Essays on Financial Stability, Systemic Risk and the Spillover Effects of Financial Crises

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Abstract

This thesis investigates in depth several aspects of economic activity through an aggregated metric, which aims to account for the inherent distressful characteristics of the financial system. This work is strongly motivated by the extraordinary evolution of the financial and economic landscape and the induced fragility within its foundations, especially during the last years.

Chapter 1 provides an overview of the theoretical considerations on the topics discussed in this thesis. Additionally, the motivations and a brief presentation of the thesis contents are provided.

Chapter 2 empirically investigates the leading indicator properties of the aggregate systemic risk indices to the real economy. In order to do that, I construct a series of financial stress indices for 25 countries. The countries are bundled into three groups (OECD, Asian, Latin American countries) and, apart from the national indexes, regional and a global index are computed. In order to do this, a number of variables from the banking sector, financial and capital markets and the foreign exchange market of each country, have been used for the implementation of these indicators. The indexes are successful early warning indicators, accurately capturing previous financial stress periods, while the financial turmoil of 2007-2009 is, without doubt, the most severe one. Forecasting exercises indicate the improved ability of indices-enhanced models to successfully predict the evolution of economic activity.

Chapter 3 investigates the interrelations and financial interconnections of the Eurozone economies. Financial stress indices are constructed for, both, countries and their four most important financial markets (banking, money, equity and bond). Using VAR models, a number of innovative conclusions are reached, such that: 1) not all peripheral countries (and especially Greece and Portugal) should be blamed for the crisis exacerbation 2) there is clear evidence of stronger interdependencies between banking and bond markets and 3) a degree of segregation (in terms of financial stress interdependence) between peripheral and core Eurozone economies.

The last essay aims to the deeper empirical investigation of potential cross-covariances and spillover effects between the Eurozone economies and financial markets. Full, asymmetric GARCH-BEKK models are estimated, both on a market (or country) wide level and, then, with the full spectrum of Euro Area markets. In other words, we complete an empirical examination, both “within” and “between” Eurozone economies and markets. The results reveal a number of interesting insights: on country wide level, there is strong volatility transmission channel from the most heavily hit, from the crisis, economies towards the rest. Additionally, the crucial importance and role on this transmission from the banking and bond markets is underlined. Contrary to common wisdom, Greece is not the main propagator of volatility uncertainty, while it is between the most important receivers of volatility risk. The same holds for other peripheral economies, while the importance of money market is also evident in the large, “between”, empirical approach.

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Author's Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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Chapter 1

Introduction

1. Background Information and Motivation

The crisis that was initiated in US subprime mortgage market (a relatively negligible, in terms of size, financial sector) quickly spread throughout the global financial system. The re-pricing of global risk conditions, due to this financial meltdown, quickly led to excessive imbalances in the world economies. In conjunction to the shifting investors' expectations and the adverse liquidity conditions, the world economy was forced to succumb to a prolonged period of heightening financial stress and economic recession, known now as the "Great Recession".

There is no doubt that the effect of this crisis is evident to the economic performance of most countries around the world. Especially for the case of Eurozone economies, the repercussions of the multifaceted crisis are still evident. A number of countries (Greece, Portugal and, until very recently, Ireland) are under international financial aid programs, while in all EU countries there was a need for financial assistance towards banks and other financial institutions. The recession still holds for the area, while the positive growth rates for some of these countries are rather anemic.

The failure to foresee the latest financial and real crisis is one of the major accusations against the economic profession. In retrospect, there is a wide belief that there were signs able to indicate the forthcoming financial catastrophe. But, in general, these signs were mostly neglected or not taken into account. Nevertheless, such kind of accusations may not entirely reflect the prevailed conditions. As it is underlined by Rivas and Quiros (2012), the economic profession was rather unprepared, in terms of empirical models and tools, for the suitable monitoring of the swiftly evolving financial conditions. Most of the macroeconomic models used by central banks and supervisory authorities, did not consider financial frictions as an important element of their framework. Instead, they used to consider markets are highly efficient and self-regulating.

On top of the above, the perplexed nature of the current crisis outbreak, as it is described by the importance of a number of liquidity, credit and money factors (Brunnermeier, 2009), as well as non financial factors (such as consumer and business confidence, increasing risk aversion, see Kenny and Morgan, 2011), amplified the negative conditions for the distressed economies. The role of the modern financial system, its shadow aspects and its structural fragility were also important contributors to the creation of excessive financial stress.

In the light of this discussion, the aim of this thesis is the detailed investigation of several aspects of the recent financial crisis, through the employment of an aggregated metric, able to capture the multilateral features of the financial conditions. That is, the financial stress index. Using this innovative and modern tool, it is feasible to study the evolution of financial stress and its effect on the real economic activity. Moreover, the study of the Eurozone crisis and the detailed investigation of crisis transmission channels is another contribution of this thesis. This examination is possible, through the development of econometric models, capable of capturing the risk perception for different segments of the European economies and financial markets. This analysis is conducted both within and between these markets and countries. Based on this work, this thesis aims to fill gaps in the relevant literature of financial crisis monitoring, systemic risk measurement and transnational risk diffusion.

The rest of this chapter is organized as follows. Section two discusses some relevant theoretical concepts, regarding financial stability and systemic risk definition. Then, since financial stress indices are an aggregate measure of the aforementioned, a short historical overview of the literature evolution towards these indices is presented. This introduction concludes with a short overview of the chapters that follow.

2. On Financial Stability, Systemic Risk and Its Metrics

One of the most difficult to define economic concepts is financial stability. It is by no chance that, until today, economists still find it easier to theorize financial stability as the period when financial instability does not exist. Another difficulty has to do with the nature of the financial system, which is quite diverse and complex. Given this situation, the provision of systematic studies for the causes and consequences of financial instability is even more perplexed. On the same time, it recently became one of the most interesting aspects of modern economies, due to the increasing integration of international financial markets, the globalization of the financial institutions activities and the tighter financial links among large groups of countries.

As this is a matter of intensive economic policy interest, economists from international organizations and central banks started to work on these issues long before the outbreak of the current financial crisis. For instance, Crockett (1996) is among the first to provide a solid and detailed discussion of the financial stability concept, underlying its importance for the rational allocation of savings and investments, along with financial health's importance on the real economy smooth operation. The role of financial intermediation is emphasized, while the assets quality problems, the assets price volatility and the network effects on the stability of the financial system are pinpointed.

In a more recent paper, Gramlich and Oet (2011) set the theoretical background for the development of a well justified early warning system for the structural fragility of financial systems. In their effort to identify the elements of financial systems, which contribute to the development of excessive systemic risk, they discuss the following features: comprehensiveness (important risk attributes should be part of the framework, from any possible perspective), consistency (in terms of the risk players connectivity and causal interactions between them), flexibility (easily adjustable to take into account new aspects of financial risk), forward looking (useful feature, especially for a timely tool, able to warn for forthcoming financial meltdowns), based on a correspondence with empirical data (that is, a model for which sufficient data volume exists) and suitability (a handy model, concentrated to the major aspects of financial markets and economies). Taking into account the combined effect of these features and the already discussed complexity in defining financial stability, the authors conclude that it is fruitful to develop early warning indicators, based on indexes of structural financial fragility. Such indices can be a weighted, single factor. It is a clear call for the usefulness and development of aggregate systemic risk indexes.

On the same vein, and closely related with the concept of financial stability and its measurement, is the concept of systemic risk. There is considerable interest among researcher in the most representative quantification of it. As early as the beginning of the previous decade, when there was still no evidence of systemic risk vulnerabilities for the developed economies, De Bandt and Hartmann (2000) provided a detailed survey of the relevant literature. In their work, the authors analyze the importance of the markets and financial institutions interconnections, while they also consider financial markets spillover effects as an important element of systemic risk propagation. Recently, the renowned interest in this concept is proclaimed, as it is evident by the recent publications of Allen and Carletti (2013) and Liang (2013) among others. According to the former, until the global financial crisis outbreak in 2007, most regulators and markets participants were focused to the default probabilities of individual financial institutions. Since then, systemic risk is at the epicenter. The authors divide its characteristics into four types: panics (banking crises attributed to changing expectations), banking crises due to asset prices falls, contagion and currencies mismatches. All of them contribute for systemic risk to build up. Gerlach (2009) is another proponent of aggregate financial soundness indicators, as tools to gauge financial conditions.

Overall, the fuzzy concept of financial stability and the measurement of systemic risk are strongly intertwined. Modern research tends towards the adoption of sophisticated, aggregate indexes, which are efficient representations of the level of systemic risk. This tendency is a natural extension of a relevant set of aggregate indicators, developed for the assessment of monetary policy efficacy. The next section briefly sketches this literature.

3. A Short Historical Account

From the above discussion, the concept of price stability is much more straightforward, compared to financial stability. Given this and the pronounced interest of central banks to safeguarding their inflation targeting mandate, many of them developed the so called monetary conditions indexes. Usually, these indices consist of a weighted average of the short term interest rate (main policy rate) and the exchange rate of the country's currency. As a tool, it was quite popular to small open economies, for which changes in these two variables are of utmost importance for the formation of aggregate demand. It performs as a tool for gauging the conduct of monetary policy.

The pioneering central banks in the construction of such aggregate indexes were Bank of Canada and the Reserve Bank of New Zealand. Gradually, many more countries adopted this framework. For instance, both developed (like UK and Australia) and developing (Turkey and India) economies assimilate this tool in the assessment of their monetary policy analysis[1].

Based on this experience, many central banks have recently decided to proceed with the research on similar aggregate indices for the assessment of their economies financial conditions. It was a decision based on the arguments presented and analyzed before. Additionally, the creation and maintenance of larger dataset, with important financial factors, rendered the computation of financial stress indicators easier.

Since the relevant literature is still to its infancy, this thesis also contributes to the quantification of systemic risk, with the development of the financial stress indicators, proposed in the subsequent chapters.

[1] For more, consult Kannan *et al.* (2006), Kesriyeli and Kocaker (1999), Batini and Turnbull (2000).

4. Thesis Overview

The thesis consists of five chapters. The main research efforts and the ensuing empirical findings and policy prescriptions are described in chapter two to four. Here, a short description of the aforementioned is provided.

Chapter 2 examines the leading indicator properties of the financial stress indices. The main research question, which is addressed at this chapter, is whether the aggregate systemic risk indicators can successfully predict real economy. Moreover, an identification of the types of financial episodes (together with their duration) is conducted, based on threshold values representing periods of excessive financial stress. Most of the scrutinized countries and regions are sensitive to securities-sourced financial instabilities. Based on the RMSFE ratios, I find that FSIs are good medium to short term predictors for the case of OECD countries. For the case of Asian and Latin American countries, the forecasts are better in longer time periods. Diebold-Mariano and Clark-West tests of equal forecasting accuracy verify these results.

Chapter 3 examines for potential interrelations and financial connections between the Eurozone countries and financial markets. One of the major innovations here is the constructions of financial stress indexes on a segmented basis. That is, for each country, I calculate five indices, one for each market examined (banking sector, money, equity and bond markets) and a national index. This is the first ever effort for such a detailed and decomposed analysis of the financial stress and its relevant sources for the Euro Area. Additionally, the dataset is large and diverge, consisting of banks balance sheet data (together with a large set of financial factors). The divergent character of the crisis is manifested in each one of the countries examined through the copious discussion of the indexes performance. Using a VAR modeling framework, my findings indicate that euro peripheral economies are not the main channels of financial shocks transmission to the rest of the Eurozone. Banking sectors and bond markets are highly interconnected. EMU is found to be disaggregated, in the sense that core and peripheral countries are mostly responsive to their own "club" financial shocks.

Chapter 4 investigates volatility comovements and spillover effects within the Euro Area economies. The separate examination of the markets is accompanied by an examination of the cross markets case. High frequency financial stress indices are employed, something not common until now. Full asymmetric BEKK-GARCH models are estimated, on a bivariate basis, in order to assess the volatility transmission channels between and within all markets involved in this examination. A long time period is covered, reaching September 2013. Results indicate the importance of the banking and bond markets in the volatility transmission of excessive financial stress. Additionally, money market is another risk transmitter, especially in the case of cross-markets analysis. Strong bidirectional effects between countries, either from the core or peripheral clusters, are established. Although, GIIPS countries significantly contribute to the cross-volatility, larger and considerably more robust European economies (like France, Belgium and Netherlands) are also consistent transmitters of volatility risk and comovements.

Chapter 5 concludes this thesis. First, a short overview of the research aim and scope is provided. Then, the main contributions and policy implications from each chapter are discussed. Finally, a few recommendations for future research efforts are made.

Chapter 2

Exploring the Financial Conditions – Economic Conditions Nexus: Empirical Evidence from Developed and Developing Countries

Abstract

Systemic financial crises can lead economies to major instabilities and, eventually, economic and financial losses. For this reason, there is a need for tools capable of indicating whether a financial catastrophe is on its way or not. This paper contributes to the relevant literature, by constructing a series of financial stress indices for 25 countries. The countries are bundled into three groups (OECD, Asian, Latin American countries) and, apart from the national indexes, regional and a global index are computed. In order to do this, a number of variables from the banking sector, financial and capital markets and the foreign exchange market of each country, have been used for the implementation of these indicators. The indexes are successful early warning indicators, accurately capturing previous financial stress periods, while the financial turmoil of 2007-2009 is, without doubt, the most severe one. Also, empirical evidence is provided on the capability of these indices to work as successful predictors of the macroeconomic conditions in the economies of our sample. Finally, some propositions are made on how this kind of financial fragility tools can be improved and further research paths are also identified.

JEL Classifications: C43, G01, G15, F37

Keywords: Financial Fragility, Financial Stress Index, Monitoring, Forecasting

1. Introduction

Financial crises are an integrated part of the function of the world economies. Their implications can be quite severe, leading to huge economic and financial losses, together with an unprecedented misallocation of income and resources in the economies. This is a major reason that substantial research effort has been devoted to the study of the effects of financial instability in economic activity, in the last two decades. A considerable number of papers have been published, dealing with this topic, suggesting and empirically applying a series of econometric techniques, mainly trying to offer useful tools for crises episodes' predictions. The results were interesting, but partial, in the sense that most of these models were dealing with specific types of financial upheavals (either balance of payments, banking or currency ones), while the modeling approaches employed could not offer a tool able to capture the current situation in the financial markets, in a timely manner and of a continuous nature. Moreover, the lack of an operational framework for measuring financial stability can be surpassed, through the adoption of metrics characterized as macro-prudential[2]. Additionally, a special interest on important financial institutions is crucial, as well as the incorporation of systemic risk into the tools policy makers and investors use (Borio and Drehmann, 2009). Such tools, satisfying the aforementioned characteristics are the financial stress indices we develop here.

The previously mentioned weaknesses of the crises models can be ameliorated by the utilization of a financial stress index (FSI henceforth), which is a composite indicator, consisting of a series of properly weighted financial variables, offering an overview of the financial markets health. This approach exhibits a number of advantages, like the easiness in the construction, together with the ability to offer a continuous, uninterrupted picture of the conditions in the financial markets. In this paper, we proceed to the construction of such indices for 25 countries, together with the computation of three regional ones, after grouping the countries in their respective bunch (OECD, Asian and Latin American countries). Moreover, we present a global financial stress index, which is the outcome of the aggregation of the three regional indexes. Additionally, an analytical exposition of the type (according to which market

[2] Macro-prudential policies or metrics are those taking into account the financial system as a whole, as oppose to micro-prudential that focuses to individual financial institutions' health.

was the source of each episode, either banking, securities or foreign exchange-related) and the average duration of the financial distress experienced by each country and region, is being provided. As it will be made clear, these indices seem to perform quite well, for most of the regions and countries. It is by no surprise the fact that the current financial crisis, initiated on 2007, has been proved to be the most severe one for most of the countries, at least for the time period that reliable data are available. Hence, we believe that this piece of work contributes towards the creation of a more efficient financial stress index, where efficiency coincides with higher accuracy on signaling forthcoming, financially stressful periods. Beyond this extremely useful feature of these indicators, it should be emphasized that FSIs are a first-rate macroprudential tool. They offer an (almost) live representation of the financial system conditions, rendering the monetary authorities able to prepare for safeguarding the stability of the financial system through the adoption of relevant macroeconomic policies.

Moreover, a forecasting exercise is materialized, aiming to provide empirical evidence on the relation between the financial conditions prevailing in an economy and the respective macroeconomic situation. Efforts to explain the connection between financial markets with real economic activity are timed from the early 90's. Important pieces of research in this respect are those by Estrella and Hardouvelis (1991) and Estrella and Mishkin (1997), among others. In there, the authors achieved to establish a relation between the two sectors. Still, this work can be characterized as incomplete. The main reason is that they only used stand alone indicators, from a specific, narrow financial market, without being able to establish a more general interconnection between the finance spectrum and economic conditions. The modern, complex financial markets require the use of more advanced metrics of the financial conditions, like the financial stress indexes. In this way, a more informative, conclusive picture of the financial conditions is provided. There are proposals for the comparative advantage of composite stress indicators as more powerful predictors of real economic variables[3], like the papers of English *et al.* (2005) and Erden and Tsatsaronis (2013). The recent financial meltdown has stimulated the production of even more research on this respect. Our work aims to extend the relevant literature in many aspects. First of all, we provide stress indices for a large group of developed and

[3] Such variables are GDP, industrial production, inflation, investment etc.

emerging economies. Until now, most papers focus on developed economies (mostly US) or to a small number of countries. Additionally, we proceed to a descriptive analysis and identification of the sources of financial stress for all these countries, based on the root causes of each systemic risk episode signaled by the indices. This is very helpful, especially for monetary policy authorities and their ability to prepare for such events outbreaks and the amelioration of their consequences in the economy. Third, it is shown that our FSI-enhanced model can provide more accurate forecasts for the future economic activity of the economies in our dataset. This is the first attempt to use such aggregate measures of financial risk and stability in such an empirical framework, for such a big and diverse group of economies. Finally, the improved ability of financial stress indices to predict real economic activity is verified by the application of two equal forecasting ability statistical tests. These are the Diebold Mariano test and the second one is the test of Clark and West (2007). There is very strong evidence in favor of using such aggregate indicators, especially for the case of OECD countries.

This paper is organized in five sections, the contents of which are as follows. In section 2, an exhaustive review of the financial stress literature is offered. Section 3 provides a description of the data, together with an analytical presentation of the empirical approach implemented in the construction of our financial stress indices. Section 4 discusses the results of our financial stress indices' construction work, while the section 5 develops a model for testing the forecasting properties of a FSI-augmented model. Finally, section 6 concludes, together with a brief discussion of further research paths, able to improve these kinds of indices functionality and usefulness as forecasting tools.

2. Financial Stress Indices: An Account of the Literature

The literature on financial stress (or, as some of the authors call them, financial fragility) indices (FSI), has mushroomed the last decade. It is a branch of the research developed as a continuation of the early warning indicators (EWI) literature, models that have been used in previous empirical work on, mainly, currency and banking crises episodes. As it will be made clear, these two approaches on modeling periods of financial crises look similar, although, they have quite distinctive characteristics. First of all, previous models were models analyzing country-specific or only specific types of crises episodes (either, currency, banking or balance of payments crises). The most recent periods of turmoil (especially, the sub-prime crisis beginning on 2007) showed that crises are systemic-wide and are not confined to a single market of the economy anymore. Also, exactly because of this nature of financial crises, there is a need to alter the modeling approach followed up to now, in order to be able to capture this special feature of modern financial abnormalities. Before, wide use of binary choice models (either probit or logit ones) has been made, predetermined in this way the outcome (being a choice between a crisis or non-crisis state) for each time period under consideration. With the FSI approach, a series with continuous values is provided, offering a timely illustration of the market conditions, thus, better monitoring of the financial system is possible. Moreover, most of the work done was focused on developing economies, something justifiable by the fact that these economies were the most vulnerable to periods of financial instability. Recent abnormal periods showed that new tools of monitoring the stability of the financial system are needed, able to anticipate the sources of financial stress and, most importantly, to be easily implementable and used as forecasting tools, in order to provide accurate and swift indication of forthcoming periods of instability. The relevant literature, discussed here, provides some answers to these complex and interesting issues.

This section is divided into three main parts. In the first one, we provide a synopsis of studies, aiming to provide a definition and the basic feature of financial stress. As Allen and Wood (2006) comment, the aforementioned concept is not that clear from the economic and financial literature, in contrast with the idea of price stability. This vagueness of financial stress is, potentially, one of the reasons that central banks failed, until recently, to accommodate the need of safeguarding this aspect of the financial system. Then, we proceed to an exhaustive overview of the financial stress indices literature. First, a discussion of the papers related with developed economies is given, while the last part of this literature review copes with aggregate financial conditions metrics for emerging markets. Our main focus here, apart from the construction of financial stress indices for the twenty five countries of our sample and the regional and global index, is the predictive power of such indices for the real economy. Thus, the analysis in the aforementioned two sections of the survey deal with forecast models for, both, real economy's variables, as well as future financial stress level.

2.1 An Attempt to Define Financial Stress

One of the challenges financial economists face is the formulation of a complete and well-rounded definition of financial stress. It is a notion hardly definable and measurable, compared to concepts like price stability or inflation targeting[4]. A very brief, but obviously incomplete, definition of this concept is offered by Illing and Liu (2006), where they define financial stress as the force exerted on economic agents by uncertainty and changing expectations of loss in financial markets and institutions. A relatively broader, but more representative (of the interacting forces within a financial system), definition of financial stability (this time) is provided by Gadanecz and Jayaram (2009). They mention that "Financial stability encompass the smooth functioning of a complex nexus of relationships among financial markets, infrastructures and institutions operating within the given legal, fiscal and accounting frameworks". Thus, a dysfunction in any or some of these channels of interaction can lead to a financial stress period. Also, such a definition is inclusive, in the sense that gives a clearer idea of the importance of the financial system for the whole economy.

A major contribution to the creation of a definition for financial stability is made by Allen and Wood (2006). In their paper, the authors underline that the wording "financial stability" has not been used by central bankers, up until 1994. In their view, in order to be able to formulate a clear and understandable definition, it should satisfy the following desired features. It should be related to welfare effects on the economy; it needs to define something observable by the public, while it also should be something controllable by the public authorities. Moreover, a clearly defined political entity has to be responsible to accommodate for the stability of the financial system and, on the same time, the definition should be broad enough. In this way, the whole spectrum of instability sources (like financial and non-financial institutions, sovereigns and others) would be included, something quite crucial for the

[4] As it is commented in Gadanecz and Jayaram (2009), very few central banks include any quantifiable measure of financial stability to their Financial Stability Reviews, compared to indicators of economic activity incorporated to their annual or semi-annual reports.

measurement of the current financial crisis effects. Finally, the definition does not need to be too precise[5]. Based on the above, Allen and Wood (2006) conclude that time periods during which a large number of economic agents (households, firms, governments) experience financial crises that are not warranted by their previous behavior are periods of financial instability. The most important aspect of such periods is that they have a strong, adverse, macroeconomic effect. As a consequence, financially stable periods are those that incidences, like the previously described, are not likely to happen. This is very important, according to the authors, since it entails the non incorporation of such negative expectations into the agents' formation of economic decisions.

In any case, the proper and accurate definition of financial stress (or financial stability, if someone would like to start from this point) remains an open issue and, probably, this is the main reason for the inexistence of any well-founded theoretical models dealing with such issues.

2.2 Financial Stress Indices: Empirical Work for Advanced Economies

The development of financial stress indices was initiated from economists in developed economies. It is reasonable, since the necessity for such tools was stronger to the economies mostl harshly hit by the recent financial crisis, while this trend was enforced from the failure of previous relevant tools to offer clear indication of the forthcoming financial meltdown. Additionally, a great deal of such research is accomplished by economists in policy making institutions, such as IMF, OECD and central banks. The majority of the papers cope with the US economy, while there is growing interest from other countries around the world and, especially, from Eurozone. Here, we provide a detailed account of the different approaches used to construct such aggregate stress indexes for advanced economies. As mentioned before, the focus here is also on papers proceeding to forecasting exercises, for the real economic activity, as well as for projections of the level of financial stress.

Apart from their effort to provide a conclusive definition for financial stability, Gadanecz and Jayaram (2009) provide an excellent review of the empirical work done on this topic up to now. They supply an exhaustive account of the different

[5] The argument behind this has to do with the necessity to avoid cases of false alarms. These are cases where the financial system becomes more turbulent but not into a crisis period.

quantitative measures used in the relevant literature, by segregating them to sectors of the economy. In particular, the real sector of the economy is described by GDP growth, inflation and the fiscal position of government, measures that can depict the risk of overheating of the economy. Then, regarding the corporate sector, its stability can be evaluated by its leverage and expense ratios, together with the foreign exchange exposure risk and the corporate defaults. The household sector is important in this kind of research as well, where emphasis has been given to measures reflecting their net assets and net disposable income. Real exchange rates, foreign exchange reserves, capital flows and currency mismatches have been used as indicators of the conditions prevailing in the external sector of the economy, while, the financial sector's situation is mirrored by monetary aggregates, real interest rates, banks' capital and liquidity ratios, credit ratings and the banks' lending activities. Finally, regarding financial markets, the most frequently measures are equity indices, liquidity premia, corporate bond spreads and volatility measurements. The authors proceed to a survey of a series of developed and emerging economies central banks' financial stability reports, aiming to investigate whether they use any composite indexes of financial stability. Surprisingly, the outcome is quite disappointing, with most of them not utilizing any such indicator or, at the best, tracking only partial ones (only for some of the markets of the economy). Those central banks' reports containing a unified index are quite diverse, in the sense that the sample includes institutions from both developed (Swiss National Bank) and developing (Czech National Bank, Hong Kong Monetary Authority) economies and, also, such measure are quite recent additions in these reports (they are traced not more than two or three years back). Hence, according to the authors, there is still great scope for research and implementation of such indices, not only because they are advantageous (compared to indices depicting the conditions in single sectors of the economy) but, also, because the challenge of using such quantitative measures as forecasting tools for the onset of financial crises, largely, remains unanswered.

Further stimulation and feedback on what kind of variables should be included to composite systemic risk indicators is given by Nelson and Perli (2007). Here, the authors discuss a number of financial indicators Federal Reserve monitors, in order to gauge the financial system's stability. There is a range of single and composite indexes, covering interest rates and asset prices-based measures, like bid-ask spreads and securities trading volumes, liquidity premiums (yields of less liquid securities –

yields of highly liquid ones), yields between riskier and less risky assets and, also, equities premium and interest rates (as well as stock prices) options. They also present indicators from the mortgage market (like the average duration of fixed-rate mortgages, included to mortgage-based securities), while indicators for individual (financial and non-financial) institutions are also monitored from the FED (creation of CDS indexes, based on weighted average value of them, since it is believed that CDS are more representative of the market conditions, compared to corporate bond yields). This is an interesting piece of work, but it should be emphasized the fact that it does not discuss or present the most recent work conducted by FED economists, in the construction of financial stress indices. Nevertheless, it does offer a good starting point, especially for the choice of indicators that can be useful and informative for the composite stress indexes.

In their work, Illing and Liu (2006) outbid for the creation of an FSI as a well-suited index of financial stress for developed economies, compared to other early warning indicators. According to their justification, such a stress index is more suitable because it is a continuous, high frequency reference variable, covering a range of markets (equity, bond, forex and banking ones), and hence, takes into consideration the complex issues of financial stability in advanced economies. The authors are mainly interested into three tasks here. First, they want to specify which time periods can be considered as stress periods for the Canadian economy, then which variables they should use to create their FSI and, finally, which one of the different FSI's they compute is the most efficient. For the first task, they conducted a survey within the Bank of Canada economists, collecting answers on a series of questions. Then, having specified the financially abnormal periods, they experiment with different methodologies and a series of variables, in order to develop a financial stress index for the Canadian economy. They construct three measures of financial stress. The first one is the standard measure, as they call it, where the variables used are those proposed by the relevant literature on the financial markets (and described afterwards), the second one, called the refined measure, contains only those variables that can be refined and, thus, potential extra information can be extracted and, finally, a measure based on GARCH techniques is constructed for the "price" variables (Canadian general and banking sector equity indices and the Can$/US$ exchange rate). In particular, the variables that were included to their index are the following: the beta of the Canadian banking equity index and the bank bond yield spread (from the long-term governmental bond yields), representing the situation in the banking sector of the country. Here, the refined measure consists of two conditions that set a threshold for the values of beta, being higher than 1 and the returns to the bank index to be lower than the overall market returns[6]. For the foreign exchange market, they focus on the Canadian dollar volatility, using the CMAX calculation as a measure of it[7]. For the refined approach, they implement the following model, in order to gauge the exchange rate to its short-run fundamental value:

$$\begin{aligned}\Delta \ln\left(rfx\right)_t &= \alpha \ln\left(rfx\right)_{t-1} - \beta_0 - \beta_c \ln(comtot)_{t-1} - \beta_e \ln(enetot)_{t-1} \\ &+ \gamma \operatorname{int} dif_{t-1} + \theta \Delta debtdif_{t-1} + \varepsilon_t\end{aligned} \qquad (2.1)^8$$

The idea behind this approach lies in the avoidance of false financial stress signals from the foreign exchange market. Since Canadian economy operates with a free floating exchange rate regime, a depreciating currency (that would, potentially, imply an increasing likelihood of a currency crash) is not necessarily against the stabilizing process of the economy. That is why the authors use model (1.1) to estimate the Canadian dollar's fundamental value, based to its fundamentals.

Then, regarding debt markets, they use the Canada-US covered interest differential and the corporate bond yield spread (from the long-term government bond yield) as indicators of the prevailing credit risk in the market, while, liquidity risk is captured here from three variables: the treasury bill bid-offer spread, the so-called TED spread, which is the difference of the commercial paper rate from the treasury bill rate and, finally, the inverted yield curve (long-term government bond yield – 90-day commercial paper rate). The refined measure of risk spreads is obtained by creating a threshold value, which fractionate the excessive corporate bond spreads from the lower values (which represent a tranquil period in the debt markets)[9]. Lastly, the conditions in the equity market are represented by the equity risk premium:

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[6] In this way, it is implied that, whenever these two conditions hold, the banking sector might confront higher stress, compared to the rest of the market. Whenever these two conditions are not satisfied, a value of zero has been put to the refined series.

[7] $CMAX_t = x_t / \max[x \in (x_{t-j} | j=0,1,..,T)]$, where x_t = value of canadian dollar vis-à-vis US dollar and T=one year time period.

[8] Here, rfx is the real exchange rate, comtot is an index of real non-energy commodity prices, enetot an index of real energy prices, intdif the Canada-US 90-day commercial paper rate differential and debtdif is the Canada-US debt/GDP differential.

[9] The threshold is estimated by a simple OLS regression, where the corporate bond yield is the dependent variable and the exogenous ones are the Moody's Issuer Based Default Rate, the 10-year

$$p_t = \left[\sum_{i=1}^{t+12} \mathrm{E}_i \mid \Omega_i \right] / P_t - r_t \qquad (2.2)$$

which is the outcome of the deduction of the annual return to equities from the risk-free real return on governmental bonds[10]. Trying to further refine their work, Illing and Liu (2006) apply different weighting scheme on their variables, so as to identify which one leads to the creation of a single FSI that outperform the rest of them and, consecutively, is the most efficient in capturing period of financial turmoil. They try four methodologies, factor analysis (which uses weighted linear combinations of the variables), credit weights (the contribution of each market to the total credit available in the Canadian economy is the important factor here), the variance-equal weights approach (by standardizing each variable by subtracting its mean and dividing the result by its standard deviation) and they also use the variables cumulative distribution functions to combine them (this scheme requires the transformation of each series into percentiles, based on its CDF and, then, average them using their arithmetic and geometric means). Based on the different indices' performance (in terms of Type-I and Type-II errors, as defined by their survey for extreme events in the Canadian economy and the capability of the indices to capture them), they conclude that the best financial stress index seem to be the credit-weighted one, although, in individual markets, some other indexes might perform quite well (for example, the GARCH measure for the stock market).

A, somehow, substitutionary approach has been followed by Aspachs *et al.* (2006), in order to create a metric of financial fragility. The advantage of their approach, according to the authors, consists on the use of a general equilibrium model [compared to the atheoretical method followed by Illing and Liu (2006)] to decide which variables to use on their index and, additionally, the construction of such indices for seven, instead of one, countries. More precisely, their model is a micro-founded, general equilibrium one, where the assumptions of endogenous default and heterogeneous agents are made[11]. An important aspect of such a model is that,

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governmental bond yield, the Bank of Canada reference rate and the Commodity Research Bureau's price index.

[10] Here, it is easily palpable that high equity risk premium would indicate a period of financial stress in the market.

[11] This is the model developed by Goodhart *et al.* (2006).

because it is based on the heterogeneity assumption, it allows dealing with a banking sector which consists of institutions with different exposure to credit risk and, because of this, they face different probabilities of default. Through numerical simulation and calibration of the model to values for the British banking system, they conclude that “The crucial aspects of the impact of shocks on the banking system are contained in two factors, bank profitability and bank repayment rate [i.e. probability of default (PD)]. Hence, they attempt to find out the variables that represent these two factors and the most appropriate weighting scheme to use, in order to end up with a financial (in-) stability indicator. In order to decide upon the necessary variables to include, they examine the welfare effects (in terms of adverse consequences on the growth rate of GDP) of a series of them, specifically, the percentage change in banking sector equity values, the country-specific banking sector PD (using the so-called distance to default indicators, developed by IMF), inflation (percentage change on CPI), property prices and short term interest rates. Implementing individual country’s VAR and a panel VAR methodology, they verify the predictions of their theoretical model (for the importance of bank profitability and PD’s as crucial for the stability of a financial system). Finally, in order to obtain a single index of financial fragility, they proceed to a variance decomposition technique, derived by a panel VAR, to decide upon a weighting scheme for their index. Thus, they calculate a financial stress measurement by considering that a country’s welfare is 90% affected by PD’s and only 10% by equities values.

Even though the use of this kind of financial distress indexes is not yet that much popularized, especially among the policymakers, a considerable effort is being made to introduce such policy tools in the central banks’ financial monitoring ammunition, especially from economists of the US Federal Reserve System. A recent example of this is the work done by Hakkio and Keeton (2009), who introduced the Kansas City FED FSI (KCFSI). Their index consists of eleven variables, representing one or more of the features financial stress has. These are the increased uncertainty for the fundamental value of assets and the behavior of other investors, while the increased asymmetry of information and the decreased willingness to hold risky assets (the so-called “flight to quality”) are also important determinants of it. Finally, the flight to liquidity (as the decreasing holdings of illiquid assets is know) also contributes to heightening financial turmoil. In more details, KCFSI consists of the following variables: the TED spread (3-month LIBOR – Treasury bill rate), the 2-

years swap spread (which is the difference between a floating rate payment, based on LIBOR, from a fixed rate payment, which derives from the treasury bill rate, augmented by a premium), the yield differential of previously issued securities from the most recently issued one, of the same maturity (called as the off-the-run – on-the-run ten year treasury spread). Additionally, a number of bond spreads are also included in this index[12], together with the correlation of the stock returns with the two-year governmental bond yield, the implied volatility of the stock prices[13] and the idiosyncratic volatility of the bank stock prices (calculating as the standard deviation of the banks stock index daily returns from the S&P 500 index). Finally, the KCFSI is completed with the inclusion of the cross-sectional dispersion of bank stock returns (computed using the interquartile range of banks' stock returns). The authors have used principal components analysis to decide upon the weights of each of these variables, while they employed monthly data for the period February 1990 to March 2009. Inspecting the performance of KCFSI, they show that it works relatively well, with only two financial crises (the Mexican and the Asian ones) not being captured by the index (according to the authors, because of the limited spillover effects of these episodes to the US financial markets). In order to test for the effect of financial stress to real economic activity, the authors proceed to a comparison of the KCFSI values with the SLOOS values[14]. Regressing SLOOS to lagged values of it and of KCFSI, they found out that KCFSI tends to lead changes in credit standards, while the same holds for the interrelation of KCFSI with CFNAI (Chicago FED's index of economic activity). Econometric estimations indicate that KCFSI helps predicting CFNAI values, showing that financial stress can lead to slower economic activity (also, the previously established relation of KCFSI with SLOOS implies such an adverse effect of financial conditions to the real economy, through the changes on the credit standards). Through impulse response analysis, the authors support that a financial shock negatively affect CFNAI, even though the effect is not big enough to create, by itself, a recession.

An investigation of the relation between US financial conditions and economic activity, through the use of both single and composite financial indicators, has been

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[12] These are the Aaa – 10-year government bond spread, the Baa – Aaa bonds spread, high yield (i.e. junk) bond - Baa bonds spread and the difference between consumer ABS from 5-years Treasury bond.

[13] The authors use the well-known CBOE volatility index, mostly known as VIX index, representing the expected volatility in S&P 500 index in the options market.

[14] It is an index showing how tight credit standards are.

accomplished by Hatzius *et al.* (2010). Apart from the empirical work, this paper provides an excellent theoretical account of the importance of the financial conditions for, both, the assessment of the monetary policy decisions effectiveness and the future economic activity. A detailed discussion of the monetary transmission mechanism – financial conditions nexus is provided, together with a summary of a number of financial conditions indices built up until now, together with their features. Their final target is the creation of a new FCI which overcomes the limitations of the previous ones. These are the limited time span, the exclusion of important financial conditions because of the aforementioned limitation and the lack of purification of previous indexes from the effects of the business cycle and of the monetary policy changes (as they are projected on the financial indicators incorporated to them). Thus, they decide to use 45 indicators for their new FCI, indicators representing interest rate spreads, asset prices, quantities and survey indicators. Two are the main criteria for the choice of variables, the wider time coverage, comparing to previous FCIs and the long data history, going back at least to 1970's. In order to construct this aggregate index, they use principal components analysis, but with some special characteristics (compared to previous cases): first, the authors allow for unbalanced panels (meaning that the data series do not cover the same time period, nor are they of the same frequency), second, they eliminate the variability of the included indicators which can be attributed to current and past influence of real economy variables and, finally, they use more than one principal components in the analysis. Their model has the following form:

$$X_{it} = \mathrm{A}_i(L)Y_t + \nu_{it} \tag{2.3}$$

$$\nu_{it} = \lambda_i F_t + u_{it} \tag{2.4}$$

where X_{it} = financial indicator i, Y_t = vector of macroeconomic indicators and ν_{it} = error term uncorrelated with current and lagged valued of macroeconomic indicators. Hence, the error term represents the financial variables purified by the business cycle effects which, in turn, is decomposed to the F_t=kx1 vector of unobserved financial factors that capture the co-movement of the financial indicators. This vector should be estimated for the acquisition of the FCI. Based on the approximate dynamic factor models' literature, which suggests that least squares estimations of this vector are accurate for use in forecasting exercises, the authors consider this approach to obtain estimates of F_t. The process is the following: first, they regress each individual financial indicator onto the current and two lagged values of the relevant macroeconomic variables (here, they use GDP and inflation) and they extract the residuals of these regressions as estimates of v_{it}. Then, through equation (1.4), they estimate the factors (vector F_t). The R^2 criterion provides evidence of great variability on the number of factors that achieve the best fit for each series. Thus, the authors decided to consider models with one, two and three factors. Nevertheless, there seems to be consensus on the loadings signs (negative ones for interest rate spreads, positive for credit flows and asset prices indicators). Inspecting the performance of the FCI, it is found that it behaves similarly to the previous indices, with the exception of the second half of 2009, where it shows a further worsening of the financial conditions. Proceeding to the evaluation of the forecasting accuracy of this and previous FCIs, the author firstly test the predictive ability of a number of single-variable financial indicators. These are the term spread (10-year Treasury note – federal funds rate), the real M2, the S&P500 stock index, the level of federal funds rate and the short-term credit spread (3-month commercial paper rate – 3-month Treasury bill rate). Using these indicators, they try to predict (in 2 and 4 quarters ahead) the growth rate of the following macroeconomic variables: real GDP, payroll employment, industrial production index and unemployment rate. They do it both in- and out-of-sample, while the regression specification is

$$y_{t+h} - y_t = \beta_0 + \sum_{i=1}^{p_y} \phi_i \Delta_{y_{t+1-i}} + \sum_{i=1}^{p_x} \gamma_i x_{t+1-i} + e_{t+i} \tag{2.5}$$

with y_t representing the real activity indicator in each case, while x_t is the respective financial indicator. The number of lags, for both cases, was restrained to four. For the post-sample prediction, the authors use the same specification as previously, recursively estimated through the end of the sample period (fourth quarter of 2009). Here, lags for the explanatory variables were chosen according to the BIC criterion. The out of sample forecasts constructed for the period 1971Q1 onwards and they were compared with forecasts from an AR model (that is, excluding the financial indicator variable). For the in-sample forecast, it is found that the financial indicators are useful in explaining the variability in real economy variables, for both two and four quarters ahead. Apart from the stock market index, the rest of them present high instability, something that can be possibly attributed to changes in the financial structure of US economy through time. Regarding the out-of-sample prediction results, the models with financial indicators provide satisfactory results, only until the mid-80's. Additionally, they become in par with the simple AR model in the most recent period (last five years), while S&P500 and the credit spread did quite well the last decade. Checking the out-of-sample predictive performance of a number of FCIs[15], the improvement on the forecasting accuracy is general, especially at periods which are recognized as financially stressful ones. But, on average, they are not better than the stock market index, while the most noticeable improvement for the FCI model performance is during the last decade. Moreover, during the 90's, some of these financial conditions index are not better than the simple AR or the single indicators models. The results are rather mixed but this does hold for the authors' FCI, which performs better than the rest of the models (and the previous FCIs models) for the last five years, but not for the second half of the 1990's. In the last section of this paper, the authors provide an evaluation of the innovative characteristics of their FCI, in terms of its forecasting performance. Thus, they first recalculate the index by using only a balanced panel of series (the longest ones). In this way, they found that the baseline FCI works better as a prediction tool. Then, they disaggregate the index into five subgroups of indicators and test each group's predictive performance. Again, no single group performs better than the aggregate FCI. Also, the FCI where the macroeconomic influences are not excluded [represented by the GDP and inflation in the Y_t vector in equation (1.3)] is compared with the baseline one and the result is in favor of the one for which these effects are purged, but only for the period since early 1990's. Finally, when also the federal funds rate is excluded from the composite index construction, the forecasting performance of this index is similar to the benchmark one, an indication that pure monetary shocks do not contribute much to the prediction of future economic activity. All in all, Hatzius *et al.* (2010) financial conditions index is effective on predicting economic activity, especially in times of high financial distress. Otherwise, results are mixed.

In order to overcome the predicaments of the existence of a wide number of interesting financial series with different time spans and frequencies, which could be

[15] The authors do this using the same specification as in equation (13), but this time the individual financial indicator x is replaced by the FCI under consideration each time.

used in the construction of a composite financial stress indicator, Brave and Butter (2011) use a dynamic factor model that allows the inclusion of unbalanced series in the index. In this way, they take into account one hundred financial indicators for the US economy, with different frequency and time coverage (47 of them are weekly, 29 monthly and 24 quarterly series, covering the period 1971-2010). In broad terms, their model consists of the following equations:

$$X_t = \Gamma F_t + \varepsilon_t \tag{2.6}$$

$$F_t = \mathrm{A} F_{t-1} + \nu_t \tag{2.7}$$

where X_t = financial indicators matrix, Γ = factors loadings, A = transition matrix and F_t = factors matrix. The transition matrix represents the evolution of the latent factors over time. In this model, the authors define the model's dynamic structure to be of finite order, namely, 15 weeks (lags). By estimating Γ, they extract their FSI. As it is obvious, this model is similar to the one discussed in the previous paragraph. Additionally, in order to capture the effects of the economic conditions (apart from the financial ones), they compute the so-called adjusted-FSI, by including the aforementioned CFNAI index and inflation in their estimation procedure. They do so by, first, regressing each individual financial indicator on current and lagged values of CFNAI and inflation and, second, the standardized residuals from these estimations are used in the construction of the adjusted-FSI. By inspecting these two indices, they conclude that both perform well, except a few cases where they do not (especially at the beginning of their sample in early 70's). Finally, the authors perform a forecasting exercise, similar to the one proposed by Hatzius *et al.* (2010) and, also, conducted here. Questioning whether FSI predicts any impacts of financial conditions to economic activity, they try to check whether the predictive ability of a model where the FSI is included, is superior to a simple AR model which includes only autoregressive lags of a number of macroeconomic variables. The model used for this forecasting exercise is

$$Y_{t+h} - Y_t = \alpha + \sum_{i=1}^{I} \beta_i \Delta Y_{t+1-i} + \sum_{j=1}^{J} \gamma_j CFNAI_{t+1-j} + \sum_{k=1}^{K} \delta_k FCI_{t+1-k} + \varepsilon_{t+h} \tag{2.8}$$

where, Y_t is the logarithm of the macroeconomic variables[16], $CFNAI$ the 3-month moving average of CFNAI and FCI the 13-week moving average of adjusted FCI, FCI residual or adjusted FCI residual[17] (depending on specification). They recursively forecast for horizons of 1, 2, 4 and 6 quarters ahead, starting with data from 1973Q1 through 1984Q4. The evaluation is done through the calculation of the mean squared forecast error (RMSFE) ratio, which provides the ratio of the AR forecasts of the macroeconomic variables over the aforementioned model. If RMSFE <1, there is an improvement on predictive accuracy, when a version of the financial stress index is included in the model. According to the results, the inclusion of the FCI residual (together with the CFNAI) improves forecasts at every horizon and for every variable. Similar results, using again a dynamic factor model for the construction of FCIs for US and Euro Area, are obtained by Matheson (2012). Again, for different GDP forecast models, the FCIs are shown to be a very useful indicator for foreseeing the evolution of economic activity.

In their next paper, Brave and Butters (2012) compare their approach to financial stability examination, to a patient's health check. They consider a number or interesting research questions, like whether the risk for the financial system is the same or not whenever an economy faces low or high values of a stress index. Also, they try to provide an answer on the perceived "normal" level of financial stress and how well it can be captured by the economic tools in use. In order to answer the aforementioned, they employ an aggregate stress index (based on the methodology used in their previous paper, they name it Chicago FED FCI). The accuracy of their index is tested, using an epidemiologic tool, called receiver operating characteristic (ROC) analysis. ROC is a non parametric approach, based on curve analysis. It helps on assigning each time period as a crisis or non-crisis period. Through this approach, the FCI evaluation can be accomplished, based on whether the index can capture deteriorating financial conditions, when prior knowledge for past financial crises exist. The past information is based on the crisis dating work produced by Laeven and Valencia (2010) and Lopez – Salido and Nelson (2010). The outcome of their empirical work shows that their index is highly predictive, both in contemporaneous

[16] These are GDP, Gross domestic purchases, Final sales, Nonfarm private inventories, residential investment, and nonresidential investment, PCE: durables, PCE: nondurables and PCE: services.
[17] FCI residual and adjusted FCI residual are the portion of the FCI and adjusted FCI that cannot be predicted from the index's historical dynamics. In other words, it corresponds with the error term from the transition function (12).

form, as well as for one and two-years ahead horizons. In order to verify the improved ability of their index on projecting future financial conditions, the authors compare its ability with the forecasting performance of other well known stress indices of the US economy (KCFSI, IMF FSI, STLFSI, credit/GDP measure of systemic risk and bank conditions measures taken from the previously mentioned crisis dating papers). In this comparison, they find a relatively better performance for Chicago FED FCI, especially for short term predictive horizon (less than a year).

The creation of synthetic stress indexes for the US banking sector has been attempted by Puddu (2008). In doing so, the author implements two approaches, the signaling one and the qualitative response analysis, in order to identify the weights to be assigned to the individual indicators included in the composite stress index. Then, their appraisal is conducted by comparing his results with indexes constructing with the two most popular aggregation techniques (these are, the variance-equal weights and factor analysis). Six variables are used in this index, covering the period 1984 through 2007, in quarterly frequency. These are the returns on assets (ROA), net loans losses/average total loans (LSTL), non-performing loans/total loans (NPTL), loan loss reserves/total loans (LLRTL), net interest margin (NIM) and the number of commercial banks failed (FAILS). At first, Puddu defines stress periods by taking into account the number of failed banks in each quarter. Then, regarding signaling approach, he defines the "noise" of each indicator included in the aggregate index, according to its type I (i.e. the existence of a crisis episode not captured by the indicator) and type II (no crisis but signal by the indicator) errors. In functional form, the noise-to-signal ration is

$$n_i = P(no\ alarm \,||\, crisis)/1 - P(alarm \,||\, no\ crisis) \tag{2.9}$$

As it can be easily concluded, the lower the noise, the higher the indicator's weight will be. After deciding about the weights in this way, the bank stress index is computed as

$$\text{Stress} = \mathrm{w}_1 ROA + w_2 LSTL + w_3 NPTL + w_4 LLRTL + w_5 NIM \tag{2.10}$$

For the second methodology (qualitative response analysis), the author uses the so-called zero-inflated regression approach, which employs a Poisson and a negative binomial distribution for the dependent variable[18]. This approach seems to have some advantages, mainly because of the many zero values that FAILS have (many quarters on which there were not any bank failures). The regression estimated is represented as follows:

$$y_t = \begin{cases} G(Z_{it}) + \varepsilon_t \text{ if } y_t = 0 \\ F(X_{it}) + \eta_t \text{ if } y_t > 0 \end{cases} \tag{2.11}$$

The first part of this specification takes care of the elements affecting the zero values of FAILS, while the second one is for the non-zero part of the dependent variable. Z_{it} and X_{it} are vectors of the explanatory variables used in the estimations (mentioned above). Under this analysis, the authors constructs a number of indices, according to the signs ascribed to the individual indicators, first according to what economic theory suggests for them, then based on the signs found for them during crisis periods and, finally, according to the signs of the estimated coefficients. The outcome is promising, with good performance from the stress indexes, capturing periods of banking abnormalities and recession periods. The results are quite similar to the one provided by the variance-equal approach (especially for the index compiled with the signaling approach). Finally, by using lagged macroeconomic variables (specifically CPI, GDP, credit ratio[19], median price of sold houses), a prediction of the bank stress index has been done, with mixed out-of-sample results.

The Cleveland Financial Stress Index (CFSI) is created by a team of economists at Cleveland FED. It is a systemic stress index for the United Stated, the background of which is presented in Oet *et al.* (2010) and their subsequent paper on 2011. They are mainly interested in the construction of an early warning system for the adequate supervision of the markets, as well as for the proper identification of systemic risk. In order to do it, they combine tools and methods of micro-prudential and macro-prudential nature. In their own words, the necessity for such an aggregate financial stress index is derived from "…lack of tools for identification of systemic-

[18] Remember, the dependent variable is the number of banks failed each quarter (FAILS).
[19] It is defined as the ratio of the sum of assets and liabilities of US commercial banks over GDP.

level distress. Without an early warning tool to identify the onset of symptoms of a banking crisis, the ability of the Federal Reserve to carry out its core financial stability functions is increasingly inhibited"[20]. The authors offer a well rounded discussion of what should constitute a useful and operationally efficient EWS for systemic stress. In addition to effects from asset prices, spreads and macroeconomic conditions, they input explanatory variables that represent risk-taking behavior, aspects of financial fragility, financial firm's connectivity and contagion risks. So, they choose to incorporate series of daily frequency from four different financial markets: interbank market (financial beta, bank bond spread, interbank liquidity spread and interbank cost of borrowing), foreign exchange market (weighted dollar crashes), credit markets (covered interest spread, corporate bond spread, liquidity spread, commercial paper to treasury bill spread, Treasury yield curve spread) and, finally, equity market (stock market crashes). The aggregate index is constructed in the following way:

$$FSI_t \overset{m}{=} \sum_j \left[w_{jt} \int_{-\infty}^{z_j} f(z_{jt}) dz_{jt} \right] * 100 \qquad (2.12)$$

z is the value of each indicator j at time t, where each one of these variables is transformed according to its cumulative distribution function (CDF). The weighting scheme followed (w_{jt} represents the weights) is based on the FED's Flow of Funds statistical table. According to this, each sector's total dollar value over the aggregate dollar value of all flows of funds in the economy represents the weight for each one of the four markets involved in this index construction. Finally, the authors transform the daily index into quarterly frequency by averaging the FSI's values for each quarter. The CFSI is maintained and regularly updated by the Cleveland FED.

A thorough review of the US financial stress indexes is provided by Kliesen *et al.* (2012), together with a forecasting exercise. In their survey, authors discuss the potential difference between FSIs and FCIs. In general terms, they conclude that the two types of indexes have significant overlap, both in terms of the stand alone indicators included, as well as to the weighting methodologies followed. Focusing in the case of US economy, it is reasonable to find that the US indices cover longer time

[20] Their first paper, in 2010, deals with an EWS for banking instability, while their work for the CFSI is completed in the following paper in 2012. In both cases, however, the methodological approach is not different and their aim is the capture of systemic risk.

periods, given the abundance of information and time series available. They also point out the lack of relevant research for emerging markets, since most work has been done for developed countries (since more data are available for those). Then, the variables most frequently used in US indexes are discussed. As it would be expected, economic fundamentals, yields and interest rate spreads (measuring term premiums or liquidity premiums), stock market indicators, volatility and foreign exchange indicators are some of the most frequently used variables. Regarding the aggregation methodologies, it is very common to standardize them (in order to avoid any predicament with the different measurement units and values of the variables) and, then, equally weights, PCA-based or model based aggregation approaches are the most popular. Finally, the authors provide some empirical evidence, in relation to the effect of financial stress on real economy. Initially, the provide evidence of negative correlation between financial stress and economic growth, represented by year-over-year changes of US industrial production index. Then, they estimate a VAR model, with industrial production and GDP growth rates, a US stock index (Wilshire index) and FSIs as endogenous variables. The forecasting exercise is conducted for horizons up to 12 months ahead. The indices evaluation is based on the root mean squared errors (RMSE). Based on this, they find little variation, in terms of ability of aggregate systemic risk indices to forecast real economic activity. FCIs are better in predicting real economic variables, while FSIs are better performers for stock market forecasts. Finally, both are equally good on forecasting GDP growth.

Another paper, dealing with the US financial conditions and their relation with economic activity, is the one by Beaton *et al.* (2009). In order to do this, these researchers construct two financial conditions indices: one based to a structural vector error correction (SVECM) model, while the other one is the outcome of Bank of Canada's MUSE general equilibrium macroeconomic model. In both cases, the effects of current and past financial shocks are taken into account to GDP growth effects. In the previously mentioned cases of indices, the variables employed are not exactly the same. In the SVECM model, they include the commercial paper rate, a business borrowing spread, the lending standards for consumer spending and the financial wealth. In the latter case, the dataset is richer, including the federal funds rate, a business borrowing rate, lending standards for consumer spending (as well as for mortgage loans), the lending standards for business investments, the financial wealth and, finally, the mortgage interest rate together with the real effective exchange rate. Their indices are aggregated, following

$$FCI_t = \sum_{j=1}^{n}\left[\sum_{i=1}^{m}(r_{t,jt-1})\right] \qquad (2.13)$$

The term in the brackets is the response of GDP growth to previous financial shocks. The sum of the GDP growth responses to each financial shock, in each time period, produces the FCI. Based on this, the authors find that, on average, US financial conditions are liable for 5% shrinkage to US growth rate for the fourth quarter of 2008 and the first and second quarter of 2009. Another interesting finding here has to do with the zero lower bound, a situation prevailing in the monetary policy of the US economy. The inability of the FED to stimulate the economy with lower interest rates is estimated to have reinforced, by almost 40 per cent, the negative effects of tightening financial conditions on the level of GDP.

An exploration of the predictive ability of 12 US financial stress indices on stock returns and a number of macroeconomic variables is carried out by Aramonte *et al.* (2013). Their modeling approach is based on the following model:

$$y_t = \alpha + \beta \times FCI_{t-1} + \varepsilon_t \qquad (2.14)$$

which is a simple regression model, incorporating lagged values of the stress indices as explanatory variable. The dependent variables include the well known S&P 500 index, seven equally weighted portfolios of equities (finance, construction, manufacturing, wholesale trade, retail trade and services), total credit (consumer credit, together with commercial and industrial loans), housing starts and manufacturing activity[21]. Their predictions are performed on monthly and quarterly basis and their main finding is that eleven out of the twelve tested indices can predict returns on finance portfolio, while only four for the S&P 500 index. Nevertheless, the RMSE are quite different in most cases, something indicative of the varying level of forecast accuracy. This is attributed by the authors to the phenomenon of non-

[21] Here, it is defined as the sum of durable goods orders, industrial production and total manufacturing inventory).

synchroneity. Since many indices include the VIX index, produced by options trading, they believe that the fact that derivatives trading stops 15 minutes after the actual trading of the underlying assets stops, can create this previously mentioned phenomenon and, hence, affects the predictive ability of the relevant stress indexes. The authors proceed to a number of extra checks of the forecasting ability of the FCIs, first by excluding the first day of each month from the sample[22] and, then, by excluding the crisis period (after 2007) from the model's sample. In the latter case, the forecasting capability of the indices is eliminated whatsoever. Similar conclusions are reached, when the macroeconomic variables are the subject of the projections. As a result, the researchers try to create a composite FCI, derived from the existent aggregate indicators. Their rationale is to avoid the sketched lack of consistency in the forecast results. In order to do this, they sort indexes according to how well they can capture information in the rest of the FCIs. This is achieved by using the adjusted R^2 from a regression of the changes in the first principal component of an index i from changes in the first principal component of the rest of the indices. Based on this approach, the best five indexes are chosen. As a second step in this routine, all possible combinations of these five indicators are created. Then, they finally estimate the first principal component of each one of these bunches of indices and follow the same regression process as before. That is:

$$\begin{aligned} PC_{\notin C} &= fpc(\{FCI_j\}_{j\notin C}) \\ PC_{\in C} &= fpc(\{FCI_j\}_{j\in C}) \\ \Delta PC_{\notin C} &= \gamma + \delta \times \Delta PC_{\in C} + \varepsilon_t \end{aligned} \tag{2.15}$$

Based on this analysis, Aramonte *et al.* (2013) note that the first principal component (fpc) of St. Louis Fed, Bloomberg, Chicago Fed and Citi stress indices is the best performing composite FCI of this piece of work.

A different approach on computing an FSI for the US economy is followed by Gallegati (2013). Here, the author adopts the wavelet multi resolution analysis, in order to get the aggregate stress index. On the same time, he evaluates its predictive power over future financial stress level. Wavelet analysis offer additional insights into the series relation, because it can decompose them in, both, time and frequency spectrum. Based on this decomposition, the author chooses the index's components,

[22] In this case, very few (five) indices could predict finance portfolio.

according to their statistical significance in each frequency band. Initially, Gallegati creates an aggregate index with the following components: TED spread, inverted term spread, corporate bond spread, Baa – Aaa spread (these are bonds ratings) and stock market returns. This index is based on simple aggregation and it covers the period 1980 to 2012, in monthly frequency. As a second step, he proceeds to the wavelet analysis, which entails decomposition of each series by applying the so-called maximal overlap discrete wavelet transform. For each one of the time scale components, the variables chosen are the statistically significant ones. Then, sub-indexes, for each one of the frequency components are constructed, weighted accordingly and create the final aggregate FSI. In mathematical forms, the wavelet methodology used, is as follows:

$$I_i \approx S_j[I_i] + D_j[I_i] + \ldots + D_j[I_i] + \ldots D_2[I_i] + D_1[I_i] \tag{2.16}$$

where, $S_j[I_i]$ is the smooth component of the signal and $D_j[I_i]$ the detail signal components (frequency components). Then, the sub-components indices are created as

$$CI_{D_j} = \omega_{1,j} D_j[I_1] + \ldots + \omega_{k,j} D_j[I_k] \tag{2.17}$$

while the final FSI is made up of the previous CI_D's. This means that FSI is

$$CI^w = CI_{S_j} + CI_{D_j} + \ldots + CI_{D_1} \tag{2.18}$$

The author's forecasting exercise used a simple AR model as the benchmark one, while the counterpart is an wavelet-based FSI enhanced model. The models are estimated for the period 1990.1 to 2006.4 and the forecast is produced for the period 2007.1 to 2012.2. The forecast horizons are one, two, four and six quarters. The recursive forecast produces improved results for the model included the FSI, especially for longer horizons[23].

A study of the impact of financial stress episodes on economic activity and the transmission mechanism of monetary policy is supplied by Li and St-Amant (2010).

[23] The forecast evaluation is, once more, conducted using the RMSE.

In this paper, Canada is the country under investigation and a threshold VAR (TVAR) model is employed for the econometric analysis. According to the authors' view, the recent literature on the previously mentioned economic phenomena emphasizes the existence of non-linearities and the respective dynamics (e.g. regime switching in output fluctuations and asymmetries in responses to different shocks). On top of that, the relevant empirical literature provides inconclusive results. As a result, they use a TVAR model, so that they can capture the economic features discussed above. They assume there are two regimes, based on whether financial stress (represented by the Canadian FSI constructed by Illing and Liu, 2006) breaches a certain threshold or not. Regime switching can be endogenous, emanating from changes in other variables as well (like interest rates). The model's specification is

$$Y_t = \Psi_0^1 Y_t + \Psi_1^1(L)Y_{t-1} + \left(\Psi_0^2 Y_t + \Psi_1^2(L)Y_{t-1}\right) I\left(c_{t-d} > \gamma\right) + U_t \qquad (2.19)$$

where Y represents a vector of Canadian data (real output growth, inflation, real overnight rate and FSI). Additionally, Ψ_1^1 and Ψ_1^2 are lag polynomial matrices, U_t are the structural disturbances, while $I\left(c_{t-d} > \gamma\right)$ is the indicator function that equals to 1 whenever $c_{t-d} > \gamma$, 0 otherwise (regimes). It should be noted that Ψ_0^1 and Ψ_0^2 are contemporaneous relationships in the two regimes, where the set causal structure precludes any effects from monetary policy (interest rate) to output and inflation but not on the FSI. Finally, the integer d in the indicator function is unknown and should be estimated along with the rest of the model's coefficients. The sample period for the analysis is 1981Q4 to 2006Q4. The model is estimated using least squares and the empirical work is completed with the employment of impulse response analysis. According to it, contractionary monetary shocks have larger effects on output than expansionary ones, while their negative output effects are bigger in the low financial stress regime. On top of that, such adverse monetary shocks increase the likelihood of moving or remaining to the high financial stress regime, indicating the strong connection between systemic risk and the monetary policy followed by central banks. Higher financial stress is characterized by weaker output growth and higher inflation and interest rates. Finally, it is shown that the effects of, both, small and large shocks are approximately proportional.

Apart from the previously discussed rich literature on, mainly, the US stress indices, there are a number of papers examining the financial stress for a wider group of developed economies. For instance, Guichard *et al.* (2009) create financial conditions indices for US, UK, Japan and the Eurozone. In this case, the weighting scheme followed is product of an OECD large structural model. The calibrated weights differ from country to country, based on each case special features (for instance, bank lending standards are more important for Euro Area and Japan, while corporate bond yields have higher importance in the case of US and UK). As a second approach to the weights computation, the authors use a VAR model, as well as reduced form equations that incorporate output gap in their explanatory variables. In all cases, the size of the weights does not diverge substantially. In brief, their major finding has to do with the severity of the current crisis. In terms of output loss, it is the biggest crisis in history for all the countries in the sample. Also, the widening of corporate bond spreads seem to be liable for almost half of the financial conditions worsening, especially since the third quarter of 2008. Moreover, the stricter credit conditions played a major role in the crisis deepening, while the deteriorating equity prices (especially in US and UK), together with the falling house prices are expected to act as a deathblow to economic activity. Given this perspective, the authors suggest that unconventional monetary policies (like those already followed by central banks around the world) are necessary, in order to overcome the growth obstacles induced by the financial meltdown of the last five years.

An attempt to project financial stress level for 13 OECD economies[24] is made by Slingenberg and de Haan (2011). Three criteria are adopted here, for the inclusion of stand-alone indicators to the aggregate stress index. These are, the coverage of the whole financial system, the availability of data in high frequency and the ability to construct comparable indices. Based on these, they end up using the following variables in their FSIs: stock price volatility (modeled as a GARCH(1,1) process), corporate bond spreads, TED spread, banking sector beta and the real effective exchange rate volatility (estimated in the same fashion as the stock price volatility). The authors' indices are created following the equally weighted approach and they define crisis periods as those periods, where the FSI value is higher than one standard deviation above the mean. In the second stage of their empirical work, the authors

[24] These are Australia, Belgium, Canada, Denmark, France, Germany, Italy, Netherlands, Spain, Sweden, UK and US.

study whether the FSIs and a number of other single financial and economic variables can accurately predict financial stress. They choose 30 variables, classified in the following categories: current account, capital account, financial sector, real sector and asset prices variables. The forecasting model is

$$FSI_t = \alpha + \varphi_m FSI_{t-m} + \lambda_n X_{t-n} + \upsilon_t \tag{2.20}$$

where the lagged X represents the variables previously discussed. This is the extended model, while the benchmark one includes only lagged values of the FSIs. In the estimation process, the first half of the sample is used for the initial estimation, while the out of sample dynamic forecast is materialized in the second half and for forecast horizons of one, two, four and eight quarters. The forecast evaluation is made through the RMSE ratio of the benchmark against the model (1.20). Finally, the McCracken (2007) test and the direction of change (DoC) statistic[25] are used for the examination of the statistical significance of the differences in RMSE. The results are quite diverse, with very poor forecasting results for some countries (only one leading indicator for Sweden) and very good for some others (Spain has 13 variables as leading indicators of its financial stress). Credit growth and business credit improve forecast in most cases. For the two quarters ahead case, oil prices and inflation are good leading indicators. Finally, the DoC statistic gave bad results, indicating that the additional explanatory variables do not offer extra information for the change of FSI. The authors' results remain the same, even after accounting for a different weighting approach for the FSI and for potential non-linear relationships between the potential leading indicators and the aggregate stress index.

The Eurozone crisis has reasonably led to an increasing interest for the study of the financial stress effects on the monetary union's growth prospects. One such paper is prepared by Van Roye (2011). In this work, the author prepare a financial market stress index (FMSI), as he call it, for Germany and Euro Area, using the proposed approximate dynamic factor model of Brave and Butters (2011). The dataset employed is of monthly frequency and there are three groups of variables included:

[25] The DoC statistic tests whether the model's forecast the direction of change of the stress index correctly. If it does, the value of the statistic is one, zero otherwise. For this case here, they sum the results of the two models used and get their ratio. If the ratio has a value of 1, this implies equal performance. Values smaller than 1 implies that the augmented model is better, the opposite for values higher than one.

those representing the banking sector (like TED spread, money market spread, banking sector beta, bank stock returns, marginal lending facility and some more), the securities market (corporate bond spread, corporate credit spread, government bond spread, the slope of the yield curve among others) and, finally, the foreign exchange market (only REER volatility here). The model is estimated for a period, spanning 1981Q1 to 2011Q3 (in quarters). The economist's interest in not that much on the behavior of the stress indices, but mostly on the impact of systemic risk on real economic activity. In order to assess this impact, he employs a Bayesian VAR (BVAR) model, with the following general form:

$$\begin{aligned} G(L)Y_t &= \mu + \eta_t \\ G(L) &= I - G_1 L - \ldots - G_p L^p \end{aligned} \tag{2.21}$$

Here, G(L) is a lag polynomial of order p, Y_t an (n*1) vector of stationary macroeconomic variables and η_t a (n*1) vector of i.i.d. error terms. Because of the difficulty to come up with a prior distribution for μ with this model, the following transformation is considered:

$$G(L)(Y_t - \mu) = \eta_t \tag{2.22}$$

which is the so-called mean adjusted VAR model. Since the author follows a Bayesian analysis, he uses Minnesota prior to specify the prior probability distribution. For the impulse response analysis, on which he bases his inference, the author follows the well known Cholesky decomposition for the shocks identification. According to the findings, the response of FMSI to its own shock is very persistent, while the stress shock presents a strong, negative effect on output but a modest one in inflation rate. On the contrary, the interest rate is slightly reduced. Regarding the Euro Area, the results from the impulse responses is similar to the German case, with the inflation rate more responsive to the stress shock. Concerning the relevant variance decomposition, it is shown that financial stress shock can explain 15% of variation in real GDP growth, 7% in inflation and 5% in interest rate. For the euro union, the relevant explanatory power of financial stress is 30%, 18% and 50% respectively. In the last part of this paper, Van Roye (2011) employs the BVAR model to perform a recursive forecasting exercise, for one to eight quarters ahead, beginning from

2003Q3 until the end of the sample. As expected, the models tested are the one including the FMSI (and one without it). RMSE is the evaluation means. As benchmarks, the author uses a no-change forecast and a recent mean forecast models:

$$\begin{aligned} &\hat{x}_{t-h|t} = x_t \text{ where } h = 1,\ldots 8 \\ &\hat{x}^{(r)}_{t+h|t} = r^{-1}\sum\nolimits_{i=1}^{r} x_{t-i+1} \end{aligned} \tag{2.23}$$

meaning that the forecast value depends on the most recent actual values. Based on these estimations, the FMSI-augmented BVAR model outperforms the rest.

