for Germany that does not respond to French shocks. Finally, the effects of a shock on the interest rate of the treasury bills on the effective exchange rate are temporary and positive for a French shock, while none for an Italian shock.

Moreover, we analyse the GIRFs following a positive shock on the prices of the equity indices for France and Italy, as reported in Figures 1.10 and 1.11. In general, we can see that there are convergences between the impulse response functions, in particular long term interest rate and effective exchange rate do not show significant dynamics regardless of the region analysed and the geographical origin of the shock. Convergence also persists on the effects on the sovereign CDS market, in particular negative and temporary generalised effects are observed. The only divergences consist in the effects on the prices of the stock indices. In

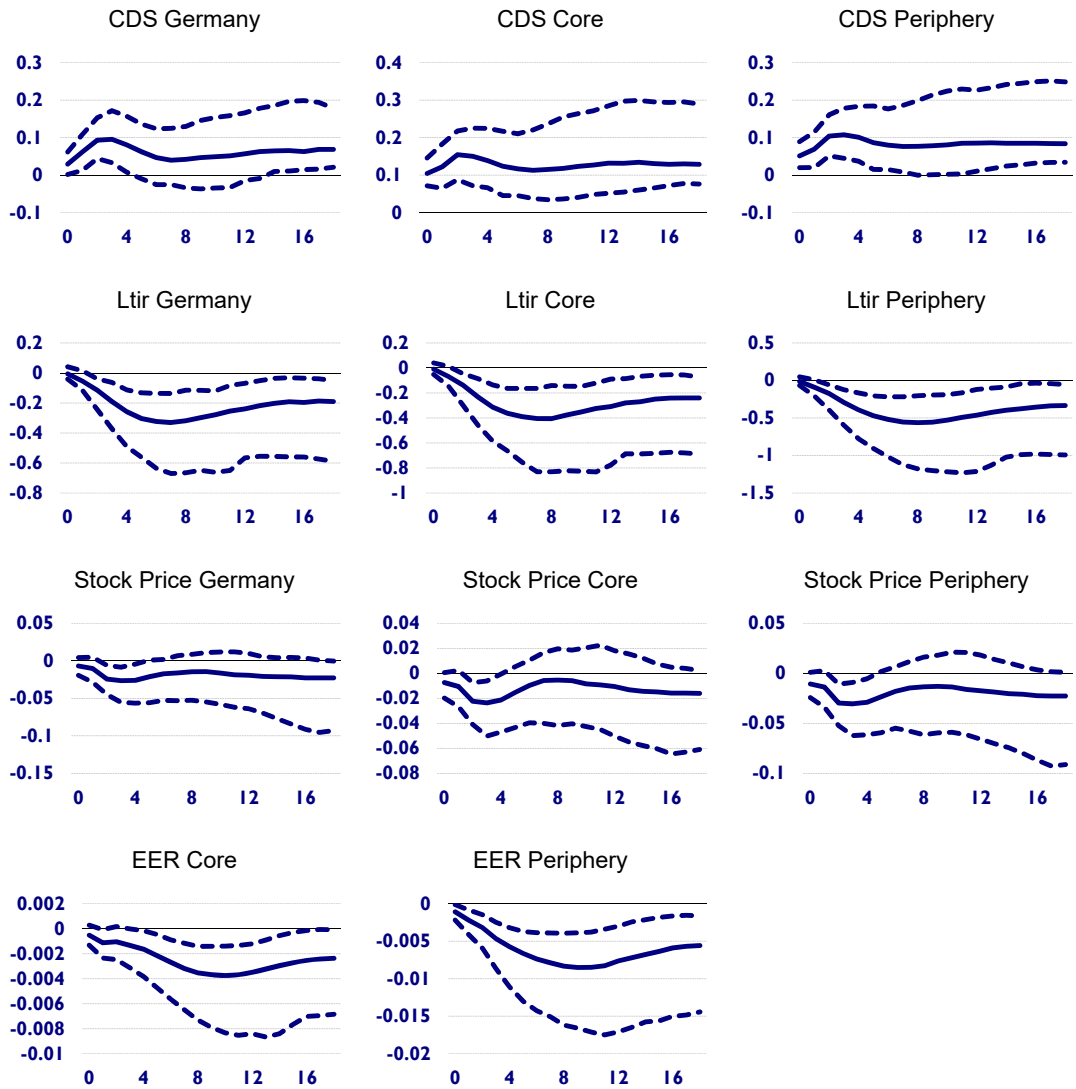

Figure 1.4: Eurozone Regions GIRF at 1 s.e. Positive Shock on French Sovereign CDS. The dashed lines indicate the 90% confidence interval.

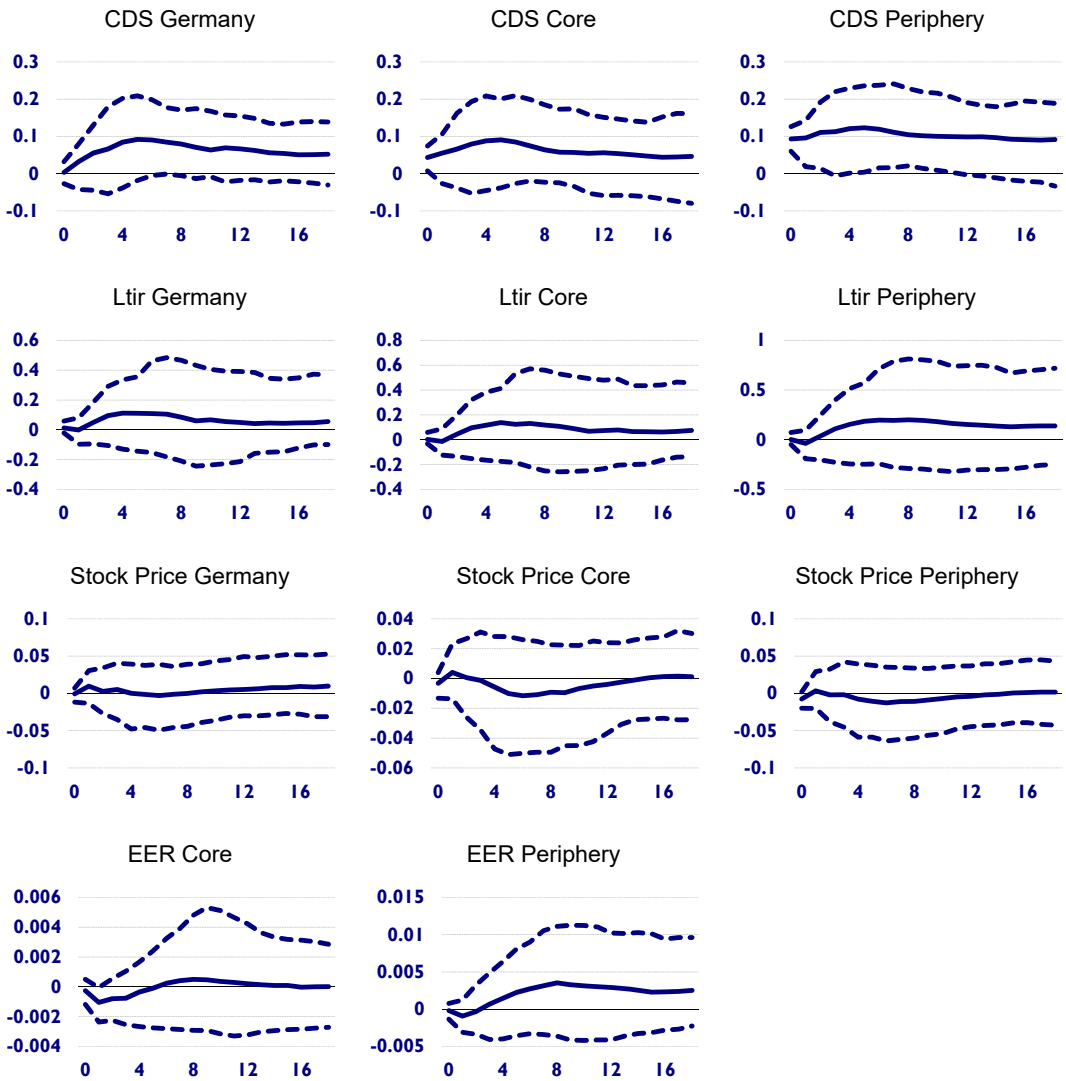

Figure 1.5: Eurozone Regions GIRF at 1 s.e. Positive Shock on Italian Sovereign CDS. The dashed lines indicate the 90% confidence interval.

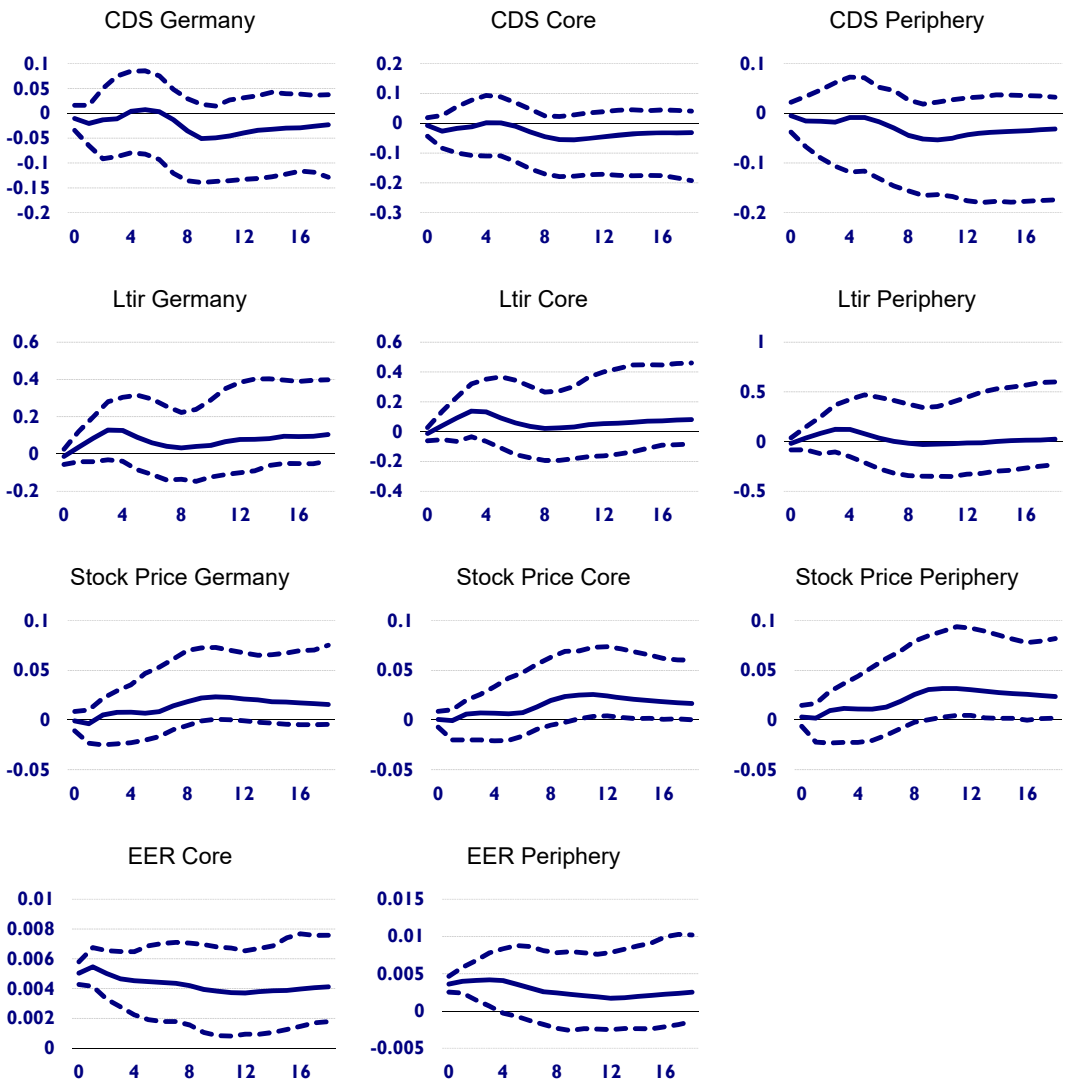

Figure 1.6: Eurozone Regions GIRF at 1 s.e. Positive Shock on French Effective Exchange Rate. The dashed lines indicate the 90% confidence interval.

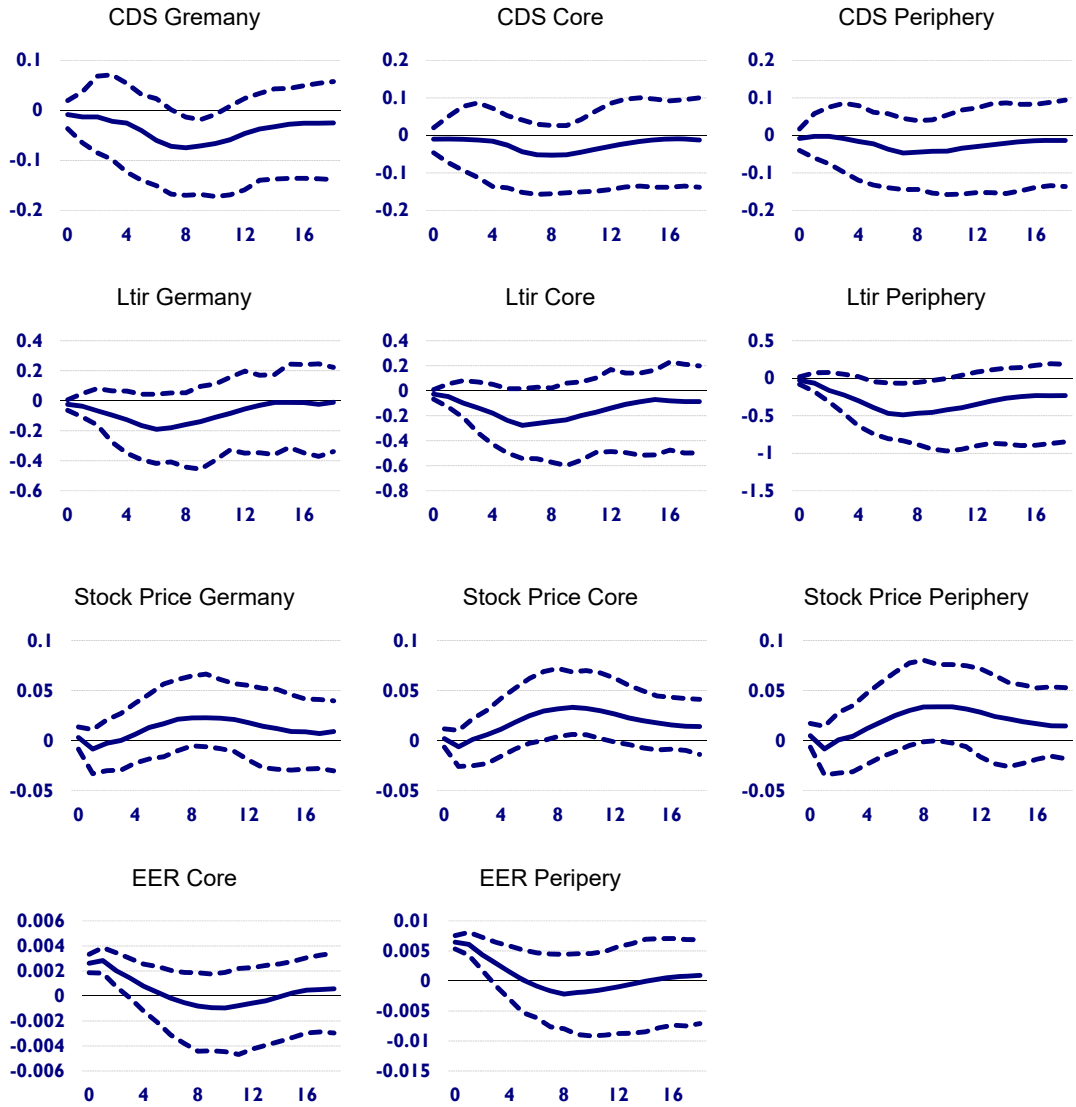

Figure 1.7: Eurozone Regions GIRF at 1 s.e. Positive Shock on Italian Effective Exchange Rate. The dashed lines indicate the 90% confidence interval.

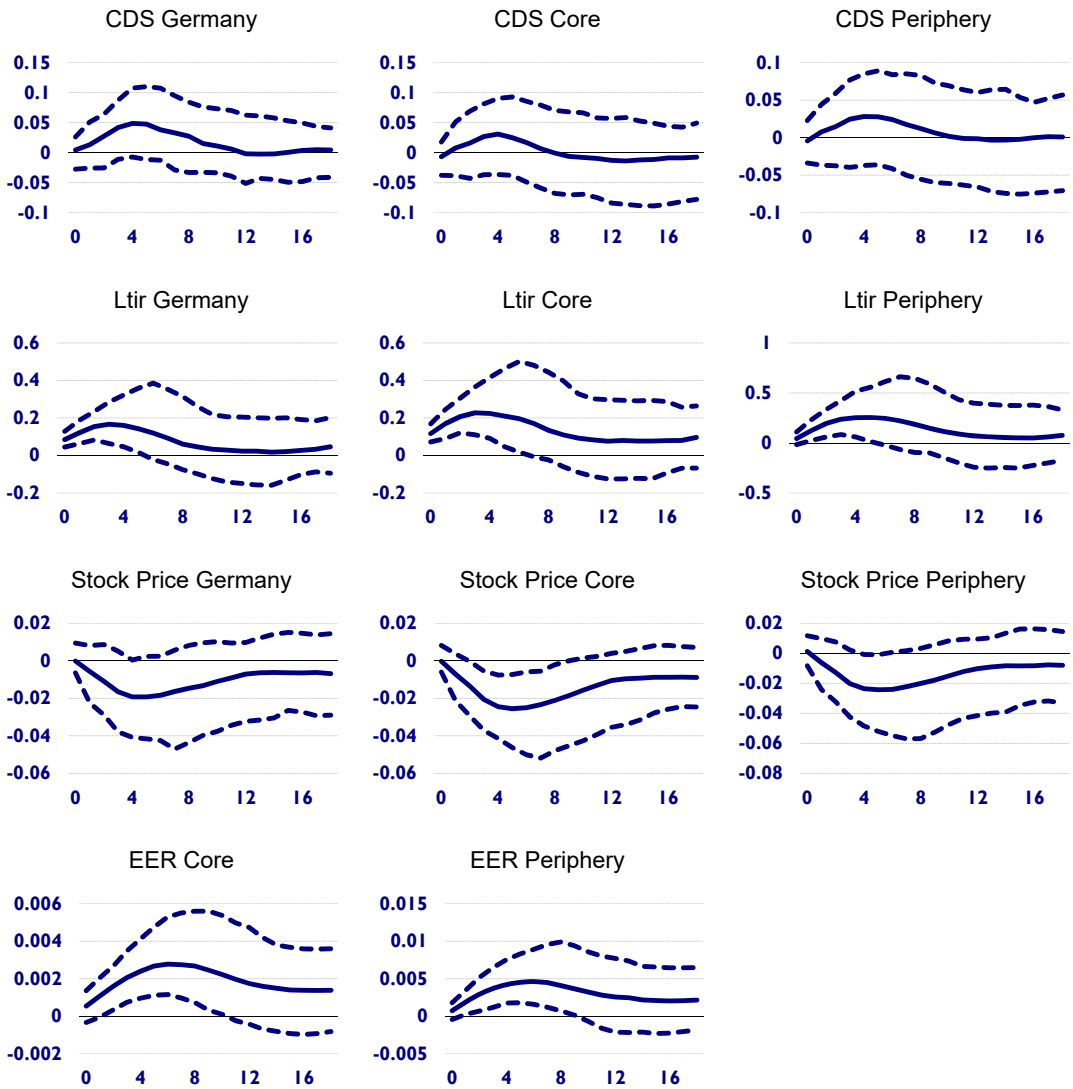

Figure 1.8: Eurozone Regions GIRF at 1 s.e. Positive Shock on French Long Term Interest Rate. The dashed lines indicate the 90% confidence interval.

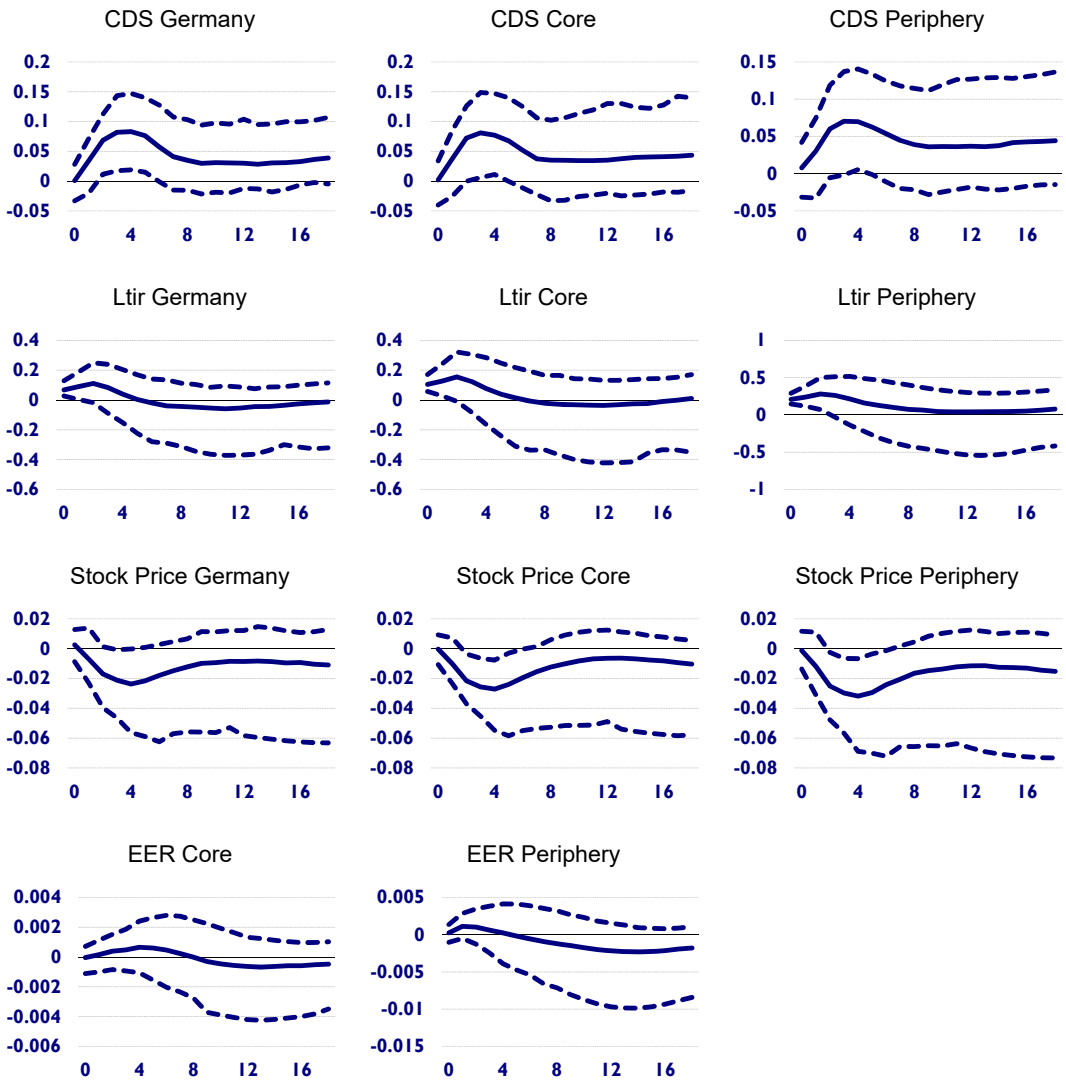

Figure 1.9: Eurozone Regions GIRF at 1 s.e. Positive Shock on Italian Long Term Interest Rate. The dashed lines indicate the 90% confidence interval.

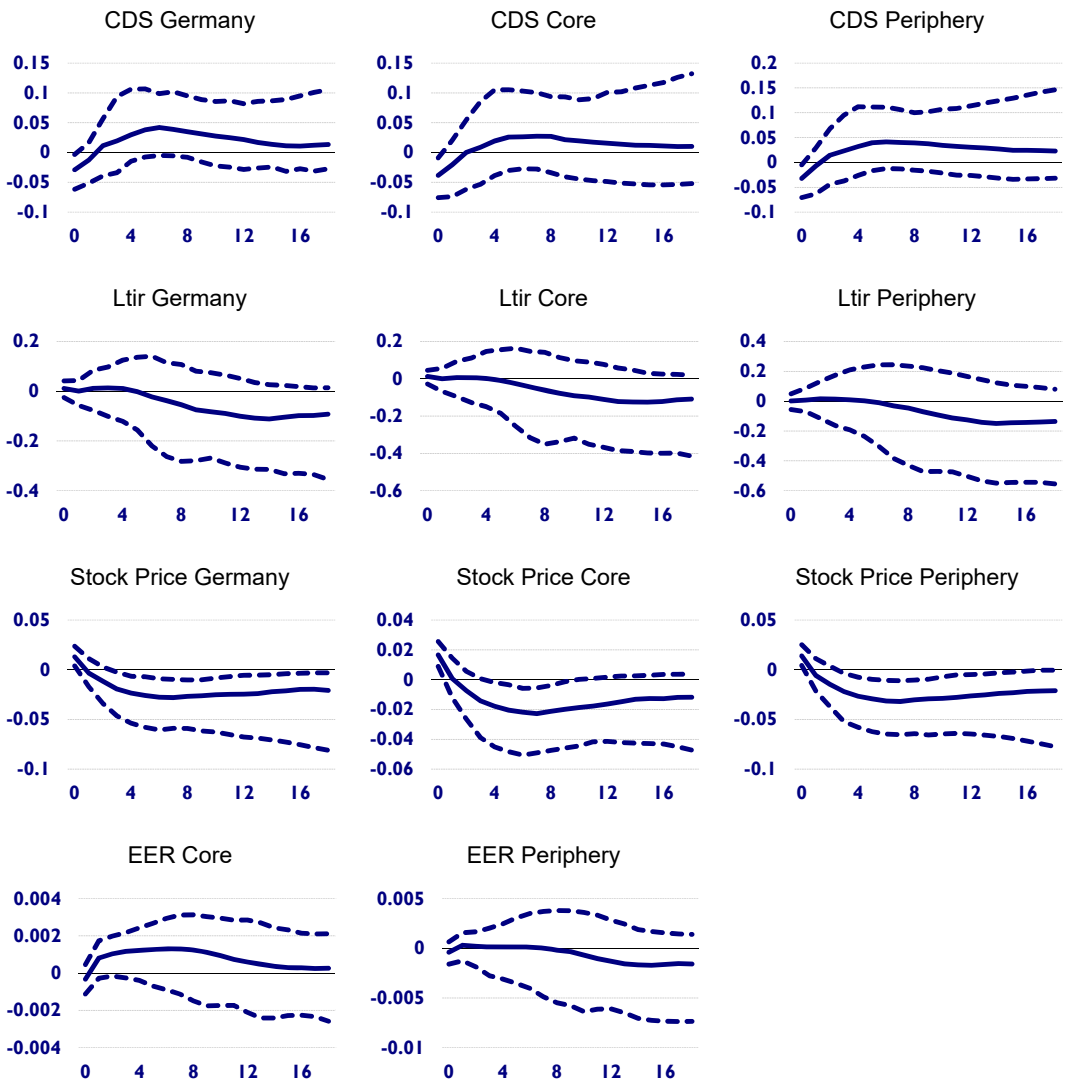

Figure 1.10: Eurozone Regions GIRF at 1 s.e. Positive Shock on French Stock Price. The dashed lines indicate the 90% confidence interval.

particular, if the shock occurs in France, the indices of the three regions bounce from positive to negative (which only reabsorbs in the case of the Core region). Otherwise, shock on the price of the Italian equity index causes positive spillover effects on the equity indices of the three regions, which are lasting in the case of the Periphery region.