The observation that monetary stability is strongly linked with financial stability, together with the fact that financial conditions can greatly affect domestic demand and the likelihood of boom-bust episodes, is empirically examined by Mallick and Sousa (2013). In order to do this, they employ an econometric framework, similar to the previously discussed paper. They use a Bayesian Structural VAR (BSVAR) model and a sign-restriction VAR. The financial shock, again, is defined as extreme values of a financial stress index, computed according to Cardarelli *et al.* (2011). Other variables that are included in the system are the ECB policy rate, real GDP, inflation rate, commodity price and the growth rate of broad money (that is, the difference between M3 and M1). The Euro wide variables are the outcome of the weighted (by each country's GDP) average of the pre-1999 eleven countries that formed the initial Euro Area. The sample period is from January 1980 to April 2008. Regarding the BSVAR model, it is formed as:

$$\begin{aligned} &\underbrace{\Gamma(L)}_{nxn}\underbrace{X_t}_{nx1} = \Gamma_0 X_t + \Gamma_1 X_{t-1} + \ldots = c + \varepsilon_t \\ &v_t = \Gamma_0^{-1}\varepsilon_t \end{aligned} \tag{2.24}$$

Here, n represents the number of variables in the system, ε_t the fundamental economic shocks and v_t the VAR innovations. According to this approach, variables X can be separated in 3 groups: those that respond to a monetary policy shock with a lag, those that contemporaneously respond and, third, the instrument in use (policy rate). Thus, $X_t = [X_{1t}, i_t, X_{2t}]$. In the signs-restrictions model, the important component of the model is the reduced form VAR and the impulse vector λ. The model's representation is:

$$
\begin{aligned}
&Y_t = A_1 Y_{t-1} + u_t \Rightarrow Y_t = (I - A_1 L)^{-1} u_t = B(L) u_t \\
&\Sigma = E\left[u_t, u_t^{'}\right] = PE\left[v_t v_t^{'}\right] P^{'} = PP^{'}
\end{aligned}
\tag{2.25}
$$

As it is evident, Y is the vector of the aforementioned variables and B(L) is a lag polynomial of order p. Σ is the covariance matrix of the vector of the reduced form residuals, while P is the identifying matrix, relating error terms u with the structural shocks v. Finally, λ is the so-called impulse vector that projects the innovation of the structural shocks to the contemporaneous impact responses of all variables in Y. The essence, here, is the use of the estimated coefficient matrix B(L) for the production of the structural impulse responses. The author's main findings here are quite interesting, underlying the amplifying effect of contractionary monetary policy to the financial stress level. Especially in recessionary periods, this effect is even stronger. Also, the unexpected fluctuation of the FSI explains a considerable part of output fluctuation. Additionally, the stress index variation suggests that monetary authorities should respond aggressively, in order to stabilize output. In the authors' view, this is a clear indication for a switch to policy makers' interest, from exclusively targeting inflation to monitor, as well, the financial conditions of Eurozone.

An attempt to forecast systemic risk and systemic events for a group of developed and emerging economies is made by Lo Duca and Peltonen (2013). These economists construct financial stress indices for 18 emerging and 10 advanced markets, with their sample covering the period from the first quarter of 1990 to the fourth of 2009. Their composite indexes include the TED spread, equity returns (with negative sign), and the realized volatility of the general stock index, the nominal effective exchange rate (NEER) and the three month treasury bill, respectively. The aggregation is achieved with the use of a simple arithmetic mean of the five stress indicators, which were first transformed, according to their quartiles[26]. In functional form, the stress index for each country is

[26] The quartiles were derived, using their cumulative distribution function.

$$FSI_{i,t} = \frac{\sum_{j=1}^{5} q_{j,i,t}(Ind_{j,i,t})}{5} \quad (2.26)$$

Since, their interest is to incorporate the indices into a logit model, they decide to identify systemic events as these cases where the FSI is above the 90th percentile of each country's distribution of the index. This definition produces 94 systemic events in their sample. The control variables in the logit model are ratios of money to GDP, M2 to GDP, REER, NEER, real GDP, CPI, credit to private sector/GDP, real money, real M2, real house prices, real equity prices, general government debt and general government deficit, P/E ratio, the stock market capitalization/GDP and several transformations of them (rate of change and others). The authors group these variables into three groups: domestic, global ones and interactions of them. Based on the estimations, they find that their baseline model is the best one, in terms of fit, significance of estimated coefficients and the signs. For both emerging and advanced economies, the factors influencing systemic risk are the same, with the former being more vulnerable to global factors. Their final comment is that the best choice for policy makers interesting in monitoring systemic risk, is to take into consideration multiple factors, compared to stand alone indicators.

2.3 Financial Stress Indices: Empirical Work for Developing Economies

Recognizing that there is a gap on financial stress measuring for Colombia, Morales and Estrada (2010), seek to compute an FSI à la Aspachs *et al.* (2006). In this sense, they include banks' profitability and probabilities of default, as components of their indexes, together with a series of variables that sketch out the capital, liquidity and credit risk conditions in the country's financial markets. In order to improve the value of their FSI, the authors construct one for each different type of financial institutions that operate in the Colombian market. These are commercial banks, mortgage banks, commercial financial companies and financial cooperatives. Their sample is comprised of 170 institutions, for the period 1995.1-2008.11, with data on monthly frequency to have been used. The variables that were invoked in their model were the following: returns on assets, returns on equity, non-performing loans/total portfolio, net loan losses/total loan portfolio, intermediation spread (lending rate –

deposit rate), liquid liabilities/liquid assets, ration of interbank funds to liquid assets, uncovered liabilities ratio and the number of financial institutions with high stress level in each time period[27]. Additionally, they apply three different weighting schemes; the most commonly used variance-equal weighting, principal components analysis and count data modeling. According to this work, the FSI behavior, irrespective of the weights applied, is similar and accurately represents the financial instability period of the Colombian economy on late 90's. The same holds for the institutional indices as well. In the final part of this piece of work, the authors perform a forecasting exercise, checking whether it is possible to predict future values of the FSI. They use two models, an ARIMA one and a VECM. In the first case, the model seems to underestimate the observed values of the index, but captures the trend, while the VECM model, where four macroeconomic variables have also been included (inflation, unemployment, an economics activity index and a home price index), the forecasted FSI decline for the next 18 months.

Important research on financial stress has been conducted by the economists of IMF (2008). In their paper, they seek to create a FSI, able to accurately catch previous crisis episodes and analyze them for 17 advanced economies. Their approach is very similar to the one followed on the empirical part of this piece of work and embodies seven variables for the banking, securities and foreign exchange markets. These are the banking sector beta, the TED spread and the inverted term spread (for the banking sector), corporate spread (corporate bond yield – long-term government bond yield), stock decline[28] and time-varying stock volatility [representing by a GARCH(1,1) volatility model of general stock index] for the securities markets and the time-varying real effective exchange rate volatility (modeled as the stock volatility) for the foreign exchange market. In order to aggregate these constituents into a single index, they follow the equal-variance weight approach and, finally, they rebase it to range from 0 to 100. They identify periods of financial stress as those where the index is at least one standard deviation above its trend. Thus, they provide individual FSI's for these 17 economies, although they provide graphical evidence only for 6 of the countries, while they do not exert to provide any aggregate (in other words, a global) FSI. Additionally, they present an account of the number of episodes, for all the

[27] In order to determine this number, they set threshold values for all the aforementioned variables and, according to these thresholds, they could evaluate whether a financial institution was or not in stress in each time period.
[28] Stock index at t-1 minus stock index at t, divided by stock index at t-1.

countries, in the last three decades, disaggregating them according to the source of each of these upheaval periods (whether they stemmed from the banking, securities of foreign exchange markets). Their index is able to capture 90 percent of the banking-led crises and more than 80 percent of the currency crises. Finally, following a methodology developed by IMF[29], the authors distinguish the stress periods identified before which were followed by a recession. Thus, they infer that banking distress periods are more often followed by severe downturns, compared with foreign exchange or securities-borne crises periods and, also, that a financial crisis can be more protracted whenever the economy is characterized by increasing expansion of credit, a surge in house prices and expanding borrowing by households and firms.

Following a similar to the IMF (2008) empirical methodology, Melvin and Taylor (2009) narrate the repercussions of the subprime crisis to the foreign exchange market, while they proceed to the creation of an FSI which, according to the authors, might be successfully used as a predictor of any future excessive negative returns in the foreign exchange market. The account they made of the effects of the current crisis to the forex market has two cornerstones: the time when a major unwinding of the carry trade occurred (in August 2007), where it was evident that the upheaval was transmitted from the other financial markets to the foreign exchange one and, later on September 2008, the Lehman Brothers incidence which rendered the market quite volatile and uncertain of the trustworthiness of the respective counterparties. Attempting to investigate whether it would be possible for a currency trader to foresee these extreme events, the authors construct a financial stress index, in the same way as IMF did before[30]. They do it for seventeen countries (the same as those used by the IMF), for the period December 1983 to October 2008. The distinctive feature of this piece of research is that they exclusively focus on the so-called global FSI, which was computed by simply averaging the national indices. According to established threshold of considering a period as a stressful one whenever the index is at least one standard deviation above its mean, they comport in favor of its performance. Especially for the current crisis, and for the situation sketched previously for the foreign exchange market, the authors believe that the index is quite effective to

[29] According to this methodology, an episode of financial stress is followed by a recession if a peak-to-trough business cycle begins within six quarters of the onset of the financial crisis.
[30] The only difference is in the way they estimated the volatility of the stock and the foreign exchange market. Here, they have used the square root of an exponential moving average of the squared deviations from the exponential moving average of each market's returns.

capture the foreign exchange market irregularities (mainly after the collapse of Lehman Brothers). Finally, the perform a simple prediction exercise, by employing a simple binary probit model, where the depended variable is a binary variable, representing periods of significant negative returns to an investment in the Deutsche Bank Carry Index and the FSI is the exogenous variable. The results are promising and provide an initial testimonial for the usefulness of such kind of indices as forecasting tools.

The questions of how severe the current financial crisis is for advanced and emerging economies, together with an investigation of whether some level of financial distress has been transmitted to emerging from the advanced economies, are provided with an answer to the paper by Balakrishnan *et al.* (2009)[31]. In order to do this, they first construct FSIs, using monthly data, for 26 countries, for a period from January 1997 to the latest available for each one. Their methodology is quite similar to the one used by Cardarelli *et al.* (2009, 2011), with two notable differences: the use of the sovereign debt spread[32] and the calculation of an exchange market pressure (EMPI) index for each of the countries. Thus, their FSIs consist of the following five variables: the banking sector beta, stock market returns, stock market volatility, sovereign debt spreads and the EMPI, which is defined as:

$$EMPI_{i,t} = \frac{(\Delta e_{i,t} - \mu_{i,\Delta e})}{\sigma_{i,\Delta e}} + \frac{(\Delta RES_{i,t} - \mu_{i,\Delta RES})}{\sigma_{i,\Delta RES}} \tag{2.27}$$

where $\Delta e_{i,t}$ is the month-over-month percentage change in the exchange rate, while $\Delta RES_{i,t}$ is the month-over-month percentage change in total reserves of the respective economy. Finally, these individual variables standardized values are aggregated, so that each country's FSI (EM-FSI) is created. Assuming that whenever the EM-FSI breaches the threshold of one and a half standard deviation above the mean is an indication of financial stress, the authors conclude that their indices perform quite well in capturing periods of intense financial upheavals. The next step in their

[31] This paper is included to this section of the chapter, since the main focus is the crisis effects on the emerging economies.
[32] It is the difference between country's bond yield from the 10 year US Treasury yield, using JPMorgan Global spreads in the construction of this interest rate differential (or, whenever such data are not available, they used the 5 year CDS spreads).

research is the use of a fixed effects panel model, in order to check if a co-movement factor of their EM-FSIs exists. Their model specification is:

$$EMFSI_{it} = \alpha_i + \sum_t \rho^t Month_t + \varepsilon_t \tag{2.28}$$

in which α_i = country-specific fixed effect and $Month_t$ = dummy variable for month t. In this way, ρ^t represents the common time-varying element of each index. By estimating the model, Balakrishnan *et al.* (2009) found that, about, 50% of the EMFSI variation is explained by this common factor. Naturally, their interest was turned to the identification of the determinants of this common component (ρ^t). In doing so, they employed the following model:

$$\rho^t = \alpha + \beta AEFSI_t + \sum_g \gamma^g GF_t^g + \varepsilon_t \tag{2.29}$$

in which AEFSI represents the advanced economies FSI (as taken by previous research from IMF) and GF are the so-called global factors[33]. From this model, they infer that 41 percent of the common component variation can be attributed to the AEFSI. Having established a relation between financial stress in emerging and developed economies, the authors proceed to further investigation of this relation, by using a two stage technique. This approach offers insights in the stress co-movement intensity (on stage 1), while stage 2 indicates cross-country variations in these co-movements. Thus, for the first stage, EMFSI is regressed on AEFSI, the global factors and EMFSI[34] with one lagged value, while they also take into account advanced economies regions (namely US/Canada, Western Europe and Japan/Australia). The model representation is the following:

$$\begin{aligned} EMFSI_{it} = \alpha_i + \sum_c \sum_{l=0,1} (\beta_i^{cl} AEFSI_{t-l}^c + \sum_{\tau=1,2} \beta_{\tau i}^{cl} D_\tau AEFSI_{t-l}^c) + \\ \sum_g \sum_{l=0,1} \gamma_i^{gl} GF_{t-l}^g + \sum_{l=0,1} \delta_i^l \overline{EMFSI_{it-l}} + \lambda_i EMFSI_{it-1} + \varepsilon_{it} \end{aligned} \tag{2.30}$$

[33] Here, they are the year-over-year changes in world industrial production, commodity prices and the 3-month LIBOR.

[34] Excluding, in each regression, the country under investigation.

Here, AEFSI can be, as the authors state, "an aggregate of 17 major advanced economies or three separate aggregates, indexed by c", for the three regions defined previously. Additionally, in the first brackets, dummy variables are included, in order to capture the effects of two (τ =1, 2) crisis episodes that could have affected the advanced economies[35]. Here, the estimation results are quite good, showing that financial stress transmission is strong enough (on average, 70% of it is transmitted from advanced to developing economies, while financial contagion from other emerging markets is also important. In most of the cases, it was found that only one to two months are needed for this transmission to happen, while the size and source of this spillover varies. Regarding the second stage of this analysis (examination of cross-country variations in these co-movements), the model used is the following:

$$\beta_{\tau i}^{c} = \alpha_i + \sum_{\kappa} \alpha_{\kappa} FL_{i\kappa}^{\tau c} + \alpha_l TL_i^{\tau c} + \sum_{m} \alpha_m X_{im}^{\tau c} + \varepsilon_{\tau i}^{c} \qquad (2.31)$$

in which the country-specific regional co-movement parameters are a function of the bank lending. Portfolio investment and direct investment to GDP ratio (FL), the total exports/GDP (TL), trade/financial openness (X). In this case, the financial linkages are proved to be more important than trade, while country-specific factors do not seem to be that crucial here. The final econometric exercise in this piece of research has to do with the potential relation of the FSI with country-specific variables. These estimations have been conducted in an annual frequency panel model, with the following form:

$$\begin{aligned} EMFSI_{it} = \alpha_t + \beta AEFSI_t + \sum_{j} \xi^j X_{it-1}^{j} + \sum_{j} \theta^j AEFSI_t \times X_{it-1}^{j} + \\ \delta \overline{EMFSI}_{it} + \sum_{g} \gamma^g GF_t^g + \varepsilon_{it} \end{aligned} \qquad (2.32)$$

where, the only extra variable is the interaction of the AEFSI with the country-specific variable X. The estimations results here provide evidence the β is highly significant, while δ is positive and larger than 1. The opposite effect is valid for the

[35] The first one is for the period 1998-2003, covering LTCM crisis, dot-com bubble and Enron, Worldcom and Arthur-Andersen corporate scandals. The second episode in the sample is the sub-prime crisis.

openness variables included in X (positive for the financial ones, negative for the trade ones). As a consequence of all this analysis, the authors suggest that emerging economies with low current account and fiscal deficits are more protected from financial stress transferred by advanced economies although, in cases of widespread crises, their effect is not that important.

Osorio *et al.* (2011) construct financial conditions indexes for thirteen Asian and Pacific Economies (namely, Australia, China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand and Taiwan). The indexes are created for the period 2001 to 2011 and are the outcome of the average values of two separate aggregate indices, estimated by a VAR and a dynamic factor model. In the first case, the VAR model is specified as:

$$X_t = A_0 + \sum_{i=1}^{p} A_i X_{t-i} + BY_t + \varepsilon_t \qquad (2.33)$$

where the dependent variable is a vector of the metrics[36] used for the FCI construction. Y is a vector of exogenous variables (VIX index and US GDP growth), which are included to some countries estimations to improve the goodness of fit. They represent global factors that affect the domestic economies. The weights for the aggregation are taken from the model's impulse responses that represent the cumulative response of GDP growth to a one unit shock to each one of the variables of the model. Thus, the index is

$$FCI_t = \sum_{j=1}^{n} w_j (x_{j,t} - \tilde{x}_j) \qquad (2.34)$$

where w is the weight of each indicator included to the FCI and the second factor in the brackets is the average value of this variable x. In the case of the generalized dynamic factor model, the FCI comes up by, first, estimating the model and extracting the common component of the variables included[37]. Then, they regress this component on inflation and GDP growth at take the residuals from this. In this way,

[36] The endogenous variables are: real GDP, equity prices, effective exchange rate, lending rate spread, bank credit to private sector. All series are deflated using CPI index, except lending rate for which one year ahead forecast is used, expressed in year over year percentage change.
[37] In this case, they are similar to the VAR model, but not exactly the same.

the final outcome of this process provides an index that is purged from business cycle fluctuations. In functional form, the model is

$$y_{i,t}^{j} = \chi_{i,t}^{j} + \xi_{i,t}^{j} = b_{i}^{j}(L) f_{i}^{j}(L) + \xi_{i,t}^{j} \tag{2.35}$$

where $\chi_{i,t}^{j}$ is the common component driven by a small number of common factors, represented by $f_{i}^{j}(L)$, while $\xi_{i,t}^{j}$ are the idiosyncratic part. Thus, first, it is necessary to estimate $f_{i}^{j}(L)$ through dynamic principal component analysis and, then, to purify the FCI from the effects of the business cycle. This is accomplished with the following regression:

$$f_{t}^{j} = A_{j}(L) Z_{j} + v_{t}^{j} \tag{2.36}$$

Inspecting their indices, the authors point out that export-oriented economies have an FCI more heavily related to REER. On the other hand, countries with an FCI more reliant on credit are those with important role for banking intermediation. Finally, the economists here proceed to an examination of their FCI properties as leading indicators of GDP growth for each economy. The model used here is

$$growth_{t+h} = a + \sum_{i=1}^{4} \beta_i growth_{t+1-i} + \sum_{i=1}^{4} \gamma_i X_{t+1-i} + \varepsilon_t \tag{2.37}$$

with X being the FCI's lagged values and Growth is the y-o-y real GDP growth. The evaluation is conducted through the statistical significance of FCI coefficients and the partial R^2 (for the in-sample case), while RMSE are used for the out of sample case. In the first case, it is found out that FCI improves model's goodness of fit and this holds true for all versions of the indices. Regarding the out of sample forecasts, RMSE for the FCE-included model are lower, emphasizing the prevailing nature of the models with the aggregate stress index.

Another paper, dealing with Asian economies, is the one by Debuque-Gonzales *et al.* (2013). Here, the authors, following the previously described methodology by Hatzius *et al.* (2010), construct financial conditions indexes for five

Asian countries (Hong Kong, Japan, Korea, Malaysia and Singapore). The countries were selected, based on the data availability, since the following methodology allows for a plethora of variables to be efficiently incorporated. Depending on the country, the sample covers a time period from early 80's until the second quarter of 2011. Inspecting their indices, the authors underline the ability of these FCIs to foresee well known financial crises episodes, while their values were deteriorating early enough, before growth slumps. Finally, they proceed to a forecasting exercise, in the same fashion as in the NBER paper mentioned above. The variables they forecast are real GDP and IP index, following a recursive process for two, four and six quarters ahead. In general, the FCI performs well, although their success depends on the range of financial variables incorporated to the respective index.

The principal components approach, followed in the previous presented paper, is also used for the construction of an FCI for South Africa by Gumata *et al.* (2012). Beyond that, they also employ Kalman filter as an alternative approach for the index. In the first case, the estimated common factor covers the period from 1999Q1 to 2011Q4. The dataset is comprised of global factors (like VIX index, S&P 500 equity index, JP Morgan EMBI total return bond index, the TED spread) and domestic factors (loans and advances to private sector, sovereign spread, non performing loans, certificates of deposits, nominal effective exchange rate, the South African stock index and a house price index). The same variables are used in the case of the Kalman filter – based FCI. The comparison of the two indices reveals their strong correlation, which is even strong in the first half of the sample (1999 – 2006). In order to evaluate the FCIs' ability to predict GDP growth, the authors perform a Granger causality test, as well as a forecasting exercise and comparison of the results with a South African leading indicator (SARB business cycle indicator). The causality test shows unidirectional causality from the FCIs to GDP. As usual, the forecasting procedure involves a benchmark, autoregressive model for GDP growth and the alternatives that include the previously mentioned indices. The forecast horizon is set to one, two and four quarters ahead, while the results evaluation is based on the sum of squared residuals (SSR) of the models involved. Based on this, the models with the aggregate indices perform better than the other with the leading indicator, with the PCA-based one is the best performer. The authors also compare the indices performance with the stand alone indicators used in their construction. Again, they find that PCA-based index exhibits the lowest SSR, while the Kalman filter index outperforms only a few of the individual indicators.

Other researchers have, lately, focused on the financial stress conditions and their relation with the real economy of transition economies. For instance, Cevik *et al.* (2013b) create financial stress indexes for Bulgaria, Czech Republic, Hungary, Poland and Russia based on the work of Balakrishnan *et al.* (2011). The variables included here are similar with previous works. One major difference is the incorporation of a trade variable (first difference of the logarithm of external short term debt as a proxy of trade finance) which is deemed to be important for such economies. The dataset is of monthly frequency, covering the period February 1995 to June 2010. The aggregation is achieved using PCA analysis, using the loadings of the first principal component as the weight for each one of the indicators included to the FSIs. For the evaluation of the indexes predictive ability on real economy, bivariate VAR models are employed. The endogenous variables are the IP index, the growth rate of foreign trade (sum of imports and exports) and the growth rate of the gross fixed capital formation of the countries in the sample. The analysis is based on impulse response functions. According to them, increased financial stress has important transmission to the real economy. Policy prescriptions are necessary, so that the potential different sources of systemic risk can be accommodated, through the application of different macroeconomic and financial policies. Based on the same approach, Cevik *et al.* (2013a) provide evidence in favor of the importance of FSI on the prediction of real economic conditions in Turkey[38].

Another paper, creating financial stress indices for a number of Central Eastern[39] and South Eastern European countries is the one by Jakubik and Slacik (2013)[40]. Here, the single indicators (representing money, foreign exchange, equity and bond markets) are double weighted, first within the group they belong and, secondly, for their contribution to the aggregate stress index. The approach for the index aggregation is the one followed by Lo Duca and Peltonen (2013). The time period covered here is from the mid 90's until 2011, depending on the data available

[38] Work on financial conditions indices for the Turkish economy has been conducted by Kara *et al.* (2012) for the Central Bank of Turkey.
[39] Czech Central Bank is one of the most research active institutions in the development of financial stress indices. Economists there realized the usefulness of such measures, even before the outset of the Great Contraction. See Gersl and Hermanek (2006) as an example.
[40] The sample consists of Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Russia. Slovakia and Ukraine.

for each country. The graphical inspection of the indices shows that most countries were affected by the current crisis, but mostly in the subsequent phase of it. Slovakia is an exception, with the index showing small response to global financial conditions. The authors also proceed to a panel regression analysis, in order to specify which macroprudential indicators are the most helpful in the financial stress level identification. They use a number of sovereign risk metrics, banking sector variables, contagion risk indicators and macroeconomic fundamentals, as explanatory variables in this panel analysis, together with interactions of them. At the end, the authors find that the most significant variables to identify financial stress are a number of interactions between public debt and fiscal deficits, credit variables interactions, as well as NPLs among others.

3. Data Description and Methodology

Our dataset is comprised of monthly data for three different groups of countries. The time span differs, not only between the groups but, sometimes, between the countries within the same group, due to problems of data unavailability. Countries' grouping has been done by taking into account the differentiation between advanced and emerging economies, but mostly, based on the regional economic links between them. Thus, we have a group of OECD economies, representing the most advanced economies in the world, a group of Asian countries[41] and, finally, a group of Latin American economies[42].

As mentioned above, for some countries, there is a lack of full data sample. In the case of the OECD group, data for most countries are available from January 1980 to May 2009, with a few exceptions like Australia, Switzerland and Finland, for which some series are shorter and, in this way, we were able to compute shorter indices. For the other two groups of countries, data availability was even more limited, with only Japan as an exception. For the rest of the Asian countries, the data

[41] In this group, we included Japan as well, even though this country could have been added to the advanced economies group. It is a matter of comparability (groups of countries from same continents, excluding the OECD group) and regionalism (ability to construct and discuss regional financial stress indices).
[42] OECD group consists of: Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK, USA. Asian group: Japan, S. Korea, Malaysia, Philippines, Thailand. Latin American group: Argentina, Brazil, Mexico, Peru, Venezuela.

sample (and, as a consequence, the FSI index) covers the period from 1997 to May 2009, while for the South American countries the period covered starts from middle 90's (Brazil from 1995, Venezuela from 1997, Peru from 1998, Argentina from 1993, Mexico from 1994) to May 2009. Following the work of Melvin and Taylor (2009), Balakrishnan *et al.* (2009) and the IMF WEO (2008), we used monthly observations for the following series: real effective exchange rates, national banking sector equity indices, national stock markets indices, governments' short-term rates or Treasury bill rates, long-term government bond yields and long-term corporate bond yields. The main sources of these series were, Bank for International Settlements (BIS) website (for the exchange rates series), Thomson Datastream, IMF International Financial Statistics database, OECD Main Economic Indicators database and, in some cases, statistical data from national central banks' websites.

The methodology followed to construct the financial stress indexes presented in the following section, is the one proposed by IMF (2008), which was also implemented by Melvin and Taylor (2009), although these authors slightly transformed their index by using an exponentially weighted moving average model to compute the exchange rate and stock market volatility. In this work, we remain faithful to the way IMF worked out the index.

The Financial Stress Index (FSI from now on) is a composite indicator, which, according to Melvin and Taylor (2009), tries to capture four essential characteristics of a financial crisis: large shifts in asset prices, abrupt increases in risk and uncertainty, shifts in liquidity and a measurable decline in banking system stability. In order to do this, seven variables are used to construct the subcomponents of this index for the following three economy sectors: the banking sector, the securities markets (stock and bond ones) and the foreign exchange market. The indicators for each one of these sectors are:

Banking Sector

1. Banking sector stocks' beta (calculated as the ratio of the moving covariance of the year-over-year percentage change of each country's banking sector equity index and the general equity index and the moving variance of the general stock index).
2. The TED spread (the difference between the 3-month LIBOR from the government short-term rate or the respective treasury bill rate)

3. Inverted Term Spread (treasury bill rate – government long-term bond yield)

Securities Market

4. Corporate Bond Spreads (the yield difference of the long-term corporate bonds from the governmental ones)
5. Stock market returns (the monthly percentage change of the general equity index performance)
6. Stock return volatility (calculated as a GARCH(1,1) model of the general equity index, modeled as an autoregressive process with 12 lags)

Foreign Exchange Market

7. Real effective exchange rate volatility (estimated on the same way as the stock return volatility)

It should be emphasized that this approach was materialized only for the OECD (and Japan) group of countries while, for the rest of them, the index was slightly reformed. This was deemed necessary because of data unavailability for the corporate bond series in Asian and Latin American countries. Thus, instead of the corporate bond spreads, we use the so-called sovereign debt spreads, which are the government bond yields minus the 10-year United States Treasury yield. In any case, this does not degrade the usefulness and applicability of the index, for two main reasons. First, the corporate bond market is quite small in emerging economies, where most of the firms are still based on traditional sources of financing (like bank borrowing). Then, the fact that a large part of the private sector financing depends on national banks (which, most of them used to or are still under state control or mainly being refinanced with state money), designates that the use of sovereign debt spreads as a credit risk indicator is good enough for these economies. Apart from this alteration, the financial stress index for all countries is constructed in the same fashion.

If we would try to sketch the financial stress index as a mathematical equation, then it should be:

$$\begin{aligned}\text{FSI} = \beta + \text{TED spread} + \text{Inverted term spread} + \\ \text{Corporate Bond spread} + \text{Stock market returns} + \\ \text{Stock market volatility} + \text{Exchange rate market volatility}\end{aligned} \tag{2.38}$$[43]

Every part of the index is standardized, by subtracting the series mean and divide by its standard deviation. Each one of the index's components has an equal weight to the formation of it. This is the most commonly used approach to the construction of financial stress indicators, the so-called equal-variance approach. As long as this has been done, the next step is the computation of the regional and global FSIs. The regional FSI's are the outcome of the average of the national indices for each group of countries (OECD, Asia, and Latin America), while the global one is the average of the regional indexes. Using these indices, we can check when and by how many standard deviations the FSI is above or below its mean value. Episodes of financial stress are identified when the index is, at least, one standard deviation above its mean. Finally, we are able to classify each episode of financial stress (i.e. whether it can be attributed to banking, securities or foreign exchange-related causes) by examining the change of FSI value prior to the start of the episode and the maximum value of it during the episode periods.

It should be noted here that the full sample information is used in the standardization process, presented above. As a consequence, a health warning is deemed necessary here. Generally, the variance-equal approach assigns a specific, fixed weight for each one of the indicators included in the financial stress index, for the whole period examined. This could have both, positive and probably some negative implications. On the positive side, the easiness and simplicity of the calculations should be underlined. Additionally, it is a standardization process that is efficient, fast in producing plausible and meaningful results, while it is not demanding in terms of econometric modeling. That is, probably, why it is the most popular aggregation methodology in the stress indices literature. On the other hand, this approach exhibits some shortcomings. The most important critique has to do with the nature of the weighting scheme. It is considered inflexible and, potentially, unable to capture and exploit the updated information that stand alone indicators provide through time. Another point of weakness is considered the equal value that is assigned

[43] Remember that, for the emerging economies, the corporate bond spread component is substituted by the sovereign debt spread.

to all variables used to the creation of the systemic risk index. Sometimes, this might not be very realistic, given the changing nature and importance of the different financial markets. In any case, the variance-equal approach remains the most popular, for the aforementioned reasons and this also one of the reasons I decided to employ it here.

It is also important to emphasize on the exact nature of these financial stress indexes. As a tool, it represents the current state of financial markets, based on the information provided by the relevant indicators included to the aggregate metric. Increasing values of the index do not necessarily represent a crisis outbreak. On the contrary, it is only arbitrary and based on experts' judgment and markets experience to tell, whether a financially stressful period is indeed, or can be deployed, to a fully blown crisis. The benchmark used here (one and two standard deviations above the mean value of the index) is clearly driven from the relevant literature and the prior experience of the users of this financial stability tool. As it is obvious, there is some debate on which one is the optimal cut-off point, in order to consider a stressful period as a crisis period. There is no, yet, a clear answer on this. Nevertheless, it is safe to follow the prior research on the area and characterize as periods with excessive financial stress, the periods where the index value is, at least, one. Of course, not all these periods coincide with financial crises. The presentation of the different indices, along with a discussion of their accuracy in the identification of different crises episodes, follows.

4. Discussion of Results

This section of the paper is attributed to the detailed presentation and discussion of the results of our investigation on financial stress periods for the 25 countries of the sample. An analytical exposition of the global FSI is being provided, together with graphs and details for the regional indices computed. Additionally, tables are provided with an exhaustive statement of the different kind of upheavals each economy faced in the recent past, together with a calculation of the average duration of these episodes. In order to make crises periods identification and comparison easier, the monthly series were transformed into quarters, by simply taking the average value of each three month period. Moreover, it should be notated that no special effort has been made to specify stress periods. We just follow the literature (which has, long ago, reached an agreement on which were periods of turmoil for most of the countries under consideration) and what the indices show us (and whether their indication coincides with a well-justified crisis period).

4.1. Global Financial Stress Index

Graph 1 depicts the composite Global Financial Stress Index. As mentioned above, it is nothing more than the outcome of the computation of the average of the three regional indices (OECD, Asia, and Latin America) constructed by the respective national indices of the countries of each region. Moreover, table 1 displays the number of stress episodes identified in each region, added up to produce the total number of them for the whole world, separated into three types (banking-related, securities-related and foreign exchange-related), according to the market each crisis episode was originated from. Additionally, the (average) duration of these episodes, measured in quarters, is being provided. The severalty of the stress periods in the categories was feasible by examining the behavior of the components of the FSI in each case, characterizing each peak period of the index according to the variables that present the highest values. In cases, where more than a single sector seems to contribute to the turmoil, adjudication is reached according to the market that has the highest attribution to this episode or, if this episode lasts for more than a quarter, according to the sector that appears to, most frequently, lead it. Stress periods are denoted by the grey areas in this graph as, of course, in all graphs used here.

The time period covered by the global FSI is limited because of the lack of data of the same time span for the three regions under investigation. For issues of equality and comparability, the global index covers the period where data for all three indices are available. That is, the period from the fourth quarter of 1998 until the second quarter of 2009. Although, an interesting period where many crises outbreaks took place, especially in the emerging markets of Asia and South America, is excluded, this time period is still quite interesting, with a variety of financial upheavals.

Graph 2.1: Global Financial Stress Index

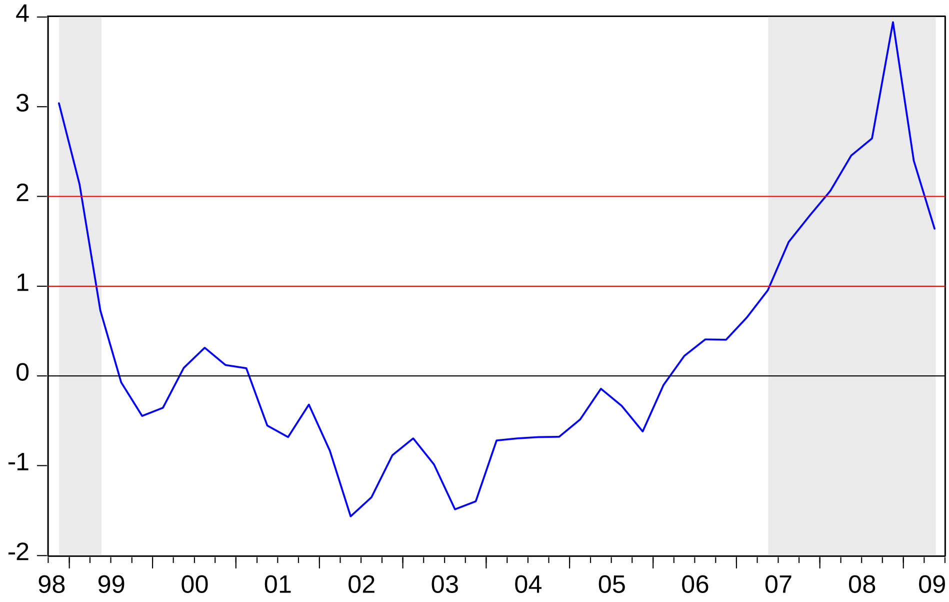


Table 2.1: Summary Statistics for Global and Regional FSI

Stress Types / **Countries**	***Banking***	***Securities***	***Foreign Exchange***	***Total***
OECD	54	68	25	147
Duration	*4*	*5*	*3*	*4*
Asia	8	10	2	20
Duration	*3*	*5*	*1*	*6*
Latin America	6	14	2	22
Duration	*2*	*4*	*0.5*	*3*
Global	68	92	29	189
Duration	*3*	*4.5*	*1.3*	*4*

Source: author's calculations. Duration of stress episodes in quarters

Inspecting graph 1, it is easy to infer that, apart from the initial phase of this period and the recent financial crisis (since 2007Q2), the last decade was a somehow tranquil period for the world economy. Of course, this does not mean that the same holds for the individual countries, as well. According to the special features and situations prevailing in each country, someone can identify country-specific instabilities. But, as it has already mentioned, the global index represents the conditions present in the world economy. Thus, it is reasonable to expect that, in some cases, worsening of a country's financial health does not, necessarily, entail a similar aggravation for the global economy. By and large, the two stress periods depicting in graph 1, seem to have had a, somehow, similar effect in the global economy. The first one, having lasted for two quarters (1998Q4 to the first quarter of 1999), shows that the index was about 3 standard deviations above the mean value of the FSI, decreasing quite fast, compared to the subprime crisis period. In the latter, the index started picking up since mid-2006, exerting the threshold of one standard deviation at the second quarter of 2007. The value of the index was constantly increasing until the fourth quarter of 2008, after which, it started to decrease. Nevertheless, it still remains close to the two standard deviations above the mean (at the end of the sample period), implying that global financial markets are still under severe strain. It will not be misleading if we would suggest that, the first stress period captured by the index can, possibly, be mostly attributed to the financial instabilities prevailing in the emerging markets at that time (financial crises was a common phenomenon in countries like Brazil and Argentina, while the Asian economies were still struggling with the serious problems caused by the crisis of 1997-99), while, the second one is (as it will also become clearer in the analysis that follows) a crisis that has, mainly, affected the developed economies. The period, from 1999 to late 2006, is a period of robust growth and prosperity in the world economy. Solitary cases of crises episodes occurred, but their effect was not that important, according to the global FSI[44]. It does worth mentioning here that, as it can be seen in the graph, the FSI present a persistently upward kinesis, since early 2004. This suggest that, although the index was rather low and did not provide any alerts for the forthcoming financial turmoil, it can be said that the increasing value of it could have worked as an early warning indicator of the forthcoming financial meltdown.

The last row in table 1 provides an account of the overall number of stress periods identified in the world, over the last 30 years. As mentioned before, they have been separated, according to the main source of instability, to banking, securities or foreign exchange market prone types of stress. Obviously, the sample is unbalanced,

[44] Still, we can notify a shift on the FSI behaviour in some cases, like during the dot-com bubble burst on 00's or during the Argentinean and Russian/LTCM crisis (second half of 2001). Of course, these upward shifts on the index values were not as strong as it would be necessary, in order to register these period as financially stressful ones.

in the sense that most of the crises episodes are from the OECD countries, for which we have the longest time series. Still, this table is quite informative for the behavior of the world economy, under different kinds of financial strains. In total, 189 stress periods were found, with an average duration of four quarters. The episodes stemmed out of the securities markets are quite often, lasting more than the banking crises, which are the second most popular source of financial instability. Surprisingly, foreign exchange markets cannot be blamed for many of the stress periods in our sample, something attributed to the shorter time periods covered by the series available for the emerging markets. It is well known that, especially during the 80's and early 90's, many financial crises in such countries can be attributed to inconsistent monetary and fiscal policies followed by these countries, where troubles were first appeared in the value of their currencies. Nevertheless, these results offer an additional reason justifying the paradigm shift from researching for market-specific crises to systemic-wide ones.

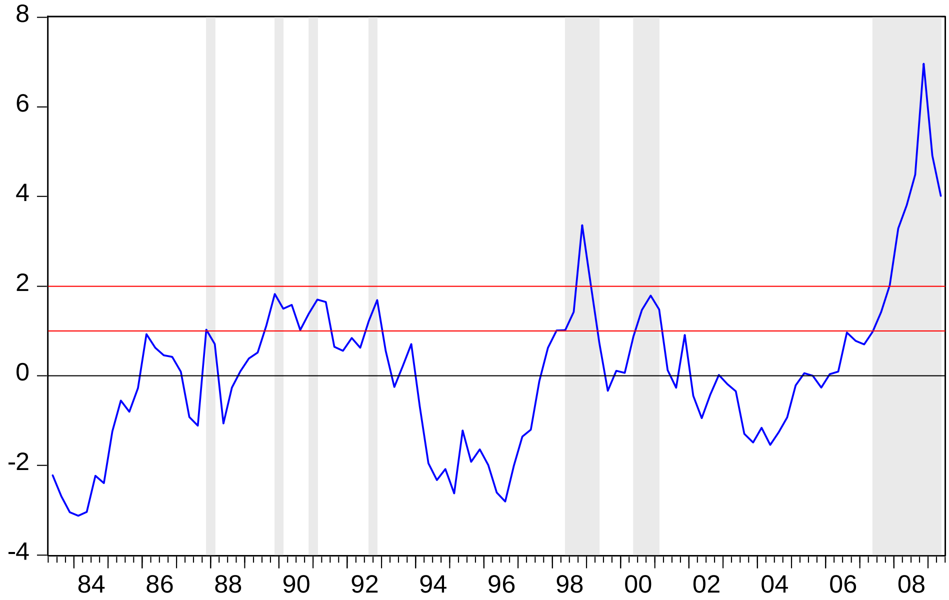
4.2.OECD and OECD Countries Financial Stress Indices

In this section, a detailed discussion of the results obtained by the construction of the individual OECD countries indices and the overall OECD FSI is provided. Graph 2 illustrates the performance of the OECD index, with the grey columns underscoring the relevant stress periods, while table 2 analytically presents the kind and the duration of financial instabilities for each country from the sample. Graphs of each country's FSI are included in this paper's appendix.

The OECD FSI covers the period 1983Q2 to 2009Q2. As it can be seen by the following graph, the index does not seem to follow a specific trend. It has a number of peaks and troughs, reaching various levels of excessive financial stress throughout the three decades covered. It is more than clear that the current crisis is the most severe one for this group of countries, having reached at its peak a value close to seven standard deviations above the average value of the FSI. Additionally, this financially instable period is the most prolonged one, having lasted nine quarters, until the end of our sample,

while it still exhibits high levels of stress, even though it was only 4 standard deviations above the mean at mid-2009. Thus, it is more than obvious that the recent crisis brutally hit the world's most advanced economies while, following the upward trend of the index, the use of such a metric of financial strain could have been proved quite useful for central bankers and financial stability surveyors.

Graph 2.2: OECD Financial Stress Index



Following the uprising crises episodes observed in this OECD FSI timeline, interesting findings can be spotted. While the index has initiated from very low values, below the mean in the beginning of the sample, its first peak is defined at the first quarter of 1986, though not assigned as a stress period[45]. Nevertheless, the following spike of it, during the fourth quarter of 1987, captures one of the most famous financial crises periods, the well known "Black Monday" stock market crash, which affected nearly every developed country's stock market[46]. Then, after a period of decreasing values for the index, it starts rising, breaching the threshold of one standard deviation from early 90's and it remains above it (with the short-lived exception of the period from the end of 1991 to mid-1992) until the last months of 1992. During these years, a number of financial upheavals took place that shook most of the global markets. Some of them, like the junk bond collapse at late 80's – beginning of 90's and the S&L crisis of the same period, were mainly focused on single country, while others (such as the Scandinavian banking crisis of early 90's and

[45] On 1986Q1, the FSI value is 0.92 <1. Thus, technically, it is not a registered stress period.
[46] Most of these countries (like USA, UK, Australia, Spain, Canada etc.) are part of the OECD FSI.

the ERM II crisis in 1992-93) had a multilateral dimension. In all these cases, the OECD FSI reached values of, almost, two standard deviations above its mean value. Then, a two-year period followed with of degrading financial stress while, afterwards, the index started to surge again. In 1998, it remained above the threshold of one standard deviation for about a year, a period characterized by a series of stress episodes inflicting serious turmoil to the markets, such as the Asian and Russian crises, the LTCM collapse and the upcoming vulnerabilities because of the crises followed to the emerging markets (many of which are major suppliers of raw materials and oil, like Brazil). Finally, graph's 1 index underscores another period of financial stress, at the end of 2000- beginning of 2001, clearly related to the dot-com bubble burst, which created a series of abnormalities to international stock markets.

Table 1 presents an analytical decomposition of the types of stress episodes that have arisen in OECD countries, together with the average duration of these episodes. In total, 147 periods of financial stress occurred in OECD area, with an average duration of 4 quarters. The most recurrent type of crises is the securities ones, with 68 episodes throughout the period under investigation, with duration of 5 quarters. Stock markets are proved to be more vulnerable, compared to the rest of the markets. Again, as in the case of the global stress index, currency-induced type of stress is not that common. Only, about, 2 out of 10 episodes have been sourced from instabilities in this market.

Focusing now in more detail to the country-specific indices, it can be supported that, for the majority of the cases, the financial stress indices computed for the OECD countries, are quite accurate and according to the financial history of these countries. As already mentioned, detailed graphs are provided in the appendix of this work, while table 2 offers an overview for each country's types of upheaval and their respective duration. Once again, the severe effects of the current financial crises are more than obvious for these economies, with highly excessive stress in their financial markets. Countries like Germany, UK, Australia, Netherlands, Canada, Austria and, of course, United States are still getting through the most financially stressful period of their recent history, with the values of their FSI's exceeding 8 standard deviations above the mean value of their indices. On the other hand, a number of countries (including France, Finland, Spain and Italy) face a more tranquil situation, although, they also experience financial stress. Focusing on United States, it can be said that this major economy faced 10 major episodes of financial instability during the last 28 years. Most of them were of banking and financial markets' nature, while only 2 of them can be attributed to pressures from the foreign exchange market. On average, these stressful periods lasted for four quarters, with banking crises running for longer than that (5 quarters). Examining the US FSI graph carefully, a clear pattern on the movement of the index cannot be identified. Instead, especially for the first 15 years of the sample, there is a continuous succession of upswings and slumps in the index's value. After mid-80's, FSI exceeds the threshold values imposed, alerting for the existence of financial instabilities in US markets. This was a period of recurrent crises phenomena, like the stock market crash of 1987 and the S&L scandal of late 80's. These conditions hold, with short tranquility's interruptions until late 1993, while FSI again provides evidence of financial markets' irregularities at the end of 90's and beginning of 00's to 2001.

A similar situation, with that of United States, prevails in UK. Here, 8 periods of financial stress were spotted, with an average duration of 3 quarters. Again, banking and capital market sectors are to be blamed for most of the convulsions in this country. Regarding the timing of these crises episodes, it can be said that the period since mid-80's until mid-90's exhibits a series of problematic situations in British financial markets.

The most intense ones arose at the beginning of the 1990's, more precisely from the third quarter of 1989 to the second quarter of 1991 and, then on 1992Q4 that lasted for a year.

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OECD's most vulnerable countries appear to be Australia, Germany and Spain, with 13 financially stressful periods, although, the average duration of these episodes is quite short (3 quarters for the first two, 2 quarters for Spain). On the contrary, France seems to be the most robust market, with only 7 stress periods recorded, while the duration of the crises here is longer (4 quarters), especially for banking instabilities are even longer (6 quarters). Also, for a group of countries, consisting of Belgium, Netherlands and Sweden, not a single stress period sprung from the foreign exchange market while, in some other cases, a record duration has been notched (like the securities' markets crises in Austria or the solitary foreign exchange-born financial instability in Canada, lasted for 23 quarters and the respective capital markets' one in Finland). Interestingly enough, a number of well-documented crises periods faced by some of the OECD countries are captured here. The Scandinavian banking crisis, mainly affected Sweden and Finland in our sample, is clearly depicted on the extremely high values of these countries' indexes at the beginning of the 90's, until 1993-beginning of 1994 (having picked in 1993). Additionally, the events related to the European Exchange Rate Mechanism crisis, during 1992-93, are depicted on the participating countries' indices performance, especially on UK, Denmark's and Finland's, Austria's, Italy's and the Belgian ones.

Table 2.2: OECD: Numbers of Episodes & Duration per Stress Type

Stress Types / Countries	*Banking*	*Securities*	*Foreign Exchange*	*Total*
Australia	5	6	2	13
Duration	*2*	*3*	*1*	*2*
Austria	2	2	4	8
Duration	*1*	*13*	*2*	*6*
Belgium	3	9	0	12
Duration	*5*	*3*	*0*	*3*
Canada	3	4	1	8
Duration	*5*	*1.5*	*23*	*6*
Denmark	3	6	1	10
Duration	*1*	*4*	*3*	*3*
Finland	5	1	3	9
Duration	*2*	*18*	*1*	*3*
France	3	2	2	7
Duration	*6*	*4*	*2.5*	*4*
Germany	4	6	3	13
Duration	*3*	*3*	*1*	*3*
Italy	4	4	1	9
Duration	*7*	*4*	*1*	*5*
Netherlands	4	6	0	10
Duration	*3*	*3*	*0*	*3*
Spain	3	8	2	13
Duration	*4*	*2*	*1.5*	*3*
Sweden	2	6	0	8
Duration	*4.5*	*4*	*0*	*4*
UK	4	2	2	8
Duration	*3.5*	*4*	*2.5*	*3*
USA	5	3	2	10
Duration	*5*	*3*	*4*	*4*

Source: author's calculations. Duration of stress episodes in quarters

4.3.Asian and Asian Countries' Financial Stress Indices

Turning to Asia now, we start by examining the behavior of the Asian FSI. Here, contrary to the available sample for the OECD countries, the index is confided to the period beginning in the second quarter of 1998, until the second quarter of 2009. In any case, it is a reasonably long period, in order to offer us a good insight in the performance of this indicator. Here, it should be mentioned that data availability for Japan is much longer, compared to the other four countries comprising the group of Asian countries under investigation.

Figure 3 shows the evolution of the Asian FSI. It starts with quite high values, around four standard deviations above the mean value, something totally expected, considering that the legendary Asian financial crisis was still unfolding at that period (mid 1998). From the end of 1998, the index has started decreasing while, during the second semester of 1999, it reached values below the threshold of one standard deviation. At the beginning of the next decade (middle to end of 2000), it exhibited a sudden surge, which did not blossom into another stress period. Until the end of 2005, the Asian FSI remained below its mean value, having initiated to mount in 2006, until it breached the value indicating the existence of financial stress on the third quarter of 2007. Thus, Asian continent seems to be influenced by the current financial crisis, with the Asian index picking on the fourth quarter of 2008, with an index equal to, almost, 3 and a half standard deviations above the average value. Beyond that date, the index has degraded, indicating the end of the stressful period with the end of our sample.

The number of financially instable periods for these five Asian countries was twenty, with an average duration of six quarters. Most of these episodes are identified as securities-related, which also present the longest stoutness. The most vulnerable country, according to the data, is Japan, with nine stress episodes in total. Of course, this can be ascribed to the longest time period covered by Japan's sample. On the other hand, Thailand exhibits only one, banking-sourced, financial stress, lasting for five quarters.

Graph 2.3: Asian Financial Stress Index

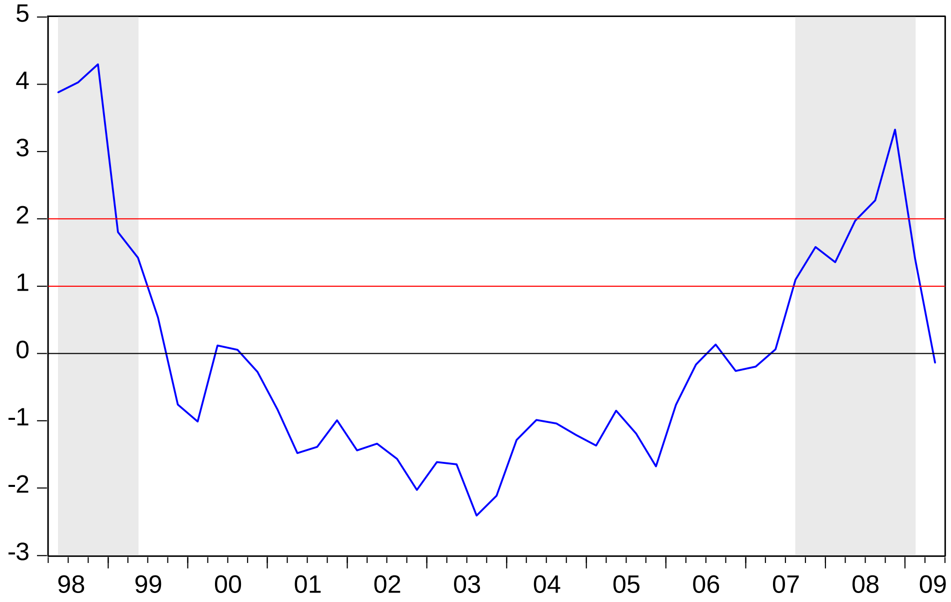

Table 2.3: Asia: Numbers of Episodes & Duration per Stress Type

Stress Types / Countries	*Banking*	*Securities*	*Foreign Exchange*	*Total*
Japan	3	4	2	9
Duration	*2*	*7.5*	*3*	*5*
Korea	1	2	0	3
Duration	*2*	*6*	*0*	*5*
Malaysia	2	2	0	4
Duration	*1*	*5*	*0*	*3*
Philippines	1	2	0	3
Duration	*6*	*7.5*	*0*	*10.5*
Thailand	1	0	0	1
Duration	*5*	*0*	*0*	*5*

Source: author's calculations. Duration of stress episodes in quarters

The other three countries of the sample (Korea, Malaysia and Philippines) were mostly affected by capital market abnormalities, while, it is distinctive the fact that only Japan faced problems on its foreign exchange market. Once again, as in the case of the OECD countries, the most troublesome and long-lasting stress periods are the ones having emanated from the stock markets.

4.4.South American and South American Countries' Financial Stress Indices

Turning to the Latin American group of countries (these are Argentina, Brazil, Mexico, Peru and Venezuela), we firstly observe that the corresponding FSI is the shortest one, covering the period from the fourth quarter of 1998 until the common end of the sample (second quarter of 2009). Again, even though this lack of data excludes the very interesting, in terms of financial irregularities, period of the 1980's and 1990's, it can still offer a good insight on whether this index can perform adequately as a timely indicator of financial stress. It should be emphasized that, for the individual FSI's, the data time span is longer, initiating for most of the countries (Argentina, Brazil and Mexico) from 1995 and, since 1997, for Peru and Venezuela.

As in the case of the Asian FSI, the South American one shows a clustering of financially stressful periods, at the beginning and the end of the sample period. More precisely, the end of 1998 and early 1999 have been proved quite volatile for Latin America, with the financial stress index having reached a value of 2.5 standard deviations above the mean. This is, clearly, the spillover outcome of the financial crisis in Asia which, later on, contributed to the emergence of financial crises in Brazil, at first, and then, in most of the countries in South America. Nonetheless, the index followed a de-escalating course, reaching its lowest value of 2.4 standard deviations below the mean (showing a, below the average, financial stability) in the second quarter of 2002. After that, a consistent increase followed, reaching values indicating financial stress since 2007. The FSI clearly exposes that, until the end of our sample, this region of the world remains in a financially instable period, with a tendency for rising stress in the future.

Graph 2.4: Latin American Financial Stress Index

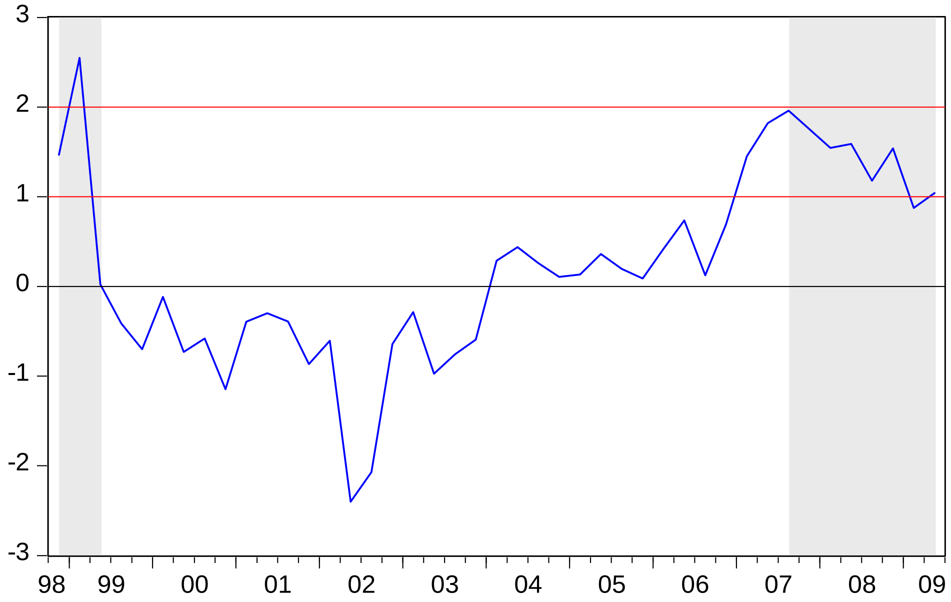

Table 2.4: Latin America: Numbers of Episodes & Duration per Stress Type

Stress Types / Countries	*Banking*	*Securities*	*Foreign Exchange*	*Total*
Argentina	0	2	1	3
Duration	*0*	*3.5*	*1*	*3*
Brazil	1	4	1	6
Duration	*2*	*2*	*1*	*2.3*
Mexico	3	3	0	6
Duration	*1*	*3.3*	*0*	*2*
Peru	1	2	0	3
Duration	*3*	*6*	*0*	*5*
Venezuela	1	3	0	4
Duration	*1*	*4.3*	*0*	*3.5*

Source: author's calculations. Duration of stress episodes in quarters

Focusing now on the types of financial stress and their duration, Latin America faced, in total, 22 such episodes, with an average duration of three quarters[47]. Again, the most frequent provenance of such crises is the stock and, in more general

[47] As it can be seen from table 1.

terms, the securities markets. Brazil and Mexico are the most vulnerable economies, both having experienced severe financial stress in two cases: the former during the famous Real crisis outbreak (1998-99), the latter during the Mexican Peso crisis in 1994-95. In general, late 90's were proved quite volatile for four of the countries of our sample, with the exception of Venezuela. Additionally, the financial crisis of the last four years has a remarkable effect on this bunch of countries, especially to Peru (where the FSI is persistently high), Venezuela (although, at the end of the sample, the index was rather low) and Argentina. On the contrary, Mexico and Brazil dealt with moderate increases on their markets' stress, having ended up to periods of non-stress in their economies (here, it should be noted that Mexican FSI has become to rise again, indicating a reversal to this situation). Table 4 summarizes this discussion on the number and types of financial stress exerted on these economies.

5. Predicting Economic Conditions with Financial Conditions

In this section, the main concern is the establishment of a clear relationship between the prevailing financial conditions and the respective economic situation. In order to do this, a number of forecast evaluations are conducted with models containing both variables of real economic activity and the financial stress indices constructed and analyzed in the previous sections of this paper. The main question here is, whether the prevailing financial markets conditions (as depicted by the financial stress indices) can offer some insights on the evolution of the real economy's conditions. In other words: whether the utilization of financial distress indicators can be useful as predictors of the forthcoming macroeconomics conditions. As it has become apparent from the literature review in section two, this is an ongoing part of the economic literature. Until recently, most of the research effort has focused on the tools and techniques that can be implemented in the construction of these composite financial indicators. Very few papers move one step further, providing evidence on the usefulness of these FSIs as tools able to predict the course of the economy. Relevant literature, like the work by Claessens *et al.* (2011), empirically supports the interweaving nature of real economy and financial conditions. Additionally, some of the papers mentioned in the review of the literature have established a relationship, with rather mixed results, between indices like the ones computed here and their predictive power for important macroeconomic variables, like GDP growth, unemployment and so on. A couple of them have also tried to forecast the index itself. The restrictive feature of these studies is that they, almost, entirely focus on US, especially those that deal with the predictive power of financial distress on the real economy. Additionally, Eurozone has been treated as a whole, for instance in the papers by Grimaldi (2010) and Mallick and Sousa (2011), while, in our knowledge, there are no studies for the prediction of the economic conditions from the financial conditions for the emerging markets yet[48]. Hence, this paper is among the first ones to provide evidence for the real economy – financial stress nexus in country level and for such a diverse group of countries (both advanced and emerging economies). In the following subsection, a discussion of the model specification and the estimation methodologies used for the forecasting applications that follow is provided, together with a short description of the data series in use. Then, the unit root test results are presented and discussed, followed by a section where the out of sample forecasting results are tabulated and commented.

5.1. Model Specification and Methodologies Used for the Forecasting Exercise

In order to evaluate how well financial conditions anticipate shifts in real economic activity, a model similar to the one used by Hatzius *et al.* (2010) is employed. As it has been analyzed in the review section, that paper's authors investigated whether both single and composite financial indicators improve the predictive performance of a number of macroeconomic variables[49], in in-sample and out-of-sample forecasts. Here, we focus on out-of-sample predictions, since this is the crucial aspect and essence of using these financial stress indexes as predictors of future economic developments. Thus, the model's specification, in this case, is the following:

[48] The paper by Chortareas *et al.* (2011) implements static and dynamic probit analysis, but for predicting the financial distress for 17 developing economies.
[49] These were real GDP, payroll employment, industrial production index, civilian unemployment rate.

$$y_{t+h} - y_t = \beta_0 + \sum_{i=1}^{p_y} \phi_i \Delta_{y_{t+1-i}} + \sum_{i=1}^{p_x} \gamma_i FSI_{t+1-i} + e_{t+i} \tag{2.39}$$

Here, y_t denotes the real economy's variables and FSI is the financial stress indices constructed here. So, the main objective here is to check whether the inclusion of lagged values of each country's FSI can improve the predictive performance of a simple autoregressive model of y_t. It is not by chance that the baseline model is a simple AR one, since it is well justified that most of the macroeconomic variables follow such autoregressive behavior[50]. If equation (2.39) is superior in predicting y_t, strong evidence in favor of using FSIs as predictors of economic activity is provided. In the aforementioned model, subscript h represents the time horizons for which forecasts were estimated. That is one, three and six months ahead forecasts, with the exception of Switzerland, for which only quarterly data for the series under investigation exist. As a proxy of real economic activity, industrial production index for each country has been used.

Two, similar, approaches were followed in the estimation of equation (2.39). First, a simple dynamic forecasting procedure was followed. According to this, the regression is estimated with data up to date *t* and, then, we use these initial estimations to obtain the forecast values for the first value in the forecast sample. Then, for period *t+2* in the forecast sample, we use the forecasted values of the previous period and so on until the end of the sample period (that is, May 2009). The second approach implements rolling regression estimations. In this approach, we consider a constant window sample, different for each group of countries because of the time coverage limitations. So, for the forecast sample period, a recursive procedure is followed, where the window sample size "rolls" over the entire forecast period, by moving the window by one observation in each estimation (and, on the same time, dropping the initial observation of the previous sample period). In this way, more accurate forecasts can be obtained, exactly because of the sample renewal and the use of the most recent information in the estimation procedure. In both cases, the forecast evaluations were based on the root mean squared forecast errors of the models, compared to the baseline AR model. That is, the roots mean squared forecast error ratios. Whenever the values of these ratios are lower than one, this implies an improvement on the

[50] Hence, previous values of the variable itself can be used to predict future ones.

forecast accuracy, when the FSI model is implemented. Finally, we should mention that the lag length selection for both AR and the FSI model has been done by the AIC criterion. In the next section, unit root testing results are presented. The forecast evaluation period cover different time periods, for the different group of countries. For instance, for the case of OECD economies, most forecast evaluations cover the period from the beginning of 1990 until the end of the sample size. For Austria, Finland and France, this period starts from January 1991 (April for France, specifically), while for Switzerland begins on the second quarter of 1992. For the case of South American economies, January 2001 is the start date of the evaluation period (for Argentina, Venezuela, Mexico), while the Brazilian and Peruvian case is slightly different (August 200 for the former, beginning of 2002 for latter). Finally, for the case of the Asian economies, Thailand's forecast evaluation starts on May 2002 and for Korea at January 2002.

5.2. Testing for Unit Roots

Before proceeding to the forecasting estimations, it is necessary to check whether our series are stationary or not. As it is well know, the existence of a unit root can render the whole analysis obsolete, due to spurious regression problems. Thus, using the well established augmented Dickey-Fuller (ADF) test, all series that are used in the following forecasts have been examined for the existence of unit roots. The general regression form for the ADF test is

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_2 t + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \qquad (2.40)$$

where α_0 is an intercept, $\alpha_2 t$ represents time trend, while lagged values of the dependent variables are also included in the equation. The crucial coefficient for stationarity is γ, and the hypothesis tested is whether it is zero (meaning the series has a unit root) against the alternative of being smaller than zero (series is stationary). The following tables present the ADF test results for, both, the industrial production and the FSI series for the countries in our sample. For each country, we provide the t-statistics for the levels and the first differences of the two series (industrial production and the financial stress index) under consideration.

Table 2.5: Unit Root Tests for OECD Countries

ADF Unit Root Tests (null hypothesis: series has a unit root)								
Countries	IP Lev.	t-stat.	IP Lev.	t-stat.	FSI Lev.	t-stat.	FSI Lev.	t-stat.
Australia	0	-2.613	1	-9.08***	0	-2.472	1	-9.11***
Austria	0	-1.77	1	-20.25***	0	-2.60*	1	-18.87***
Belgium	0	-1.199	1	-4.959***	0	-5.208***	1	-12.42***
Canada	0	-2.951	1	-4.858***	0	-5.222***	1	-22.37***
Denmark	0	-1.263	1	-8.044***	0	-5.963***	1	-31.91***
Finland	0	-0.807	1	-2.93**	0	-5.032***	1	-12.72***
France	0	-0.342	1	-8.835***	0	-4.98***	1	-21.23***
Germany	0	-2.517	1	-24.67***	0	-3.469***	1	-19.37***
Italy	0	0.809	1	-28.23***	0	-3.725***	1	-23.02***
Netherlands	0	-1.983	1	-6.607***	0	-3.879***	1	-20.66***
Spain	0	1.752	1	-4.203***	0	-6.913***	1	-21.36***
Sweden	0	-0.881	1	-26.97***	0	-5.31***	1	-16.92***
Switzerland	0	-2.513	1	-9.946***	0	-4.589***	1	-9.55***
UK	0	0.18	1	-21.75***	0	-4.243***	1	-15.63***
US	0	-0.158	1	-5.961***	0	-2.705*	1	-14.90***

Note: Series level: 0 – level; 1 – 1st difference. Number of lags was chosen based on Schwartz Information Criterion, with maximum number considered = 12. *, ** and *** denote rejection of null hypothesis at 10%, 5% and 1% level, respectively.

Table 2.5 summarizes the unit root test results for the OECD countries. As it is easily observable, industrial production series, for all countries, are stationary on first differences. This is not unusual, given the nature of most macroeconomic series. Regarding the financial stress indices, their stationarity in levels is verified. The only exception is the Australian FSI, which index is stationary in first level. In this way, it is insensible to use it for forecasting the evolution of the industrial production. Thus, excluding Australia, we can proceed to the necessary estimations for this group of countries, in order to obtain the respective forecasting results.

Table 2.6: Unit Root Tests for Asian Countries

ADF Unit Root Tests (null hypothesis: series has a unit root)								
Country	IP Lev.	t-stat.	IP Lev.	t-stat.	FSI Lev.	t-stat.	FSI Lev.	t-stat.
Japan	0	-1.677	1	-9.664***	0	-4.206***	1	-19.8***
Korea	0	-1.857	1	-10.95***	0	-7.342***	1	-16.7***
Malaysia	0	-2.659	1	-2.641	0	-3.071**	1	-8.95***
Philippines	0	-5.528***	1	-4.349***	0	-1.953**	1	-9.85***
Thailand	0	-2.461	1	-14.14***	0	-3.775**	1	-13.1***

Note: Series level: 0 – level; 1 – 1st difference. Number of lags was chosen based on Schwartz Information Criterion, with maximum number considered = 12. *, ** and *** denote rejection of null hypothesis at 10%, 5% and 1% level, respectively.

Results are, somehow, different, in table 2.6. Here, the results for the Asian countries' series are presented. As it can be seen, only three out of the five countries' series have the desirable results. In particular, Malaysian industrial production is an I(1) process, both in levels and first differences[51], rendering it improper for our analysis. On the other hand, Philippines industrial production is stationary in levels, again excluding this country from further econometric investigation[52]. Finally, Latin American countries' ADF tests results are summarized in table 2.7. Thankfully, all FSI series are stationary in levels, while IP series are I(0) in first differences.

[51] This series was stationary in 2nd differences.

[52] According to the specification of the model we use here for prediction, we need to use the first difference of industrial production (i.e. the rate of change or growth rate of the variable) as regressand.

To sum up, after the ADF tests, we proceeded to the forecasting estimations for twenty one out of the initial twenty five countries of our sample[53]. Following the estimation procedures discussed in section 5.1, the obtained results are presented and discussed in the following subsection.

Table 2.7: Unit Root Tests for Latin American Countries

ADF Unit Root Tests (null hypothesis: series has a unit root)								
Country	IP Lev.	t-stat.	IP Lev.	t-stat.	FSI Lev.	t-stat.	FSI Lev.	t-stat.
Argentina	0	-2.147	1	-4.727***	0	-4.612***	1	-15.33***
Brazil	0	-2.896	1	-12.40***	0	-5.475***	1	-12***
Mexico	0	-0.51	1	-13.94***	0	-6.459***	1	-17.95***
Peru	0	-1.777	1	-4.812***	0	-4.008**	1	-10.26***
Venezuela	0	-2.847	1	-13.22***	0	-3.600***	1	-7.33***

Note: Series level: 0 – level; 1 – 1st difference. Number of lags was chosen based on Schwartz Information Criterion, with maximum number considered = 12. *, ** and *** denote rejection of null hypothesis at 10%, 5% and 1% level, respectively.

5.3. Forecasting Results

The following four tables present the outcome of the forecast estimations conducted with the simple dynamic and the rolling window approach. The first two tables depict OECD countries and the performance of their FSIs as predictors of their respective industrial production, while the last two focus to the other two regions studied in this paper (Asia and Latin America). As mentioned above, one, three and six periods ahead predictions were computed, with the third, fourth and fifth column in each table representing the RMSFE for the AR, Dynamic and Rolling estimations respectively. Then, the important results are the ones depicted in the last two columns of the tables, where the RMSFE ratios are provided. Just to remind, that when the

[53] Spain is also excluded from the forecasts, not because of stationarity issues, but because the results obtained from the estimations did not offer any kind of statistical and economic intuition.

RMSFE ratio is below one, this is a clear indication that the model where the FSI is included performs better, in terms of forecasting accuracy.

Table 2.8.A: Out of Sample Forecasting Performance for OECD Countries - 1

		RMSFE			RMSFE Ratios	
Countries	h	(a) AR	(b) Dynamic	(c) Rolling	(b)/(a)	(c)/(a)
Austria	1	0.0197	0.0198	0.0153	1.0062	0.7750
	3	0.0198	0.0195	0.0161	0.9837	0.8128
	6	0.0198	0.0196	0.0157	0.9926	0.7929
Belgium	1	0.1031	0.1020	0.0644	0.9895	0.6244
	3	0.1032	0.1020	0.0779	0.9886	0.7548
	6	0.1030	0.0806	0.0656	0.7824	0.6366
Canada	1	0.0060	0.0072	0.0048	1.1987	0.8083
	3	0.0059	0.0066	0.0049	1.1056	0.8240
	6	0.0060	0.0065	0.0048	1.0778	0.7986
Denmark	1	0.0655	0.0656	0.0388	1.0016	0.5923
	3	0.0655	0.0655	0.0477	0.9996	0.7284
	6	0.0655	0.0647	0.0493	0.9871	0.7525
Finland	1	0.1099	0.1093	0.0659	0.9944	0.5994
	3	0.1102	0.1098	0.0749	0.9966	0.6799
	6	0.1103	0.1095	0.0805	0.9930	0.7299
France	1	0.0121	0.0123	0.0101	1.0138	0.8280
	3	0.0121	0.0122	0.0103	1.0014	0.8516
	6	0.0122	0.0121	0.0097	0.9915	0.7983
Germany	1	0.0157	0.0154	0.0131	0.9829	0.8351
	3	0.0157	0.0153	0.0125	0.9740	0.7941
	6	0.0157	0.0156	0.0133	0.9948	0.8472

Note: Column h represents the time horizons for which forecasts are provided. These are 1, 3 and 6 months ahead forecasts. (a), (b) and (c) columns report the root mean squared forecast errors (RMSFE) for the AR, dynamic and rolling window models respectively.

Table 2.8.B: Out of Sample Forecasting Performance for OECD Countries – 2

		RMSFE			RMSFE Ratios	
Countries	h	(a) AR	(b) Dynamic	(c) Rolling	(b)/(a)	(c)/(a)
Italy	1	0.0139	0.0152	0.0126	1.0913	0.9063
	3	0.0144	0.0145	0.0119	1.0107	0.8280
	6	0.0145	0.0145	0.0123	1.0035	0.8478
Netherlands	1	0.0758	0.0762	0.0609	1.0044	0.8024
	3	0.0758	0.0751	0.0568	0.9909	0.7495
	6	0.0757	0.0762	0.0600	1.0071	0.7923
Sweden	1	0.0199	0.0197	0.0163	0.9946	0.8196
	3	0.0198	0.0198	0.0162	0.9996	0.8184
	6	0.0198	0.0197	0.0161	0.9948	0.8105
Switzerland	2	0.0231	0.0223	0.0187	0.9619	0.8072
	4	0.0230	0.0223	0.0177	0.9682	0.7688
UK	1	0.0092	0.0097	0.0078	1.0595	0.8540
	3	0.0092	0.0099	0.0078	1.0835	0.8538
	6	0.0092	0.0098	0.0076	1.0701	0.8298
US	1	0.0070	0.0075	0.0050	1.0767	0.7181
	3	0.0070	0.0085	0.0053	1.2204	0.7576
	6	0.0070	0.0081	0.0055	1.1639	0.7812

Note: Column h represents the time horizons for which forecasts are provided. These are 1, 3 and 6 months ahead forecasts (except Switzerland where the horizons are 2 and 4 quarters, because of the data frequency). (a), (b) and (c) columns report the root mean squared forecast errors (RMSFE) for the AR, dynamic and rolling window models respectively.

As a first general comment, we can say that the results are quite promising. In all cases, the forecast error when rolling window approach is employed is lower for the FSI model. In some cases, especially for some of the OECD countries, there is an improvement even with the simple dynamic forecasting approach, even though it is a rather negligible one. For instance, for table 2.8.A, Austria, Belgium, Denmark, Finland and Germany are countries with RMSFE lower than one, in the case of dynamic forecasting. The same holds for Sweden and Switzerland in table 2.8.B. In any case, the striking improvement is the one with the rolling window approach. Even for the countries that exhibit lower forecast errors with the first approach in the FSI model, the improvement is even bigger with the rolling window estimations. The cases of Denmark, Belgium are impressive, in terms of forecast error decline between the two approaches used, while the same holds for UK and, especially, US forecasts. On average, it can be said that forecast errors are smaller by around 31 percent, when rolling window methodology is implemented. Regarding forecasting horizons, the improvement is impressive in all three cases, with somehow better results in the case of short and medium term forecasts (one and three months ahead, which are improve, on average, by thirty to thirty five percent when the second methodology was followed). Focusing on the Euro zone member countries included in our sample[54], the predictive performance of both models is quite good, especially for the rolling regression forecasts. Even with the simple dynamic approach, the FSI model performance, even if it is worse than the AR forecasts in general, for some of them there is an improvement in the index-augmented model in case like Germany or Finland[55]. But again, with the second approach, the declines in forecast errors provide strong evidence in favor of using financial distress indicators as predictors of future economic activity.

Turning to the other two groups of countries, Asian and Latin American ones, the effect of the financial stress indexes on the prediction of industrial production growth rate is, again, important. As it can be observed from tables 9 and 10, the forecast errors when the rolling window approach was adopted, are decreased in an important extent. Again, there are two countries (Korea and Brazil), for which even the first forecasting methodology gave, marginally, better results with the FSI model. But, in broad terms, this approach does not offer satisfactory results. On the other hand, it is easily verifiable that the FSI model here is not that effective, as in the case of OECD countries. Even if there are more favorable results, in terms of higher

[54] These are Austria, Belgium, Finland, France, Germany, Italy, Netherlands,

[55] Even if this improvement cannot justify the FSI usefulness as predictor.

forecasting accuracy with the implementation of the FSI model, the change is not that big, especially for the countries that FSI model showed promising results with the simple dynamic approach as well (Korea, Brazil). Another distinctive feature of these groups of countries is the thing that, the lower RMSFE ratios are mostly observable in the three-month and six-month forecast horizon, in contrary to the OECD countries where the short and medium term forecasts exhibited the greatest improvement. It is also noteworthy that, for countries like Thailand (from the Asian group), Brazil and, especially, Venezuela (from South American cluster) the short term forecasts are on the verge of proclaiming the FSI-augmented model as the appropriate one for real economy's conditions forecast. Particularly, Venezuela's results are, by far, the worst ones for the countries under scrutiny.

Table 2.9: Out of Sample Forecasting Performance for Asian Countries

		RMSFE			RMSFE Ratios	
Countries	h	(a) AR	(b) Dynamic	(c) Rolling	(b)/(a)	(c)/(a)
Japan	1	0.0179	0.0180	0.0149	1.0042	0.8315
	3	0.0179	0.0182	0.0148	1.0167	0.8296
	6	0.0179	0.0187	0.0150	1.0474	0.8393
Korea	1	0.0283	0.0281	0.0249	0.9924	0.8796
	3	0.0282	0.0281	0.0236	0.9946	0.8358
	6	0.0282	0.0280	0.0235	0.9907	0.8344
Thailand	1	0.0306	0.0379	0.0298	1.2356	0.9717
	3	0.0339	0.0388	0.0286	1.1433	0.8431
	6	0.0316	0.0339	0.0263	1.0736	0.8322

Note: Column h represents the time horizons for which forecasts are provided. These are 1, 3 and 6 months ahead forecasts. (a), (b) and (c) columns report the root mean squared forecast errors (RMSFE) for the AR, dynamic and rolling window models respectively.

Table 2.10: Out of Sample Forecasting Performance for Latin American Countries

		RMSFE			RMSFE Ratios	
Countries	h	(a) AR	(b) Dynamic	(c) Rolling	(b)/(a)	(c)/(a)
Argentina	1	0.0185	0.0193	0.0158	1.0407	0.8537
	3	0.0187	0.0188	0.0147	1.0058	0.7824
	6	0.0185	0.0185	0.0149	1.0003	0.8044
Brazil	1	0.0217	0.0214	0.0195	0.9881	0.9014
	3	0.0217	0.0216	0.0176	0.9988	0.8114
	6	0.0217	0.0217	0.0178	0.9988	0.8212
Mexico	1	0.0111	0.0121	0.0093	1.0941	0.8454
	3	0.0110	0.0119	0.0092	1.0750	0.8358
	6	0.0111	0.0118	0.0091	1.0705	0.8190
Peru	1	0.0457	0.0484	0.0367	1.0600	0.8023
	3	0.0461	0.0467	0.0385	1.0134	0.8359
	6	0.0461	0.4438	0.0429	9.6286	0.9299
Venezuela	1	0.1763	0.1861	0.1625	1.0559	0.9219
	3	0.1763	0.1846	0.1732	1.0475	0.9829
	6	0.1755	0.1621	0.1616	0.9237	0.9208

Note: Column h represents the time horizons for which forecasts are provided. These are 1, 3 and 6 months ahead forecasts. (a), (b) and (c) columns report the root mean squared forecast errors (RMSFE) for the AR, dynamic and rolling window models respectively.

To sum up, there is evidence that financial conditions can offer a clear indication of forthcoming changes in real economic activity. Especially for OECD countries, the results are quite promising, while the same hold for emerging markets in Asia and South American, to a similar extent. Of course, as it has been emphasized before, this is the first main effort to empirically investigate this interrelation of financial stress indices and macroeconomic variables in such a big and divergent group of countries. Many more can be done, from implementing alternative forecast techniques to trying to get deeper in to the nature of this interrelation. For instance, it would be interested to study whether excessive financial stress in linked with periods of recession and, if this is the case, if the continuous nature of these aggregate indicators can offer useful insights in the duration and the magnitude of the recessionary periods. Also, the study of the several financial stress transmission channels seems promising, as a research avenue, given the fact that modern economies are quite interconnected. Thus, the contagion of financial stress from one country to another, or from a region to another one is crucially important, due to the established relation between financial stress and changes in the macroeconomic environment. This kind of questions is left for future research.

5.4. Forecast Evaluations

In order to support the results of the previous forecasting exercise, we proceed to the evaluation of our forecasting results, using two relevant statistical tests. The first is the Diebold-Mariano (1995) test, which offers the chance to compare whether the forecasts of two models are different. In other words, it checks the forecast accuracy of the two models and offers a statistical test for the significance of their forecast error difference. In general terms, if we assume that the series forecasted is noted as y_t, then the forecasts from the two different models are represented as y^1_{t+h} and y^2_{t+h} respectively. It is customary that model 2 should be the model with the smaller RMSE. Given the above, we construct the forecast errors of the two models, which are the difference between the actual and forecasted values of the series under consideration. In functional form, it is

$$\begin{aligned} e^1_{t+h} &= y_{t+h} - y^1_{t+h} \\ e^2_{t+h} &= y_{t+h} - y^2_{t+h} \end{aligned} \tag{2.41}$$

Each function in (1.41) represents a loss function for the models under consideration. That is, the inability of the models to offer accurate enough forecasts of future values of the series under investigation. Diebold and Mariano (1995) exhibit that their statistic can test whether one of the models predicts better than the other based on the following null hypothesis

$$\begin{aligned} H_0 &: d_t = 0 \\ H_1 &: d_t \neq 0 \end{aligned} \tag{2.42}$$

where $d_t = e^1_{t+h} - e^2_{t+h}$ is the loss differential between the two models under examination[56]. The Diebold-Mariano test statistic is $DM = \frac{\bar{d}}{\sqrt{V(\bar{d})}}$, where $\bar{d} = \frac{1}{T_0}\sum_{t=t_0}^{T} d_t$ is the sample mean of the loss differential and $V(\bar{d}) \approx \frac{1}{n}\left[\gamma_0 + 2\sum_{k=1}^{h} -1\gamma_k\right]$, with γ_k being the kth autocovariance of d_t. The examined series is autocorrelated and the authors show that the statistic follows an asymptotically standard normal distribution.

It is documented that the Diebold-Mariano test may not be justified, in cases of nested competing models. The problem lies on that the forecasts of the two models are asymptotically perfectly correlated and, thus, the DM statistic is not reliable at the population level. In order to overcome such complexities and be able to provide clear evidence in favor or not of the FSI-enhanced forecast model, we provide additional evidence on the forecasting ability of our models. This is done through the use of the statistic suggested by Clark and West (2007). This test is robust to the type of models (nested and non-nested). The authors follow similar terminology with the case of DM test, where the baseline model (model 2) is the one nesting model 1 (the smaller model). Apart from the already mentioned forecast errors of models 1 and 2, Clark and West (2007) introduce an "adjustment" term as they call it. This is nothing more than the sample average of the squared differences of the forecasted series from the two models. In functional form, $adj = P^{-1}\sum(\hat{y}_{1t,t+\tau} - \hat{y}_{2t,t+\tau})^2$. The hypothesis tested is similar to (1.42), but this time the loss differential includes the adjustment term as well. This means that $d_t = e^1_{t+h} - e^2_{t+h} + adj.$. The authors describe the estimation procedure, in order to obtain the relevant t-statistic, which includes the regression of

[56] Diebold-Mariano test can be applied for several different types of loss functions. In our case, we use the most popular one. That is, the quadratic loss function.

the aforementioned loss differential on a constant, using an OLS estimator with autocorrelation consistent standard errors. The null hypothesis of equal predictive ability can be rejected if the statistic is greater than 1.282 or 1.645 (for 10% and 5% significance levels, respectively).

The following tables present the outcome of the DM and CW tests. We first report the results from the case of the FSI-enhanced model (based on the rolling regression approach) used as the benchmark model, while the other two tables refer to the dynamic forecasting case. Our focus is on the first case, since the rolling forecasting offers the lowest forecast errors and it is the best predictor, based on the RMSEs.

The most striking result from table 11 is the limited ability of the DM test to provide clear cut evidence in favor of the FSI-enhanced model. Out of thirteen countries, it only provides such evidence in six OECD countries. In some cases, like US, Italy and Netherlands, the evidence is partial, offering justification for using FSI as predictor of real economic activity for limited forecasting horizon cases (for one month ahead for Italy and US, for three and six months in case of US again and Netherlands). Very strong evidence in favor of the model with the FSI is provided for the case of Belgium, Denmark and Finland. In these three countries, the DM test strongly rejects the null of equal predictive ability. Since, as we discussed earlier, DM test is not that suitable for the case of competing nested models, we also provide the results of the CW test, where the nesting effect does not falsify the statistical results. In this case, the results are too strong in favor of our model with the financial stress index. In all countries and in all different forecast horizons, the leading indicator properties of our aggregate systemic risk index are profoundly verified. There is only one exception, namely Switzerland. In this case, there is no statistical evidence whatsoever that a simple AR model can be beaten for the industrial production forecast. Additionally, in the case of Italy and UK, it is evident that FSI can be useful only in case of very short horizon forecasting. In both countries, the FSI-enhanced model is better in predicting real activity on one month time window.

The situation is very different in the case of table 12, where the results for the developing economies are presented. Here, both tests fail to provide strong evidence in favor of the model including the systemic risk index. In case of the DM test, only Mexico has favorable results for the aforementioned model, while Venezuela and Thailand have such evidence in the cases of the three month and one month ahead forecasts, respectively. The Clark and West (2007) test provides more evidence in favor of our baseline model. Nevertheless, only in two Latin American countries (Peru and Venezuela), the “equal predictive power” hypothesis is rejected in all three forecast windows. Mexican case is rather weak this time, with only the three month case in favor of FSI model. Finally, in the case of Asian countries, the results are extremely poor, rendering the ability of FSI to work as real economy’s predictor in serious doubt.

Table 2.11: Tests of Equal Predictive Ability for OECD Countries – Rolling Forecasting Case

Forecasting Results Evaluation using Diebold - Mariano and Clark - West tests

H_0: equal predictive ability (forecast errors are equal from the two competing models)

Country	*h*	D-M test	C-W test
Austria	*1*	1.205	4.557 **
	3	-0.396	1.876 **
	6	0.901	3.065 **
Belgium	*1*	4.374 ***	6.457 **
	3	2.581 ***	5.533 **
	6	4.337 ***	6.198 **
Canada	*1*	0.840	4.698 **
	3	-0.357	3.882 **
	6	0.725	4.286 **
Denmark	*1*	5.204 ***	7.065 **
	3	2.701 ***	5.153 **
	6	2.209 **	5.481 **
Finland	*1*	4.971 ***	7.860 **
	3	7.779 ***	9.585 **
	6	5.794 ***	8.203 **
France	*1*	-0.385	2.500 **
	3	-0.843	1.375 *
	6	0.599	2.135 **
Germany	*1*	-0.400	2.986 **
	3	0.962	1.930 **
	6	-0.929	-0.127
Italy	*1*	-1.684 *	1.273 *
	3	-0.150	1.069
	6	-1.030	0.460
Netherlands	*1*	1.322	4.610 **
	3	4.305 ***	8.282 **
	6	1.608 **	5.040 **
Sweden	*1*	-0.111	2.649 **
	3	-0.003	1.490 *
	6	0.428	2.086 **
UK	*1*	-0.838	1.794 **
	3	-1.028	0.952
	6	-0.312	0.970
US	*1*	1.997 **	2.454 **
	3	1.653 *	2.472 **
	6	1.350	2.660 **
Switzerland	*2*	-0.165	-0.143
	4	0.453	0.468

Note: The table presents the Diebold-Mariano and Clark-West statistics for the null hypothesis of equal predictive ability of two forecasting models.. These are the FSI-enhanced model (estimated using rolling regression approach) and a simple AR model.

Notes: The tests are performed for all forecast horizons h (which are 1, 3 and 6 months ahead). *, **, *** denote rejection of null hypothesis at 10%, 5% and 1% level, respectively.

Table 2.12: Tests of Equal Predictive Ability for Developing Economies – Rolling Forecasting Case

Forecasting Results Evaluation using Diebold - Mariano and Clark - West tests

H_0: equal predictive ability (forecast errors are equal from the two competing models)

Argentina			**Brazil**		
h	D-M test	C-W test	*h*	D-M test	C-W test
1	-1.535	1.119	*1*	-1.042	-0.831
3	-0.254	1.900 **	*3*	-0.696	0.148
6	-1.528	-0.395	*6*	-0.975	-0.300

Mexico			**Peru**		
h	D-M test	C-W test	*h*	D-M test	C-W test
1	-1.721 *	0.074	*1*	0.765	4.259 **
3	-1.651 *	1.481 *	*3*	0.399	3.727 **
6	-1.676 *	0.081	*6*	-0.605	2.845 **

Venezuela			**Japan**		
h	D-M test	C-W test	*h*	D-M test	C-W test
1	-0.755	1.944 **	*1*	-0.074	1.910 **
3	-1.818 *	2.014 **	*3*	-0.208	0.980
6	-0.913	1.593 *	*6*	-0.427	0.282

Korea			**Thailand**		
h	D-M test	C-W test	*h*	D-M test	C-W test
1	-0.961	-0.115	*1*	-1.847 *	1.160
3	-1.057	0.245	*3*	-1.118	1.275
6	-0.672	1.185	*6*	-1.432	0.581

Note: The table presents the Diebold-Mariano and Clark-west statistics for the null hypothesis of equal predictive ability of two forecasting models. These are the FSI-enhanced model (estimated using rolling regression approach) and a simple AR model. The tests are performed for all forecast horizons h (which are 1, 3 and 6 months ahead). *, **, *** denote rejection of the null hypothesis at 10%, 5% and 1% level, respectively.

We now turn to the case of dynamic forecasting models, depicted in tables 13 and 14. As there are only some cases where the expanded, with the financial stress index, model has lower forecast error from the AR model, we applied the two tests in these cases only. Regarding the OECD countries, the results are tantamount to the previous case. The DM test fails to provide any strong evidence in favor of FSI ability to predict real economy. The most notable case is the Belgian and Danish one, where the DM test in the rolling forecast case provided very strong results in favor of the FSI model. On the other hand, the CW test offers more convincing results in favor of the latter model. With a few exceptions, it verdicts for the models that incorporates FSI index as a predictor.

Table 2.13: Tests of Equal Predictive Ability for OECD Countries – Dynamic Forecasting Case

Forecasting Results Evaluation using Diebold - Mariano and Clark - West tests

H_0: equal predictive ability (forecast errors are equal from the two competing models)

Austria			Belgium			Denmark		
h	D-M test	C-W test	*h*	D-M test	C-W test	*h*	D-M test	C-W test
1	–	–	*1*	1.151	1.923 **	*1*	-0.128	0.578
3	2.282 **	4.227 **	*3*	0.199	2.093 **	*3*	0.253	0.927
6	0.945	2.658 **	*6*	4.344 ***	6.048 **	*6*	1.096	1.898 **
Finland			**France**			**Germany**		
h	D-M test	C-W test	*h*	D-M test	C-W test	*h*	D-M test	C-W test
1	1.023	1.384 *	*1*	–	–	*1*	0.668	2.108 **
3	0.943	1.090	*3*	–	–	*3*	1.974 **	2.689 **
6	1.482	1.725 **	*6*	0.728	1.898 **	*6*	0.824	2.118 **
Netherlands			**Sweden**			**Switzerland**		
h	D-M test	C-W test	*h*	D-M test	C-W test	*h*	D-M test	C-W test
1	–	–	*1*	0.926	1.682 **	*2*	1.101	2.966 **
3	1.301	1.801 **	*3*	0.036	0.624	*4*	0.877	2.777 **
6	–	–	*6*	1.372	2.045 **			

Note: The table presents the Diebold-Mariano and Clark-West statistics for the null hypothesis of equal predictive ability of two forecasting models. These are the FSI-enhance model (recursivelly estimated) and a simple AR model. The tests are performed for all forecast horizons h (which are 1, 3 and 6 months ahead). *, **, *** denote rejection of the null hypothesis at 10%, 5% and 1% level, respectively.

The case of the developing economies is, again, similar to the previous discussion. Here, the forecasting results tested are even less than in the OECD countries case. For once more, the FSI-enhanced model is shown to be better in predicting real economic activity in only half of the cases examined. Korean case has the strongest evidence in favor or the latter, while the evidence in the case of Latin American countries is, again, limited. Of course, this does not mean that FSI is not useful altogether, as a measure of financial stress and the forthcoming effects of adverse financial conditions on the economy, since there is evidence in favor of this feature of the latter.

Table 2.14: Tests of Equal Predictive Ability for Developing Economies – Dynamic Forecasting Case

Forecasting Results Evaluation using Diebold - Mariano and Clark - West tests

H_0: equal predictive ability (forecast errors are equal from the two competing models)

Korea			Brazil		
h	D-M test	C-W test	*h*	D-M test	C-W test
1	0.230	1.420 *	*1*	1.099	2.154 **
3	0.146	1.515 *	*3*	0.112	0.648
6	0.398	0.988	*6*	0.141	0.824

Peru			Venezuela		
h	D-M test	C-W test	*h*	D-M test	C-W test
1	–	–	*1*	–	–
3	–	–	*3*	–	–
6	-2.256 **	0.239	*6*	0.625	1.501 *

Note: The table present the Diebold-Mariano and Clark-West statistics for the null hypothesis of equal predictive ability of two competing models. These are the FSI-enhanced model (recursively estimated) and a simple AR model. The tests are performed for all forecast horizons h (which are 1, 3 and 6 months ahead). *, **, ***, denote rejection of null hypothesis at 10%, 5% and 1% level, respectively.

6. Conclusions and Implications for Future Research

Financial crises are recurrent and catastrophic phenomena for the world economies. It affects both developed and emerging economies, with severe repercussions on their economic growth and welfare. Previously, research on crises was mainly focused on solitary kind of crises, either balance of payments, currency or banking crises and, in this way, the authors were trying to offer type-specific proposals for overcoming each kind of financial turmoil. Today, it is well justified and established the view that modern economies face systemic-wide financial upheavals which, as it is commonly agreed, require special attention and monitoring modeling. On the other hand, previous econometric approaches do not seem to adequately cover the need for timely and accurate representation of the degree of (in-) stability of the financial markets. Additionally, there is a lack of empirical investigation on whether financial conditions and, particularly, excessive financial stress can offer some insights and work as a kind of predictor for changes in future economic activity, as represented in several macroeconomic variables and indicators. Hence, there is a need for the development of new tools, able to satisfy these policymakers' needs.

This paper contributes towards the aforementioned targets. It does so by, first, constructing a number of financial stress indices, following the approach proposed by Lall *et al.* (2008) and propagated by Melvin and Taylor (2009), slightly transformed for a number of emerging economies, for which we faced a lack of suitable data. The advantage and distinctive features of our work can be traced into several points: the extended number of countries for which this kind of research is applied to, the first-ever analytical exposition of the performance of the FSI for each country, together with an exhaustive account of the types of stress periods and the duration of these episodes and, finally, the computation and discussion of the performance of three regional financial stability measures, one for each region under examination (OECD, Asia, Latin America), together with a global FSI.

The examination of the performance of our financial stress indices is promising, indicating their ability to accurately capture well-known past financial distresses. Another important feature of these macroprudential measures is the ability to provide early warning signal of such forthcoming financial meltdowns. The changes of FSIs' values through time can be a strong indication for the monetary authorities, in order to adjust their policies and face forthcoming financial strains with confidence. On the same time, the FSI offers an evaluation of the severity of these stress periods, allowing to count the duration of each episode, together with the identification of the main source of instability in the markets (be it banking, securities of foreign exchange related). From this empirical work, it can be confirmed the fact that, for most of the countries and for each region, securities-prone financial abnormalities are the most frequent one, also lasting longer than any other type of crises, while banking turmoils are, also, quite frequent. Moreover, the recent financial crisis, initiated in 2007 is, by far, the most strenuous one, causing huge losses, in financial and economic terms, to the world's markets, especially those of the most advanced economies. Then, depending on the country-specific or regional case, there are other periods of distress that had a significant impact on the world economies, like the ERM crisis in European countries, the Asian crisis in late 90's to the Asian economies and the currency and financial crises of late 90's again in South American countries. Hence, this kind of financial stress index performs quite well, efficiently capturing past stress episodes and it is promising as a predictor of future financial instabilities.

We also moved one step further by providing empirical evidence on the interrelation of financial and economic conditions. In doing so, we employ an autoregressive model of each country's industrial production, where lagged values of the respective financial stress index were included. Using this model, we compared it's out of sample forecasting performance with a baseline AR model. In our knowledge, this is the first attempt to empirically test FSI functionality as a predictor of a macroeconomic variable in such a diverse group of (developed and emerging) economies. Using the RMSFE ratios, it was shown that financial conditions can be used from the monetary authorities as trustworthy indicators of forthcoming changes in real economy, especially for short and medium term periods (in the case of OECD countries) and longer period for Asian and Latin American economies. It is also the very first time that the predictive performance of models incorporating financial stress indexes is evaluated, using tests of equal predictive performance. Such tests are those we implemented, based on the work of Diebold and Mariano (1995) and Clark and West (2007). These tests provide additional evidence in favor of the FSI as a predictor of real economic activity, especially for the case of OECD countries and the rolling window model.

Of course, many more should be done, in order to improve these tools and render them efficacious forecasting tools. First of all, it is important to work towards the improvement of the accuracy of such financial stability measures, through the implementation of better weighting schemes. The equal-variance approach is a good initial approach, offering simple and quick indexes' calculations, although it might not be the most proper one, due to the fact that it assumes normality in the series distributions (something rarely happened in financial data). Additionally, as was mentioned before, the importance of each of the three financial sectors incorporated in the indices, changes through time. Thus, it is reasonable to assume that a weighting scheme of a time-varying nature should be more appropriate. It is also noteworthy, for the case of the regional and global indexes, to take into account the relevant importance of each economy to the total effect exerting to its region. Thus, the relevant contribution of each country's financial markets to the overall performance of the regional indices should, somehow, be measured. In the same line of thought, contagion issues, not included in this piece of research, would be interesting to be embodied (through the use of relevant variables of interest).

Financial stability issues are quite crucial nowadays. After the shock of the subprime crisis, policymakers around the world are more than interested in the development of relevant tools, able to provide clear and on time evidence of the financial system health. It is an uncharted territory, yet to (and should) be discovered.

Chapter 3

An Investigation of Systemic Stress and Interdependencies within the Eurozone and Euro Area Countries

Abstract

Eurozone is getting through its most serious financial crisis, putting at stake the whole European integration project and set a number of crucial questions for the viability of the Eurozone as an economic and political entity and of the euro as a common currency. One of the most interesting aspects of this financial turmoil is the identification of the sources of this instability. More precisely, it is important for policymakers and market participants to be able to spot the channels through which the crisis has affected European markets. Such a work can contribute to the creation of an appropriate policy framework, in order to establish an adequate framework for financial markets' regulation and supervision, along with the necessary macro-prudential policies. Moreover, the detection of possible financial risk transmission channels is very significant for these aforementioned policies. For all the above reasons, we focus on the main source of this financial crisis, that is, the financial and banking markets. Here, instead of focusing to single indicators of financial instability, we move one step forward, by using financial stress indices, in order to have a clear-cut idea of the size and the severity of the financial turmoil through time. Using a wide number of series, we first proceed to the construction of financial stress indicators for the money market, bond market, banking sector and the stock market of each Eurozone country, while an overall index for each country is also provided. By employing these indices, it is possible to have a clear narrative of the evolution of the current crisis for the whole Eurozone, as well as for each country and, even more important, for the markets that drove the crisis in each country. It is the first time such detailed, in the number of countries as well as in the decomposed nature of the indices, financial stress analysis is offered for the Euro Area. Then, VAR models are employed, both for each country, as well as for each (money, banking, bond, equity) group of markets for the examination of excessive financial risk transmission. A number of innovative conclusions are reached, such that: 1) not all peripheral countries (and especially Greece and Portugal) should be blamed for the crisis exacerbation 2) there is clear evidence of stronger interdependencies between banking and bond markets and 3) a degree of segregation (in terms of financial stress contagion) between peripheral and core Eurozone economies.

JEL Classifications: C43, C58, G01, G15

Keywords: Systemic Risk, Financial Stress Index, VAR, Impulse Responses

1. Introduction

Since 2007, the global economy is getting through one of the most unstable periods in modern history. The problems that were raised in the sub-prime mortgage market in United States quickly spread to the global financial system and created an unprecedented financial crisis, which greatly affected the growth prospects of the world economy for many years. The interconnectedness of the various markets and national economies are so tight, that monetary authorities were forced to proceed to economic policies never applied before to such a wide scale and number of developed countries. It is not by accident that the current period is now known as the Great Recession.

The fundamental reason for reaching such levels of recession is the strong and perplexed interrelation of the financial system with the real economy. Moreover, the fact that financial markets consist of a number of different markets, like the banking market, the bond market, money market and so on, each one driven by its own distinctive forces, makes things even more complex and difficult for assessing the underlying causes of financial turmoils and deciding on the optimal policies for the alleviation of market instabilities. Central bank authorities employ monetary policy measures, in order to intervene and stabilize the economy, while the financial stability and financial stress assessment was a recent addition to their mandate. Even the so-called monetary policy transmission channel is not, yet, thoroughly evaluated and tracked down the different ways through which it can affect the aforementioned. In order to perform such an evaluation, a measure able to identify financial system impairments is necessary. Hence, there is a need for using financial stress indices, able to clearly depict systemic risk.

Another reason, rendering the employment of such financial stress measures necessary, is the fact that the same nature of financial crises has been multifaceted. As it has been evident in the last few years, during Great Recession, the sources and causes of a financial crisis can significantly vary, in accordance to changes taking place in the financial market conditions and investors sentiment. For instance, the current financial crisis begun from a, relatively small, uninteresting, financial sector, the sub-prime mortgage market in the United States. Soon, it has infected several markets and economies around the world, with this crisis reaching its peak with the

Lehman Brothers collapse in September 2008. This situation brought a major disruption in money markets, as well as the interbank funding market, leading to a drying up of liquidity in a global level. In turn, this had major repercussions on capital struggling companies, households and countries, brining up more transformation of this crisis into a banking one and, lately, a sovereign debt crisis. Thus, it is evident, as it is also emphasized by Sandahl *et al.* (2011), that the thorough study of each market, that is part of what economists call financial system, is of utmost importance and can easier be done using financial stress measures. In this way, a clear and timely depiction of the prevailing conditions in each financial market is possible, while it is also an efficient way to assess the market-wide systemic risk for the economy. Finally, as it was previously implied, these indices can be used to evaluate the effectiveness of the monetary policies followed by central banks, since tools used by the aforementioned are integral parts of the aggregate financial stress indexes.

As it is clear from the previous discussion, there is great scope for the implementation of financial stress indices, especially in the present situation, where the need for accurate and timely indicators of systemic-wide financial instabilities is extremely important. In this chapter, we are going to construct a series of financial stress indicators, in order to analyze the current Eurozone crisis. This is an important motivation for this piece of research, since the unprecedented level of financial and sovereign turmoil in the Euro Area should be investigated and scrutinized. In order to do it, we employ a wide number of indicators, originated from the most important financial markets. These are the banking sector, the money, equity and bond market of each one of the eleven original Eurozone countries[57]. In this way, we construct five stress indices for each country (four sectoral, one country-wide), while an index for the whole union is also provided. Three different approaches are used to aggregate the individual indexes, namely the equally weighted, the first principal component from a principal components (PCA) analysis and, finally, the weighted loadings approach, again stemming from a PCA analysis.

In the second stage of this empirical assessment of the Eurozone crisis, we provide initial evidence on the implied interrelation between the markets and the countries financial (in)-stability. The existence of trade and tight financial connections

[57] Luxembourg is not included, since it is a small economy, without major interactions with the other core Eurozone countries. Also, even though Greece joined the common currency a bit later (2001), its alleged contribution to the current crisis renders its inclusion to the analysis quite important.

between euro currency countries, along with the existence of a unified monetary authority (the European Central Bank), deciding on the kind of monetary policies followed by all these countries, justifies and strengthens the necessity of such an econometric investigation. The provision of such empirical evidence leads to the establishment of interactions among the markets and the countries under exploration, providing further evidence in one of the hottest debates of concurrent financial literature. That is, the existence of channels of interdependence and contagion of the financial crisis from one country to another. With our work here, we expand the literature in many ways. First, it is possible to examine channels of crisis transmission using aggregate indexes of systemic risk, both in country level, as well as in individual markets. Thus, a more detailed analysis of potential stress sources and markets interactions is possible. Additionally, such an empirical evaluation of intra-Euro area interdependencies is useful for policy purposes, since the detailed and exhaustive indagation of the aforementioned indices and interrelations prove the necessity of different kind of policies in different markets, countries and cases of financial upheavals. Moreover, these stress indexes are ideal as early warning indicators of forthcoming financial abnormalities, since their advantage is the timely information they provide for the current state of the financial markets.

The empirical work involves the usage of vector autoregressive (VAR, hereafter) models, in order to examine the interrelations of the aforementioned economies, through the financial stress indices. The analysis is based on the impulse response functions, with which the effects of financial stress shocks of each country and market to the level of systemic risk of the rest of them in the system are examined. This type of work is conducted in the Euro Area level, as well as for each country separately. It is also repeated for each one of the three versions of the financial stress indices created. On top of these, the robustness of our findings is checked, first by estimating alternative impulse response functions (the generalized impulse response functions), while we also control for any causal relationship between our indices using block exogeneity tests. In brief, the results are surprisingly illuminating, emphasizing the fact that it is too simplistic to focus to the most heavily indebted Euro Area countries as the sole propagators of the current crisis. Depending on the market, the sources of financial stress dissemination varies. Additionally, there is a degree of segregation on the countries interrelations and financial stress comovement. Here, the core Eurozone countries seem to be more financially interconnected, while the same holds (up to a certain degree) for the peripheral economies. This is strong evidence against the necessity to follow common type of policies in the whole union. In terms of policy making, there is a clear call for adaptation, based on the specific features and market peculiarities in each country or group of countries, in order to tame the crisis effects sooner.

This chapter is organized as follows. In section two, a discussion of the most important papers, dealing with the measurement of European countries financial stress is provided. Then, in the third section, the dataset employed is presented, emphasizing the usefulness and importance of the indicators included in the systemic stress indexes. Also, the econometric methodology adopted is presented. In section four, the constructed indices are discussed, together with their features, their effectiveness as tools of financial system safeguarding and the potential implications stemming from each country index's decomposition to its constituents. Then, the next sub-chapter provides an exposition and justification of the econometric results, while the last one recaps and concludes.

2. Financial Stress Measures for Eurozone and European Countries: An account of the relevant literature

This literature overview is focused on the discussion of the literature of aggregate systemic risk indicators, with a special interest on Euro Area applications. It is not an exhaustive survey, since part of this literature is covered in the previous chapter. Also, a more specialized account on issues of contagion and spillover effects is provided in the next chapter (but, in this case, it is not solely concentrated to Euro Area economies). Here, we present some interesting work that, mostly, has to do with Eurozone financial stress indices development and some applications of them, with special interest on potential policy making implications. Finally, some important papers on the Euro Area crisis analysis and its escalation are also discussed since they are directly linked to the topic of this chapter.

A first attempt to construct an FSI for the Euro area has been made by Grimaldi (2010). Based on the indicators proposed by Nelson and Perli (2007), the author has a threefold intention: to specify the actual stress period for the Euro zone markets, to compute relevantly accurate indices and test whether her index can work as a leading indicator of stressful events. For the first goal, the author employs information contained in European Central Bank's communication (using ECB's Monthly Bulletins) to help her measuring financial market stress. In this way, she indicates periods that seem to reflect periods of financial upheaval[58]. In order to verify these findings, a financial fragility index is built, using sixteen variables from the bond, banking, equity and money markets. Specifically, the difference between each Euro zone's country long term bond yields from the German one represents the sovereign bond spreads. Then, for the banking sector, bank equity prices index and the AA-rated corporate bond spreads are used as proxies of the conditions prevailing in this sector. General equity index, actual earnings per share and equities risk premium were chosen for the equity market component of the indicator. Finally, regarding money markets, one and three month Euribor-EONIA rates spreads, together with the spread of the main refinancing rate and the two year bond yield were utilized. Moreover, a string of risk aversion measures have been included, like implied bond, stock and futures volatility. All these variables were then integrated into two indices, the first being the weighted (by the inverse of each variable's variance) average of them, while the second one is the rate of change. Finally, these two indexes were combined into a single indicator, with the help of a logit model, so that extraction of information on stressful periods to be more effective. The logit model is of the following form:

$$S_{t+h} = L\left(\beta_0 + \beta_1 \lambda_t + \beta_2 \delta_t\right), h \geq 0 \tag{3.43}$$

where λ_t and δ_t are the weighted and the rate of change indices respectively, L is the logit probability distribution function, β's are the model's coefficients and S_{t+h} is a binary (0,1) variable, representing stress or tranquil periods. As it is obvious, whenever h is equal to zero, the model exhibit the contingent FSI, otherwise, the estimated model provides a forward indicator. Using weekly data for the period July 1999 to October 2009, the contingent financial stress index works well and captures crises periods of the last 10 years. Grimaldi confirms the good functionality of her FSI, comparing its performance with the VSTOXX index[59] and the signaling

[58] This has been done by counting how many times specific words appear in the bank's bulletin.
[59] It is an implied volatility index, based on equity option prices.

methodology, popularized by Kaminsky, Lizondo and Reinhart (1998). The last of the previously mentioned goals of this research (testing whether this index can be a leading indicator for stressful events) was accomplished by using the forward indicator version of the logit model, together with a slight transformation of its dependent variable. Now, the regressand has the following form:

$$S_{t+h} = \begin{Bmatrix} 1 \text{ if } \exists h = 1,\ldots k \ s.t.\ S_{t+h} = 1 \\ 0 \text{ otherwise} \end{Bmatrix} \tag{3.44}$$

stating that the occurrence of a stress event can be at any point within a specific time frame. The author uses this model for a time window of 24 periods and figures out that it performs efficiently in this task as well.

Beyond the construction of aggregate Eurozone- wide financial stress indices, some economists have proceeded to the creation of country – specific indices. Especially for countries that are in the centre of the current debt crisis, the interest in examining their financial conditions is quite intensive. For instance, Louzis and Vouldis (2012) compute an FSI for Greece, using both market and balance sheet data, which is the novel feature of their index. According to the authors, such an index is useful for, both, policy design (through the identification of the state of the financial system), as well as for the dating and prediction of financial stress. Additionally, such measures offer a unique chance to study the potential propagation channels of a crisis, mainly by inspecting the stress index components. In more details, they follow the framework proposed by Hollo *et al.* (2012), who use the components' correlation, in order to assess systemic stress. Moreover, they extend this approach, by using multivariate GARCH modeling, so that they can be able to capture time-varying correlations of the index components. In this way, it is expected to improve the index performance, in terms of identifying financial crises episodes. The choice of the variables that are included in their analysis is based on their relevance to economic theory and the respective empirical literature. Thus, they focus on series capturing systemic stress, increased uncertainty and chancing expectations in the financial markets. Their set of variables consists of the following segments. First, they include variables related to the fundamentals of the Greek economy. These are, the sovereign bond spread (the yield difference of the long-term Greek governmental bond from the

German one), the realized volatility of the Greek government bond and the correlation of the Greek stocks returns with the German Bund. These are indicators, able to capture liquidity risk, uncertainty in the assets prices, together with potential flight to quality phenomena. Then, these economists include variables from the Greek banking sector, such as the banks stock index from the Greek stock exchange (a series, indicative of the investors' expectations on banks performance and health). Additionally, the realized volatility of the banks index is included, as well as the idiosyncratic risk of bank stock prices (modeled as the bank equities' beta). Another interest rate spread that is included here, is the bank bond spreads (that is, the spread of the bond yields issued by Greek banks from the German governmental bond). This is considered as an indicator of the risk in the banking sector, while it is also a good proxy for the funding cost of the banks. Regarding balance sheet data, the so-called deposit and loan gaps are incorporated in the analysis. These are the cyclical component of the total deposits (loans, respectively), estimated by the usage of the Hodrick – Prescott filter. Finally, the bank profitability is depicted by the interest rate margin of banks (that is, the difference between loans interest from the deposit one). Turning now to the equities market, the authors choose to use the stock market general index, decreasing prices of which indicate potential market stress. Also, the general stock index realized volatility is taken into account, in the same fashion as the banking index volatility. The final variable in use is the one for the money market. Specifically, the authors include the well known TED spread (the difference between the three month Euribor from the similar German treasury bill, an important measure for the representation of the liquidity and counterparty risk). Of course, it is questionable how useful the inclusion of such a variable is, since the intention of the authors is the creation of a systemic stress index for Greece. In our view, it seems more appropriate to create such a spread, using the Greek Treasury bill rate.

Turning to the authors' construction methodology for their index, they first use principal components analysis to construct sub-indices for the aforementioned groups of variables. They do this, using the first principal component in each case, which they rescale to range from zero to one, through a logistic transformation. Then, as it was mentioned above, the framework by Hollo *et al.* (2012) is followed. The authors consider portfolio based approach to aggregate the sub-indices into a common FSI. The rationale is that, whenever correlation among the different markets increases, financial upheaval increases as well. Thus, their stress index is of the following form

$$FSSI_t = \sqrt{s_t^{'} C_t s_t} \tag{3.45}$$

where $s_t = w \otimes y_t$ is the vector of the weighted stress variables, with w being the weights and y the five sectoral stress indicators, while C_t is the time-varying correlation matrix. Hence, according to this empirical approach, there are two things that need to be estimated: the weighting vector (w) and the correlation matrix, in order to get the FSI. The former is estimated, according to each sub-index relative importance on the industrial production growth rate. In this way, an effort is made to link the evolution in the financial conditions with the real economy. According to the authors' calculations, the biggest effect comes from the fundamentals sector, while the smallest weight is ascribed to the banks' balance sheet data. Then, regarding the correlation matrix, two approaches were followed. First, the correlation structure of the stress sub-indices is derived from an exponential weighted moving average model, an approach with limitations[60]. Then, the well established BEKK model was used, especially a diagonal representation of it, so that to avoid any dimensionality issues. The model's representation is

$$\Sigma_t = CC^{'} + \sum_{i=1}^{p}\sum_{k=1}^{q} A_{ki}^{'} \bar{s}_{t-i} \bar{s}_{t-i}^{'} A_{ki} + \sum_{j=1}^{q}\sum_{k=1}^{K} B_{kj}^{'} \Sigma_{t-j} B_{kj} \tag{3.46}$$

where C is a lower triangular matrix, A and B are n*n parameter matrices, k specifies the generality of the process and p and q are the number of lags in the specification used.

In order to evaluate the usefulness of their FSI, the authors graphically inspect its behavior. There is evidence that the index can accurately capture periods of financial turmoil, while the sub-indices inspection reveals the relevant importance of the different market segments. According to this decomposition, the money market seems to be the most important contributor to the present crisis, while economic fundamentals are also quite important. It is interesting that the banks' balance sheet index minimally affect the level of financial risk, probably because of the limited

[60] In this approach, the decay parameter choice is arbitrary, while a random shock in the model can be proved quite persistent.

exposure of Greek banks to "toxic assets" effects. A final evaluation of the index is provided from a survey that was conducted among financial experts of the Greek financial market. In this way, a number of international financial crises episodes were evaluated, for their importance to the conditions prevailing in Greek markets. From this survey, a binary variable was constructed, which represents periods of financial turmoil and tranquility. Thus, this variable is used in a probit model, in order to assess the FSI usefulness as a leading indicator of such events:

$$\Pr(Crisis_t) = \Phi\left(c + \alpha x_t + \sum_{k=0}^{1} b_k \Delta x_{t-k} + e_t\right) \tag{3.47}$$

In (2.5), the dependent variable is the aforementioned binary one, x_t is the FSSI and, respectively, the lagged growth rate of the FSSI[61]. According to these estimations, all versions of the FSI provide some evidence of predictability, with the time-varying correlation modelling one to be the most accurate.

A similar effort to the previous one is made by Angelopoulou *et al.* (2012). Again, the authors try to construct financial conditions indexes for the Euro area as a whole, together with indices for some Eurozone countries (Germany, Greece, Ireland, Portugal and Spain). In their case, three different types of indices are formulated, one including monetary variables (so that the monetary policy effect can be evaluated), one without the aforementioned variables and, finally, one which is the difference between the previous one and an index computed through a principal components analysis, where the monetary policy loading are set to zero by the authors. It should be emphasized here that this family of indices, the so called financial conditions indices are similar, but not exactly the same, with the financial stress indices we study in this piece of research. It is argued that financial stress indices are more useful acting as early warning indicators of forthcoming stress, while the financial conditions indexes are better in the analysis of the macro-financial linkages in an economy. In any case, this distinction is still blurred and many researchers use these terms interchangeably[62]. Proceeding to their data selection, the authors choose twenty four variables, for the Eurozone aggregate index, while twenty are those included in the country specific

[61] Here, all three versions of the FSI are used, namely the weighted-average one, the multivariate GARCH one and the exponentially weighted moving average modelled one.
[62] An interesting methodological discussion on this issue is provided by Carlson et. al (2012).

ones. The choice is driven from, both, data availability, as well as based on the previous literature on this research topic. In this line of thought, the researchers incorporate several types of interest rate spreads (such as spreads between different types of loans and deposits), together with spreads from the interbank market (for instance, the three-month Euribor from the EONIA rate). Moreover, a number of quantity indicators are also included, like the value of debt securities issued by non-financial corporations and monetary institutions. Finally, a number of survey series (related to banks' liquidity position and consumer creditworthiness), along with series representing the volatility risk of stock and bond prices are also included in their stress indices. In order to create their aggregate indexes, these authors proceed to their analysis based on principal components methodology. According to this empirical approach, the variables under consideration are linearly combined, in such an order that the newly produced variables capture as much as possible of the variability of the initial set of variables. As it is emphasized by the writers, it is a way to compress the data, without losing much information. The process of acquiring the principal components of a dataset is by calculating the eigenvalues and eigenvectors of the variance – covariance matrix of the variables. Beginning from the highest eigenvalue, the eigenvectors are set in an ascending order, with the elements of each one of these eigenvectors representing the so called loading of each variable for the specific vector. Based on this kind of analysis, it is assured that each component is orthogonal to the rest. In their work, Angelopoulou *et al.* (2012) use the first three principal components for the Euro Area, while for the country specific indices the first four. The decision criterion is that the components included in the analysis to explain, about, 70% of the total variance. Then, the contribution of each one of the series in the final index is calculating, based on the loading of them in each component, weighted according to the level of variance explained by each one of these principal components. The final step is to weight the computed indices by the exact share of variance that the components which are included in the analysis explain.

Based on the loading weights, the authors suggest that each principal component represent different kind of influence in the financial conditions. For instance, it is evident that the most important variables in the first principal component are the survey variables, while interbank market spreads and bond volatility are also important. On the other hand, bank credit variables and securities issuance ones seem to be more important in the second component, while the third component emphasizes the role of the spreads between loans and deposits. In the weighted loading case, the magnitude of the variables is, in general terms, as it is expected to be. By inspecting the FCIs graphs, useful comments can be made. Beginning with the Euro-wide index, there seems to be a tendency to loosen financial conditions, since the beginning of the sample (2003, with end of 2011 to be the end of the sample here)[63]. This situation prevailed until early 2007, when the financial conditions began to worsen. Several incidents rendered the conditions gloomier, like the liquidity shock induced by Bear Stearns failure in March 2008, as well as the Lehman Brothers default in September 2008. Since late 2009 and until 2011, financial conditions are improved, whereas the situation worsens in the second half of this year, given the increasing uncertainty, due to the outbreak of the debt crisis in Greece and Portugal. In the case of the countries FCIs, it is evident the existence of asymmetric responses of the different economies to the varying financial conditions. The situation in Germany diverges from the other countries under investigation (which are the ones most seriously hit by the debt crisis), both in the pre-crisis period (where the financial conditions were tighter to the other countries but Germany) and in the post-crisis period. In the last two years of the sample (since 2010), situation worsens in Greece and Portugal mainly, while in Germany are improved. Generally, it is shown that monetary policy effects are not unanimous in the whole Eurozone, something that indicates the need for particular attention on the kind of policies prescriptions proposed by ECB.

The interest on these aggregate systemic risk indices is strong from the financial market participants, as it is evident from the development of financial stress indices from private financial institutions as well. For instance, the most systemically important Greek bank has developed its own FSI, in order to monitor the evolution of financial conditions in the Greek economy (Lekkos *et al.*, 2010). Their main interest, as it is described in their technical report, is tracing the funding needs for, both, the governmental sector, as well as the banking sector, non-financial institutions and the households. In more details, their index contains a 12-month moving average of government bond issues (capturing the funding needs of the government), the sovereign bond spread (against the German 10-year government bond) and the volatility of this spread as indications of the bond market fluctuations. Then, the

[63] in the case of Financial Conditions Index, loosening conditions are captured by increasing level of the index, while tighter conditions by decreasing level of it.

current account balance is included, as indication of the financing needs of the private sector, due to mismatches between savings and investments. Regarding banks financing gap, they authors propose the use of two variables, namely the difference of loans and deposits of domestic (non-financial) firms and households and the wholesale deposits from abroad. Finally, the ability of the private sector to cover its debt obligations is represented by unpaid bank checks. The aggregation into a single index is the outcome of a principal components analysis, where the weight for each one of the stand alone indicator is the relevant loading from the first principal component. Based on the latter, the stress index increases whenever the governmental funding needs increase, along with the spreads and their fluctuation. Additionally, the volume of unpaid checks is important in this respect. The index covers the period from January 2002 until November 2009, with the index skyrocketing right after the third quarter of 2008. Comparing the index performance with an economic sentiment index for the Greek economy, the authors find a consistently negative relation between them.

Following previous literature on the strong link between monetary policy reactions and the asset prices fluctuation, Montagnoli and Napolitano (2006) attempt to further examine the aforementioned relation, based on the development of financial stress indices for a number of countries (US, Canada, UK and Euro Area). Their FCI is an extension of the monetary conditions indices used by central bank. Apart from the usual real effective exchange rate and the short term interest rate, they also include stock prices and house prices as well. The aggregation of the aforementioned entails the use of Kalman filter methodology, in order to capture potential time varying behaviour of the chosen indicators. Finally, the importance of the aggregate indices in the conduct of monetary policy is evaluated with the implementation of Taylor rules that incorporate these FCIs. In the case of Eurozone, the index is not statistically significant, while the opposite holds for the rest of the countries in the sample. Similar results are obtained from Baxa *et al.* (2013). Here, for a similar group of countries (US, UK, Australia, Canada and Sweden), it is found that monetary policy reaction functions that are enriched with a financial stress index can efficiently capture the central banks' policies in periods of financial stress, as well as the interaction of monetary policy with financial stability. In their analysis, the author find out that central bankers change their policies depending on the level of financial stress, with loosening conditions in times of excessive financial stress. Additionally, their response is stronger in cases of stock market and banking stress, while exchange rate stress is more important in open economies. As it is expected, in all cases examined, the response of central banks in the recent period was, predominantly, driven by the current financial crisis.

Hansen (2006) has developed a risk index, very similar to the financial stress indices, in order to assess the risk exposure of euro-denominated assets. His index is focused on Euro Area and it emphasizes another useful feature of such aggregate metrics. That is, the ability of such systemic risk indicators to act as risk assessment tools for financial markets' investors and help them formulating their investment strategies. Here, the index is based on variables, covering credit spreads, implied volatilities of government bonds and of equity markets, as well as the performance of the stock markets. The chosen aggregation method is the variance-equal one, where each one of the index components is demeaned and divided by its standard deviation. In this way, it is ensured that none of the previously mentioned indicators would prevail in the formation of the aggregate risk measurement. Based on this approach, the risk index here represents higher risk premium for euro denominated assets, whenever the value of the aggregate index is higher (which implies riskier investments on euro denominated assets). The period covered here lies from 1999 to October 2005 (daily observations). Based on the graphical inspection of the index, it can be said that it is successful on capturing the most important shocks that have affected investors' risk perception in the markets. The same holds for the monetary policy decisions by ECB, where all case of policy rate and refinancing rate changes are foreseen by the index. This is in accordance with the previous work discussed, where the aggregate systemic risk index is empirically shown to be directly linked with monetary policy stance. A simple regression analysis verifies the importance of the aforementioned factors on the formulation of risk premiums for euro denominated assets (except euro volatility and ECB surprise decisions). Additionally, PCA analysis provides evidence on the existence of a common risk factor, affecting the whole spectrum of financial markets representing in the aggregate risk index. A final important observation here has to do with the relevance of such an aggregate risk index with financial stability. The author provides evidence of increasing covariation between the risk index and the correlation of its sub-components, indicating the increasing degree of markets integration and interconnection. Also, the effects of higher risk premiums (i.e. higher values of risk index) are more pronounced compared to smaller risk exposure, indicating the potential serious repercussions of excessive financial risks. Finally, it is pinpointed that the risk index tends to be mean reverting, probably due to the cyclical nature of most variables incorporated in the risk index.

The development of a stress index for the Swiss banking sector and the study of its forecasting determinants is the aim of Hanschel and Monnin (2005). Their argument, in favour of using such aggregate risk indices is the inappropriateness of binary choice models for developed economies, since banking crises episodes are too rare in this case. Additionally, such models do not offer any insight for near-crisis events, when the conditions in the banking sector are grim but do not deploy to a fully blown crisis. For their index, the authors use four types of data: market price (comprised of bank stock prices, bank bonds yield spreads vis-à-vis governmental bonds), balance sheet data (total interbank deposits, returns on assets, variation in bank capital measured as y-o-y differences in banks' capital and banks' provision rate[64]) and, finally, non-publishable data (total assets of banks under scrutiny from banking supervisory authorities) and the variation in bank branches (as indicator of any restructuring taken place at the banking sector). Once again, the stress index is constructed with the variance-equal approach being the relevant aggregate method. The FSI here identifies three periods of increasing stress for Swiss banks in the early 90's, 1998 and during 2001 – 2002. In order to forecast the level of stress, the authors use the gaps of the following variables as explanatory variables: share price index, housing price index, credit ratio (coinciding with the claims on private sector over GDP), investment ratio (similar definition as the latter) and the Swiss and Euro Area GDP[65]. The model used for this forecasting exercise is the following:

$$y_t = \beta_1 x_{1,t-z_1} + \beta_2 x_{2,t-z_2} + \ldots + \beta_k x_{k,t-z_k} + \varepsilon_t \qquad (3.48)$$

The model's regressands are the previously discussed variables, with the lags included according to the specification used. The criteria imposed for choosing the most appropriate model have to do with the statistical significance of the coefficients (at least 10%), the number of lags (no more than four years) and the existence of, at least,

[64] It is the ratio of new provisions and amortizations over the aggregated assets of the Swiss banks. According to the authors' view, it represents banks' own perception of current financial stress, since, whenever more strain is expected, the aforementioned ratio should increase.
[65] Gaps are defined as the difference between the actual series and the trend of it, estimating using a rolling Hodrick – Prescott filter. This difference is standardized before incorporating to the models.

three explanatory variables. Based on these, the model used has a good forecasting performance, indicating both tranquil and turmoil periods. It only fails to foresee the 1998 financial stress episode.

A recent work that offers a composite systemic risk index for Euro Area is the one by Islami and Kurz-Kim (2013). Focusing on indicators that are highly correlated with the real economy and are parsimonious, the authors end up with the inclusion of six series in their analysis. These are two CDS spreads (on iTraxx Europe Crossover and iTraxx non-financial index respectively), the implied volatility of the EUR/USD exchange rate, the volatility of the future oil price, the difference of earnings-to-price ratio from the 10-year euro interest rate[66] and the spread between the 3-month Euribor from the 3-month EONIA index. The aggregation is achieved through the standardization process, while the index is rescaled to range from zero to one. The data are of daily frequency, covering the period from January 1, 2007 up until April 30, 2013. Their empirical application, using cointegration analysis, provides evidence in favour of the Euro Area FSI as predictor of financially stressful periods, as well as of the real economy.

Van den End (2006) praises the comparative advantage of aggregate systemic risk indicators as measures of financial stability, in contrast to previous stand alone macroprudential indicators or early warning systems. Using an approach similar to Van den End and Tabbae (2005), he proceeds to the construction of a financial stability conditions index for Netherlands (initially) and a number of other countries (US, Japan, Norway, Denmark, Finland and Sweden). Based on previous work on monetary conditions indexes and financial conditions indexes, the author creates his own, by including a solvency buffer and a financial institutions equity price index volatility term in an, otherwise, well known specification of financial conditions index (short term interest rates, real effective exchange rate, house price index, stock price index). The weights for the aggregate index are the outcome of a structural model, comprising of an IS curve and, alternatively a VAR model, while a variance-equal index is also calculated. All versions are estimated in levels, as well as on changes. In the subsequent correlation analysis with previous period of increasing risks in Dutch financial system, the author finds that the equally weighted index is the most

[66] This interest rate is calculated as the GDP-weighted average of the long-term interest rates of highly rated Euro Area sovereigns (Germany, France, Netherlands, Belgium, Austria, Finland, Slovakia).

representative of the risk prevailing to the financial markets of Netherlands. Similar situation prevails for the rest of the countries in the sample.

A, somehow, divergent piece of research is the one produced by Kappler and Schleer (2013). In this paper, the authors support that, even though the use of financial stress indices is a useful addition to the examination of systemic risk and financial stability, it is not complete. The financial system complexities and idiosyncratic features of the markets comprising the aforementioned dictates the study of more than one potential "dimensions" of the shocks and the respective propagation mechanisms of financial instability. For this reason, they proceed to a dynamic factor analysis of a number of Euro Area countries, based on 21 single indicators. These indicators cover the banking systems, the securities markets and the foreign exchange market of eleven Eurozone countries. Their approximate dynamic factor modelling provides evidence for four factors that seem to have distinctive role in the explanation of the markets behaviour during the period examined (monthly data from 2002 until 2012 for the same countries as those included in our work here). In order to achieve this, the authors estimate regressions of each one of the financial indicators of their sample against the four factors produced from the previous dynamic factor model. In this way, using the produced R^2's, they ascend the importance of each factor for these indicators. In this way, they support that the first factor has greater explanatory power on the banking sector variables, especially of the debt ridden countries. That is why they name it "peripheral banking crisis" factor. The second factor, called "stress" factor, is more important for the cases of equity price volatility, while the third one (the "yield curve" factor) is crucial for the inverted term spread, as well as for banks' balance sheet data (like the ratio of total assets to liabilities). The most interesting thing here has to do with the fact that the explanatory power of this factor is much bigger for the core Eurozone countries and the Nordics. Finally, the fourth factor, although with lower R^2's, seems to be more important for the exchange rate variables. Hence, it is called the "foreign exchange rate volatility" factor. The main contribution of this work lies on the interpretation and the importance of standalone indicators on the background information that can be extracted by them. It can be an informative guidance on the process of choosing the most important variables to be included to an early warning system for financial crises or an aggregate systemic risk index. As it will be evident from our empirical work, their findings, especially in terms of the effects of different factors to different types of variables, are similar with our investigation to the individual markets (money, equity, banking, and bond) financial stress indices.

Since the focus of this and the subsequent chapter is on the multifaceted Eurozone crisis, we complete this section by discussing two important additions to the literature that examines the roots and underlying causes of this crisis. They do not involve any aggregate systemic risk index in their analysis. Nevertheless, these papers set a theoretical, as well as empirical, foundation that is useful for, both, the necessity for the creation of financial stress indices and their involvement in empirical work. It is of utmost importance to further enhance empirical evidence that can shed light on one of the most serious crises even hit the world economy.

Drawing from the literature on the second and third generation currency crises models, Arghyrou and Tsoukalas (2011) suggest that the current crisis is the outcome of systemic and macroeconomic risks, which together would normally result to a currency appreciation for the crisis hit economies. Since, in the Euro Area case, this is impossible, the whole situation is perfused to the sovereign bond market. This effect is reinforced by the existence of default risk for the weaker economies. Their modelling framework focuses on the development of a rational exit model from EMU. Here, a government should decide whether it is on its interest to remain or abandon the common currency. This is the control variable of this model. EMU participation is considered as a commitment to a fixed exchange rate regime. According on this structure, a country should decide on its actions, based on the costs of the two alternative options. If C represents the cost of exiting euro (which is perceived as constant for analytical purposes), the cost of staying in Eurozone is defined as a positive quadratic function, of the deviation of the exchange rate with which a country has joined EMU, from the PPP-consistent one. According to the authors, this difference is adequately represented by the real exchange rate, a rate able to capture the costs associated with overvaluations of the currency. On the side of the private sector, there are two control variables, namely the determination of the government to remain or not in EMU (being credible or non-credible) and the existence or lack of guarantees of fiscal liabilities from other members of the monetary union. Considering that governmental decisions are dependent on the private sector expectations, the model ends up with three[67] possible regimes. In the first case

[67] Actually, they are four, but the fourth one has similar intuition with the first regime.

(credible EMU participation and guaranteed fiscal liabilities), the government's loss function is

$$L_1 = \left[\gamma_1 (s^* - \overline{s}) \right]^2 \tag{3.49}$$

with γ being zero or positive. The intuition here is that, when this coefficient is zero, markets believe that (given full commitment to remain in Eurozone) government will do whatever necessary to fix any macroeconomic imbalances. A positive γ is a signal (in the form of increasing debt servicing costs) of the private sector to take measures for these imbalances, while it is certain that the authorities will proceed to such ones. The second regime represents the case where markets perceive fiscal liabilities as guaranteed but the EMU commitment is not credible. This could be due to the costs of the economically painful measures that a government might need to implement, compared to the cost of exiting the currency union. In this case, the loss function would be

$$L_2 = \left[(\gamma_1 + \gamma_2)(s^* - \overline{s}) \right]^2 \tag{3.50}$$

Now, an extra coefficient, representing the effect of non-zero probability of EMU exit is added. Here, an exchange rate risk premium is present to bonds' yields. In the last regime, (non credible EMU commitment and non guaranteed fiscal liabilities), a default premium is also incorporated to bond yields. Hence, the cost of remaining in the union is given by the following loss function

$$L_3 = \left[\left(\gamma_1 + \gamma_2 + \gamma_3 \right) \left(s^* - \overline{s} \right) \right]^2 \tag{3.51}$$

As a result, the model implies that the decision a country should make depends on the associated costs: the one related with the abandonment of the common currency and the other of staying in. The outcome is greatly affected by the markets' expectations.

Inspired by the previous theoretical outlay, Arghyrou and Kontonikas (2012) try to answer a number of testable hypotheses for the EMU bond spreads movements. First, prior to the credit crunch crisis (before July 2007), the real exchange rate (used as a metric of the overall macroeconomic performance) should not be important in explaining spreads movements. Then, the opposite should hold for the following period, while Greek spread should be significant for the rest of Eurozone countries' spreads. This hypothesis represents the case of sovereign risk contagion, even if real appreciation and a global risk aversion (due to the Great Recession) is taken into consideration. This empirical work uses a monthly dataset, covering the period January 1999 to April 2010. The data used are the sovereign bond yield spreads (vis-à-vis the German Bund), the real effective exchange rates, the VIX index (as a proxy of international risk aversion), the bond market liquidity (proxied by the ratio of each country's outstanding public debt to euro-area-wide total), the expected fiscal position[68], the industrial production index (business cycle proxy) and, finally, the CDS spreads for the long-term governmental bonds. As implied before, the econometric investigation is divided into three distinctive periods: pre-crisis (1999.1 – 2007.7), crisis period (2007.8 – 2010.4) and Greek debt crisis period. In the first case, the model used is

$$spread_t = \alpha + \beta_1 spread_{t-1} + \beta_2 q_t + \beta_3 vix_t + u_t \qquad (3.52)$$

with the sovereign spread as dependent variables. The explanatory ones are the lagged dependent variable, the logarithm of the exchange rate and the VIX index. The regressions results show a strong and persistent effect from the lagged dependent variable, while the other regressands being not significant[69]. The inclusion of the other proxies (IP growth, liquidity, expected fiscal position) does not improve the results. The use of fixed effects panel estimation, still, does not affect the empirical outcome. Hence, the authors suggest that the econometrics approve the so-called "convergence hypothesis", in the sense that the bond yields and investors' perception are not based on macro-fundamentals or relevant sovereign risk.