Finally, we analyse the impact of a positive shock on the equity price for Germany. Figure 1.12 shows that the effects are initially negative, to be then reabsorbed with regard to the risk of sovereign CDS of the three regions. Opposite dynamic (first positive and subsequently reabsorbed) is observed for the equity prices of the European regions. Dynamics not too dissimilar to the effects of a

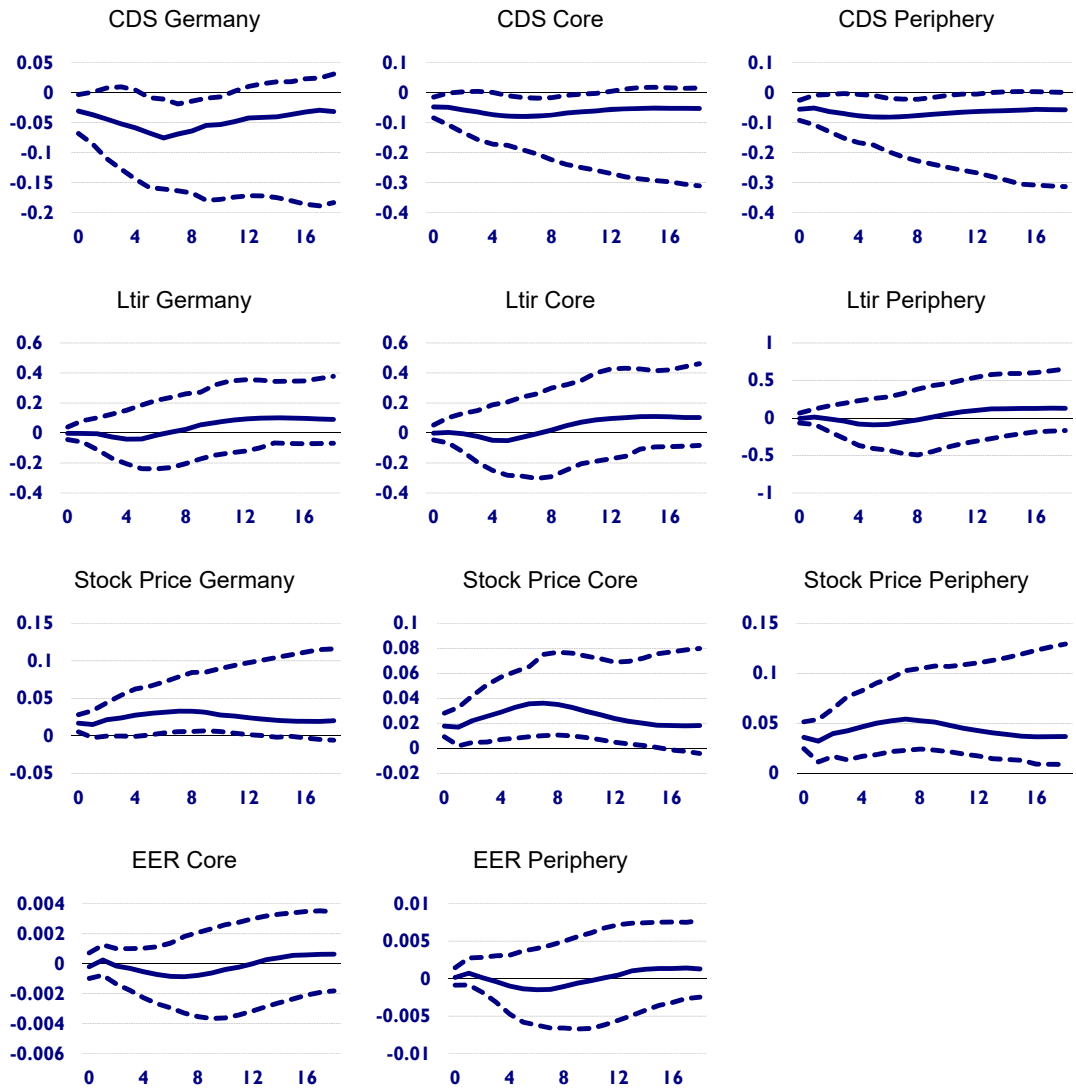

Figure 1.11: Eurozone Regions GIRF at 1 s.e. Positive Shock on Italian Stock Price. The dashed lines indicate the 90% confidence interval.

positive shock on the German equity price are observed for the long-term interest rate and the effective exchange rate. In both cases the effects are initially positive and persist for the whole (or at least most part) of the forecast window.

1.4.5 Global Forecast Error Variance Decomposition Analysis

Table 1.7 presents the sources of disturbance for two types of variables, a purely financial (Stock Index) and an economic one (EER) for France and Italy. In this context, following the method proposed by Boschi et al. (2015), and with the aim of making understanding easier, we decided to reduce the forecast window to just 4 periods (namely: impact, 6, 12 and 18 months ahead) and not one for each of the 18 individual forecast observations. Moreover, as for the analysis of the GIRFs, we decided to report the results for the considered regions, Core and Periphery. Table 1.7 shows the results (normalised to 100, as in Caporale and Girardi (2013)), of the influence that the variables considered, for each country (collected in the two specific areas), have in the different periods, following the impact analysed by the GIRFs.

As regards the effective exchange rate we notice that the higher disturbance, provided by France, referes to its own region. In particular, the disturbance spreads between all the variable considered, the only exception are equity prices, but at 18 month horizon.

On the contrary, the Italian role of disturbance for EER spreads to the Core region, especially for financial variables (equity and CDS prices), while for macroeconomic variables (effective exchange rate and long term interest rate), at least for the first horizons, the role of Italy is stronger in its own region.

Moving to the equity prices analysis, we can notice a more confused pattern. As regards Italy, we observe that its disturbance role especially affects Periphery region. The only exception regards the long term interest rate, even if the higher disturbance in Core region decreases over time.

Finally, considering the France effect on equity prices, we notice that, for effective exchange rate and CDS prices, the higher disturbance is focused in Periphery region, while for the long term interest rate it is focused in Core region (only exception in horizon 0). The effects on equity prices are less clear. At horizon 0 the disturbance is largerly based in Core region, but its level alternately decreases over time.

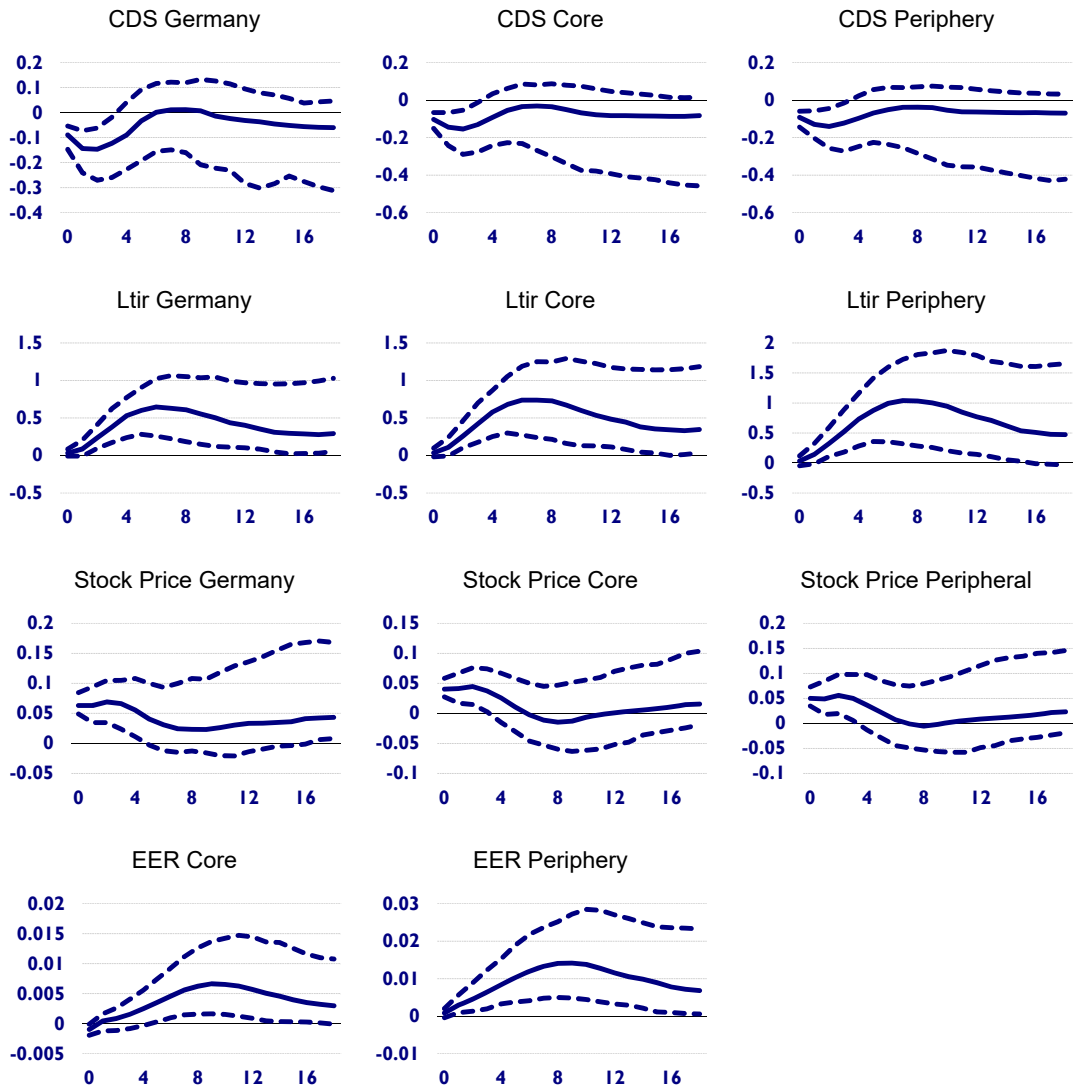

Figure 1.12: Eurozone Regions GIRF at 1 s.e. Positive Shock on German Stock Price. The dashed lines indicate the 90% confidence interval.

1.4.6 Forecasts

As presented in the literature and methodological review sections, GVAR models are often used for predictive analysis. Unlike other methodologies suitable for making predictions based on rich databases (such as Lasso, Ridge or elastic net, factor model or partial leas square), the GVAR technique allows to exploit the panel structure that is consistent with the presence of cross-sections. In our analysis we propose, in addition to the classic ex-ante forecast, also the conditional forecast, as introduced by M. Pesaran et al. (2007). For both types of forecast, we decided to consider a 12-month forecast window. Furthermore, as regards the conditional prediction, we have decided to put the predicted values for the common variable (VIX) as a condition, in order to avoid having to make assumptions about the variables of greatest interest.

The VIX values for the 12 observations of the prevision window have been computing using an AR(12) ($vix_t = \alpha + \sum_{i=1}^{12} \beta_i vix_{t-i} + \epsilon_t$) model that explains about 75% of the dependent variable, from which we extracted the out of sample forecasts with a 95% confidence interval. Figures 1.13 and 1.14 present the ex-ante forecast and the conditional ones respectively. From a first glance it seems clear that the two forecasting techniques give similar results, especially if we consider the trend for these predictions. In particular, we observe that equity prices and CDS prices increase over time for all the regions, while the effective exchange rate and the long-term interest rate decrease. Figure 1.15 highlights the differences between the results that the two techniques propose. First of all it should be emphasised that the values estimated with the ex-ante forecast and the conditional ones for Germany are exactly super-imposable, since Germany plays the role of large economy. As for the equity prices of the two regions (Core and Periphery), the conditional forecasting technique proposes values that are consistently lower than the ex-ante one. On the other hand, an opposite dynamic is observed on CDS prices. Moreover, by observing the results for the effective exchange rate and the long-term interest rate, it is noted that the conditional forecasting technique gives greater results than the ex-ante one for the first observations out of sample, whereas subsequently the values are lower that those obtained with the other technique.

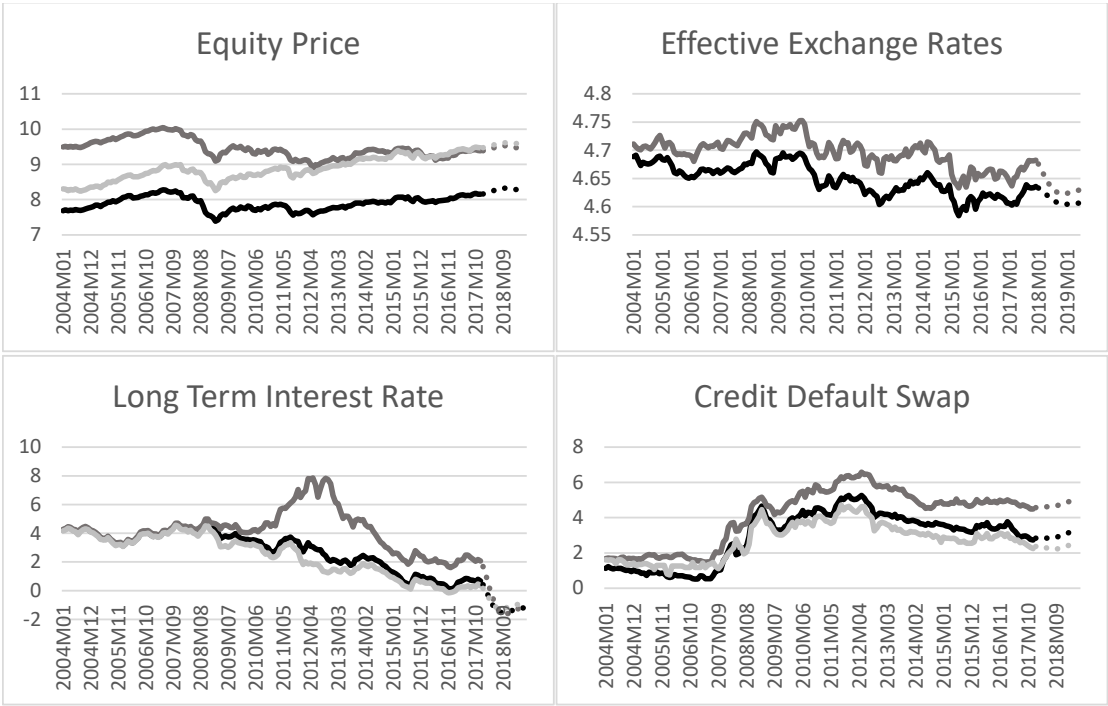

Figure 1.13: Black line identifies the Core region, while the dark and the light grey ones the Periphery region and Germany respectively, the dotted lines represent the forecast window.

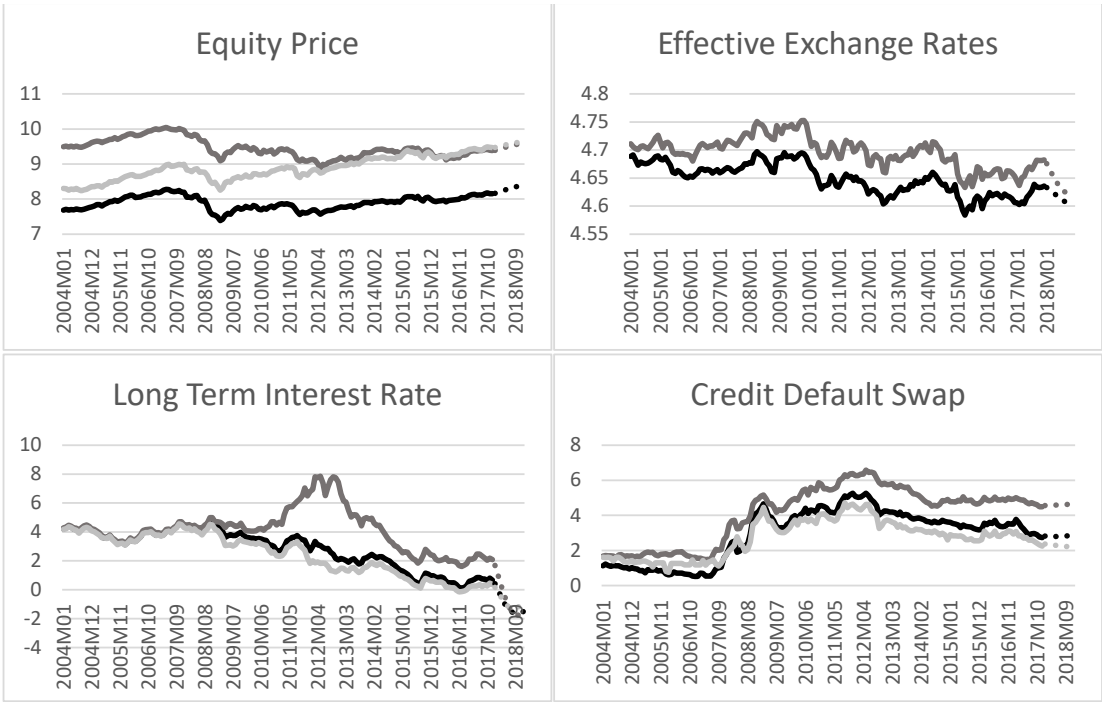

Figure 1.14: Black line identifies the Core region, while the dark and the light grey ones the Periphery region and Germany respectively, the dotted lines represent the forecast window.

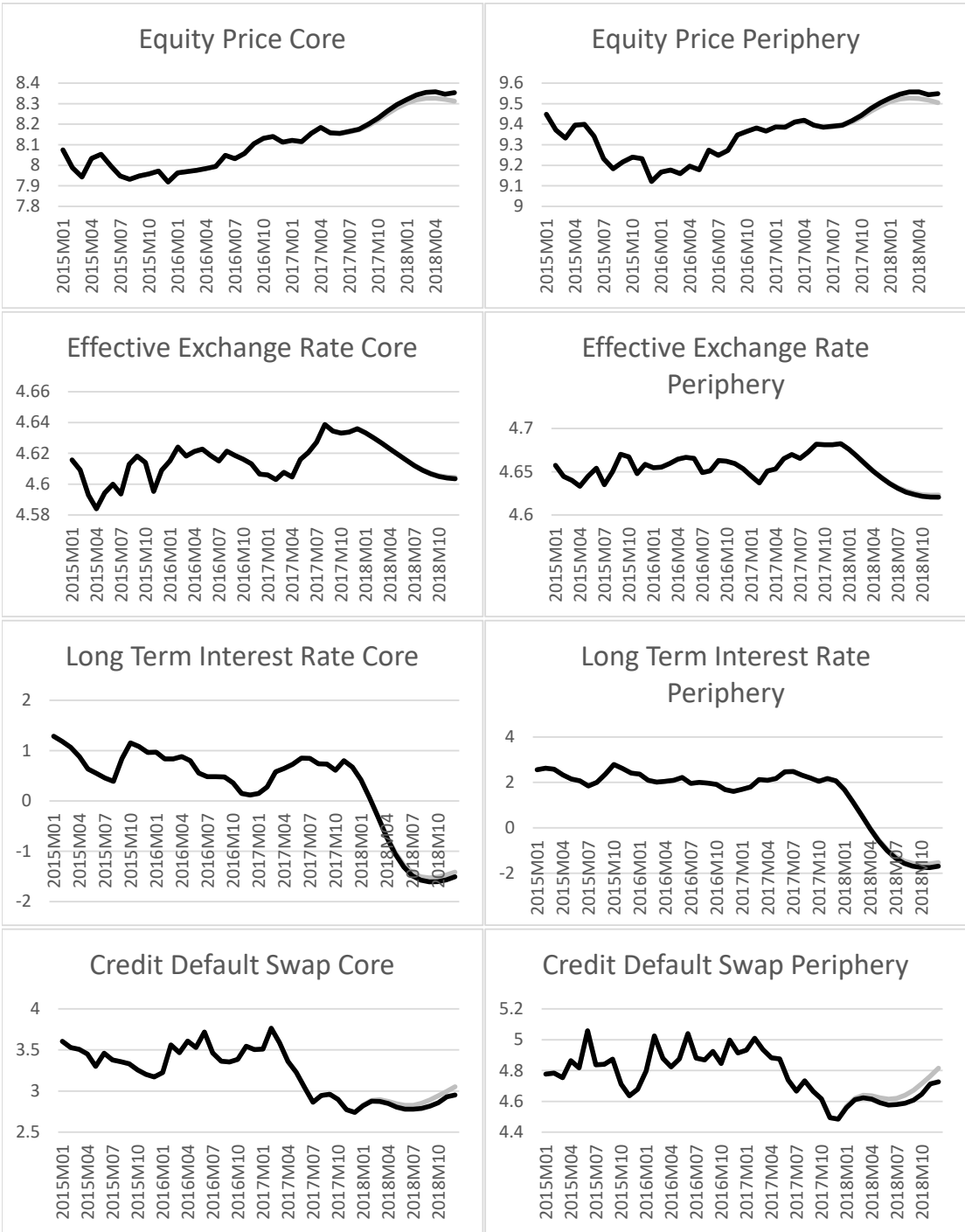

Figure 1.15: Black lines identify the Conditional Forecasts, while the grey ones the Ex-Ante Forecasts respectively. For a better understanding we present only the final part of the historical series, in particular from January 2015 to December 2017 for the observations and until December 2018 for the forecasts. For the computation of the values the series were used in their entirety (from January 2004).

1.5 Conclusions

In this paper, we analysed the interdependent relationships between France and Italy in relation to three macro-regions of the Eurozone, namely Germany, Core (composed by Austria, Belgium, Finland, France and the Netherlands) and Periphery (composed by Greece, Ireland, Italy, Portugal and Spain). In order to evaluate the spillover effects between prices of sovereign CDSs, long-term interest rates on the treasury bills, the effective exchange rate and the equity prices, we have implemented the GVAR methodology, introduced by M. Pesaran et al. (2004). From the analysis of the GIRFs, the role of France (the main country of the Core region) turns out to be more significant than the Italian one (the most important country in the Periphery region). In fact France based shocks spread on other countries the 66% of times, while for Italy based shock the 52%. Furthermore, we can observe how the main differences in impulse responses lie in the CDS price and in the long term interest rate variables. In particular, a shock on the price of Italian CDSs is generally little or not at all significant for the other regions (regardless of the spillover effect variables), while when the shock hits the price of the French CDS the answer is not always significant, but often the shock is not reabsorbed in the next 18 months. Otherwise, a shock on the long-term interest rate spreads more easily, among regions and analysed variables, occurring in Italy. In this work, using the GFEVDs, we also evaluated the sources of disturbance for a financial and a real variable, namely the equity prices and the effective exchange rates, for France and Italy. Results show that, as for the equity price variable, regardless of the country of observation, the greater impact is given by the Periphery component, while for the EER, Core component makes the greatest disturbance. Furthermore, in general, when we consider the equity price, all the variables show an important relative weight, though the price of the CDS is less relevant. On the other hand, as regards the EER variable, the actual exchange rate plays the most important role.

Table 1.1: Descriptive Statistics, EQUITY are the log prices of the main national stock indices; EER are the Effective Exchange Rates; LTIR are the Long Term Interest Rates for the 10 years bond and CDS are the Credit Default Swap log prices for the sovereign debt; VIX is the CBOE Volatility Index.

VARIABLE / COUNTRIES	**Mean**	**Median**	**Max**	**Min**	**Std. dev.**	**Skew.**	**Kurt.**	**J-B (p-value)**
EQUITY								
AUSTRIA	7.8937	7.8268	8.494	7.3009	0.2695	0.5736	2.5213	10.786 (0.0045)
BELGIUM	8.0122	8.04	8.4549	7.4364	0.2352	-0.1618	2.0869	6.266 (0.0436)
GREECE	7.3468	7.2812	8.582	6.2475	0.71	0.1584	1.6216	13.641 (0.0011)
SPAIN	9.2184	9.2336	9.6735	8.7144	0.187	0.3052	2.854	2.742 (0.2538)
FINLAND	7.8181	7.8100	8.3008	7.1438	0.2675	-0.1838	2.2253	4.879 (0.0872)
IRELAND	8.4876	8.583	9.1957	7.6374	0.4005	-0.2735	1.7998	11.856 (0.0027)
ITALY	10.0532	9.9828	10.6864	9.463	0.311	0.4365	2.0862	10.960 (0.0042)
NETHERLANDS	6.3901	6.3893	6.7366	5.8316	0.2028	-0.2712	2.4535	3.968 (0.1375)
PORTUGAL	8.8474	8.8666	9.5056	8.4015	0.281	0.5069	2.5093	8.810 (0.0122)
FRANCE	8.3481	8.3626	8.7167	7.9019	0.179	-0.0611	2.2378	3.892 (0.1429)
GERMANY	8.8662	8.8439	9.4902	8.2389	0.3347	-0.0133	2.0638	5.819 (0.0545)
EER								
AUSTRIA	4.6165	4.6169	4.6494	4.5723	0.0162	-0.2424	2.5942	2.657 (0.2649)
BELGIUM	4.6802	4.6799	4.7169	4.6317	0.0175	0.04	2.9381	0.051 (0.975)
GREECE	4.7065	4.7102	4.7692	4.6258	0.0325	-0.2502	2.3853	4.189 (0.1231)
SPAIN	4.7236	4.7229	4.7787	4.6706	0.0254	0.1206	2.3736	2.917 (0.2326)
FINLAND	4.6207	4.6176	4.6904	4.5589	0.0264	0.3283	2.7073	3.547 (0.1697)
IRELAND	4.7413	4.7479	4.8678	4.6149	0.0663	-0.1274	1.9931	7.226 (0.027)
ITALY	4.6762	4.6802	4.7318	4.6125	0.0271	-0.1988	2.3941	3.458 (0.1775)
NETHERLANDS	4.6583	4.6596	4.7075	4.6144	0.0216	0.0415	2.2355	3.858 (0.1453)
PORTUGAL	4.6703	4.6717	4.7181	4.6131	0.0238	-0.2691	2.2545	5.677 (0.0585)
FRANCE	4.6474	4.6493	4.709	4.567	0.0366	-0.2113	1.8494	10.186 (0.0061)
GERMANY	4.6177	4.6124	4.6811	4.5327	0.0364	-0.0326	-1.1645	11.580 (0.011)
LTIR								
AUSTRIA	2.8073	3.305	4.8	0.11	1.3988	-0.5261	1.847	16.841 (0.0002)
BELGIUM	3.01	3.555	4.85	0.15	1.3833	-0.7149	2.0587	20.448 (0)
GREECE	8.1822	6.095	29.24	3.3	5.3954	1.8766	6.4092	185.462 (0)
SPAIN	3.7404	4.015	6.79	1.01	1.3281	-0.3693	2.5182	5.314 (0.0702)
FINLAND	2.6901	3.185	4.78	0.06	1.3959	-0.3861	1.7333	15.116 (0.0005)
IRELAND	4.0602	4.03	12.45	0.4	2.3138	0.8176	4.1824	29.692 (0)
ITALY	3.8317	4.15	7.06	1.18	1.2489	-0.4585	2.7955	6.198 (0.0451)
NETHERLANDS	2.6827	3.2	4.73	0.03	1.3932	-0.4277	1.7883	15.129 (0.0005)
PORTUGAL	5.0188	4.25	13.85	1.74	2.5264	1.7814	5.5396	138.006 (0)
FRANCE	2.8324	3.32	4.73	0.15	1.3045	-0.5753	1.9966	16.148 (0.0003)
GERMANY	2.4548	3.02	4.56	-0.15	1.4469	-0.2912	1.641	14.973 (0.0006)
CDS								
AUSTRIA	2.9468	3.2956	5.4524	0.6518	1.4733	-0.3164	1.8013	12.551 (0.0019)
BELGIUM	3.2237	3.6532	5.7565	0.7715	1.5149	-0.3463	1.8602	12.160 (0.0023)
GREECE	5.4193	6.2335	10.1434	1.0984	2.4022	-0.2615	1.8528	10.808 (0.0045)
SPAIN	3.8314	4.4368	6.3957	0.9651	1.7376	-0.5611	1.8447	17.961 (0.0001)
FINLAND	2.6554	3.138	4.4716	0.3365	1.1333	-0.6197	2.167	15.506 (0.0004)
IRELAND	3.5222	4.0598	6.674	0.1138	2.2402	-0.4698	1.8301	15.516 (0.0004)
ITALY	4.2141	4.7487	6.3328	1.7375	1.3779	-0.5241	1.7837	17.824 (0.0001)
NETHERLANDS	2.5371	3.1835	4.8534	0.0795	1.6225	-0.5	1.674	19.063 (0.0001)
PORTUGAL	4.4005	5.1004	7.3024	1.4081	1.7979	-0.4167	1.7302	15.872 (0.0004)
FRANCE	3.0577	3.5083	5.404	0.5596	1.4479	-0.4235	1.8291	14.354 (0.0008)
GERMANY	2.724	2.891	4.7205	0.7538	1.0517	-0.1133	1.8944	8.574 (0.0137)
GLOBAL VARIABLES								
VIX	2.9067	2.8432	4.0925	2.2523	0.3663	0.6523	3.0182	14.701 (0.001)

Table 1.2: Stock Index per Country

Countries	Stock Index
Austria	ATX
Belgium	BEL 20
Finland	OMXH 25
France	CAC 40
Germany	DAX 30
Greece	ATHEX
Ireland	ISEQ
Italy	FTSE MIB
Netherlands	AEX
Portugal	PSI 20
Spain	IBEX 35

Table 1.3: Weights Matrix, weights are based on trade relationships.

	AUT	BEL	FIN	FRA	GER	GRE	IRE	ITA	NET	POR	SPA
AUT	0	0.038	0.008	0.066	0.656	0.006	0.005	0.130	0.058	0.004	0.030
BEL	0.0132	0	0.010	0.246	0.294	0.006	0.043	0.076	0.260	0.009	0.044
FIN	0.029	0.094	0	0.104	0.400	0.013	0.015	0.086	0.194	0.012	0.053
FRA	0.019	0.179	0.008	0	0.331	0.007	0.020	0.156	0.115	0.020	0.145
GER	0.123	0.144	0.008	0.216	0	0.011	0.017	0.144	0.228	0.009	0.081
GRE	0.024	0.071	0.014	0.123	0.275	0	0.013	0.271	0.107	0.009	0.088
IRE	0.016	0.278	0.012	0.146	0.230	0.008	0	0.085	0.137	0.012	0.078
ITA	0.057	0.084	0.010	0.239	0.340	0.025	0.014	0	0.095	0.016	0.118
NET	0.019	0.240	0.019	0.132	0.429	0.008	0.018	0.074	0	0.011	0.050
POR	0.010	0.051	0.007	0.162	0.194	0.004	0.009	0.081	0.073	0	0.411
SPA	0.017	0.065	0.008	0.278	0.248	0.010	0.016	0.157	0.085	0.117	0

Table 1.4: Break Data, Quandt Likelihood Ratio test.

Variables	Stock Index	EER	Ltir	CDS
AUSTRIA	2009M03	2014M11	2012M08	2008M03
BELGIUM	2008M11	2014M10	2012M01	2008M06
FINLAND	2012M05	2015M02	2010M08	2006M11
FRANCE	2010M03	2014M10	2012M04	2007M01
GERMANY	2010M01	-	2012M02	2008M09
GREECE	2014M11	2012M07	2012M06	2011M12
IRELAND	2010M10	2012M11	2011M11	2008M02
ITALY	2008M11	2014M12	2011M10	2009M04
NETHERLANDS	2008M12	2009M03	2012M01	2008M10
PORTUGAL	2015M10	2009M03	2011M05	2010M08
SPAIN	2010M08	2012M09	2010M08	2008M06

Table 1.5: Country Weights

Country	Stock Index	EER	Ltir	CDS
AUSTRIA	0.031038	0.042832	0.031038	0.031038
BELGIUM	0.034916	0.048184	0.034916	0.034916
FINLAND	0.018374	0.025356	0.018374	0.018374
FRANCE	0.210482	0.290465	0.210482	0.210482
GERMANY	0.275361	-	0.275361	0.275361
GREECE	0.027972	0.038601	0.027972	0.027972
IRELAND	0.015246	0.02104	0.015246	0.015246
ITALY	0.190794	0.263295	0.190794	0.190794
NETHERLANDS	0.054754	0.075561	0.054754	0.054754
PORTUGAL	0.022351	0.030845	0.022351	0.022351
SPAIN	0.118712	0.163823	0.118712	0.118712

Table 1.6: Regional Weights, defined as the contribution of each county in its region.