The crisis period inquiry is achieved using the following model

[68] It is defined as the one-year-ahead net lending or borrowing (% of GDP) and one-year-ahead expected gross debt of the general government (% of GDP). It is assumed to represent the credit quality and risk associated with sovereign default.
[69] Using SUR estimator, the results are slightly different, with a stronger international risk aversion effect. This would imply that financial markets' volatility is a non-negligible determinant of sovereign spreads.

$$spread_t = \alpha + \beta_1 spread_{t-1} + \beta_2 q_t + \beta_3 vix_t + \beta_4 spread_t^{GR} + \nu_t \tag{3.53}$$

This time, the effect of the Greek sovereign spread is explicitly taken into account. The results now are quite different, with the country specific fundamentals and the global risk aversion being important determinants of the sovereign spreads. Greek contagion effect is significant for almost all countries. For the other specifications (with the additional proxies presented before), liquidity is significant for some countries, but IP growth is not. Hence, in this case, it is evident the investors' differentiation, depending on sovereign bonds and the relevant macroeconomic risks. The last case examined (called "Greek debt crisis"), the model implemented is the same as (2.11), while the authors estimate it for the whole time period. Here, the initial estimations do not provide the expected results, since the VIX index and the effective exchange rate are not significant, while the liquidity variables has the opposite than expected sign. Even after the addition of the business cycle variables and the exclusion of liquidity, the results remain similar. Since the theoretical model presented before, dictates that an expectations regime shift took place during the latest period of the current crisis, the authors re-estimate their model, but this time they exclude the months on which these shifts were supposedly took place. In this case, their results were improved, with the expected signs for the exchange rate and the risk aversion factor. The inclusion of a dummy variable (taking a value of one right after 2009.11), the results are in favour of the states hypothesis. That is, the Greek spreads are more responsive to changing fundamentals. The analysis is repeated, using CDS spreads as the dependent variable. In relation to the Greek case, the authors find that CDS spread reflects country-specific fundamentals as well (as opposed to the other periphery countries, where the fundamentals effect is not that important).

The previous discussion reveals some interesting aspects of the Eurozone crisis. First, it is evident that, prior to 2007, markets were pricing macro-fundamentals and sovereign risks in the sovereigns' ratings. There was no uncertainty on the Euro Area members' ability and commitment to strongly support their union membership. This situation changed dramatically after the crisis outbreak. For the case of the Greek debt crisis, there was a significant deterioration of the country's fundamentals, while there was also an abrupt shift to investors' expectations towards this economy. This is a reason for the significant difference between the Greek spreads and the spreads of the other debt distressed countries. Moreover, it seems that the Greek problem was contagious to the rest of the Eurozone countries, especially to Portugal and Spain. The authors believe that the Greek bond yields can be considered as an EMU-specific systemic risk proxy, since this country's situation renders it more difficult to borrow for the whole union. Finally, there was no evidence of speculation to the CDS market, whatsoever. The pricing of these financial assets was based on fundamentals and markets expectations. A number of policy implications are stated by the authors. Most of them have to do with the need for Eurozone's peripheral countries to achieve fiscal sustainability, external competitiveness and full commitment to improving their macro-fundamentals. Additionally, the need for EU wide institutional reforms for effective fiscal supervision, policy co-ordination and mechanisms for timely detection, prevention and confinement of future crises is emphasized. Even though this research is indirectly linked to the methodological and econometric approach applied in this chapter, it does provide useful insights to the Eurozone crisis and its potential underlying causes. The necessity of studying multiple contagion effects in Eurozone is crucial, according to the authors, as well as the measurement of their potential size and combined effect on European sovereign bond yields. This is exactly what takes place in this and the subsequent chapter of this thesis and not only, since our modelling framework involves the examination of many more financial markets and relevant risks than just the sovereign bond market. Given the nature of the financial stress indices, the disaggregated study of them (based on the indices for each one of the relevant markets of each one of the Euro Area countries), we can extend and improve the relevant empirical literature, on the systemic risk and contagion transmission channels from different countries and different markets, within the Eurozone area.

3. Data and Empirical Methodology

Having completed the brief account of the literature on financial stress indices and the relevant research conducted for Eurozone and European countries, we now proceed to a discussion of the dataset used in this piece of research, along with a description of the methodological approach adopted for the indexes calculation and their incorporation to econometric analysis. Our aim is the construction of financial stress indices, able to accurately capture periods of increasing abnormality in the markets, as well as indices that can act as indicators of heightening systemic risk. In this way, an evaluation of the systemic financial stability can be conducted, while the relevant sub-indices can perform in the same fashion, for each one of the market sector examined.

3.1 Dataset Description

In order to depict the effects of a financial turmoil in a systemic wide level, we employ data from four markets, for each one of the initial Eurozone members[70]: the banking sector, money market, equity market and bond market. In all cases, we use monthly data, ranging from January 2004 until August 2011. The selection of variables is based, partly, on previous work done on systemic risk issues, as well as on variables that are important on the formulation of the state of the financial systems. In the following table, we provide an overview of the series used. As it is evident, a plethora of variables has been employed, in order to represent as accurately as possible the prevailing conditions in the financial markets of Eurozone countries. An important innovation here, compared to the previous literature in this area is the inclusion of an extensive number of balance sheet data, for a wide number of European banks. The multifaceted nature of the current crisis that hit hard many major banks around Europe, in many cases without obvious underlying reasons, stated the examination of balance sheet indicators very crucial. Depending on data availability, the number of banks for each country that has been incorporated to the construction of the bank and the aggregate index varies (from one bank to Belgium and Netherlands to eight for Greece).

[70] These are: Austria, Belgium, Finland, France, Germany, Greece (since 2001), Ireland, Italy, Netherlands, Portugal and Spain.

Table 3.1: Indicators of Financial Stress

Variables Used in Financial Stress Indices		
Banking Sector		
Operational/ Profitability	***Liquidity***	***Assets Quality***
ROA	Interbank Ratio	NPL/Gross Loans
ROE	Net Loans/Total Assets	Loan Loss Reserves/Total Loans
EPS	Loans/Deposits	Loan Loss Reserves/Impaired Loans
P/E	Total Liabilities/Liquid Assets	Size
Inefficiency	Interbank Funds/Liquid Assets	Market Power
Net Interest Margin		
Capital Adequacy	***Volatility Risk***	***Overall Market Conditions***
Tier 1 Capital Ratio	Stock Returns	Deposit Gap
Total Capital Ratio	Dividend Yield	Loan Gap
	Market Value	Bank Equities Realized Volatility
	Turnover by Volume	Banking Sector Beta
		Bank Equities Returns
Money Market		
TED Spread		M2 Growth
Inverted Term Spread		M2/Foreign Exchange Reserves
Treasury Bill Realized Volatility		Intermediation Rate
Main Refinancing Rate - 2yr Government Bond Yield		Main Refinancing Rate - 5yr Government Bond Yield
Equity Market		**Bond Market**
Stock Returns		Sovereign Spread
EPS		Government Bond Realized Volatility
Dividend Yield		Corporate Spread
P/E		Government Bond Duration
Stocks Realized Volatility		Stock Returns/German Bund Realized Correlation

As a result, our sample consists of 41 banks, covering major banks from all countries and banks with big market capitalization, size and market power. The limitation on the number of the financial institutions is dictated by the fact that many of them are not listed to a stock exchange and, as a consequence, there is a lack of data on their market performance. There are five groups of variables for each one of the bank, while the last one, called "overall market conditions", represent the general conditions prevailing in the banking sector of each country (here, the series are market wide, not bank specific ones). So, the number of the indicators included for the banking stress index of each country varies from 27 variables (in cases where only one bank for a country is used) to 181 variables (in the case of Greek banks). The data are retrieved from various sources, but most of the balance sheet ones are from

Bureau Van Dijk Bankscope database. Since most of these series are provided in yearly or quarterly basis, they are interpolated into monthly frequency. The interpolation was performed, using the Matlab function interpft. Using this function, the quarterly (or yearly) data are interpolated, using a fast Fourier transformation (FFT) algorithm. Such types of algorithms decompose the values of a series into different frequencies, in order to compute the discrete fourier transform. The FFT algorithms are efficient and fast in these computations and the most popular one is the Cooley-Tukey algorithm. I also experimented with other types of interpolation (using polynomials of second and fourth order). The results remained quantitatively similar.

In the first category, there are series representing the operational characteristics and banks' profitability determinants. Here, returns on assets (ROA), as well as returns on equity (ROE) are crucial ratios for the evaluation of the smooth performance of a bank. As indicated by Morales and Estrada (2010), these two variables depict the efficiency of the banks on employing their available funds, while on the same time are accurate representations of the level of profits they produce. Thus, it is evident the importance of their inclusion in this fragility index, since banks with low level of profitability are more susceptible to default. Additionally, regarding ROE, Louzis *et al.* (2012) emphasize its importance as a measure of the cost efficiency and of the efficacy with which banks use their internal and external financing. On the other hand, earning per share (EPS) ratio and P/E ratio are also indicative of the financial health of these institutions. The former is a well known metric of profitability, the behavior of which is indicative of the banks' ability to cope with strenuous financial conditions[71]. Price-to-earnings ratio works in the same fashion. Since a decline of the P/E ratio would represent decreasing profitability for a financial institution, it is reasonable to include this variable with a negative sign in the following empirical work. Inefficiency, which is the ratio of operating expenses with operating income, is a very efficient proxy for how prudent a bank is. In their work for the determinants of non-performing loans, Louzis *et al.* (2012) propose the use of inefficiency as a measure of banks management quality, in terms of their ability to monitor and avoid excessive funding to default – like investments. Thus, it is natural to include this indicator to our dataset. Finally, net interest margin, defined as the

[71] Grimaldi (2010) and Louzis and Vouldis (2012) pinpoint the negative relation of EPS ratio with cases of increasing financial stress. Thus, we incorporate it with negative sign in the stress indexes construction.

bank's income from its intermediation activities, is also included in the set of indicators as an important contributor to the banks financial robustness.

The second group of variables consists of liquidity indicators. The interbank ratio represents the value of funds a bank lent to other banks over the money it has borrowed by others. In this way, interbank ratio is a good proxy for financial instability transmission, since it represents the exposure of each bank to funds from other banks. The ratio of net loans to total assets is a ratio of dual nature, in the sense that it, concurrently, depicts the degree of liquidity of an economy (since the higher the financial leverage of a banking system, the higher should be this ratio), but on the same time it is a variable mirrored the banks portfolio quality and sustainability. Thus, it is a metric with ambiguous sign, regarding its contribution to excessive systemic risk or not. On the other hand, the loans-to-deposits ratio is another important variate. A higher value of this testifies lower liquidity available for banks, while the exposure to default risk is, also, greater. It can be considered as a good funding proxy, as well, if its usefulness as a measure is viewed from the economy's aspect. This set of indicators concludes with two liquidity risk ratios, namely the total liabilities to liquid assets and the interbank funds – liquid assets one[72]. The reason behind the inclusion of these two indicators has, mostly, to do with their importance for the capability of a bank to cope with situations of increasing default rates and deepening recession of the economy. In this sense, the higher these ratios are, the more vulnerable the banks become.

Moreover, the quality of the assets a bank has to its portfolio is of utmost importance for its survival in an uncertain financial environment. As it is well known, credit risk is the main type or risk that banks must manage and be cautious towards it. Thus, the reserves of such a financial institution, which are capital provisions for cases of bad loans writing offs, compared to its loans portfolio (both total and the impaired ones) is crucial. As Puddu (2008) indicates, these measures are proxies of the quality deterioration in banks' balance sheets[73]. Thus, a positive contribution on the crisis index should be expected. On the same time, the credit risk they face is

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[72] Morales, M. and Estrada D. (2010), "A Financial Stability Index for Colombia", *Annals of Finance*, 6:555-581

[73] The tendency to increase loan loss reserves is indication of worsening balance sheets, since banks in this way admit their concern on losses on their loans portfolio. On the same time, it can be considered as a sign of prudence from their side. In any case, in the literature, the first case is considered as more important and effective on the role of this indicator.

negatively related their size and market power[74]. Finally, the analogy of non-performing loans to total loans is, clearly, evident of the quality of loans in a bank's portfolio and a positive sign is expected for its contribution to the financial stress index.

The capital adequacy indicators are those dictated by the Basel Accord, related to the minimum capital needed for the default risk coverage by the banks[75]. In the group of volatility risk variables, we include those series which abnormal behavior renders the bank vulnerable to market risks and instabilities. For instance, higher stock returns indicate heightened uncertainty among investors, something that can have serious effects on the bank's operation and viability. Moreover, dividend yield can, potentially, give negative signal for a bank, since it is negatively related to the robustness of a financial institution's fundamentals. Market value and turnover by volume are, also, closely related to market sentiment, with a feedback loop existing between their level and market uncertainty (and, of course, with the level of financial stress). Turnover by volume is defined as the number of a bank's equities traded on any particular date, usually given in thousands of stocks. Thus, increasing turnover for a bank's equity provides signals against this institution's viability and vigor.

General conditions of the banking sector of each Euro Area economy are sketched out by the last bunch of variables used for this market. In the same fashion as Louzis and Vouldis (2012), we employ the so called deposit and loan gaps. These are produced, using the Hodrick – Prescott filter, proposed by the aforementioned economists in 1997, in order to extract the cyclical component of the deposits and loans of each bank from the trend element of them. This is a useful approach, indicating the cumulative dynamics of these two important elements of banks balance sheets. Increasing deposit gap is indication of deposit shortage, while a loan gap can be interpreted as higher market uncertainty and, thus, reluctance from the banks to provide loans. The level of investors' uncertainty is depicted by the realized volatility of the bank equities index for each country. Increasing values of this volatility measure represent increasing financial upheaval. A very common component for

[74] Size is the value of each bank's assets, compared to market's total, while market power is related to loans given, to total value of them. For details, consult Louzis *et al.* (2012).

[75] The necessity of monitoring capital adequacy indicators, as well as asset quality ones is emphasized from the earlier work of Evans *et al.* (2000).

stress indices is the beta coefficient of the banking sector index[76]. High beta values are an indication of banking sector equities to be considered as riskier and, thus, investors' sentiment is against them. Finally, we also include the bank sector index returns, in the same logic as the stock price returns of the individual banks.

Proceeding with the discussion of the variables included in the other three markets investigated here, we begin with the money market. Here, eight variables are included in the dataset. One of the most frequently used series for financial stress indices construction is the so called TED spread. It is the difference of the uncovered interbank short term lending towards a short term treasury bill (usually the 90-days treasury bill). For the case of Eurozone, the former is the well known 3-month Euribor, which is the benchmark and basic rate based on what European banks offer funds in the interbank market. The use of this indicator is popular, since it represents both, counterparty risk and liquidity risk in the markets. In times of increasing uncertainty and financial instability, problems of adverse selection can rise, since lending banks would be unable to identify the most financially reliable banks while the need for funds can be excessively high. Thus, increasing TED spread is expected for times of heightening financial fragility. Additionally, the slope of the yield curve is used, sometimes called inverted term spread. It is nothing more than the difference of the yield of short –term governmental securities from the long term ones (here, the 3 month treasury bill from the 10 year government bond yield is used). The reason for including this variable has to do with the well justified, from the literature, ability of the yield curve to work as leading indicator of the real economic activity[77]. Hence, a forthcoming recession greatly affects the financial position of many debt ridden firms and the default risk is highly exacerbated. Additionally, it is a good indicator of the investors' expectations on future short term interest rates. Since, during period of financial turmoil, the need for liquidity is higher and more intensive, investors turn to more easily liquidated securities, like the treasury bills. In turn, this affects their returns, expanding the spread between the aforementioned securities. The next two indicators, namely the spread of the main European refinancing rate from the two and three – year government bond yields are also strong indicators of monetary liquidity. As it is emphasized by Grimaldi (2010), the decrease of these spreads represents

[76] It is used in most cases of FSI construction. For instance in Louzis and Vouldis (2012), and Melvin and Taylor (2009) among others.

[77] Mishkin, F. S. and Estrella, A. (1998), "Predicting U.S. Recessions: Financial Variables as Leading Indicators", *The Review of Economics and Statistics*, vol. 80(1): pp. 45-61

liquidity worsening situation. For this reason, we incorporate these two indicators with negative signs in the analysis, so that their deterioration can indicate increasing level of financial suffocation. Growth of money supply and the ratio of money stock to the economy's foreign exchange reserves are two series, coming from the prior literature on early warning indicators of currency and banking crises. As it is evident from Kaminsky *et al.* (1998) and Demirguc-Kunt and Detragiache (1998), the previously mentioned variables are among the successful leading indicators for forthcoming currency and banking crises. Since both can produce signals, long before the actual outbreak of a crisis event, and since they both represent values of utmost importance for the economy's growth rate and the total credit available, their inclusion to this dataset is advantageous. The realized volatility of the Treasury bill rate is incorporated here, representing the uncertainty and excessive abnormality of the money market, since treasury bills are those securities with the highest value of transactions in short term borrowing markets. Finally, the intermediation spread is the difference between lending rate and deposit rate. Even though, it is a variable that is, partly, reflects the level of profitability of financial intermediaries, it is contained in this group of variables, since it is also a strong indication of the available sources of credit and its supply level into the economy.

In the equity market group, we include five variables. Firstly, the stock returns are incorporated, with negative signs since the large negative returns are those that create the greatest uncertainty for investors. Then, the earnings to price ratio (with a negative signs in the formation of the stress indices, because of the reasons stated in the banking sector analysis) and the P/E ratio are chosen, as major variables representing the profitability and health of the market participants. Moreover, dividend yield is another series, reflecting the robustness of the stock market. Thus, its inclusion is important, since its behavior is a sign of listed companies' ability to cope with financial strain. This set of indexes is concluded with the realized volatility of the stock markets' general indexes. As in all previous cases, the realized volatility is computed, using daily data, as the sum of squared logarithmic returns, adjusted by the trading days of each year in the sample.

The last set of series has to do with the bond markets of Euro Area countries. An important contributor in this group is the sovereign bond spread, calculated as the difference between each country's long term government bond yields from the German long term bond yield. It is reasonable to follow this convention, since the

German economy is considered as the strongest, most prudent economy of the union[78]. This indicator represents the sovereign risk each country faces. Then, the realized volatility of each country's long term bond is used, again using daily data on their yields. Increasing uncertainty and flight-to-quality phenomena, sprung by excessive systemic stress level, would lead to higher volatility. The corporate bond spread, defined as the spread between the corporate bond yield from the governmental one. In this way, the default risk and inability of firms in times of financial strain to acquire the necessary capital for their operation, is depicted. An innovative feature of the dataset is the use of government bond duration. It is an interesting variable, since it represents the sensitivity of bonds prices to changes in interest rates. In general, it is expected to have a negative relation between bond duration and interest rates. Based on the volatile behavior of interest rates in periods of financial uncertainty, there not seems to be a consensus on the kind of effects a financially instable period have on bonds duration. On the other hand, recent research by Lee *et al.* (2012) and Lee *et al.* (2011), indicates the strong effect that excessive sovereign risk has on governmental bonds. According to these authors, the duration decreases, especially for bond with lower ratings. As a result, the heightening investors' concerns on possible default of debt strangled countries with low rated bonds, should lead to lower duration for the bonds of these troubled countries. The last indicator here is the so called realized correlation of each country's stock returns with the German Bund. With this variate, we aim to include the effects of the financial instability on the investors' decision to withdraw their invested funds from a troubled economy to one that is perceived as safe (in Eurozone's case, Germany). Again, this indicator is computed using daily data on our sample's general stock indices and the German long term government bond yield.

3.2 Methodological Approach

This section is attributed to the presentation and discussion of the methodologies employed for, first, the calculation of the sectoral, national and Euro Area wide financial stress indices and, second, the econometric modelling. In the first

[78] For the case of the Germany itself, we just include the yield of its 10 year governmental bond.

case, we decide to use three alternative approaches on the aggregation of the financial indicators in each market, into a single systemic stress index. For the examination of the interdependencies of European markets, we are going to use the very popular Vector Autoregressive (VAR, hereafter) model.

3.2.1 Financial Stress Indexes Construction

Our decision, regarding the construction methodology of our financial stress indices, follows the literature. We intend to calculate the FSIs in three different ways. First of all, we are going to aggregate our series, based on the equally – weighted approach. According to this approach, an equal weight is attributed to all variables in each of the markets. In this way, the market - level indices are computed, while the same approach is followed for the country – wide one. It should be emphasized here the fact that each series is demeaned and divided by its standard deviation. This is useful for two reasons: it helps avoiding problems of mis-measurement in the series, while it is also a necessary transformation, before proceeding to a principal component analysis (PCA, hereafter). In general, the equally – weighted approach is quite popular, since it is very easy to implement, but also it provides qualitatively similar result to more advanced aggregation methods, like some reduced form econometric models or dynamic factor modelling[79].

In order to be able to evaluate and verify the well functioning of the indices produced with the aforementioned approach, we also proceed with the computation of financial stress indexes, based on PCA analysis. As it is well known, PCA analysis is a multivariate statistical approach for reconstructing a large dataset, through obtaining linear combinations of the variables included in it. It is a useful technique, since it does not use any reduced form model and, on the same time, it decomposes the series variability, according to their importance in the dataset correlations. In this way, alternative combinations of the series can be obtained, which can have more interest for the researcher, in terms of the data patterns indicated, the economic and financial phenomena that can interpret and, of course, the relevant policy recommendations (or

[79] Carlson et. al (2012) provide an interesting summary of the methodologies used to construct FSIs and FCIs, together with empirical evidence on their identical performance in forecasting real economic activity.

portfolio design guidance) that this analysis can provide. PCA deals with the covariance matrix of the dataset, which is decomposed, according to its eigevalues, to the principal components that are orthogonal to each other. In this way, the independence of each linear combination of the original variables (i.e. the principal components) from the rest is secured, while they also provide the loading (weight – coefficient) of each one of the original variables that contribute to the new dataset combinations. It is important to emphasize that the aforementioned principal component are ascended according to the eigenvalues, from the highest to lowest. Thus, the eigenvectors, interpreting most of the co-movement of the initial series are ranked first. That is why this statistical methodology was named principal components.

As it has been underlined above, we initially use the first principal component for the index of each market. The rationale is that this principal component captures a significant share, the greatest from all components, of the dataset co-movement. Thus, using the implied loadings from the first principal component, we aggregate our series into the financial stress index. In the third version of our indicators, we use an approach similar to Angelopoulou et. al (2012), which we call weighted loadings approach. Here, we use some of the principal components (in the case of banking sector the first four, in the other three markets the first three), each one weighted according to the share of variance explained. On top of that, in the case of the banking sector, since there is a cross-sectional dimension in our dataset (each variable in this sector, excluding the common ones, is extracted for more than one bank), we used an extra weight level, based on the size of each bank (so that, the used banking balance sheet dataset to be more balanced and according to the systemic importance of each financial institution). After we produce the national level indexes, the Euro Area wide one is prepared, again by aggregating, with equal weight attributed to each country, the national financial stress indices.

3.2.2 Vector Autoregressive Empirical Analysis

In the second stage of our analysis, we intend to explore potential existence of interactions and interrelations of the stress indices, both in country level as well as between the different markets. In order to do this, we are going to employ unrestricted VAR models, one of the most popular empirical approaches for analysing causal relationships between macroeconomic and financial variables. Since this model was proposed by Sims (1980), it became something like a workhorse for macroeconomic and macro-financial empirical investigation. Especially, in cases where prior economic theorizing or established causal relations between some economic or financial measures do not exist, the use of such a data driven econometric approach is considered sufficient.

In general, a VAR model consists of a number of equations, where all variables are considered as endogenous. Each equation consists of lagged values of the dependent variable, in addition to lagged values of the rest of the variables. In the case of our model, denoting as fsi_{kt} the financial stress index of country *k* at time *t*, and assuming the existence of *k* variables and *k* error terms, the VAR(*p*) model is of the following form:

$$FSI_t = \Gamma_1 FSI_{t-1} + \Gamma_2 FSI_{t-2} + \ldots + \Gamma_\rho FSI_{t-\rho} + \varepsilon_t \tag{3.54}$$

where $FSI_t = \left[fsi_{1,t} \; fsi_{2,t} \; \ldots \; fsi_{k,t} \right]'$ is a vector of all the endogenous variables of our model and $\varepsilon_t = \left[\varepsilon_{1,t} \; \varepsilon_{2,t} \; \ldots \; \varepsilon_{k,t} \right]'$ is the vector of the error terms of the model, which are usually considered to be white errors, with a zero mean and constant variance. Finally, $\Gamma_i \; (i = 1, \; \ldots \; , \rho)$ are the *kxk* matrices of the coefficients that need to be estimated. For this chapter's case, we first employ a VAR model with eleven equations[80], while the examination of the country confined models consists of four equations (one for each market a stress index has been compiled for).

In the case of an unrestricted VAR model, the estimation can be done, using the usual OLS estimator. In order to have stable and robust results, it is necessary to test our series for their order of integration. Thus, before proceeding to our models' specification, we proceed with the performance of stationarity testing for the original series. The main test used is the augmented Dickey – Fuller (1979) test, while in case where the results were dubious, Phillips – Perron (1988) and KPSS (1992) test were also performed to verify whether or not a specified variable is stationary or not. The next step is the models' specification selection. The optimum number of lags for the

[80] This is the case of country wide models, where we estimate models for financial stress index in national level and, then, for the European bank, money, equity and bond markets.

equations is chosen based on a number of lag selection criteria. These are the Akaike information criterion, the Schwarz criterion and the Hannan – Quinn one. As it is reasonable, not all of these criteria should indicate the same number of lags for a model. Luetkepohl (2011) comments that Akaike criterion is usually the most tolerant (provides evidence for higher lag order), while Schwarz criterion chooses the shorter order. The general idea is to begin modelling with a moderate lag structure, which is what we do, given the time span covered and the number of equations involved in the estimations. Models' adequacy is examined through the inspection of the residuals behaviour[81], even though, as indicated by Luetkepohl (2011), residuals non-normality is not a problematic situation for the validity of the inference conducted with these models.

In any case, the importance of this empirical investigation lies on the detection of channels of financial stress propagation from country to country and from one European market to another. Canova (2007) mentions that inference through the estimated VAR coefficients is not an efficient approach to use these models. Instead, he suggests the use of impulse responses, as the appropriate way to study the interrelations and transmission channels of the endogenous variables included in a VAR model. Impulse response analysis traces the responsiveness of the dependent variables to innovations to system's variables. The innovations or shocks enter the system of equations through the residuals vector. Due to the model's structure and the endogenous nature of the variables, it is expected that a shock on one of the variables will have effects on the rest of them in the VAR model. The crucial element is to trace the effect of these shocks on the dependent variables through time. In order to do it, the VAR should be re-parameterized to its vector moving average (VMA) form. That is:

$$FSI_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{3.55}$$

where, the left hand side of this equation is as defined to the previous equation, u are the reduced form residuals and Φ_i is a coefficients matrix. The elements of this matrix determine the cumulative effect on the dependent variables (in our case the financial

[81] That is, whether they are normally distributed, heteroskedastic or autocorrelated.

stress indexes). Assuming that our variables are stationary, we should expect the effect from the shock on the indices to gradually die out. Otherwise, the system would face stability issues. On the other hand, it is reasonable the model's residuals to be contemporaneously correlated. This means that an innovation to the residuals of one of the variables has an effect on the other variables' residuals and, on the same time, affects the other endogenous variables of the system. In order to overcome this problem and offer an economic intuition in the impulse response analysis, extra restrictions should be applied on the model. Cholesky decomposition is the most commonly used approach here, setting a minimum number of restrictions in the model. Here, the researcher decides which variables have no contemporaneous effects on the rest (so that their relevant coefficients in the Φ_i matrix are set equal to zero) and, in this way, set an ordering on the sequence of the shocks that hit the VAR system. As it is evident, the choice of the variables sequence is somehow arbitrary. If there is no solid theory justifying a specific ordering, economists have to apply different ones and verify the results robustness. In the case of our work, we try different orderings, based on the relevant concepts and ideas behind the possible sources of financial instability in Eurozone. This means that we first try the variables ordering, by setting first the countries mostly blamed for excessive financial distress in the EMU. These are Greece, Portugal, Ireland and Spain. Gradually, we tried most of the countries, so that our results can be conclusive. The impulse responses results are discussed in section five. In general, this approach is really useful on pointing and analysing the effect of a abrupt change to any of the included financial stress indicators to the level of financial stress in the Euro Area countries and markets[82].

Moreover, we perform a series of multivariate Granger causality tests, in order to provide further evidence concerning the interconnection of the financial stress indices. As it is well known, Granger (1969) examines whether a variable x is better explained from an equation including, both past values of x itself, along with lagged values of another variable, say y. In equational form, for the case of two variables (x and y) it should be:

$$\begin{aligned} y_t &= c + \beta_1 y_{t-1} + \ldots + \beta_i y_{t-i} + \delta_1 x_{t-1} + \ldots + \delta_i x_{t-i} + \varepsilon_t \\ x_t &= c + \beta_1 x_{t-1} + \ldots + \beta_i x_{t-i} + \delta_1 y_{t-1} + \ldots + \delta_i y_{t-i} + u_t \end{aligned} \tag{3.56}$$

[82] An additional robustness check is the estimation of generalized impulse responses, as proposed by Pesaran and Shin (1998). More details are presented in the relevant section.

where the number of lags included in each equation is determined from the usual information criteria. Using F-type statistics, they null hypothesis examined is whether y does not Granger cause x (and vice versa). In case of a VAR model, with more than two endogenous variables, the Granger causality testing procedure remains similar. In our case, since we use a VAR model, a generalized version of the Granger causality test is performed. The block-exogeneity test is useful for testing whether the lagged values of a variable do not Granger cause the dependent variable. It is very similar to the aforementioned Granger causality test, adapted for the case where more than one lagged variables are included in the model's equations. In order to perform this test, the coefficients of the lagged values of the variable to be tested, are set equal to zero and a likelihood ratio statistic is used to evaluate the potential causality relationship of this variable with the regressand. Using this test, extra evidence is provided, regarding the existence of potential financial risk transmission channels between the Eurozone economies and their respective markets. As it is emphasized elsewhere in this work, this is one of the very first attempts to provide solid and clear picture of such interconnections for Eurozone in such a detailed and disaggregated level.

As already emphasized, the core of this research is the investigation of crisis transmission channels between the Euro Area economies and financial markets. In this respect, the decision was to limit the empirical analysis in these economies and markets only. I did not include US, which might seem puzzling, given the importance of this economy in the initial exacerbation of the global financial crisis. This might put in doubt the empirical results, since a potentially major effect and channel of crisis transmission is not taken into account. On the other hand, I support that, given the specific research question here, the shifted interest and the size and magnitude of the Eurozone financial and sovereign crisis, the negligence of the US economy should not be a problem. In any case, the time period covered here is longer, compared to the period where the US subprime crisis initiated and propagated in the global economy. Finally, the robustness of our results, under different specifications and types of indices, indicates that the exclusion of US from the analysis should not be an important threat to the reliability of the results.

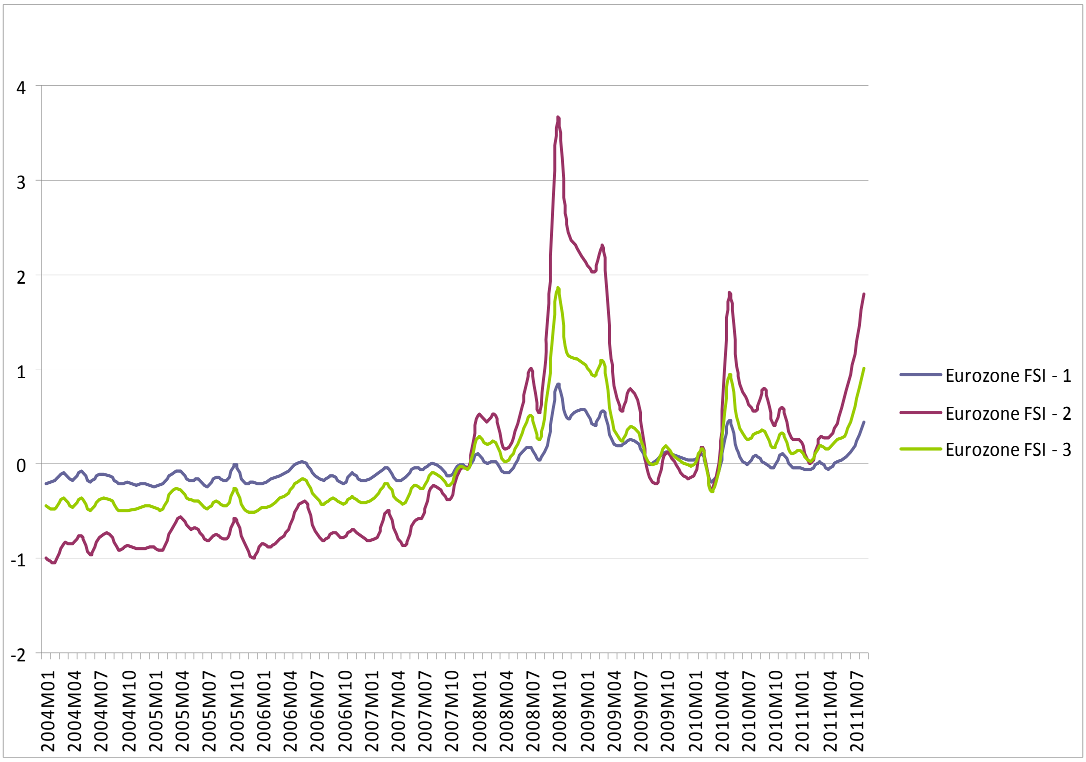
4. Eurozone Financial Stress Narrative

In the present section, a discussion of the three Eurozone financial stress indices is provided. They are analyzed and evaluated, in terms of their ability to represent financially instable periods and the financial conditions of the Euro Area in general. As it has been already emphasized, using the different market sub-indices, we are able to conjecture for the markets that are the main proponents of the financial instability. This markets' decomposition provides valuable extra information for, both, policymakers as well as the investors' community. Moreover, besides the Euro Area indices, we present the results of the PCA analysis, the relevant loadings and common variability explanatory power of the aforementioned approach. Moreover, the distress indicators of the eleven countries under considerations are also presented and discussed.

4.1 Eurozone Financial Stress Indices

Graph 3.1 depicts the aggregate Euro Area- wide Financial Stress Indexes. As it is previously noted, the period covered is from January 2004 to August 2011. In this sense, there is a wide coverage of, both, the initiation of the global financial crisis, its evolution and transformation to the current situation faced by the most indebted members of the monetary union. In general, the indices indicate some minor fluctuations to their value, prior to 2007, without any of those presenting a serious threat for the stability of the markets. On the other hand, it is evident a slow but steady, gradual increase in the level of financial stress, which reached its climax in the third quarter of 2008. The reason cannot be other than the Lehman Brothers collapse that took place in September 2008, with a number of major repercussions to the global financial system. In this case, the index reached its maximum value of 0.84 (in the case of the equally weighted FSI, FSI -2 value is 3.64 and 1.85 for FSI -3, respectively) on October 2008, while it remained in high level until the end of the first quarter of 2009.

Graph 3.1: Euro Area Financial Stress Indexes



Source: Author's calculations

In the meantime, the European Central Bank, through a number of unconventional monetary policies initiatives, tried to stabilize the increased systemic risk and uncertainty in the markets. For instance, right after the Lehman Brothers collapse and the consecutive drying up of the interbank money market, the Eurozone's monetary authority proceeded to the acceptance of more financial assets, as collateral for the emergency funding, while on 2009 the covered bonds program was populated. Together with the decrease of the main refinancing rate by ECB, all these policies led to an abatement of the financial stress level. But this would not last for long, since the evolving crisis in Greece led to another outbreak of financial stress, on April and May 2010. The agreement on a rescue program seemed to tranquil the European economy, for a while, until another spike in the index came out as a consequence of the need for financial assistance and fiscal austerity measures, this time for Ireland (towards the end of 2010) and Portugal in early 2011. The financial stress remained excessively high, until the end of our sample, which includes the decision for the haircut on the Greek public debt.

4.2 Euro Area Countries Financial Stress Indices

Turning now to the national indices of financial distress, it is interesting to notice the usefulness of the aforementioned indexes. In all cases, irrespective of the country or the type of index under investigation, these metrics are proved to be accurate representations of the financial conditions prevailing in each country and, of course, are indicative of the heightened financial bottlenecks they faced in times of financial hardship. The thirty three figures at the appendix provide an exhaustive, detailed and disaggregating analysis of the effects each financial market have on the total financial stress. For each country, there are three graphs, one for each financial distress index, together with the relevant disaggregated contribution of each market (namely, bond, stock, money and banking) to the economy's financial risk. Each graph has two vertical axes. The right hand-side axis represents the size of the total financial stress index, while the left axis depicts the scale for the components. Each market has its own coloured bar, so that the graphs' examination is easier. Finally, we should note that, by construction, the left y-axis represents the cumulative value of the four components, which does not necessarily coincide with the reflecting value of the stress index to the right vertical axis (since the aggregate index is a product of the weighted values of the markets' indices).

We start by analysing the case of equally weighted financial distress indexes. Before the details of each country's case are discussed, some general comments should be made. In a nutshell, these indexes are proved to provide more balanced results, in the sense that their values are smoother, without always an easy distinction of the real forces driving the financial conditions. Additionally, the indices values are the lowest, compared to the other two aggregation methodologies. This, probably, has to do with the fact that the contribution of each one of the markets to the total stress index is deemed to be equal. This assumption might not be always realistic, especially in cases where a specific market or markets are the main roots of financing the national economy or the actual propagator of the prevailing financial instability.

Turning into country specific analysis, the first thing to observe is that the highest values are spotted to Belgium, Finland and Italy. Nevertheless, the de-escalation of these countries indices is fast, without remaining to excessive levels, compared to other countries. For the rest of the sample's economies, we detect seasonal outbreaks of the stress indices, most of them in 2008 and afterwards. This situation is prevalent to France and the countries under serious financial strain (Greece, Ireland, Portugal and Spain). The study of the indexes' components is enlightening for the major contributors to the stress level in each case. In Austria, the equity market, along with the bond sub-index is the most important channel of financial stress. The same holds for Belgium and Finland, as well as for France. On the other hand, the German equity and bond components are crucial only until the second quarter of 2008 and towards the end of the sample. In the meantime, the index value is quite low, indicating the safe haven role of the German financial markets. Sovereign risk is proved to be the major stress components in Greece, throughout the sample, with its top values reached before and on the bail-out decision period. Additionally, it is important to underline the growing importance of the banking sector in the overall stress index, especially from the beginning of 2010. The evolution and the transformation of the nature of the crisis are evident in Greece. The Irish case is similar to Greece, while money market contribution is also important here. This emphasizes the fact that Irish crisis evolved mainly as a banking crisis, since money market stress index represents, mostly, interbank market stress conditions. The stock and bond components are the major players in the case of Italy, while Dutch index does not provide any strong evidence of excessive financial stress whatsoever. Finally, the Portuguese financial stress is mostly shaped through excessive sovereign risk and equity market stress, while liquidity issues (expressed through the money market component) are more important since August 2010. Excessive stress from the bond market is the major effect, in the case of Spain, whereas the situation changes during the time of Eurozone crisis. In this particular period, Spanish financial instability is expressed with deteriorating financial conditions in all sectors studied here.

The lower two graphs in each set of countries' FSI graphs, represent those indices and the subsequent decomposition, calculated using the PCA analysis approach. As already stated, the second graph in each case is the FSI, where the first principal component's loadings are used as the weights of the individual indicators for the aggregate systemic risk index. The last plot is the index produced from the weighted loadings approach. Here, the investigation of the graphs is conducted with the additional use of tables A.1 to A.5, where the respective loadings are presented in details.

The first two tables of the appendix present the factor loadings for the banking sectors of the economies under scrutiny. As it is obvious, there is a great variety of indicators and wealth of information provided here. Six panels group the variables into their respective category, with the size and the magnitude of each one of them. In the case of the first principal component, the percentage of the common variability explained ranges from, about, 32% in Netherlands to 49.5% in Spain. In the case of the weighted loadings, the number of principal components used for the construction of the aforementioned is five. Here, the commonality explained is quite high, beginning from 74% in the case of Finland and reaches 85% in the Spanish economy. Focusing now to the loadings, a general observation is that the majority of them demonstrate the expected signs, while there is some variation on the importance of each group of variables to the different banking markets. In all cases, the market-level indicators have prominent role. This is reasonable, given the feature of these indicators, as these affect the conditions prevailing in the whole market during the period examined. The Dutch case is rather peculiar, in the case of the first principal component, since all but the bank equities index returns loadings have a negative sign. Nevertheless, the size of these indicators for the case of Netherlands, as well as for the Belgian case, is negligible. On the contrary, the market level indicators carry large loadings for the rest of the Euro Area countries. Especially, the deposit and loan gaps, along with the realized volatility of the bank equity index are the most prominent factors in the financial stress index synthesis. Their largest loadings can be found in the cases of France, Greece, Ireland, Italy and Spain. Moreover, major role in the formation of the banking stress conditions have the liquidity indicators, along with the operational/profitability ones. Assets quality and capital adequacy ratios moderately contribute to the banking stress level, with the exception of Greece (with very low loadings) and Finland (where the relevant weights are stronger than the average values in the rest of the monetary union). Volatility risk proportion is relatively low for the hardest hit economies, indicating the stable and potentially positive expectations of investors, towards the systemic risk issues in this financial sector. These results, as discussed already, hold for the case of the weighted loadings, presented at table A.2. The only slight modification is in the different signs of some of the loadings, although they do not considerably affect the rationale and effects of the results. From the above, it is evident the importance of a number of crucial indicators, shaping the financial stability conditions in the banking sectors of Euro Area. Crucial elements are the level of bank profitability, along with the liquidity conditions prevailing. On top of them the overall, market-wide, indicators are very important, especially the deposit and loan gaps. Again, these two represent indicators emphasizing the importance of liquidity and the importance of excessive funding needs in the creation of unhealthy financial institutions.

The next table in the appendix reports the PCA-based weights for the money market index. In the first principal component case, the common factor explains about 44% of the indicators' variance (on average), with Italy presenting the lowest and Spain the highest percentage respectively. In the weighted loadings case, Italy has again the lowest level of explanatory power from these loadings (70.8%), while Greece's money market situation is explained by 87.3% from the first three principal components this time. Signs, in most cases, are the expected ones with a special interest pointed to the negative signs of the Euribor-short term governmental bonds for the financially safest countries (Austria, Belgium, Germany and Netherlands). Only exception here is Italy. TED spread and the yield curve positively contribute to the formation of the money market indices, for most of the countries under consideration (both core Eurozone and peripheral ones). The larger size for the interbank leverage conditions is observed to Greece, Ireland, Spain and Portugal, indicating the importance of sovereign and credit risk in these economies. The same holds for France as well, which is the only large Euro Area country with this feature. As it should be expected, the results are qualitatively similar for the weighted loading case as well. The only notable difference is the importance of credit growth, through the M2 growth, for the financially healthier economies of our sample (Austria, Belgium, Finland and Germany). Once again, the critical effect of monetary and credit conditions are emphasized, together with the important role monetary policy can exercise in controlling the development of such conditions (since many of the most important indicators in this category can be directly affected by central bank policies).

In the case of equity markets, it is clear cut the importance of stock returns, as a very important indicator of the financial stress there. In both cases of PCA analysis, they have some of the highest weights. Additionally, realized volatility is also important, in both cases. It is an interesting finding, since both indicators underline the volatile nature of equity markets, which usually work as instant propagators of financial distress news and adverse expectations of the investors. On top of that, dividend yield has a significant contribution to the aggregate risk index. Once more, this is indication of the importance of firms' fundamentals in shaping the level of financial stress in stock markets. EPS does not carry the expected positive sign, in the case of the first principal component. Nevertheless, this does not bear any serious concerns, since the weight attribute to this indicator is smaller, while such a sign issue is not existent in the case of weighted loadings.

The last table of PCA loadings deals with the European bond markets. The common variability explained, in the first case, ranges from 37.3% for Spain to 53.8% in Finland, while the weighted loadings explain much more of it (on average 86%). In this market, we do not spot any unexpected signs, while the most important contributors to the stress indices are the sovereign bond spread, the realized volatility of the government bond yield and the corporate bond spread. The highest infliction to sovereign risk is found to Greece and Ireland, while most countries (with the exception of Germany and the surprising low value of Spain) sovereign spread heavily increases the relevant stress indices. Especially for the Spanish case, the puzzling sovereign spread result is offset by the government bond duration weight, which is another strong evidence of excessive uncertainty, investors' negative outlook for the country's sovereign prudence and an indication of flight to quality (the same holds for Greece as well, where the relevant weight is also big). A similar behaviour can be detected in the case of weighted loadings and the weights of the realized correlation with the German governmental bond. Especially for the Greek case, the importance of this factor is strong in both cases of PCA analysis, while for other countries is not.

The inspection of the rest of the FSI graphs in the appendix verifies the previous discussion on the weights ascribed to each one of the single indicators. As already mentioned, the second and third FSI graph for each country represent the stress indices calculated, using the first principal component and the weighted loadings approach, respectively. Beginning from Austria, the only notable period of high financial stress is the period of Lehman Brothers collapse, during the third quarter of 2008. This is the peak for the financial stress in most Eurozone countries, with the exception of the economies under austerity programmes. The Austrian case is rather tranquil, with the financial stress decreasing fast after the aforementioned incident. The following period is characterized by mild financial conditions, with only an upward trend towards the end of the sample period. Regarding the stress composition, all sectors contribute to the level of financial stress, with bond, equity and banking sector being the most prolific ones before 2010. Later on, only bond-born stress leads to the relevant peaks of the Austrian systemic risk. Belgium's case is similar to Austria, only this time the banking sector stress is much stronger during the whole period examined. Nevertheless, the overall stress index for the case of this country is relevant lower than Austria's, especially in the last two years of our sample. A somehow different picture is the one for Finland, where money market was the major contributor to country's stress index, until the index's climax in 2008. Since then, the role of the banking sector, along with the equity (initially) and the bond market lately is underlined. In the case of weighted loading index, the banks' effect remains throughout the end of the sample period. In this case, as well as the French case, there is another strong peak of the level of stress index on May 2010, date where the decision of the Greek government for filing a bail out application was taken. It is also interesting to note the culmination of sovereign risk in France, both in the latter case as well as at the second quarter of 2011 (with gradual financial stress increase since late 2010, when the Irish crisis reached its peak). Here, banks' stress prevails in the formation of the overall systemic risk index, while there is strong evidence of the French economy's vulnerability due to the events taking place in the peripheral countries. The German case is rather different, with level of financial stress remaining in low level, except the cases previously discussed. In the peak of the index, the banking sector contribution and the liquidity conditions (as expressed from the money market index) are the major sectors leading the economy's systemic risk. Greek and Irish stress indices perform similarly, with both having very low values up until 2008. As expected, both are very responsive to the global crisis apogee in September 2008 (with their indices climbing up from the beginning of that year). For the Greek economy, the most important event is, of course, the adoption of the austerity measure package, while the index remains elevated for the whole period thereafter. It is a fully-blown crisis, stemming from all financial sectors of the economy with the sovereign risk leading the stress index in the case of May 2010 peak of the index. Subsequently, the sovereign risk remains a crucial issue, while the liquidity and credit conditions, as propagated through the money market index, is also important. Surprisingly, while the banking sector has a significant effect on the systemic risk, it gradually fades away into negative values for this sector index. This holds, up to a certain degree, for

Ireland as well, where the money market index is very important as well. Based on the previous discussion, we can infer that the liquidity shortages and heightening credit risk are among the main driver of the crisis in these countries. These are mostly captured by the money market indices (representing interbank conditions and the overall credit creation and funding conditions for Euro Area banks). The banking indexes predominantly include bank specific and bank balance sheet data, depicting the conditions within the banks of the sample. The situation is rather opposite, in the case of Italy. Here, the banking sector dominates in the modulation of financial stress. It is mainly a banking led crisis, with the bond market risk to be very important as well. The Dutch stress index remained low during the Eurozone crisis, with only minor shafts in the periods where the Greek, Irish and Portuguese crisis accentuated. Then, Portugal stress index has an evolution, similar to Greece and Ireland. The effects on the systemic risk of this economy from the Greek and Irish bail outs are evident from the graphs, with the indexes reaching their top values at the end of the sample, which is the period where Portugal requested financial assistance. Again, it is a multifaceted crisis, mostly driven by sovereign risk concerns, along with money and equity markets excessive distress levels. The Spanish case is, as the Italian one, considered as a major banking led crisis, since the banking sector index and the money market index formulate the aggregate financial stress. While the bond market importance is strong enough during the whole crisis period, it is more important in the first two years of the crisis outbreak (from 2008 until 2010).

5. Empirical Analysis

In this section, we proceed to a more systematic analysis of the interconnections and the level of transmission of systemic stress from one country of the Eurozone to the others. In order to do this, a Vector Autoregressive (VAR) model is employed, which includes the financial stress indexes of the eleven Euro Area countries under examination. As a result, a model with eleven equations is used, the lags of which were chosen according to the usual well-known criteria[83]. Based on the different specifications, the residuals normality and autocorrelation tests, the model

[83] AIC, SIC, HQ criteria.

chosen to be presented is a VAR(1) model[84]. In what follows, the discussion is based on the impulse responses estimated from these Euro-wide models for, both, the aggregate financial stress indices, as well as those for the banking sector, the money, equity and bond markets. Moreover, a country-specific analysis is provided, where we examine the effects of financial stress shocks taken place within each one of the eleven economies studies here. Finally, extra empirical evidence is provided in the last subsection of this subchapter, in order to strengthen the validity of our inference. The additional evidence is based on an alternative specification for the estimation of the impulse response functions, the so-called generalized impulse response functions. Additionally, a number of block exogeneity tests are performed, while additional VAR models are estimated and their impulse responses reported. The latter use the financial stress indexes, produced with the PCA analysis.

As it is clear, the main block of analysis is built upon the equally weighted stress indices. This is partly dictated by the stationarity tests conducted to the series of our sample. Table 3.2 present the results of the augmented Dickey – Fuller test. The results clearly show that the equally weighted stress indices are all stationary, while there is a mixture of I(0) and I(1) series in the other two sets of indexes. Hence, we proceed in our empirical investigation, using the variance-equal financial stress indices in our baseline model. On the other hand, the PCA-based stress indices are used in additional VAR models, where the first differences for all the financial stress indicators are used. This transformation is necessary, in order to avoid any stationarity issues, while on the same time all series are uniform (both in terms of non-existence of unit roots, as well as the transformation applied to all of them).

[84] In the case of money market, a VAR(2) specification is used.

Table 3.2: ADF Test Results

Unit Root Testing for Financial Stress Indexes											
Stress Indicator	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Panel A: Equally Weighted											
Bank	-2.46**	-2.71***	-2.37**	-1.53*	-3.92***	-3.66**	-3.06***	-1.52*	-2.18**	-3.49***	-2.35**
Money	-3.18***	-4.94***	-1.67*	-5.02***	-4.39***	-2.68***	-2.31**	-2.54**	-5.04***	-1.92*	-6.72***
Equity	-2.13**	-4.73***	-3.11***	-2.02**	-1.75*	-3.41***	-3.07***	-6.37***	-3.52***	-1.95**	-5.33***
Bond	-3.54**	-2.38**	-3.59**	-4.65***	-4.66***	-5.95***	-7.53***	-3.86***	-3.81**	-5.76***	-1.75*
Country	-4.13***	-1.67*	-2.47**	-3.96**	-1.96**	-5.69***	-4.27***	-4.02***	-3.6***	-4.43***	-3.45***
Panel B: First Component											
Bank	-2.22**	-1.26	-1.34*	-1.49	-2.01**	-2.29**	-3.12*	-1.45	-0.72	-4.51***	-1.62*
Money	-1.80*	-1.12	-1.65*	-1.93*	-1.75*	-3.52**	0.76	0.14	-1.84*	2.09	-0.47
Equity	-2.02**	-2.71***	-2.75***	-3.24***	-4.07***	-1.91*	-3.049***	-2.76***	-3.73***	-3.29***	-4.05**
Bond	-1.90*	-2.24**	-1.41*	-1.93**	-2.24**	-1.49	-3.78**	-3.16*	-1.85*	-1.42	-0.44
Country	-2.09**	-1.84*	-2.05**	-1.70*	-2.03**	-1.41	-1.70*	-1.98**	-2.13**	-1.25	-1.34
Panel C: Weighted Loadings											
Bank	-2.84***	-1.31	-4.45***	-1.15	-1.81*	-2.96***	-2.53**	-3.46**	-0.77	-4.34***	-1.74*
Money	-1.5	-1.86*	-1.73*	-1.79*	-1.7*	-2.07**	0.19	-0.43	-1.61*	0.48	-0.67
Equity	-2.31**	-4.51***	-1.91**	-3.12***	-2.93**	-3.23***	-2.95***	-4.18***	-3.79***	-4.71***	-5.12***
Bond	-2.25**	-2.39**	-4.28***	-4.13***	-5.29***	-4.05***	-6.60***	-1.14	-2.29**	-4.64***	-2.00**
Country	-2.36**	-2.51**	-1.13*	-1.55	-2.37**	-2.61***	-2.69***	-3.80**	-2.74***	-3.86**	-3.28**

Note: Series in levels. Number of lags was chosen based on Schwartz Information Criterion, with maximu number considered = 12. *, ** and *** denote rejection of null hypothesis of unit root existence at 10%, 5% and 1% level of significance, respectively. For Finland's FSI in panel C, stationarity is confirmed by Phillips - Perron test.

5.1 Euro – Wide VARS

The following graphs represent the impulse responses of the baseline model, where the effects of a financial shock in each one of the countries we examine are depicted. In the first set of impulse response plots, the aggregate country financial stress indices shocks are discussed, while the other four examine the cases of banking sector, money, equity and bond markets respectively. Since these are large systems of equations and the ensuing produced graphs are 121 in each case, we provide tables that succinctly summarize the effects of each one of the financial stress shocks to the Euro Area countries and markets respectively.

We begin our analysis with the country level financial stress indices. The impulse responses results are depicted in graph 3.2 and tables 3.3.A and 3.3.B. In all

Graph 3.2: Response of Financial Stress Indices to Financial Stress Shocks

cases, we first present the impulse responses for the most heavily hit economies from the current crisis, in order to assess their potential effects on the rest of the Euro Area countries and markets. For the sake of clarity, we use specific narrative terminology for characterizing the financial stress shocks effects between the examining variables. In cases where there is no substantial effect, we put the word “negligible” in the tables. Whenever there is a minor response that does not have a lasting effect, we call it “slightly positive” or “slightly negative”, depending on the magnitude of the relevant reaction. Finally, “negative” or “positive” are the outcomes of a persistent negative or positive reaction to a specific shock in the VAR system, respectively.

Table 3.3.A: Summary of Financial Stress Shocks in Eurozone Countries

Effects of Financial Stress Shocks in Eurozone Countries - 1 (FSI - 1 case)

Response to	**Greece**	**Portugal**	**Spain**	**Ireland**	**Italy**
Austria	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	*negative*
Belgium	*negligible*	*slightly positive - minor*	*slightly positive - minor*	*slightly positive - minor*	*negative - minor*
Finland	*negligible*	*slightly positive - minor*	*negligible*	*negligible*	*negative*
France	*negligible*	*negligible*	*slightly positive - minor*	*slightly positive - minor*	*negative*
Germany	*slightly negative - minor*	*negligible*	*negligible*	*slightly positive - minor*	*negligible*
Greece	---	*negligible*	*negligible*	*slightly positive - minor*	*negative*
Ireland	*positive*	*slightly positive - minor*	*negligible*	---	*negligible*
Italy	*negligible*	*slightly positive - minor*	*slightly positive - minor*	*slightly positive - minor*	---
Netherlands	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	*negative - minor*
Portugal	*slightly positive - minor*	---	*negligible*	*negligible*	*negative - minor*
Spain	*negligible*	*slightly positive - minor*	---	*slightly positive - minor*	*negative - minor*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

The results offer some quite interesting and intriguing illustrations for the Eurozone crisis. First of all, it seems that, in all cases, countries are mostly responsive to their own financial shocks. With the exceptions of Finland, Belgium, Italy and Greece, the excessive financial stress soon returns to its prior levels. In case of Greece, the effect lasts for almost a year after the initial shock, while Finland's one is even more persistent. Additionally, some degree of regionalism is apparent in the results. According to the impulse responses, the peripheral debt-ridden countries are more responsive to the increasing financial stress of the same countries, while the similar effect is sketched for the major Euro Area countries, notably Germany, France, Netherlands and Finland. This implies the existence of disparities in the way that financial shocks reflect on the union's member countries, while it can be also an indication to ECB for adoption of different policies in countries that face divergent financial and economic deterioration.

Table 3.3.B: Summary of Financial Stress Shocks in Eurozone Countries

Effects of Financial Stress Shocks in Eurozone Countries - 2 (FSI - 1 case)

Response to	**Austria**	**Belgium**	**Finland**	**France**	**Germany**	**Netherlands**
Austria	---	*negligible*	*positive*	*negligible*	*negligible*	*slightly positive - minor*
Belgium	*negligible*	---	*positive*	*negative*	*negligible*	*slightly positive - minor*
Finland	*negligible*	*negligible*	---	*negligible*	*negligible*	*negligible*
France	*negligible*	*negligible*	*positive*	---	*negligible*	*negligible*
Germany	*negligible*	*negligible*	*positive*	*negative*	---	*negligible*
Greece	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Ireland	*negligible*	*negligible*	*positive*	*negative*	*negligible*	*negligible*
Italy	*negligible*	*negligible*	*negligible*	*negative*	*negligible*	*negligible*
Netherlands	*negligible*	*negligible*	*negligible*	*negative*	*negligible*	---
Portugal	*negligible*	*negligible*	*positive*	*negligible*	*negligible*	*negligible*
Spain	*negligible*	*negligible*	*positive*	*negligible*	*negligible*	*negligible*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

Another important finding, which appears to contradict the mainstream view on the current crisis, is the minor effect that increasing financial stress in Greece and Portugal seem to have to the rest of the Eurozone countries. According to the impulse response graphs above, there is no evidence of transmission of heightening financial risk from these troubled countries to the rest. On the other hand, the Italian financial upheaval has some effect on most countries, although not always in the expected way (negative effect on the level of financial stress). In any case, the previously mentioned finding, for the minor role of Greece and Portugal in the crisis transmission is concurrent to a recent piece of research by Gonzalez-Hermosillo and Johnson (forthcoming). In this work, the authors emphasize the fact that, according to their stochastic volatility model, most of the sovereign risk associated with the current Eurozone countries is country specific, while they could not provide any hard evidence to blame Greece or Portugal as major channels of crisis contagion to the rest of the Euro Area. In the same line of thought, Giordano *et al.* (2013) examine whether the excessive sovereign spreads of Euro Area countries with respect to Germany can be attributed to country-specific deteriorating fundamentals (wake-up call contagion) or to irrational and herding behaviour by the markets (pure contagion). Again, the authors find no evidence of pure contagion between the Eurozone economies. In fact, the Greek crisis outbreak turned the investors' interest towards the existence or not of sound macroeconomic fundamentals, which they did not take into account prior to 2009. These are very interesting results, validating the outcome of our empirical investigation. On the other hand, their work is confined to the study of sovereign risk channels, while our framework incorporate multiple potential channels of risk transmission.

The following two tables and the respective impulse responses figure describe the situation prevailing in the banking sectors of EMU countries. Some interesting findings can be underlined here. Once again, there is no strong evidence in favour of stress transmission from the periphery to the core economies. In fact, Greece and Portugal negatively affect German banking stress index, while only the Italian case aggravate the financial stress in Belgian and French banking sectors. On top of that, Italy has a clear positive effect on the stress level for some of the peripheral economies, namely Ireland and Portugal. On the other hand, the stress transmission between the core Euro Area banks are much stronger, as it can be seen from table 3.4.B. France is the weakest link here, since its banking stress leads to deteriorating banking conditions in Germany, Belgium and Netherlands. Germany has also some negative repercussions to Finland and Belgium. Finally, Italy is also a risk channel for Portugal and Ireland.

Table 3.4.A: Summary of Banking Stress Shocks in Eurozone Countries

Effects of Banking Stress Shocks in Eurozone Countries - 1 (FSI - 1 case)

Response to	**Greece**	**Portugal**	**Spain**	**Ireland**	**Italy**
Austria	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Belgium	*negative*	*negligible*	*negligible*	*negligible*	*positive*
Finland	*negligible*	*negligible*	*negligible*	*negligible*	*negative*
France	*negligible*	*negligible*	*slightly negative - minor*	*negligible*	*positive*
Germany	*negative*	*negative*	*negligible*	*negligible*	*negligible*
Greece	---	*negative*	*negligible*	*slightly positive - minor*	*negative*
Ireland	*negligible*	*negligible*	*negative*	---	*positive*
Italy	*negligible*	*slightly positive - minor*	*negligible*	*negligible*	---
Netherlands	*negligible*	*negligible*	*negative*	*slightly positive - minor*	*negligible*
Portugal	*negligible*	---	*slightly negative - minor*	*negligible*	*positive*
Spain	*negligible*	*negative*	---	*negligible*	*negligible*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

Table 3.4.B: Summary of Banking Stress Shocks in Eurozone Countries

Effects of Banking Stress Shocks in Eurozone Countries - 2 (FSI - 1 case)

Response to	**Austria**	**Belgium**	**Finland**	**France**	**Germany**	**Netherlands**
Austria	---	*negligible*	*negligible*	*negative*	*slightly positive - minor*	*negligible*
Belgium	*negative*	---	*negligible*	*positive*	*positive - negative*	*negligible*
Finland	*negligible*	*negligible*	---	*negligible*	*positive*	*negligible*
France	*negligible*	*negligible*	*negligible*	---	*negligible*	*negligible*
Germany	*negligible*	*negligible*	*negligible*	*positive*	---	*negligible*
Greece	*negligible*	*negligible*	*negligible*	*negligible*	*slightly negative - minor*	*negligible*
Ireland	*slightly positive - minor*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Italy	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Netherlands	*negligible*	*negligible*	*negligible*	*positive*	*negligible*	---
Portugal	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Spain	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

Graph 3.3: Response of Banking Stress Indices to Banking Stress Shocks

The situation does not differ, in the case of the money market VAR model. Even though the evidence is not as strong as in the latter cases, again there is no link established between crisis-wiped economies and the others. Greece, as well as Spain and Portugal do not have any excessive risk effect to the rest of the EMU countries. In general, only minor segregated effects can be traced between the money markets of the monetary union. With this term, we mean transmission effects between the peripheral countries and between the major Euro economies.

Table 3.5.A: Summary of Money Stress Shocks in Eurozone Countries

Effects of Money Market Stress Shocks in Eurozone Countries - 1 (FSI - 1 case)

Response to	**Greece**	**Portugal**	**Spain**	**Ireland**	**Italy**
Austria	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Belgium	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Finland	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
France	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Germany	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	*slightly positive - minor*
Greece	---	*negligible*	*negligible*	*negligible*	*negligible*
Ireland	*negligible*	*slightly positive - minor*	*negligible*	---	*negligible*
Italy	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	---
Netherlands	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Portugal	*negligible*	---	*negligible*	*slightly positive - minor*	*negligible*
Spain	*negligible*	*positive*	---	*slightly positive - minor*	*negligible*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

Table 3.5.B: Summary of Money Stress Shocks in Eurozone Countries

Effects of Money Market Stress Shocks in Eurozone Countries - 2 (FSI - 1 case)

Response to	**Austria**	**Belgium**	**Finland**	**France**	**Germany**	**Netherlands**
Austria	---	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Belgium	*negligible*	---	*negligible*	*negligible*	*negligible*	*negligible*
Finland	*negligible*	*negligible*	---	*negligible*	*negligible*	*negligible*
France	*negligible*	*positive*	*negligible*	---	*negligible*	*negligible*
Germany	*negligible*	*negligible*	*negligible*	*negligible*	---	*positive*
Greece	*negligible*	*negligible*	*slightly positive - minor*	*negligible*	*negligible*	*negligible*
Ireland	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Italy	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Netherlands	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	---
Portugal	*negligible*	*slightly negative - minor*	*negligible*	*negligible*	*negligible*	*negligible*
Spain	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

Turning now to the case of equity markets stress, we see that Ireland has a more significant role, compared to the rest of the PIIGS group of countries. The stronger link appears to be the one towards Greece and Germany, while more weak transmission of financial stress exists towards another group of core countries (Austria, Belgium and Finland). On the other hand, Italy exhibits a slightly negative effect on the stress level for most of the countries in the sample. Nevertheless, it is not a sustainable or strong enough channel of negative financial stress evolution. In the case of the group of the robust Euro economies, Belgium's increasing financial stress empowers systemic risk into Austria, Finland and Germany. Greece seems also to be affected, while France equity market stress positively leads the Greek and Irish markets as well. This is another strong evidence of the interconnections and the vulnerability of French markets with the crisis hit economies.

Graph 3.4: Response of Money Market Stress Indices to Money Market Stress Shocks

Table 3.6.A: Summary of Equity Stress Shocks in Eurozone Countries

Effects of Equity Markets Stress Shocks in Eurozone Countries - 1 (FSI - 1 case)

Response to	**Greece**	**Portugal**	**Spain**	**Ireland**	**Italy**
Austria	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	*negative*
Belgium	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	*slightly negative - minor*
Finland	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	*negative*
France	*negligible*	*negligible*	*negligible*	*negligible*	*slightly negative - minor*
Germany	*negligible*	*negligible*	*negligible*	*positive*	*slightly negative - minor*
Greece	---	*negligible*	*negligible*	*positive*	*slightly negative - minor*
Ireland	*negligible*	*negligible*	*negligible*	---	*slightly negative - minor*
Italy	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	---
Netherlands	*negligible*	*negligible*	*negligible*	*slightly positive - minor*	*slightly negative - minor*
Portugal	*negligible*	---	*negligible*	*slightly positive - minor*	*slightly negative - minor*
Spain	*negligible*	*negligible*	---	*negligible*	*slightly negative - minor*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

Table 3.6.B: Summary of Equity Stress Shocks in Eurozone Countries

Effects of Equity Markets Stress Shocks in Eurozone Countries - 2 (FSI - 1 case)

Response to	**Austria**	**Belgium**	**Finland**	**France**	**Germany**	**Netherlands**
Austria	---	*positive*	*negligible*	*negligible*	*negligible*	*negligible*
Belgium	*negligible*	---	*negligible*	*negligible*	*negligible*	*slightly negative - minor*
Finland	*negligible*	*positive*	---	*negligible*	*negligible*	*slightly negative - minor*
France	*negligible*	*negligible*	*negligible*	---	*negligible*	*negligible*
Germany	*negligible*	*positive*	*negligible*	*negligible*	---	*negligible*
Greece	*negligible*	*positive*	*negligible*	*positive*	*negative*	*negligible*
Ireland	*negligible*	*negligible*	*negligible*	*positive*	*negligible*	*negligible*
Italy	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Netherlands	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	---
Portugal	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*slightly negative - minor*
Spain	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

Graph 3.5: Response of Stock Market Stress Indices to Stock Market Stress Shocks

Table 3.7.A: Summary of Bond Stress Shocks in Eurozone Countries

Effects of Bond Stress Shocks in Eurozone Countries - 1 (FSI - 1 case)

Response to	**Greece**	**Portugal**	**Spain**	**Ireland**	**Italy**
Austria	*negligible*	*slightly positive - minor*	*positive*	*negligible*	*negligible*
Belgium	*negligible*	*slightly positive - minor*	*positive*	*negligible*	*negligible*
Finland	*negligible*	*slightly positive - minor*	*positive*	*negligible*	*negligible*
France	*negligible*	*negligible*	*positive*	*negligible*	*negligible*
Germany	*negligible*	*negligible*	*positive*	*negligible*	*negligible*
Greece	---	*negligible*	*negligible*	*negligible*	*negligible*
Ireland	*negligible*	*negligible*	*negative*	---	*negligible*
Italy	*negligible*	*negligible*	*positive*	*negligible*	---
Netherlands	*negligible*	*negligible*	*positive*	*negligible*	*negligible*
Portugal	*negligible*	---	*positive*	*negligible*	*negligible*
Spain	*negligible*	*negligible*	---	*negligible*	*negligible*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

The last financial market we empirically examine is the most debated one in the current financial crisis. It is the bond market, where most economists have focused into the examination of the ensuing sovereign risks emanated in the last four years. Figure 3.6, along with tables 3.7.A and 3.7.B depict the financial stress conditions of these markets. As emphasized in the initial discussion of the country-level systemic risk indexes, there is clear cut evidence of sovereign risk transmission from specific peripheral countries and not all of them. In more details, Spain's excessive bond stress is positively transmitted to most of the EMU countries (Greece is an exception, while Ireland's market stress decreases). Additionally, Portugal has only a mild and non persistent effect on a few of the core Eurozone economies (Austria, Belgium and Finland). Despite the previous, there is no further evidence of sovereign risk transmission from other peripheral economies to the Northern European countries.

Table 3.7.B: Summary of Bond Stress Shocks in Eurozone Countries

Effects of Bond Stress Shocks in Eurozone Countries - 2 (FSI - 1 case)

Response to	**Austria**	**Belgium**	**Finland**	**France**	**Germany**	**Netherlands**
Austria	---	*negligible*	*positive*	*negligible*	*negligible*	*negligible*
Belgium	*negligible*	---	*positive*	*negligible*	*negligible*	*negligible*
Finland	*negligible*	*negligible*	---	*negligible*	*negligible*	*negligible*
France	*negligible*	*negligible*	*positive*	---	*slightly negative - minor*	*negligible*
Germany	*negligible*	*negligible*	*negligible*	*slightly negative - minor*	---	*negligible*
Greece	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Ireland	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Italy	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Netherlands	*negligible*	*negligible*	*slightly positive - minor*	*negligible*	*negligible*	---
Portugal	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*	*negligible*
Spain	*negligible*	*negligible*	*slightly positive - minor*	*negligible*	*negligible*	*negligible*

Note: This is a summary of the impulse responses, produced using the baseline VAR model where the variance - equal financial stress indices are used. The table is read column by column, where each one of the latter represents a specific shock and each row shows the respective receiver of the shock (and the producing result).

On the other hand, the inspection of table 3.7.B with the responses to the shocks stemming from the core Eurozone economies provides some further useful insights. First, as reasonably expected, there is no risk transmission from these countries to the weaker economies of the monetary union. Then, an interesting bidirectional channel of negative stress transmission between Germany and France is spotted. As the two biggest economies in the Euro Area, it seems that their bond markets are interconnected, with any negative outlook or expectations for one of them to positively reflect to the other market. Another innovative finding here is the role of Finland as propagator of bond stress to the rest of the Eurozone economies. Here, the impulse response analysis indicate a strong and positive reaction of Austrian, Belgian, French and Dutch bond markets to increasing Finnish stress. Interestingly, the same holds for Spain as well, up to a certain degree. Nonetheless, these findings shed new light to the strongly debated issue of whether peripheral countries, especially Greece and Portugal, bear the burden of the exacerbation of Eurozone crisis. As it is apparent from our analysis, in all these markets and economies there exist some channels of interconnection between these economies but not exactly these propagandized before.

Graph 3.6: Response of Bond Stress Indices to Bond Stress Shocks

5.2 Country – Specific VARS

In this section, a brief discussion of the country-specific VARS and, more specifically, of their impulse responses is provided. The relevant figures are presented in the appendix of the chapter[85]. Aim of this section is the examination of any potentially strong interrelations between the different markets within each economy and the inference on their effect to their relevant financial stress.

As a first general comment, it is evident the very strong and positive, persistent response of most stress indices to their own shock. In particular, the banking and bond stress indices exhibit such behaviour for a wide number of countries, including Austria, France, Spain, Greece and Italy (the last three for the banking sector index only). Especially for Spain, its banking index remains elevated and do not converge by the end of the estimation window (even though it has already started to decay). In many cases, there is a positive feedback effect of banking and bond stress levels. For instance, in Belgium, France, Germany and Greece there is a positive response of bond index to a sudden increase to banking stress index. On the other hand, the Austrian case is distinctive, since we observe a negative bidirectional effect between the two aforementioned markets. In Finland, the bond market's sudden increase of stress leads to a positive reaction of the equity stress index, while the banking stress increase has a positive effect on the equity market in Greece. Finally, for Portugal, the banking sector is positively related to an equity market effect, while for Ireland and Netherlands no particular interconnections are established.

5.3 Further Evidence and Robustness Checks

In order to examine our results resilience, we provide further evidence in favour of our baseline model results. Such evidence is provided in three ways. First, an alternative specification for the estimation of the relevant impulse response functions is provided. This is the generalized version of impulse responses and it is discussed in the following section. Then, block exogeneity tests are also presented. These are multivariate version of the Granger causality test, as already analysed in the methodological part of this chapter. Finally, our VAR models are re-estimated, using

[85] They are the graphs labeled A.34 to A.44.

the PCA-induced financial stress indices. Since there are stationarity issues, the indexes are used in their first differences, so that the systems' stability can be safeguarded. We should note that these models are only estimated for the Euro-wide case.

5.3.1 Generalized Impulse Responses

Generalized impulse response analysis was proposed by Koop *et al.* (1996) and Pesaran and Shin (1998), as an alternative to shocks' orthogonalization, proposed by Sims (1980). In this respect, there is no need to apply any judgemental decision on the variables ordering. The produced shocks are invariant to ordering and the outcome is robust. The generalized impulse responses were estimated for the five major cases discussed with the baseline model. In other words, there are five sets of graphs, one for the aggregate financial stress indices and their relevant shocks and four for the markets under scrutiny (banking, money, equity and bond markets). Inspecting the relevant plots, one can concur on their unanimity with the initial impulse response analysis. There exist some minor discrepancies on the banking indexes figures as well as on the national indexes. Nevertheless, most of them are negligible, in the sense that the numerical values of the reactions to the shocks are quite small or dies out relatively fast in time.

5.3.2 Block Exogeneity Tests

Additional evidence is provided by the examination of the results of the block exogeneity tests. The relevant tables follow the generalized impulse responses figures in the appendix of this chapter. In these tables, the respective p-values, indicating the statistical significance of the potential causal relationship between the variables under examination, are reported. The hypothesis tested is whether the financial stress of each country reported in every row (or country's market in the case of the sectoral stress indices) does not Granger cause the level of financial stress for each country or market depicted on every column.

The results confirm the previous discussion, on the lack of extensive and sustainable channels of crisis transmission from peripheral to core Euro Area countries, along with the special cases (in terms of specific markets interrelations) indicated above. In the case of country-level financial stress indices, Finland provides a surprising result. According to this test, there is a unidirectional causal relationship with most of the countries in the sample, except Italy where the relationship becomes bidirectional. There is no obvious explanation for this outcome, especially since it does not manifest itself again in any of the other cases examined. Once more, the North Europe's countries seem to have some causal effect to each other, while Spain's aggregate systemic risk has a unidirectional effect to core countries and Italy. In the case of banking sectors, the regionalism is again evident, with most economies to interrelate with their respective group (North or South). Apart from this, Greece and Ireland provide some indications of causality to Germany, France and Belgium, while Spain and Italy do not. Money markets follow the pattern already described (in terms of the existence of causal relationships), while the equity markets of Italy and Ireland have statistically causal effects to the rest of the Eurozone economies. Finally, in the case of bond markets, countries' grouping is evident again, with the biggest economies appearing to have causal effect to each other[86]. Moreover, Spain is proved to be the main propagator of sovereign risk to the rest of the EMU.

5.3.3 VARS with PCA-based Financial Stress Indexes

The final group of figures in the appendix presents the generalized impulse responses for the VAR models estimated using the PCA-based financial stress indices as endogenous variables. As mentioned above, the first differences of these indices are taken, due to the existence of unit roots for a number of these aggregate systemic risk indicators. Based on the generalized version of the impulses presented, it is fair to say that there is not any contradictory evidence to what has already been established. Of course, we should mention here that differencing the series is not the most efficient way to deal with a dataset. It cannot be avoided in the present case, though. Nevertheless, it is not the type of series used before and it is necessary to affront these results with caution. In any case, the least that can be mentioned here is that there is no any noteworthy difference in the discussion we offered already, due to the outcome of these impulse responses.

[86] The same holds for the rest, especially Spain and Portugal. Greece and Ireland do not provide statistically significant causal effects.

6. Concluding Remarks

Aim of this chapter is the empirical study of the Eurozone crisis and the investigation of its multifaceted nature. There is a strong debated going on, regarding the nature of this crisis. The major focus is to the potential channels of risk transmission to countries and markets and, of course, the creation and implementation of tools that will be able to work as early warning systems of future financial catastrophes. Especially for the monetary authorities around the world, one of the biggest challenges they face lately is the development of robust macro-prudential framework, which can render them able to react as early as possible to forthcoming financial distresses. Since most of the studies until now have tried to examine the conditions of the sovereign and, sometimes, banking risks, we decided to implement a set of innovative tools, in order to measure Euro Area's financial stress. These are the financial stress indexes, which are aggregate systemic risk metrics, able to provide clear cut evidence for the current state of the financial system. On top of that, we move one step further from current literature by incorporating a very large set of data to the development of our indices. For instance, for the case of banking stress measurement, we use both market level data, together with a rich set of balance sheet data for a wide number of European banks. In our knowledge, this is the first time such type of data is used to the construction of systemic risk metrics. Moreover, we provide both market-specific stress indices, for banking (as already mentioned), money, equity and bond markets and country-specific indices for the eleven initial members of the Euro Area (except Luxembourg). Again, this is the first research work providing such detailed, in terms of the number of countries and the decomposition of the analysis to a wide number of markets, analysis of financial stress in Eurozone economies.

In the first part of our analysis, we provide a narrative of the Eurozone crisis, based on the performance of our financial stress indicators. Regarding them, we create three sets of them, each one with a different aggregation approach: the variance – equal and two PCA-based (the first taking the weights from the first principal component, the second using the so called weighted loadings methodology). Here, one of the most important findings is the great importance of credit and liquidity indicators and conditions in the formation of the financial stress. Moreover, an initial picture of the varying performance of the markets, towards financial stress, is provided through the graphs and their discussion.

The second stage of our work emphasizes the role and importance of economies' interrelations. We incorporate our indices, representing a wide number of financial risks, into VAR models. Using impulse response functions, we achieve to dwell in the analysis of the potential risk transmission channels. VARS are employed for Euro-wide analysis and country-specific one. Many important inferences are made here, the most crucial one being the lack of systematic and consistent risk transmission to Eurozone economies by the debt ridden countries. Especially for the case of Greece and Portugal, there is not any strong empirical evidence, able to justify the accusations of being propagators of any type of risk (sovereign or not). On the other hand, it seems that Spain's bond market financial stress agitates core Eurozone countries level of stress in these markets. It is also important to emphasize the degree of segregation that exists in the Euro Area. Results show that countries react to financial stress innovations, mostly, as "clubs" of North or core Eurozone economies and peripheral ones. This is an interesting finding that can be useful for the implementation of macroeconomic, monetary and stabilization policies from the governments and central banks (Constancio, 2012). Additionally, positive feedback loops between bond stress and banking stress levels are traced, indicating the strong interdependencies between sovereigns and banking institutions. Such evidence complements recent calls for the development of pan-European or Eurozone-wide monitoring and regulatory bodies (Merler and Pisani-Ferry, 2012). A number of robustness checks have been successfully implemented in order to verify the validity of these results.

Further empirical work on transmission channels of contagion within the European markets should be done. One aspect of this that is still to be studied is the existence of such channels, not only within each type of market, but also cross-sectional. This would enrich our understanding of the way the current crisis works its way through Europe and its economies. Such empirical investigation, under a different type of models, even more acute for volatility issues, is provided to the next chapter of this thesis.

Chapter 4

Volatility Co-movements and Spillover Effects within the Eurozone Economies: A Multivariate GARCH Approach using the Financial Stress Index

Abstract

Aim of this chapter is the deeper empirical investigation of potential cross-covariances and spillover effects between the Eurozone economies and financial markets. There is a growing interest in the relevant literature, stimulated by the recent financial and sovereign crisis in this monetary union. Our work is innovative, in certain aspects. Focusing on the analysis of volatility comovements and spillovers, we employ financial stress indexes, as systemic risk metrics in our model. In order to provide a more accurate and complete picture of the financial conditions within the Eurozone, we construct such systemic risk indices for the first eleven Euro Area members. Additionally, extra indices for the four most important financial markets (namely, banking, money, equity and bond markets) are also provided. Given the series nature, we decide to employ a multivariate GARCH framework, which is able to capture markets' dependencies and volatility spillovers. Thus, a full GARCH-BEKK model is estimated, both on a market (or country) wide level and, then, one with the full spectrum of Euro Area markets. In other words, we complete an empirical examination, both "within" and "between" Eurozone economies and markets. The results reveal a number of interesting insights: on country wide level, there is strong volatility transmission channel from the most heavily hit, from the crisis, economies towards the rest. Additionally, the crucial importance and role on this transmission from the banking and bond markets is underlined. Contrary to common wisdom, Greece is not the main propagator of volatility uncertainty, while it is between the most important receivers of volatility risk. The same holds for other peripheral economies, while the importance of money market is also evident in the large, "between", empirical approach. Overall, this work provides further insights to the ongoing debate, regarding the volatility comovements and financial stress spillovers within the EMU economies.

JEL Classifications: C43, C58, G01, G15

Keywords: Financial Crisis, Volatility Spillover Effects, Systemic Risk, GARGH-BEKK model

1. Introduction

Unquestionably, the recent financial and sovereign crisis outbreak, within the Euro Area countries, is one of the most important economic events of the last decade. It creates an unprecedented reaction, in terms of non conventional monetary and fiscal policies, from the side of the global and local policy makers. The main reason for them to proceed to such a large scale bail out programs, for financial institutions as well as for a number of heavily indebted countries, indicate the heightening uncertainty for the already identified financial, fiscal and real economic meltdown, together with the uncertainty for even worse future conditions. Furthermore, the lack of a consistent and supra-national macroprudential and crisis mitigating framework, leads to even more intensive uncertainty.

Bearing all the above in mind and, given the lack of conclusive and clear cut evidence for the potential risk transmission channels within the Eurozone economies, we aim to shed further light in the issue of volatility comovement and spillover effects among the EMU countries. In contrast to the existing literature, we move beyond the usual focus on sovereign and, sometimes, banking risk channels. Instead, we try to investigate a full set of potential volatility transmission channels, by implementing a number of financial stress indices for a wide group of financial markets.

Until now, most researchers have focused on the sovereign risk and the relevant contagion issues, arising from it. In this paper, we proceed one step further. Instead of focusing only to CDS spreads or governmental bond yields, to unveil the risk of sovereign default, we employ the aforementioned stress indices, in order to provide a more conclusive picture of the risk transmission channels from one country and market to another. In order to do this, a number of multivariate GARCH-BEKK model are being employed, where the returns of financial stress indices for the Eurozone countries are incorporated. The empirical work is conducted into two directions: "within" each one of the sectors we produce financial stress indexes for (banking sector, money market, equity and bond market) and "between" all of the above markets and countries. The outcome of the empirical investigation reveals some innovative and very interesting features for the links of the Eurozone economies.

We extend the relevant economic research in several respects. First of all, the employment of financial stress indices, within the specified analytical and theoretical framework, takes place for the first time. Moreover, the estimation of multivariate GARCH model for this kind of analysis is rather neglected. Also, it is the first time that such a detailed, in terms of the number of countries and markets examined, empirical investigation is conducted. Another important innovation in our work is the cross market analysis of spillover effects, since the relevant research has focused to specific markets only, until now.

The structure of this chapter is as follows. First, a section where we discuss some important papers examining the volatility spillovers or contagion issues, due to the Eurozone crisis, is provided. Thereafter, a description of our financial stress indices and their components, along with the aggregation method, is presented. Moreover, the GARCH-BEKK modeling approach is analyzed. Section 4 is where the estimations outcome is discussed, for both the market level and the cross market cases. The last part of this chapter recaps, underline the results of our econometric work and suggests further extensions in this literature.

2. Eurozone Crisis and Modeling of Spillover Effects

There is a growing part of the literature, dealing with the empirical modeling of Eurozone crisis contagion and spillover effects. A number of econometric techniques have been used, including multivariate GARCH models. In any case, as it is already stated above, most researchers have solely analyzed potential crisis transmission channels of sovereign risk. A few of them take into account the role and effects of the banking sector of Euro Area. Nevertheless, the research on the Eurozone crisis and the potential interconnections of these economies is expected to endure for the following years. In this section, we discus some important pieces of research, mostly related to the current EMU financial crisis. In some cases, we also include papers that do not directly cope with the aforementioned event, but they present interesting aspects and analytical contributions in the crisis spillovers literature. It should also be noted that, at least in our knowledge, there is still no use of financial stress indices in this strand of literature. This is another strong motivation for implementing our modeling framework by using such successful (in terms of signaling forthcoming crises, as well as macroprudential tools) aggregate systemic risk indicators. Moreover, it should be stressed that the literature presentation is based, mainly, on the econometric methodologies used, in order to summarize papers into distinctive groups. Finally, this short overview should not be considered as exhaustive.

Using factor models and panel regression analysis, Bruyckere *et al.* (2013) examine the existence of contagion channels between the sovereigns and the banking markets of fifteen EU countries. In their model, the authors use CDS spreads for a number of sovereigns and banks, covering the period from 2007 to 2012. They decide to depict contagion as the excess correlation among the aforementioned, measured as the degree of correlation that cannot be explained by the economies fundamentals. In order to achieve this data refinement, they regress the CDS spreads returns into a number of factors, as follows:

$$\Delta CDS_{i,t} = c + \beta_1 Market_t + \beta_2 Itraxx_t + \beta_3 Vstoxx_t + \beta_4 Term_t + \varepsilon_{i,t} \tag{4.1}$$

where $Market$ is a total EU stock market index, $Itraxx$ represents a pan-European CDS index, $Vstoxx$ is the well known VSTOXX index and, finally, $Term$ is the yield curve for each one of the countries involved. Then, they employ a fixed effect panel regression, in order to examine the importance of a number of factors in the formation of the excess correlation. Their model is specified as:

$$Corr_{i,j,t} = \alpha + \beta_1 X_{i,t} + \eta_{z,j,t} + \varepsilon_{i,j,t} \tag{4.2}$$

The dependent variable is the excess correlation between a bank i and a country j at time t, X a vector with bank specific measures (size, Tier 1 capital ratio, loan ratio, non-interest income/total revenues ratio). The final specification used by them is the one where the fixed effects are bank specific, while the explanatory variables are country specific (debt-to-GDP ratio, recapitalization, guarantees and asset relief measures, all as percentages of GDP). Based on their empirical work, the authors find evidence of bank and sovereign risk contagion. Especially since 2009, the contagion becomes more intensive, especially between domestic banks and their countries. This fact is even more evident for the case of peripheral economies. Regarding the measures affecting excess correlation, it is found that capital adequacy and the level of short-term funding are important, for the case of banks CDS spreads. On the other hand, the debt-to-GDP ratio is an important determinant for the countries CDS spreads. Another paper investigating the banking – sovereign risk nexus is the one by Barth *et al.* (2012). In this case, the authors study 44 large banks and 13 countries, not all of them being part of EU or Euro Area[87]. Their model is based on OLS regressions, where the regressand is the changes of sovereign CDS spreads and the explanatory variables consist of dummies, representing the European debt crisis and the bailout periods for the banks in the sample. They also include country and banks dummy variables. Their main finding is the strong linkage between sovereign and banking risks, while this link varies according to the country or market scrutinized. For instance, the authors provide supportive evidence that those banks that are more heavily exposed to public debt from the GIIPS are more prone to abrupt risk shifts. Additionally, higher bank – sovereign risk interdependencies exist for countries, in which the relative (towards the country's GDP) banks assets are quite high. The question of whether the adoption of a common currency, like euro, can mitigate the sovereign risk premiums, Gabrisch *et al.* (2012) use a panel regression approach, in order to examine the influence of internal and external factors into the aforementioned variable. Their model's specification is the following:

$$\begin{aligned} \Delta SRP_{it} = \gamma_0 + \alpha_1 \Delta y_{i,t+\tau} + \alpha_2 \Delta(G/Y)_{i,t+\tau} + \alpha_3 \Delta(D/Y)_{i,t+\tau} \\ + \beta_1 TED_{t+\tau} + \beta_2 FCD + \beta_3 e_{i,t+\tau} + \xi_t \end{aligned} \tag{4.3}$$

The dependent variable is the change of the sovereign bond spreads of the economies examined (vis-à-vis the German Bund) and the explanatory ones are real GDP growth, government spending-to-GDP, public debt over GDP, the TED spread, a financial crisis dummy and the exchange rate towards US dollar, respectively[88]. The sample period is 2001Q1 to 2012Q1 and the pooled least squares estimator is employed. According to this modelling approach, the peripheral euro countries are driven, mostly, by the real GDP growth, the government spending and the debt ratio, while the exchange rate is an important external factor. On the other hand, the euro candidate countries are mostly influenced by the rate of economic growth. A notable

[87] Their sample consists of: Australia, China, France, Germany, Greece, Ireland, Italy, Japan, Portugal, Spain, Switzerland, UK and US.
[88] The countries of the sample are the GIIPS ones, from the EU, while the euro candidates are Poland, Hungary and the Czech Republic.

finding here is that increasing government spending leads to lower sovereign risk spreads. This is in contrast to the following policies in Eurozone right now.

A number of relevant recent studies have employed VAR models for the examination of sovereign risk transmission within the Euro Area. For instance, Alter and Schuler (2012) use unrestricted and cointegrated VAR models, in order to examine the credit risk interdependencies between a group of European countries and their banks. Their analysis is isolated into country level. That is, they do not take into account potential interactions between banks from different countries and the potential risk transmission from them abroad. Their dataset consists of CDS spreads (for both sovereign and banks), on daily frequency, covering the period from 1 June 2007 to 31 May 2010. Having analyzed their sample in a pre- and post-state aid to banks, they find that (for most of the cases) the banks CDS spreads used to lead the sovereign ones, while the opposite holds for the period after the bail outs. Bruttin and Saure (2012) employ SVAR analysis of sovereign CDS for eleven Eurozone countries. Following the narrative approach, they extract a number of information shocks, related to the Greek sovereign state. They find that exposure to Greek sovereign debt and Greek banks assets are sources of intensive transmission of risk. On the other hand, Kohonen (2012) uses ten year government bond yield differentials for the PIIGS countries, into a similar SVAR framework[89]. Here, the author suggests that there was a default risk transmission from the Greek bonds, but only at the beginning of the crisis. Moreover, this was not the only risk channel within the countries under scrutiny, since relevant evidence for other countries (notably, Portugal) is also provided. A combined VAR-event studies approach is used by Arezki *et al.* (2011) in order to study the effects of sovereign rating news from rating agents on a number of financial markets and the sovereign CDS spreads. The markets examined are represented by the general stock index, insurance and bank sector stock indices, while the countries of the sample are Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands and Spain. The inclusion of impulse dummies (so as to capture the potential changes in the markets behavior due to rating changes) is the innovative factor into their VAR approach. Covering the period until 2010, the authors find a statistically significant role for sovereign downgrades, implying their importance on the potential outbreak of financial instability periods. Another

[89] The PIIGS governmental bond differentials are calculated against the German long term government bond yield.

interesting point in their research is the systemic importance (in terms of increasing spillover effects) from the countries downgrades to near speculative grades (like in the case of Greece or Ireland).

A recent extension in the VAR-based literature is the spillover index approach of Diebold and Yilmaz (2012). Taking advantage of the generalized VAR framework, which is invariant to the variables ordering, the aforementioned authors develop a variance decomposition approach. This is based on the decomposition of the H-step ahead forecast error variance for the variables included in the system. In this way, the researchers are able to calculate the contribution of each variable's i shocks to the forecast error variance of the variable j. It is a rather straightforward way to assess the level of volatility spillover among the variables of interest. As it would be expected, there is a recent interest in applying such a technique to the Euro Area financial crisis. For instance, Antonakakis and Vergos (2013) make an effort to assess the spillover effects of the sovereign bond yields with a number of European economies[90]. Using daily data from March 2007 until June 2012, the authors emphasize that own countries bond yields explain most of the forecast error variance. On top of that, they also indicate a degree of clustering between the core and peripheral economies, at least in terms of sovereign risk transmission. Additionally, Belgium is one of the major transmitters of volatility spillovers, while Greece, Portugal and Netherlands are the main receivers. Finally, Greece is considered as a source of volatility transmission until 2010, when it turned to be a net receiver. Implementing a similar framework, but this time for both sovereign and banking risk analysis, Alter and Beyer (forthcoming) identify an increasing degree of interdependence in Euro Area, since the initiation of the crisis. Furthermore, a shock to Spanish CDS transmits to the rest of the union, especially in the first half of 2012. Finally, the adoption of economic consolidation programs from the hardly hit economies (Greece, Portugal and Ireland) led to the decrease of their contribution to spillovers to the other economies. In contrast, Louzis (2013), mentions that the three aforementioned countries are spillovers' transmitters during 2011 and 2012. On top of that, he also underlines the importance of stock and money markets in volatility transmission during the Eurozone crisis.

Similar argument (for the intensity of the risk propagation channel from countries like Greece to the rest of the euro union) is provided by Caporin *et al.*

[90] For the periphery, they included Greece, Ireland, Italy, Spain and Portugal. For the core countries, their sample consists of Austria, Belgium, France and Netherlands.

(2013). Here, using a quantile regression model (with Bayesian inference process), the authors indicate that contagion effects were not that strong, even though peripheral countries went through serious strains because of their heightened fiscal burden. Another interesting outcome of their work is that the sovereign risk transmission (as measured by the governmental bond yields) is actually smaller, compared to the period prior to the Lehman Brothers collapse. On the contrary, Metiu (2012) identifies strong contagion effects for the period 2008 to 2012, using the canonical contagion model. It appears a lack of clear identification of the true effects among the Eurozone countries, based on these papers.

Turning now to the case of multivariate volatility models, a very popular framework is the DCC model[91]. Developed by Engle (2002), the model is specified as follows:

$$
\begin{aligned}
r_t &= \mu_t(\theta) + \varepsilon_t \\
\varepsilon_t &= H_t^{1/2} u_t \\
H_t &= D_t R_t D_t
\end{aligned}
\tag{4.4}
$$

where r_t is a vector of the series used in the model, the first term in this equation is the conditional mean vector of the aforementioned indices. Also, H_t represents the conditional variance covariance matrix, while $D_t = diag(h_{iit}^{1/2} \ldots h_{nnt}^{1/2})'$ is the diagonal matrix of square root conditional variances. Here, the elements of the aforementioned matrix h_{iit} are estimated, based on individual GARCH type models. Moreover,

$$R_t = diag(q_{11,t}^{-1/2}, \ldots, q_{nn,t}^{-1/2}) Q_t diag(q_{11,t}^{-1/2}, \ldots, q_{nn,t}^{-1/2}) \text{ or } \rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{4.5}$$

is the matrix containing the time-varying conditional correlations. Q_t is a nxn symmetric positive definite matrix, computed by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \tag{4.6}$$

[91] DCC has been, and still is, extensively used for the analysis of financial contagion and spillover effects cases, both for developed as well as for developing economies. For the latter, some examples are the papers by Chiang *et al.* (2007), Yiu *et al.* (2010) and Kim *et al.* (2012).

where u_t is a nx1 vector of standardized residuals, $\bar{Q}$ the nxn unconditional variance matrix of the residuals and α and β are non negative scalar parameters, such that $\alpha+\beta<1$. Dajcman (2012) uses a flight-to-quality indicator to examine the co-movements of stock returns with bond yields for Germany and PIIGS. The results, using the aforementioned modeling approach, are concurrent with Kohonen (2012) and Caporin *et al.* (2013), where the Greek debt crisis, along with the ones in Portugal and Italy do not indicate important contagion effects to the rest of the Eurozone. Moreover, the flight-to-quality indicator has higher values prior to 2010, indicating increasing uncertainty for investors, who turned towards the safe haven of German Bunds. Then, Audige (2013) employs a smooth transition conditional correlation (STCC-GARCH) model, with long term governmental bond yields, in order to check for spillover effects from the Greek crisis. Once more, the author pinpoints contagion effects from Greece to Ireland and Portugal in 2010, while such effects weaken after that year. The sovereign risk premium for seven Euro Area countries (Austria, Belgium, Netherlands, Italy, Greece, Portugal and Spain) is examined with DCC models by Mission and Watzka (2011). According to these authors, there was contagion effect from the excessive Greek sovereign risk, especially towards peripheral economies. On top of that and in accordance with Arezki *et al.* (2011), the Greek bonds rating downgrades are found to be contagious to some of the other economies.

Similar research work has been conducted, using alternative GARCH models. We report some of them, which are somehow related to the purposes and the scope of this chapter. Grammatikos and Vermeulen (2012) examine the transmission of financial and sovereign debt shocks through the Eurozone stock markets, for the period 2007 – 2010. In order to do this, GARCH modeling of stock returns are employed, while the effect of US markets is also taken into consideration. They split EMU into three groups of countries, namely the North, South and Small economies[92]. Their findings show strong crisis transmission from US non-financials to European non-financials[93], while the financial ones from both sides of the world are not that interconnected. Additionally, Greek CDS spreads seem to play a much more

[92] North consists of Austria, Belgium, Finland, France, Germany and Netherlands. The South group includes Greece, Ireland, Italy, Portugal and Spain while the Small one from Cyprus, Luxembourg, Malta and Slovenia.
[93] Non-financials consists of the returns of stocks, if the financial institutions listed to the market are excluded from the sample.

important role in the period after the Lehman collapse, but not for the non-financial firms. Caceres *et al.* (2010) aim to explain the high volatility of the sovereign swap spreads in Europe, until 2010. Three reasons are investigated: global risk aversion, country-specific risks (countries' fundamentals) and spillover effects from other sovereigns (contagion). Each one of the aforementioned are represented by a global risk aversion index (computed using distress dependencies approach), a Spillover Coefficient (it is a metric for the dependence of a country's probability of default to other countries financial distress) and, finally, country specific factors[94]. A GARCH(1,1) specification reveals the importance of global risk aversion (decreases the spreads), the role of fundamentals (although, decreasing when fiscal burdens arise) and the fact that contagion decreases the swap spreads. Finally, there are a couple of studies that have used a BEKK model, similar to ours. For example, Groba *et al.* (2013) use the latter, in their preliminary investigation of the CDS spreads, their role to sovereign risk spillover and their determinants. The essence of their work is finding of spillover effects, up until 2010. Since then, the intensity of this channel is minimized. The contagion channels between mature and emerging stock markets are the interest of Beirne *et al.* (2013). Employing a GARCH-BEKK (1,1) model, with the addition of dummies (in order to be able to capture any cases of "shift contagion"), they conclude that there is volatility transmission from mature to emerging stock markets and this situation changes (intensifies or not) during periods of financial instability.

3. Dataset and Methodological Approach

The third section of the chapter is dedicated to the discussion of our dataset, together with the presentation of the methodological approach followed in the econometric analysis. Regarding the set of variables used for our renewed stress indices, we should stress that most of them have also been implemented and analyzed to the previous chapter. As a result, the relevant discussion is greatly based to the one

[94] These are the public debt and debt/GDP ratio (both series interpolated to obtain daily series out of the quarterly data).

preceeded. This does not hold for the multivariate GARCH modeling, which is the focus of our empirical work in this chapter.

3.1 Dataset Description and Aggregation Method

Since our aim is the depiction of systemic risk on a timely and up to date basis, we proceed with the creation of aggregate financial stress indices (FSIs). These indexes provide information on the financial markets conditions, based on a range of stand-alone indicators representing important features of these markets. Our focus is on Eurozone crisis and, thus, the sample of our countries consists of the initial eleven euro economies (excluding Luxembourg). These countries are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain. Once again, our interest is in the calculation of four market-level indicators, along with a systemic risk index for each country individually. These markets are the banking one, money, equity and bond markets. The major difference, compared to the previous chapter, is the development of FSIs on weekly frequency. The reasons are twofold: first, we decided to examine the spillover effects of the Euro Area crisis, both within each market (and countries) level, together with a deeper cross-sectional investigation of this crisis effects. That is, we explore the transmission channels existing between different markets and different countries (e.g. whether there are stress spillovers from the, say, Greek banking sector to the French bond market or if the Irish equity market affects the Italian money market and so on). Secondly, since such an empirical work requires the employment of multivariate GARCH modeling and such an econometric approach is highly demanding, in terms of degrees of freedom, there is a necessity to employ high frequency dataset. Hence, the variables that are used are restrained to those that can be retrieved in such frequencies.

Table 4.1: Indicators of Financial Stress

Variables Used in Financial Stress Indices	
Banking Sector	***Money Market***
Dividend Yield	TED Spread
Market Value	Inverted Term Spread
Turnover by Volume	Treasury Bill Realized Volatility
P/E	Main Refinancing Rate - 2yr Government Bond Yield
Bank Equities Realized Volatility	Main Refinancing Rate - 5yr Government Bond Yield
Banking Sector Beta	
Bank Equities Returns	
Equity Market	***Bond Market***
Stock Returns	Sovereign Spread
Dividend Yield	Government Bond Realized Volatility
P/E	Corporate Spread
Stocks Realized Volatility	Government Bond Duration
Market Value	

Table 4.1 summarizes the variables included in the financial stress indices of the economies in our sample. As already mentioned, the aforementioned include high frequency only variables. As a result, it is not possible to include a number of macro-financial and balance sheet variables, as in the previous chapter. In any case, a significant number of financial indicators remain at play. Our dataset is of weekly frequency, covering the period from January 2001 until 20th of September 2013. There are 664 observations in total, which covers the pre- and post-crisis period. We do not use daily data for avoiding potential mismatches in public holidays and trading days (Yiu *et al.*, 2010). In this way, a uniform dataset is created, without any discrepancies in the countries' series used. Getting into more details, the banking sector index comprises of seven variables, while five variables are used in the case of money and equity markets and four for the case of bond market. Focusing to the banking market, variables representing banks' sensitivity to market conditions, along with their level of profitability and risk level there are included. Dividend yield is negatively related to fundamentals of banking institutions and, thus, excessive dividend yields can be a signal of increasing default risk for them. On the same time, market value is also

important, since its size directly affects the stability of the market. Increasing uncertainty can lead to a significant adverse effect to market value, which is also tied to these institutions' book value. Thus, their financial health is at stake. Another strong indicator of instability for banks is the turnover by volume. This increases, according to market sentiment and the perceived level of risk and uncertainty by the investors. Profitability is also an important metric here, represented by the P/E ratio. Here, since banks' operational efficiency and profitability is indicated by higher values for the aforementioned ratio, we impose a negative sign to this variable (so, higher P/E ratio coincides with excessive financial stress). Finally, the three last variables here (these are, realized volatility of banks equity index, the beta coefficient of the aforementioned index and the (negative) stock returns) depict the risk perception and the volatility level of this market. At this point, a note of caution should be added. Given the nature of our observations (high frequency data) and the types of indicators chosen for inclusion to the aggregate systemic risk index, it would be fair to say that the variables fragmentation into different types or markets is, somehow, tricky. For instance, in the case of the banking sector variables, it would be justifiable to say that they are not entirely distinctive (in nature and on what they capture) from the stock market indicators. Moreover, many of them include features that are highly affected by the price changes and volatility of the banking sector equities. Nevertheless, it should be fair to emphasize that the choice of these stand alone indicators is driven, among other reasons, from the necessity to keep our dataset homogenous and comparable. Additionally, this fragmentation does make sense, especially since the source of data for the banking group of indicators is entirely based on listed banks sources. I acknowledge the fact that their nature is multifaceted (especially, due to the observations frequency), but, I strongly believe they still represent the conditions prevailing in the banking markets.

The aggregate index for the money market sector includes some of the most important liquidity, credit and counterparty risk indicators. TED spread (the difference between the 3-month Euribor and the respective Treasury bill of the same maturity) is one of these measures. It is expected to observe increasing values for this spread, in periods of worsening financial conditions. In such times, interbank funding markets seize to operate smoothly, while the risk perception reaches unprecedented levels. In the same line of thought, inverted term spread is incorporated, as indicator of interest rate setting expectations, along with the representation of default risk in money markets. Moreover, the spreads of the main refinancing rate from the short term governmental bills yield is another indicator of deteriorating liquidity conditions. Negative values in these spreads coincide with higher financial stress and, hence, the need to incorporate them in our aggregate index with a negative sign. Lastly, the realized volatility of the Treasury bills of the countries in our sample depicts the formed risk volatility in this market.

The conditions in the equity markets are captured by five variables. The (negatively signed) stock returns are a good indication of investors' uncertainty and lack of trust to listed firms underlying fundamentals. In periods of increasing financial stress, it is expected to have higher volatility in the stock markets. Then, market value is included and the dividend yield as well. The rationale is similar to the case of the banking sector, emphasizing the level of default risk, lack of credibility and funding sources in the market. Again, the level of financial sustainability of the firms is sketched by the P/E ratio, while the realized volatility of the general equity market index is indicative of the historical risk perception on the specific equity market.

The last market considered here is the most scrutinized in the current Eurozone crisis research. That is, the bond market. Here, we employ the sovereign bond spread, vis-à-vis German bond yield, which is considered as a safe haven for bond market investors. This is a strong and popular indicator of the perceived sovereign risk of the countries under investigation. Then, the realized volatility of the long term governmental bond yields is used, as another variable illustrating the volatility risk of this market. Then, the corporate bond spread (towards the government long term bond yield) is a factor showing the default risk and the financial obstacles operating firms in each one of the EMU countries face. Bond duration is also included (for the long term government bonds). As explained in the previous chapter, it is expected that decreasing credit ratings and increasing concerns for the countries solvency, will lead to lower duration for their bonds. Hence, decreasing duration represents increasing financial stress and uncertainty.

The FSIs are computed, following the variance-equal aggregation method. Based on this approach, an equal weight is attributed to all variables in each of the markets. In this way, the market - level indices are computed, while the same approach is followed for the country – wide one. Before the aggregation, each one of the single indicator is standardized. That is, its mean value is subtracted by each observation and, then, divided by its standard deviation. In this way, problems of mis-measurement are avoided. Then, all series are expressed as deviations from the long run mean value of them. Thus, there is no any issue, regarding the units of measurement of variables that can be of very different nature otherwise. The variance – equal approach is rather frequently used in the relevant literature. The most important reason for this has to do with the simplicity of the relevant calculations, while it is quite efficient approach for the creation of well behaved financial stress indices. This means that the aggregate indices produced in this way effectively represent the conditions in the financial markets and there is not important value added if the relevant weights and aggregation is made through some more sophisticated approach[95].

3.2 Spillovers Definition

At this point, it would be useful to discuss the theoretical definitions and pursuit of our empirical work. It is true that the long lasting crisis of the last four years in Eurozone ignited research on the roots and cause of the aforementioned crisis event. Many economists also tried to analyze potential contagion channels and interdependencies within the Euro Area economies, in order to infer on the catastrophic effects of the crisis and relevant policies to ameliorate them. A major issue here is what exactly is investigated in these papers and whether the empirical evidence provided is actually accurate of what the authors try to capture. Many economists use the term “contagion”, without really specifying the meaning of it. There is a large debate, still intensive, on what constitutes contagion and what are the most accurate and sensible tools to represent contagion channels. Seminal work in the creation of a well sounded definition of contagion is the one by Forbes and Rigobon (2001 and 2002). The authors make a distinction between comovements or interdependencies of the markets, which can be the case of high correlations between them in both pre- and post-crisis periods and “shift-contagion”, as they call it. The latter is the observation of excessive markets comovements after a significant financial or real economic shock. Hence, someone has to be very careful when he examines complex phenomena like crisis transmissions. In most cases, researchers

[95] Of course, the same health warning, related to the use of such a fixed weighting scheme on the index aggregation, applies here (as in the previous empirical chapters of this thesis).

ignore these delicate differences and their argumentation can be problematic. In our piece of research, the focus is on the variance-covariance comovements of the European economies and markets. On top of that, the modeling framework we use lies in the tradition of multivariate GARCH models that try to capture volatility spillovers among the constituent markets of the sample. It is closer, as a concept, to the "meteor showers" hypothesis of Engle *et al.* (1990). In this important paper, the authors try to explain volatility clustering in the foreign exchange market returns. In order to do it, they define spillover effects as the effects of the variance of market one in time t-1, to the variance of market two on time t. Hence, our empirical effort mainly focuses on spillover effects among EMU markets, with a special emphasis on the different transmission channels (as evident from the disaggregated, market-based analysis). On the same time, it is the first effort that financial stress indices are employed in this type of empirical analysis.

3.3 Volatility Transmission Models: Empirical Methodology

Turning now to the MGARCH model employed, the decision is to use one of the most successful models in relevant applications, namely the BEKK model (Marcal and Pereira, 2008). It is quite useful, in ensuring that the variance covariance matrix will be always positive definite and, as a consequence, the estimation of a model with a significantly high number of parameters is less burdensome. Additionally, they are also helpful for studying the time-varying properties of covariances and correlations.

As already mentioned, the GARCH-BEKK model is an alternative to the prototype multivariate VEC model, proposed by Bollerslev *et al.* (1988), ensuring the positive definiteness of the conditional variance matrix H_t (Bauwens *et al.*, 2006). Let us first describe the BEKK model, as introduced by Engle and Kroner (1995). The basic set up includes the mean equation

$$r_t = r_{t-i}(\theta) + \varepsilon_t, \text{ where } \varepsilon_t \left| \Omega_{t-1} \sim N(0, H_t) \right. \tag{4.7}$$

where r_t is a Nx1 vector of the financial stress indices returns, $r_{t-i}(\theta)$ is the conditional vector of the indices lagged returns (again of the same dimensions as the previous vector) and ε_t is the vector of the model's vector of residuals. The latter, based on the information set available until period t-1 (Ω_{t-1}), is assumed to follow a zero mean distribution, with a variance covariance matrix H_t. According to this model, the NxN matrix H_t has the following form:

$$H_t = C_0^{'}C_0 + A^{'}\varepsilon_{t-1}\varepsilon_{t-1}^{'}A + B^{'}H_{t-1}B \tag{4.8}$$

where C_0 is the constants vector, A and B are parameter matrices, ε_{t-1} is the lagged disturbance vector and H_{t-1} is the lagged variance covariance matrix. The constants vector is restricted to be upper triangular, while the parameter matrices are not restricted. As emphasized by Bollerslev (2010), this quadratic parameterization guarantees that the covariance matrix is positive definite, while the number of parameters to be estimated is more compact, compared with the MGARCH model firstly proposed by Bollerslev *et al.*(1988)[96]. Since out interest is in the potential spillover effects of each Eurozone country (or market) to the other participants in the common currency area, the main focal point here is on the estimated coefficients of matrices A and, especially, B. The type of BEKK model that interests us is the one allowing for interactions between the variances of the markets. These are represented by the off-diagonal elements of matrix B. Additionally, matrix's A coefficients depict the effects of lagged innovations in equation (4.2) to the conditional variance covariance matrix. As it is commonly said in the relevant literature, matrix A provide information on "news effect", while matrix B depict the "volatility spillover" effect (Kim *et al.*, 2012). Both effects can provide important insights for the potential volatility transmission channels established within the Euro Area countries and markets.

Given the number of variables and the ensuing computational procedures, we proceed with the estimation of bivariate BEEK models, for all the cases examined here. These are, the BEKK models for the countries and the market level indices (banking, money, equity and bond markets), while the same holds for the case of the intra-markets analysis. Thus, for the bivariate case, the model will look as follows:

[96] In this way, model's convergence is more easily achieved. See, among others, Bauwens *et al.* (2006) and Brooks (2008).

$$
\begin{aligned}
H_t = C_0^{'}C_0 + &\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}^{'} \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \\
&+ \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}^{'} H_{t-1} \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}
\end{aligned} \tag{4.9}
$$

In more details, after the matrices' multiplications, the detailed representation of the conditional variance elements is:

$$
\begin{aligned}
h_{11,t} &= \alpha_{11}^2\varepsilon_{1,t-1}^2 + \alpha_{21}^2\varepsilon_{2,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{11}^2 h_{11,t-1} + \beta_{21}^2 h_{22,t-1} + 2\beta_{11}\beta_{22}h_{12,t-1} \\
h_{22,t} &= \alpha_{12}^2\varepsilon_{1,t-1}^2 + \alpha_{22}^2\varepsilon_{2,t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{12}^2 h_{11,t-1} + \beta_{22}^2 h_{22,t-1} + 2\beta_{11}\beta_{22}h_{21,t-1}
\end{aligned} \tag{4.10}
$$

Given the above description of the model, our interest is focused on the statistical significance of α_{21} and β_{21} in the first part of (4.4). These two coefficients represent the volatility spillover from market (or country) 2 to market 1. On the other hand, for the second part of the previous equation, α_{12} and β_{12} are the coefficients of interest. It should be noted here that, since all of these parameters are squared, their signs do not have any importance. The models are estimated, using the quasi maximum likelihood estimator, using the Matlab algorithms provided by Kevin Sheppard. In what follows, a detailed presentation of these computations, along with a discussion on them is provided. All models here are estimated, using the quasi maximum likelihood (QML) estimator under a multivariate student distribution. In this way, any issues arising from the potential non normality of the models' residuals can be statistically accommodated.

4. Discussion of Results

This section is dedicated to the discussion of the computational results obtained by the BEKK models estimated. Before getting into them, we briefly show some descriptive statistics, along with unit root testing for the financial stress indices returns. Regarding the multivariate conditional volatility models, we first present the five single market (banking, money, equity and bond one) or country models, while this subchapter is completed with the case of cross-market models and the respective volatility spillovers.

4.1 Indexes Descriptive Statistics and Stationarity

The following table (4.2) provides a complete descriptive analysis of all the financial stress series returns used in this chapter. They are organized in five different panels, according to the type of indices and the market they represent. In the appendix, we also provide the graphs of the series, both in levels as well as in returns. The table provides a full set of statistics for the distribution of the indexes returns, together with their normality and the type of their data generating process. Moreover, the results of the ADF test are reported, in order to account for the existence or not of unit roots. The inspection of these results provides useful insights to the nature of our dataset. First of all, it is evident that the banking and equity stress indexes exhibit the highest standard deviations. This is also evident from the respective graphs in the chapter's appendix, where the banking and equity FSIs returns have the most dispersed values, compared to the rest of the dataset. In almost all cases, the series' distributions are positively skewed, while the statistically significant kurtosis coefficients indicate the non-normality of returns. The latter is strongly verified by the Jarque-Berra test, which offers a clear indication of the non-acceptance of the null hypothesis of normally distributed FSIs returns.

On top of the above, table 4.2 reports the Ljung-Box Q and Q^2 statistics. Here, the purpose of this test is the verification for the existence or not of serial correlation for the returns and the squared returns, respectively. Again, in the majority of the cases examined, the results are in favor of serially correlated series, exhibiting higher order correlation and non-linear dependencies as well (indicated by the Q^2 statistic). The only exception here is the Dutch bond market financial stress index, while the Ljung-Box Q^2 test fails to provide relevant evidence for the cases of Greece, Portugal and Spain (in the case of the bond markets indices). The same holds for the money market stress indexes of Greece and Finland. Nevertheless, the aforementioned are limited exceptions to the general conclusion of the existence of autocorrelation. The Engle's ARCH test is also concurrent with the previous findings, emphasizing the need to employ GARCH models for the implementation of our empirical work that aims to study the spillover effects of financial stress among the Euro Area markets and countries. The last row in each one of the table's panels provides the ADF unit root test. As expected, all series are proved to be stationary.

Table 4.2: Descriptive Statistics of Financial Stress Indexes Returns

Descriptive Statistics for Financial Stress Indexes Returns											
Countries	**Austria**	**Belgium**	**Finland**	**France**	**Germany**	**Greece**	**Ireland**	**Italy**	**Netherlands**	**Portugal**	**Spain**
Panel A: Country Indexes											
Mean	0.0002	0.0002	-0.0003	0.0000	-0.0007	0.0007	-0.0004	-0.0003	-0.0004	-0.0002	0.0010
Std. Deviation	0.0563	0.0520	0.0748	0.0431	0.0609	0.0525	0.0715	0.0489	0.0799	0.0595	0.0503
Skewness	0.039	0.212**	-0.073	0.496**	-0.074	0.07	0.204*	0.804**	-0.152	-0.366**	0.787**
Kurtosis	2.71**	2.428**	7.562**	3.99**	3.741**	7.705**	7.201**	4.812**	8.855**	9.067**	6.783**
J-B Test	203.06**	167.9**	1580.7**	467.19**	387.34**	1640.7**	1437.4**	711.26**	2169.1**	2286.3**	1339.6**
Q(10)	67.78**	29.06**	102**	20.83*	61.15**	89.91**	116.81**	24.12**	56.16**	113.81**	72.2**
Q^2(10)	378.06**	93.87**	121.08**	173.83**	77.18**	396.18**	161.23**	121.66**	77.2**	188.18**	140.33**
ARCH(5)	24**	9.07**	40.45**	18.15**	11.32**	36.94**	28.09**	10.36**	11.3**	30.68**	23**
ADF	-18.51**	-15.23**	-18.51**	-14.53**	-18.54**	-17.65**	-19.39**	-15.63**	-18.89**	-17.05**	-17.73**
Panel B: Banking Sector Indexes											
Mean	0.0000	-0.0001	0.0016	0.0007	-0.0009	0.0008	0.0008	0.0002	-0.0014	0.0008	0.0021
Std. Deviation	0.2268	0.2204	0.2578	0.2361	0.2328	0.2414	0.2443	0.2263	0.2197	0.2251	0.2344
Skewness	0.257**	0.591**	0.423**	0.283**	0.885**	0.852**	-0.077	0.828**	0.948**	0.445**	0.911**
Kurtosis	3.303**	6.676**	10.316**	3.03**	7.001**	10.927**	8.691**	3.93**	13.021**	6.381**	6.277**
J-B Test	309.9**	1270**	2959.6**	262.61**	1440.8**	3378.8**	2087.5**	502.65**	4783.2**	1147**	1180.4**
Q(10)	147.03**	149.63**	178.02**	198.72**	156.15**	169.08**	179.32**	173.05**	118.52**	136.88**	157.4**
Q^2(10)	481.28**	305.53**	145.51**	566.97**	387.89**	492.56**	209.03**	155.27**	290.14**	172.64**	160.34**
ARCH(5)	24.67**	20.99**	57.54**	45.99**	33.11**	49.52**	42.78**	11.86**	28.72**	23.77**	21.59**
ADF	-21.85**	-21.02**	-22.24**	-22.32**	-21.75**	-18.67**	-22.39**	-20.23**	-21.25**	-22.09**	-23.43**
Panel C: Money Market Indexes											
Mean	-0.0008	-0.0007	-0.0006	-0.0006	-0.0007	-0.0001	-0.0001	0.0003	-0.0003	-0.0010	0.0001
Std. Deviation	0.0867	0.0885	0.0748	0.0980	0.0738	0.0483	0.0578	0.0911	0.1739	0.0437	0.0568
Skewness	1.419**	0.911**	1.731**	1.296**	1.241**	3.215**	3.036**	1.14**	-0.861	0.118	-0.177
Kurtosis	8.958**	8.602**	11.555**	6.288**	7.973**	77.115**	84.406**	13.077**	30.869**	11.913**	4.431**
J-B Test	2439.8**	2136.3**	4019.3**	1278.1**	1926.7**	165420**	197830**	4867.8**	26405**	3921.8**	545.88**
Q(10)	25.84**	11.30	26.47**	19.01*	21.57*	21.61*	100.95**	15.81	59.74**	37.56**	62.18**
Q^2(10)	55.58**	140.53**	7.21	89.33**	77.54**	4.53	75.04**	44.25**	85.82**	297.05**	144.62**
ARCH(5)	2.99*	22.37**	1.31	6.08**	2.88*	0.86	2.72*	4**	22.48**	29.07**	13.42**
ADF	-16.42**	-14.54**	-13.48**	-15.74**	-15.68**	-15.4**	-13.88**	-14.65**	-18.43**	-12.99**	-15.6**
Panel D: Equity Market Indexes											
Mean	0.0011	0.0007	-0.0023	-0.0010	-0.0003	-0.0013	-0.0011	-0.0010	-0.0011	-0.0001	0.0007
Std. Deviation	0.2802	0.2689	0.2610	0.2777	0.2760	0.2636	0.2808	0.2738	0.2759	0.2687	0.2803
Skewness	0.655**	0.469**	0.292**	0.506**	0.51**	0.477**	-0.01	-0.838	-0.367**	-0.641**	-0.542**
Kurtosis	10.015**	3.601**	2.098**	4.415**	4.73**	4.575**	8.246**	7.547**	4.952**	5.807**	3.859**
J-B Test	2818**	382.75**	131.02**	567.04**	646.89**	603.48**	1878.5**	1651.2**	692.43**	977.27**	444.11**
Q(10)	199.94**	203.66**	209.86**	250.71**	263.4**	167.36**	226.7**	228.91**	217.08**	206.24**	256.23**
Q^2(10)	383.69**	206.51**	233.54**	541.81**	539.49**	101.5**	455.26**	256.27**	388.87**	400.24**	459.89**
ARCH(5)	32.92**	21.35**	22.02**	55.04**	67.92**	16.75**	41.68**	42.12**	40.05**	67.98**	64.76**
ADF	-25.33**	-24.41**	-22.34**	-23.93**	-24.63**	-24.65**	-27.96**	-23.33**	-23.95**	-24.26**	-24.58**
Panel E: Bond Market Indexes											
Mean	0.0005	0.0010	0.0002	0.0011	-0.0007	0.0033	-0.0013	-0.0009	0.0013	-0.0006	0.0010
Std. Deviation	0.0704	0.0642	0.0833	0.0748	0.0982	0.0357	0.0918	0.0561	0.1050	0.0768	0.0555
Skewness	1.331**	0.735**	1.28**	0.87**	0.928**	9.693**	-1.873	0.617**	1.947**	-0.722**	1.592**
Kurtosis	17.613**	14.634**	20.532**	2.688**	13.601**	173.17**	57.139**	5.564**	16.422**	52.808**	11.774**
J-B Test	8766.1**	5976.2**	11827**	283.41**	5205.2**	838780**	90579**	897.48**	7869.5**	77095**	4109.8**
Q(10)	21.54*	30.26**	22.1*	38.98**	21.77*	172.7**	59.1**	24.65**	6.3	27.67**	26.88**
Q^2(10)	2.06	32.38**	109.1**	55.73**	21.64*	0.49	89.04**	208.85**	0.98	0.55	6.73
ARCH(5)	0.35	3.95**	25.1**	6.66**	1.95	0.04	17.98**	15.02**	0.13	0.01	0.76
ADF	-13.83**	-14.94**	-14.65**	-13.81**	-14.58**	-10.63**	-12.66**	-13.96**	-14.36**	-15.46**	-14.43**

Notes: J-B test is the Jarque-Bera test for normality. Q(10) and Q^2(10) is the Ljung-Box statistic for serial correlation in raw series and squared series, respectively. ARCH(5) is the Engle's ARCH effects test. ADF is the Augmented Dickey-Fuller test for stationarity. * and ** denote statistical significance at the 5% and 1% level, respectively.

An inspection of the FSIs (levels and returns) figures in the appendix (graphs labeled A.1 to A.10) provide an overview of their evolution through the period examined. In most cases, it is evident (in the case of the original FSI series) an upward trend of the early enough. Even from back to 2005, indices exhibit a worrisome increase to the financial stress level. In this respect, these metrics could provide a timely warning, regarding future financial meltdowns. Something similar is depicted in the cases of the returns series. There is higher volatility clustering for all countries and markets, especially after 2008 and, even more, since 2010. This is an indication of the increasing uncertainty in the markets, due to the financial and sovereign turbulence in the area.

Finally, we also report the unconditional correlation matrices for each one of the groups of financial stress indexes used here. Almost all correlation coefficients are positive, indicating a positive relation between the levels of financial stress in these economies. In the case of country-wide indicators, the core countries are stronger related, as it is the case with the periphery ones. Larger correlation exists for the cases of the equity and banking markets, while Greece does not seem to be strongly tied to the rest of the Euro Area economies. Similar evidence exists for the cases of Ireland and Portugal, especially for the case of the bond market and, even more importantly, towards the larger economies of the monetary union (Germany and France).

4.2 BEKK Results

In the previous section, we discussed the nature of our series and, also, established the suitability of MGARCH modeling for the investigation of volatility spillovers between Euro Area markets. It is time now to proceed to the presentation of the GARCH-BEKK results, establish the existence of spillover effects (or not) and infer on the time-varying dynamics of the current financial and sovereign crisis. As mentioned before, we follow two estimating strategies. First, we estimate models, examining potential spillover channels between each one of the financial markets for which we have created stress indices. These are the banking sector, the money, equity and bond markets of Euro Area countries. Additionally, we also employ a BEKK model for the case of country-level financial stress metrics. After examining potential spillover channels in the aforementioned cases, the next step is the major contribution of this chapter. We strive to get into a deeper analysis of the links between the, previously, single examined markets. In order to do this, bivariate GARCH-BEKK models are estimated for all possible combinations of stress indices returns of our sample. In this way, it is possible to examine the existing spillover effects from any market (or country) towards any other taken into account. This is an important step towards the detailed and careful consideration of the perplexed nature of the crisis and volatility transmission channels among some of the most important economies of the world. Also, it is a first step towards assessing the relative importance (in terms of risk aggravation) of the different markets analyzed here. Finally, the extraction of, potentially, useful policy prescriptions for the amelioration of the effects of current turmoil in the markets and their future safeguarding is an additional valuable feature of this piece of research.

4.2.a Market Level and Country – Wide Models

The following ten tables report the estimation results of the MGARCH-BEKK models employed in our empirical investigation. Each set of tables has the same structure. The first table is always the estimated coefficients for the "news surprises" effects between the markets examined. They are the α_{ij} coefficients from equation (4.4), representing the lagged squared innovations effect on the conditional covariance of each one of the sample series. Moreover, the second table in each case depicts the β_{ij} estimated coefficients of our models. As previously mentioned, these coefficients represent the volatility spillovers between the markets, while it is also an indicator of the persistence of the news shocks among them. In all cases, the p-values are reported under each one of the reported coefficients, while statistical significance is marked with asterisks, right next to the significant parameters.

Table 4.3: BEKK-MGARCH Model for α_{ij}: Countries Case

α_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		-0.071	-0.012	-0.002	-0.036	-0.016	0.001	0.017	0.020	0.012	-0.087
		0.305	*0.965*	*0.549*	*0.904*	*0.801*	*0.665*	*0.701*	*0.899*	*0.124*	*0.240*
BE	0.133		0.056	-0.001	-0.106 *	-0.008	0.004	0.098	0.044	-0.032	-0.057
	0.547		*0.582*	*0.753*	*0.091*	*0.837*	*0.725*	*0.241*	*0.987*	*0.993*	*0.809*
FI	0.003	0.059		-0.431	-0.033	0.003 ***	-0.172	0.002	-0.006	-0.046	0.154 **
	0.979	*0.342*		*0.244*	*0.499*	*0.002*	*0.183*	*0.620*	*0.978*	*0.614*	*0.016*
FR	0.228	0.061	0.051		0.004	-0.113 ***	0.118	-0.062	0.206	0.073	-0.014
	0.206	*0.521*	*0.735*		*0.676*	*0.000*	*0.218*	*0.451*	*0.184*	*0.901*	*0.653*
GE	0.062	0.009	-0.064	0.003		0.017	-0.005	0.007	0.056	0.048	0.132 ***
	0.198	*0.330*	*0.390*	*0.616*		*0.820*	*0.888*	*0.929*	*0.944*	*0.473*	*0.004*
GR	0.002	-0.037	-0.046 ***	0.167 ***	0.017		0.085 ***	0.045	-0.123 **	-0.079 **	0.007 ***
	0.749	*0.405*	*0.000*	*0.000*	*0.937*		*0.000*	*0.817*	*0.021*	*0.017*	*0.000*
IR	0.080	0.031	0.008	-0.002	-0.079 ***	0.003 ***		0.048	0.054	0.016	-0.013 ***
	0.143	*0.975*	*0.440*	*0.888*	*0.004*	*0.002*		*0.837*	*0.741*	*0.799*	*0.000*
IT	-0.079 *	-0.174	-0.061	0.024	-0.022	-0.167 **	-0.006		0.069	0.072 ***	-0.008 ***
	0.079	*0.263*	*0.507*	*0.475*	*0.815*	*0.011*	*0.985*		*0.675*	*0.000*	*0.000*
NE	-0.025	-0.002	0.042	-0.049	-0.019	0.057 ***	0.058	-0.204 *		-0.041	-0.055 **
	0.795	*0.986*	*0.863*	*0.185*	*0.986*	*0.005*	*0.388*	*0.050*		*0.490*	*0.030*
PO	0.004	-0.003	0.002	-0.032	-0.026	0.045	0.036 *	-0.219 ***	0.006		-0.065 ***
	0.651	*0.994*	*0.983*	*0.490*	*0.688*	*0.332*	*0.060*	*0.000*	*0.958*		*0.000*
SP	0.106	-0.072	-0.039	-0.123 **	-0.021	-0.042 ***	0.184 ***	0.140 ***	0.228 **	0.043 ***	
	0.302	*0.504*	*0.711*	*0.030*	*0.707*	*0.000*	*0.000*	*0.000*	*0.024*	*0.000*	

Notes: This table reports the "news surprises" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

Before proceeding with the discussion of the results, we should also explain the tables' diarthosis. In the first column and row, the initials of the countries are reported. Because of that, the main diagonal of each table is empty, since there is no point in reporting own effects for the economies we examine. Then, the correct way to read the tables is by following each row towards each column. For instance, the first row reports the estimated coefficients for the news and volatility spillover effects from Austria (or the Austrian markets, respectively) to the rest of the sample economies. The same is true for Belgium, in the case of the third row, until the Spanish case that concludes each one of the tables[97]. In other words, the spillovers' direction here is from the rows towards the columns (the rows represent the volatility spillover sources while the columns the shocks' recipients).

[97] As it is easily understandable, each country's case uses two rows from the table: one for the estimated parameters, the other one for the p-values. Hence, in the case of Belgium, the analysis starts from the third row. The same holds for all countries and markets analysed here.

Table 4.4: BEKK-MGARCH Model for β_{ij}: Countries Case

β_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		0.039	-0.021	0.012	-0.048	0.024	0.004	0.008	0.041	-0.035	0.055
		0.113	*0.987*	*0.891*	*0.388*	*0.845*	*0.817*	*0.780*	*0.473*	*0.000*	*0.028*
BE	-0.048		0.007	0.061 **	-0.004	-0.030	0.125	0.007	0.058	-0.005	0.037
	0.255		*0.822*	*0.029*	*0.602*	*0.417*	*0.822*	*0.737*	*0.906*	*0.992*	*0.564*
FI	0.038	-0.022		-0.022 ***	0.098	0.021 ***	0.157 ***	0.043 **	0.046	0.074	-0.076 ***
	0.944	*0.418*		*0.000*	*0.629*	*0.000*	*0.000*	*0.021*	*0.908*	*0.955*	*0.000*
FR	-0.106	-0.131 **	0.000		-0.051	0.182 ***	0.036 *	-0.025	-0.048	-0.064 *	0.014 **
	0.568	*0.015*	*0.178*		*0.347*	*0.000*	*0.065*	*0.758*	*0.511*	*0.098*	*0.030*
GE	0.034	0.015 **	-0.014	0.005		0.023	0.006	0.007	-0.031	0.001	0.104
	0.808	*0.016*	*0.829*	*0.870*		*0.891*	*0.831*	*0.817*	*0.854*	*0.936*	*0.102*
GR	-0.003	0.008	-0.003 ***	-0.093 ***	-0.050		-0.096 ***	0.003	-0.084 ***	-0.117 ***	-0.030 ***
	0.836	*0.684*	*0.000*	*0.000*	*0.768*		*0.000*	*0.948*	*0.000*	*0.001*	*0.000*
IR	-0.082 **	-0.277	-0.002 ***	-0.002	-0.167	0.175 ***		-0.031	-0.027	-0.064 *	0.002 ***
	0.017	*0.824*	*0.000*	*0.904*	*0.506*	*0.000*		*0.374*	*0.859*	*0.065*	*0.000*
IT	-0.017	0.000	-0.019	0.047	-0.008	0.004	0.023		0.038 ***	-0.001 ***	-0.009 ***
	0.611	*0.677*	*0.704*	*0.458*	*0.891*	*0.428*	*0.827*		*0.000*	*0.000*	*0.000*
NE	-0.011	-0.041	-0.033	0.018 **	0.017	0.008 ***	-0.015	-0.126 **		-0.038	0.104 ***
	0.750	*0.488*	*0.383*	*0.047*	*0.838*	*0.000*	*0.840*	*0.042*		*0.192*	*0.000*
PO	0.019 ***	0.003	-0.010	0.013	0.007	0.023 ***	0.022 ***	-0.026 ***	0.009		0.076 ***
	0.000	*0.997*	*0.976*	*0.418*	*0.905*	*0.001*	*0.008*	*0.000*	*0.856*		*0.000*
SP	-0.069	-0.020	0.045	-0.036 ***	-0.072 **	0.160 ***	-0.049 ***	0.011 ***	-0.216 ***	-0.020 ***	
	0.358	*0.873*	*0.179*	*0.000*	*0.050*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	

Notes: This table reports the "volatility spillover" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

We initialize the results discussion with tables 4.3 and 4.4. Here, the investigation of the country-wide financial stress spillovers is examined. According to the estimations, the most heavily affected countries are those with the strongest spillovers to the rest of the Euro Area countries. Especially Greece and Spain present significant news and volatility spillover effects to the rest of the economies. On the same time, these two countries are the major recipients of financial stress spillovers, together with France. It is interesting to notice that Germany is highly immune to volatility transmission in this respect. As a first comment, we can say that surprises, regarding the financial conditions in Greece and Spain, are widely dispersed with the monetary union and this is a long lasting effect (as it is evident from the volatility risk transmission depicted in table 4.4). On the hand, the effects on the Greek case are rather small, judging by the size and magnitude of the relevant parameters. Moreover, there is a bidirectional spillover effect between Greece and France, while the respective French – Spanish comovements are rather weak. Ireland has a statistical significant and strong effect to Greece. Finally, Portugal is also an important contributor to the financial stress transmission, at least in terms of statistical significance. The size of the relevant estimated parameters is quite small. Another interesting feature of our results is the strong links between the economies of North

Europe. A bidirectional link exists between Belgium and France, while Germany spillovers to the former as well.

Turning now to the case of the banking stress transmission, the picture is somewhat different. In general, Ireland, together with the Italian and Portuguese banking sector is the major volatility risk recipients. Similar vulnerability is indicated for the case of Austria, even though, on a more limited size compared to the aforementioned cases. Italian banks seem to greatly affect the Irish and Portuguese market, with strongly significant parameters. Once again, it is interesting to underline the total lack of volatility spillover towards German banking market, with similar results holding for the French case as well. Overall, even though there seem to be some transmission channels of banking stress among the economies of our sample, the effects are not strong enough or lasting (comparing the news effect with the results from the second table of this group of stress indexes).