Region	**Country**	**Weight**
Germany	Germany	1
Core	Austria	0.088789
Core	Belgium	0.099885
Core	Finland	0.052562
Core	France	0.602128
Core	Netherlands	0.156636
Periphery	Greece	0.074576
Periphery	Ireland	0.040649
Periphery	Italy	0.508681
Periphery	Spain	0.316503
Periphery	Portugal	0.059591

Table 1.7: Generalised Forecast Error Variance Decomposition. Values in brackets represent the weight of each variable for the specific GFEVD.

France Equity Price

Horizon	Core (Periphery) Equity Price [30.86]	Core (Periphery) EER [29.69]	Core (Periphery) Ltir [24.42]	Core (Periphery) CDS [15.03]
0	85.59 (14.41)	14.5 (85.5)	49.04 (50.96)	44.78 (55.22)
6	47.86 (52.14)	29.01 (70.99)	65.39 (34.61)	47.57 (52.43)
12	53.35 (46.65)	44.88 (55.12)	69.01 (30.99)	29.78 (70.22)
18	36.25 (63.75)	42.65 (57.35)	52.51 (47.49)	30.69 (69.31)

France EER

Horizon	Core (Periphery) Equity Price [5.15]	Core (Periphery) EER [89.02]	Core (Periphery) Ltir [3.67]	Core (Periphery) CDS [2.15]
0	62.83 (37.17)	62.43 (37.57)	53.03 (46.97)	51.42 (48.58)
6	78.94 (21.06)	64.27 (35.73)	88.7 (11.3)	66.05 (33.95)
12	92.97 (7.03)	69.51 (30.49)	84.27 (15.73)	69.61 (30.39)
18	47.54 (52.46)	72.08 (27.92)	82.08 (17.92)	50.12 (49.88)

Italy Equity Price

Horizon	Core (Periphery) Equity Price [33.48]	Core (Periphery) EER [31.27]	Core (Periphery) Ltir [18.07]	Core (Periphery) CDS [17.17]
0	37.25 (62.75)	30.28 (69.72)	60.79 (39.21)	46.79 (53.21)
6	25.34 (74.66)	31.26 (68.74)	54.63 (45.37)	49.3 (50.7)
12	33.27 (66.73)	48.39 (51.61)	59.09 (40.91)	35 (65)
18	26.41 (73.59)	44.89 (55.11)	43.08 (56.92)	32.57 (67.43)

Italy EER

Horizon	Core (Periphery) Equity Price [16.60]	Core (Periphery) EER [61.92]	Core (Periphery) Ltir [11.62]	Core (Periphery) CDS [9.86]
0	69.52 (30.48)	38.1 (61.9)	27.97 (72.03)	53.16 (46.84)
6	61.98 (38.02)	47.82 (52.18)	83.84 (16.16)	62.19 (37.81)
12	91.31 (8.69)	53.28 (46.72)	81.68 (18.32)	51.42 (48.58)
18	80.75 (19.25)	53.93 (46.07)	68.39 (31.61)	56.76 (43.24)

Chapter 2

Does a negative shock on the Treasury Bonds yields decrease the probability of being in a vulnerable state? A multinomial logit analysis.

2.1 Introduction

Over recent years, both academic papers and divulging articles, have mainly focused on the European 10 years treasury bond interest rates dynamics. In particular, the well known spread performance (as a yield differential between the individual 10 years European government bonds and the German counterparts) is considered, especially from the divulging literature, as one of the main thermometers to analyse the macroeconomic context. This index represents the reliability of a country and, consequently, its dynamics are a first clue about investors' reactions about a particular economic policy, macroeconomic announcements and all other news influencing the economy. Since the second half of 2007, spreads have greatly worried both policy makers and investors, making the financial markets extremely volatile.

The aim of this work is to check if a decline in the European treasury bonds yields translates into a decline in the probability of being in a vulnerable state. To achieve this we act as follows.

First, we create a "crisis" variable following Laeven and Valencia (2012) able

to capture the periods of pre-crisis, crisis and recover. Second, we set an Early Warning System (EWS) that exploits a Multinomial Logit technique able to overcome the so called "post-crisis" bias. Our model achieves up to the 88% of correct predictions. Third, through the Early Warning model, we evaluate the probability of being in a moment of turbulence based on the optimal threshold that minimises the fact that our model may miss a crisis (Type 1 error) or issue a false alarm (Type 2 error). In our case, the optimal threshold that minimised the Type 1 and Type 2 errors, moves from 8.87 to 23.67 according to the model selected. These values are in line with Bussiere and Fratzscher (2006) that, for a similar framework, obtain an optimal threshold of 20%. Fourth, exploiting the Generalise Impulse Response Function (GIRF), based on a Global Vector Auto-Regression (GVAR), we observe how our variables respond to a negative shock on long term interest rate (with a magnitude of a standard error). In particular, we observe that the equity prices are generally characterised by a growth that becomes significant only after some periods but this growth often is lasting. Differently, CDS prices are characterised by a significant initial decline which, in many cases, is reabsorbed. The effective exchange rate does not show significant deviations, although for all the countries considered there is a sudden (but short-term) drop immediately after the shock. Finally, the interest rate on ten-year sovereign bonds shows a re-absorption by some European countries, while for the so-called Mediterranean countries, the drop in rates lasts. In conclusion, we estimate again the EWS model, for the sole observations deriving from the GIRFs and we compute the reduction in the probability of being in a vulnerable state, following the contribution of Behn et al. (2016). According to our empirical results we can notice that a negative common shock for the long term interest rate has the merit of significantly reducing the likelihood of being in a vulnerable state.

In the Appendix, we report a similar empirical application but, instead of the observations obtained through the GIRFs, we perform an out of sample conditional forecast, based on a Global VAR methodology. We use these "new" observations to enrich our original database and then we evaluate the EWS model for both, the conditional forecast observations and the whole data set (original time series and the forecast observation) and evaluate the optimal thresholds once. Our results show that, in the case of the whole data set we experience an enlargement in the probability of being in a vulnerable state.

The rest of the paper is developed as follows: Section 2.2 presents a review of the literature with a particular focus on the empirical literature about Early Warning Systems based on Multinomial Logit models and shock propagation with

particular reference to the GVAR literature. Section 2.3 presents the methodology, specifically we focus on logit and Multinomial logit EWS, GVAR and GIRF. Then, we present how to combine the observations generated by the GIRF and the Multinomial logit EWS. In Section 2.4 we firstly present the database, the original EWS models, the GIRF results, the computation of the new EWS based on the new observations and the reduction in the probability of being in a vulnerable state. Finally Section 2.5 concludes. In the Appendix (Section 2.6) we consider a similar exercise based on GVAR forecast properties.

2.2 Literature review

In this section we introduce Early Warning literature, whit a particular focus on logit-based models. As regards the spillover transmission and GVAR literature we refer to Section 1.2.3.

Recent years of crisis have shown that, especially for policy makers, it is really useful to have models able to predict particular moments of tension, regardless of whether they concern different industries, markets or countries. The increasingly strong interconnection between economies has, in fact, not only brought economic benefits, but has actually increased the risk of economic crises because of contagion among linked economies. A recent significant example is the Great Recession transformation from a banking crisis exposed in 2007 to a global crisis that has significantly affected other countries and markets like, for instance, the sovereign debt crisis in European.

Setting a useful Early Warning System is extremely important. In this respect, Caprio and Klingebiel (1999) estimate that the amount of direct and indirect costs of a systemic crisis could reach 10% of the GDP of the country in crisis. The authors point out how in special cases, like the Mexican crisis of 1994 or the Jamaican crisis of 1996, the cost in percentage terms on the GDP was respectively 20 and 37%. Moreover, Hoggarth et al. (2002) show that the costs, in percentage terms on GDP, are greater in the event that the crisis affects OECD countries (on average 23.8%) compared to emerging economies (13.9%). Considering these premise, an important part of the research, has implemented and tested methodologies capable of predicting crisis periods.

The first work that, in general, is considered as a forerunner of Early Warning literature is the one by Ramser and Foster (1931). In this paper the authors aim to predict corporate crises and focus on individual financial ratios as indicators of particular periods of vulnerability. With a similar aim, Beaver (1966) analyses the

predictive power of financial ratios, trying to predict companies' default. With his research, the author also manages to show the predictive power of company accounting variables in deciphering crises and corporate failures. With Altman (1968) the analysis on financial ratios is done in a multivariate way. The author analyses several variables at the same time and, consequently, weighs on the predictive contribution of each individual financial ratio in predicting corporate crises. This type of methodology is called Discriminant Analysis (DA) and it is also exploited by Taffler and Abassi (1987), that consider 95 developing countries for the period of 1967-1977. The authors show that international reserves (including gold) play a crucial role for debt rescheduling. In particular, they find that the ratio between total debt and GDP is insignificant to predict a sovereign debt crisis, while the ratio between reserves and debt is negatively correlated. Less clear is the ratio between total debt and export, according to Taffler and Abassi (1987) it is negatively correlated to a sovereign debt crisis, while for Frank Jr and Cline (1971) the correlation sign is positive.

The DA represents the first step into a rich strand of literature that considers EWS. Recently, Holopainen and Sarlin (2017) compare different Early Warning methodologies proposed in the literature. Following their review, it is clear that Signal Extraction (SE) and Logit-based techniques are two of the most used methodologies. With these two techniques, states of tension can be analysed on what are considered the most important markets, namely stock markets, sovereign debt markets and currency markets. The success of these techniques is due to their flexibility in adapting to different contexts.

The Signal Extraction, that was introduced by Kaminsky et al. (1998), considers the behaviour of a variable supposed to be an indicator-variable. The model defines a threshold and an alarm when the indicator-variable exceeds this threshold which on the one hand identifies the will of the policy maker and on the other optimises the usefulness function. The simplicity and immediacy of this methodology has led many authors to exploit it for different types of crises, and it is certainly one of the most used methods in Early Warning. In particular, among others, we consider Alessi and Detken (2011), where the authors, exploiting a set of 28 emerging markets and advanced economies with quarterly data since 1990 until 2007, identify systemic events following Laeven and Valencia (2012), and evaluate the joint role of domestic and global vulnerabilities. Furthermore, they also analyse the role of the interactions between domestic factors and the interplay of global developments with domestic conditions, and evaluate these macroprudential indicators of vulnerabilities and composite indicators calculated using Signal

Extraction. Similar results are obtained by Duca and Peltonen (2013) using the same methodology. Knedlik and Von Schweinitz (2012) analyse the European sovereign debt crisis, focusing on the same 11 countries that we consider for the period 1997-2011 (quarterly data). The authors create a rich set of variables, including the unemployment rate, internal demand, deficit, and many others. In particular, they create a single predictor variable by equal-weighting the most meaningful variables in their sample. Knedlik and Von Schweinitz (2012) conclude that the cumulative imbalances led to debt crises in the peripheral crisis countries. One of the weaknesses of this methodology lies in the fact that it does not allow interactions and consequently weights between the indicator-variables.

Most of the empirical literature regarding Early Warning Systems uses logit models. Exploiting the characteristics of a logistic function, logistic models study the probability that an observation is in a quiet period versus stress, as a function of a number of variables. The applied logit literature for EWS purposes is rich. In their survey, Berg et al. (2005) expose the models used by large financial companies to predict moments of tension on the markets. The authors show how the methodologies developed by Goldman Sachs (WATCH) and Credit Suisse (First Boston's Emerging Markets Risk Indicators) are based on logit models. More recently, several papers have continued to use logit models in order to anticipate moments of tension on the markets, in particular the contributions of Behn et al. (2013). The authors exploit a sample of 23 European countries based on quarterly data from 1982 until 2012. Using a logit model, they find that both credit variables, domestic and global financial factors, such as equity and house prices and banking sector variables, help to predict macro-financial vulnerabilities in Europe.

Li and Wang (2014) focus on the Chinese financial system. They build a logit based early warning system for Chinese companies. Differently from other papers that aim to investigate financial early warning using logit models, the authors do not just consider financial indicators, that can be controlled or manipulated, but a logit model considering non-financial efficiency indicators like Discriminated Analysis (DA). Getting closer to the root of our contribution, Behn et al. (2016) propose logit based model to study banking crisis for 14 European countries from 1995 until 2014 (quarterly data). In their paper the authors consider a GVAR based model to evaluate both banking and sovereign markets. Exploiting the impulse response function, they obtain the out of sample observations studied by the logit model. In place of a robustness test, the authors apply the Multinomial logit model, obtaining very similar results.

As Caggiano et al. (2016) point out, the Multinomial logit methodology out-

performs the classical binomial logit methodology. Particularly, the authors develop a EWS for predicting systemic banking crises in a panel of 35 low income countries, between 1980 and 2008, based on the Multinomial logit model. They follow this approach to address the concern that the econometric results of traditional binomial logit models may be affected by variable behaviour during crisis years other than the first, defined as the crisis duration bias. Their main results suggest that a decline in economic growth, banking system illiquidity and widening currency mismatches in banks' balance sheets are the main predictors of systemic banking crises. Most importantly, results show that moving from a binomial logit model to a Multinomial logit model improves the predictive power of the EWS. Bussiere and Fratzscher (2006) add that the Multinomial logit methodology allows to overcome the so-called "post-crisis" bias (see Section 3.3) and consequently the regression allows better estimates. Among the works that are based on Multinomial logit models for Early Warning topics, Ciarlone and Trebeschi (2005) consider more than 25 countries from 1980 until 2002. The authors show that the Multinomial logit approach is better than the classical logit model to highlight the significant variables in explaining debt crises. Particularly, they are mainly those that measure the burden of external indebtedness and foreign-currency. The "post-crisis" bias is firstly pointed out by Bussiere and Fratzscher (2006) that show that moving from a binomial to a Multinomial logit improves the predictive power of the EWS. They consider 20 emerging economies from 1993 until 2001 (monthly data), focusing particularly on currency crisis.

To conclude, according to Davis and Karim (2008), the logit methodology is, generally speaking, more indicated than Signal Extraction for the identification of EWS, in particular when the analysed sample is wide at the cross section level. Usually SE models have higher forecast qualities if the cross section is internal to a single country, for example in the case of a banking crisis focusing on a single banking system, while logit models are more suitable for capturing information in cases where the cross section component is more diverse.

2.3 Methodology

2.3.1 Logit Early Warning System

In general, the probability of a crisis cannot be described by a linear function, so one of the most common solutions to this problem is to design a non linear

function $F(X\beta)$ exploiting a logistic distribution. The logit model is:

$$\mathbb{P}(Y = 1|X) = F(X\beta) = \frac{e^{X\beta}}{1 + e^{X\beta}}. \tag{2.1}$$

For a richer presentation of the logit models we refer to Cramer (2003). In our framework, to define a panel logit model, we consider N entities, $i = 1, 2, ..., N$, that we observe for T periods, $t = 1, 2, ...T$. For each entity we observe a binary dependent variable Y which takes value 1 in crisis periods and 0 otherwise. The aim of the log model is to describe the crisis variable Y by a set of variables X. X is a $KN \times T$ matrix of observations, where K is the number of independent variables. Our goal is to observe how the set of variables X influences the probability P of being in crisis. The vector of the K marginal effects is defined as:

$$\gamma = \frac{dP}{dX'}, \tag{2.2}$$

Where P is defined as $\mathbb{P}(Y = 1|X)$. The way to evaluate the performance of an Early Warning model is to compare the predicted probability with the actual occurrence of crisis. In general, the predict probability is a continuous function and, consequently, we must define a value (threshold) beyond which the advent of a crisis is more likely. The goal is to make this threshold as reliable as possible. To define this optimal threshold, consider Table 2.1. In particular, the policy maker has to face this problem, she has to define a threshold above which a danger signal is emitted by the system, considering two types of errors; Type 1 (T1) indicates failure to report a crisis while Type 2 (T2) indicates a false alarm. Analytically we can define $T1 = FN/(FN + TP)$ and $T2 = FP/(FP + TN)$, where FN and FP are, the false negative and false positive previsions respectively, while TN and TP are the true negative and true positive previsions respectively. In general, the most worrisome error type (from a policy maker perspective) is $T1$.

2.3.2 Multinomial Logit Early Warning System

The "simple" logit models, especially if adopted in EW research, may suffer from the so-called "post-crisis bias" described in Bussiere and Fratzscher (2006). The authors describe this concept as an important econometric issue, in fact what "EWS models with two outcomes do is comparing the pre-crisis observations with the observations both during quite periods and post-crisis/recovery periods. This can lead to an important bias because the behaviour of the independent variables

is very different during quite times as compared to recovery episodes." There are two different ways to overcome this problem. The first way is to drop out all the post-crisis observations which is adopted for instance by Behn et al. (2016) and Demirgüç-Kunt and Detragiache (1998). Following this procedure we risk getting two problems, on the one hand we could thin the database in a sensitive way, and on the other we could lose some information that could be useful for our analysis. Another important way to overcome the post-crisis bias is to exploit the Multinomial logit regression. In this case, the dependent variable becomes:

$$Y_{i,t} = \begin{cases} 1, & if \quad \exists \text{j=1,...J} \quad s.t. \quad C^i_{t+j} = 1 \\ 2, & if \quad \exists \text{j=1,...J} \quad s.t. \quad C^i_{t-j} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{2.3}$$

where C^i_t describes the crisis occurrence for the ith country at time t and it takes value 1 when at least 2 of the 4 variables considered are in downturn[1]. The variable Y takes values 1 in pre-crisis periods, 2 in post-crisis/recovery periods and 0 in tranquil times. Referring to the canonical logit formulation we can define:

$$\begin{aligned} \mathbb{P}(Y_{i,t} = 0|X) &= \frac{1}{1 + e^{X_{i,t-1}\beta^1} + e^{X_{i,t-1}\beta^2}}; \\ \mathbb{P}(Y_{i,t} = 1|X) &= \frac{e^{X_{i,t-1}\beta^1}}{1 + e^{X_{i,t-1}\beta^1} + e^{X_{i,t-1}\beta^2}}; \\ \mathbb{P}(Y_{i,t} = 2|X) &= \frac{e^{X_{i,t-1}\beta^2}}{1 + e^{X_{i,t-1}\beta^1} + e^{X_{i,t-1}\beta^2}}. \end{aligned} \tag{2.4}$$

where β^1 measures the marginal effect of a change in the independent variable $X_{i,t-1}$ on the probability of being in a pre-crisis period relative to the probability of being in the tranquil regime. β^2 is the marginal effect of a change in the probability of being in a recovery period relative to the probability of being in the tranquil regime. From Equation (2.4), we can finally derive:

$$\begin{aligned} \frac{\mathbb{P}(Y_{i,t} = 1|X)}{\mathbb{P}(Y_{i,t} = 0|X)} &= e^{X_{i,t-1}\beta^1} \\ \frac{\mathbb{P}(Y_{i,t} = 2|X)}{\mathbb{P}(Y_{i,t} = 0|X)} &= e^{X_{i,t-1}\beta^2}. \end{aligned} \tag{2.5}$$

The X matrix composes the regressors used in the GVAR model with which we proceed to perform the GIRFs and the out-sample forecasting. Since we also

[1]The variable considered in our model are defined Section 1.4.1

	S=0 No Signal Issued	**S=1 Signal Issued**
Y=0 No Crisis	True Negative	False Positive
Y=1 Crisis	False Negative	True Positive

Table 2.1: Contingency Matrix: trade-off problem of choosing the optimal threshold.

consider country dummy variables, we can capture the idiosyncratic effects of each economy. The presence or lack of these dummy variables is equivalent to the use of fixed effects or random effects for our panel.

2.3.3 Impulse Response Functions and Global VAR

As presented in Section 1.3.4, to obtain the impulse response observations we evaluate GIRFs. This technique is based on GVAR methodology. In particular we perform a VARX model each entity i, with $i = 0, ..., N$ with p_i and q_i represent the lag for domestic and foreign variables. So, the VARX(p_i, q_i, s_i) equation is:

$$x_{i,t} = \theta_{i,0} + \theta_{i,1}t + \sum_{\ell=1}^{p_i} \alpha_{i,\ell} x_{i,t-\ell} + \sum_{\ell=0}^{q_i} \beta_{i,\ell} x^*_{i,t-\ell} + \sum_{\ell=0}^{s_i} \gamma_{i\ell} d_{t-\ell} + \epsilon_{it} \tag{2.6}$$

where $x_{i,t}$ is a $k_i \times 1$ vector of endogenous variables, $x^*_{i,t}$ is a $k^*_i \times 1$ vector of country-specific foreign variables, d_t a vector of common global variables that appear in every country VARX, $\theta_{i,0}$ a constant, t a linear trend and ϵ_{it} a $k_i \times 1$ vector of serially uncorrelated innovations, $\epsilon_{it} \sim iid(0, \Sigma_{\epsilon,i})$. $\alpha_{i,\ell}$, $\beta_{i,\ell}$ and $\gamma_{i,\ell}$ are the coefficient matrices.

Following the derivation described in Section 1.3.3, we define the canonical representation of the GVAR model as in Equation (1.16).

As described in M. Pesaran and Shin (1998), we estimate the GIRF by using Equation (1.28). We negatively shocked of 1 standard error the long term interest rate. GIRF allows to collect the observation of the shock responses.

2.3.4 Compute the Optimal Threshold and GVAR

One of the objectives of this work is to estimate the optimal threshold (τ^*) beyond which our model indicates the approach to a period of crisis. Table 2.1 shows the

typical EWS model. Once the table is filled we can evaluate $T1(\tau)$ and $T2(\tau)$, that are the fact of missing a crisis ($T1(\tau)$) or a false alarm ($T2(\tau)$). It is evident that the optimal threshold (τ^*) depends on the choice of the policy maker, based on how much he wants to avoid Type I or II errors. Rigorously:

$$T_1(\tau) = FN/(TP + FN) \; and \; T_2(\tau) = FP/(FP + TN).$$

Considering the frequencies of crises $P_1 = P(C_{it} = 1)$ and tranquil periods $P_2 = P(C_{it} = 0)$ we can define:

$$L(\tau) = \mu P_1 T_1(\tau) + (1 - \mu) P_2 T_2(\tau) \tag{2.7}$$

where μ collects the policy maker preferences. The higher is μ, the higher are the policy maker prefers to avoid the Type I error. The optimal threshold is defined as:

$$\tau^* = argmin_\tau L(\tau) \tag{2.8}$$

Following the methodology described above we are able to evaluate the optimal threshold for the analysed sample. Now, following Behn et al. (2016) work, we can enrich the sample with the observations obtained through the GVAR methodology, described below. In particular we obtain observations exploiting the forecast properties of the GVAR methodology, and through the EWS model, we can calculate the probability of being in a "vulnerable" state, Δp, as the difference between the predicted probability from the EWS model at the last useful observation, p_T, and the new observations that belong from GIRFs (or out of sample forecasts), p_{hor}:

$$\Delta p = p_T - p_{hor}. \tag{2.9}$$

2.4 Empirical Application

In this section we first analyse an EW model based on multinomial logit methodology. Then, We compute the optimal threshold based on the original data. Subsequently, using the GVAR and GIRF methodology we create the observations in response to the shock on the yields of the treasury bills. Finally, We calculate the new optimal threshold with the "new" observations and we check the difference with the one obtained initially.

2.4.1 Data

In order to give a more complete representation of the dynamics that characterise the European Union, and in particular the countries belonging to the Monetary Union, we analyse time series with monthly frequency ranging from January 2004 until December 2017. The dynamics captured by our database include, on the one hand, the convergence of the main economic indicators driven by monetary unification, on the other the great economic / financial stress deriving from the great recession of 2008 and the consequent crisis of European sovereign debts in 2011. From the former section we know that the GVAR models admit the so-called common variables, that is, variables that fall into all the VARX models, capturing the fluctuations of the markets on an international and global level. In order to capture both financial and macroeconomic dynamics we consider the following variables:

a) Equity Prices: this variable, as described in the Table 1.2, considers the log prices of stock index with the greatest capitalisation of all the European countries considered in this survey. Data belong from Bloomberg.

b) Real Effective Exchange Rate, (EER): this variable measures the value of a specific currency in relation to an average group of others major currencies, and represents the competitiveness of a country with respect of others. Data belong from Eurostat economic and financial database.

c) Sovereign Credit Default Swaps, (CDS): these are the log prices of each European sovereign CDS. d) Long Term Interest Rate, (Ltir): this variable represents the interest rates for 10 years government bonds in Euro for each country.

In our model we also consider the CBOE Volatility Index as common variable, in fact VIX is often used in jobs that consider periods of crisis, between the works they use in VIX and the GVAR methodology we remember Chudik and Fratzscher (2011) and Niehof (2014).

Since the database is the same of the one used in Chapter 1, we refer to Section 1.4.1 for the descriptive statistics.

2.4.2 Multinomial Logit

Bussiere and Fratzscher (2006) suggest that a Multinomial logit analysis allows to overcome some typical limits of a classical logit model. Following this setting we decided to set up a Multinomial Logit model as described in Section 2.3.2. First, we create a discrete variable that captures crisis periods and takes value 2 in case of periods of crisis and post-crisis (recover), value 1 for pre-crisis periods

and value 0 in quiet periods. To determine the periods of crisis we rely on Laeven and Valencia (2012) and Duprey et al. (2017). Once the periods of crisis have been identified for each specific country of the sample, we need to identify the periods of pre-crisis and post-crisis period. For a greater robustness of the results and a sensitivity analysis, we have created different variables characterised by different amplitudes of the pre-crisiand post-crisis components. This is because it is not always easy to grasp the speed at which a country falls into or exits a crisis, often some countries are characterised by a post-crisis stagnation that lasts for several months while others resume pre-crisis values much more quickly. Capturing these idiosyncratic aspects goes beyond the scope of this work, consequently the choice of different time windows seems to be able to capture the dynamics, if not of all, at least of the most countries considered. In particular we set 6 different dependent variables defined as:

- Model 1: 3 periods before crisis as "1" and 3 periods of crisis and recover as "2";
- Model 2: 6 periods before crisis as "1" and 3 periods of crisis and recover as "2";
- Model 3: 6 periods before crisis as "1" and 6 periods of crisis and recover as "2";
- Model 4: 12 periods before crisis as "1" and 3 periods of crisis and recover as "2";
- Model 5: 12 periods before crisis as "1" and 6 periods of crisis and recover as "2";
- Model 6: 12 periods before crisis as "1" and 12 periods of crisis and recover as "2".

Table 2.2 reports the results for each model obtained by estimating Equation (2.4) where the independent variables are the ones presented above. For each model we consider the cases of fixed and random effect, in particular in the case of fixed effect we add to the set of independent variables also the country dummy variables.

It is very interesting to note that the results of the regressions are very similar among all the investigated models, in particular it is observed that the prices of sovereign CDS are positively correlated to the dependent variable regardless of

whether the country dummies are included and disregarding that we are evaluating $Y = 1$ (pre-crisis periods) or $Y = 2$ (crisis or post-crisis periods), while $Y = 0$ is the comparison group. Furthermore, it is possible to observe how the long-term interest rate has almost always a significantly negative coefficient, the only exception is in Model 1 in the presence of the country dummies, where in the case when $Y = 1$ the long term interest rate is not significant. It is interesting to note that the effective exchange rate is never significant in the case of $Y = 1$ while it has a significantly positive effect in the event that $Y = 2$ and the model foresees the country dummies. Finally, as regards the equity price variable, it is noted that it has positive and significant coefficients only if the dummies of the countries are included in the regression, regardless of the Y values. Finally, the last row of Table 2.2 presents the probability differences, that are defined as the difference between the conditional probability of being in a vulnerable state while a signal is issued, and the absolute probability of being in a vulnerable state.

Table 2.3 enriches the results presented in Table 2.2 by considering several parameters. First we consider the percentage of correct predictions that represents the number of correct calls (in percentage) obtained for each specific model. In three cases the presence of country dummies has an improvement effect on the correct forecasts, while in three cases the contribution is even negative, albeit slightly. Moreover, we can see that the cases in which the contribution of the country dummies is positive are those in which the windows of post-crisis and pre-crisis are extreme (Models 1, 2 and 6) while for the "central" Models (3, 4 and 5) random effects are more performing. Wa can also notice that the "correct prediction function" seems to have a concave trend in relation to the enlargement of the pre and post-crisis windows. These results are in agreement with Behn et al. (2016), even in their case the duel of the fixed effects is not clearly positive.

Second, we present the percentage of correct predictions, and the optimal threshold evaluated following Equation (2.8). Bussiere and Fratzscher (2006) suggest to set $\mu = 0$ while, for instance Behn et al. (2016) set $\mu = 0.85$, the value represents the will of the policy maker to avoid Type 1 and 2 errors. In other words, μ is the weight that is given to issue a false alarm and, consequently, $1 - \mu$ is the weight of missing alarm (not recognised crises). In this work, our approach is not to prefer one type of error to another, and therefore we have defined $\mu = 0.5$. For greater completeness, and to allow a better evaluation of the dynamics deriving from a weight variation we have also calculated the optimal threshold in the case of $\mu = 0.25$ and $\mu = 0.75$.