The next two tables analyze the case of the money market volatility spillovers. Once more, the main recipients of the relevant effects are, mainly, Greece and Portugal (for the case of "news effects" coefficients), with Ireland and Portugal to take the lead in the volatility transmission risks. Nevertheless, the strong statistical results are accompanied by very small parameters. On top of that, Greek money market shocks greatly affect the Finnish and Spanish cases, as it is evident by table 4.7. Stronger volatility spillovers can be traced in the cases of Spain and Portugal, with Greece being another important contributor here. Most of the estimated β_{ij} coefficients in the latter case are positive, transmitting turmoil to Belgium, France and Netherlands. Portugal and Spain perform poorly here (coefficients with almost negligible size). The only exception here is the strong positive effect towards Ireland. Another interesting finding here is the case of France. As an extra evidence of the

Table 4.5: BEKK-MGARCH Model for α_{ij}: Banking Sector Case

α_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		0.071	-0.017	0.056	0.036	0.008	0.179	0.128 ***	0.029	-0.051 ***	0.015
		0.851	*0.900*	*0.396*	*0.287*	*0.888*	*0.128*	*0.000*	*0.829*	*0.000*	*0.520*
BE	0.283		0.001 ***	-0.022	0.020	0.238	0.044	0.058	0.072	-0.092 ***	-0.141 ***
	0.690		*0.000*	*0.780*	*0.994*	*0.403*	*0.433*	*0.962*	*0.192*	*0.000*	*0.003*
FI	0.011	0.076 ***		0.025	0.008	0.330 ***	-0.207 ***	0.010	0.018	-0.027 ***	0.120 ***
	0.920	*0.000*		*0.494*	*0.797*	*0.000*	*0.000*	*0.992*	*0.457*	*0.000*	*0.003*
FR	0.004	-0.073	-0.023		0.096	-0.071 ***	0.040	-0.060	0.049	-0.015	0.102
	0.926	*0.741*	*0.708*		*0.541*	*0.000*	*0.488*	*0.924*	*0.949*	*0.761*	*0.783*
GE	-0.036	-0.129	-0.001	-0.046		0.020	-0.123	0.087	0.001	-0.021	-0.019
	0.236	*0.975*	*0.791*	*0.758*		*0.904*	*0.136*	*0.348*	*0.977*	*0.993*	*0.950*
GR	-0.161 ***	-0.125	-0.060 ***	0.059	0.001		0.130	0.003	0.117	-0.013 ***	0.002
	0.002	*0.689*	*0.001*	*0.344*	*0.993*		*0.955*	*0.999*	*0.938*	*0.000*	*0.809*
IR	-0.025	-0.047	-0.025 ***	0.065	-0.086	0.048		0.113 **	-0.095	-0.309 ***	-0.085
	0.574	*0.356*	*0.000*	*0.404*	*0.167*	*0.971*		*0.014*	*0.709*	*0.000*	*0.902*
IT	-0.049 ***	-0.034	0.018	0.022	-0.050	0.155	-0.068 **		0.000	0.071 ***	-0.028
	0.000	*0.963*	*0.953*	*0.925*	*0.654*	*0.811*	*0.015*		*0.804*	*0.000*	*0.865*
NE	-0.028	-0.022	-0.014	-0.011	-0.005	-0.130 ***	0.055	-0.075		-0.001	-0.021
	0.929	*0.847*	*0.918*	*0.979*	*0.960*	*0.002*	*0.930*	*0.159*		*0.984*	*0.778*
PO	-0.217 ***	0.186 ***	0.052	0.000	0.114	0.115 ***	0.011 **	-0.007 ***	0.024		0.015
	0.000	*0.000*	*0.172*	*0.976*	*0.990*	*0.000*	*0.016*	*0.000*	*0.683*		*0.279*
SP	0.033	0.097	0.040	-0.007	0.033	-0.020	0.085	0.012	-0.002	0.009	
	0.759	*0.516*	*0.146*	*0.832*	*0.786*	*0.981*	*0.246*	*0.929*	*0.922*	*0.387*	

Notes: This table reports the "news surprises" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

Table 4.6: BEKK-MGARCH Model for β_{ij}: Banking Sector Case

β_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		0.003	0.001	0.018	-0.003	0.001	0.036 ***	0.031 ***	0.005	0.021 ***	0.002
		0.971	*0.971*	*0.657*	*0.712*	*0.974*	*0.008*	*0.000*	*0.960*	*0.000*	*0.412*
BE	-0.080		-0.014 ***	0.052	-0.015	0.500	0.013	-0.009	-0.004	0.012 ***	0.063
	0.361		*0.000*	*0.143*	*0.990*	*0.629*	*0.701*	*0.860*	*0.905*	*0.009*	*0.323*
FI	0.018	0.059 ***		0.012	0.013	0.008 **	-0.043 ***	0.060	0.013	0.001	0.058 **
	0.922	*0.000*		*0.850*	*0.767*	*0.028*	*0.000*	*0.976*	*0.815*	*0.437*	*0.015*
FR	-0.002	0.001	0.020		-0.022	-0.014	0.020	-0.004	-0.032	0.065	0.042
	0.918	*0.987*	*0.729*		*0.877*	*0.293*	*0.145*	*0.886*	*0.941*	*0.374*	*0.680*
GE	-0.020 ***	-0.038	0.000	0.008		0.028	0.033 ***	-0.100 *	-0.001	0.020	0.011
	0.000	*0.929*	*0.727*	*0.941*		*0.789*	*0.003*	*0.051*	*0.980*	*0.990*	*0.968*
GR	0.024 **	-0.032	0.002	0.006 ***	-0.024		-0.001	-0.001	0.024	-0.123 ***	0.003
	0.042	*0.149*	*0.417*	*0.002*	*0.884*		*0.996*	*0.999*	*0.960*	*0.000*	*0.987*
IR	-0.021	-0.015	0.037 ***	-0.029	0.005	-0.011		-0.088 ***	-0.186	0.016	0.030
	0.520	*0.725*	*0.000*	*0.380*	*0.766*	*0.969*		*0.000*	*0.748*	*0.157*	*0.831*
IT	-0.098 ***	0.003	-0.012	0.026	0.071	0.036	0.069 ***		-0.043	0.195 ***	0.002
	0.000	*0.965*	*0.991*	*0.911*	*0.118*	*0.860*	*0.000*		*0.454*	*0.000*	*0.967*
NE	-0.029	-0.113 ***	-0.010	0.005	-0.016	-0.020	0.015	0.064		0.040	-0.050
	0.865	*0.000*	*0.950*	*0.988*	*0.901*	*0.925*	*0.464*	*0.237*		*0.759*	*0.652*
PO	-0.136 ***	-0.028 ***	-0.007 **	0.000	-0.096	0.022 ***	-0.001	-0.033 ***	-0.028		0.035 ***
	0.000	*0.000*	*0.015*	*0.929*	*0.948*	*0.000*	*0.516*	*0.000*	*0.828*		*0.000*
SP	-0.025 ***	-0.021	-0.026 *	0.000	-0.020	-0.011	-0.014	0.078	0.010	-0.124 ***	
	0.000	*0.504*	*0.057*	*0.989*	*0.615*	*0.975*	*0.618*	*0.523*	*0.495*	*0.000*	

Notes: This table reports the "volatility spillover" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

Table 4.7: BEKK-MGARCH Model for α_{ij}: Money Market Case

α_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		0.015	-0.064	0.048	0.143	0.037	-0.027	-0.199	0.102	-0.075	0.046
		0.821	*0.541*	*0.277*	*0.815*	*0.616*	*0.774*	*0.375*	*0.930*	*0.215*	*0.240*
BE	-0.062		-0.004	-0.031	-0.156	0.006	-0.055	-0.094	-0.013	0.109	-0.095
	0.338		*0.832*	*0.798*	*0.600*	*0.938*	*0.208*	*0.377*	*0.992*	*0.521*	*0.481*
FI	0.105	-0.015		0.006	-0.045	-0.147	0.004	0.186 *	-0.059	0.007 ***	0.045 ***
	0.329	*0.620*		*0.782*	*0.690*	*0.121*	*0.310*	*0.056*	*0.981*	*0.000*	*0.000*
FR	-0.057	-0.063	-0.003		-0.055	0.070 **	0.002	-0.095	-0.225	-0.240 ***	-0.296 ***
	0.110	*0.651*	*0.985*		*0.949*	*0.032*	*0.991*	*0.991*	*NaN*	*0.009*	*0.000*
GE	-0.021	-0.009	0.025	-0.007		0.046	0.005	-0.002	-0.065	-0.033	-0.002
	0.984	*NaN*	*0.193*	*0.997*		*0.151*	*0.953*	*0.928*	*0.974*	*0.912*	*0.431*
GR	-0.002	0.020	0.122 **	-0.138 **	-0.032		-0.156	-0.045	0.054	0.003 ***	0.256 ***
	0.938	*0.975*	*0.015*	*0.037*	*0.322*		*0.353*	*0.363*	*0.825*	*0.005*	*0.000*
IR	0.009	0.108	-0.110	0.039	-0.012	0.070		-0.020	-0.052	0.004	-0.002
	0.861	*0.164*	*0.152*	*0.895*	*0.941*	*0.669*		*0.227*	*0.801*	*0.983*	*0.947*
IT	-0.043	0.126	0.138	-0.007	0.002	-0.001	0.075		-0.004	-0.064 ***	-0.037
	0.882	*0.413*	*0.619*	*1.000*	*0.956*	*0.993*	*0.241*		*0.995*	*0.000*	*0.165*
NE	-0.118	-0.015	-0.007	0.041	-0.006	-0.080 ***	0.016	-0.026		-0.020	-0.015
	0.812	*0.964*	*0.958*	*NaN*	*0.972*	*0.008*	*0.482*	*0.994*		*0.492*	*0.699*
PO	-0.018	-0.267	0.000 ***	-0.024	0.108	-0.023 ***	0.043	0.032 ***	0.077		-0.014
	0.883	*0.611*	*0.000*	*0.771*	*0.918*	*0.000*	*0.951*	*0.000*	*0.772*		*0.128*
SP	0.008	0.096	-0.065 ***	-0.057 ***	-0.013 ***	-0.080	0.027	0.171	0.000	0.010	
	0.795	*0.739*	*0.000*	*0.000*	*0.003*	*0.361*	*0.433*	*0.331*	*0.896*	*0.823*	

Notes: This table reports the "news surprises" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

Table 4.8: BEKK-MGARCH Model for β_{ij}: Money Market Case

β_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		-0.001	0.015	-0.001	-0.027	0.039	0.004	-0.028	0.014	0.021	0.031
		0.858	*0.576*	*0.920*	*0.990*	*0.450*	*0.924*	*0.905*	*0.976*	*0.325*	*0.138*
BE	0.013		0.005	-0.004	0.089	-0.002	0.020	-0.026	-0.090	0.024	-0.018
	0.516		*0.856*	*0.953*	*NaN*	*0.942*	*0.442*	*0.209*	*0.887*	*0.441*	*0.822*
FI	-0.005	0.009		0.013	-0.035	0.029	-0.006 ***	0.053	0.006	0.001 ***	-0.002
	0.806	*0.741*		*0.522*	*0.440*	*0.510*	*0.006*	*0.548*	*0.962*	*0.001*	*0.582*
FR	0.002	0.021	0.000		0.015	-0.048 ***	0.014	0.003	0.002	-0.091 ***	0.115 ***
	0.867	*0.469*	*0.928*		*0.989*	*0.000*	*0.735*	*1.000*	*NaN*	*0.000*	*0.000*
GE	0.004	-0.001	0.001 ***	0.002		0.045	0.000	0.025	0.029	0.023	0.007
	0.994	*NaN*	*0.010*	*0.999*		*0.213*	*0.948*	*0.600*	*0.987*	*0.806*	*0.801*
GR	-0.003	0.161 *	-0.051 ***	0.140 *	-0.019		0.044	0.012	0.138 **	0.002 ***	-0.081 ***
	0.952	*0.070*	*0.000*	*0.090*	*0.498*		*0.345*	*0.995*	*0.036*	*0.000*	*0.000*
IR	0.000	-0.070	0.013	-0.092	-0.025	0.013		0.021 ***	0.041	-0.001	-0.002
	0.879	*0.281*	*0.853*	*0.837*	*0.736*	*0.940*		*0.000*	*0.221*	*0.943*	*0.407*
IT	0.023	0.035	-0.045 *	0.005	-0.002	-0.026	-0.122 ***		-0.029	0.003 ***	0.015
	0.943	*0.505*	*0.080*	*0.999*	*0.949*	*0.957*	*0.000*		*0.994*	*0.000*	*0.108*
NE	0.012	0.007	0.005	0.001	0.034	-0.013 **	-0.116 ***	0.025		-0.001	-0.016
	0.768	*0.921*	*0.976*	*NaN*	*0.893*	*0.040*	*0.000*	*0.975*		*0.905*	*0.884*
PO	-0.069	0.003	-0.131 ***	0.040 *	-0.220	-0.090 ***	-0.096	0.010 ***	0.155		0.002
	0.540	*0.986*	*0.000*	*0.056*	*0.877*	*0.000*	*0.749*	*0.000*	*0.468*		*0.883*
SP	-0.003	0.071	0.004	-0.026 ***	-0.007	0.071 ***	0.173 ***	-0.072	0.004	-0.050 ***	
	0.610	*0.625*	*0.645*	*0.000*	*0.885*	*0.000*	*0.000*	*0.142*	*0.978*	*0.000*	

Notes: This table reports the "volatility spillover" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

tight links of this country with the more vulnerable economies of Eurozone, the cross-volatility relation this country exhibits with Greece, Portugal and Spain are statistically significant. But, once more, only Spain's parameter is not negligible.

A very different situation appears in the case of equity markets' volatility spillovers. In essence, the identified links are scarce. In both cases, cross-innovations and variance volatility transmission parameters, there are very few statistically significant parameters. In the case of news shocks, Greece has the prominent role. The effect from the Greek stock market is strong for the cases of Germany, Italy and Netherlands. Nevertheless, this is not a long lasting effect, since the reflecting parameters in the second table are not significant. In fact, only three cases are found to be non negligible in table 4.10. Still, the lack of evidence in favour of volatility spillovers in the case of equity markets is rather unexpected. It could, probably, be a sign of the, rather limited, financial risk propagation taken place through that market in the Eurozone case.

The final set of markets under consideration is the bond ones. In general, there is stronger evidence here for the existence of spillovers between the EMU economies. The results, reported at table 4.11, indicate the existence of significant and sizeable "news effect" between most of the markets. The case of Spain is the most profound one, with results being very strong but, on the same time, with very small parameters values. Surprisingly, the same does not hold for this country in table 4.12. There, the only significant parameter is the one representing the spillover effect to Portugal. Beyond the previous results, it is also interesting the fact that other heavily criticized economies (for their role as sources of financial instability propagators), like Greece and Ireland, do not perform as it would be expected. They are both limited to a minor initial shock to Austria while, in the case of volatility spillover parameters, their contribution to the financial stress interspersion is rather limited. In the same vein, Portuguese bond risk is transmitted to the other member of the PIIGS groups of countries but, again, with the size of this transmission to be minimal. This is the only sector where the German case produces some significant results, both as propagator and received or spillover effects. Another aspect of the bond financial stress conditions is the links between the core Euro economies. Austria has a bidirectional connection with Belgium, while the same holds for Finland and Germany. The Dutch

Table 4.9: BEKK-MGARCH Model for α_{ij}: Equity Market Case

α_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		0.024	0.006	0.032	0.012	-0.019	0.018	0.135	0.014	0.022	0.057
		0.990	*0.912*	*0.953*	*0.904*	*0.971*	*0.951*	*0.931*	*0.925*	*0.935*	*0.420*
BE	0.006		0.193 ***	0.003	0.006	-0.051	-0.025	0.248	0.141	-0.004	0.047
	0.981		*0.005*	*0.893*	*0.969*	*0.733*	*0.974*	*0.934*	*0.898*	*0.991*	*0.940*
FI	-0.011	-0.160 *		-0.015	-0.060	-0.291 *	-0.027	-0.009	0.001	-0.024	0.075
	0.893	*0.065*		*0.934*	*0.438*	*0.055*	*0.862*	*0.941*	*0.988*	*0.727*	*0.790*
FR	-0.003	-0.002	0.006		-0.007	-0.101	-0.033	-0.080	0.001	-0.028	0.052
	0.948	*0.799*	*0.967*		*0.989*	*0.641*	*0.971*	*0.792*	*0.869*	*0.838*	*0.820*
GE	-0.001	0.009	-0.079	-0.011		0.013	-0.010	0.009	0.009	0.017	0.007
	0.813	*0.946*	*0.528*	*0.963*		*0.946*	*0.967*	*0.976*	*0.968*	*0.840*	*0.986*
GR	0.020	0.056	0.048	0.067	0.137 **		0.002	0.247 **	0.178 ***	0.002	0.009
	0.946	*0.784*	*0.489*	*0.345*	*0.038*		*0.935*	*0.027*	*0.006*	*0.938*	*0.970*
IR	-0.010	0.007	-0.016	0.016	-0.011	-0.039		0.044	0.039	0.107 ***	-0.036
	0.943	*0.960*	*0.965*	*0.978*	*0.958*	*0.604*		*0.643*	*0.719*	*0.000*	*0.869*
IT	-0.024	-0.018	0.001	0.099	0.001	0.007	-0.013		0.011	0.006	-0.004
	0.974	*0.949*	*0.964*	*0.688*	*0.775*	*0.872*	*0.939*		*0.891*	*0.986*	*0.966*
NE	0.009	0.042	0.017	0.008	-0.009	-0.039	-0.007	0.000		-0.010	-0.027
	0.952	*0.975*	*0.908*	*0.948*	*0.945*	*0.769*	*0.995*	*0.936*		*0.956*	*0.847*
PO	-0.012	0.023	0.013	0.056	0.112	0.000	-0.006	0.033	0.003		0.179
	0.983	*0.931*	*0.890*	*0.304*	*0.235*	*0.902*	*0.225*	*0.938*	*0.987*		*0.791*
SP	0.048	0.013	0.069	0.034	0.011	-0.094	-0.023	0.012	0.075	0.037	
	0.517	*0.950*	*0.680*	*0.793*	*0.993*	*0.396*	*0.922*	*0.928*	*0.574*	*0.926*	

Notes: This table reports the "news surprises" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

Table 4.10: BEKK-MGARCH Model for β_{ij}: Equity Market Case

β_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		-0.028	-0.037 ***	-0.020	-0.033	0.024	-0.019	-0.060	0.009	-0.027	-0.026
		0.986	*0.000*	*0.970*	*0.665*	*0.952*	*0.962*	*0.994*	*0.929*	*0.804*	*0.435*
BE	-0.002		-0.045	0.000	0.009	0.052	0.038	-0.265	0.115	-0.012	0.006
	0.986		*0.208*	*0.887*	*0.954*	*0.813*	*0.944*	*0.839*	*0.942*	*0.954*	*0.982*
FI	0.028	0.040		-0.005	0.030	0.111 ***	-0.013	0.003	-0.003	0.008	0.012
	0.680	*0.357*		*0.973*	*0.703*	*0.004*	*0.898*	*0.936*	*0.989*	*0.902*	*0.931*
FR	0.011	-0.002	0.024		0.002	0.006	0.030	0.014	0.021	-0.026	0.014
	0.778	*0.799*	*0.849*		*0.978*	*0.977*	*0.947*	*0.951*	*0.855*	*0.760*	*0.918*
GE	0.024	-0.007	0.058	0.039		-0.037	0.027	0.009	-0.005	-0.005	0.019
	0.599	*0.953*	*0.440*	*0.815*		*0.890*	*0.917*	*0.979*	*0.980*	*0.947*	*0.943*
GR	-0.025	-0.058	-0.009	0.043	-0.026		-0.001	-0.119	0.000	0.000	0.006
	0.923	*0.834*	*0.905*	*0.246*	*0.696*		*0.946*	*0.130*	*0.860*	*0.946*	*0.981*
IR	0.059	-0.004	0.043	-0.022	-0.002	0.052		-0.009	-0.025	-0.007 **	0.024
	0.861	*0.952*	*0.856*	*0.960*	*0.993*	*0.475*		*0.928*	*0.869*	*0.039*	*0.841*
IT	0.015	0.020	0.003	0.095	-0.011	0.001	-0.004		0.011	-0.019	0.004
	0.974	*0.984*	*0.905*	*0.650*	*0.980*	*0.869*	*0.918*		*0.836*	*0.982*	*0.947*
NE	-0.005	-0.091	-0.001	-0.005	-0.013	-0.029	0.016	0.000		-0.020	0.013
	0.968	*0.962*	*0.975*	*0.914*	*0.973*	*0.824*	*0.984*	*0.936*		*0.888*	*0.898*
PO	0.003	0.016	-0.004	-0.001	-0.056	-0.001	-0.005 ***	0.026	0.012		-0.046
	0.994	*0.964*	*0.943*	*0.960*	*0.499*	*0.907*	*0.000*	*0.891*	*0.921*		*0.938*
SP	-0.012	-0.014	-0.067	-0.016	-0.012	0.015	-0.013	-0.010	-0.039	-0.016	
	0.754	*0.975*	*0.290*	*0.843*	*0.995*	*0.731*	*0.944*	*0.811*	*0.805*	*0.947*	

Notes: This table reports the "volatility spillover" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

Table 4.11: BEKK-MGARCH Model for α_{ij}: Bond Market Case

α_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		0.093 ***	0.013	-0.051	-0.026	-0.021 ***	0.197	-0.071 ***	-0.096	0.205 ***	0.176 ***
		0.000	*0.960*	*0.620*	*0.759*	*0.000*	*0.213*	*0.000*	*0.841*	*0.005*	*0.000*
BE	0.108 ***		0.009	-0.124 **	0.100	-0.047	-0.019	-0.072	0.007	0.044	0.025
	0.000		*0.749*	*0.035*	*0.227*	*0.180*	*0.641*	*0.338*	*0.856*	*0.984*	*0.828*
FI	-0.005	0.000		-0.106	-0.097 ***	-0.019	0.013	-0.075	0.110 ***	0.098	0.000
	0.959	*0.878*		*0.174*	*0.000*	*0.594*	*0.669*	*0.279*	*0.001*	*0.240*	*0.960*
FR	0.008	0.200 ***	0.222 *		0.110	-0.017	0.069 *	0.004	-0.161 *	0.035	0.005
	0.934	*0.005*	*0.053*		*0.565*	*0.290*	*0.062*	*0.890*	*0.066*	*0.130*	*0.846*
GE	0.074 ***	-0.098 *	0.008 ***	0.015		0.041 ***	0.216	0.020	0.027	-0.184	-0.004 ***
	0.002	*0.065*	*0.000*	*0.720*		*0.006*	*0.146*	*0.345*	*0.340*	*0.125*	*0.000*
GR	0.093 ***	0.290	0.030	0.146	-0.028		0.144 **	-0.067	0.031 ***	0.144	0.007
	0.000	*0.152*	*0.988*	*0.319*	*0.597*		*0.021*	*0.136*	*0.009*	*0.711*	*0.920*
IR	-0.169 ***	0.017	0.078	-0.022	-0.048	-0.018		-0.040	-0.003	-0.052	0.000
	0.000	*0.606*	*0.532*	*0.771*	*0.650*	*0.322*		*0.158*	*0.931*	*0.127*	*0.934*
IT	0.060 ***	0.081	-0.004	-0.125	-0.081	0.001	0.020		0.212 ***	-0.009	0.004
	0.000	*0.382*	*0.959*	*0.350*	*0.277*	*0.954*	*0.896*		*0.000*	*0.920*	*0.958*
NE	0.101	0.010	0.111 ***	0.072 **	0.079	-0.291 ***	-0.007	-0.002		0.024 ***	-0.036
	0.481	*0.284*	*0.002*	*0.014*	*0.139*	*0.000*	*0.914*	*0.836*		*0.000*	*0.195*
PO	-0.106 *	0.183	-0.050	0.039	0.088	0.008	0.120 ***	0.268 *	-0.024 ***		-0.031
	0.087	*0.950*	*0.444*	*0.687*	*0.591*	*0.173*	*0.000*	*0.068*	*0.000*		*0.435*
SP	0.029 ***	0.047 ***	0.001 ***	0.001 ***	-0.006 ***	-0.059 ***	0.004 ***	0.015 ***	-0.093 ***	0.022 ***	
	0.269	*0.614*	*0.963*	*0.080*	*0.129*	*0.193*	*0.976*	*0.952*	*0.606*	*0.502*	

Notes: This table reports the "news surprises" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

Table 4.12: BEKK-MGARCH Model for β_{ij}: Bond Market Case

β_{ij}	AU	BE	FI	FR	GE	GR	IR	IT	NE	PO	SP
AU		0.007 ***	-0.005	0.147 ***	-0.033 **	0.002 ***	-0.051	0.031 ***	0.000	-0.045	-0.028 **
		0.008	*0.964*	*0.000*	*0.019*	*0.000*	*0.441*	*0.000*	*0.940*	*0.138*	*0.034*
BE	-0.011 ***		0.001	-0.026	-0.031	0.002	0.002	-0.011	-0.021	0.012	0.014
	0.000		*0.798*	*0.728*	*0.773*	*0.920*	*0.957*	*0.737*	*0.718*	*0.966*	*0.877*
FI	0.000	-0.004		0.005	0.102 ***	0.026	-0.037 **	-0.034	0.018	-0.046 ***	0.002
	0.992	*0.650*		*0.900*	*0.000*	*0.777*	*0.040*	*0.859*	*0.215*	*0.000*	*0.955*
FR	0.000	0.041 **	-0.143		-0.016	0.013 **	0.018	0.076 ***	-0.027 ***	0.074	0.003
	0.866	*0.028*	*0.131*		*0.806*	*0.042*	*0.801*	*0.000*	*0.000*	*0.418*	*0.900*
GE	0.021 *	0.026	-0.011 ***	0.011 *		0.047 ***	0.045 ***	0.025	0.034 ***	0.064	0.000
	0.075	*0.122*	*0.000*	*0.092*		*0.002*	*0.000*	*0.198*	*0.000*	*0.244*	*0.640*
GR	-0.012 ***	-0.039	-0.021	-0.040	-0.088 ***		-0.025	-0.052 ***	-0.006 ***	-0.022	0.089
	0.000	*0.812*	*0.978*	*0.193*	*0.000*		*0.111*	*0.000*	*0.000*	*0.196*	*0.234*
IR	0.049	0.022 ***	0.122	-0.036	-0.003	0.019 ***		0.002	-0.002	0.040 ***	0.003
	0.209	*0.009*	*0.209*	*0.871*	*0.833*	*0.003*		*0.929*	*0.924*	*0.000*	*0.858*
IT	0.004 ***	0.001	0.003	-0.066	-0.014	0.000	0.014		-0.099 ***	0.014	0.000
	0.000	*0.958*	*0.970*	*0.445*	*0.891*	*0.944*	*0.694*		*0.000*	*0.390*	*0.868*
NE	0.004	0.019 **	-0.044 *	0.095 ***	-0.035 ***	0.040 ***	0.034	0.008 ***		0.020 ***	-0.008
	0.932	*0.038*	*0.069*	*0.000*	*0.000*	*0.000*	*0.297*	*0.005*		*0.000*	*0.170*
PO	0.022 *	-0.015	0.021	-0.035	-0.034	0.001 **	-0.004 ***	-0.036 **	-0.002 ***		0.028 ***
	0.087	*0.985*	*0.229*	*0.333*	*0.370*	*0.046*	*0.000*	*0.012*	*0.000*		*0.000*
SP	0.007	-0.021	-0.001	-0.001	0.000	-0.035	-0.004	0.008	0.105	-0.151 ***	
	0.469	*0.817*	*0.964*	*0.846*	*0.794*	*0.305*	*0.967*	*0.964*	*0.371*	*0.000*	

Notes: This table reports the "volatility spillover" estimated coefficients from bivariate BEKK-GARCH models. P-values are reported in italics, under each parameter reported. The direction of the effects is from each row towards the columns. Countries/Markets are reported, according to their initials: AU (Austria), BE (Belgium), FI (Finland), FR (France), GE (Germany), GR (Greece), IR (Ireland), IT (Italy), NE (Netherlands), PO (Portugal) and SP (Spain).

bond stress is also evident of its volatility spillover towards, mostly, the stronger EMU economies (Belgium, Germany, and France). In general terms, the bond market is profoundly succumbed to strong volatility spillovers, from both peripheral and core bond markets. The news shocks turn into important and enduring stress transmission, so that it can be said that this Eurozone financial sector is one of the most volatile and susceptible to increasing financial distress and episode of financial catastrophes.

Overall, the market-level analysis provides some useful insights in the conditions prevailing to Euro Area economies and markets. We find evidence of strong spillover effects among most of the economies under scrutiny. Moreover, the most volatile and vulnerable to risk transmission are the bond market (mostly representing sovereign risk) and the banking sector (sketching the operational efficiency, profitability and risk tolerance of financial institutions). A notable exception is the equity markets analysis, where no suitable conditions for volatility spillover were detected. With regards to the sector analyzed, the main risk spillover propagators vary but, again, there is no clear cut evidence whatsoever against a specific country or group of countries as the major contributors of these financial risks.

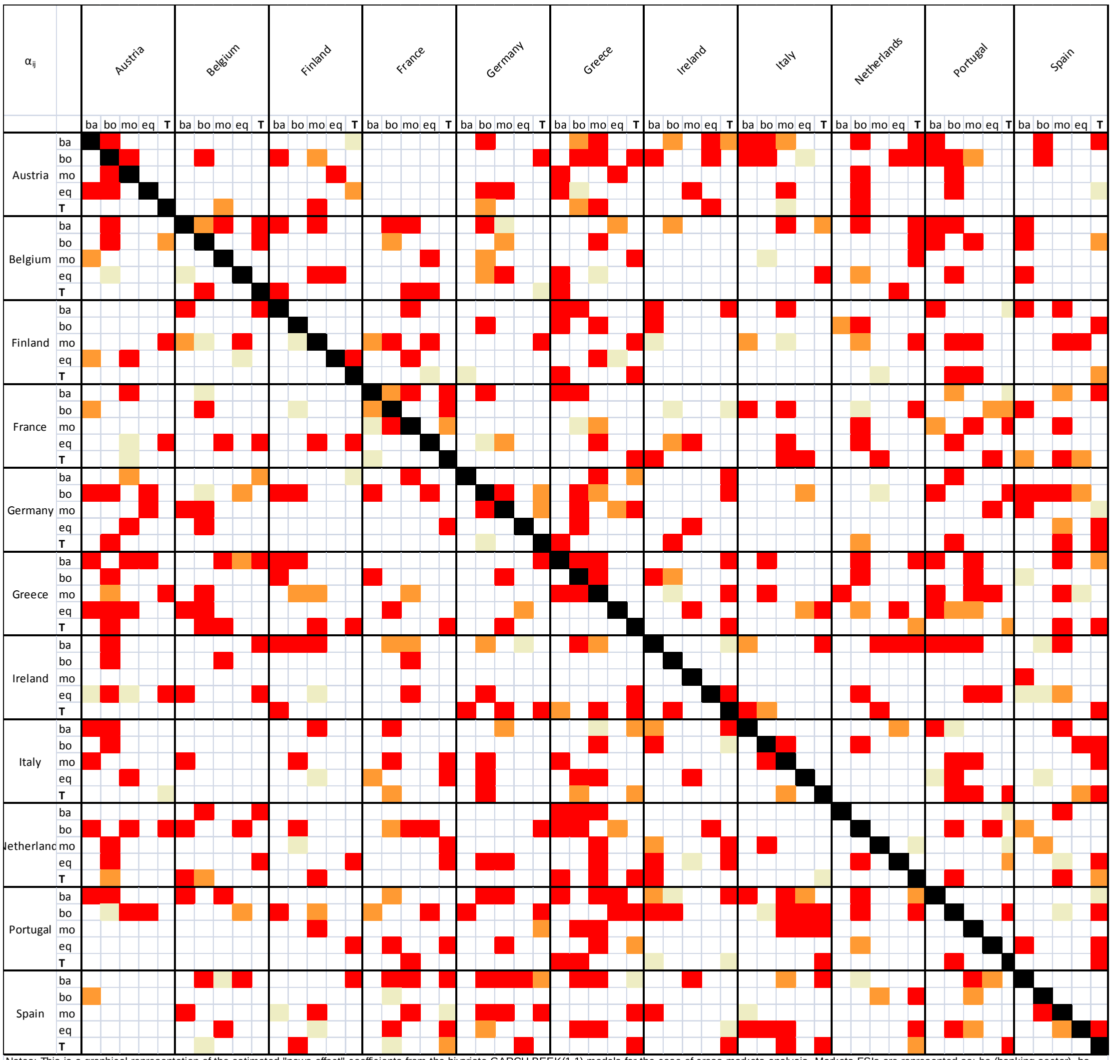
4.2.b Cross-Market Models

The previous section provided interesting insights into the links and causality-in-variance relations between the different financial stress levels of the markets under consideration. Some useful points were made, together with directions toward the macroeconomic and financial policies should be switched to. In order to provide further insight, we proceed to the empirical investigation of the potential spillover effects among all the previous financial markets together. Instead of isolating the possible sources of instability within each one of them, the models employed here allows for any kind of volatility transmission channels. To put it differently, the analysis is cross-sectional, in the sense that any market can influence any other of them. It is a major step further in this research area, for a number of reasons. First, it is the first ever effort to apply such a multivariate GARCH framework for the analysis of the Eurozone case, in such detailed level and markets' decomposition. Then, it is also interesting the chance to implement this empirical work, using financial stress indices, since they successfully bespeak the past, present and forthcoming financial conditions. Finally, it should be emphasized that this is the first piece of research applying such computational effort and in such deep analysis (in terms of countries and markets included in the empirical work) for the EMU economies. Instead of eliminating the scope of our research in a few countries and only in indicators of sovereign risk or banking instabilities, we provide evidence based on many more features of the financial system. In this respect, a deeper understanding of the comovements and financial links of the economies under the recent financial strain can be provided. Such fully fledged work can be proved fruitful for the market participants, along with the interested policymakers.

As it is easily understood, that the complexity of the econometric computations, together with the number of cases taken into account, make it almost impossible to present the results with tabulated estimated parameters and relevant statistics. In order to make things more comprehensible, we present the results using a graphical representation of them. Tables 4.13 and 4.14 summarize the relevant parameters of interest, as in the previous section. The difference is the usage of coloured cubes, which represent the statistically significant coefficients. For the sake of consistency and for emphasizing the importance of the spillover effects, we use three different colours (depending on the level of statistical significance). The red cubes are indicative of meaningful spillovers, for which the model provides evidence of strong significance (1%). Then, the orange ones are those with a milder effect (significant at 5% level), while the light grey ones are those that have a smaller statistical power (10% level). As in the previous case, the direction of the spillover effects is from the rows towards the columns of these tables.

Table 4.13 summarizes the cross-markets case of financial stress spillovers, for the surprises effects from the Euro Area markets. It is obvious the large number of news leakages, although, they are not as many as in the following table that presents the volatility spillover persistence. In the case of α_{ij} parameters, we detect the importance of banking sector and bond markets, as the sectors from which most of the cross-innovations are sourced from. Especially for the case of PIIGS, the banking sector is the market with the greatest importance, based on the above terms. The same holds for the case of Belgium, from the group of the more robust Euro Area economies. On the country financial stress level (as measured by the total aggregate index), we detect an intensive transmission of news surprises from Ireland and Greece, predominantly. Also, the Italian index contributes significantly here. This

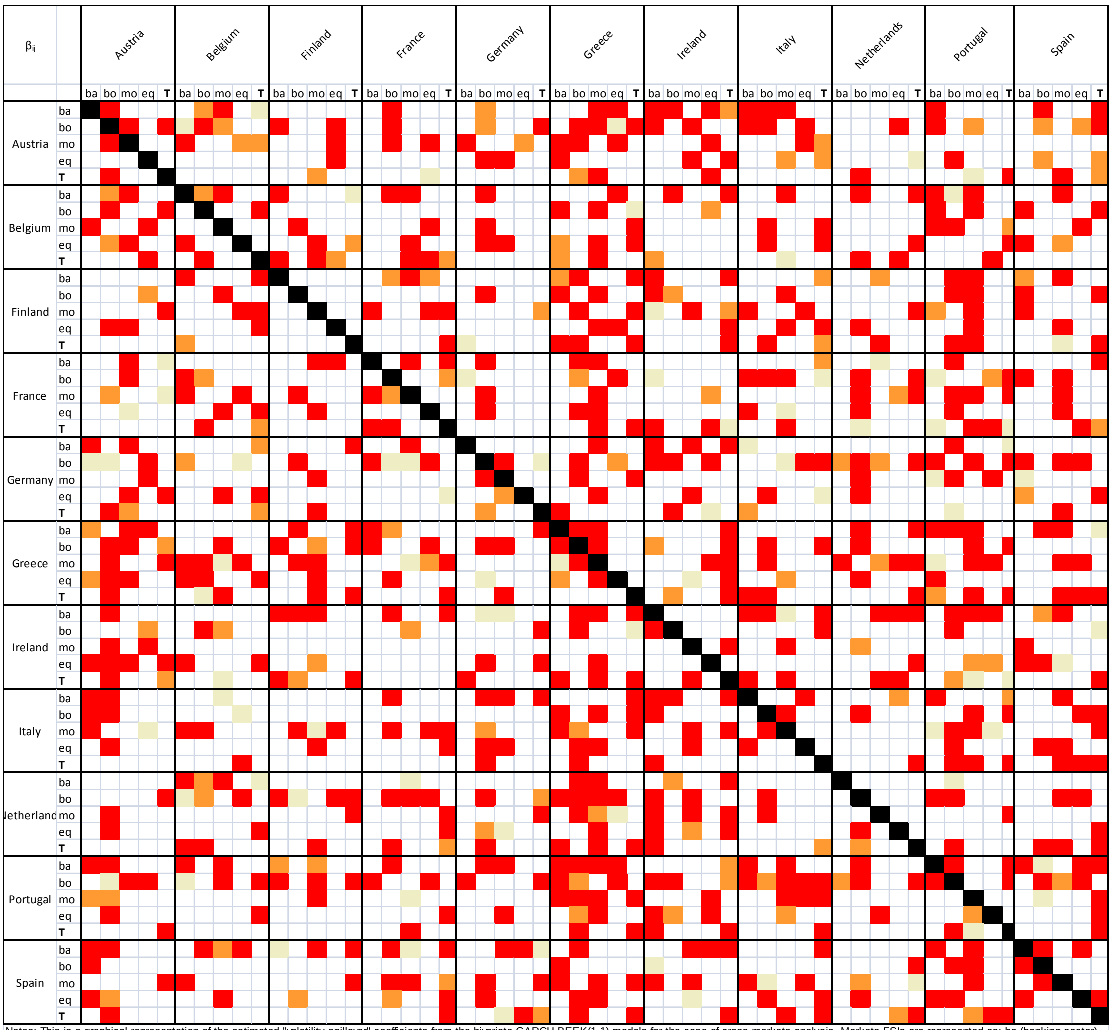
Table 4.13: BEKK-MGARCH Model for α_{ij}: Cross-Markets Case



Notes: This is a graphical representation of the estimated "news effect" coefficients from the bivariate GARCH-BEEK(1,1) models for the case of cross-markets analysis. Markets FSIs are represented as: ba (banking sector), bo (bond market), mo (money market), eq (equity market) and T (country). Red colour is the strong effect (1% significance level), orange the mild effect (5% significance level) and the light grey is the marginal effect (10% significance level). The white cubes represent the lack of any statistically significant effect.

outcome is in accordance with the priors of the Eurozone financial conditions and the evolution of the relevant crisis, since all of these countries were at the epicenter of the debate between economists, market participants and politicians, regarding their potential contribution to the aggravation of the union's financial instability. These countries affect, in a certain degree, the bond markets' conditions, for both core and peripheral economies of our sample. On top of that, the money markets are also affected by Greece and Ireland, emphasizing the important role of liquidity and interbank funding strains in the current crisis. Another interesting finding is the fact that Greece is also a news shocks receiver, especially for the case of bond and money markets. This tight link of all countries and markets within the Euro Area is sensible,

Table 4.14: BEKK-MGARCH Model for β_{ij}: Cross-Markets Case



Notes: This is a graphical representation of the estimated "volatility spillover" coefficients from the bivariate GARCH-BEEK(1,1) models for the case of cross-markets analysis. Markets FSIs are represented as: ba (banking sector), bo (bond market), mo (money market), eq (equity market) and T (country). Red colour is the strong effect (1% significance level), orange the mild effect (5% significance level) and the light grey is the marginal effect (10% significance level). The white cubes represent the lack of any statistically significant spillover effect.

given the existence of a common monetary policy maker, the formation of markets' expectations from the ECB decisions and, also, the commonality of the unconventional monetary policies followed by the union members. Again, as in the case of single markets analysis in the previous section, some countries are less responsive to cross-innovations, such as Germany, Finland and France. Spain is also rather neutral, in this respect. Portuguese news effects are primarily spill over to Greece and, secondarily, to Italy. In line with this, we also pinpoint the bidirectional banking spillovers from this peripheral economy to most of the other markets (with the exception of Finland, France and Spain.

In contrast to the previous discussion, the table representing the cross-markets volatility persistence indicates the existence of significant and multiple spillover effects. It is of great importance and interest that the GIIPS are among the major receiver of such spillovers. On the same time, a number of them (namely Portugal, Italy and Greece) are also significant contributors to the cross-volatility persistence effects. Again, this is reasonable, if we take into account the uncertainty, lack of credibility and the crisis unfolding in the past few years. Additionally, table 4.14 provides further evidence for the main drivers of these spillover channels. Again, the banking and bond markets are the most influential ones, in the case of North European economies, while the money market case is, also, of interest for the peripheral countries. In either way, especially in the latter case, this can be perceived as an indication of the crisis changing nature. It has evolved from a purely banking and liquidity meltdown to a sovereign crisis. Furthermore, the results here are supportive of the existence of markets' segregation, given the very strong ties between the Club Med countries (like Greece, Portugal, Spain and Italy) and the North European economies. Especially for the cases of periphery, the statistical significance of the estimated parameters is very strong (almost all of them significant at 1% level). Finally, again against the common wisdom, the spillover effects towards the larger European economies (i.e. Germany, Netherlands, Finland, Belgium and France) exist but are relatively limited. Overall, these findings dictate the necessity for the implementation of custom-made policies, based on the distinctive features and economic imbalances of each economy or groups of economies. Nevertheless, the lack of unanimity in the relevant economic research, regarding the major propagators of financial stress transmission, indicates the need for further analysis and investigation in this field of research.

5. Concluding Remarks

Our aspiration for this chapter is the Eurozone crisis that is fully fledged and prevalent to the economic profession debates during the last four years. On its peak, this crisis rendered the European economy under severe strains, while a prolonged recessionary period is its reflection to the real economy. Additionally, both governments and market participants were alerted for the eventuality of crisis transmission from the most vulnerable economies of the EMU to the rest of them. It is not by chance that the economic research interest soon turned towards the quest of empirical verification of such conditions. Lately, there is a growing production of pieces of research focusing on the examination of contagion among some of the major protagonists of the Euro crisis.

As a result, our work aims to extend the relevant literature in several ways. First of all, our interest is to study the crisis to its fully diverse nature. That is, we do not limit our study only to the sovereign risk or the banking instability issues, as most of the research have done until now. Instead, we try to encapsulate the necessary information into a number of metrics that are able to provide clear cut insights to the crisis and its constituents. In order to do it, we employ the so-called financial stress indices. These are aggregate indicators, representing the level of systemic risk in each one of the markets we analyze. These are, the banking sector, the money market, the equity and bond markets, while we also provide an index for each national economy. The next important extension is the adoption of a multivariate GARCH framework for the empirical investigation of potential spillover effects among the aforementioned markets. To the best of our knowledge, it is the first time that such a modeling approach is used in conjunction to such successful systemic risk indicators. In our view, it is an excellent combination, given the very nature of the financial stress indexes and the ability of the MGARCH type of models to estimate time-varying co-variances. Another important step further in our research is the simultaneous assessment of potential volatility spillover channels between and within the previously mentioned markets and countries. Finally, our dataset covers the Eurozone crisis until very recent, since our sample stops at September 2013.

In brief, our results shed new light into the Euro Area's volatility transmission. There is strong evidence that there exist multiple links between the EMU markets. Depending on the sector discussed, the main receivers and transmitters of the spillover effects vary. For instance, it is true that the GIIPS countries significantly contribute to the cross-volatility, especially in the case of the country level analysis and the banking and bond markets. On the same time, the core is also an important channel of variance volatility transmission, both within the North European countries, but also towards the peripheral ones. Such a, somewhat surprising, result for part of the profession is in accordance to latest findings (Antonakakis and Vergos, 2013, Kohonen, 2012). Moreover, we find strong bidirectional effects between countries of the same group (for instance between Germany, Belgium and France as well as between Greece, Portugal and Spain). Equity market, on its single market analysis, does not provide convincing evidence as a sector where volatility spillovers take place. On the contrary, the banking and bond markets are, in both the "within" and the "between" econometric investigation, found to be the most volatile and risky from the markets scrutinized. Also, the case of money market is interesting. In the cross-markets case, it proves itself as a major player in the volatility spillovers. Given the representation of the interbank funding conditions, along with the relative volatility measures and the yield curve, this sector manifests itself as one which central bankers should pay special attention to. Once more, the aforementioned facts underline the direction towards macroprudential policies should aim to.

The work in this area is, by no means, conclusive. There are many more that can be done, in order to further investigate the root causes of the Eurozone crisis. This is a first step only. Some recommendations for further work are the employment of alternative MGARCH specifications. It would be interesting to use a DCC framework, in order to capture the time-varying conditional correlations of the markets under examination. It is a rather flexible modeling approach, allowing for a number of different specifications for the computation of the initial univariate GARCH processes. Even in the case of our BEKK-GARCH model, modifications, in terms of the series filtering approach, can be applied. Other potential extensions have to do with the grouping of the most linked economies or markets and the empirical examination of them solely. In any case, this research area is currently expanding and it will keep so, as long as the need for solid evidence in the formation of relevant policies is vivid.

Chapter 5

Conclusions

1. Overview

This thesis investigates in depth several aspects of economic activity through an aggregated metric that aims to account for the inherent distressful characteristics of the financial system. This thesis is strongly motivated by the extraordinary evolution of the financial and economic landscape and the induced fragility within its foundations especially during the last years.

For quite a while, most economists argued that the combination of stable, steady growth rates, together with a controllable monetary policy under the prevailing inflation targeting framework (what has been called as "Great Moderation"), rendered the economic environment stable and safe from any considerably serious crisis. In short, policymakers and relevant researchers have connived at the fact that past crises is just a phenomenon of the past. Thus, the only challenge was the safeguarding of these, relatively low, but steady growth rates. Alas, this was only a veil of what was going on in financial markets. On an ex-post basis, the consequences induced by global financial crises, were assessed critically underling the importance and the necessity of the development of metrics that would account for the nature and the persistence of potential distressed periods. Beyond this, the added value of such developments would come up in a quantitative and qualitative framework the implications of which are strong mostly for policy makers.

The objective of this thesis is twofold; the exposition of conventional financial stress indices throughout a wide set of countries and the proposal of innovative methodologies on the quantification of stress indices. While the former objective aims to investigate whether stress indices could be used as indicators of future state of the economy, in a worldwide sense, the latter one proposes a methodology that considers the segments of economic activity. To this end an application is attempted in the

Eurozone era in order to investigate further the transmission channels of these distressed characteristics within and between economies.

2. Key Findings and Policy Implications

Chapter 1 provides an introduction to the thesis. In this chapter, we set the research questions, the motivation behind this research effort, while a discussion of the theoretical background on systemic risk and financial stability is provided. The perplexed nature of the financial system is emphasized, together with the necessity for the development of the relevant macroprudential metrics. Additionally, an overview of the construction of aggregate indices (in the nature of financial stress indexes) is supplied. It is proved that central banks have tried to compute such indices, like the monetary conditions indices. Of course, these metrics are useful for different type of policy analysis, like the assessment of the monetary policy conditions. At the end of this chapter, an overview of the contents of this thesis is compiled.

Chapter 2 is an effort to examine the leading indicator properties of the financial stress indices. The main question here is how successful such systemic risk indicators are, to the improvement of the forecasting performance of models aiming to predict the evolution of real economic activity. The first step here is the creation of FSIs for a wide number of countries, namely twenty five. This is one of the first efforts to construct systemic risk indices of the same fashion and directly comparable, for such a wide number of developed and developing economies. We separate them into three groups of countries. These are the OECD, Latin American and Asian economies. Then, an analysis of their properties, in terms of capturing past financial stress events and the increasing vulnerabilities towards them, is provided.

We also proceed to an identification of the types of financial turmoil events in each one of the regions examined (together with their duration), based on threshold values representing periods of excessive financial stress. Regarding the forecasting exercise, we model the evolution of the real economic activity as an autoregressive model for the industrial production index, while the alternative specification includes the (contemporaneous and lagged) FSIs effects. We employ two estimations processes, a dynamic and a rolling window forecasting procedure. According to our findings, most of the scrutinized countries and regions are sensitive to securities-sourced financial instabilities, which are the most frequent and durable ones. Banking excessive risk episodes are also quite frequent. The most pronounced period of financial abnormality is, by far, the recent financial crisis, with the indexes reaching their climax since 2007 onwards. The forecasts evaluations are based on the RMSFE ratios, together with extra evidence from two equal forecast accuracy statistical tests (the Diebold-Mariano and the Clark-West tests). The outcome is that the aggregate financial conditions indexes can be used for the assessment of the forthcoming economic conditions as well, beyond their apparent utility as systemic risk metrics.

Additionally, there is evidence that these indices perform better, in the case of OECD economies, for short and medium term forecasts, while they are slightly better in longer periods for Asian and South American economies. These results are very acute, given the apparent strong interwoven nature of financial and economic conditions. It is a clear signal for monetary authorities to develop such tools and effectively incorporate them into their macroprudential toolbox. It is not by accident that there is large research effort conducted by central banks and international economic organizations, attributed exactly to these financial stress indices. Finally, since these indexes are representations of the expectations formation in financial markets, while they also provide a timely depiction of their conditions, they can be very useful for those agents or investors acting into the global financial markets. For instance, they can be an additional risk assessment measure, in order to decide on the formation of their investment portfolios and exposure to global financial risks.

In the following two chapters, our interest is focused on the still evolving Eurozone financial and sovereign crisis. We decide to empirically examine the conditions of this crisis, using the financial stress indices. In chapter 3, the main question to be answered is whether we can identify interrelations and any tight financial connections between the Euro Area economies and financial markets. In order to do this, we first calculate aggregate systemic risk indexes for eleven EMU countries and their four, most important, financial markets. These are the first economies that joined the euro (excluding Luxembourg), while the sectoral analysis incorporates the banking sector, the money, equity and bond markets. This is the first ever effort for such a detailed and decomposed analysis of the financial stress and relevant sources of it, for the Euro Area.

Another innovative feature of our work is the employment of a large and diverge dataset. The latter includes many stand alone indicators that were never being employed for such a research before. For example, the incorporation of bank's balance sheet variables, along with the number of banks included in the sample verifies the distinctive characteristics of our financial stress indicators and their improved properties and ability to represent the prevailing financial conditions. The narrative analysis of these indices' performance reveals the divergent character of the crisis, as it is manifested in each one of the countries examined. For instance, the crucial role of credit and liquidity indicators is underlined, while a number of countries (like Italy, Ireland) is mainly affected by banking sector instabilities and others (like Spain and Portugal) from the level of perceived sovereign risk. The time-varying nature of the financial stress composition is also evident, for the period investigated. Regarding the examination of financial stress interconnections among these economies, we use a wide number of empirical modeling for the inference on them.

The baseline approach consists of VAR models, each one of which examines the prevailing conditions in each financial market. In other words, we do provide evidence based on a country specific and market wide level. The analysis is based on impulse response functions, where different recursive orderings are followed. The empirical findings are in contrast to the common wisdom of blaming Greece and Portugal for the potential "curse" of financial shocks transmission to the rest of the Eurozone, while the Spanish bond market agitates excessive risk in the aforementioned market. Positive interactions between banking and bond markets are found. Furthermore, a degree of disaggregation is evident within EMU, in the sense that core and peripheral countries are mostly responsive to their own "club" financial shocks.

A number of robustness checks and further empirical examination verifies these results. The outcome of our work provides clear and obvious evidence for the necessity to follow alternative macroeconomic and financial policies, depending on the conditions prevailing in different countries or groups of countries. Additionally, it should be considered as a wake-up call for the final implementation of a common regulatory and monitoring program for the financial markets of all EU or EMU countries. The current multilateral framework, where the national authorities have the main responsibility for overseeing and intervening to each economy, is not optimal.

Chapter 4 focuses on the investigation of volatility comovements and spillover effects within the Euro Area economies. This time, apart from the separate examination of the markets, an investigation of the cross markets case is also provided. The renewed features of our work are numerous. First, we decide to proceed with high frequency financial stress indices, something not common until now. Then, we employ multivariate GARCH modeling, which is also a rather different approach from what has been done until now. Furthermore, as already indicated, we do not restrict our analysis into a single market or a limited number of countries. We, rather, decide to provide solid evidence for the most important Eurozone economies and, of course, markets. Finally, our research covers a long time period, reaching the third quarter of 2013. In this way, we take into account the whole crisis period, both the initiation of it from outside Eurozone, the evolvement of the crisis within the union, as well as the most recent period after the implementation of the several bail-out programs and funding assistance to the debt ridden economies.

The results indicate, once more, the importance of the banking and bond markets in the volatility transmission of excessive financial stress. On top of that, it is evident the crucial role of money market as risk transmitter, especially in the case of cross-markets analysis. Strong bidirectional effects between core, as well as peripheral, countries are established, while the equity markets do not provide sufficient evidence for their role in the financial risk transmission. Although, GIIPS countries significantly contribute to the cross-volatility, larger and considerably more robust European economies (like France, Belgium and Netherlands) are also consistent transmitters of volatility risk and comovements. These results lead to questions, regarding earlier findings and the common perception of economists, the public and policy makers, related to the interest of the markets to specific economies. Given the combination of macroeconomic and financial shocks for some of the hardest hit Euro economies, as well as the lack of clear cut evidence of excessive volatility transmission from these economies, it would be fair to say that the followed policies from the EMU should be rectified. Since a degree of disaggregation and asymmetries in the response to financial shocks exists, the ECB and the relevant national authorities should decide on policies specifically adjusted for the needs of the economies under serious strain. The combination of such policies, with the creation of the necessary supranational monitoring and regulatory body, together with macroeconomic policies to stimulate growth again, would probably be a more successful recipe for the quicker exit from the Eurozone crisis. As it is emphasize by Manasse (2013), the perils for the monetary union are still present and loud.

3. Future Research Avenues

This thesis is completed and the findings reflect on the specific assumptions, conditions, models and dataset used. It should not be considered as a flawless work, since the evolution of the swiftly changing financial conditions can create different situations where further work should be conducted. Nevertheless, they provide useful insights, which can further expand and improve. Here, some suggestions for such extra research effort are provided.

Additional research is feasible in the improvement and refinement of the financial stress indices. These improvements can take place in two respects. First of all, improvements in the selection and aggregation methods of the stand alone indicators can be applied. Until now, the most popular approaches are those based on the variance-equal approach, as well as some model-based approaches (like factor models or VAR models). It would be interesting to further explore this issue, with techniques that can explicitly model the relation between the potential indicators that can be included in the aggregate index and the real economy. A quantile regression approach seems like a promising econometric framework, able to help researchers to the variables selection, based on the specific characteristics of the economy in each period examined (for instance, connect indicators' performance with the existence of economic peaks or troughs). Moreover, the use of Bayesian techniques, both in indexes' construction, as well as on the development of forecasting models, is still rather limited.

In terms of the dataset employed in the creation of these indices, it is fair to say that there still lack of full markets coverage. This happens, for a number of reasons. The major one is the lack of consistent variables, covering many markets and long time periods. For example, house prices (which would be representative of one of the most important asset classes in modern economies) series are not available for a wide number of countries. The same holds for other financial markets as well, like the hedge funds positions and transactions (it is believed that a major part of global investment positions are taken from such funds but relevant data are not publicly available or, at best, scarce). As a result, we do believe that the greater transparency and further availability of relevant data will improve the synthesis of these indices and their suitability as systemic risk monitoring tools.

Another useful extension would be the employment of financial stress indices, in order to provide an accurate crisis time line. The identification of crisis periods is possible, through the establishment of optimal cut-off points. This is feasible with the implementation of regime switching models. For instance, a Markov-Switching modeling framework is relevant. Additionally, threshold VAR models can be estimated, with the stress indices being the variable of interest to specify the regime changing periods. Such an empirical investigation would be particularly useful, both for investors as well as central bankers, since the crisis definition is a crucial aspect on the decision, from the side of central banks or governments, to intervene to the economy or not.

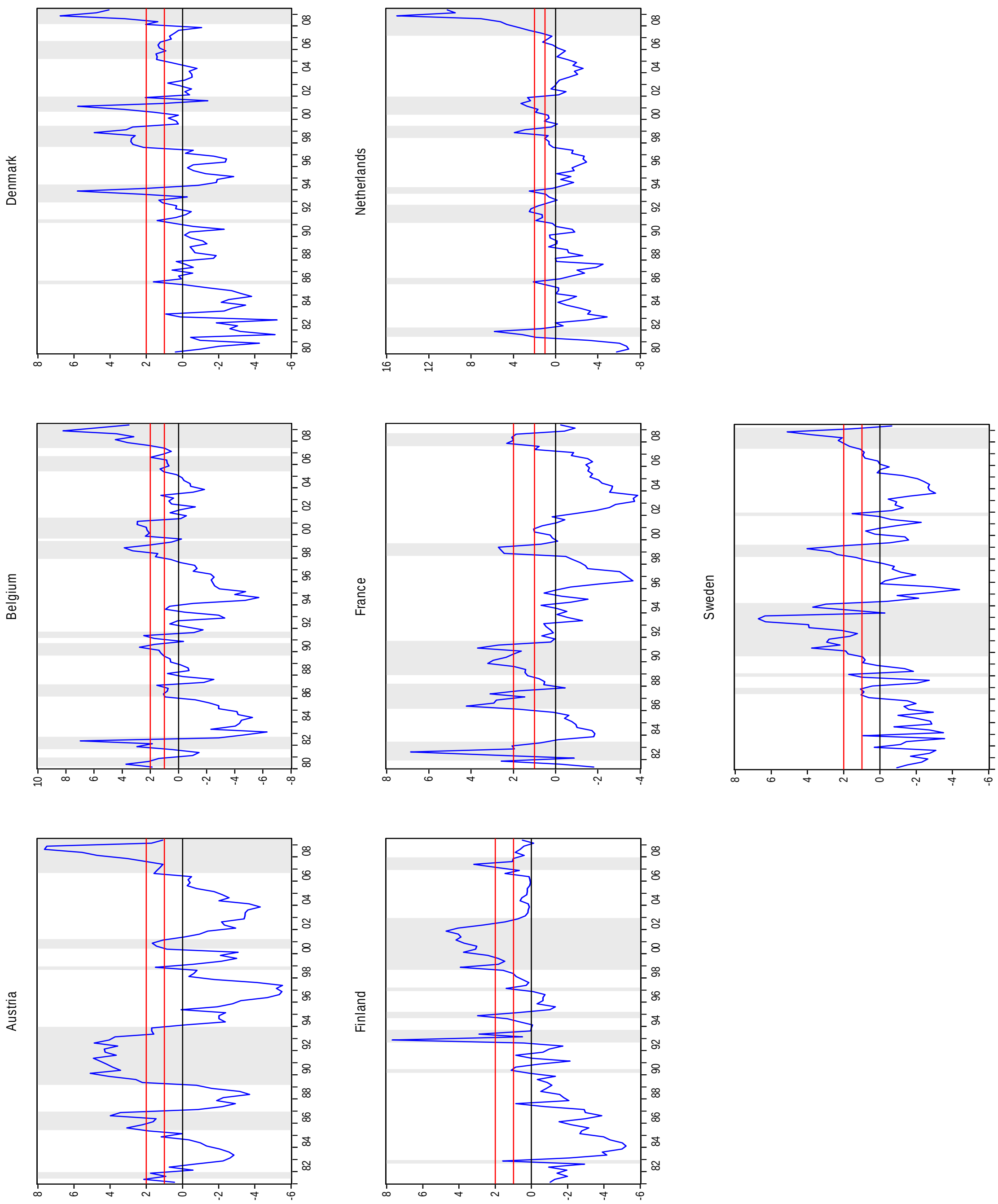
Focusing on the study of crisis transmission and interconnections, further investigation with the help of alternative multivariate GARCH models seem feasible. The time varying nature of the crises, together with the multifaceted nature of the most recent of them, renders such models particularly helpful. Of course, it is still an open question the accurate examination of contagion channels. In order to do this, the development of models, in the tradition of the true contagion ones, is necessary.

The strong interaction between financial upheaval and the fiscal imbalances, as evidenced by the current Eurozone crisis, dictates the simultaneous examination of them. The development of fiscal stress indices, representing the fiscal stance of the economies, is interesting and possible. Hence, apart from being a tool for the assessment of countries fiscal prudence, they would be useful in the development of models able to analyze and indicate channels of risk transmission between these two sides of the economy.