In the last row we report one of the most used way to evaluate EWS models,

Table 2.2: Multinomial Logit Early results, $Y = 0$ is the comparison group, each model is based on 1848 observations and standard errors are in parenthesis.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Y=1												
constant	0.057	1.494	-8.936	-15.790	-7.722	-15.296	-0.582	-4.855	0.741	-4.240	-1.769	-9.161
	(9.27597)	(15.554)	(7.242)	(12.072)	(7.526)	(13.109)	(5.901)	(10.132)	(6.105)	(10.855)	(6.650)	(12.928)
equity	0.049	1.292	0.053	1.579	0.066	1.814	0.061	1.877	0.046	2.090	-0.007	3.447
	(0.083)	(0.328)	(0.066)	(0.272)	(0.070)	(0.289)	(0.057)	(0.231)	(0.059)	(0.244)	(0.067)	(0.315)
effective exchange rate	-0.707	-3.599	1.369	-0.267	1.089	-0.836	-0.253	-3.017	-0.496	-3.570	0.175	-4.034
	(2.02731)	(3.227)	(1.581)	(2.527)	(1.644)	(2.750)	(1.290)	(2.116)	(1.328)	(2.272)	(1.444)	(2.670)
long term interest rate	-0.079	-0.056	-0.131	-0.101	-0.145	-0.101	-0.141	-0.086	-0.171	-0.102	-0.241	-0.106
	(0.033)	(0.039)	(0.028)	(0.033)	(0.030)	(0.035)	(0.024)	(0.030)	(0.026)	(0.031)	(0.032)	(0.042)
CDS	0.301	0.417	0.372	0.536	0.390	0.574	0.391	0.562	0.420	0.611	0.506	0.852
	(0.301)	(0.073)	(0.045)	(0.060)	(0.046)	(0.063)	(0.036)	(0.047)	(0.038)	(0.049)	(0.044)	(0.062)
Y=2												
constant	-9.419	-37.419	-11.058	-40.789	-9.769	-42.267	-8.733	-38.723	-6.831	-40.508	-12.041	-58.784
	(6.614)	(10.681)	(6.272)	(9.792)	(5.854)	(9.285)	(6.401)	(9.988)	(6.050)	(9.664)	(6.102)	(10.634)
equity	-0.053	0.973	-0.046	1.251	-0.041	1.506	-0.030	1.656	-0.034	1.958	-0.083	3.216
	(0.065)	(0.270)	(0.06)	(0.263)	(0.058)	(0.254)	(0.065)	(0.278)	(0.061)	(0.272)	(0.060)	(0.321)
effective exchange rate	1.502	5.224	1.878	5.679	1.639	5.525	1.380	4.458	1.032	4.281	2.327	6.711
	(1.441)	(2.154)	(1.365)	(2.010)	(1.272)	(1.876)	(1.393)	(2.055)	(1.315)	(1.956)	(1.327)	(2.105)
long term interest rate	-0.131	-0.143	-0.148	-0.156	-0.155	-0.151	-0.174	-0.167	-0.191	-0.174	-0.238	-0.185
	(0.028)	(0.036)	(0.027)	(0.034)	(0.025)	(0.031)	(0.029)	(0.037)	(0.027)	(0.034)	(0.028)	(0.043)
CDS	0.479	0.659	0.552	0.765	0.602	0.852	0.622	0.864	0.681	0.966	0.866	1.319
	(0.479)	(0.070)	(0.049)	(0.067)	(0.044)	(0.062)	(0.051)	(0.069)	(0.046)	(0.064)	(0.042)	(0.065)
Country Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Probability Difference	0.680	0.412	0.408	0.304	0.188	0.152	0.138	0.118	0.160	0.154	0.160	0.180

Table 2.3: Multinomial Logit Optimal Threshold (Opt. Thr.), percentage of correct predictions and usefulness for each model.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Country Dummies?	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Correct Predictions (%)	88.15	88.71	77.57	78.37	80.58	80.58	63.89	62.08	72.42	68.68	79.15	83.73
Opt. Thr. % ($\mu = 0.5$)	15.88	15.29	19.54	18.55	19.94	21.45	23.20	23.67	17.70	18.30	12.21	8.87
Opt. Thr. % ($\mu = 0.25$)	7.94	8.06	9.96	10.49	16.78	18.65	21.68	23.25	19.70	20.64	12.91	10.19
Opt. Thr. % ($\mu = 0.75$)	23.82	22.53	29.11	26.62	23.09	24.25	22.74	24.09	15.67	15.97	11.52	7.55
Usefulness %	34.12	34.71	30.46	31.45	30.06	28.55	26.80	26.33	32.30	31.70	37.79	41.13

the so called Usefulness. Precisely, following Alessi and Detken (2011), we define Usefulness as:

$$min\,[\mu; 1-\mu] - L(\tau).$$

In practise, when μ is bigger than 0.5, assuming a signal is issued, we have that $TN = FN = 0$ while in the opposite case (μ lower than 0.5) we have that $TP = FP = 0$.

As said above, we just consider the case of $\mu = 0.5$, so we can notice that the Usefulness moves from 26.8% of Model 4 without country dummies to 41.13% in Model 6 with country dummies. The interpretation is that, on average, the preference weighted errors can be reduced by the 41.13% compared to the loss resulting if the indicator would be disregarded.

Finally, to evaluate the best performance among our models we consider three factors. First, the probability difference[2], in Table 2.2 we can notice that except Model 2 and Model 1, the others share a probability difference that spreads from 18.8% for Model 3 (no country dummies) to 11.8% for Model 4 (with country dummies). The lower is the probability difference is, the higher is the probability of not missing a crisis. Second, we consider the percentage of correct predictions that moves from 88.71, for Model 1 with country dummies to 62.08 for Model 4 with country dummies. Finally, we consider the usefulness. The best level is the one obtained for Model 6 with country dummies. Considering all these three parameters we can conclude that Model 6 with country dummies is our benchmark.

2.4.3 GIRF Results

In this Section we describe the consequences on the variables considered in the model (equity price, long term interest rate, credit default swap and effective exchange rate) following a widespread negative shock (of one standard error) on

[2]Defined as the difference between the conditional probability of being in a vulnerable state while a signal is issued, and the absolute probability of being in a vulnerable state.

the long-term interest rate. We first consider the CDS price reaction after a negative (1 s.e.) shock on long term interest rate (Figure 2.1). As we expect, in general the CDS prices decrease, at least immediately after the shock. In the case of Austria, Greece, Ireland, Portugal and Spain we can notice that the shock is reabsorbed (in the case of Greece, Portugal and Spain, the effect returns to be significantly negative towards the end of the analysis period). As regards France, Germany, Italy and the Netherlands, we can observe how the negative shock on the LTIR variable maintains a negative effect on the price of CDS throughout the observation window. Particular evidence is that for Finland, the CDS price series does not seem to be significantly affected by a negative increase in long-term interest levels. In the case of Austria, Finland and Greece, the response (the absolute minimum point) of CDS prices to the shock is about -0.1. In other cases, the minimum value is about the double.

According to Figure 2.2 we can notice that a 1 standard error (negative) shock for long term interest rate on 10 years treasury bond for all the countries considered does not cause particular consequences for the effective exchange rates. In fact, we can observe that the zero-line is between the upper and the lower bound, meaning that no reaction is statistically different from 0. However, it is noted that for all the countries a negative reaction of the EER variable is recorded in the first observations' downstream of the shock. In the cases of Greece, Italy and Spain, there is the absolute minimum point, of the entire data set, around -0.005.

Looking at Figure 2.3 we can see the reactions of the equity prices for all the countries considered in our analysis. Already at first sight it is easy to see how the dynamics are similar among all the cross sections. In particular, some periods after the shock are necessary to make the reaction of stock index prices significantly positive. Only in the case of Austria and Portugal, however, a shock resorption can be seen towards the end of the time window. It is interesting to note how the magnitude of the response is at similar levels (0.05) for the great majority of the series.

Finally, we consider the long-term interest rate (Figure 2.4). It is interesting to note that only in the case of Ireland, Italy and Portugal, the decline in the interest rate is lasting. In other cases this shock is reabsorbed as early as 4 months. In absolute terms, the impact is more pronounced in the case of Greece, Italy and Portugal.

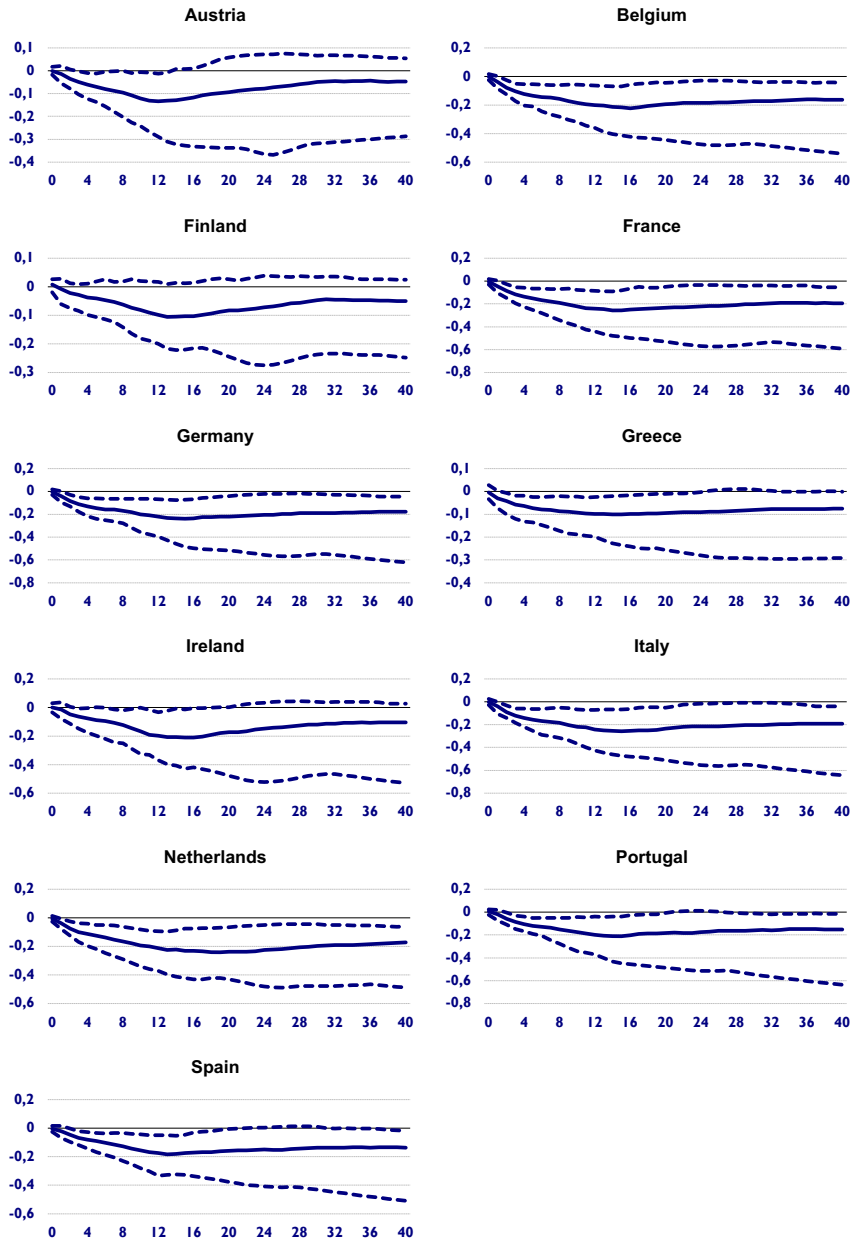

Figure 2.1: CDS Prices' reaction after a negative 1 standard error shock generalised for all the countries. Dashed lines are the 5th and the 95th percentiles.

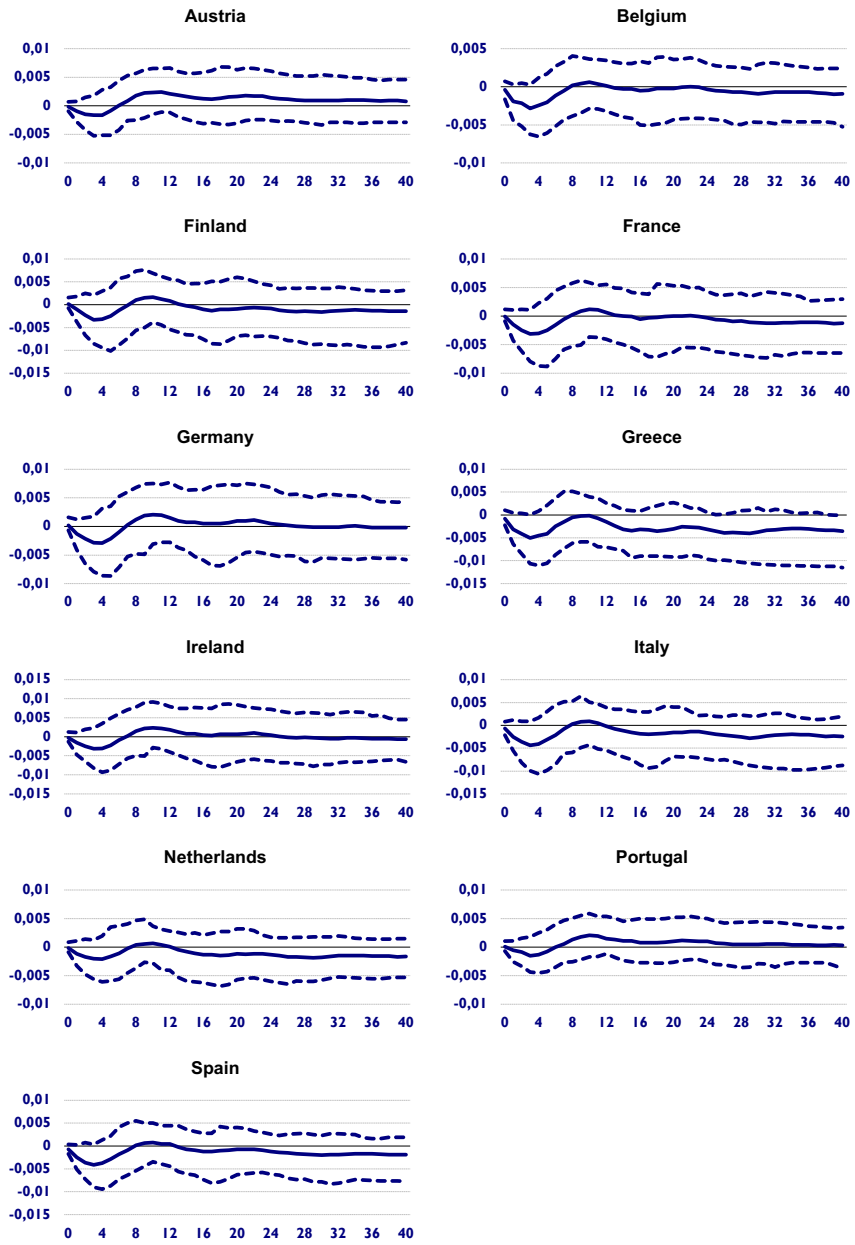

Figure 2.2: Effective Exchange Rate reaction after a negative 1 standard error shock generalised for all the countries. Dashed lines are the 5th and the 95th percentiles.

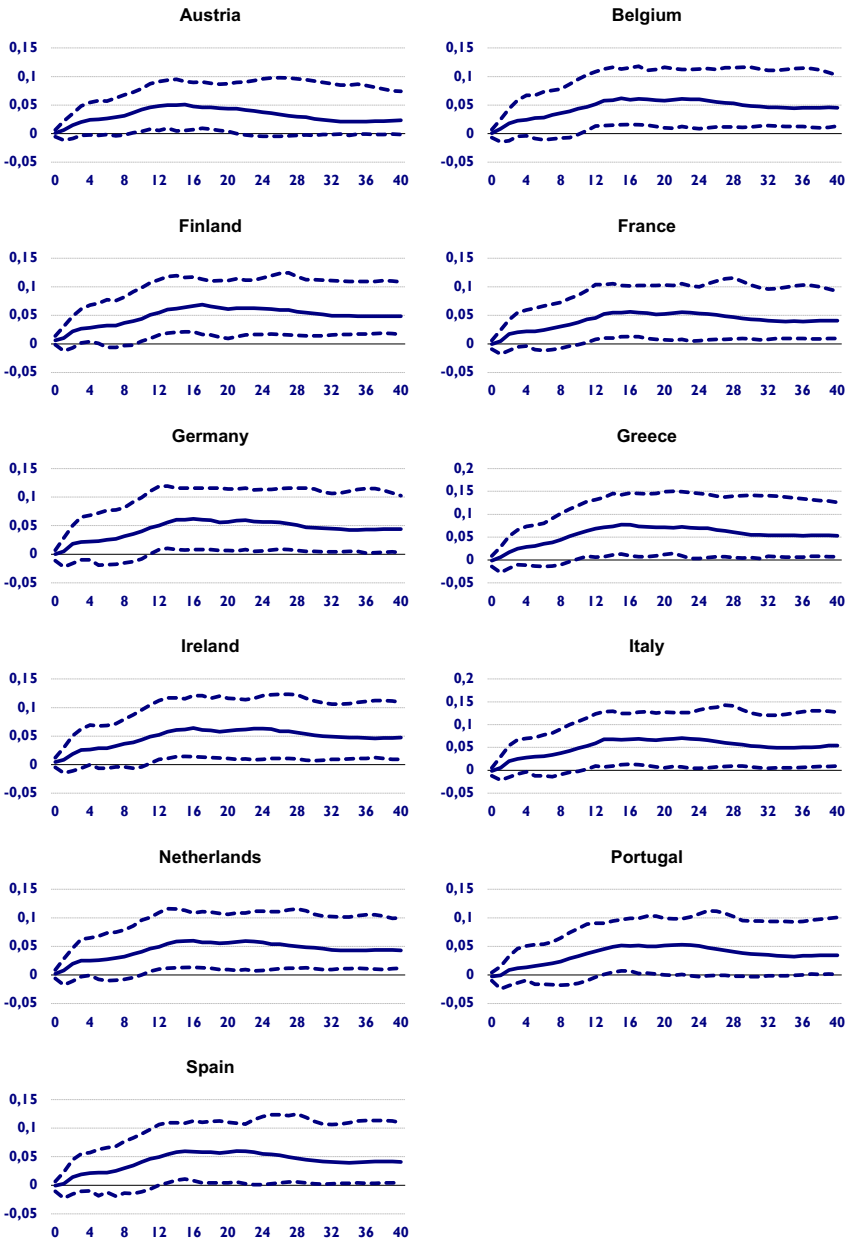

Figure 2.3: Equity Prices' reaction after a negative 1 standard error shock generalised for all the countries. Dashed lines are the 5th and the 95th percentiles.

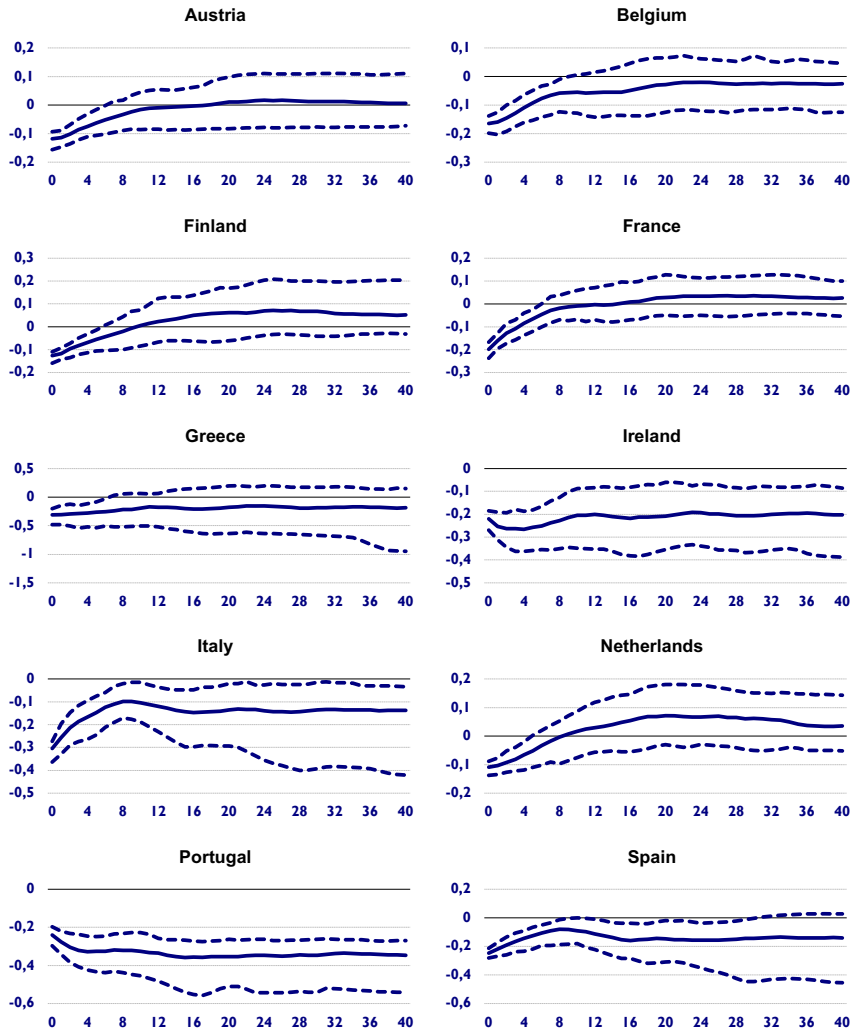

Figure 2.4: Long term interest rate reaction after a negative 1 standard error shock generalised for all the countries. Dashed lines are the 5th and the 95th percentiles.

2.4.4 GIRF Multinomial Logit

In this section we analyse the changes in the probability of being in a period of vulnerability following a negative shock on the long-term interest rate (the ten-year treasury yields ones). In order to observe the dynamics we decided to follow the methodology proposed by Behn et al. (2016). First, we estimate an Early Warning model similar to the one estimated for the original time series, but this time we enrich the original database with the post-shock observations obtained by the GIRFs. Table 2.4 reports the results for the percentage of corrective predictions, the optimal thresholds for $\mu = 0.5$ (like before we also consider the optimal threshold for $\mu = 0.25$ and $\mu = 0.75$ just to appreciate the threshold dynamics) and the Usefulness for each model described above. First we can see that, except for Models 4 and 5, the optimal threshold is higher in case of country dummies, particularly the gap goes from around 1.5% to more than 4%. Second, considering the models usefulness, we notice that the higher level is for Model 6 with country dummies, exactly like what we have in Table 2.3. Finally, except for Model 4 which is enriched by country dummies, the optimal thresholds are higher than the ones obtained for the original time series.

We can, now, consider Equation (2.9) to evaluate the reduction in probability of being in a vulnerable state. Since the new optimal threshold, that is the one obtained by the series enriched by the post-shock observation, is higher than the original one we can conclude that, coeteris paribus, a negative shock on the long term interest rate has a role to decrease the probability of being in a stress state (Table 2.4).

Table 2.4: Multinomial Logit Optimal Threshold (Opt. Thr.), percentage of correct predictions and usefulness for each model after a -1 Standard Error Shock for the Long Term Interest Rate.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Country Dummies?	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Correct Predictions (%)	86.16	87.62	75.47	78.76	80.25	81.50	63.42	61.05	74.21	70.61	77.24	80.00
Opt. Thr. % ($\mu = 0.5$)	18.93	16.65	22.71	18.63	23.70	22.55	23.28	23.11	17.94	18.00	12.47	9.66
Opt. Thr. % ($\mu = 0.25$)	10.06	11.47	14.01	12.92	24.16	23.73	25.06	24.31	20.97	20.00	13.77	10.79
Opt. Thr. % ($\mu = 0.75$)	27.80	23.83	31.41	24.34	23.24	21.37	21.49	21.91	14.91	16.00	11.17	8.53
Usefulness %	31.07	32.35	27.29	31.37	26.30	27.45	26.72	26.89	32.06	32.00	37.53	40.34

2.5 Conclusions

In this paper we developed an Early Warning model based on a multinomial logit technique referring to the European situation from January 2004 to December 2017 using monthly data. The objective of this work is to analyse the reduction of the probability of being in a vulnerable situation after a negative shock on long-term interest rates on 10-year treasury bonds. First of all, we created a variable able to intercept stress states. We then estimated an EW model based on multinomial logit methodology obtaining the optimal threshold that minimises the probability of incurring Type 1 and Type 2 errors. The thresholds we have obtained vary from 8.87 to 23.67% in relation to the "length" of the pre-crisis and crisis period considered. Based on the index of Usefulness we have opted for the optimal model of 12 pre-crisis observations and 12 crisis and recovery observations. These results are aligned with the previous literature. Then, we estimated a GVAR model to evaluate, through the GIRF technique the spillover effects after a shock. GIRFs showed that after a sudden drop in long-term interest rates we had a widespread increase in the prices of the equity indices for the European countries considered; at the same time we noticed that the prices of sovereign CDS suffer a significant drop, although not always lasting. If the effects on the effective exchange rates are not significant, we have noticed instead that the decline in interest rates on 10-year bonds is significant and, especially in the case of Ireland, Italy and Portugal, lasting. Finally we estimated again the EWS with the original time series enriched by the observations obtained by the GIRFs. In line with Behn et al. (2016) contribution, we observed that following a decline in interest rates on 10-year treasury bonds, the probability of being in a vulnerable situation drops significantly.

In the Appendix we proposed a similar exercise, but this time based on out of sample conditional forecasts (instead of GIRF). We first performed a GVAR model with forecast purposes, and we obtained out of sample forecasts conditioned on German equity prices. We noticed that an out of sample forecast on our series describes contrasting effects for European economies. If on the one hand there is a fall in the effective exchange rates (that is a competitive improvement of the single economy against the others), on the other hand, it is possible to notice that the price of sovereign CDS has a positive trend. Interest rates on 10-year treasury bills show a fairly widespread decline, while the prices of individual country indices respond (generally) positively in the short term and then retrace in the long run.

Finally we estimated the model where the original time series were enriched

by the observations obtained from the forecast. We observed that the probability of being in a state of vulnerability decreases over time.

This application is linked to the one made in the GIRF context; it is interesting to note that, in the benchmark model, the probability of being in a state of stress is lower in the application that considers forecasts. There are different ways to expand the research, one would be to consider other countries, another way would be to consider other variables, perhaps considering the banking sector. And finally it would be possible to consider other methods for early warning systems, like for instance signal approach, but also for evaluating shock responses and out of sample forecasting.

2.6 Appendix: Empirical Application exploiting out of sample Conditional Forecast

2.6.1 Introduction

Similarly to what was done for the GIRFs, it is possible to observe the change in the probability of being in a state of vulnerability by exploiting also, the properties of the GVAR methodology in the forecasting environment.

In this appendix we present an empirical application of a multinomial logit model that considers observations obtained from an out of sample conditional forecasting process.

As regards the methodological description of our work we refer to Section 1.3.5 in which we present the forecast model based on the GVAR methodology. In this application we consider the dynamics obtained by the conditional forecast (and by the classical forecast way), adding to the series 24 out of sample observations. Then, the results are analysed in the Early Warning model based on multinomial logit methodology using data obtained from forecasts, and a final comment concludes the section.

2.6.2 Forecast Results

From the methodological section we know that GVAR models are often used to make predictions, generally in macroeconomics. Through these models it is possible to perform two types of predictions, one based on the "classic" properties of the VAR models, and one conditioned by one (or more) forecast window calculated exogenously to the model through a dedicated equation or ad hoc assumptions by

the analyst. In order to obtain conditional forecasts, we decided to consider the DAX 30 index. In particular, we considered the Equation:

$$x_t = \sum_{i=1}^{I} x_{t-i} + \sum_{j=0}^{J} X^*_{t-i} + \epsilon, \tag{2.10}$$

where x_t is the DAX 30 log-price at time t and X^* is the $J \times 10$ matrix of the others main European stock indices until the Jth lag. Through the Equation (2.10) the vector x has been calculated, giving us a result the series of the 24 future observations for the German stock index. These values were then used for the conditional forecast. Let us now consider the results of the forecasts obtained with both the "classical" and the conditioned methodology.

Figure 2.5 shows the results of the forecasts on the log-prices of the main European stock indices. The gray line shows the predictions obtained based on the VAR properties of the GVAR methodology, while the black one outlines the values obtained through the conditional prediction. The first evidence concerns the fact that the gray line represents higher and higher values at the corresponding black line and, in addition to a smoother pattern, presents an increasing steepness trend up to the maximum point, generally, around September 2018, followed by a slow decline until the end of the series, where the concavity of the curve is reversed in the last observations. The conditional forecasts, on the other hand, show a more turbulent trend (especially in the first part of the series), this turbulence finds a positive peak in June 2018, in almost all countries this peak corresponds to the maximum point, except for Ireland and Portugal, where for the former the maximum is traceable in the first quarter of 2019, while for Portugal the maximum point is exactly the first observation of the forecast. Following this peak the curve takes negative concavities, sometimes decisively as for Greece and Italy. It is interesting to note that, in general, conditional predictions anticipate the trends described also by the "classical" forecasting methodology. Trends are common to the two methodologies except for the last observations of the series, where they slowly diverge. The conditional forecast for Germany corresponds to the curve defined by the Equation (2.10).

Although conditional predictions, even in the case of log-prices of sovereign CDS, have a smoother trend than the corresponding grey lines, as described in Figure 2.6, in our investigation it is precisely the black lines that have higher values. Unconditional forecasts are characterised by a minimum point, sometimes absolute (as in the case of Austria, Belgium, Finland, Germany, Greece, Ireland,

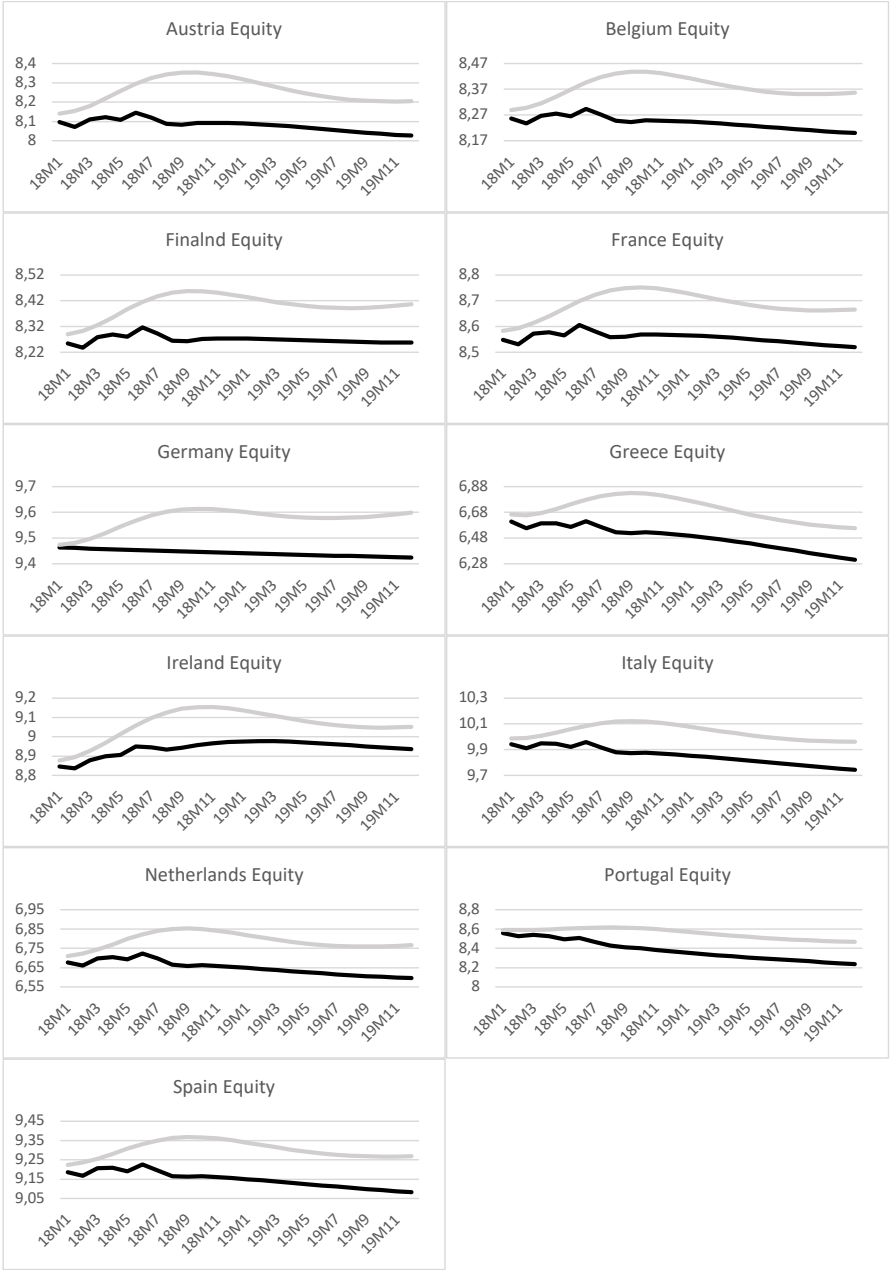

Figure 2.5: Out of sample Equity Prices' forecast. Black line is the conditional forecast, while the grey one is the simple forecast.

Figure 2.6: Out of sample CDS Prices' forecast. Black line is the conditional forecast, while the grey one is the simple forecast.

Netherlands and Spain), between the second and third quarters of 2018. This is precisely the period in which the differential between the black and the grey line is more pronounced.

The Figure 2.7 shows the forecasts for actual rates for the 11 countries considered. The first evidence is that the two estimation methodologies seem to coincide, especially in the first part of the series. The most marked differences are for Belgium, Greece, Ireland, Italy and Portugal starting from January 2019. In these cases, the conditional forecasts always show slightly lower values than the unconditional method.

Figure 2.8 presents the results of forecasts for the long-term interest rate on sovereign debt. From the figure we note that, generally, until the third quarter of 2018 the conditional and unconditional forecasts coincide. The only differences, in fact, are for Italy and Portugal, where the conditional forecasts show higher values than those not conditioned since the second quarter of 2018. In the second part of the series, the non-conditional methodology presents for all countries, with the only exception of Portugal, higher values. If for Greece, Ireland and Spain the gap is limited, for Austria, France and Germany it is more marked.

In conclusion, we know how complicated it is to make predictions, especially in the macroeconomic sphere, where it is almost impossible to include all the variables that can influence the trend of the quantities considered. From this model are excluded, for example, variables capable of capturing the European political evolution and the evolution of the individual countries considered; in addition to this, relations with the US, China and Japan, the three largest economies, are not considered, the three largest economic powers.

The first thing we notice, observing the economic significance of the forecasts made, is the consistency between the different variables considered and their trend. In particular, it can be noted that the model as a whole estimates widespread economic growth among the countries considered, for the first part of the analysed time window. In particular, we note that stock markets are growing, the price of sovereign CDS is stable or decreasing (considering the unconditional forecast) the productivity of countries is increasing (given the fall in the effective exchange rate) and the interest long-term public debt is declining. However, in the second part of the series economic growth seems to stop and this can be deduced from the increase in CDS and from a stagnation of all the other variables considered by the model.

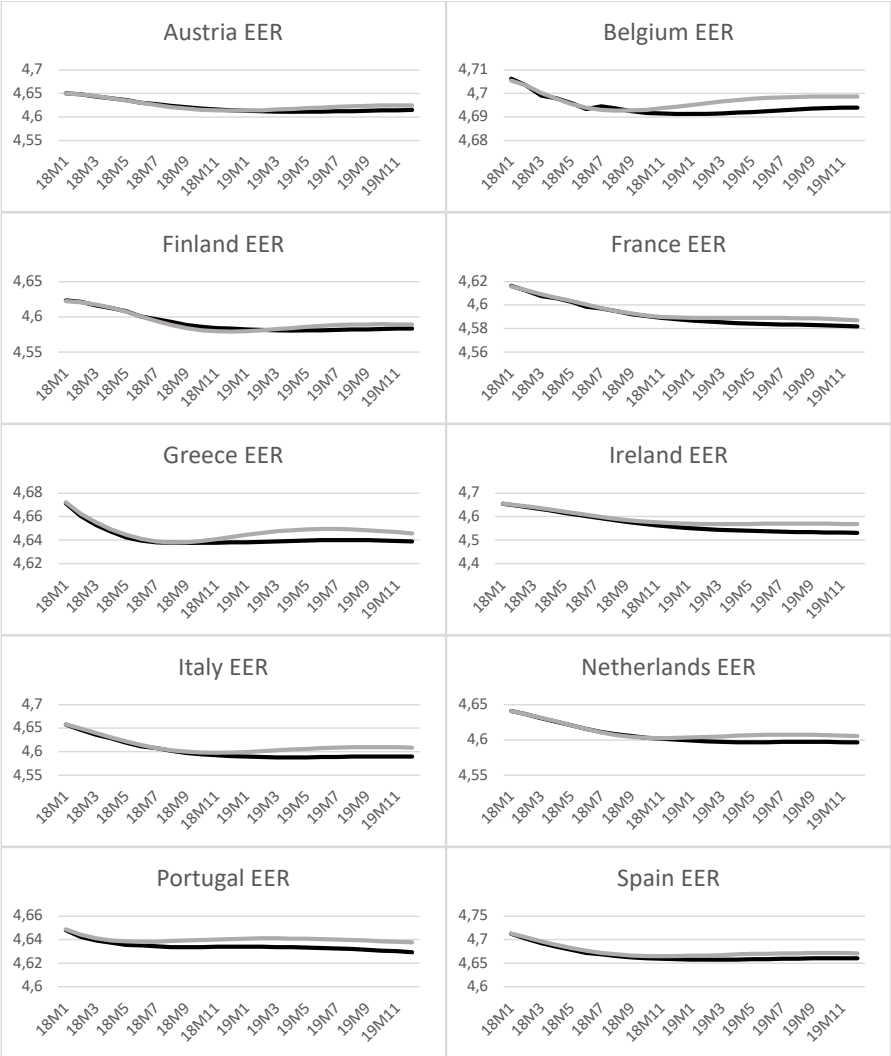

Figure 2.7: Out of sample Effective Exchange Rate's forecast. Black line is the conditional forecast, while the grey one is the simple forecast.

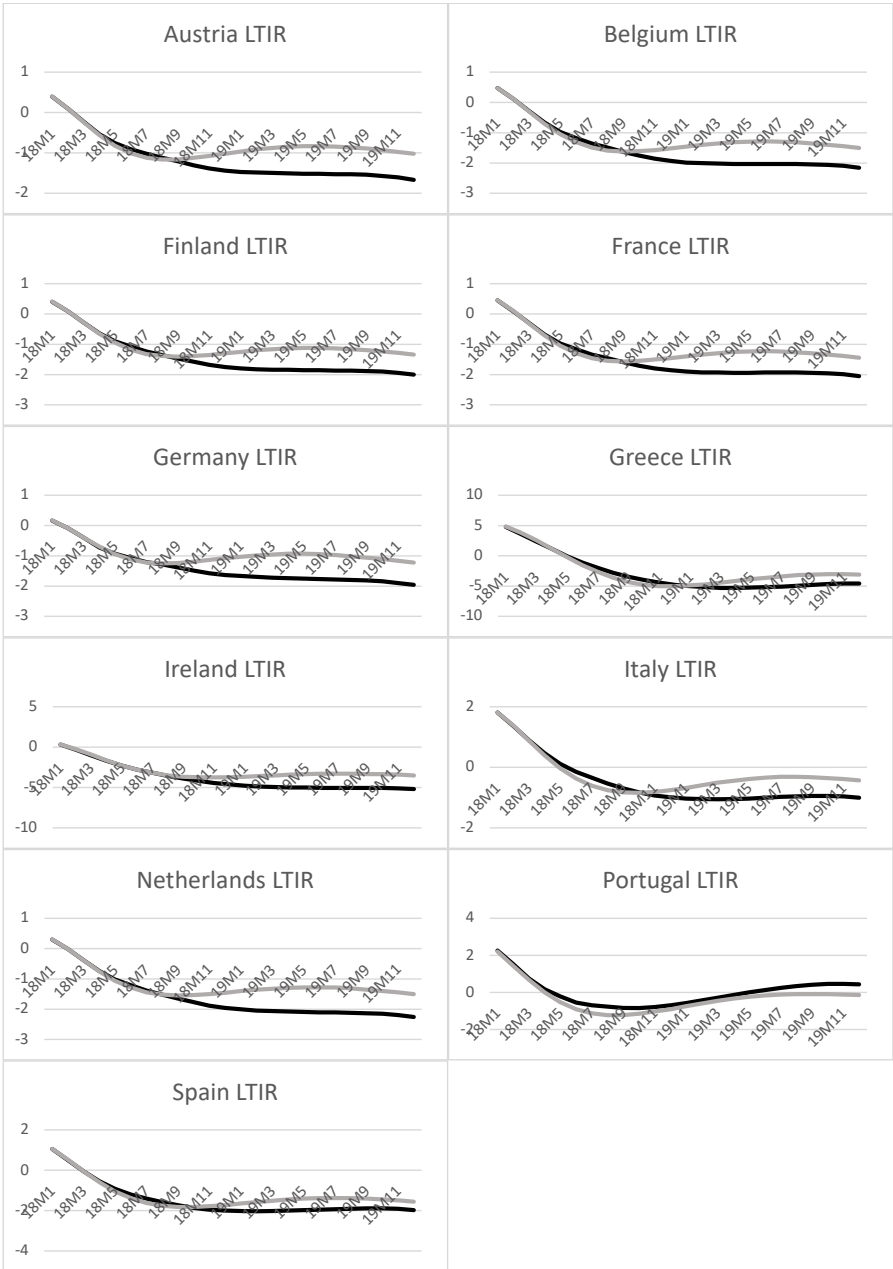

Figure 2.8: Out of sample Long term interest rate's forecast. Black line is the conditional forecast, while the grey one is the simple forecast.

2.6.3 Out of Sample Multinomial Logit and Discussion

The optimal threshold evaluated for the original data set is, actually, an average among the 11 countries considered in our database. As described above, one of the most important properties of GVAR is to consider the linkages among cross sections, defined by the so called "foreign variables" defined by weights based on trade relationships. This means that the forecast observations contain themselves the relationship among countries; in other words we enrich the EWS by the linkages in cross sectional way.

In this section we want to analyse the reduction in the probability of being in a vulnerable state as defined by the Equation (2.9). To achieve this goal we add to the original data set the out of sample forecast observations (obtained by the GVAR methodology) evaluating the new optimal threshold and the Usefulness levels.

Table 2.6 presents both optimal threshold and Usefulness for the forecast observations. It is interesting to note that for the extreme models, Model 1, 6 and 5 (here just the version without country dummies) the optimal thresholds are higher than the respective ones obtained from the initial series (shown in Table 2.3). This means that Δp is negative and the probability of being in a vulnerable state is lower than the one seen for the original series.

Differently from the sample used to obtain the values in Table 2.2, we now enrich the time series adding the conditional forecast gathered through the GVAR methodology exposed before. Comparing the original results and the new ones, regardless of the magnitudes, we can observe a strong consistency. We can just appreciate some differences about the Probability Difference, especially for the first two models. As regards the percentage of correct predictions we can notice that, using the whole data set (original time series enriched by the conditional forecasts), for Model 1 and for Model 6 (in the case of country dummies) values are lower than the original results, for Models 2 to 5 and 6, in the case of no country dummies, the percentage of correct predictions is higher. Moreover, considering the Usefulness percentage, we can observe that the level increases for Model 2, 3, 4 and 5 (just for the case of country dummies), for Model 1, 6 and for the no-country dummies version of Model 5 the Usefulness level decreases. Considering now the Optimal Threshold (τ^*) and, consequently, the reduction probability of being in a vulnerable state (Δp) we have to firstly identify our benchmark in the case of county dummies for Model 6 our benchmark. We select this sub-model because it is the one with the higher Usefulness level. Now, since τ^* moves from

Table 2.5: Multinomial Logit Early results with out of sample forecast observations, $Y = 0$ is the comparison group, each model is based on 1848 observations and standard errors are in parenthesis.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Y=1												
constant	-13.276	-41.704	-10.569	-38.755	-7.524	-45.035	-3.367	-42.177	-1.886	-51.428	-10.740	-83.537
	(8.883)	(13.553)	(6.753)	(10.725)	(7.214)	(12.100)	(5.452)	(9.395)	(5.752)	(10.517)	(6.355)	(13.106)
equity	0.011	1.361	0.005	1.333	0.005	1.748	-0.019	1.769	-0.058	2.222	-0.120	3.511
	(0.077)	(0.289)	(0.061)	(0.225)	(0.065)	(0.248)	(0.054)	(0.206)	(0.058)	(0.232)	(0.066)	(0.319)
effective exchange rate	2.259	5.635	1.847	5.227	1.213	5.773	0.552	5.300	0.315	6.397	2.319	10.687
	(1.932)	(2.789)	(1.468)	(2.219)	(1.568)	(2.497)	(1.185)	(1.926)	(1.250)	(2.135)	(1.378)	(2.611)
long term interest rate	-0.138	-0.145	-0.144	-0.149	-0.163	-0.159	-0.169	-0.167	-0.195	-0.183	-0.239	-0.209
	(0.028)	(0.034)	(0.023)	(0.027)	(0.025)	(0.030)	(0.202)	(0.023)	(0.023)	(0.025)	(0.030)	(0.038)
CDS	0.313	0.531	0.344	0.538	0.350	0.609	0.037	0.610	0.413	0.723	0.518	0.995
	(0.049)	(0.080)	(0.038)	(0.059)	(0.040)	(0.064)	(0.032)	(0.048)	(0.034)	(0.053)	(0.042)	(0.070)
Y=2												
constant	-8.952	-38.888	-9.463	-43.491	-10.945	-57.556	-8.071	-55.326	-8.745	-73.679	-17.365	-126.746
	(5.732)	(8.614)	(5.824)	(8.877)	(5.341)	(8.282)	(6.075)	(9.747)	(5.724)	(9.642)	(6.034)	(11.806)
equity	-0.041	1.040	-0.041	1.210	-0.048	1.581	-0.053	1.732	-0.084	2.248	-0.139	3.988
	(0.053)	(0.194)	(0.055)	(0.201)	(0.053)	(0.204)	(0.059)	(0.226)	(0.058)	(0.239)	(0.060)	(0.324)
effective exchange rate	1.526	5.772	1.643	6.428	2.236	8.776	1.408	7.972	1.659	10.962	3.665	18.924
	(1.244)	(1.772)	(1.264)	(1.824)	(1.159)	(1.667)	(1.319)	(1.987)	(1.243)	(1.915)	(1.313)	(2.269)
long term interest rate	-0.146	-0.168	-0.170	-0.192	-0.160	-0.177	-0.215	-0.236	-0.213	-0.230	-0.222	-0.231
	(0.020)	(0.023)	(0.021)	(0.026)	(0.019)	(0.021)	(0.023)	(0.026)	(0.023)	(0.024)	(0.027)	(0.037)
CDS	0.437	0.634	0.491	0.710	0.541	0.847	0.576	0.859	0.651	1.050	0.800	1.508
	(0.037)	(0.059)	(0.039)	(0.061)	(0.035)	(0.056)	(0.042)	(0.065)	(0.038)	(0.062)	(0.038)	(0.071)
Country Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Probability Difference	0.435	0.378	0.325	0.359	0.255	0.264	0.229	0.261	0.149	0.158	0.147	0.156

Table 2.6: Out of Sample Optimal Threshold (Opt. Thr.), percentage of correct predictions and usefulness for each model.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Country Dummies?	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Correct Predictions (%)	88.06	88.51	81.19	82.71	82.99	85.11	73.16	74.93	72.75	69.12	80.20	81.72
Opt. Thr. % ($\mu = 0.5$)	15.96	15.52	18.24	17.01	18.30	17.23	18.20	17.08	17.78	16.93	12.56	10.52
Opt. Thr. % ($\mu = 0.25$)	8.44	8.81	10.12	9.92	12.73	13.15	14.91	13.39	20.21	18.96	14.10	12.75
Opt. Thr. % ($\mu = 0.75$)	23.49	22.22	26.54	24.11	23.88	21.30	21.48	20.78	15.33	14.91	11.01	8.29
Usefulness %	34.04	34.48	31.76	32.99	31.70	32.77	31.80	32.92	32.22	33.07	37.44	39.48

8.87 to 10.52, according to Behn et al. (2016), we can say that the probability of being in a vulnerable state, adding to the historical variables the ones obtained by the conditional forecast, decreases over time, in fact Δp is negative.

In agreement with the results obtained, we can conclude that, by adding the observations obtained from a prediction, the model proposes a probability of being in a state of vulnerability lower than the one obtained by estimating the model with only the original observations. This allows us to conclude that the European economy seems (on average) to have left the focus of the crisis behind itself.

Chapter 3

Operational Losses, Determinants and Effects. An Empirical Analysis in the Banking Context.

3.1 Introduction

The last two decades have been characterised by dramatic changes in financial markets. Technological improvements, product innovation, economic fluctuations, corporate scandals and the stronger interconnections among national and international financial institutions have posed, more than ever, attention to the risks faced by banks and other financial institutions. In addition, some financial events such as the Bernard Madoff's $50bln Ponzi scheme in 2008, the $7.2 bln trading loss at Société Générale in 2008, the $6.2 bln trading fiasco from JP Morgan in 2012, the Bank of America loss in 2013 and the Deutsche Bank $7.3 bln loss in 2016 after fixing benchmark interest rate and violating international sanctions, led the Basel Committee on Banking Supervision (here after, BCBS) to a growing interest in capital adequacy schemes. The need was to consider a new frontier of risk which goes beyond the classical framework based on market, credit and interest risks: the role of operational risks.

Operational risk is "the risk of loss resulting from inadequate or failed internal processes, people and system or from external events."[1] (BCBS, 2005). By differentiating from other types of risk, several points of view lead to an interesting heterogeneity in describing the operational risk (Sironi & Resti, 2007).

The aim of this paper is to answer to these three questions: (i) what are the

[1]This definition includes legal risk, but excludes strategic and reputational risk.

main drivers that influence the frequency and severity of operational loss events? (ii) Do the most significant operating losses affect the bank's returns? (iii) Do operational losses really have idiosyncratic nature?

For this purpose we have collected a dataset of all operational losses[2] related to an European Systemic Bank.

Differently from other former works we deal with a complete database, this means that our database collects all the operational losses occurred in a specific time window. In general, in fact, data providers have biased databases that underestimate the impact of the high frequent but low impact losses. Consequently, we do not need to make any assumptions about the operational losses distribution, both for frequency and severity. Our findings can help researchers to face this topic, and although it is a case study, the fact that our results are in line with several other contributions from the reference literature they allow us to be confident about the robustness of our results.

To answer the research questions we separately consider operational losses frequency and severity, differentiating for five different models based on the event types provided by Basel II, in order to identify the mains corporate drivers.

We use an OLS model to investigate the relationship between the loss severity and the idiosyncratic variables. In addition, we test the relationship between each idiosyncratic variable and the percentage of operational loss through a Poisson regression. The variable size is positive and highly statistically significant in all the considered models. The size plays a crucial role in the loss severity of a bank; particularly, the larger is a bank the higher will be the operational losses associated. The positive relationship corroborates the "too big to fail" hypothesis. The negative and statistically significant relationship between CapAR and the dependent variable emphasises the absorption of capital when an event occurs. This particular evidence sheds light on the importance of the capital issue stressed by the Basel Committee. A positive and statistically significant relationship comes from the leverage variable. As the leverage ratio gets higher, internal control gets better.

In the second part of the paper, we analysed the effects of large operating losses on the bank's returns. Our goal is to see if, in the presence of significant operating losses, the bank's returns fall significantly more than the market. To achieve this objective we have estimated a three-factor model that, in addition to the bank's returns, also considers those of the main stock index of the European banking sector (Stoxx 600) and the main national index in which the bank is listed.

[2]Larger than 500 euros.

Through this regression, and after identifying the most significant operational losses, we have defined the abnormal returns and, subsequently, the cumulative abnormal returns. Exploiting the t test, we were able to observe that operating losses have a significantly negative effect on the bank's returns, particularly in cases where these losses are attributable to an event type with high idiosyncratic factor and, generally, for limited time windows.

The remainder of the paper is developed as follows; a literature review about operational risk and operational losses analysis is presented in Section 3.2. Section 3.3 presents the empirical application, particularly, we present the methodology and the database considering some descriptive statistics and the main stylised facts. We then present our main findings related to both, frequency and severity analysis and large operational losses effects. Finally, Section 3.4 concludes.

3.2 Literature Review

We consider both institutional and academic papers. Particularly, institutional literature allows us to approach the issue of operational risk introducing both definitions and features, focusing on the banking context.

The literature provides different results in relation to the operational risk. This diversity explains why there are many dimensions to describe operational risk. Sironi and Resti (2007) highlight some peculiarities of operational risk. First of all, operational risk is not taken on a voluntary basis, because it is simply the consequence of different activities undertaken by the bank. For this reason, operational risk, differently from other risks, cannot be entirely avoided, indeed, the Basel Committee on Banking Supervision in its Supervisory Guidance on Operational Risk (Advanced Measurement Approaches for Regulatory Capital) underlies the diversity of operational risk by arguing that it can occur in any activity, function, or unit of the institution. The intrinsic character of operational risk is also underlined by Hoffman (1998), who argues that operational risk transcends all business lines, and spans front, middle and back-office operations, and that it is broader that the realm of conventionally insured risks. Moreover, one of the main barrier to operational risk hedging is the lack of secondary liquid market where selling risk transfers instruments. Another important characteristic of operational risk is its nature of pure risk which opposes to speculative risk. Whilst financial risks (e.g., interest rate, market and credit risks) are referred to be speculative risks, because they are originated from the volatility of returns, which can lead to both profits or losses, operational risk gives rise only to the possibility of

losses: from here the connotation of pure risk. As specified by Sironi and Resti (2007), an exception is represented by events belonging to the risk factor external events. In fact, changes in regulatory, fiscal or political context in which bank operates, may give rise both to unexpected losses and to unexpected profits if these changes affect the bank's profitability favourably. Moreover, differently from financial risks, in which higher risks are associated with higher returns, operational risk does not involve an increasing relationship between risk and expected returns. This peculiarity leads operational risk to be known as a one-sided risk, because the risk-return trade-off typical of market risk, has no equivalence in the case of operational risk. Herring (2002) refers to operational risk as downside risk, while Crouhy et al. (2004) argue that by assuming more operational risk, a bank does not expect to yield more on average and that there is no reward in the form of higher returns from bearing operational risk. Moreover, Buchmuller et al. (2006) state that operational risk is usually not taken to create a profit. Again, Lewis and Lantsman (2005) motivate the adjective one-sided referring to the facts that there is a one-sided probability of loss or no loss, and lastly, Alexander (2003) suggests that operational risk is on the cost side, while market and credit risks are on the revenue side. All these views indicate that while it is possible to obtain a higher rate of return by assuming more market or credit risk, this is not possible with operational risk. However, the one-sided characteristic of operational risk is debated: in fact, starting from the assumption that, taking on operational risk, firms earn income while being exposed to the risk of incurring operational losses, Moosa (2007) argues the possibility of operational losses exists in each generating income activity; likewise, banks expose themselves to operational risk in these activities because they generate income. Hence, one can argue that operational risk is not one-sided because it is also taken for profit.

One more peculiarity of operational risk is its complexity, with particular reference to its identification, understanding and measurement. Particularly, as underlined by Sironi and Resti (2007), the variety of definitions found in the financial industry and in the scientific literature, as well as the heterogeneity of the factors that generate OR losses, are drivers of this complexity. Moreover, Buchelt and Unteregger (2003) explain the diversity of operational describing it as a highly varied and interrelated set of risks with different origins. With reference to the understanding of operational risk, some authors debate whether the characteristic of operational risk is not distinguishable from from market and credit risks. In fact, it can prove difficult to separate the loss events attributed to the three kinds of risk.

Furthermore, Kohn and Kaiser (2006) argue that a large number of losses in the credit area cannot be considered as genuine credit risk, as they result from events in the whole area of operational risk. The general consensus states that the distinguishing factor of an operational loss event is the cause rather than the consequence of the event. Finally, operational risk is characterised by the lack of hedging instruments because a liquid secondary market for the OR hedging does not yet exist. DeKoker (2006) proposes two additional features that distinguish operational risk from other financial risks. First, the concept of risk exposure of operational risk is not comparable to that of financial risks because operational risk is not closely related to any financial indicator. Furthermore, the author refers to the distribution of operational risk losses, which is more fat-tailed than that of credit risk.

Another distinguishing feature of operational risk is also a controversial one: idiosyncrasy. Idiosyncratic means that once an operational loss hits one firm, it does not spread to other firms. This is a characteristic not applicable to credit and market risks events, which in turn affect all firms. While some authors believe that operational risk is idiosyncratic, others demonstrate the opposite. For example, both Lewis and Lantsman (2005) and Danielsson et al. (2002) describe operational risk as being idiosyncratic. They state, respectively, that the risk of loss tends to be uncorrelated with general market forces and there is no need to regulate operational risk because it is idiosyncratic.

On the other hand, Moosa (2007), criticises this point of view by presenting some spectacular operational failures of famous financial institutions, such as Barings Bank in 1995 and Long-Term Capital Management in 1998, highlighting that also other banks were affected. Moreover, Moosa (2007) points out that the requirement of Basel II to hold regulatory capital against rare but fatal operational loss events, demonstrates that the belief of the Basel Committee is that operational risk can be systemic. Let's now introduce some useful definitions in order to frame operational risk. According to the BCBS (2005) definition of Operational Risk, we can consider four risk factors.

The first risk factor, **people**, refers to losses coming from events such as human errors, frauds, violations of internal rules and procedures and, in general, incompetence and negligence of human resources. The second risk factor, **system** refers to information systems and technology in general, for example hardware and/or software failures, computer hacking or viruses, and telecommunications failures. This risk factor has become increasingly important due to the increasing dependence of Financial Institutions on technological resources. Third, **processes** refers

to losses originated from inadequacies in the internal processes and procedures, for example: violation of the information system security due to insufficient controls, errors in execution and/or settlement of securities and foreign currency transactions, inadequate record-keeping, accounting and taxation errors, mispricing and errors in risk measurement due to problems in the internal models and methodologies, and breaches of mandates. The fourth risk factor, **external events**, includes losses arising from a wide range of external events, which are not controlled by the bank's management. Examples of external events are: changes in the political, regulatory and legal environment, operational failures at suppliers or outsourced operations, criminal acts such as theft, vandalism, robbery, or terrorism, and natural events such as fire, earthquake and other natural disasters. Differently from the risk factors, external events cannot be minimised because they do not depend on the bank's internal investments, policies and efforts.

Another notable way to classify operational risk is the so called event type. Specifically Basel defines seven different types of operational losses:

- **ET 1**, Internal fraud: Losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations, the law or company policy, excluding diversity/discrimination events, which involves at least one internal party;

- **ET 2**, External fraud: Losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party;

- **ET 3**, Employment Practices and Workplace Safety: Losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events;

- **ET 4**, Clients, Products & Business Practices: Losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements), or from the nature or design of a product;

- **ET 5**, Damage to Physical Assets: Losses arising from loss or damage to physical assets from natural disaster or other events;

- **ET 6**, Business disruption and system failures: Losses arising from disruption of business or system failures;

- **ET 7**, Execution, Delivery & Process Management: Losses from failed transaction processing or process management, from relations with trade counterparties and vendors.