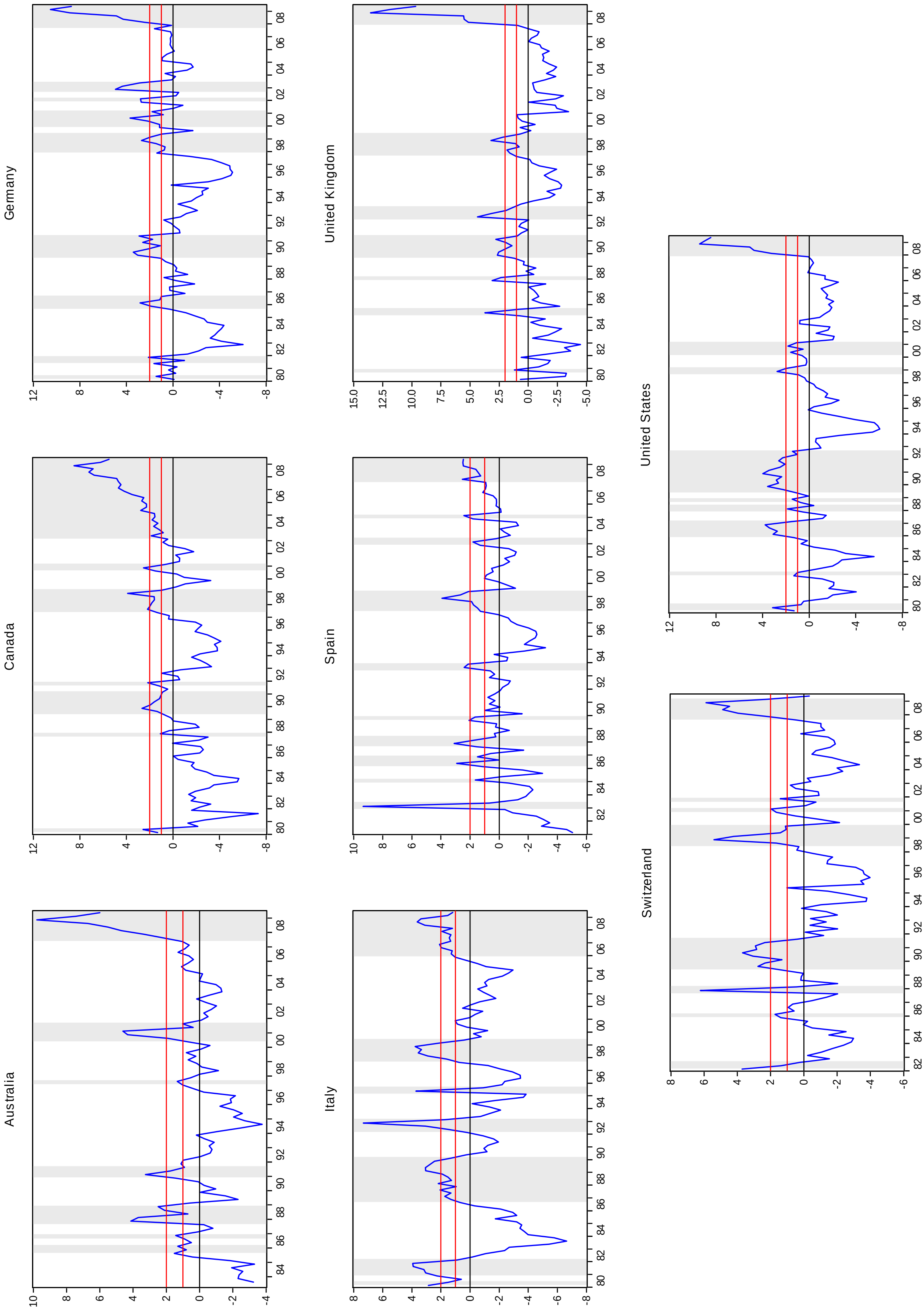
Appendix

Chapter 2

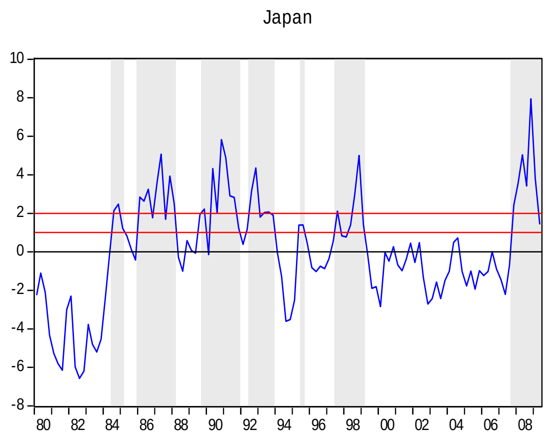
Graph A.1: OECD Countries FSI Indices – 1

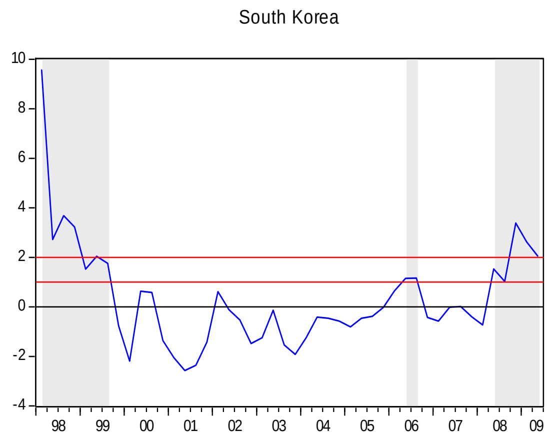


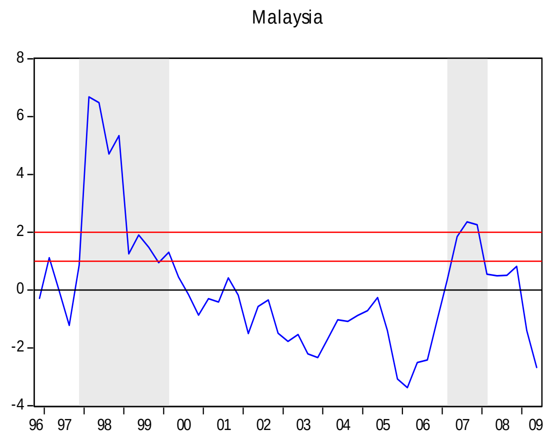
Graph A.2: OECD Countries FSI Indices – 2

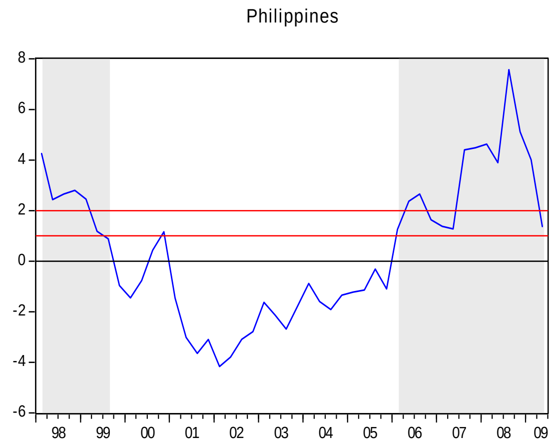


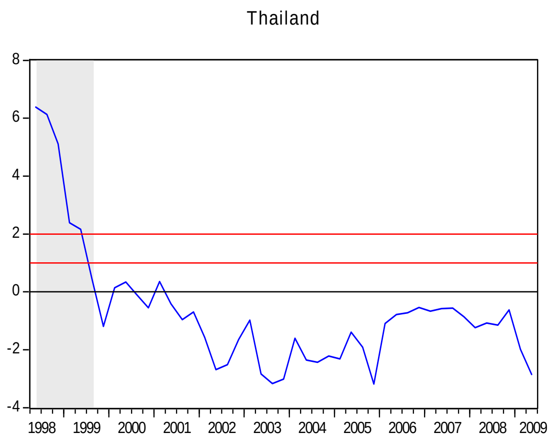
Graph A.3: Asian Countries FSI Indices



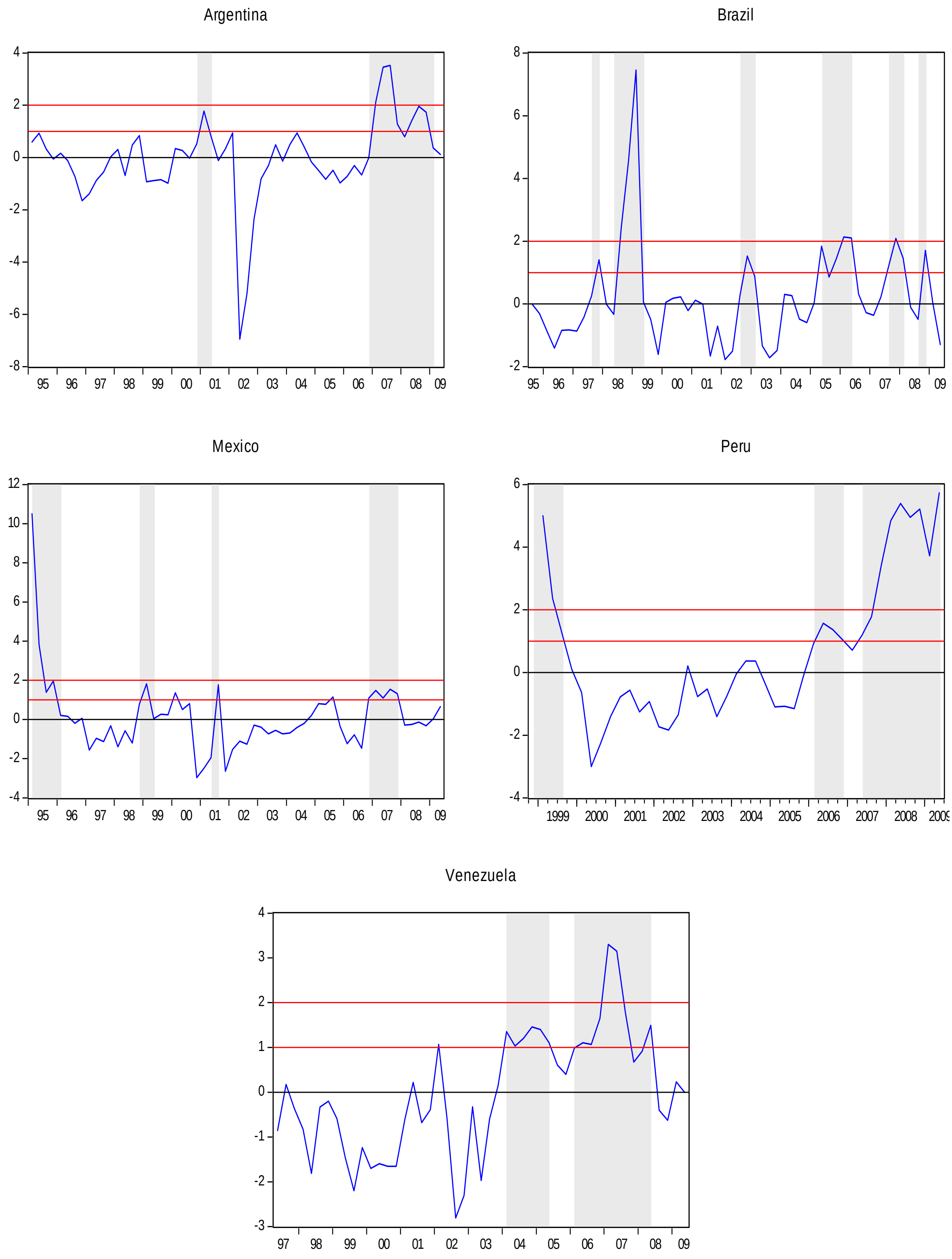






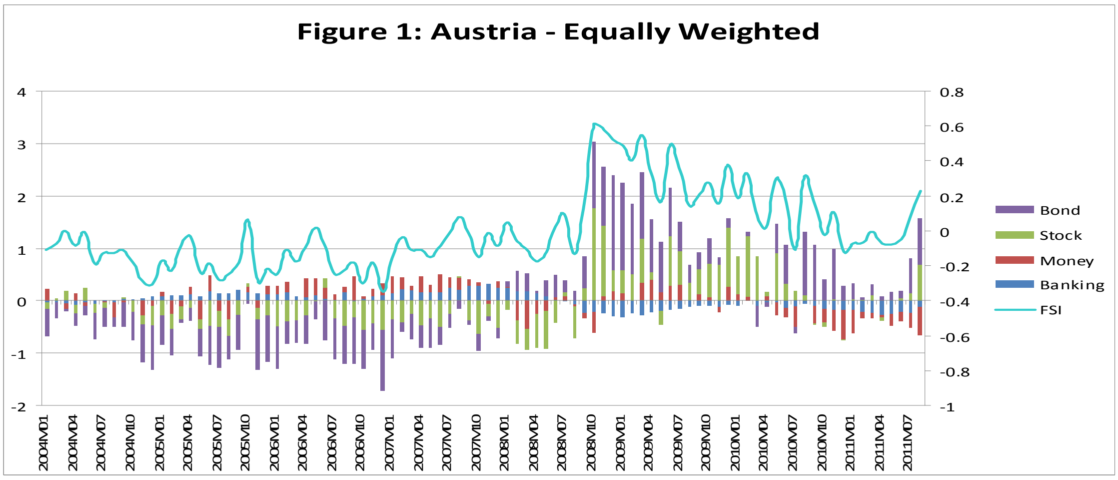


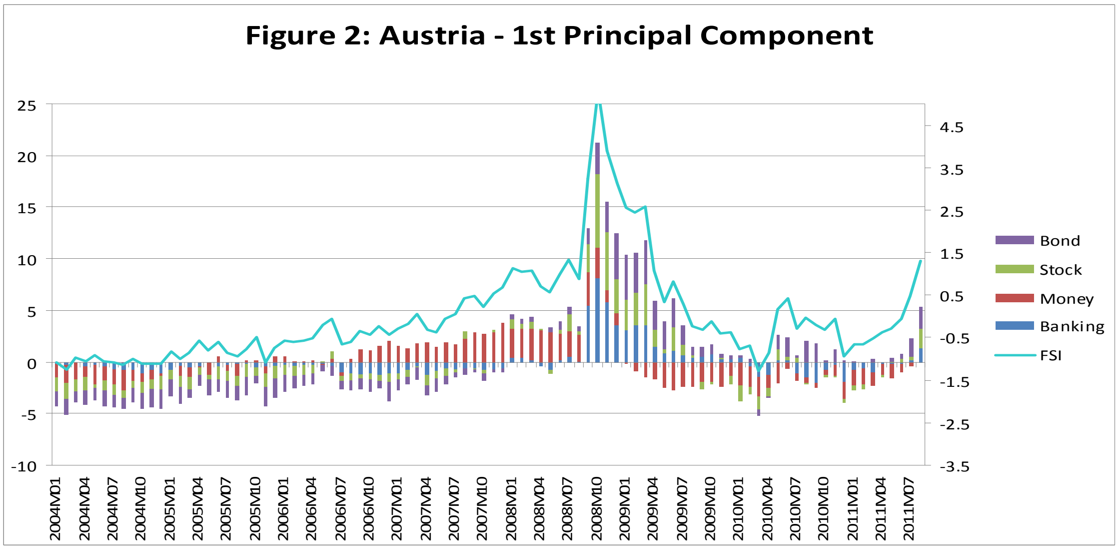
Graph A.4: Latin American Countries FSI Indices

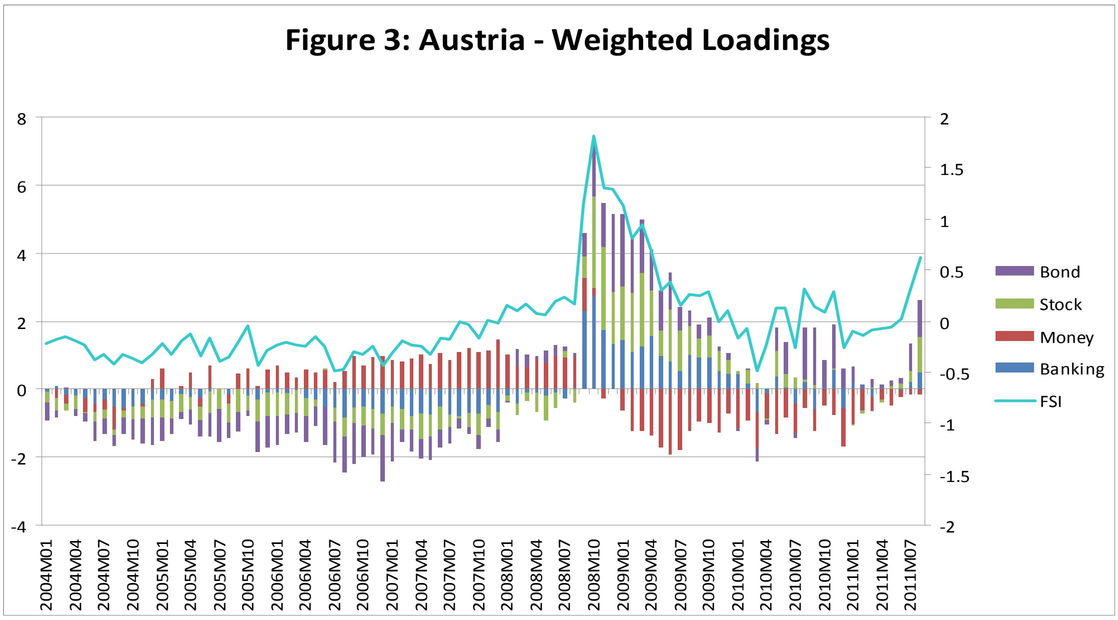


Chapter 3

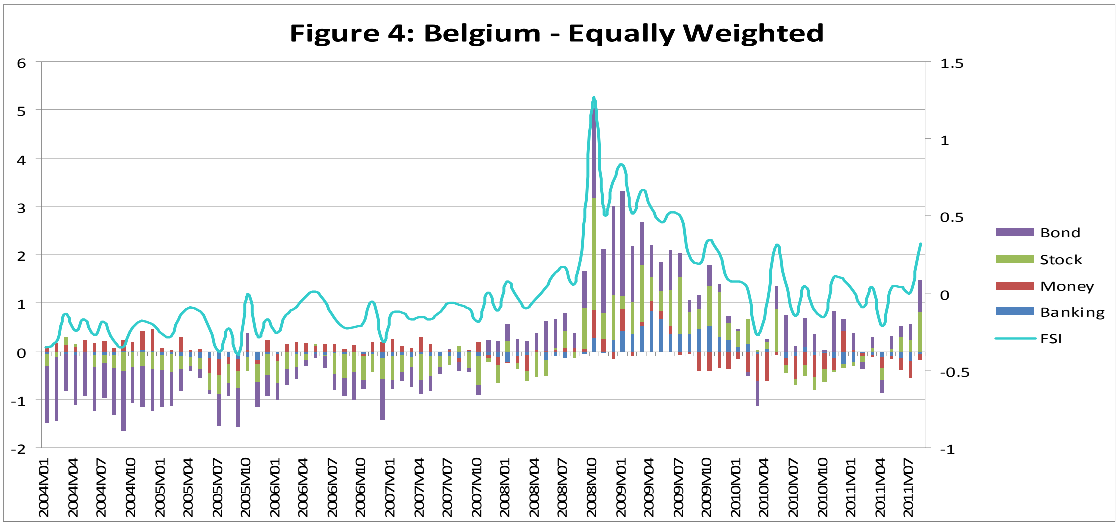
Figures 1 – 3: Austrian Financial Stress Indices

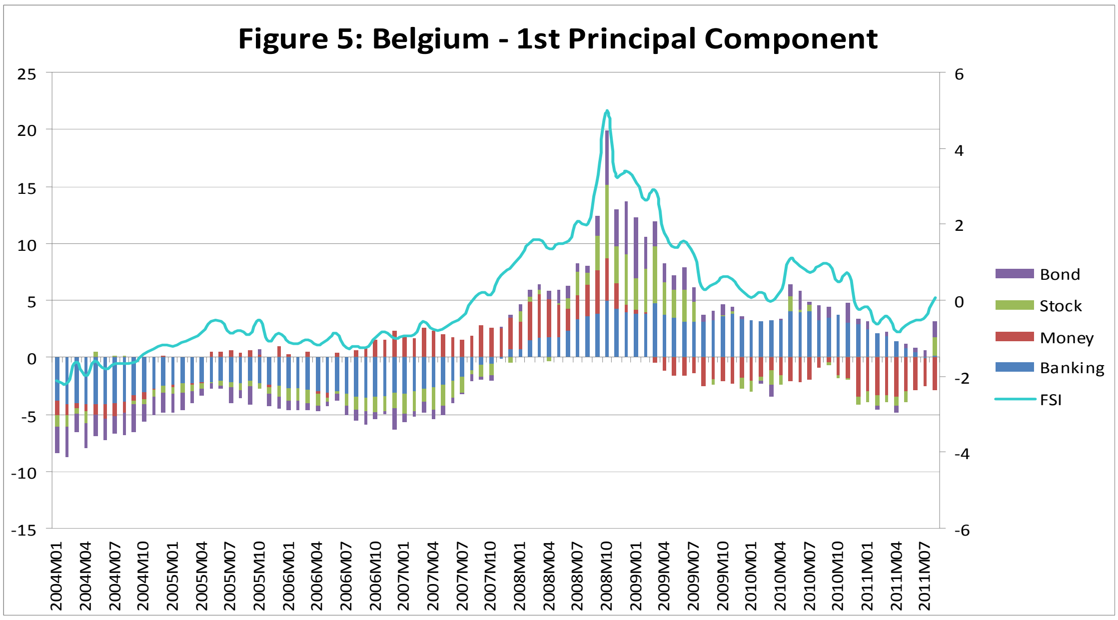


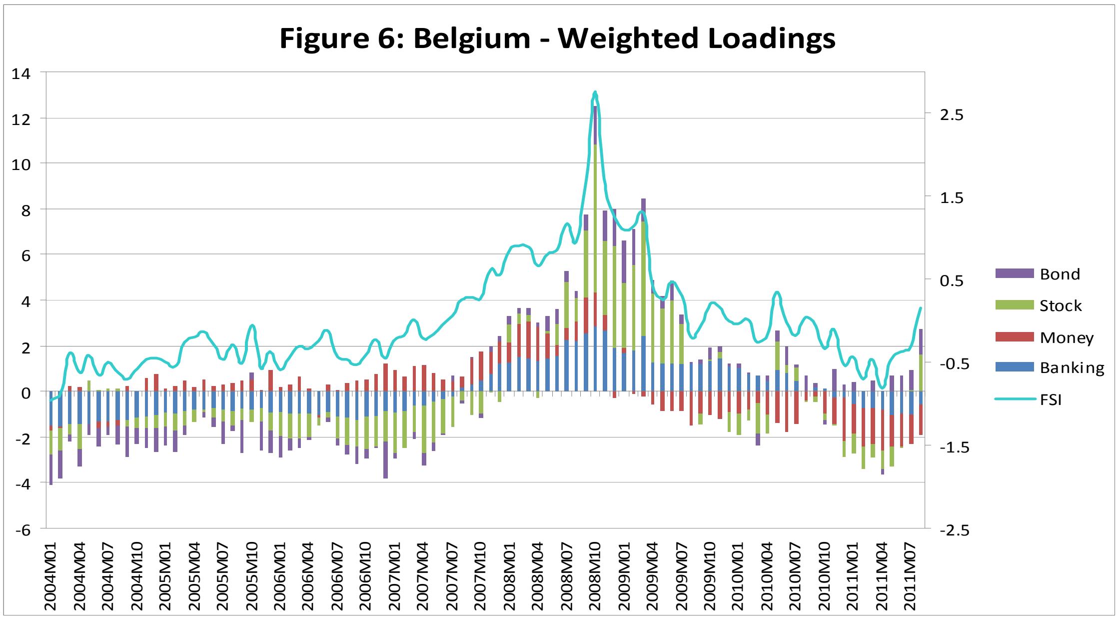




Figures 4 – 6: Belgian Financial Stress Indices







Figures 7 – 9: Finnish Financial Stress Indices

Figure 7: Finland - Equally Weighted

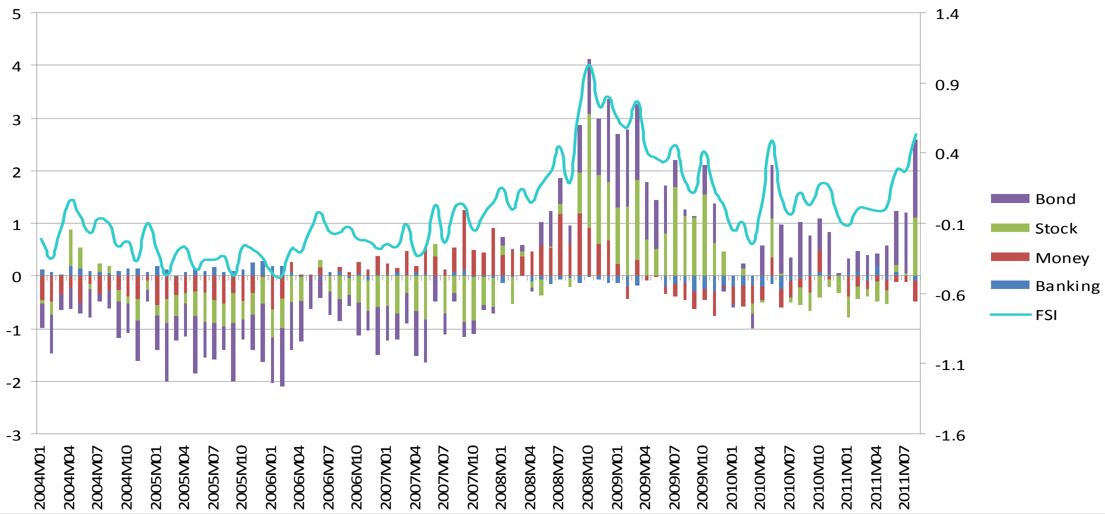


Figure 8: Finland - 1st Principal Component

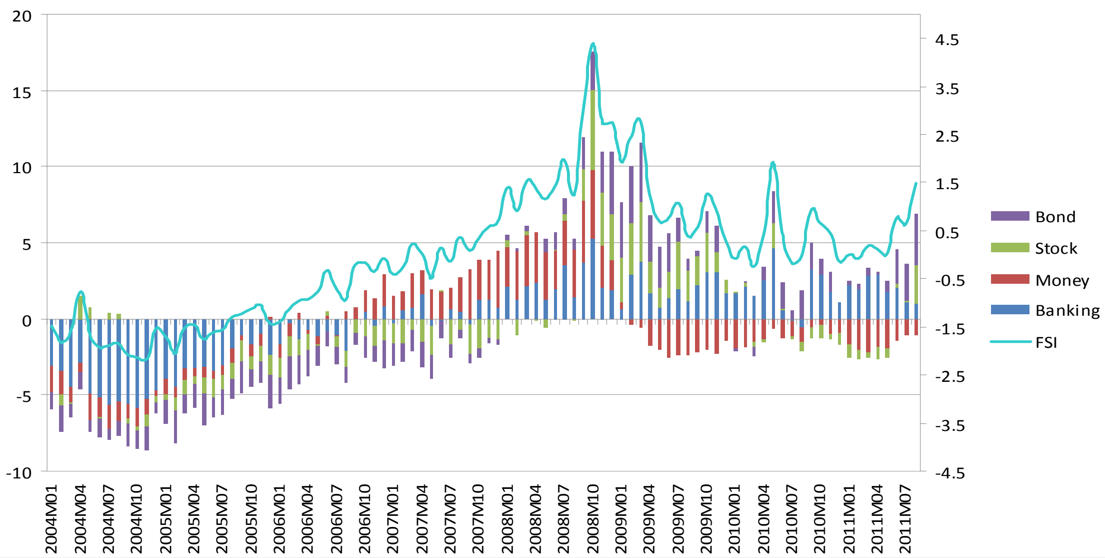
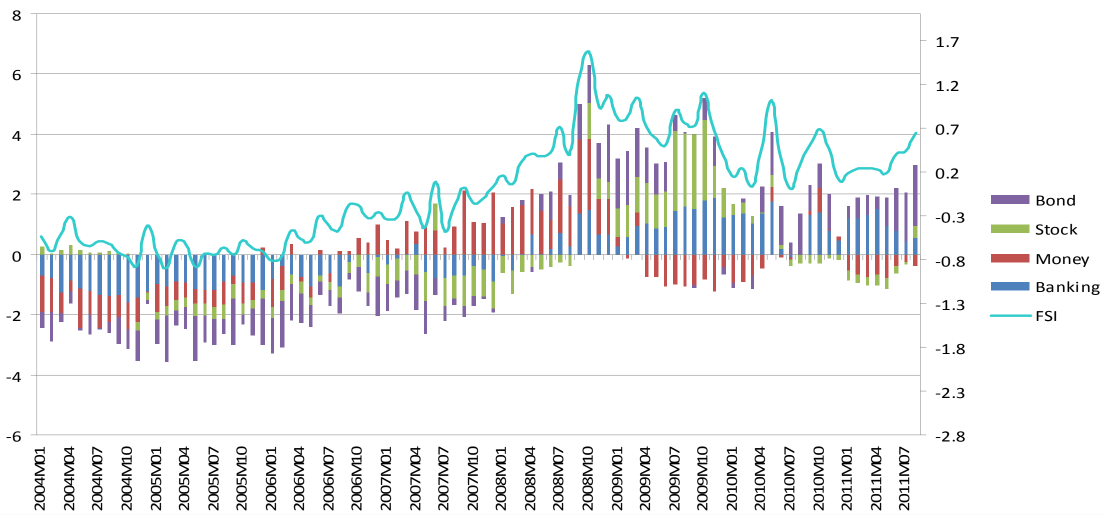
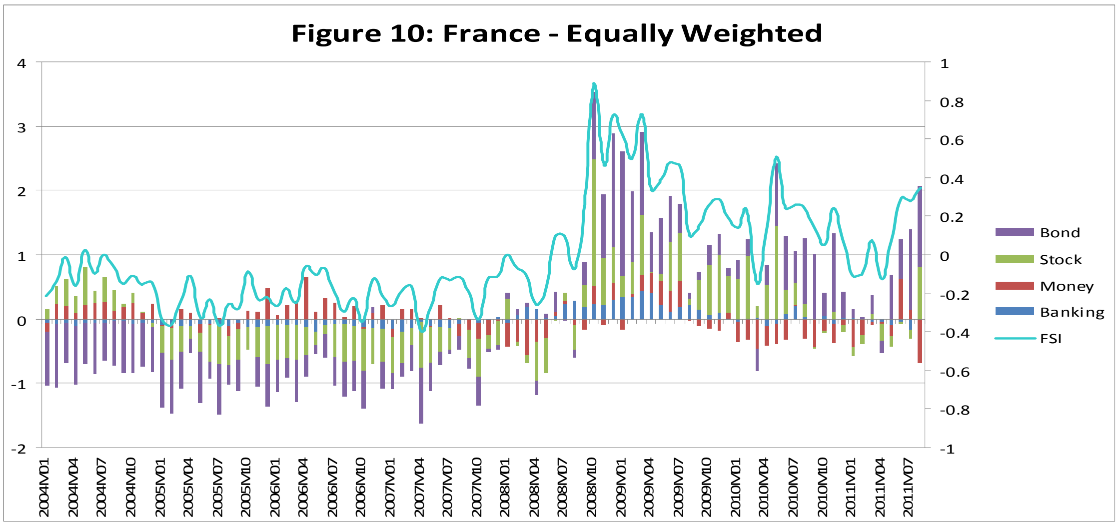
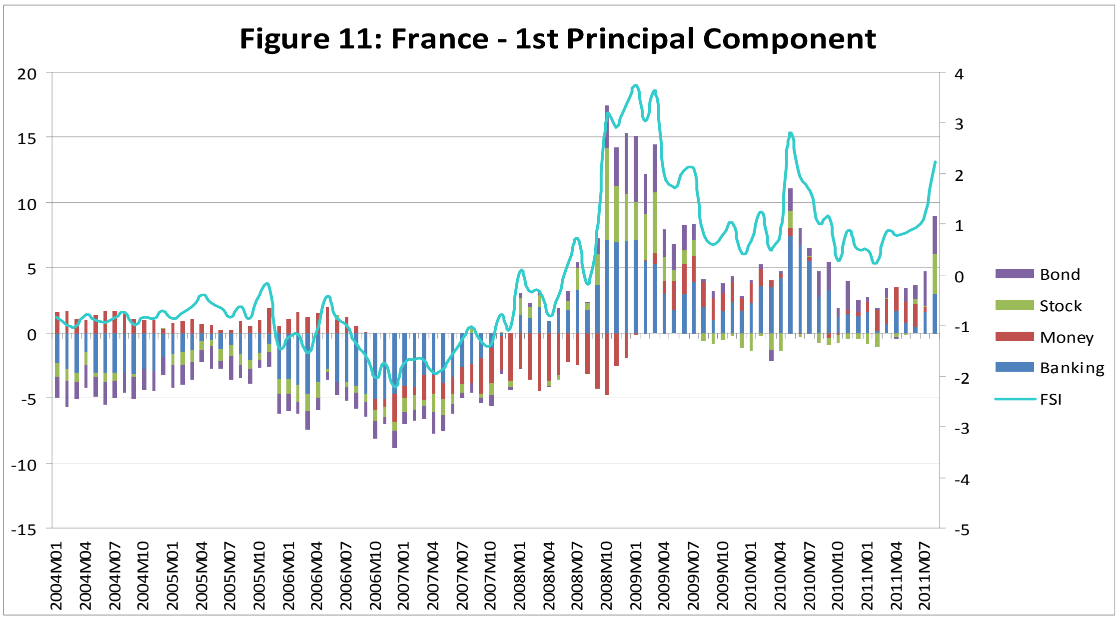


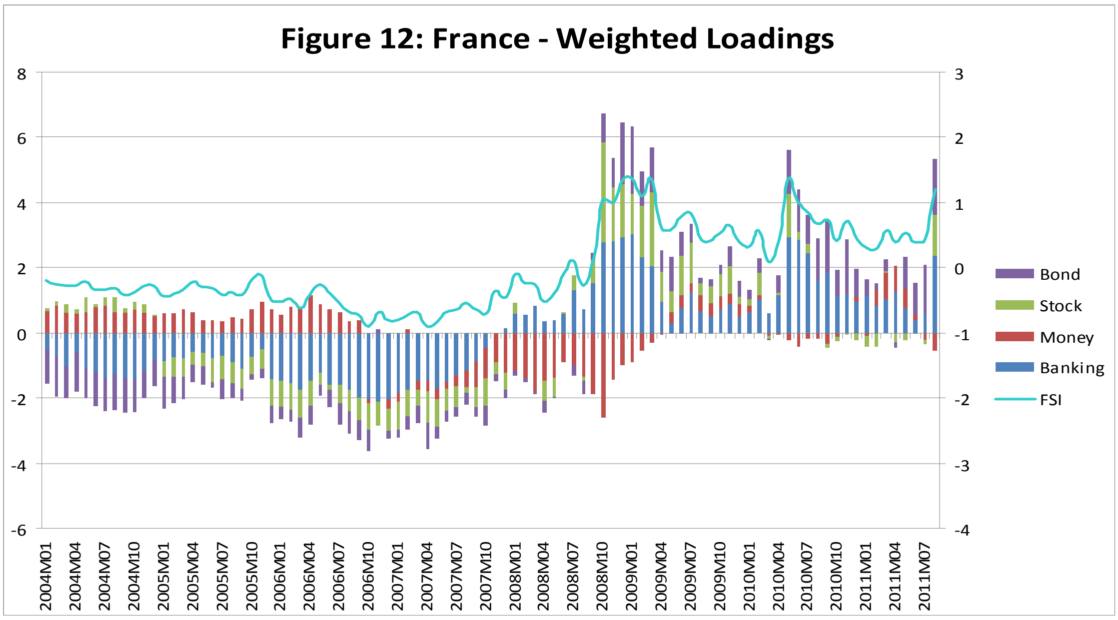
Figure 9: Finland - Weighted Loadings



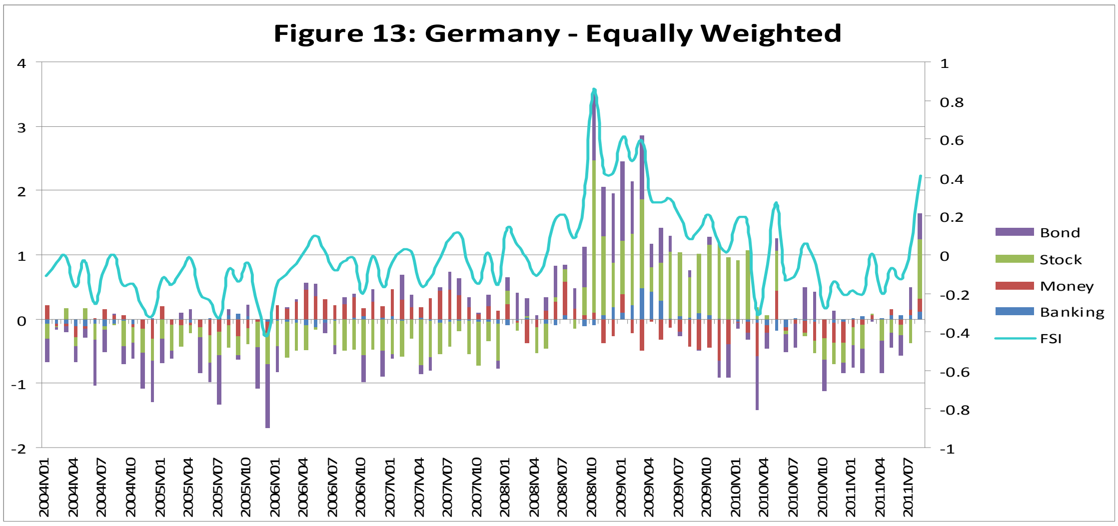
Figures 10 – 12: French Financial Stress Indices

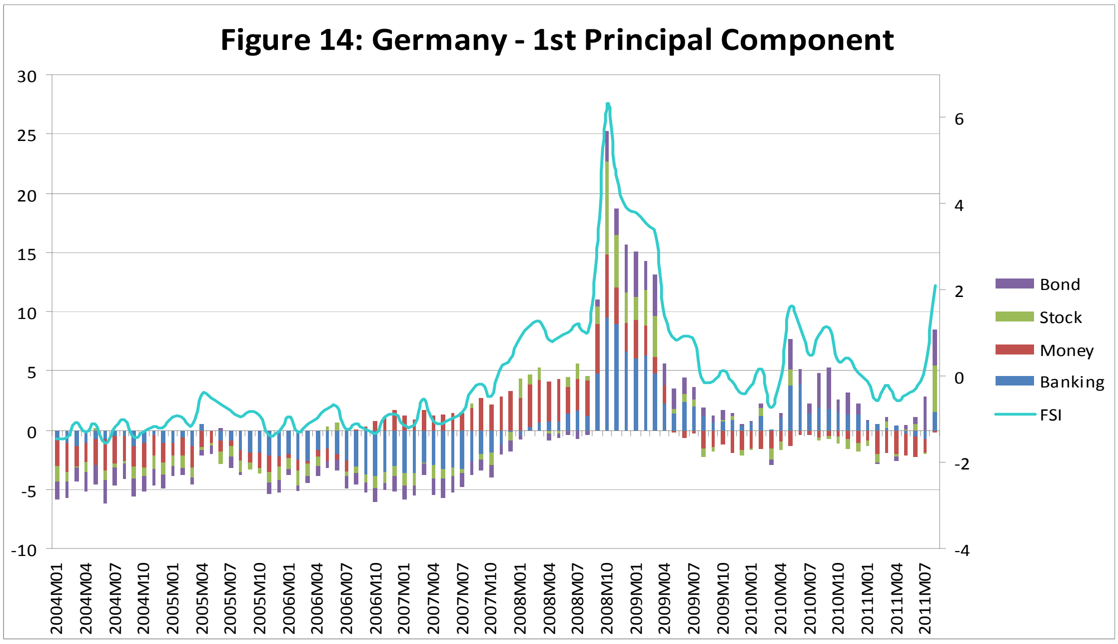


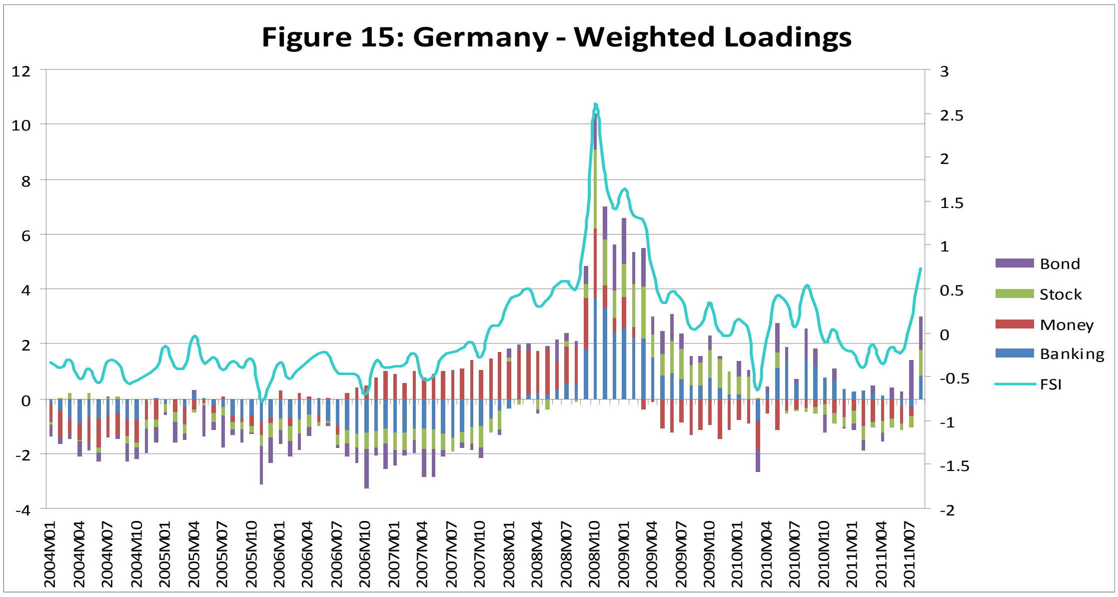




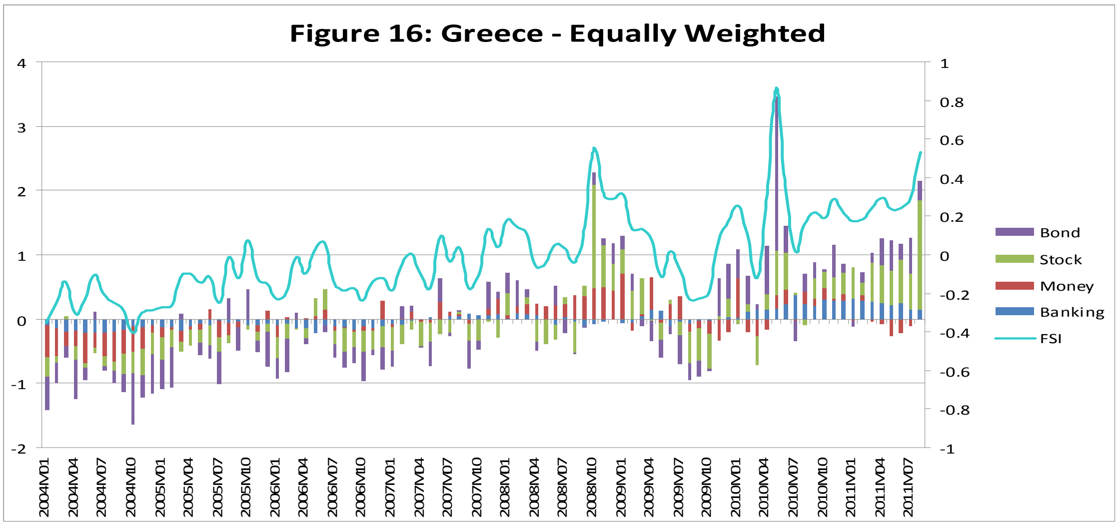
Figures 13 – 15: German Financial Stress Indices

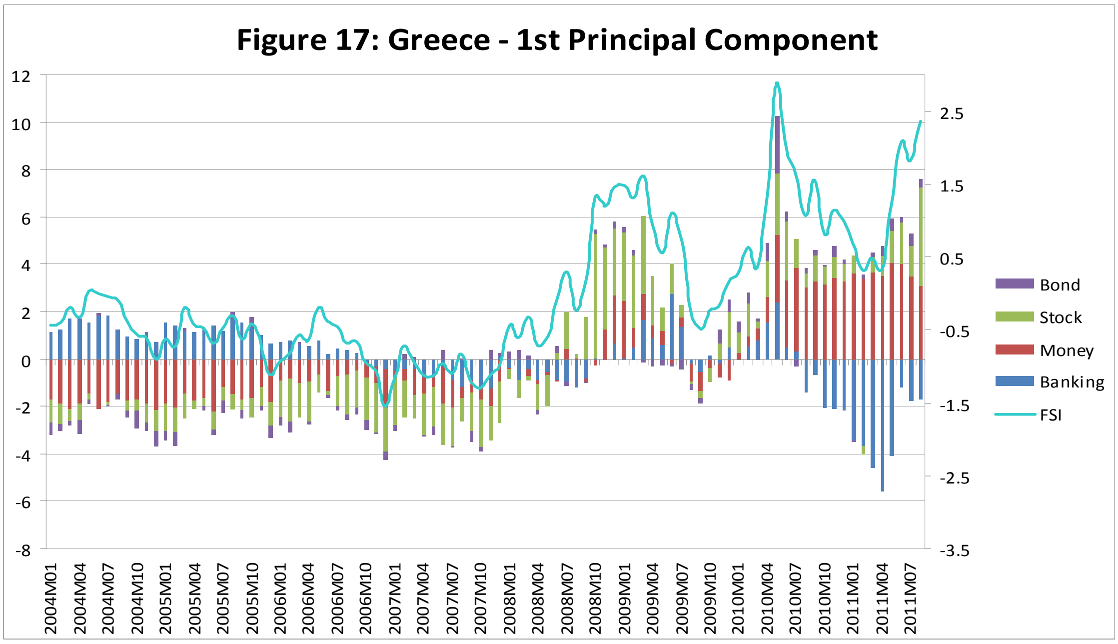


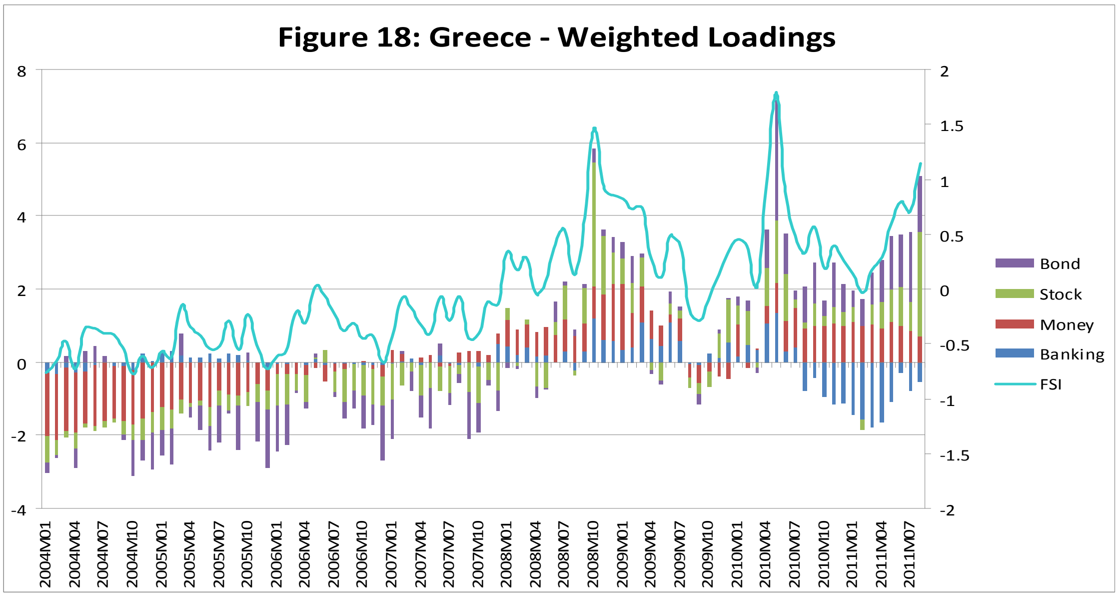




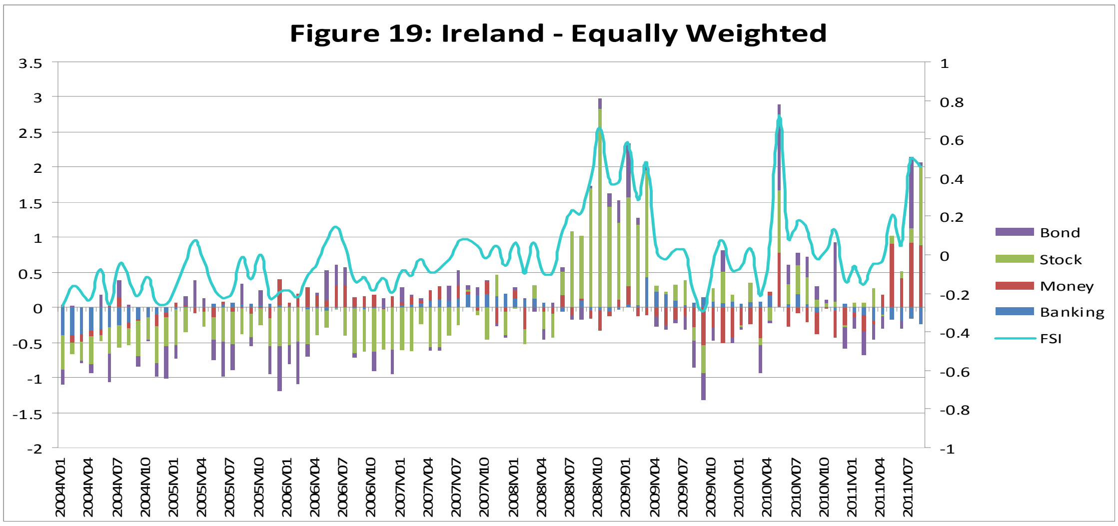
Figures 16 – 18: Greek Financial Stress Indices

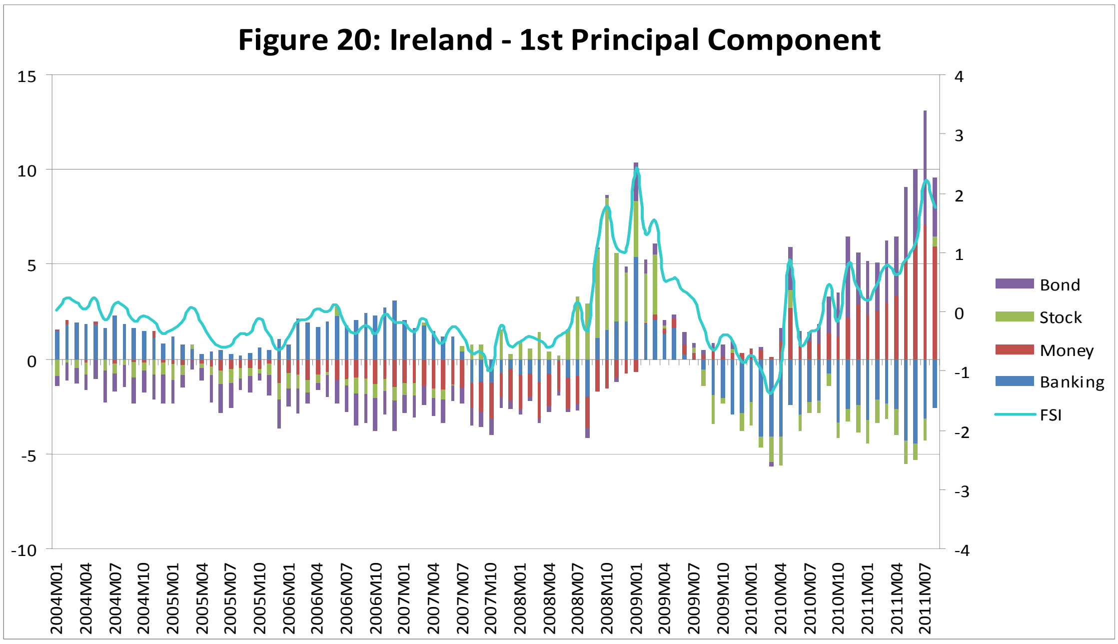


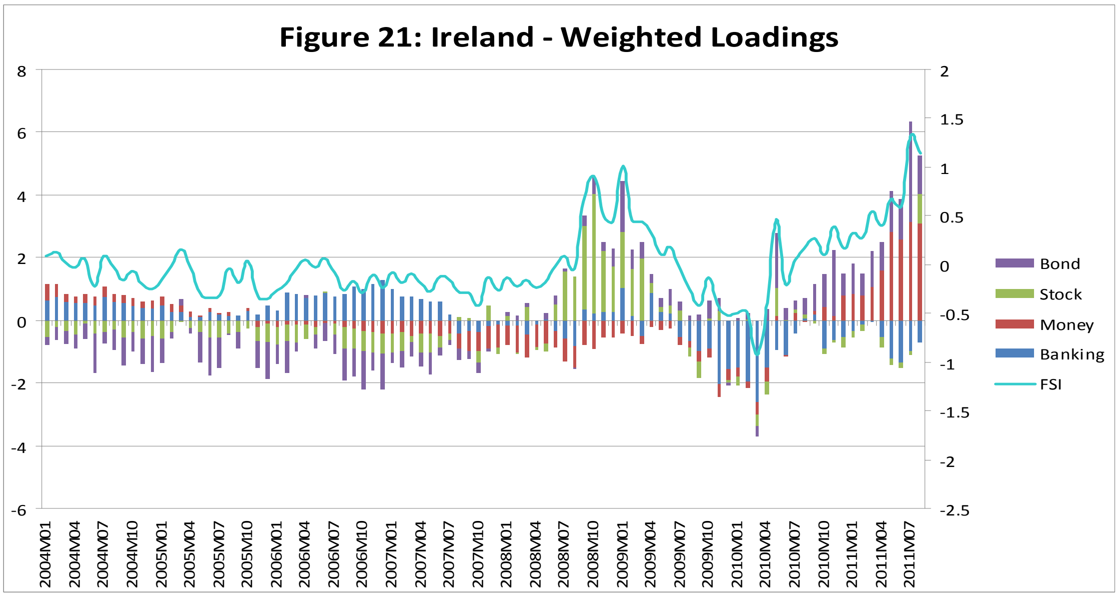




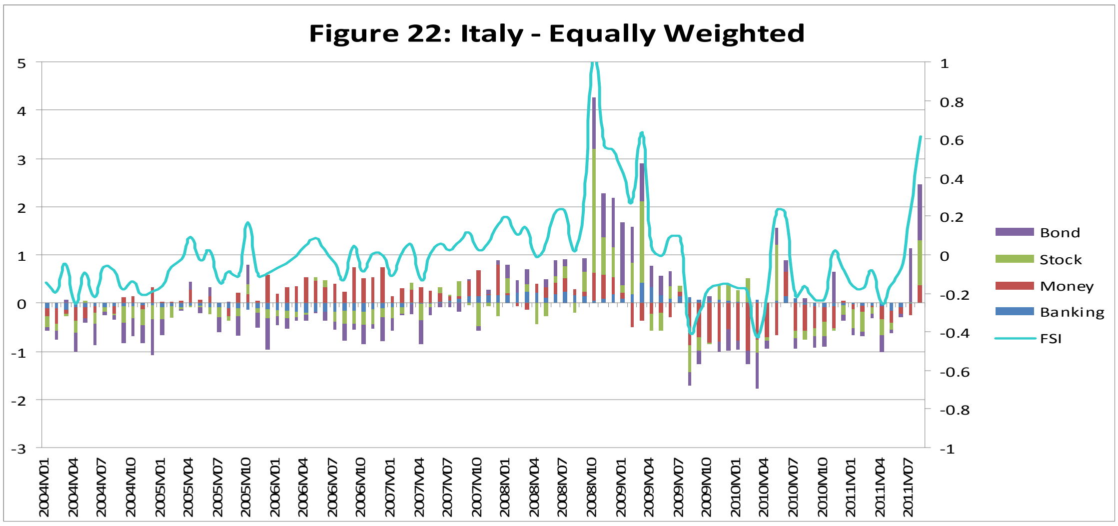
Figures 19 – 21: Irish Financial Stress Indices

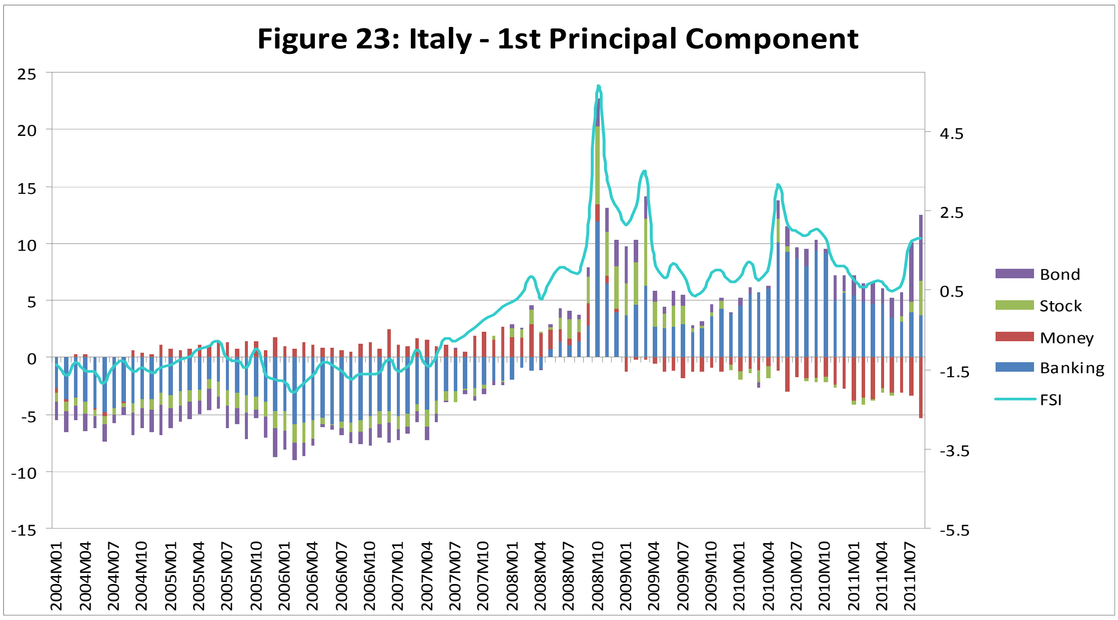


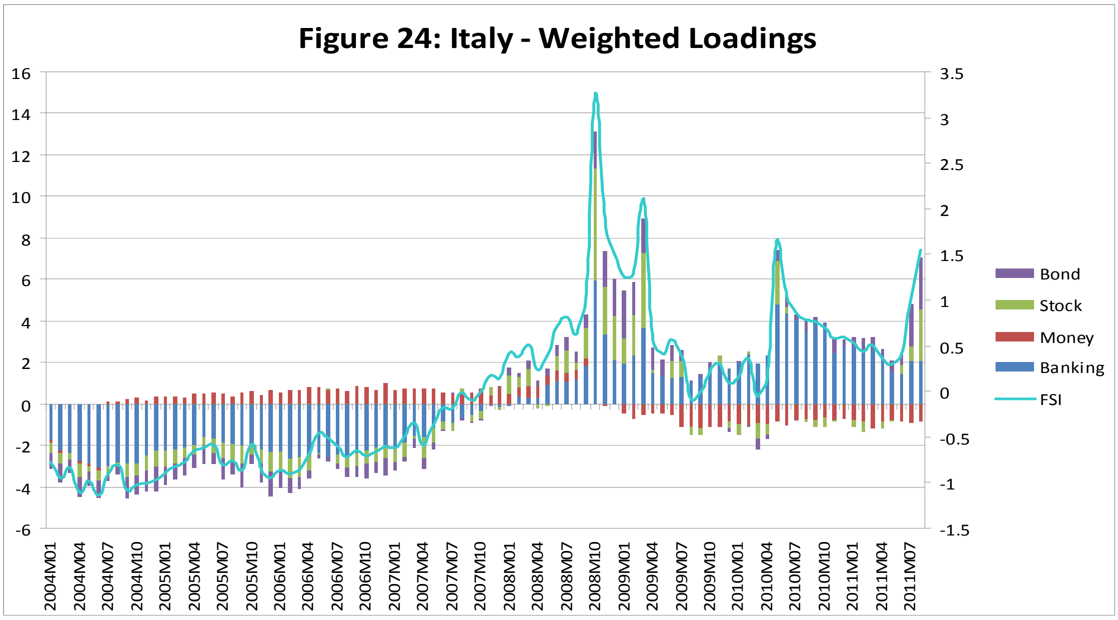




Figures 22 – 24: Italian Financial Stress Indices







Figures 25 – 27: Dutch Financial Stress Indices

Figure 25: Netherlands - Equally Weighted

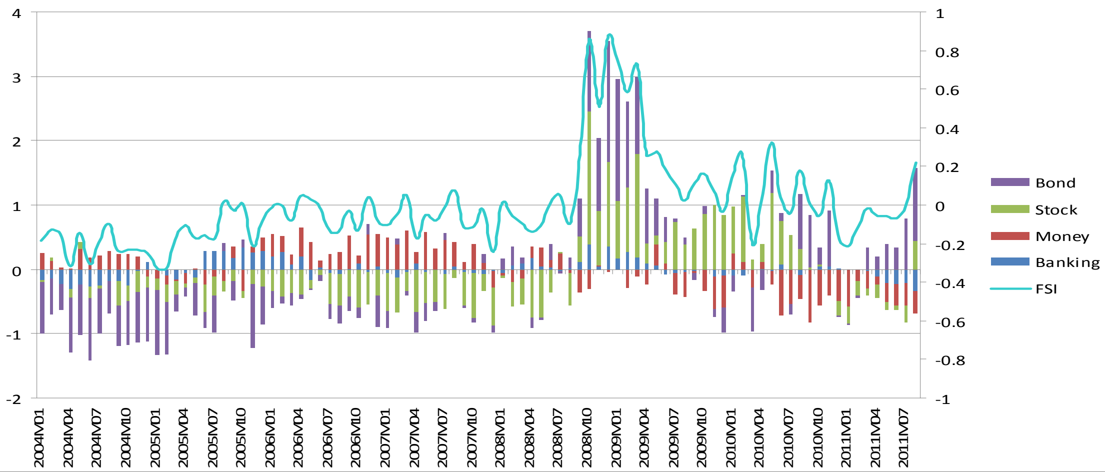


Figure 26: Netherlands - 1st Principal Component

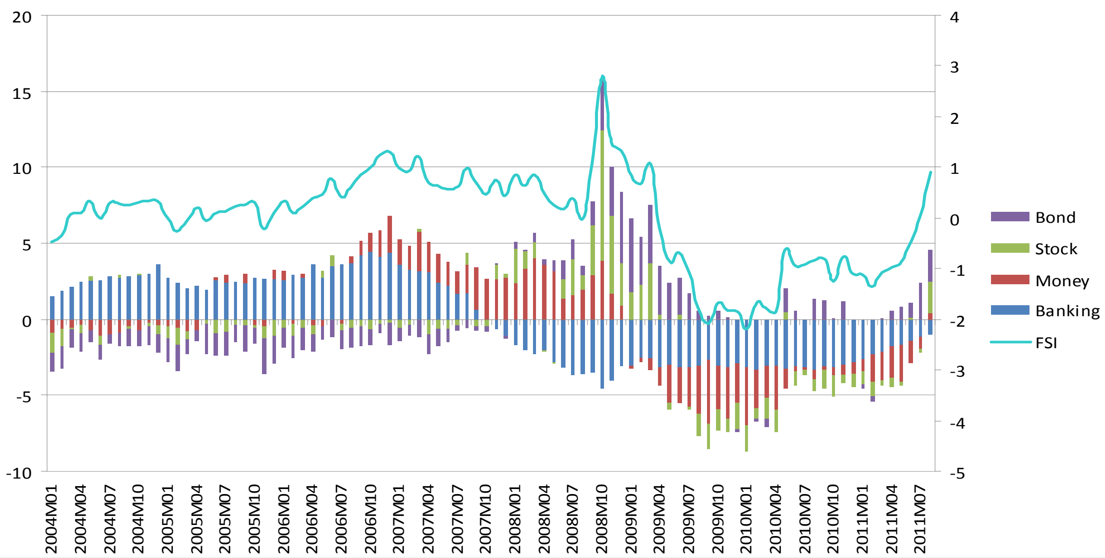
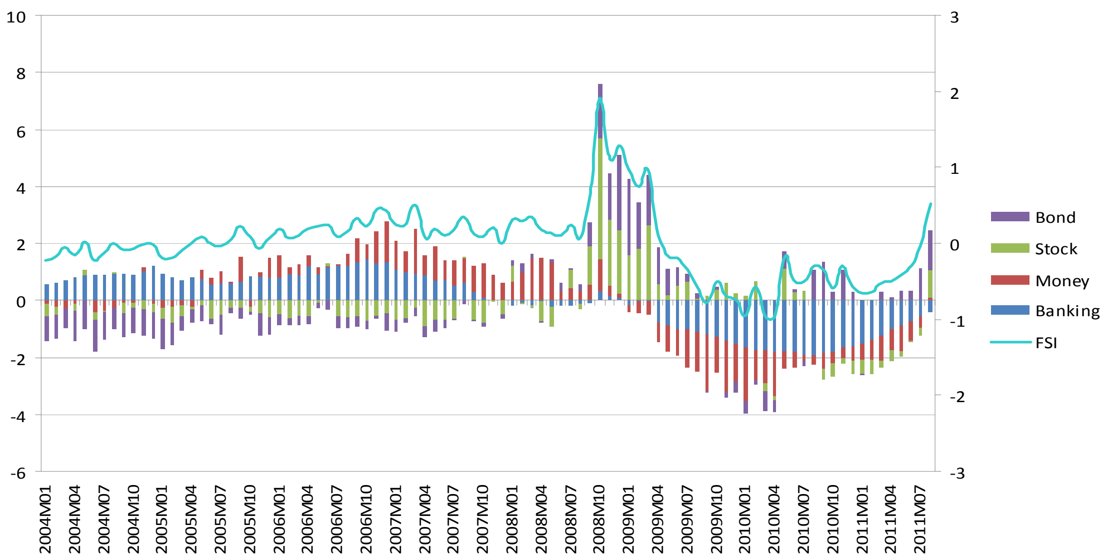
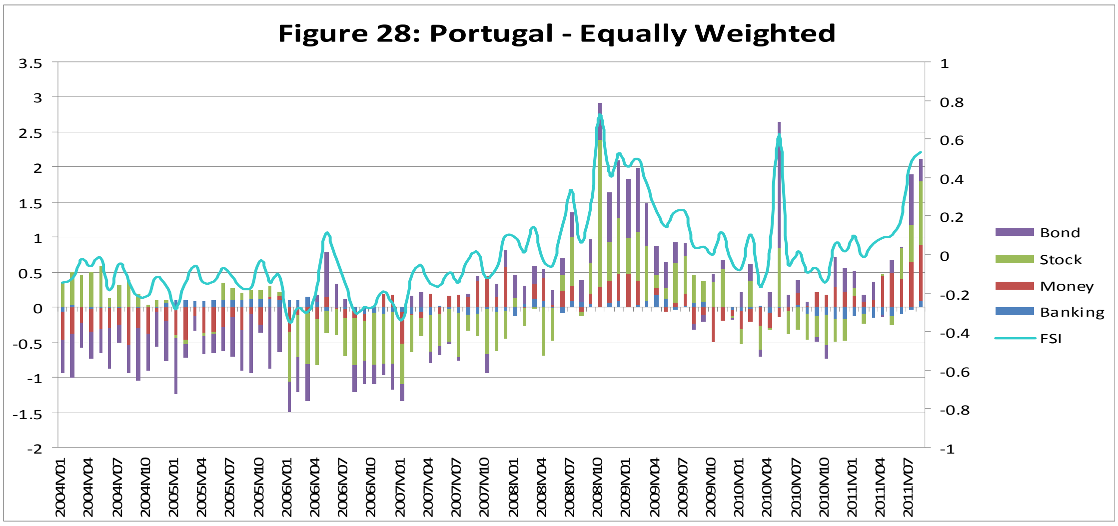
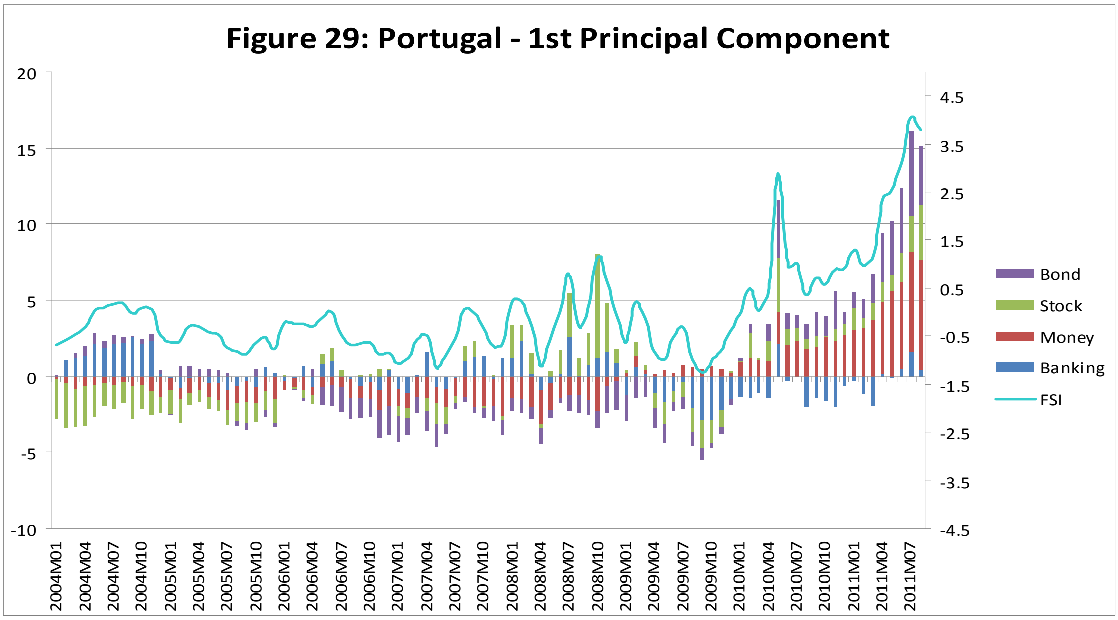


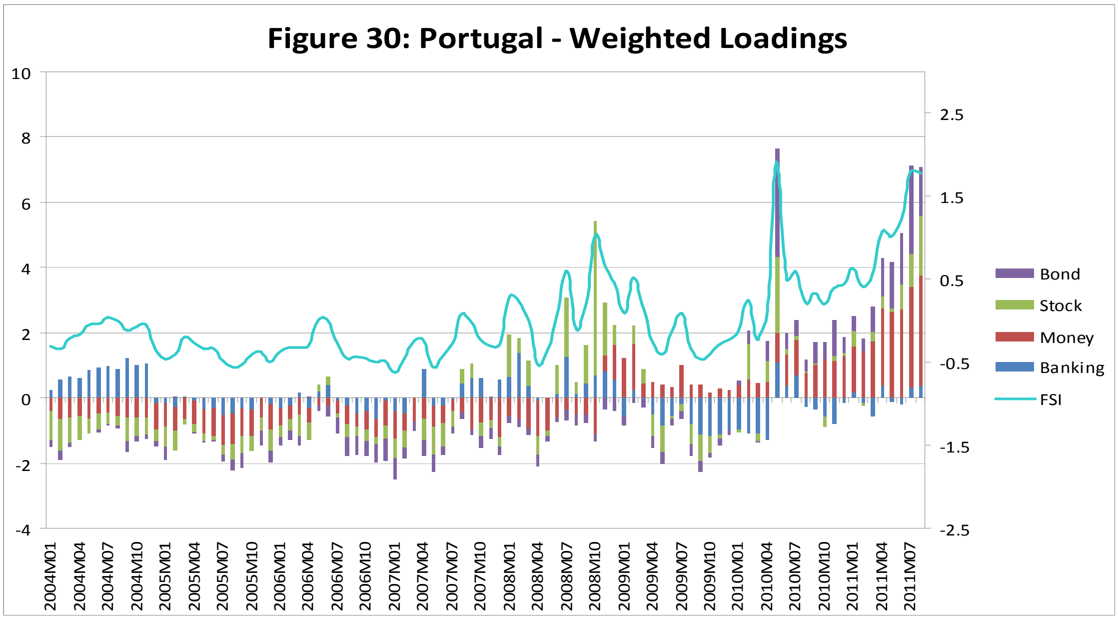
Figure 27: Netherlands - Weighted Loadings



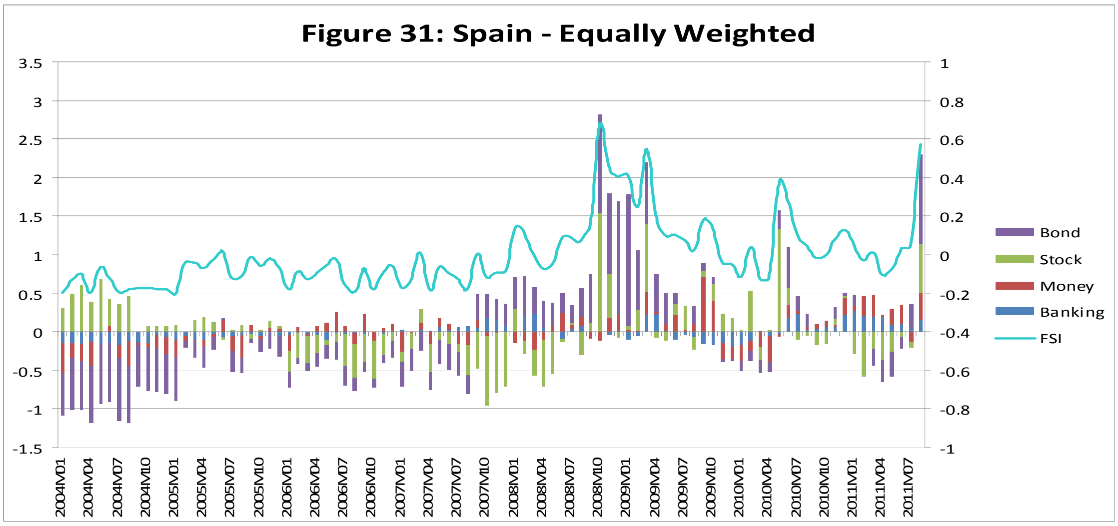
Figures 28 – 30: Portuguese Financial Stress Indices