This clustering is very useful to banking institutions because it allows to identify more accurately (compared to the four risk drivers) the causes from which the losses arise and consequently define where to intervene to limit these events.

3.3 Empirical Application

In this section we present the methodological framework applied to our research questions. We observe that operational losses frequency and severity follow different distributions, so we decide to study their dynamics separately. With respect to the frequency we define a Poisson regression framework, while for the severity we consider an OLS model. Considering the effects of large operational losses on bank returns we first define what we consider a large operational loss at event type level, then we perform a three factor model able to identify the systemic and the idiosyncratic dynamics, we then compute Abnormal Returns (AR) and Cumulative Abnormal Returns (CAR), for different time windows, in correspondence with the most significant operating losses, both for the bank's returns and for the regressors of the three-factor model. We finally observe if the difference between the CARs (respectively for the bank and for the regressors) are significantly different from zero.

3.3.1 Methodology

Operational Losses Drivers

In order to address our research questions we now analyse the distribution with which operational losses occur.

Pillar I of Basel II allows banks to follow three different approaches to face potential future losses following an increasing sophistication. Particularly, we have (i) the Basic Indicator Approach (BIA), (ii) the Standardised Approach (SA) and, finally, (iii) the Advanced Measurement Approach (AMA). For the first two approaches the capital charge, defined to face losses, is proportional to a fix percentage of the bank's gross income, while for the third-one the bank's risk management determines the capital charge exploiting both internal and external historical data. One of the most used methodology in the AMA framework is the

so called Loss Distribution Approach (LDA). This approach suggests to analyse separately the frequency and severity of the operational loss events and then to combine the results in order to have a more robust estimate regarding the total losses in a defined time interval.

With reference to frequency, let us define the interval $[0, t]$ and N_t be the frequency of operational losses events in the interval. The probability mass function is defined as:

$$\mathbb{P}(N_t = n) = p(n),\ n = 0, 1, 2, ... \tag{3.1}$$

Assuming that the events are independent of each other we denote $N(t)$ a standard Poisson process and, consequently, $N_t = N(\lambda t)$ where $\lambda > 0$ is a constant that defines the expected count per unit of time. Holding this assumption we define:

$$p(n) = \frac{(\lambda t)^n}{n!} e^{-\lambda t},\ n = 0, 1, 2, ... \tag{3.2}$$

The use of Poisson processes for these cases is often used in literature. In particular Ebnother et al. (2003), at the beginning of the literature referring to operational losses, define Poisson processes for frequency in order to identify a VaR methodology to quantify operational risk. Differently, Chernobai et al. (2011) study separately frequency (through Poisson process) and severity with the aim of identifying the drivers that influence operating losses. Again, Mizgier et al. (2015), through simulations, demonstrate how the improvement of business processes and a better capital adequacy are able to significantly reduce the losses coming from low-frequency, high-impact operational disruptions (both in banking and manufacturing), also in this case the authors use Poisson processes to describe the frequency of operational disruptions.

Moving to the second input, severity, we can define the density function for the ith loss X_i as:

$$f_{X_i}(x) = f_X(x|i),\ n = 0, 1, 2, ..., N_t \tag{3.3}$$

Consequently, the total loss over the time horizon can be defined as:

$$L := S_t = \sum_{i=1}^{N_t} X_i \tag{3.4}$$

Now, as we said above, we exploit the fact that frequency and severity are

independents and the losses X are i.i.d. draws from a continuous distribution function $F_X(x)$ with common density $f_X(x)$. Combining into a unique probability distribution we obtain:

$$G_L(s) := \mathbb{P}[L \leq s] = \begin{cases} \sum_{n=1}^{\infty} p(n) F_X^{n*}(s) & s > 0 \\ p(0) & s = 0 \end{cases} \tag{3.5}$$

where $F_X^{n*}(x)$ denotes the $n-$fold convolution of $F_X(x)$ with itself.

We can conclude that frequency and severity should be studied separately. To confirm this choice also from the empirical level, we note that in the section dedicated to the description of the data, the impact of an average operating loss (defined as the ratio between the sum of the impacts and the number of events in a certain period of time, $\frac{\sum_{i=1}^{N} I}{N}$) is unstable both in time and at the event type level, also this empirical feature suggests an independent pattern between frequency and severity. Another question that pushes us to analyse the two quantities separately is the fact that the output of the frequency model is a number of events expected to occur in the selected period (quarter)[3], so we need to consider a discrete distribution, while for severity it is not necessary to set limits to the distribution.

In this contribution we consider that both frequency and severity are stochastic, driven by several time-varying variables. Particularly, in the case of frequency analysis we can set that the arrival of operational losses follows a conditional Poisson process. This is a counting process defined as $N_t^{'} = N(\Lambda(t))$, where

$$\Lambda(t) = \int_0^t \lambda(u) du, \tag{3.6}$$

with the stochastic intensity $\lambda(t) > 0$. Consequently, combining operational losses frequency and severity we have $f_{X_t}(x) = f_X(x|t)$, this process yields the aggregate loss process $L^{'}$ of the form

$$L^{'} := S_t^{'} = \sum_{i=1}^{N_t^{'}} X_{t(i)}, \tag{3.7}$$

where $t(i)$ is the arrival time of the ith loss.

Finally, Chernobai and Yildirim (2008) suggest that operational loss frequency distribution can be modelled by a doubly-stochastic Poisson process so we set the

[3]The estimation of this kind of model is equivalent to estimating the time series of stochastic intensity $\lambda(t)$ of a count process

following equation to investigate the operational loss arrival events:

$$OF_{\psi} = exp(\alpha_0 + \sum_{j=1}^{J} \beta_j CV_{j,t} + \epsilon_{0,t}), \tag{3.8}$$

where OF_{ψ} is the operational loss frequency for the event type ψ, α_0 denotes the fixed effects and $CV_{j,t}$ are the matrix that collect all the J corporate variables at time t. Poisson regression is also a more appropriate model for operational risk frequency than OLS regression because operational risk frequencies are counts and only take on non-negative integer values, whereas in an OLS regression it is assumed that the distribution of the dependent variable can take on both positive and negative continuous values. Moving on severity analysis we consider the following OLS panel model:

$$OS_{\psi,t} = \alpha_{0,t} + \sum_{j=1}^{J} \beta_j CV_{j,t} + u_{0,t}, \tag{3.9}$$

where OS_{ψ} is the impact of operational losses for each event types and CV_j represents every single variable of those defined as corporate variables.

3.3.2 Operational Loss Effects on Stock Returns

After investigating the methodology with which we analyse the drivers that influence operational losses, differentiating our analysis by frequency and severity, we now consider the effects that operating losses have on the bank. In particular, how the news concerning large operating losses affect the returns of the shares of the bank affected by these events. To achieve this goal it is necessary, first of all, to identify those that can be considered large operating losses. In this work, we define significant operating losses as those with an impact greater than or equal to 99.9 percentile of the distribution of all loss events from 1 January 2004. Finally, our case study is based on the fact that 75 operational losses were identified with at least 1 001 535.51 euros of single impact.

To the best of our knowledge, Cummins et al. (2006) are the first that analyse the impact of operational loss events on the market values of financial companies (banks and insurance). Authors' results reveal a strong, statistically significant negative stock price reaction to announcements of operational loss events. After this contribution, several other papers follow Cummins et al. (2006) methodology. Particularly, Perry and De Fontnouvelle (2005), Murphy et al. (2009) and Gillet

et al. (2010) focus on reputational risk, authors assume that if the loss on the stock market is greater, this difference is attributable to the reputational repercussions that these events have brought to the firm. Perry and De Fontnouvelle (2005) focus on internal and external events (also Gillet et al. (2010) stress a similar topic) and the difference among weak and strong shareholder rights. Murphy et al. (2009) examine the market impact of allegations of firms misconduct such as anti-trust violations, bribery, copyright infringements, or accounting fraud. Among the main findings authors demonstrate a significant declines both in reported earnings and analyst's estimates, while an increased stock return volatility. Again, Biell and Muller (2013) focus on the timing of markets' reactions considering both the start and the speed of stock markets' responses. Authors observe that when operational losses are caused by internal fraud the negative market reaction materialises earlier and faster. Not only reputation risk is investigated, for instance Moosa and Silvapulle (2012) focus on the Australian banking sector and their results show that the announcement of operational losses has an adverse effect on the stock price and market value of the announcing bank.

Let's now introduce the original Cummins et al. (2006) framework: let assume that the bank's market value decline consistently with the impact of operating losses suffered. This is because it is assumed that stock markets are efficient and public information is incorporated in prices in a short period of time. Analytically, we define the following three-factor model:

$$r_t = \alpha + \beta_1 r_{p,t} + \beta_2 r_{q,t} + \epsilon_t, \tag{3.10}$$

where r_t, $r_{p,t}$ and $r_{q,t}$ are the bank returns, the national equity index and the European industry index (in this case we consider the Stoxx Europe 600 Banks) respectively. Finally, ϵ_t is the disturbance term. For each event we estimate Equation (3.10) using ordinary least square regressions with daily data.

The operating losses are characterised by a time gap between the recording date and the occurrence date, and often the latter, although temporally antecedent, can only be defined later. For example, in the case of fraud it is not easy to identify the start date of the fraudulent behaviour. We identify the interval τ defined as $[\tau_0, \tau_1]$ that considers respectively τ_0 and τ_1 days before and after the operational event disclosure. Moreover we define abnormal returns (AR) as:

$$AR_t = r_t - (\widehat{\alpha} + \widehat{\beta}_1 r_{p,t} + \widehat{\beta}_2 r_{q,t}), \tag{3.11}$$

where $\widehat{\alpha}$, $\widehat{\beta}_1$ and $\widehat{\beta}_2$ are the Equation (3.10) estimates.

In order to quantify the impact of an announcement over the event window, we need aggregate abnormal returns. Particularly, we construct cumulative abnormal returns (CARs) over the interval $[\tau_0, \tau_1]$ for each event i with $i = 1, 2, ..., I$ (in our case I is equal to 75 that are the large operational losses identified by the 99.9^{th} percentile of operational losses severity distribution) using the abnormal returns estimated in Equation (3.11):

$$CAR_{i,\tau} = \sum_{t=\tau_o}^{\tau_1} AR_t. \tag{3.12}$$

We then compute the average CAR at event type level and for each different time windows in order to compute the difference between the values obtained for the bank returns and the regressors ones. Finally we check if these differences are significantly different from zero and if the equity indices CARs are significantly higher then the bank ones.

3.3.3 Data

In order to answer to the research questions we consider three different databases. The first is referred to the banks operational losses, considering characteristics like severity, frequency and event type. The second one considers the main corporate variables used to define the operational losses drivers and finally we consider the financial variables in order to identify operational losses effects.

Operational Losses Data

This section presents the main features of the operational losses data. The database collects more than 90000 loss events[4] for a ECB Significant Supervised Entity (SSE) from January 2000 to August 2018. The aggregate loss for the time window considered is larger than 960 million of euros. Because of the database completeness, differently for instance from De Fontnouvelle et al. (2006), we do not need to make assumptions regarding distribution and so we can avoid corrections to overcome bias is misleading databases. Because of the larger importance devoted to the operational risk both for academia and industry, databases (cfr. the Operational Riskdata eXchange ORX - database[5]) are definitely characterised by larger

[4]In order to avoid distortions, we apply a 500 euros floor. According to Table 3.4 this constraint is not very limiting for our analysis.

[5]https://managingrisktogether.orx.org

accuracy. In fact, very often operational losses databases were affected by a bias due to a high number of large losses while just few low losses were collected. Our dataset Although our database is limited to a single institution, and consequently makes our work a case-study, the completeness of the database allows accurate estimates.

Year	ET1	ET2	ET3	ET4	ET5	ET6	ET7	Full Sample
2000	4	80	1	8	2	0	32	127
2001	10	126	12	92	8	88	423	759
2002	5	171	31	108	3	103	588	1009
2003	7	304	150	141	15	95	908	1620
2004	10	1005	244	307	80	97	845	2588
2005	16	2169	225	555	76	119	1056	4216
2006	22	3695	203	547	83	111	702	5363
2007	21	3880	332	514	83	98	774	5702
2008	20	7974	240	514	56	162	869	9835
2009	16	6057	271	474	83	185	1521	8607
2010	29	5896	352	437	188	143	864	7909
2011	28	2100	377	506	138	158	909	4216
2012	52	1726	340	522	111	91	768	3610
2013	28	1682	229	961	113	103	1200	4316
2014	38	793	203	2470	68	187	877	4636
2015	17	464	162	4880	74	129	686	6412
2016	9	396	225	8344	106	56	552	9688
2017	8	196	182	7001	61	19	261	7728
2018	0	55	51	1890	10	4	105	2115
Total	340	38769	3830	30271	1358	1948	13940	90456
%	0.37587335	42.8595118	4.23410277	33.464889	1.50128239	2.15353321	15.4108075	100

Table 3.1: Operational Losses events distribution over time, yearly frequency.

Year	ET1	ET2	ET3	ET4	ET5	ET6	ET7	Full Sample
2000	531123	1708029	206583	324737	25488	-	2168364	4964323
2001	6139940	1922403	858117	8371941	3480890	170329	14317828	35261449
2002	748130	3040812	2438063	7322350	11197	88327	3059739	16708618
2003	2852273	3775167	1244551	8463037	85888	10491793	4068095	30980805
2004	8835167	8751318	2514328	26783584	583783	383938	11254654	59106772
2005	589350	12461962	3638118	32940704	469635	363053	8615553	59078375
2006	2096813	15211451	1605366	27813980	397117	138764	10464013	57727503
2007	4827435	16732019	2289486	37947913	1936345	442752	10185910	74361860
2008	2600795	73726468	1545949	45104399	612255	1259888	21604695	146454449
2009	1790464	41924721	3822834	31012733	390272	4753370	16366581	100060974
2010	4515645	14667423	3178468	17586257	5028769	2628732	18535032	66140328
2011	990374	6632948	5657342	19986399	3160367	1152882	20693664	58273976
2012	2058832	12385564	4654352	10654871	1197954	490757	13350625	44792956
2013	2446321	27372139	2378067	13674624	1744702	353508	22711690	70681052
2014	1183916	5039140	1560824	18722575	456558	417262	11178272	38558546
2015	1690180	4988976	1312433	19087758	546444	411760	14683451	42721002
2016	335262	4713445	986184	18667055	680603	582716	7782750	33748015
2017	185336	2667693	1017175	13060078	373421	338159	1822095	19463957
2018	-	441130	164734	3417925	20451	21877	485470	4551586
Total	44417357	258162808	41072974	360942920	21202138	24489867	213348481	963636546
%	4.61	26.79	4.26	37.46	2.20	2.54	22.14	100.00

Table 3.2: Operational Losses severity distribution over time, yearly frequency.

Tables 3.1 and 3.2 show, the number of events and the cumulative losses for the seven types of events (defined by Basel II) referring to the time series 1ts January 2000 - 31st August 2018 with annual granularity respectively. In particular, from Table 3.1 we note that the most frequent event type is undoubtedly external fraud (ET 2). This alone is worth about 42.86% of the events, while at the level

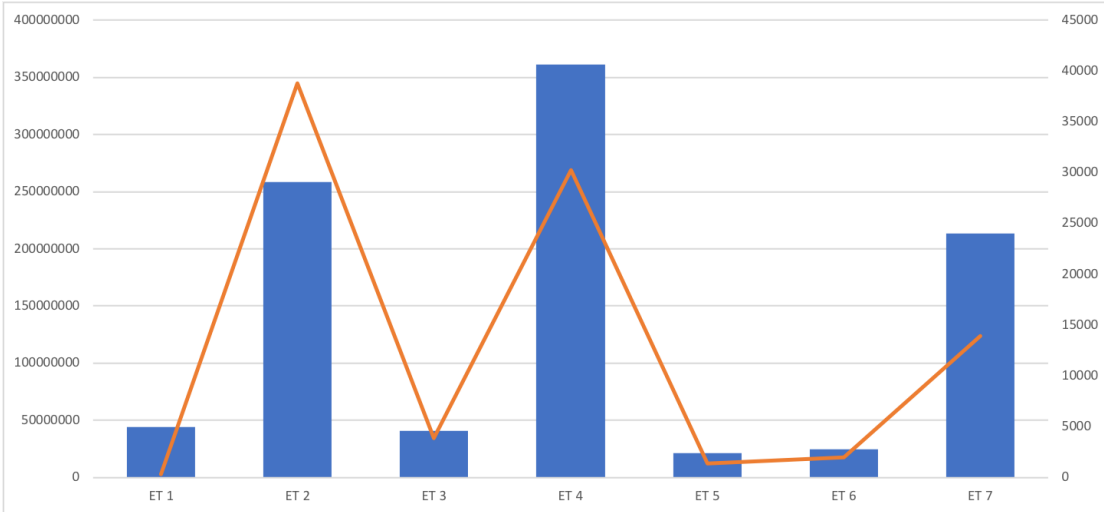

Figure 3.1: Severity (left axe and blue histogram) and Frequency (right axe and orange line) operational losses for Event Types. Where: ET 1 is "Internal Fraud"; ET 2 is "External Fraud"; ET 3 is "Employment Practices and Workplace Safety"; ET 4 is "Clients, Products, and Business Practices"; ET 5 is "Damage to Physical Assets"; ET 6 is "Business Disruption and System Failures" and ET 7 is "Execution, Delivery, and Process Management".

of aggregate losses, ET 2, stands at around 258 million euros, 26.79% of the total. This suggests that although more numerous, external fraud events are, on average, less stringent. The second case for frequency of occurrence is ET4 with over 33% of the events registered. This type of event type leads the classification of accumulated losses with over 370 million euros, about 37% of the total. In this case we can conclude that ET 4, on average, has greater losses on a single event level than the total average. Another relatively frequent case, with over 15% of events, is the ET 7 which is worth over 213 million euros (22% of the total). From this first analysis we can see that ET 2, 4 and 7, together, represent 90% of the events of operating loss, representing over 85% of losses in a monetary sense. From these data we can note the weight, in terms of frequency, of ET2 events. In fact, as we have seen, ET4 and ET7 have a greater weight in terms of severity than frequency. However, if we consider the union of the first 3 cases we note that the weight in terms of frequency is greater than the severity.

The remaining categories, ET 1, 3, 5 and 6 are the least frequent found in our sample. In particular, these cases represent 0.38%, 4.23%, 1.50% and 2.15% of the observations respectively (in total about 8.3%). Referring to losses in aggregate terms, we note that these cases represent a total of 13.5% (4.61, 4.26, 2.20 and 2.54% respectively). Furthermore, referring to the average loss we can

note that in the case of ET 4 the average impact is about 11900 euros. More generally, on average the operating losses, considering the split by event type, amount to a maximum of 15300 euros per event (ET 7). From these values, which are fairly constant for all event types, the case of internal fraud is distinguished, the average of the losses attributable to ET 1 is over 130,000 euros. This last observation points out that, although the events classified ET 1 are largely the least frequent, they are (in average terms) the most significant in terms of impacts. These evidences are clear also in the light of Figure 3.1, which shows the frequency and severity of operational losses in relation to the different event types.

So far we have considered only a static analysis. Referring to the entire sample, without the event type split, we can see that 2008 is the year characterised by the highest level of operational losses, both in terms of frequency and impact. Instead, concentrating our analysis on the different event types we can see that in the case of the ET 6, 1 and 4 cases the years with a greater aggregate loss are, respectively, 2003, 2004 and 2008, while the years with a greater frequency are 2014, 2012 and 2016. In the case of ET 5 severity and frequency find the maximum in two contiguous years (2009 and 2010 respectively) while for ET 2 and ET 3 frequency and severity are maximised in the same year, 2008 and 2011 respectively. The only example in which the maximum frequency is prior to the maximum severity is ET 7, 2009 and 2013 respectively.

Tables 3.3 and 3.4 report the main descriptive statistics on a quarterly basis for frequency and severity at the individual event type level. In particular, from Table 3.3 we observe that the events of the type ET2 and ET4 are the most frequent and those characterised by greater standard deviation. On the other hand, the events of the types ET 1, ET 5 and ET 6 are the rarest. It is also interesting to note that the skewness is generally contained, the maximum value is 2.73 (ET7), moreover in the case of ET6 (and of the entire sample) the distribution is characterised by negative kurtosis. Table 3.4 presents descriptive statistics for the severity of operating losses at the quarter level. In particular, we note that on average ET4 the greatest losses occur (the maximum value is greater than 60 million euros) for ET2. Furthermore, for all event types (and the entire sample) the distribution is characterized by skewness and positive kurtosis which define a heavy right tail.

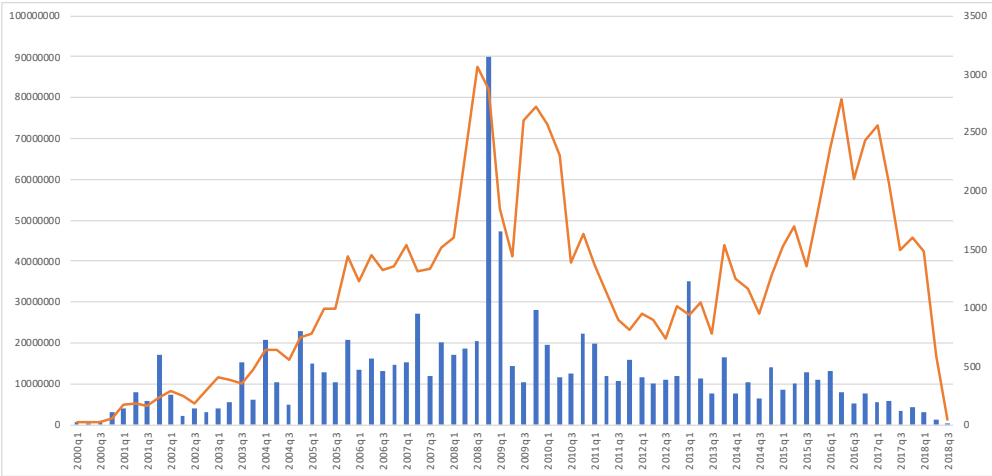

Figure 3.2: Severity (left axe and blue histogram) and Frequency (right axe and orange line) operational losses distribution over time.

	Mean	St. Dev.	Min	Max	1st Quartile	Median	3rd Quatile	Skewness	Kurtosis
ET1	4,53	3,960	0	20	2	3	6	1.598	3.102
ET2	516,92	623,620	2	2672	60,5	260	872,5	1.412	1.506
ET3	51,07	30,414	0	152	36	52	69	1.088	2.977
ET4	403,61	624,125	0	2421	68,5	127	298	1.613	1.367
ET5	18,11	12,971	0	59	8	19	24,5	1.163	2.502
ET6	25,97	15,575	0	61	17,5	25	35	0.241	-0.569
ET7	185,87	113,060	0	769	132	184	234,5	2.730	12.244
Total	1206,08	789,159	19	3061	614,5	1225	1569,5	0.578	-0.191

Table 3.3: Operational losses Descriptive Statistics over time, quarterly level.

	Mean	St. Dev	Min	Max	1st Quartile	Median	3rd Quatile	Skew.	Kurt.
ET1	592231,43	1197904,335	0	8214833,76	56881,915	226433,17	486102,3	4.56	24.13
ET2	3442170,77	7904105,711	8372,27	60335644,87	741633,28	1609854,6	3409548,24	5.248	30.582
ET3	547639,65	515606,213	0	2251808,72	205143,35	404242,87	644592,1	1.390	1.358
ET4	4812572,27	4069946,332	0	21123587,89	2259819,805	3914551,8	6448137,335	1.865	4.194
ET5	282695,18	531104,282	0	3434918,1	45395,33	100223,13	253400,505	2.690	7.925
ET6	326531,56	1242586,924	0	10238225,25	19383,28	79589,3	194301,96	5.626	36.502
ET7	2844646,42	2425114,851	0	12053113,65	1151883,25	2191783,64	3859387,785	1.480	3.153
Total	12848487,28	12125553,820	91479,17	89963471,95	5954238,66	11145564,3	15544846,2	3.917	20.915

Table 3.4: Operational losses severity Descriptive Statistics over time, quarterly level (data are in thousands of euros).

Figure 3.2 presents both severity and frequency distribution over time, which for simplicity we aggregate in quarterly observations. We notice that, neither distributions are monotone over time. Particularly, we can observe that until the third quarter of 2008, both severity and frequency seem to follow the same increasing trend, while decreasing until the third quarter 2013. Later the two distributions diverge, the severity decreases while the frequency increases until the last quarter of our time series window, we have to consider that since the last observation lays in August, the last quarter in not complete. Another explanation is that some losses need time to be discovered and registered. Some of them, that

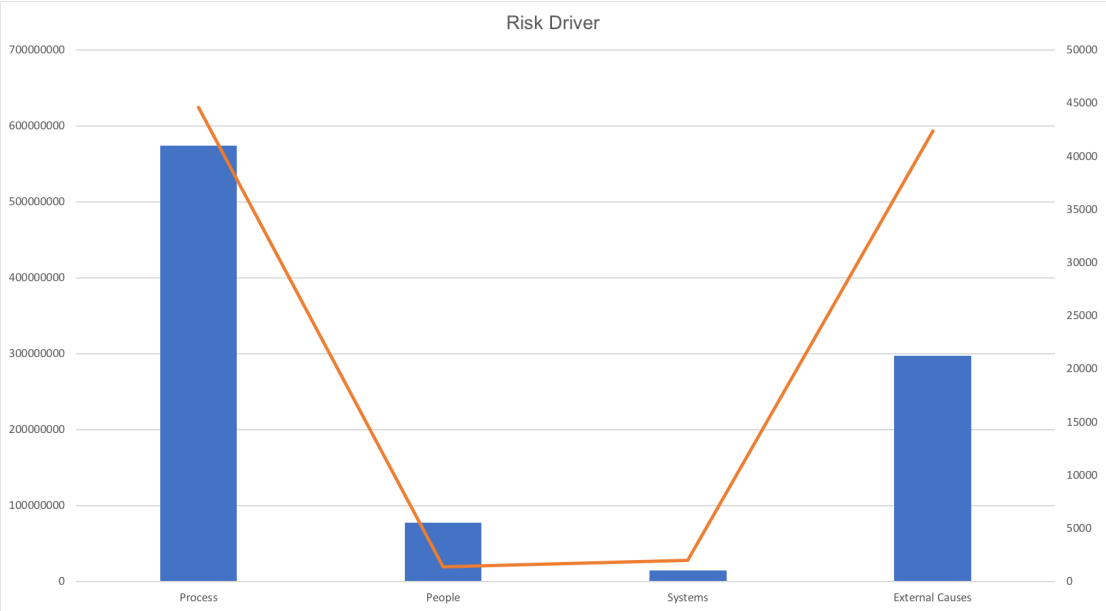

Figure 3.3: Severity (left axe and blue histogram) and Frequency (right axe and orange line) operational losses distribution over risk drivers.

already happened, were not discovered yet in August 2018. Observing the severity trend, we can see how the bank's managers have defined more effective controls to limit large losses. However, these corporate policies for managing operational risks have made it possible to significantly reduce the impact of losses, but on the other hand, there have been many events of limited impact. These evidences suggest the fact that frequency and severity are two very distinct characteristics of operational loss events, and that for this reason it is more useful to study these two quantities individually.

Basel II defines operational loss events as attributable to four risk drivers, nominally Processes, People, Systems and External Causes. Figure 3.3 presents both frequency and severity for these risk drivers, particularly we can observe that both processes and external factors are the most frequent events, even if the Processes are the risk driver that, if considered in its entirety, has greater impacts. It is also interesting to notice that although people is the less frequent risk driver, it is, on average, the most severe.

Another source of analysis that involves operating loss events is, of course, the business line that identifies the branch in which losses are recorded. Particularly, Figure 3.4 presents both frequency and severity of operational losses grouped by business lines. It is interesting to notice that the most frequent business line is "retail banking" that also reaches the highest level of aggregate severity. Moreover,

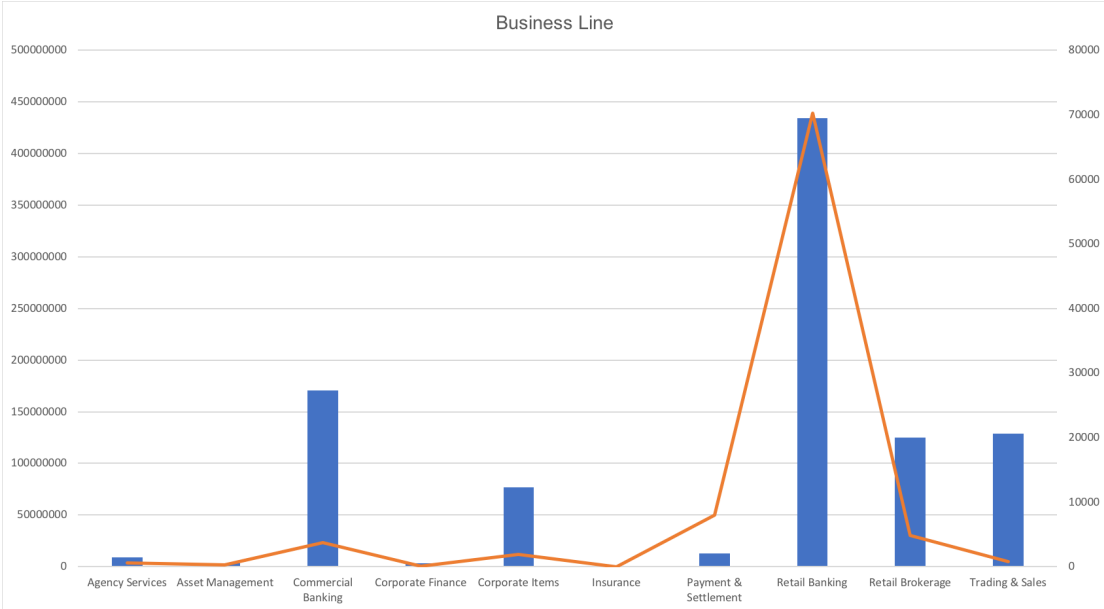

Figure 3.4: Severity (left axe and blue histogram) and Frequency (right axe and orange line) operational losses distribution over business lines.

"payments and settlements" unless it is the second most frequent kind of business line, is just the 6th for aggregate severity. Again, "commercial banking" and "trading and sales" are characterised by the highest average severity.

Finally, Figure 3.5 shows us the operational losses duration, particularly, a operational loss need some time to be discovered, evaluated and finally solved. The graph suggests that around 32% of operational loss events last more that a year, while just the 22% last max one month. This means that our database could be affected by lack of data, in particular in the dynamic part of our time window. This may suggest the drastic drop in frequency observed in the last period of Figure 3.2.

Corporate Data

In addition to data regarding operational losses, in order to identify the determinants of these events (both on the frequency and the severity side), we identified several variables that intercept the dynamics that characterise the bank in an idiosyncratic way. In particular, in regards to the corporate-type variables we have identified:

- Market to Book Ratio, which represents the ratio between the Market Value and the Book Value of the bank;

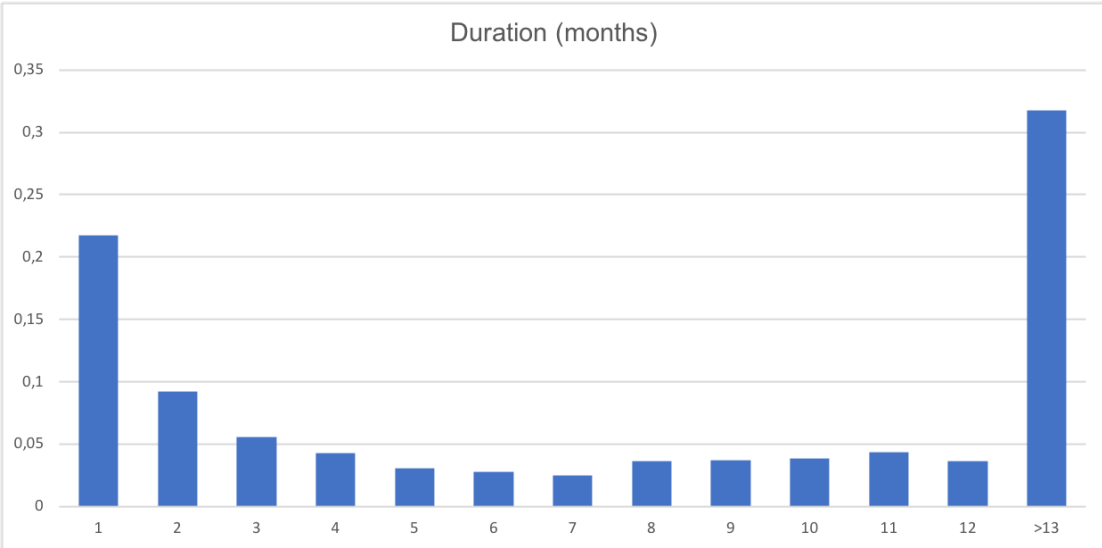

Figure 3.5: Operational losses duration in month

- Size, which is the Total Asset in logarithm terms;
- CapAR, which is the Capital Adequacy Ratio determined as the ratio between CET 1 and the Risk Weighted Assets (RWA);
- Levarage, which is the ratio between the Total Debt and Total Equity;
- Loans Ratio, which is the ratio between Total Outstanding Loans (net value) over the Total Asset.

To get some initial evidence we propose some graphs that relate corporate variables with frequency and severity.

Particularly, Figures 3.6, 3.7, and 3.8 compare the frequency and severity of operational loss events with corporate variables. It is interesting to note that the equity price and market capitalisation variables share a similar trend to the frequency one, even if the maximum point of these two variables is anticipated with respect to the target variable. The common shareholders equity variable is characterised by at least 2 regime changes, the first in 2007 while the second in 2017. The same shocks are also common to the net loan and total asset variables. These regime changes are a clear indication of a structural change in the analysed company, such as an important aggregation or acquisition. The market value to book variable also peaked in 2007, which is then slowly reabsorbed and, furthermore, at least until 2016 shares a trend similar to the frequency of operational loss events. As for provisions, for loan losses there is a trend similar to that which characterises the severity of operating losses, but with an interesting feature: in

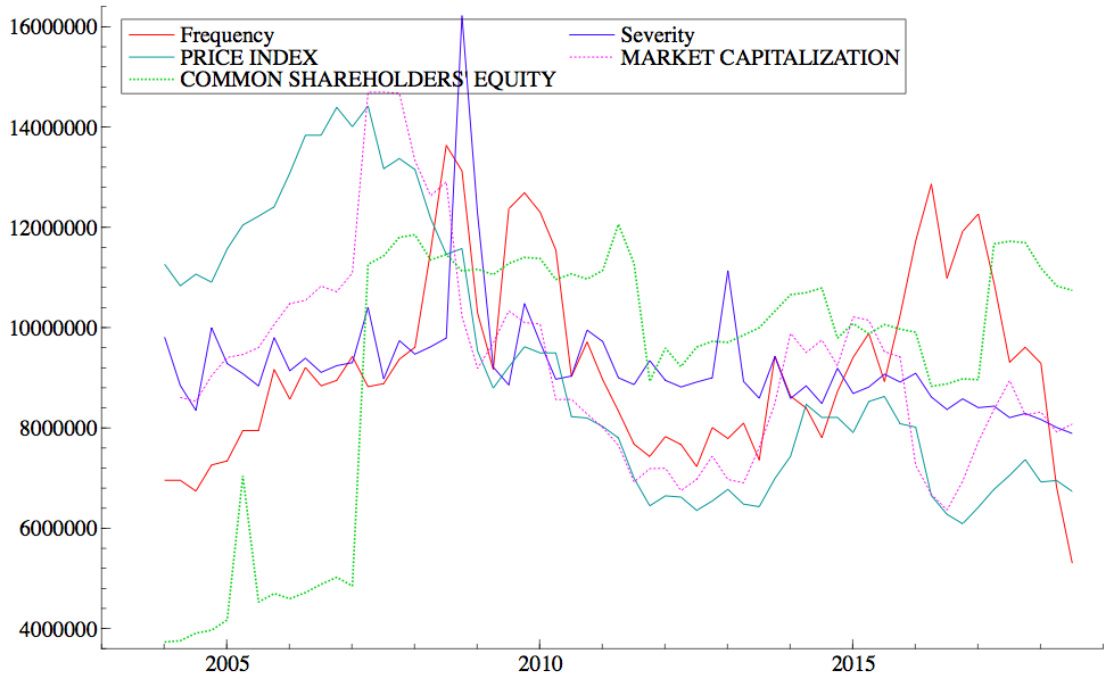

Figure 3.6: Severity (blue line), Frequency (red line), Equity Price (green line), Common Shareholder Equity (green dotted line) and Market Capitalisation (dotted pink line).

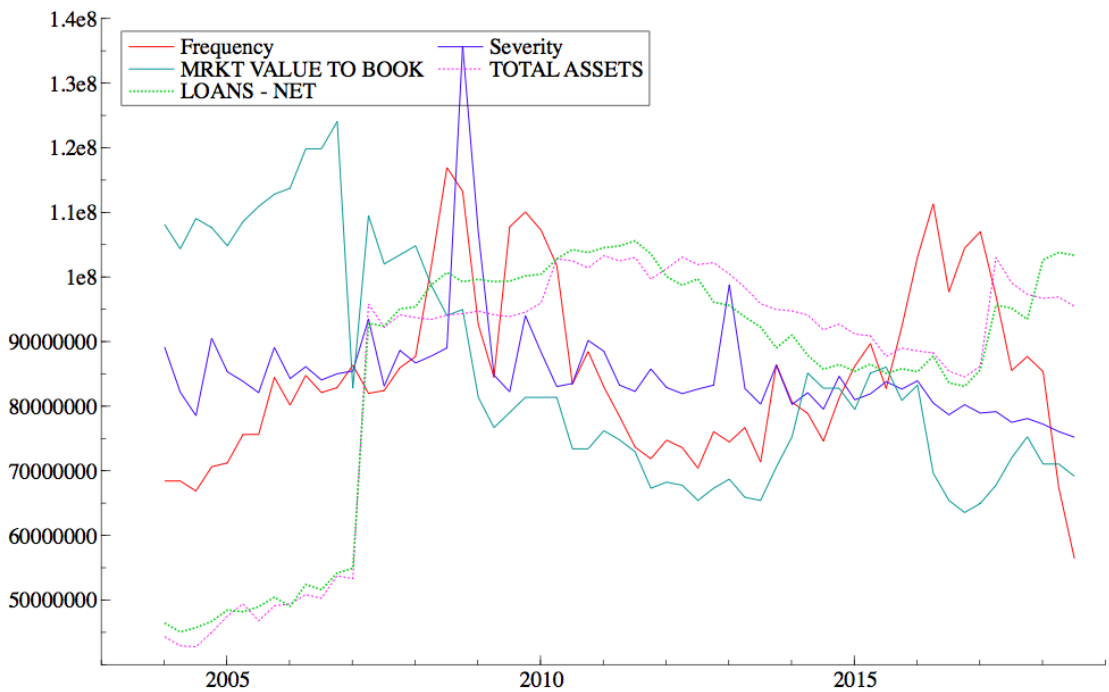

Figure 3.7: Severity (blue line), Frequency (red line), Market Value to Book (green line), Net Loans (green dotted line) and Total Asset (dotted pink line).

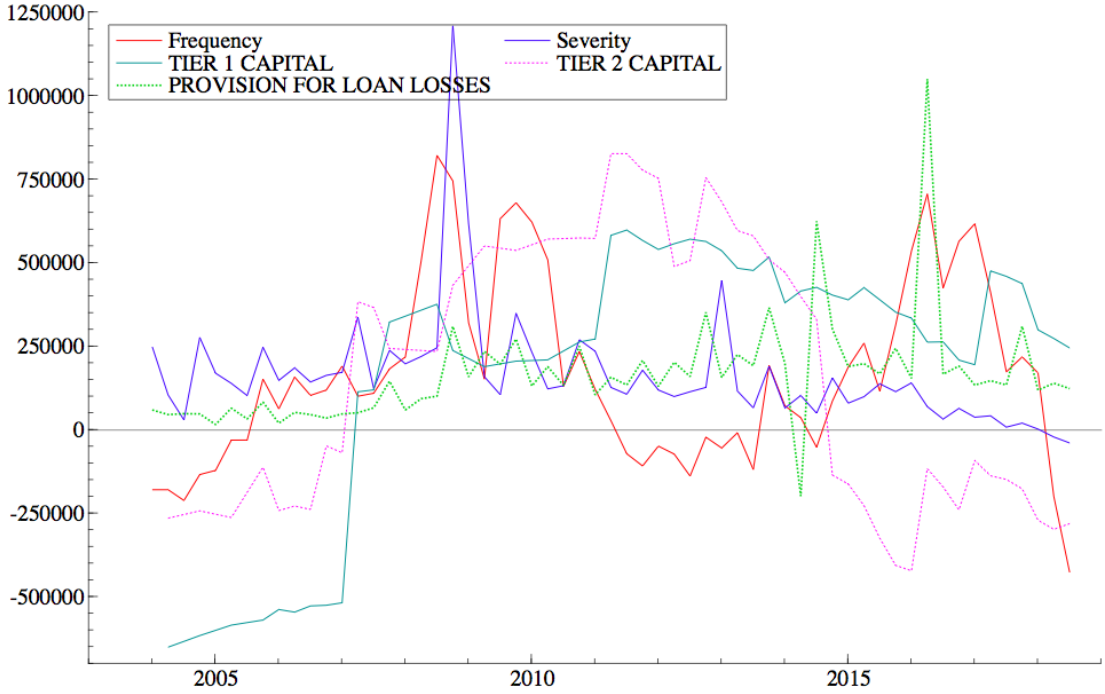

Figure 3.8: Severity (blue line), Frequency (red line), Tier 1 Capital Requirements (green line), Provision for Loan Losses (green dotted line) and Tier 2 Capital Requirements (dotted pink line).

the first part of the series, the variability of the target variable is greater than the independent variable one, this relationship is reversed starting in 2012. The two variables that identify the capital requirements (Tier 1 and Tier 2) share a similar trend at least until 2014, after Tier 2 it is characterised by a significantly greater drop than the one of Tier 1.

In conclusion, the selected variables seem, at least from this first graphical analysis, to capture different characteristics of operational losses, both from the point of view of frequency and severity. Table 3.5 shows the main statistics describing the corporate ones (Panel B). These data are derived from Eikon Thomson Reuters database.

Daily Returns Data

Looking at Figure 3.9 (in which, for convenience, we have scaled the ordinate axis to make the three series more easily comparable) it is possible to analyse the behaviour of the natural logarithm of daily prices of the of the bank's shares that we are analysing in this paper, of the the stock index of the financial center in which the stock is listed, and finally the Stoxx 600 banks index which is composed

	Mean	St. Deviation	Min	Max	1st Quartile	Median	3rd Quatile	Skewness	Kurtosis
Panel A									
Size	18.492	0.257	17.927	18.696	18.524	18.611	18.651	-1.292	2.895
CapAR	0.095	0.024	0.066	0.132	0.074	0.087	0.118	0.234	1.361
Leverage	542.798	93.116	356.140	730.130	467.960	545.260	617.890	-0.156	2.172
Loans_Ratio	0.768	0.037	0.702	0.844	0.739	0.751	0.802	0.513	2.020
Panel B									
MRKT VALUE TO BOOK	0.660	0.371	0.200	1.490	0.355	0.580	1.035	0.669	-0.874
PRICE INDEX	72.405	46.098	16.500	163.500	31.450	54.200	112.250	0.598	-1.036
TOTAL ASSETS	110495.5	23859.2	61053.3	131683.3	111286.7	120980.1	125321.8	-1.229	-0.192
MARKET CAPITALIZATION	5386.6	2463.3	1842.2	12047.9	3566.3	5211.2	6462.3	1.080	1.145
COMMON SHAREHOLDERS' EQUITY	9269.1	2653.6	3742.3	12073.0	8914.3	10073.0	11189.1	-1.124	-0.242
TIER 1 CAPITAL	6655.0	1617.4	3357.6	8401.5	6756.0	7086.9	7708.3	-1.151	-0.167
TIER 2 CAPITAL	2593.7	1006.8	1095.3	4279.9	1590.4	2773.8	3554.0	0.127	-1.594
LOANS - NET	85230.1	20171.6	45157.3	105670.1	84449.9	92899.5	99756.5	-1.080	-0.395
PROVISION FOR LOAN LOSSES	166.4	163.6	-197.9	1051.0	66.1	146.2	198.8	3.009	15.055

Table 3.5: Descriptive Statistics for the models variable (Panel A) and raw corporate variables (Panel B) used to define the former ones. Corporate variables belong from Thomson Reuters database.

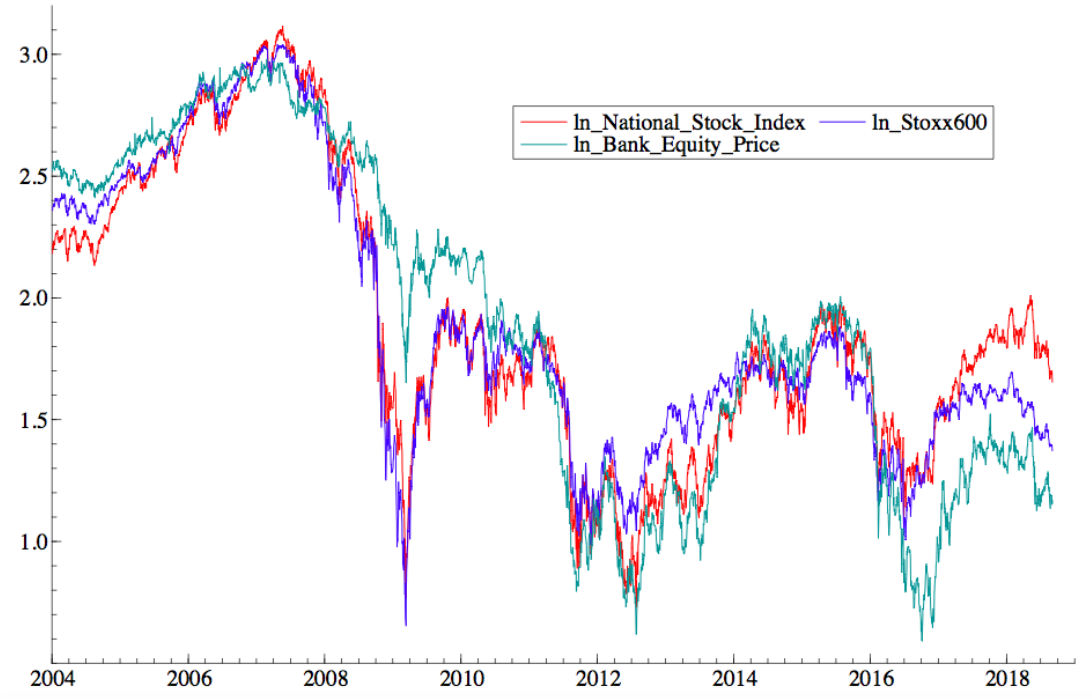

Figure 3.9: Log Prices of studied Bank (green line), National Stock Index (red line) and the Stoxx 600 Banks (blue line).

of 600 financial institutions with various capitalisation (large mid and small) from 17 European countries.

Figure 3.9 shows that the three variables share, in large part, a common trend. Going a little more specifically, we can see that in the first big shock, the banking title seems to have suffered less, compared to the other two series considered, of the impact of the great recession. Moreover, in the 2012-2014 period we observe that the European banking sector has better performances (on average) than either the national stock index or the single bank stock, this can be considered an indication of the fact that, at least in this situation, the role of the national economy (of environmental variables) has a greater weight, playing a crucial role. On the contrary, we can note that, from the second instalment of 2016 to the end of our time window, the national index has performed better than both the Stoxx 600 banks and, above all, the bank's share price. This allows us to hypothesise that the credit sector is characterised by greater stress than in other sectors. Finally, Table 3.6 shows the main descriptive statistics of the series considered. These data are derived from Bloomberg database.

	Mean	St. Deviation	Min	Max	1st Quartile	Median	3rd Quatile	Skewness	Kurtosis
r National Index	0.000	0.002	-0.011	0.014	-0.001	-0.000	0.001	0.276	6.436
r Stoxx600	0.000	0.003	-0.028	0.032	-0.001	0.000	0.001	0.093	10.840
r Bank	0.000	0.0194	-0.136	0.176	-0.005	0.000	0.006	0.548	11.125
ln National index	10.051	0.305	9.422	10.700	9.843	9.989	10.280	0.430	-0.783
ln Stoxx600	5.439	0.417	4.503	6.289	5.158	5.292	5.816	0.573	-0.880
ln Bank	1.906	0.669	0.593	2.983	1.286	1.875	2.557	-0.011	-1.295

Table 3.6: Descriptive Statistics for bank, national stock market index and Stoxx 600 banks index returns and log-prices. Data belong form Bloomberg database.

3.3.4 Empirical Results

In this section we first present the results regarding the empirical losses drivers, both for frequency and severity. Then, we move to the operational losses effects on bank's returns. We first identify the most significant operational losses in our database and then we compute CAR values for different time windows, as sensitive analysis. Finally, we compare the bank's and market's results in order to evaluate the effects of large operational losses.

Operational Losses Determinants

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	-21.947**	23.323**	-4.153	-6.627	-5.060
	(8.642)	(8.191)	(4.771)	(8.089)	(6.211)
MtB Ratio	0.628*	-0.960**	0.026	0.028	0.021
	(0.356)	(0.354)	(0.193)	(0.355)	(0.269)
Tot. Asset	1.218**	-0.473	0.534	0.935**	0.823**
	(0.532)	(0.493)	(0.327)	(0.470)	(0.385)
CapAR	-29.752***	10.275**	-9.097**	-3.414	-4.458
	(7.318)	(4.775)	(4.250)	(4.581)	(4.336)
Leverage	0.001	-0.003***	0.002**	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Loans Ratio	9.808**	-8.546**	-0.128	-2.504	-1.990
	(4.036)	(3.134)	(3.026)	(3.459)	(3.109)
Pseudo R^2	.67	.57	.21	.24	.21

Table 3.7: Operational Losses drivers, Frequency. Standard errors are in parenthesis, ***, ** and * denote the coefficients statistical significance at 1, 5 and 10 percent respectively.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	-34.012	-16..555	-29.141	-16.876	-20.783
	(17.314)	(11.043)	(18.271)	(11.422)	(12.339)
MtB Ratio	0.822	0.607*	0.712	0.617	0.664
	(0.617)	(0.329)	(0.609)	(0.399)	(0.418)
Tot. Asset	3.190**	2.111**	2.605**	2.278**	2.365**
	(1.159)	(0.882)	(1.275)	(0.838)	(0.927)
CapAR	-42.945**	-22.315**	-24.916*	-29.063**	-26.805**
	(12.700)	(10.543)	(13.440)	(9.938)	(10.804)
Leverage	0.003**	0.003**	0.005***	0.004	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Loans Ratio	-11.178	-8.045	-6.350	-10.234	-8.046
	(9.166)	(7.630)	(9.306)	(7.550)	(7.946)
R^2	.50	.42	.40	.44	.45
Adj. R^2	.46	.36	.34	.39	.40

Table 3.8: Operational Losses drivers, Severity. Standard errors are in parenthesis, ***, ** and * denote the coefficients statistical significance at 1, 5 and 10 percent respectively.

Tables 3.7 and 3.8 reports the results for the models defined by Equations (3.8) and (3.9) respectively. According to Chernobai et al. (2011) we define the following 5 different models:

- Model 1, Frauds: ET 1 and ET 2;
- Model 2, All but Frauds: ET 3, ET 4, ET 5, ET 6 and ET 7;
- Model 3, Internal Events: ET 1, ET 3, ET 6 and ET 7;
- Model 4, External Events: ET 5, ET 4 and ET 2;
- Model 5, All Events.

We use the OLS estimator to investigate the relationship between the loss severity and the idiosyncratic variables. In addition, we test the relationship between each idiosyncratic variable and the percentage of operational loss through a Poisson regression.

The variable size is positive and highly statistically significant in all the models considered. The size plays a crucial role in the loss severity of a bank; particularly, the larger is the bank a higher will be the operational losses associated. The

positive relationship corroborates the "too big to fail" hypothesis due to the systemic importance of the Group. These evidences are in contrast with Moscadelli (2004) that finds a significant negative relation. However we argue that, especially with regards to operational risk and differently from credit and market risks, size drives banks to face more operational losses events with respect to smaller ones, because this kind of risk requires a peculiar approach. The negative and statistical significant relationship between CapAR and the dependent variable emphasises the absorption of capital when an event occurs. This particular evidence sheds light on the importance of the capital issue stressed by the Basel Committee. Particularly, regarding Models 3 and 4, we can notice that the variable CapAR is significantly negative and the magnitude of the coefficients are larger for severity losses. In addition, just referring to frequency, the statistically significance disappears for external events. Again in relation to the variable CapAR, we can observe that a crucial role is played by internal frauds. In fact, when we consider ET 1 observations we have a negative and significant coefficient while, when we avoid internal frauds we have, in general, no significant coefficient (even positive in the case of Model 2). Considering Leverage, we can notice a different behaviour depending on observing frequency or severity. In the first we have, in general, a negative and statistically significance. This sign is inverted just in the case of internal events (Model 3). Moving to the severity analysis we notice that the sign is always significant and positive, the only case where it is significantly negative is the external events (Model 4). Referring to Loans Ratio, we do not have any evidences for severity, while considering frequency we understand that a higher loans ratio is associated to a higher number of frauds, evidence supported by the bank core business, especially the retail banking activity (see Figure 3.4). Differently, in Model 2, which considers all the other event types, an increase in lending activity decreases operational losses different form frauds. This can be explained by a growing sustainable relationship between bank and costumers and consequently more effective controls on internal processes.

Operational Losses Effects

In this section we try to identify the reactions that the bank's returns have following the disclosure of large operating losses. Before going into the analysis of the results it is right to underline some considerations. First of all, unlike losses deriving from other types of risk, operating losses are characterised by a time gap between the occurrence and the reporting date. In particular, as we have seen in

Figure 3.5, operating losses need significant time to be detected. A further point of discussion is the one concerning the definition of large operating losses. As we saw in the Section 3 about data analysis, the event types defined by Basel have significantly different characteristics, both from the point of view of the frequency of occurrence, and from the severity (average and maximum) that the different event types have in our database. These considerations allow us to conclude that identifying the effects (on the bank's returns) of operating losses is certainly more complex than other events, such as macro announcements or particular events which are certainly easier to certainly identify date and impact.

After these premise, we define the significant operational losses as, for each event type, the 99th percentile of the distribution of the same losses in the time window that we consider. In particular, for this analysis we decided to consider the daily returns of the bank, the national reference index and the sector index (Stoxx 600 Banks) starting from 1st January 2004. We have identified the 99th percentile for the 7 event types defined by Basel II. In particular, we defined 4 events classified as ET 1, 341 for ET 2, 37 for ET 3, 259 for ET 4, 10 for ET 5, 15 for ET 6, and finally 109 for ET 7.[6]

[6]In the case of multiple events with single impact greater (or at least equal) to the 99th percentile of the respective event type recorded on the same date, we have decided to account for only one operational loss event with an impact equal to the sum of all the significant events that occurred on that date.

	ET 1	ET 2	ET 3	ET 4	ET 5	ET 6	ET 7
(-1; +5)	-0.0010	-0.0011	0.0000	-0.0020	0.0178	0.0146	-0.0019
	(0.8957)	(0.0000)	(0.9984)	(0.0010)	(0.1927)	(0.4205)	(0.0000)
(-1; +10)	-0.0070	-0.0043	0.0048	-0.0033	0.0363	0.0132	-0.0052
	(0.5589)	(0.0000)	(0.7277)	(0.0000)	(0.1598)	(0.5933)	(0.0004)
(-1; +15)	-0.0013	-0.0031	-0.0003	-0.0037	0.0248	0.0160	-0.0054
	(0.8907)	(0.0000)	(0.9872)	(0.0000)	(0.3663)	(0.5611)	(0.0051)
(-5; +5)	-0.0039	-0.0040	-0.0036	-0.0015	0.0199	0.0061	-0.0002
	(0.3521)	(0.0000)	(0.7731)	(0.0261)	(0.3796)	(0.7736)	(0.8550)
(-5; +10)	-0.0125	-0.0041	0.0013	-0.0028	0.0385	0.0047	-0.0004
	(0.2960)	(0.0000)	(0.9425)	(0.0016)	(0.2397)	(0.8514)	(0.7805)
(-5; +15)	-0.0067	-0.0029	-0.0018	-0.0033	0.0270	0.0076	-0.0005
	(0.4725)	(0.0005)	(0.8445)	(0.0004)	(0.4702)	(0.7939)	(0.7562)
(-10; +5)	0.0014	-0.0016	-0.0038	-0.0027	0.0284	0.0089	0.0016
	(0.4934)	(0.0678)	(0.5046)	(0.0004)	(0.1515)	(0.6696)	(0.3848)
(-10; +10)	-0.0090	-0.0016	-0.0026	-0.0040	0.0470	0.0075	0.0014
	(0.4411)	(0.1052)	(0.8006)	(0.0000)	(0.1426)	(0.7841)	(0.5085)
(-10; +15)	-0.0104	-0.0004	-0.0001	-0.0044	0.0355	0.0103	0.0013
	(0.5596)	(0.6919)	(0.6162)	(0.0000)	(0.2892)	(0.7365)	(0.5859)

Table 3.9: Large Operational Losses Effects; for each event type and each time window we report the value of ϵ defined as the difference among average bank and indices CARs. P value are reported in parenthesis.

As defined in the methodological section, first of all we estimated the three-factor model defined by Equation (3.10) for the bank's returns, also considering two stock indexes that took into account the sectoral context (Stoxx 600) on one side and the context on the other economy in which the bank operates (main national stock index). This model allows us to identify the "systemic" dynamics of the bank's returns, while the residuals of the regression capture all the "idiosyncratic" component typical of the institution we are analysing. Our objective is to assess whether, considering different time windows in which the most significant operational losses occurred[7], the difference between the bank's returns and those defined by the two indices (weighted for the beta obtained from the regression) is significantly different from 0. To pursue this goal, we first calculated the abnormal returns (AR) as described by Equation (3.11) and then the CARs based on Equa-

[7] 99th percentile at the event type level

tion (3.12). Finally, following Cummins et al. (2006) and Moosa and Silvapulle (2012), we have individually considered the average of the CARs (at the level of single event type) for the bank's returns and the values obtained with the right side of Equation (3.10), excluding residues. Through a t-test we verified that the residuals of the regression, which correspond to the difference described above, are significantly different from 0. Table 3.9 shows the results of the analysis just described. First of all we can notice that in the cases of ET1, 3, 5 and 6 the impact of operational losses is not statistically significant. A possible explanation for this evidence derives precisely from the type of operating losses. In particular, labour contracts and the related legislation concerning workplace safety, as well as the effects of natural disasters have a transversal effect on the whole system (defined as banking system or geographical area) and, only in exceptional cases such losses have effects limited to a single institution. As far as ET 1 and ET 6 are concerned, which should contain idiosyncratic information, the fact that epsilon is not significant may depend on the low number of events analysed (respectively 4 and 15) on the total number of events identified (775). Considering, on the other hand, the ETs that have at least one significant epsilon value, we note that these cases are characterised by a higher and higher idiosyncratic factor. ET 2 deals with external frauds which, indirectly, consider the efficiency of the measures put in place to deal with this type of action. In the case of ET 2 it is significant for the more limited time windows. Even more than the previous one, the ET4 case characterises the operating losses deriving from the bank's business policies. In this case, epsilon is significant regardless of the width of the time window considered. Lastly, ET 7, which identifies the losses relating to the management of company processes, is characterised by the presence of a significant delta between the returns of the bank and the ones of the indices, even if only for the time windows with a smaller amplitude.

Moreover, it is interesting to notice that, in all the cases where epsilon is statistically different from 0, the sign is negative. This evidence indicates that the bank's returns are significantly smaller than the ones reached by the indices. These results are particularly interesting for at least two reasons. First, some operational losses event types are characterised by a higher level of idiosyncrasy. Secondly, although the operational losses impacts were not very high (and the bank returns are indirectly consider into the two indices), the statistical significance shows us how the market reacts to this type of loss.

To sum up, we can say that in determining the main drivers that influence operating losses, frequency and severity have several points in common, in par-

ticular size and leverage are positively significant, while CapAR is significantly negative. We can also observe some differences, particularly considering Model 2 (all events except frauds). Finally, considering the effects of the large operating losses, we were able to distinguish between the different types of event types by identifying those that seem to intercept the idiosyncratic characteristics of the bank. This allows us, on the one hand, to confirm the idiosyncratic nature of operational losses, but on the other, the fact that different event types are not significant gives us proof of the systemic nature of some types of operating losses, as suggested by Moosa (2007).

3.4 Conclusions

In this paper we have analysed the role of operational risk for a systemic bank within the context of the European monetary union. First of all, we focused on the trend of operating losses, focusing particularly on the frequency of events over time and on the impacts that characterise these events.

To analyse the determinants and effects of operating losses we have considered a complete database, that collects all the operational losses recorded by a European systemic bank, without the need to make assumptions about the distribution, something common in many papers analysing public databases. From the distribution of events (frequency) it is observed that a first peak is in correspondence with the Great Recession (2008 Q1 on-wards) subsequently followed by a significant drop reaching the local minimum between 2012 and 2013 and then growing again. The severity, instead, up until 2009 shares the frequency trend, while afterwards it shows a significant decline. The fact that, in our investigation window, the two quantities have different trends has led us to consider independent frequency and severity, as suggested by the literature and, consequently, to analyse them separately.

We used the OLS estimator to investigate the relationship between the loss severity and the idiosyncratic variables. In addition, we tested the relationship between each idiosyncratic variable and the percentage of operational loss through a Poisson regression. The variable size is positive and highly statistically significant in all the models considered. The size plays a crucial role in the loss severity of a bank; particularly, the larger is a bank the higher will be the operational losses associated. The positive relationship corroborates the "too big to fail" hypothesis. The negative and statistically significant relationship between CapAR and the dependent variable emphasises the absorption of capital when an event

occurs. This particular evidence sheds light on the importance of the capital issue stressed by the Basel Committee. A positive and statistically significant relationship comes from the leverage variable. The higher the leverage ratio is, the better is the internal control (Chernobai et al., 2008).

In the second part of the paper we focused on the effects of operational losses. To identify the impacts of operating losses on the bank's returns, we first identified the most significant losses at the event type level, and subsequently estimated a three-factor model that, in addition to the bank's returns, included the returns of the Stoxx 600 index (which considers 600 European banks) and the main national index in which the financial institution we are considering, operates. Following this methodology we then identified the abnormal returns and, consequently, the respective cumulative abnormal returns. With these figures we were able to observe when the operating losses had a significantly negative effect on the bank's returns. In particular it was interesting to note that the significance was reached only in the cases in which the considered event types had a very high idiosyncratic rate, allowing us to conclude that the market is able to recognise when an operating loss is strictly related to the individual financial institution or when this loss can be transversal to the entire sector or to the reference market.

In this paper we have tried to study operational losses by identifying the main drivers and the effects that follow. On this front the literature is quite meager, especially if we consider the other risks faced by the banks. For future research we suggest focusing on the idiosyncratic concept of operational losses which, as we have observed, seems to be limited to some event types.

In conclusion we can say that operational risk is, without a doubt, one of the most fascinating issues related to the banking system. Unfortunately, the lack of available databases has constrained the proliferation of literature as it has been with other types of banking risk. Today various institutions, public and private, have the objective of collecting this type of data in order to allow a more in-depth analysis. As input for future research, after noting that certain event types are more transversal to the system than others, we suggest evaluating the systemic impact of operational losses.

Conclusions

The aim of this thesis was to analyse the interconnections between economic systems in periods of particular tension. We explored this objective from different points of view. In order to investigate the relations between the banking system and the governmental one, we consider both micro and macroeconomics variables. This strong relationship was underlined, among others, by Alter and Schüler (2012) and Acharya et al. (2014) who analyse a strong links between the turbulence of public finance with banks. These close relationships became very evident even looking at Figures 1.1 and 3.2, which respectively show the interest rates on the public debt of the Eurozone countries and the frequency trend of the bank's operating losses. The two charts share a very similar trend over time. Therefore, we decided to analyse the links between European economies and financial systems (Chapter 1), the effects of a decline in interest rates on sovereign debt (Chapter 2) and the drivers and the effects of operating losses in the banking system (Chapter 3).

In Chapter 1, we analysed the interdependent relationships between France and Italy in relation to three macro-regions of the Eurozone, namely Germany, Core (composed by Austria, Belgium, Finland, France and the Netherlands) and Periphery (composed by Greece, Ireland, Italy, Portugal and Spain), considering both macroeconomic and financial variables. We implemented a GVAR framework and then we performed GIRFs technique in order to evaluate the shock reactions. To summarise our main findings, we performed 110 GIRFs. We shocked equity prices, long term interest rates, CDS prices, the effective exchange rates and VIX. In 69 cases we observed spillover effects. In particular, we studied 44 shock reactions for both, France and Italy, and 11 for Germany and VIX (the model common variable). A France based shock spread between other countries the 66% of cases, while the 52% for the Italian based. In particular, we noticed that, for France based shocks, 17 out of the 22 regarding equity and CDS prices (that captured financial dynamics) showed significant contagion effects. As regards Italy, only 9 response functions based had clear spillover effects. On the other

hand, considering macroeconomic variables we noticed an opposite behaviour. For France based shocks we found spillover effects in 12 cases out of 22, while for Italy they were 14. Finally, as regards GIRFs we observed that financial shocks spread more if occurred in Core countries (or in Germany). Differently, Periphery based shocks spread more if concerned real variables. These results are corroborated by the GFEVD analysis. We evaluated the disturbance sources for both, equity prices and the effective exchange rates. We observed that for the equity price variable the greater disturbance is given by the Periphery countries. Differently, considering effective exchange rates Core countries had the greatest disturbance.

In Chapter 2, we aimed to observe the change in the probability of being in turbulence due to a fall in the yield rates on 10-year treasury bills for Eurozone countries. To do this, first we created "crisis" variable able to capture the periods of pre-crisis, crisis and recover. This framework allowed us to overcome the so called "crisis/post-crisis bias". Second, we set an Early Warning System (EWS) based on a Multinomial Logit technique for a panel of Eurozone countries. Our model achieved up to the 88% of correct predictions. Third, we evaluated the probability of being in turbulence period based on the optimal threshold, we minimised the occurrence of both Type 1 (miss a crisis) and Type 2 errors (issue a false alarm). In our case, the optimal threshold that minimised the Type 1 and Type 2 errors, moved from 8.87% to 23.67% according to the model selected. These values are in line with literature that, for a similar framework, obtained optimal thresholds around the 20%. Fourth, we considered a GVAR technique to perform the GIRFs function in order to observe the model variables responses to a negative shock on long term interest rate (with a magnitude of a standard error). In particular we noticed that equity prices were generally characterised by a growth that becomes significant only after some periods but this growth often was lasting. Differently, CDS prices were characterised by a significant initial decline which, in many cases, however was reabsorbed. The effective exchange rate did not show significant deviations, although for all the sample countries there was a sudden (but short-term) drop immediately after the shock. Finally, the interest rate on ten-year sovereign bonds showed a re-absorption by some European countries, while for the so-called Mediterranean countries, the drop in rates lasted. Fifth, we estimated again the EW model considering the new observations derived by the GIRFs. Finally, we computed the new probability of being in a vulnerable state. Our results showed that a negative shock on long term interest rate significant decrease the probability of moving in a crisis state.

Finally, in Chapter 3 we analysed the role of operational risk for a systemic

bank within the context of the European monetary union. First of all, we focused on the trend of operating losses, focusing particularly on the frequency of events over time and on the impacts that characterise these events. We used the OLS framework to investigate the relationship between the loss severity and corporate variables. In addition, we tested the relationship between corporate variable and the percentage of operational loss through a Poisson regression. The variable size was positive and highly statistically significant in all the models considered. The size played a crucial role in the loss severity of a bank; particularly, the larger is a bank the higher will be the operational losses associated. The positive relationship corroborated the "too big to fail" hypothesis. The negative and statistically significant relationship between the capital adequacy ratio and the dependent variable emphasised the absorption of capital when an event occurred. This particular evidence shed light on the importance of the capital issue stressed by the Basel Committee. A positive and statistically significant relationship came from the leverage variable. We also considered the effects of operational losses on the bank's returns. We estimated a three factor model and then abnormal and cumulative abnormal returns for both, the bank and the market (defined by the other two factors). In particular it was interesting to note that the significance was reached only in the cases in which the considered event types had a very high idiosyncratic rate, allowing us to conclude that the market is able to recognise when an operating loss is strictly related to the individual financial institution or when this loss can be transversal to the entire sector or to the reference market. We could conclude that in the case of (even) large operational losses, based on non-idiosyncratic event type, the effects spread in the whole market.

In order to investigate further developments we consider two different ways. Particularly, we could enlarge the cross-sectional component of our analysis considering more economic entities but also other variables able, for instance, to capture the economic cycle. Furthermore, especially linked to Chapter 2 we could perform alternatives models for early warning estimations (among others signal approach and artificial neural networks). As regards Chapter 3, we could enrich the database with other banks' operational losses and collect other variables to investigate the operational losses main drivers considering, for instance, also specific variables to identify downturn periods.

Chapter 4

References

Acharya, V., Drechsler, I. & Schnabl, P. (2014). A pyrrhic victory? bank bailouts and sovereign credit risk. *The Journal of Finance*, *69*(6), 2689–2739.

Alessi, L. & Detken, C. (2011). Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *European Journal of Political Economy*, *27*(3), 520–533.

Alexander, C. (2003). *Operational risk: regulation, analysis and management.* Pearson Education.

Alter, A. & Schüler, Y. S. (2012). Credit spread interdependencies of european states and banks during the financial crisis. *Journal of Banking & Finance*, *36*(12), 3444–3468.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, *23*(4), 589–609.

Antonini, M., Lee, K. & Pires, J. (2013). Public sector debt dynamics: the persistence and sources of shocks to debt in 10 EU countries. *Journal of Money, Credit and Banking*, *45*(2-3), 277–298.

Baele, L. (2005). Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis*, *40*(2), 373–401.

Bailey, N., Pesaran, M. H. & Smith, L. (2014). A multiple testing approach to the regularisation of large sample correlation matrices.

Baldi, G. & Staehr, K. (2016). The European debt crisis and fiscal reactions in Europe 2000–2014. *International economics and economic policy*, *13*(2), 297–317.

Barrios, S., Iversen, P., Lewandowska, M., Setzer, R. et al. (2009). *Determinants of intra-Euro area government bond spreads during the financial crisis* (Tech. Rep.). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

BCBS. (2005). Compliance and the compliance function in banks. *Basel Committee on Banking Supervision*.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of accounting research*, 71–111.

Becker, B. & Ivashina, V. (2018). Financial repression in the European sovereign debt crisis. *Review of Finance*, *22*(1), 83–115.

Behn, M., Detken, C., Peltonen, T. A. & Schudel, W. (2013). Setting countercyclical capital buffers based on early warning models: Would it work? ecb working paper, no 1604.

Behn, M., Gross, M. & Peltonen, T. A. (2016). Assessing the costs and benefits of capital-based macroprudential policy.

Beirne, J. & Gieck, J. (2014). Interdependence and contagion in global asset markets. *Review of International Economics*, *22*(4), 639–659.

Bekaert, G. & Harvey, C. R. (2003). *Market integration and contagion* (Tech. Rep.). National Bureau of Economic Research.

Berg, A., Borensztein, E. & Pattillo, C. (2005). Assessing early warning systems: how have they worked in practice? *IMF staff papers*, *52*(3), 462–502.

Bickel, P. J. & Levina, E. (2008). Regularized estimation of large covariance matrices. *The Annals of Statistics*, 199–227.

Biell, L. & Muller, A. (2013). Sudden crash or long torture: the timing of market reactions to operational loss events. *Journal of Banking & Finance*, *37*(7), 2628–2638.

Black, L., Correa, R., Huang, X. & Zhou, H. (2016). The systemic risk of european banks during the financial and sovereign debt crises. *Journal of Banking & Finance*, *63*, 107–125.

Blundell-Wignall, A. (2012). Solving the financial and sovereign debt crisis in Europe. *OECD Journal: Financial Market Trends*, *2011*(2), 201–224.

Boschi, M., Marzo, M. & Salotti, S. (2015). Domestic versus international determinants of European business cycles: a GVAR approach. *Empirical Economics*, *49*(2), 403–421.

Broto, C. & Perez-Quiros, G. (2015). Disentangling contagion among sovereign CDS spreads during the European debt crisis. *Journal of Empirical Finance*, *32*, 165–179.

Brutti, F. & Saure, P. (2015). Transmission of sovereign risk in the Euro crisis. *Journal of International Economics*, *97*(2), 231–248.

Buchelt, R. & Unteregger, S. (2003). Cultural risk and risk culture: Operational risk after basel i. *Financial Stability Report*(6), 86–97.

Buchmuller, P., Haas, M., Rummel, B. & Sticklemann, K. (2006). Ama implementation in germany: Results of bafins and bundesbanks industry survey. In E. Dvais (Ed.), *The advanced measurement approach to operational risk* (p. 295-336). London: Risk Books.

Bussiere, M., Chudik, A. & Mehl, A. (2013). How have global shocks impacted the real effective exchange rates of individual Euro area countries since the Euro's creation? *The BE Journal of Macroeconomics*, *13*(1), 1–48.

Bussière, M., Chudik, A. & Sestieri, G. (2009). Modelling global trade flows: results from a GVAR model.

Bussiere, M. & Fratzscher, M. (2006). Towards a new early warning system of financial crises. *journal of International Money and Finance*, *25*(6), 953–973.

Caggiano, G., Calice, P., Leonida, L. & Kapetanios, G. (2016). Comparing logit-based early warning systems: Does the duration of systemic banking crises matter? *Journal of Empirical Finance*, *37*, 104–116.

Caporale, G. M. & Girardi, A. (2013). Fiscal spillovers in the Euro area. *Journal of International Money and Finance*, *38*, 84–e1.

Caprio, G. & Klingebiel, D. (1999). *Bank insolvencies: cross-country experience.* The World Bank.

Cesa-Bianchi, A., Pesaran, M. H., Rebucci, A., Xu, T. & Chang, R. (2012). China's Emergence in the World Economy and Business Cycles in Latin America . *Economía*, *12*(2), 1–75.

Cetorelli, N. & Goldberg, L. S. (2011). Global banks and international shock transmission: Evidence from the crisis. *IMF Economic Review*, *59*(1), 41–76.

Chan-Lau, J. A., Liu, E. X. & Schmittmann, J. M. (2015). Equity returns in the banking sector in the wake of the Great Recession and the European sovereign debt crisis. *Journal of financial stability*, *16*, 164–172.

Chernobai, A., Jorion, P. & Yu, F. (2008). The determinants of operational losses. *Syracuse University*.

Chernobai, A., Jorion, P. & Yu, F. (2011). The determinants of operational risk in us financial institutions. *Journal of Financial and Quantitative Analysis*, *46*(6), 1683–1725.

Chernobai, A. & Yildirim, Y. (2008). The dynamics of operational loss clustering. *Journal of Banking & Finance*, *32*(12), 2655–2666.

Chudik, A. & Fratzscher, M. (2011). Identifying the global transmission of the 2007–2009 financial crisis in a GVAR model. *European Economic Review*, *55*(3), 325–339.

Chudik, A., Grossman, V. & Pesaran, M. H. (2016). A multi-country approach to forecasting output growth using PMIs. *Journal of Econometrics*, *192*(2), 349–365.

Chudik, A. & Pesaran, M. H. (2011). Infinite-dimensional VARs and factor models. *Journal of Econometrics*, *163*(1), 4–22.

Chudik, A. & Pesaran, M. H. (2016). Theory and practice of GVAR modelling. *Journal of Economic Surveys*, *30*(1), 165–197.

Ciarlone, A. & Trebeschi, G. (2005). Designing an early warning system for debt crises. *Emerging Markets Review*, *6*(4), 376–395.

Cipollini, A., Coakley, J. & Lee, H. (2015). The European sovereign debt market: from integration to segmentation. *The European Journal of Finance*, *21*(2), 111–128.

Cramer, J. S. (2003). The origins and development of the logit model. *Logit models from economics and other fields*, 149–158.

Crouhy, M. G., Galai, D. & Mark, R. (2004). Insuring versus self-insuring operational risk: Viewpoints of depositors and shareholders. *The Journal of Derivatives*, *12*(2), 51–55.

Cuadro-Sáez, L., Fratzscher, M. & Thimann, C. (2009). The transmission of emerging market shocks to global equity markets. *Journal of Empirical Finance*, *16*(1), 2–17.

Cummins, J. D., Lewis, C. M. & Wei, R. (2006). The market value impact of operational loss events for us banks and insurers. *Journal of Banking & Finance*, *30*(10), 2605–2634.

Danıelsson, J., Jorgensen, B. N. & De Vries, C. G. (2002). Incentives for effective risk management. *Journal of Banking & Finance*, *26*(7), 1407–1425.

Davis, E. P. & Karim, D. (2008). Comparing early warning systems for banking crises. *Journal of Financial stability*, *4*(2), 89–120.

Dees, S., Hashem Pesaran, M., Vanessa Smith, L. & Smith, R. P. (2014). Constructing Multi-Country Rational Expectations Models. *Oxford Bulletin of Economics and Statistics*, *76*(6), 812–840.

Dees, S., Holly, S., Pesaran, M. H. & Smith, L. (2007). Long run macroeconomic relations in the global economy. *Economics: The Open-Access, Open-Assessment E-Journal*, *1*.

Dees, S., Mauro, F. d., Pesaran, M. H. & Smith, L. V. (2007). Exploring the international linkages of the Euro area: a global VAR analysis. *Journal of applied econometrics*, *22*(1), 1–38.

De Fontnouvelle, P., DeJesus-Rueff, V., Jordan, J. S. & Rosengren, E. S. (2006). Capital and risk: new evidence on implications of large operational losses. *Journal of Money, Credit, and Banking*, *38*(7), 1819–1846.

DeKoker, R. (2006). Where do we go from here? In E. Dvais (Ed.), *The advanced measurement approach to operational risk.* London: Risk Books.

Demirgüç-Kunt, A. & Detragiache, E. (1998). The determinants of banking crises in developing and developed countries. *IMF Staff Papers*, *45*(1), 81–109.

De Waal, A., van Eyden, R. et al. (2013). *The impact of economic shocks in the rest of the world on South Africa: Evidence from a global VAR model* (Tech. Rep.). EcoMod.

Diebold, F. X. & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158–171.

Di Mauro, F. & Pesaran, M. H. (2013). *The GVAR handbook: Structure and applications of a macro model of the global economy for policy analysis.* OUP Oxford.

Dovern, J. & van Roye, B. (2014). International transmission and business-cycle effects of financial stress. *Journal of Financial Stability*, *13*, 1–17.

Dreger, C. & Zhang, Y. (2013). *Does the economic integration of China affect growth and inflation in industrial countries?* (Tech. Rep.). FIW Working Paper.

Duca, M. L. & Peltonen, T. A. (2013). Assessing systemic risks and predicting systemic events. *Journal of Banking & Finance*, *37*(7), 2183–2195.

Duprey, T., Klaus, B. & Peltonen, T. (2017). Dating systemic financial stress episodes in the eu countries. *Journal of Financial Stability*, *32*, 30–56.

Ebnother, S., Vanini, P., McNeil, A. & Antolinez, P. (2003). Operational risk: A practitioner's view. *Journal of Risk*, *5*, 1–16.

Echevarria-Icaza, V. & Sosvilla Rivero, S. (2017). Yields on sovereign debt, fragmentation and monetary policy transmission in the Euro area: A GVAR approach.

Ehrmann, M. & Fratzscher, M. (2017). Euro area government bonds–fragmentation and contagion during the sovereign debt crisis. *Journal of International Money and Finance*, *70*, 26–44.

Ehrmann, M., Fratzscher, M., Gürkaynak, R. S. & Swanson, E. T. (2011). Convergence and anchoring of yield curves in the Euro area. *The Review of Economics and Statistics*, *93*(1), 350–364.

Ehrmann, M., Fratzscher, M. & Rigobon, R. (2011). Stocks, bonds, money markets and exchange rates: measuring international financial transmission. *Journal of Applied Econometrics*, *26*(6), 948–974.

Ejsing, J. & Lemke, W. (2011). The Janus-headed salvation: Sovereign and bank credit risk premia during 2008–2009. *Economics Letters*, *110*(1), 28–31.

Engle, R. F., Ito, T. & Lin, W.-L. (1988). *Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market.* National Bureau of Economic Research Cambridge, Mass., USA.

Eun, C. S. & Shim, S. (1989). International transmission of stock market movements. *Journal of financial and quantitative Analysis*, *24*(2), 241–256.

Fan, J., Fan, Y. & Lv, J. (2008). High dimensional covariance matrix estimation using a factor model. *Journal of Econometrics*, *147*(1), 186–197.

Favero, C. A. (2013). Modelling and forecasting government bond spreads in the Euro area: a GVAR model. *Journal of Econometrics*, *177*(2), 343–356.

Frank Jr, C. R. & Cline, W. R. (1971). Measurement of debt servicing capacity: An application of discriminant analysis. *Journal of international Economics*, *1*(3), 327–344.

Friedman, J., Hastie, T. & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, *9*(3), 432–441.

Garratt, A., Lee, K. & Shields, K. (2016). Forecasting global recessions in a GVAR model of actual and expected output. *International Journal of Forecasting*, *32*(2), 374–390.

Gillet, R., Hübner, G. & Plunus, S. (2010). Operational risk and reputation in the financial industry. *Journal of Banking & Finance*, *34*(1), 224–235.

Gorea, D. & Radev, D. (2014). The Euro area sovereign debt crisis: Can contagion spread from the periphery to the core? *International Review of Economics & Finance*, *30*, 78–100.

Greenwood-Nimmo, M., Nguyen, V. H. & Shin, Y. (2012). Probabilistic forecasting of output growth, inflation and the balance of trade in a GVAR framework. *Journal of Applied Econometrics*, *27*(4), 554–573.

Gross, M. (2013). Estimating GVAR weight matrices. *Working Paper Series 1523, European Central Bank*.

Gross, M. & Kok, C. (2013). Measuring contagion potential among sovereigns and banks using a mixed-cross-section GVAR.

Hamao, Y., Masulis, R. W. & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *The review of financial studies*, *3*(2), 281–307.

Herring, R. J. (2002). The basel 2 approach to bank operational risk: Regulation on the wrong track. *The Journal of Risk Finance*, *4*(1), 42–45.

Hoffman, D. G. (1998). New trends in operational risk measurement and management. *Operational risk and financial institutions*, 29–42.

Hoggarth, G., Reis, R. & Saporta, V. (2002). Costs of banking system instability: some empirical evidence. *Journal of Banking & Finance*, *26*(5), 825–855.

Holopainen, M. & Sarlin, P. (2017). Toward robust early-warning models: A horse race, ensembles and model uncertainty. *Quantitative Finance*, *17*(12), 1933–1963.

Kaminsky, G., Lizondo, S. & Reinhart, C. M. (1998). Leading indicators of currency crises. *Staff Papers*, *45*(1), 1–48.

Kapetanios, G., Pesaran, M. H. & Yamagata, T. (2011). Panels with non-stationary multifactor error structures. *Journal of Econometrics*, *160*(2), 326–348.

Kempa, B. & Khan, N. S. (2017). Spillover effects of debt and growth in the Euro area: Evidence from a GVAR model. *International Review of Economics & Finance*, *49*, 102–111.

Knedlik, T. & Von Schweinitz, G. (2012). Macroeconomic imbalances as indicators for debt crises in europe. *JCMS: Journal of Common Market Studies*, *50*(5), 726–745.

Kohn, M. & Kaiser, T. (2006). *An introduction to operational risk*. Bloomberg Press.

Konstantakis, K. N. & Michaelides, P. G. (2014). Transmission of the debt crisis: from EU15 to USA or vice versa? A GVAR approach. *Journal of Economics and Business*, *76*, 115–132.

Konstantakis, K. N., Michaelides, P. G., Tsionas, E. G. & Minou, C. (2015). System estimation of GVAR with two dominants and network theory: Evidence for BRICs. *Economic Modelling*, *51*, 604–616.

Laeven, L. & Valencia, F. (2012). Systemic banking crises database: An update.

Lane, P. R. (2012). The European sovereign debt crisis. *Journal of Economic Perspectives*, *26*(3), 49–68.

Ledoit, O. & Wolf, M. (2004). A well-conditioned estimator for large-dimensional covariance matrices. *Journal of multivariate analysis*, *88*(2), 365–411.

Lewis, C. M. & Lantsman, Y. L. (2005). What is a fair price to transfer the risk of unauthorized trading?: A case study on pricing operational risk.

Li, S. & Wang, S. (2014). A financial early warning logit model and its efficiency verification approach. *Knowledge-Based Systems*, *70*, 78–87.

Mizgier, K. J., Hora, M., Wagner, S. M. & Jüttner, M. P. (2015). Managing operational disruptions through capital adequacy and process improvement. *European Journal of Operational Research*, *245*(1), 320–332.

Moosa, I. (2007). *Operational risk management.* Springer.

Moosa, I. & Silvapulle, P. (2012). An empirical analysis of the operational losses of australian banks. *Accounting & Finance*, *52*(1), 165–185.

Moscadelli, M. (2004). The modelling of operational risk: experience with the analysis of the data collected by the basel committee. *Available at SSRN 557214*.

Murphy, D. L., Shrieves, R. E. & Tibbs, S. L. (2009). Determinants of the stock price reaction to allegations of corporate misconduct: Earnings, risk, and firm size effects. *Journal of Financial and Quantitative Analysis*, *43*(3), 581–612.

Niehof, B. (2014). *Spillover effects in government bond spreads: Evidence from a GVAR model* (Tech. Rep.). Joint Discussion Paper Series in Economics.

Perry, J. & De Fontnouvelle, P. (2005). Measuring reputational risk: The market reaction to operational loss announcements. *Available at SSRN 861364*.

Pesaran, M., Schuermann, T. & Weiner, S. M. (2004). Modeling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business & Economic Statistics*, *22*(2), 129–162.

Pesaran, M. & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, *58*(1), 17–29.

Pesaran, M., Vanessa Smith, L. & Smith, R. P. (2007). What if the UK or Sweden had joined the Euro in 1999? An empirical evaluation using a Global VAR. *International Journal of Finance & Economics*, *12*(1), 55–87.

Pesaran, M. H. (2015). *Time series and panel data econometrics*. Oxford University Press.

Pesaran, M. H., Schuermann, T. & Smith, L. V. (2009a). Forecasting economic and financial variables with global VARs. *International journal of forecasting*, *25*(4), 642–675.

Pesaran, M. H., Schuermann, T. & Smith, L. V. (2009b). Rejoinder to comments on forecasting economic and financial variables with global VARs. *International Journal of Forecasting*, *25*(4), 703–715.

Ramser, J. & Foster, L. (1931). A demonstration of ratio analysis. bureau of business research, university of illinois, urbana. *IL, Bulletin*, *40*.

Rigobon, R. (2016). Contagion, spillover and interdependence.

Samarakoon, L. P. (2017). Contagion of the Eurozone debt crisis. *Journal of International Financial Markets, Institutions and Money*, *49*, 115–128.

Sander, H. & Kleimeier, S. (2003). Contagion and causality: an empirical investigation of four Asian crisis episodes. *Journal of International Financial Markets, Institutions and Money*, *13*(2), 171–186.

Sander, H. & Kleimeier, S. (2004). Convergence in euro-zone retail banking? what interest rate pass-through tells us about monetary policy transmission, competition and integration. *Journal of International Money and Finance*, *23*(3), 461–492.

Sironi, A. & Resti, A. (2007). *Risk management and shareholders' value in banking: from risk measurement models to capital allocation policies* (Vol. 417). John Wiley & Sons.

Swanson, N. R. & Granger, C. W. (1997). Impulse response functions based on a causal approach to residual orthogonalization in vector autoregressions. *Journal of the American Statistical Association*, *92*(437), 357–367.

Taffler, R. J. & Abassi, B. (1987). Country risk: a model for predicting debt servicing problems in developing countries. In *International debt and central banking in the 1980s* (pp. 187–223). Springer.

Tamakoshi, G. & Hamori, S. (2013). Volatility and mean spillovers between sovereign and banking sector CDS markets: a note on the European sovereign debt crisis. *Applied Economics Letters*, *20*(3), 262–266.

Vansteenkiste, I. & Hiebert, P. (2011). Do house price developments spillover across euro area countries? Evidence from a global VAR. *Journal of Housing Economics*, *20*(4), 299–314.

Xu, T. (2012). The role of credit in international business cycles.

Yunus, N. (2013). Contagion in international financial markets: A recursive cointegration approach. *Journal of Multinational Financial Management*, *23*(4), 327–337.