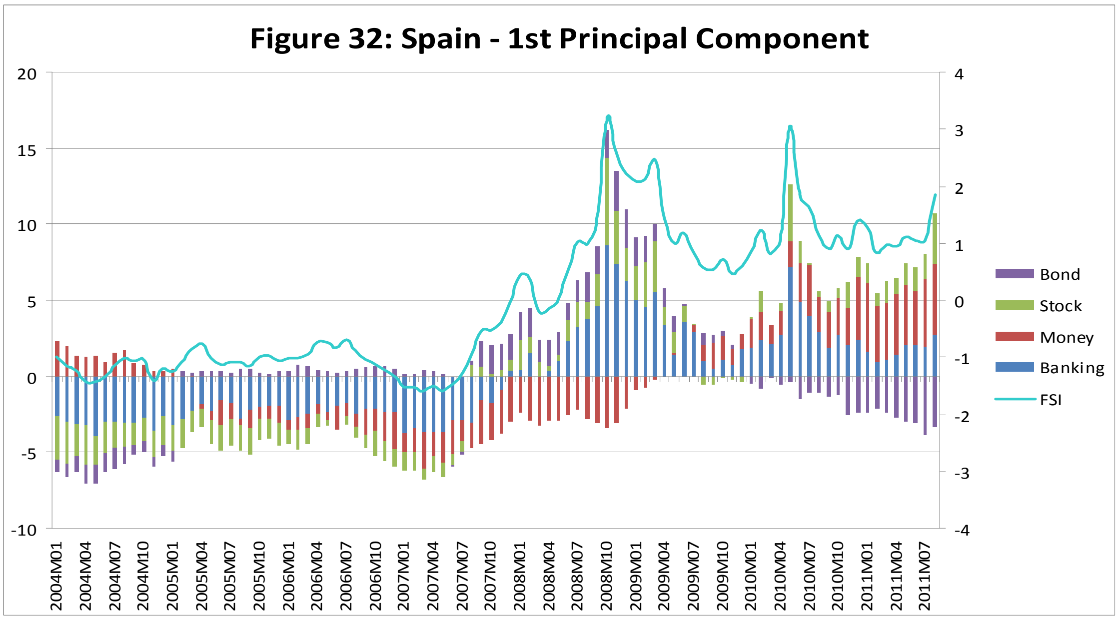






Figures 31 – 33: Spanish Financial Stress Indices





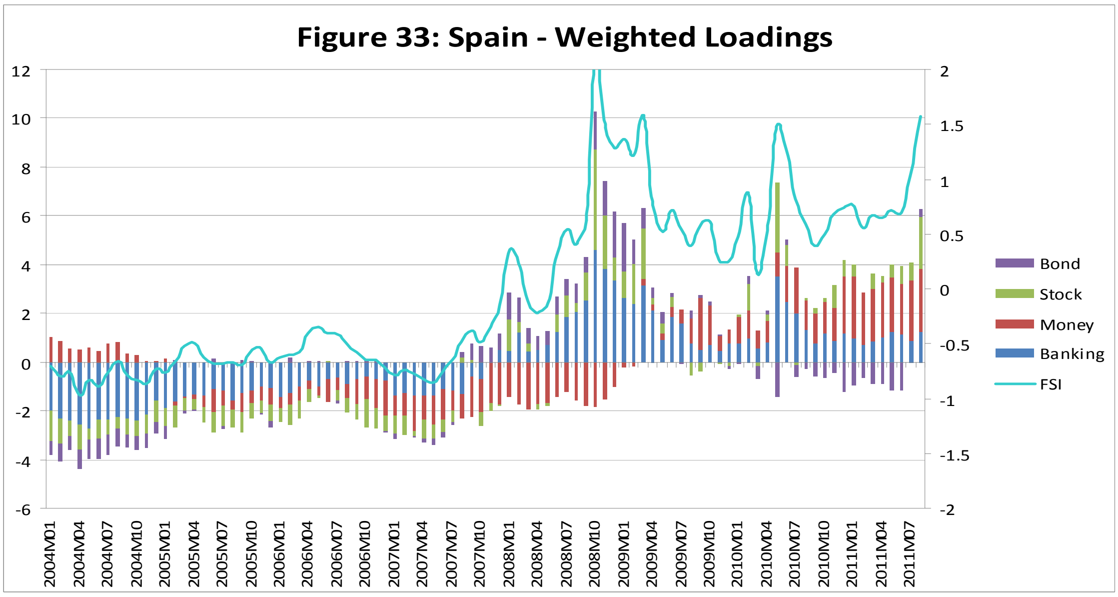


Table A.1: Principal Component Analysis for Banking Sector - 1

Principal Components Loadings for Banking Sectors - First Component Case											
Indicators	**Austria**	**Belgium**	**Finland**	**France**	**Germany**	**Greece**	**Ireland**	**Italy**	**Netherlands**	**Portugal**	**Spain**
Panel A: Operational/Profitability											
ROA	-0.048	-0.166	-0.120	-0.058	-0.039	0.010	0.053	-0.049	0.331	0.031	-0.023
ROE	0.079	-0.137	-0.124	-0.061	-0.042	0.014	0.052	-0.049	0.335	0.028	-0.026
EPS	0.019	-0.204	-0.038	-0.047	-0.050	0.008	0.054	-0.026	0.188	0.029	0.026
P/E	-0.005	-0.239	0.097	0.028	-0.040	0.027	0.047	0.019		-0.013	-0.033
Inefficiency	0.034	-0.122	0.054	-0.017	0.030	-0.008	-0.059	0.021	-0.266	-0.004	-0.023
Net Interest Margin	0.072	-0.134	-0.028	0.079	0.079	0.021	0.064	-0.013	-0.015	0.065	0.047
Panel B: Liquidity											
Interbank Ratio	0.068	-0.143	0.055	0.041	0.086	0.008	0.049	-0.029	0.293	-0.050	-0.029
Net Loans/Total Assets	-0.062	0.275	-0.047	0.061	-0.023	0.000	0.017	0.042	-0.214	0.001	0.010
Loans/Deposits	0.025	0.111	0.065	0.020	-0.031	-0.006	-0.034	0.026	-0.006	0.016	-0.026
Total Liabilities/Liquid Assets	0.054	0.304	0.131	0.048	-0.056	-0.013	-0.031	0.044	-0.261	-0.006	0.013
Interbank Funds/Liquid Assets	0.012	0.201	-0.016	0.028	-0.063	0.001	-0.053	0.034	-0.167	0.056	0.039
Panel C: Assets Quality											
NPL/Gross Loans	-0.005	0.297	0.262	0.043	0.074	-0.007	-0.066	0.056	-0.312	-0.027	0.039
Loan Loss Reserves/Total Loans	-0.051	0.294	0.136	0.062	0.061	-0.004	-0.065	0.052	-0.233	-0.022	0.037
Loan Loss Reserves/Impaired Loans	-0.057	-0.268	0.242	-0.015	-0.039	0.006	0.061	-0.042	0.339	0.024	-0.038
Size	0.040	0.241	-0.105	0.028	0.033	0.004	0.038	-0.004	0.104	0.043	-0.021
Market Power	0.032	0.259	-0.138	0.027	-0.015	0.021	0.013	-0.009	0.121	0.042	-0.014
Panel D: Capital Adequacy											
Tier 1 Regulatory Capital Ratio	0.029	0.054	0.180	0.058	0.081	-0.007	-0.042	0.045	-0.226	-0.022	0.039
Total Regulatory Capital Ratio	-0.008	0.143	-0.047	0.047	0.081	0.001	-0.033	0.046	0.111	0.004	0.042
Panel E: Volatility Risk											
Equity Price Returns	0.010	-0.054	-0.014	-0.002	-0.002	0.000	0.005	-0.006	0.109	0.009	-0.001
Dividen Yield	-0.013	0.095	-0.109	0.011	0.029	-0.002	-0.004	0.002	0.122	0.007	0.028
Market Value	0.019	-0.254	0.133	-0.044	-0.077	0.009	0.061	-0.021	-0.062	0.023	0.005
Turnover by Volume	-0.011	0.249	0.092	0.043	0.059	-0.006	-0.032	0.038	0.164	0.002	0.027
Panel F: Market - Level Indicators											
Deposit Gap	0.575	0.045	0.485	0.602	0.565	0.687	0.626	0.591	-0.071	0.417	0.574
Loan Gap	0.561	0.030	-0.392	0.566	0.552	0.667	0.596	0.568	-0.082	0.450	0.557
Banks Index Realized Volatility	0.527	0.190	0.587	0.466	0.502	0.201	0.468	0.498	-0.074	0.512	0.540
Banking Sector Beta	0.131	0.061	0.070	-0.045	0.145	-0.206	0.184	-0.053	-0.063	-0.153	0.008
Bank Equities Index Returns	-0.244	-0.065	-0.511	-0.313	-0.321	-0.018	0.000	-0.276	0.103	-0.581	-0.260
% of Variance Explained	36.9%	33.7%	33.3%	38.4%	35.8%	40.0%	38.8%	44.9%	31.3%	44.8%	49.5%

Table A.2: Principal Component Analysis for Banking Sector - 2

Principal Components Loadings for Banking Sectors - Weighted Loadings Case

Indicators	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Panel A: Operational/Profitability											
ROA	-0.004	-0.004	-0.024	-0.022	-0.015	0.007	0.036	-0.020	0.081	0.018	-0.002
ROE	0.032	0.020	-0.020	-0.023	-0.014	0.008	0.036	-0.021	0.092	0.016	-0.004
EPS	0.007	0.002	-0.018	-0.014	-0.023	0.011	0.026	0.001	0.133	0.018	0.024
P/E	-0.004	-0.023	0.013	0.007	0.004	0.015	0.021	-0.003		-0.005	-0.022
Inefficiency	0.008	0.022	-0.025	-0.002	0.002	-0.005	-0.006	0.018	-0.084	-0.001	-0.020
Net Interest Margin	0.036	0.051	0.011	0.022	0.028	0.012	0.027	0.006	-0.072	0.037	0.026
Panel B: Liquidity											
Interbank Ratio	0.033	-0.096	0.003	0.024	0.031	-0.002	0.040	-0.003	0.074	-0.017	-0.015
Net Loans/Total Assets	-0.029	0.140	-0.019	0.025	0.021	0.006	0.011	0.030	-0.002	-0.005	0.020
Loans/Deposits	0.014	0.131	0.007	0.012	0.011	0.000	-0.020	0.016	0.085	0.001	0.000
Total Liabilities/Liquid Assets	0.024	0.124	0.071	0.029	-0.013	0.000	0.001	0.019	-0.046	-0.004	0.015
Interbank Funds/Liquid Assets	0.030	0.133	0.029	0.023	-0.009	0.007	-0.019	0.009	0.030	0.022	0.019
Panel C: Assets Quality											
NPL/Gross Loans	0.021	0.069	0.147	0.020	0.041	-0.004	-0.021	0.024	-0.128	-0.012	0.018
Loan Loss Reserves/Total Loans	-0.003	0.084	0.116	0.027	0.012	-0.004	-0.019	0.022	-0.133	-0.007	0.017
Loan Loss Reserves/Impaired Loans	-0.009	-0.028	0.125	-0.001	-0.032	0.000	0.032	-0.017	0.108	0.017	-0.019
Size	0.010	0.106	-0.044	0.026	0.009	0.003	0.011	-0.009	0.055	0.034	-0.011
Market Power	0.023	0.137	-0.042	0.023	0.016	0.014	0.011	-0.008	0.056	0.027	-0.006
Panel D: Capital Adequacy											
Tier 1 Regulatory Capital Ratio	0.019	0.054	0.110	0.020	0.034	-0.003	0.012	0.025	-0.144	-0.007	0.018
Total Regulatory Capital Ratio	0.011	0.064	0.035	0.018	0.032	0.001	0.016	0.026	0.016	0.004	0.018
Panel E: Volatility Risk											
Equity Price Returns	-0.003	-0.065	0.015	-0.005	0.003	0.004	-0.006	-0.001	0.032	0.009	0.008
Dividen Yield	-0.006	0.081	-0.040	0.012	0.017	0.002	-0.006	0.005	0.137	0.009	0.017
Market Value	0.014	-0.038	0.028	-0.018	-0.031	0.011	0.028	0.003	-0.017	0.015	0.009
Turnover by Volume	-0.008	0.121	0.030	0.019	0.025	-0.004	-0.015	0.022	0.064	0.008	0.021
Panel F: Market - Level Indicators											
Deposit Gap	0.250	0.089	0.289	0.224	0.160	0.276	0.281	0.230	0.011	0.325	0.241
Loan Gap	0.261	0.073	-0.197	0.195	0.171	0.259	0.205	0.211	0.015	0.160	0.259
Banks Index Realized Volatility	0.172	0.114	0.142	0.243	0.259	0.278	0.120	0.347	0.032	0.230	0.339
Banking Sector Beta	0.123	0.048	0.079	0.187	0.258	0.094	0.184	0.144	0.020	0.064	0.181
Bank Equities Index Returns	0.114	-0.079	-0.052	-0.108	-0.016	-0.033	0.197	-0.099	-0.017	-0.227	-0.108
% of Variance Explained	82.5%	80.0%	74.4%	81.5%	81.6%	84.9%	83.7%	84.3%	76.2%	82.9%	85.1%

Table A.3: Principal Component Analysis for Money Markets

Principal Components Loadings for Money Markets											
Indicators	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Panel A: First component											
TED Spread	0.475	0.371	0.457	-0.483	0.462	0.234	-0.539	0.056	0.386	-0.329	-0.364
Inverted Term Spread	0.484	0.481	0.517	-0.417	0.337	-0.426	-0.038	0.541	0.396	-0.490	-0.359
Euribor - 2yr Govt. Bond Yield	-0.359	-0.375	-	0.440	-0.354	0.512	0.521	-0.217	-0.316	0.461	0.428
Euribor - 5yr Govt. Bond Yield	-0.477	-0.503	-0.496	0.527	-0.478	0.519	0.544	-0.415	-0.499	0.487	0.441
M2 growth	0.331	0.109	0.231	-0.130	0.219	-0.330	-0.186	0.200	0.079	-0.130	-0.231
M2/Foreign Reserves	-0.141	0.422	0.192	0.017	0.439	0.098	-0.212	0.493	0.386	-0.072	-0.347
Treasury Bill Realized Volatility	-	-0.217	0.065	0.132	-0.043	0.036	0.233	-0.130	-0.299	0.051	0.073
Intermediation Rate	-0.233	0.006	0.428	0.297	-0.276	-0.337	0.078	0.430	0.317	0.422	0.427
% of Variance Explained	41.7%	45.5%	47.5%	39.1%	44.8%	40.9%	39.1%	34.6%	41.8%	48.7%	57.4%
Panel B: Weighted Loadings											
TED Spread	0.105	0.088	0.215	-0.229	0.211	0.280	-0.241	0.035	0.085	-0.247	-0.184
Inverted Term Spread	0.289	0.238	0.207	-0.077	0.263	-0.080	0.138	0.247	0.249	-0.214	-0.269
Euribor - 2yr Govt. Bond Yield	0.005	-0.145	-	0.232	-0.119	0.141	0.228	0.112	-0.032	0.220	0.269
Euribor - 5yr Govt. Bond Yield	-0.307	-0.224	-0.246	0.175	-0.267	0.148	0.213	-0.002	-0.169	0.233	0.287
M2 growth	0.219	0.192	0.243	0.075	0.220	-0.122	0.054	0.045	0.191	0.021	-0.120
M2/Foreign Reserves	-0.157	0.187	0.193	-0.089	0.121	0.240	-0.130	0.248	0.206	0.107	-0.128
Treasury Bill Realized Volatility	-	-0.184	0.188	-0.042	-0.083	0.124	0.003	-0.069	-0.155	0.173	0.185
Intermediation Rate	0.051	0.147	0.099	0.240	0.046	-0.275	0.175	0.218	0.161	0.208	0.195
% of Variance Explained	80.8%	78.4%	82.4%	73.2%	81.9%	87.3%	76.7%	70.8%	73.7%	81.5%	83.1%

Table A.4: Principal Component Analysis for Equity Markets

Principal Components Loadings for Equity Markets											
Indicators	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Panel A: First component											
Stocks Returns	0.419	0.365	0.357	0.465	0.578	0.385	0.524	0.372	0.538	0.471	0.373
EPS	-0.043	0.359	0.443	0.021	-0.030	0.248	-0.258	-	-0.133	-0.365	-0.405
Dividend Yield	0.476	0.540	0.569	0.474	0.474	0.463	0.542	0.516	0.335	0.363	0.421
P/E	-0.487	-0.477	0.265	-0.472	-0.053	-0.562	-	-0.556	-0.479	-0.539	-0.562
Stocks Realized Volatility	0.599	0.469	0.532	0.580	0.661	0.510	0.604	0.535	0.593	0.472	0.450
% of Variance Explained	43.1%	47.9%	42.6%	43.5%	38.8%	47.8%	50.8%	62.5%	45.1%	48.8%	53.6%
Panel B: Weighted Loadings											
Stocks Returns	0.168	0.377	0.036	0.220	0.160	0.365	0.249	0.391	0.304	0.383	0.331
EPS	0.261	0.078	0.358	0.293	0.282	0.176	0.145	-	0.201	-0.023	-0.039
Dividend Yield	0.344	0.136	0.161	0.310	0.270	0.041	0.339	0.190	0.288	0.124	0.222
P/E	-0.091	-0.114	0.382	-0.027	0.100	-0.176	-	-0.229	-0.018	-0.140	-0.237
Stocks Realized Volatility	0.273	0.396	0.116	0.288	0.274	0.346	0.383	0.474	0.352	0.377	0.377
% of Variance Explained	89.1%	91.7%	89.2%	92.5%	83.0%	89.2%	91.4%	96.2%	93.3%	89.6%	90.9%

Table A.5: Principal Component Analysis for Bond Markets

Principal Components Loadings for Bond Markets											
Indicators	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Panel A: First component											
Sovereign Bond Spread	0.586	0.429	0.575	0.562	-0.509	0.621	0.618	0.578	0.598	0.557	-0.470
Bond Realized Volatility	0.481	0.521	0.505	0.530	0.632	0.263	0.409	0.422	0.463	0.345	-0.016
Corporate Bond Spread	0.571	0.558	0.520	0.551	0.548	-	-0.514	0.157	0.561	-0.544	0.627
Government Bond Duration	0.038	0.327	0.252	0.162	0.079	-0.623	-0.368	-0.571	-0.199	-0.470	0.616
Realized Correlation with Bund	0.313	0.354	0.284	0.270	0.188	0.396	0.227	0.370	0.271	0.232	-0.081
% of Variance Explained	48.2%	44.5%	53.8%	47.8%	39.5%	51.4%	47.5%	48.9%	47.0%	40.6%	37.3%
Panel B: Weighted Loadings											
Sovereign Bond Spread	0.297	0.261	0.260	0.333	-0.078	0.214	0.219	0.232	0.247	0.280	-0.063
Bond Realized Volatility	0.274	0.133	0.266	0.219	0.245	0.295	0.328	0.240	0.333	0.353	0.196
Corporate Bond Spread	0.209	0.196	0.173	0.162	0.256	-	-0.114	0.331	0.299	-0.140	0.309
Government Bond Duration	0.287	0.066	0.286	0.335	-0.077	-0.220	-0.223	-0.248	0.167	-0.049	0.277
Realized Correlation with Bund	0.148	0.376	0.324	0.116	0.351	0.421	0.285	0.162	0.124	0.126	0.216
% of Variance Explained	86.8%	81.8%	90.0%	87.4%	82.5%	94.7%	85.0%	86.0%	86.8%	79.6%	85.8%

Table A.6: Sample of European Banks

Austria				
Unicredit Bank Austria	Raiffeisen Bank	Oesterreichische Volksbank	Oberbank AG	
Belgium				
Dexia Bank				
Finland				
Pohjola Bank	Bank of Aland			
France				
BNP Paribas	Credit Agricole	Societe Generale	Natixis	
Germany				
Deutsche Bank	Commerzbank			
Greece				
National Bank of Greece	EFG Eurobank	Alpha Bank	Piraeus Bank	
ATE Bank	Marfin Egnatia Bank	Hellenic Postbank	Attica Bank	
Ireland				
Bank of Ireland	Allied Irish Bank	Irish Life and Permanent		
Italy				
Unicredit Spa	Intesa Sanpaolo Spa	Banca Monte dei Paschi di Siena	Banco Popolare	
UBI Banca	Mediobanca Spa	Banca Popolare dell' Emilia Romagna		
Netherlands				
Van Lanshot NV				
Portugal				
Bank Comercial Portugues	Banco Espirito Santo SA	Banco BPI SA	Banco International do Fuchal SA	
Spain				
Banco Santader SA	BBVA	Banco Popular Espanol SA	Banco Espanol de Credito SA	Banco de Sabadell SA

Figure A.34: Response of Austrian Financial Stress Indices to Financial Stress Shocks

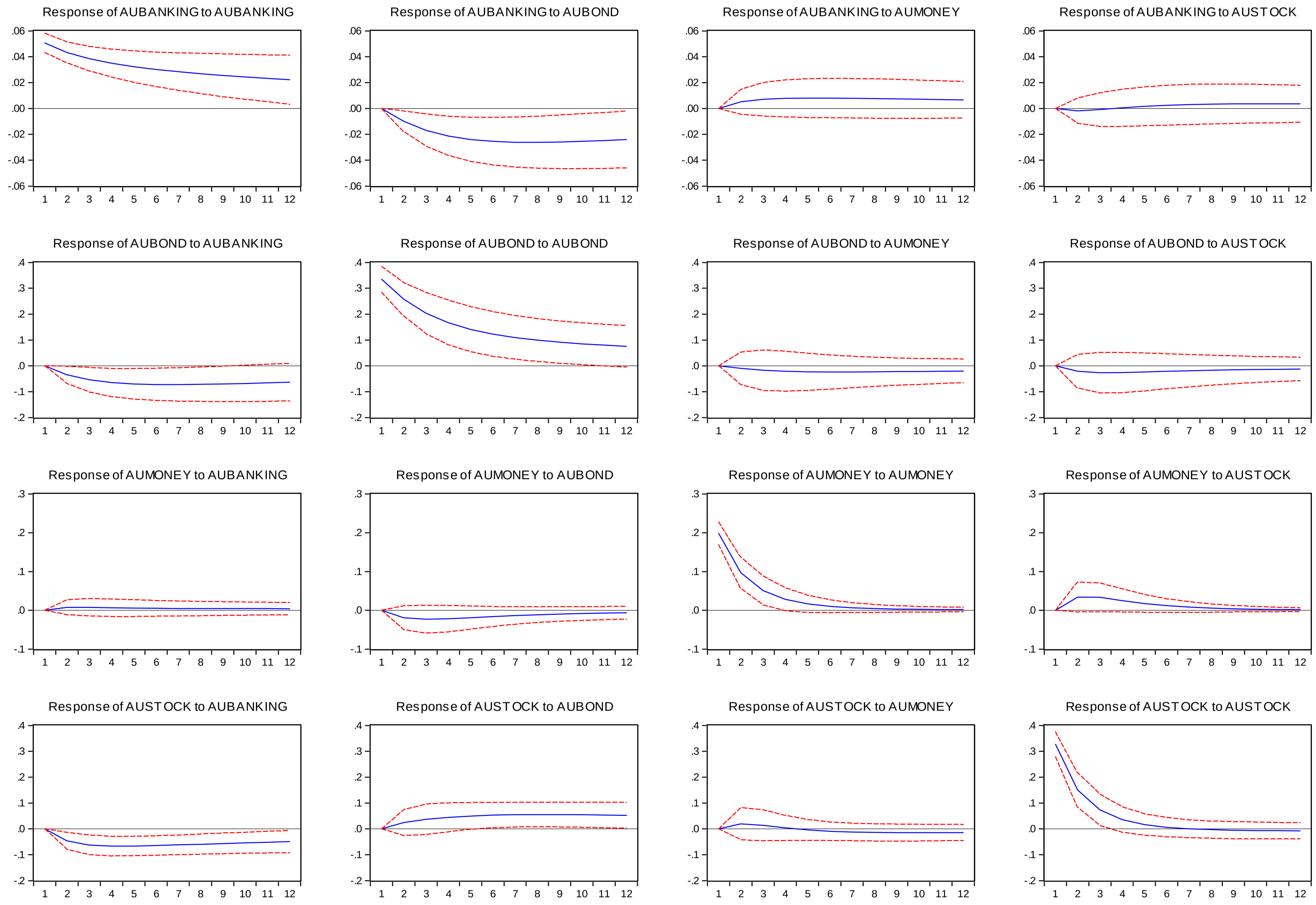


Figure A.35: Response of Belgian Financial Stress Indices to Financial Stress Shocks

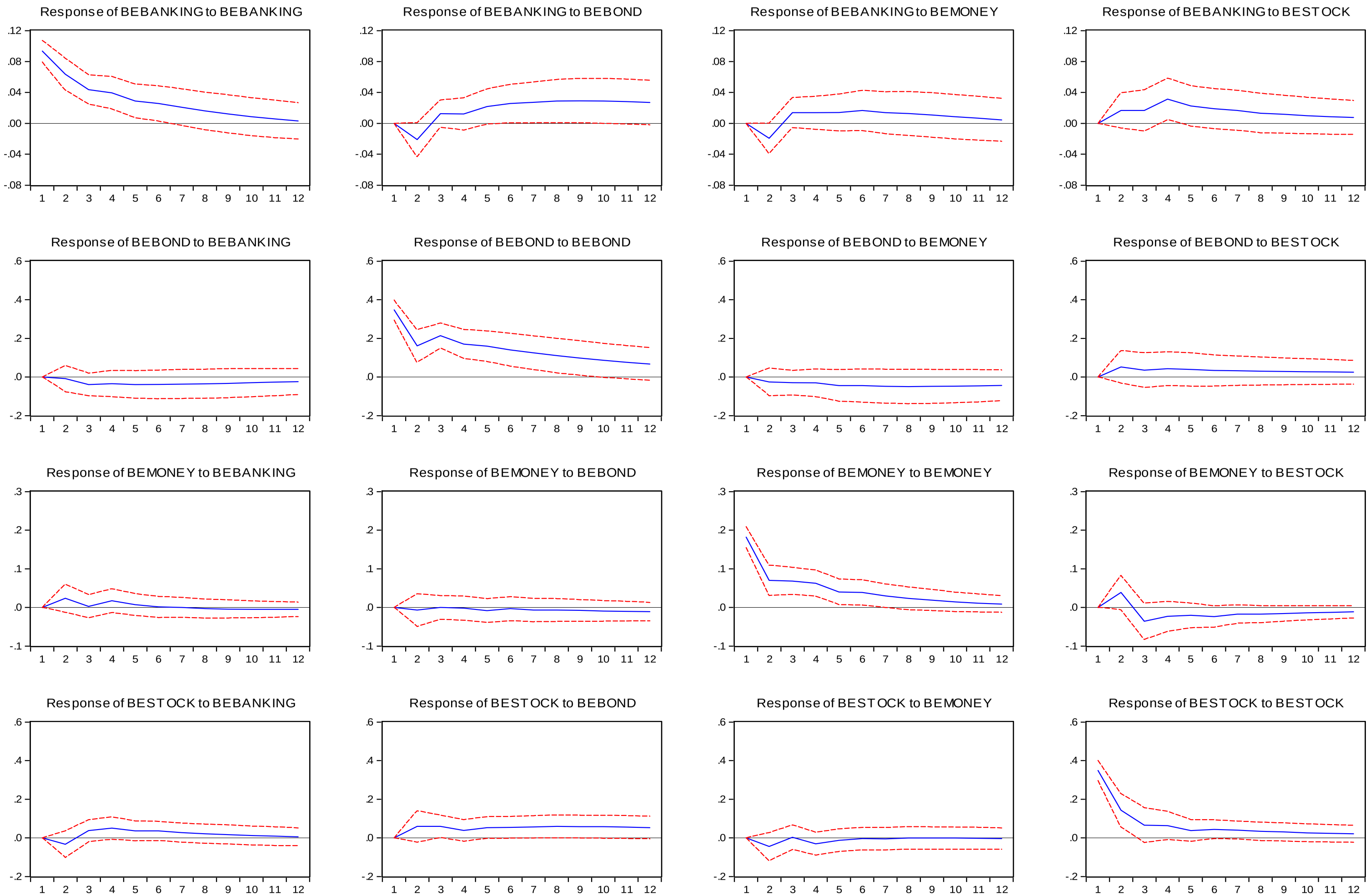


Figure A.36: Response of Finnish Financial Stress Indices to Financial Stress Shocks

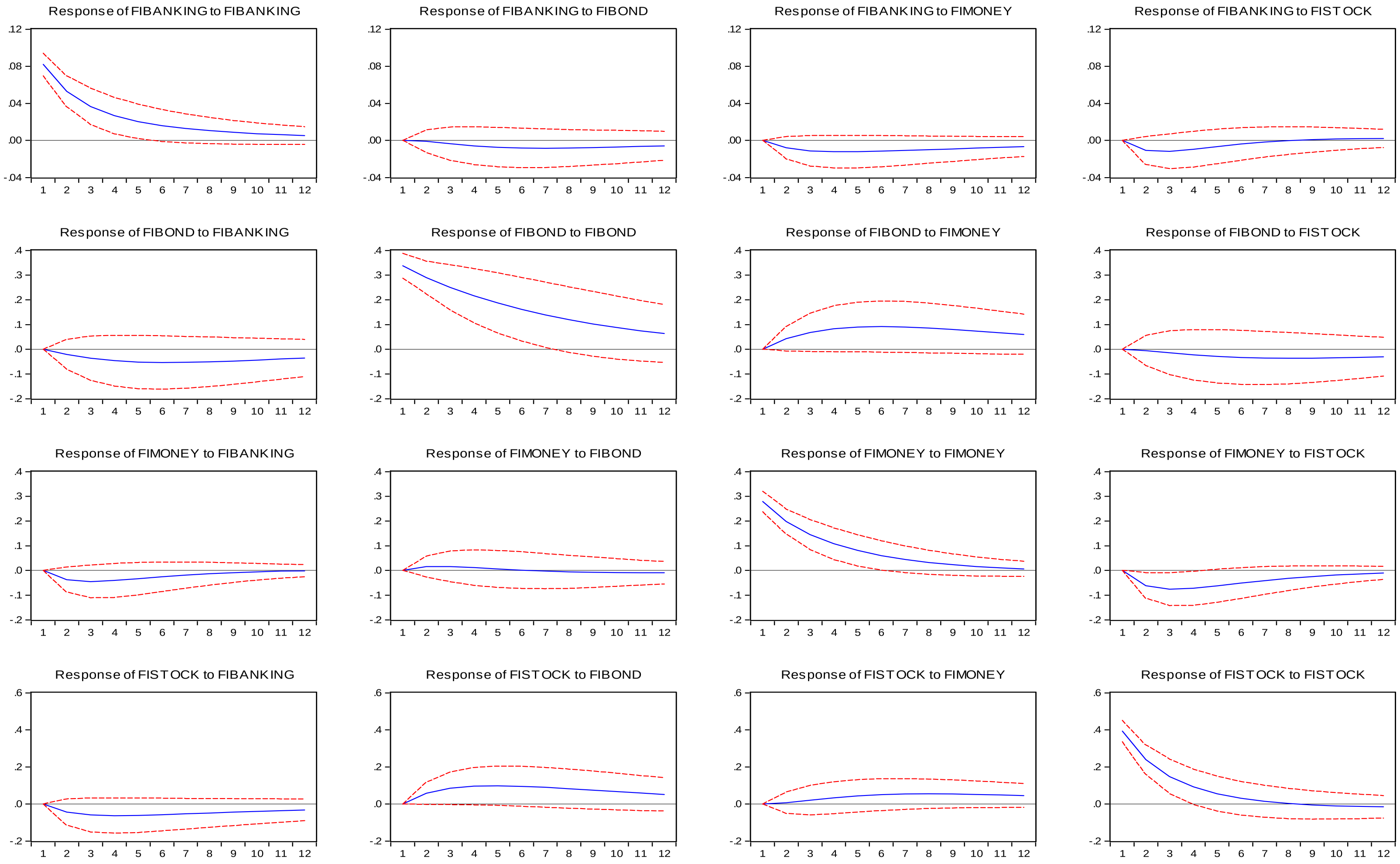


Figure A.37: Response of French Financial Stress Indices to Financial Stress Shocks

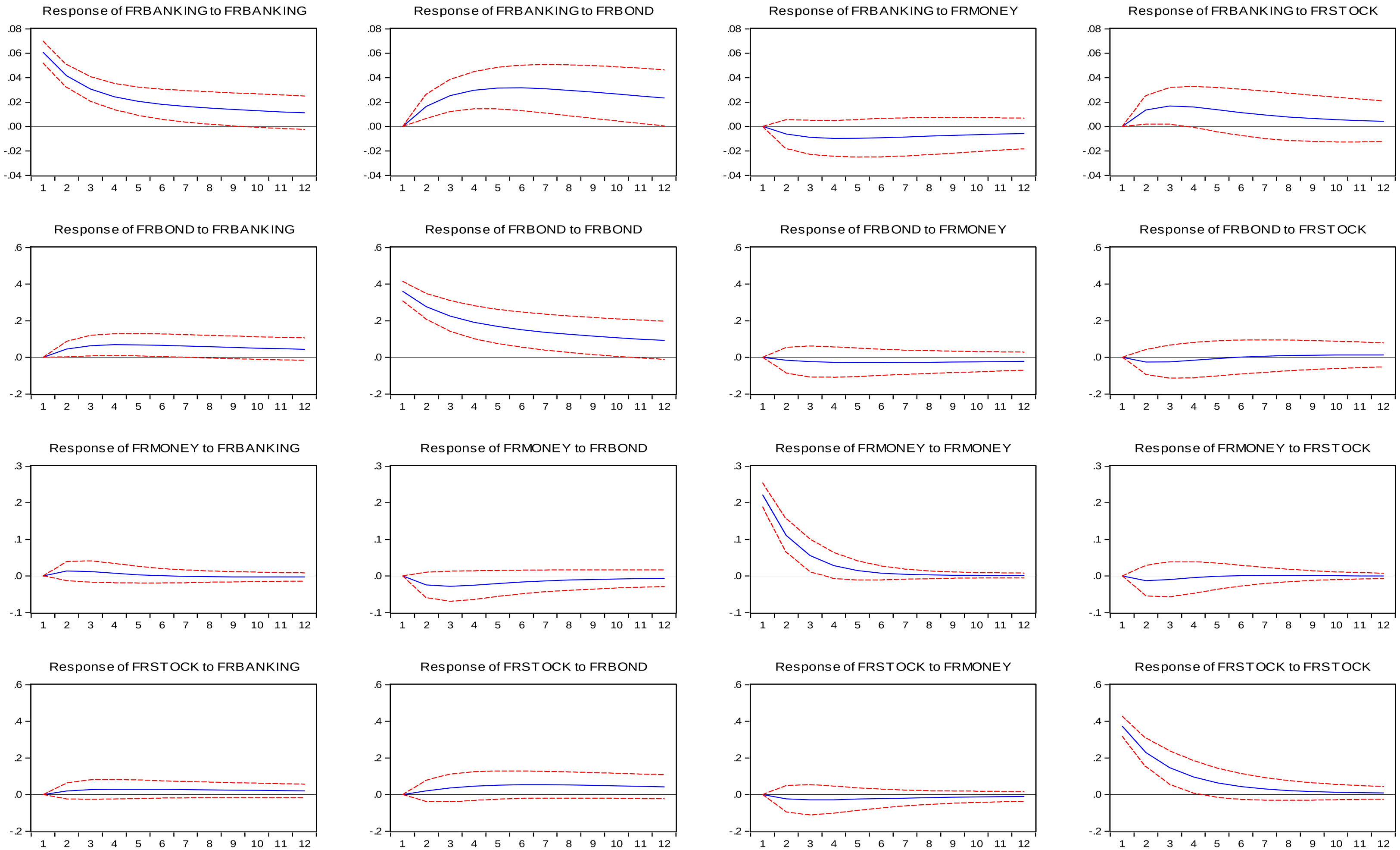


Figure A.38: Response of German Financial Stress Indices to Financial Stress Shocks

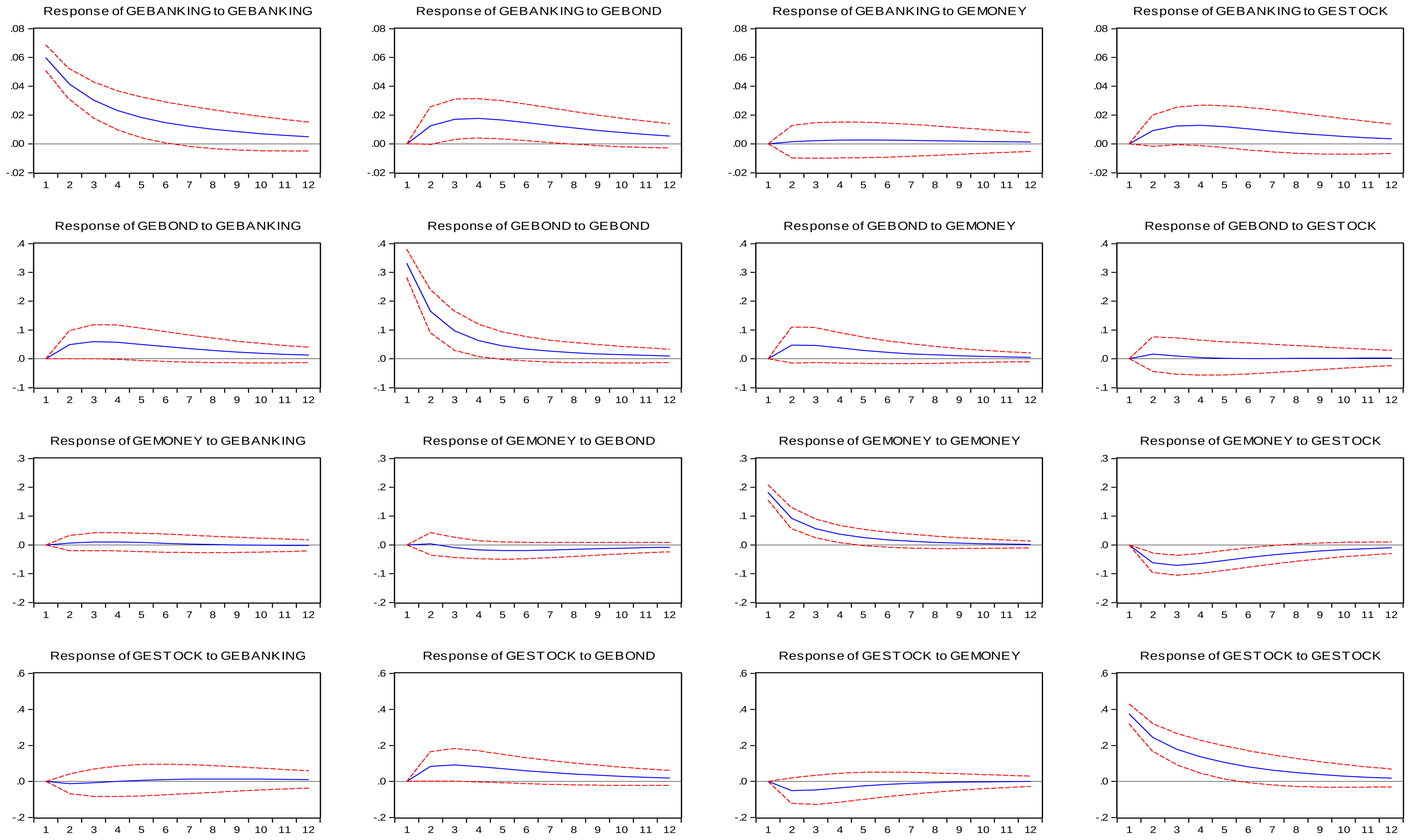


Figure A.39: Response of Greek Financial Stress Indices to Financial Stress Shocks

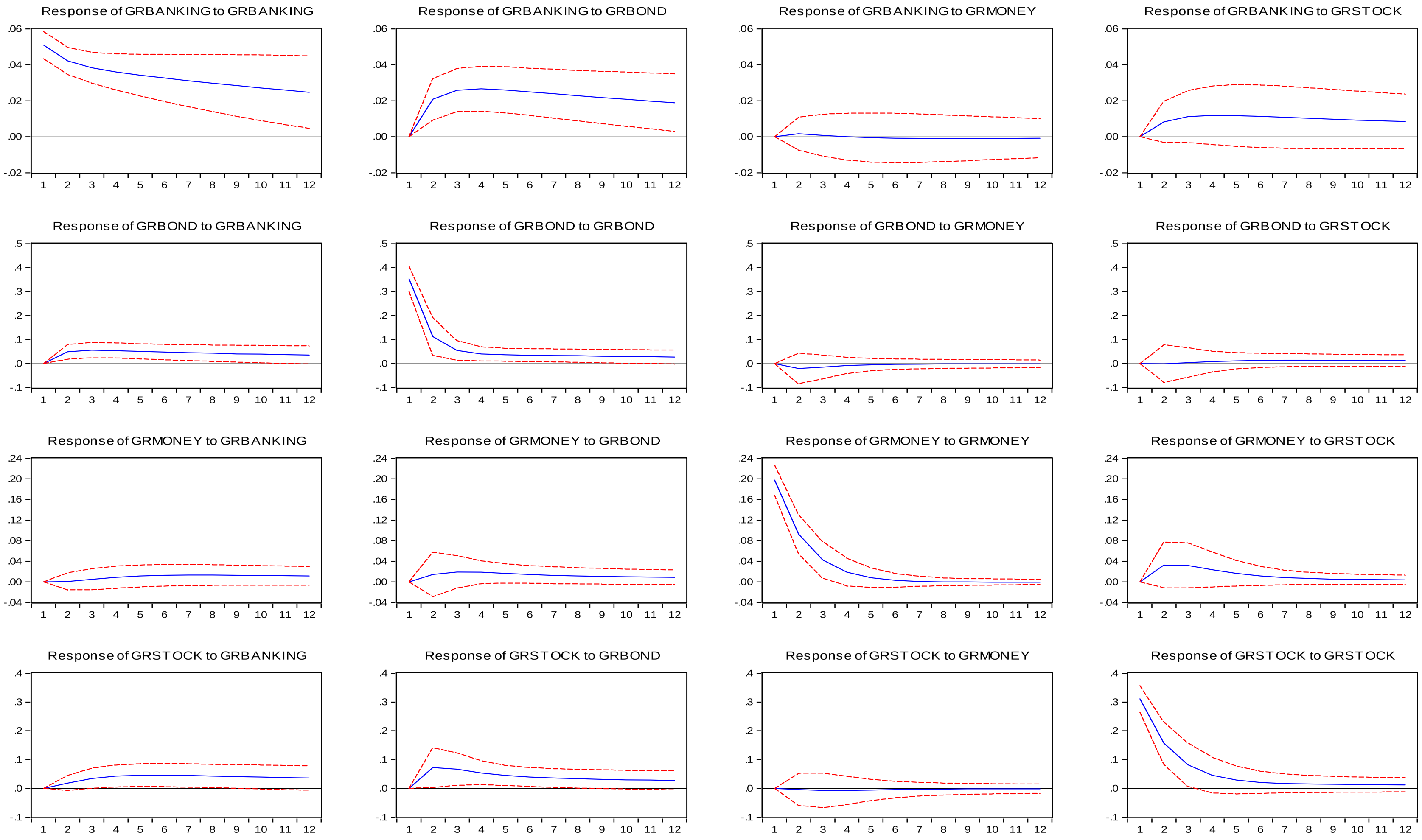


Figure A.40: Response of Irish Financial Stress Indices to Financial Stress Shocks

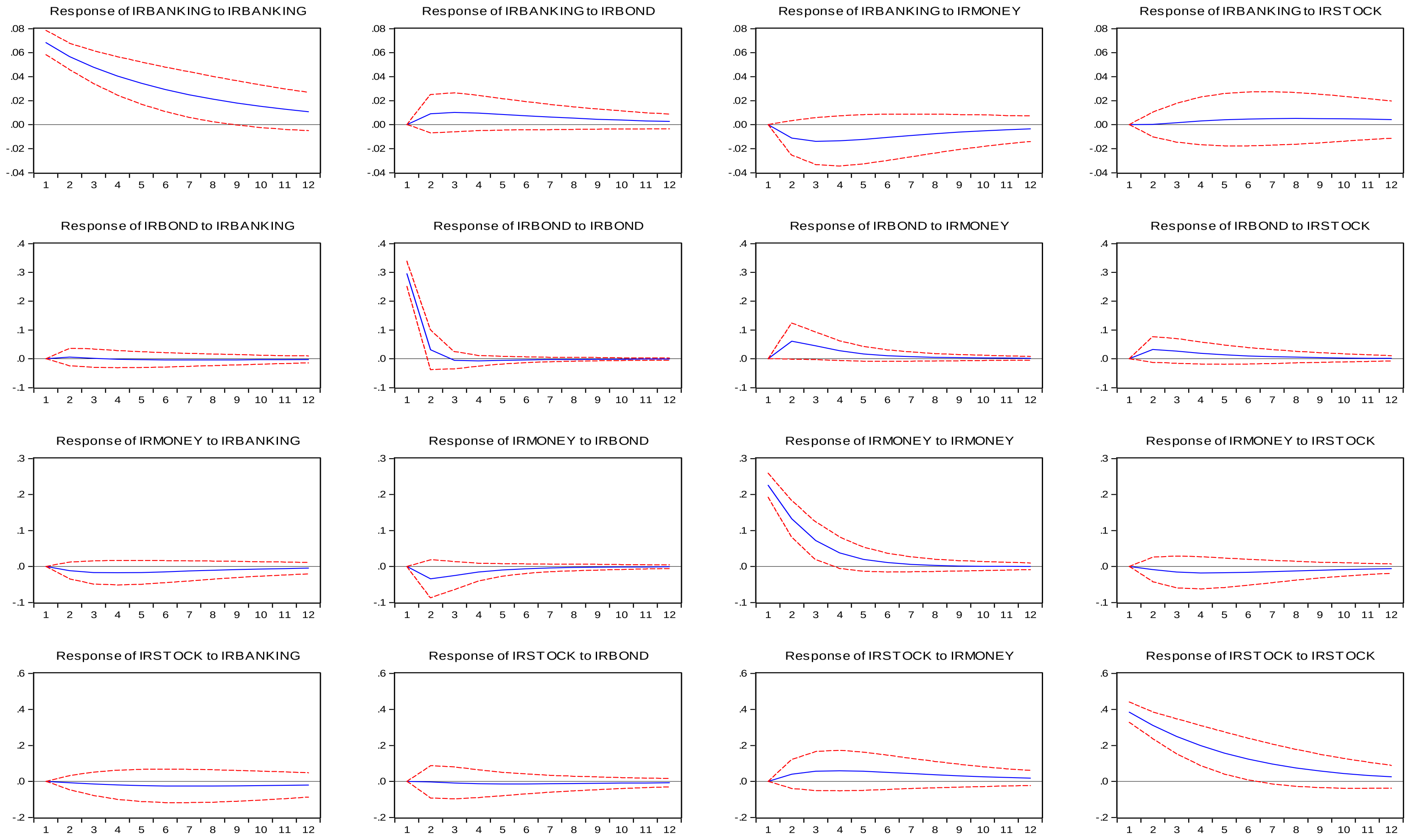


Figure A.41: Response of Italian Financial Stress Indices to Financial Stress Shocks

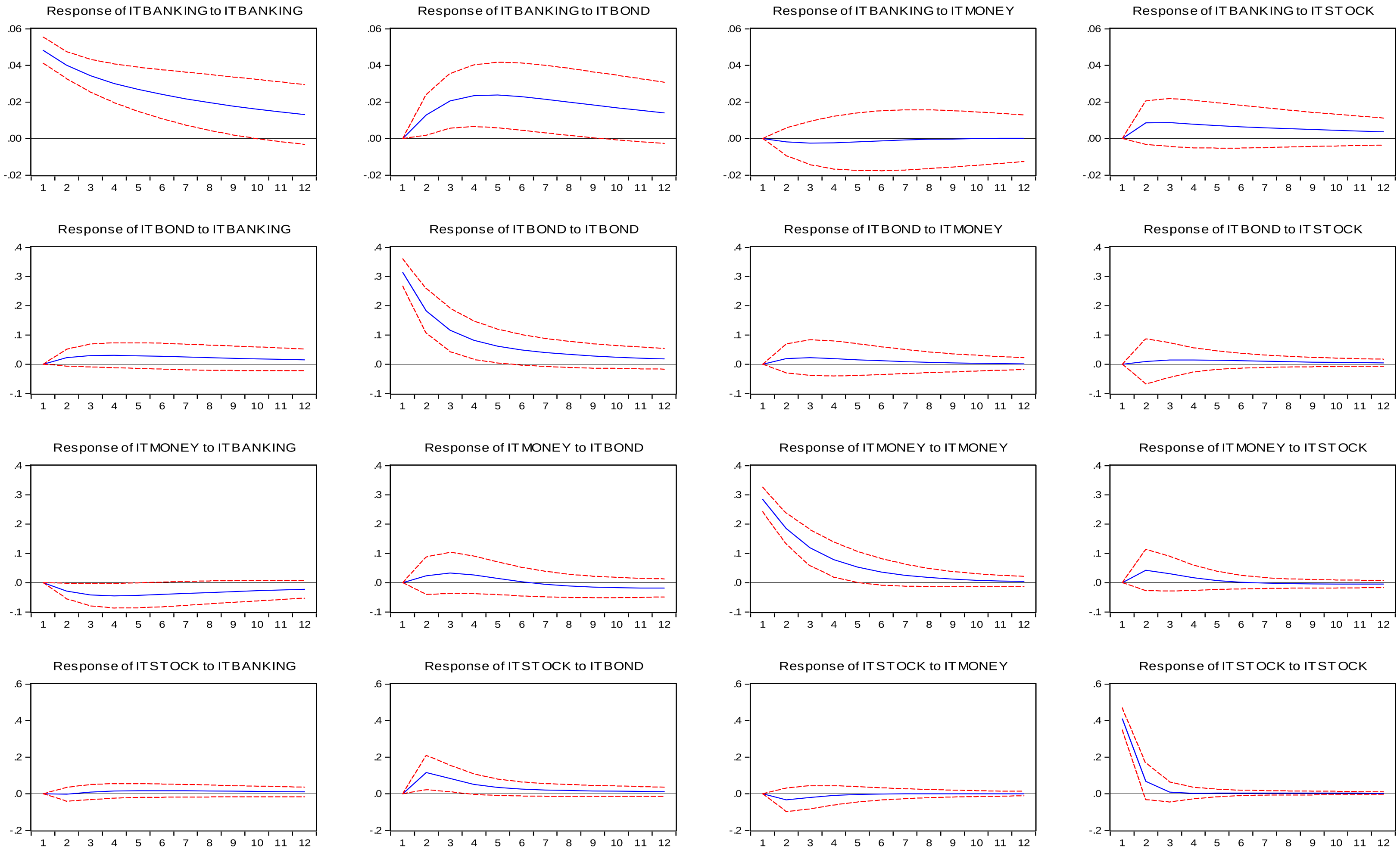


Figure A.42: Response of Dutch Financial Stress Indices to Financial Stress Shocks

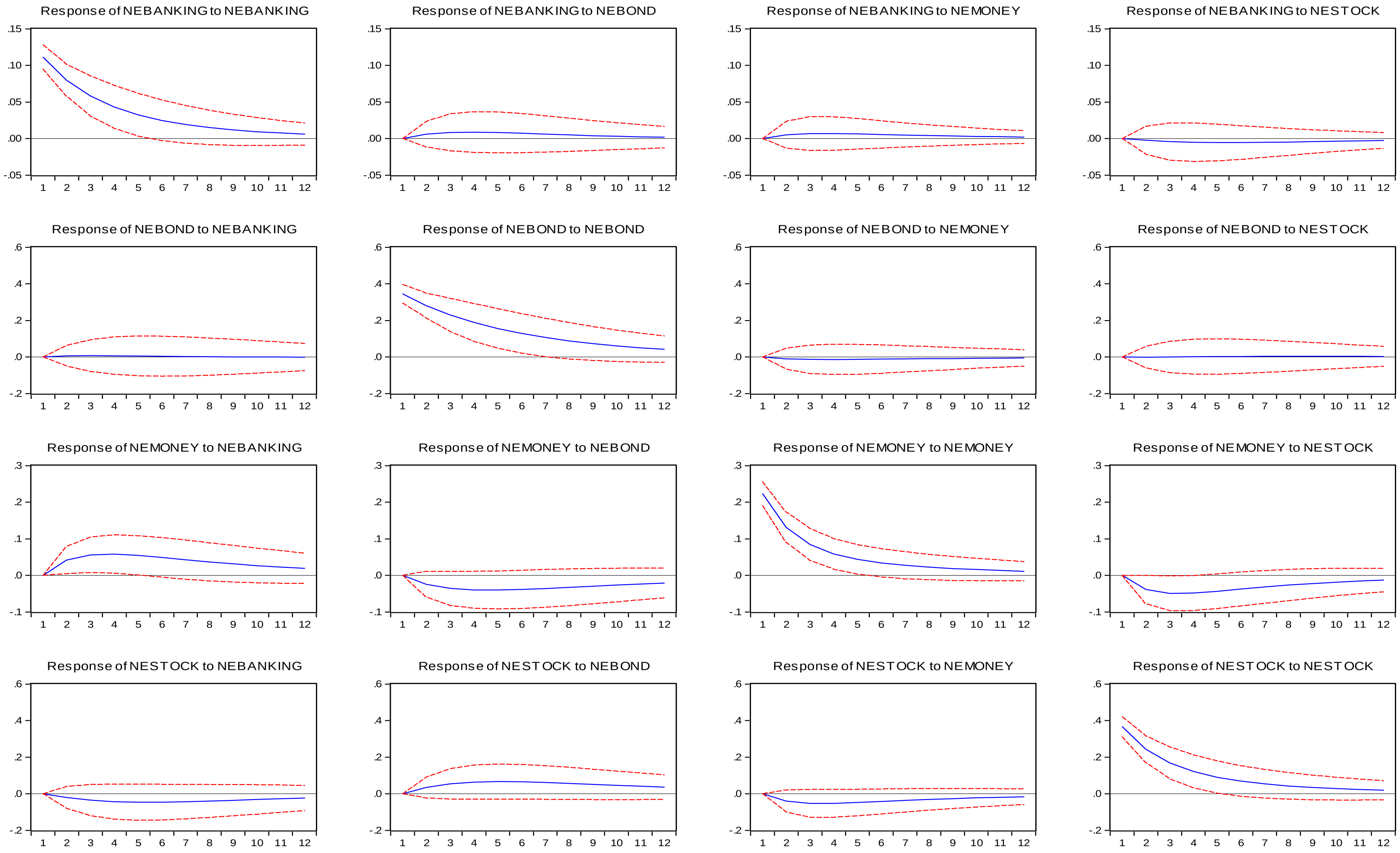


Figure A.43: Response of Portoguese Financial Stress Indices to Financial Stress Shocks

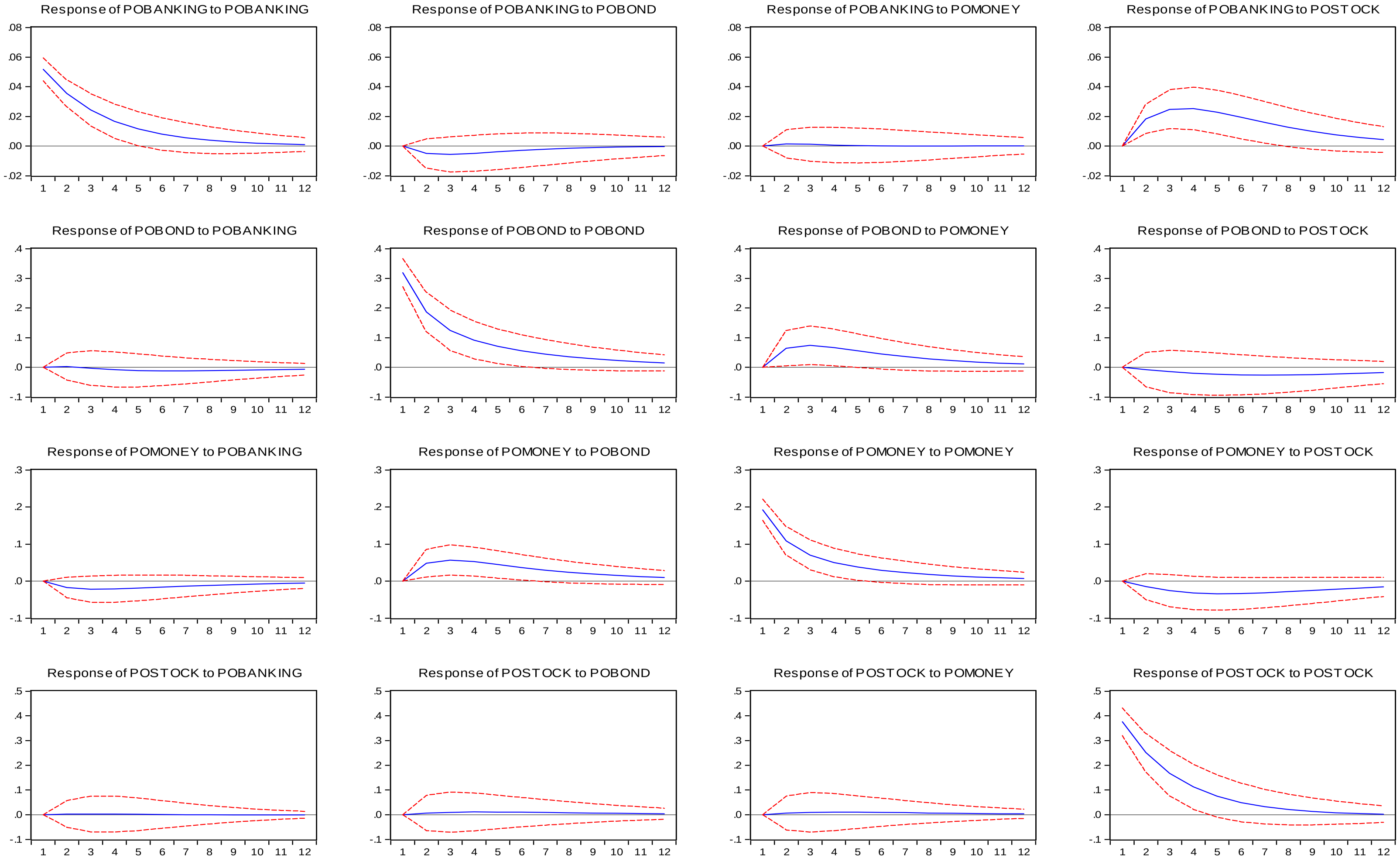
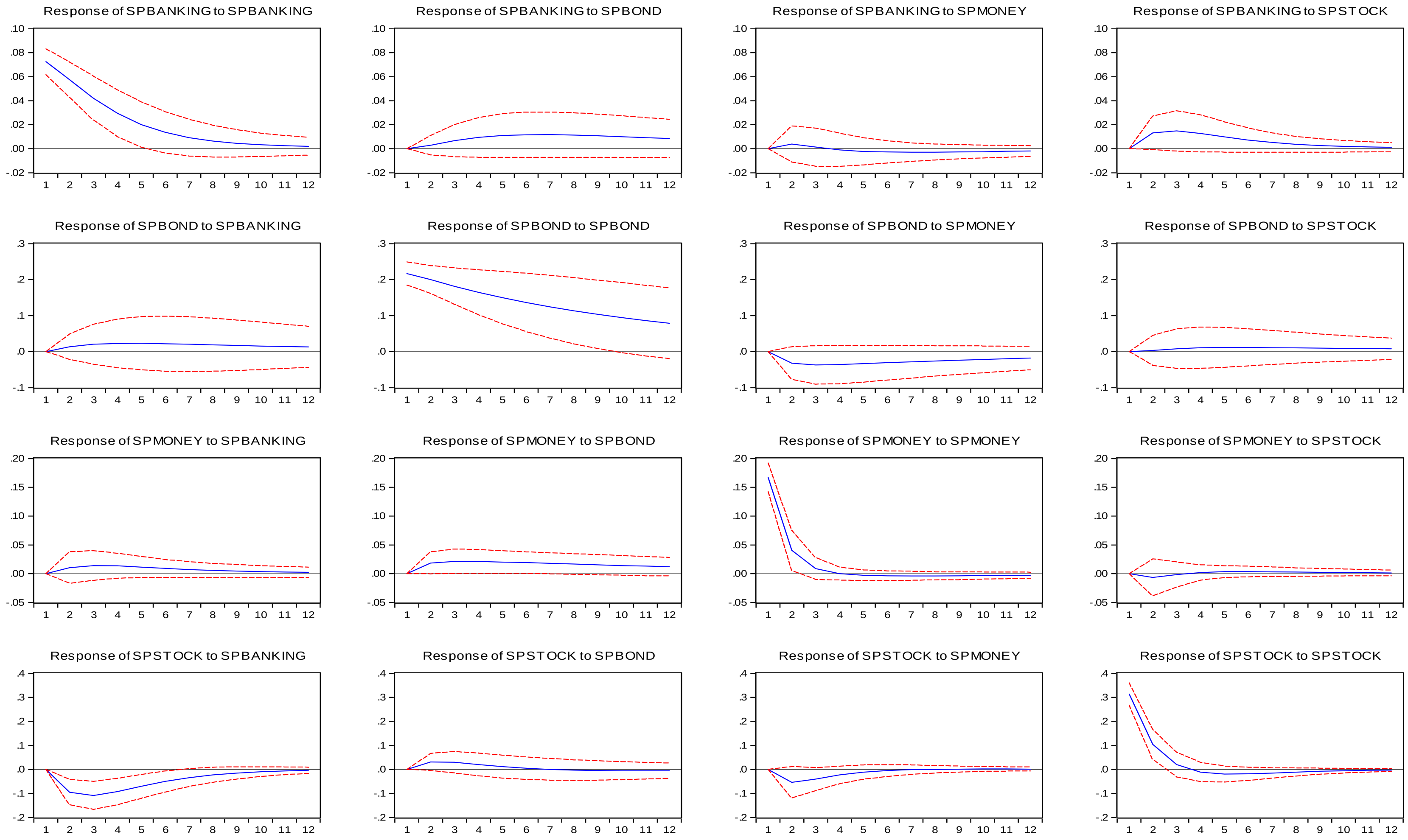


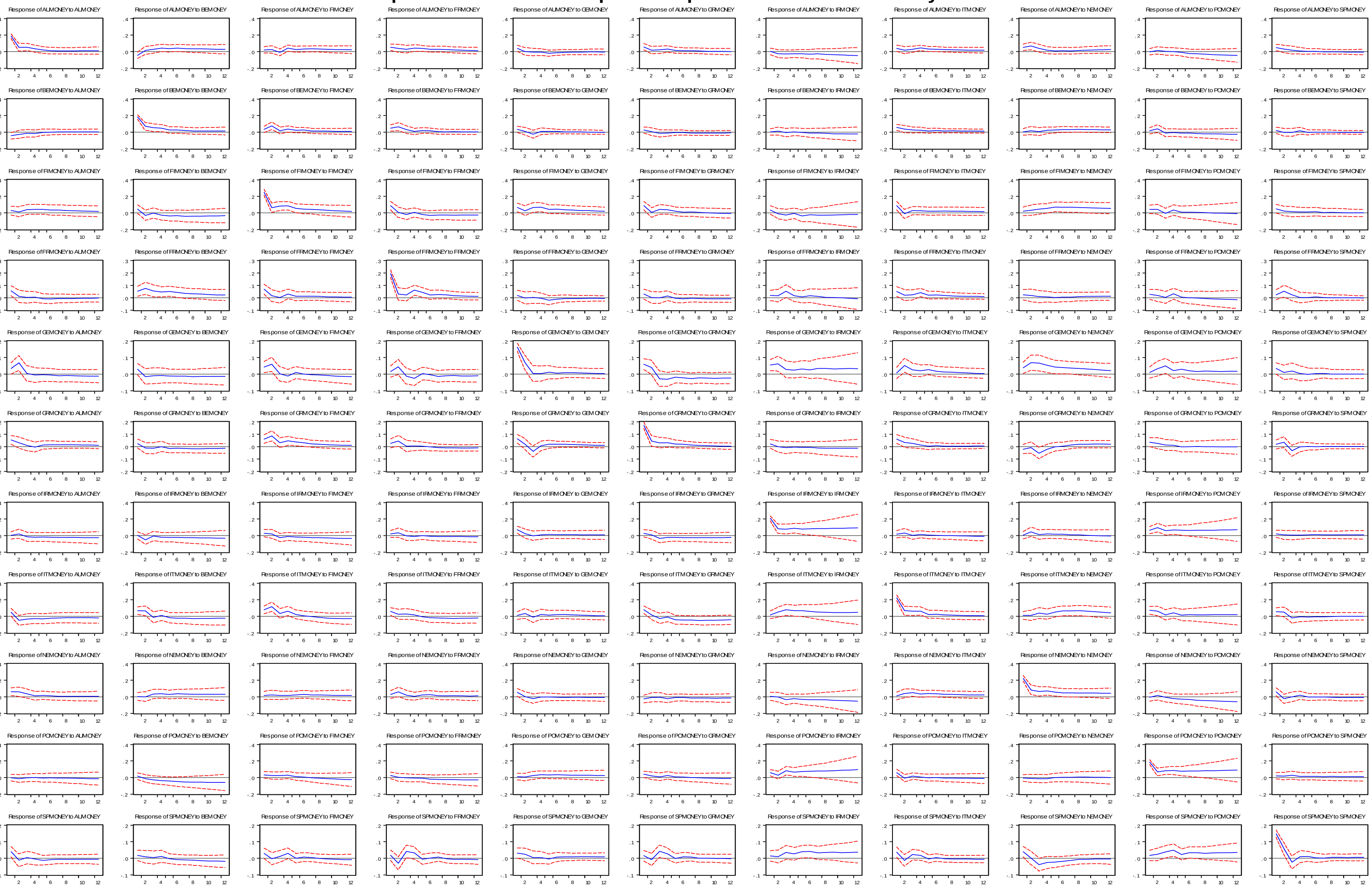
Figure A.44: Response of Spanish Financial Stress Indices to Financial Stress Shocks



Graph A45: Generalized Impulse Responses for Eurozone Countries

Graph A46: Generalized Impulse Responses for Eurozone Banking Sectors

Graph A47: Generalized Impulse Responses for Eurozone Money Markets



Graph A48: Generalized Impulse Responses for Eurozone Equity Markets

Graph A49: Generalized Impulse Responses for Eurozone Bond Markets

Table A.7: Block Exogeneity Wald Tests for Financial Stress Indices of Eurozone Countries (variable of each row do not Granger Cause variable of each column)

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria		0.963	0.595	0.513	0.762	0.718	0.516	0.247	0.610	0.774	0.845
Belgium	0.460		0.466	0.378	0.265	0.739	0.413	0.623	0.390	0.382	0.480
Finland	0.087 *	0.000 ***		0.001 ***	0.001 ***	0.059 *	0.001 ***	0.006 ***	0.005 ***	0.009 ***	0.031 **
France	0.697	0.042 **	0.287		0.136	0.292	0.328	0.007 ***	0.017 **	0.649	0.157
Germany	0.327	0.196	0.510	0.203		0.063 *	0.479	0.656	0.165	0.986	0.406
Greece	0.532	0.077 *	0.979	0.688	0.136		0.214	0.786	0.406	0.258	0.837
Ireland	0.214	0.112	0.496	0.111	0.302	0.033 **		0.024 **	0.167	0.763	0.096 *
Italy	0.001 ***	0.037 **	0.044 **	0.002 ***	0.586	0.043 **	0.695		0.141	0.562	0.298
Netherlands	0.171	0.054 *	0.881	0.194	0.070 *	0.236	0.127	0.134		0.855	0.230
Portugal	0.736	0.991	0.190	0.747	0.761	0.689	0.699	0.337	0.936		0.085 *
Spain	0.948	0.668	0.992	0.888	0.107	0.759	0.406	0.222	0.962	0.462	

*, ** and *** denote significance at 10%, 5% and 1%, respectively

the numbers represent the corresponding p-values

each element of the matrix examines whether the variable of each row Granger cause the variable of each column

Table A.8: Block Exogeneity Wald Tests for Banking Stress Indices (variable of each row do not Granger Cause variable of each column)

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria		0.000 ***	0.444	0.000 ***	0.073 *	0.019 **	0.170	0.670	0.836	0.208	0.155
Belgium	0.985		0.104	0.080 *	0.040 **	0.223	0.683	0.406	0.003 **	0.142	0.179
Finland	0.440	0.606		0.867	0.959	0.203	0.086 *	0.362	0.383	0.269	0.954
France	0.003 ***	0.636	0.673		0.514	0.070 *	0.844	0.942	0.023 **	0.160	0.147
Germany	0.605	0.005 ***	0.037 **	0.429		0.678	0.193	0.514	0.977	0.172	0.368
Greece	0.012 **	0.000 ***	0.297	0.002 ***	0.008 ***		0.824	0.541	0.701	0.087 *	0.993
Ireland	0.024 **	0.018 **	0.120	0.921	0.671	0.102		0.678	0.004 ***	0.754	0.381
Italy	0.192	0.167	0.558	0.000 ***	0.545	0.068 *	0.288		0.288	0.003 ***	0.025 **
Netherlands	0.372	0.199	0.186	0.001 ***	0.035 **	0.100	0.010 **	0.077 *		0.067 *	0.122
Portugal	0.651	0.493	0.629	0.072 *	0.003 ***	0.002 ***	0.210	0.000 ***	0.661		0.000 ***
Spain	0.437	0.731	0.345	0.583	0.829	0.887	0.343	0.056 *	0.114	0.164	

*, ** and *** denote significance at 10%, 5% and 1%, respectively

the numbers represent the corresponding p-values

each element of the matrix examines whether the variable of each row Granger cause the variable of each column

Table A.9: Block Exogeneity Wald Tests for Money Markets Stress Indices (variable of each row do not Granger Cause variable of each column)

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria		0.612	0.969	0.094 *	0.348	0.700	0.634	0.034 **	0.244	0.653	0.971
Belgium	0.448		0.492	0.000 ***	0.313	0.248	0.153	0.440	0.822	0.545	0.821
Finland	0.165	0.006 ***		0.546	0.212	0.000 ***	0.603	0.000 ***	0.925	0.230	0.941
France	0.849	0.348	0.353		0.134	0.486	0.421	0.305	0.293	0.991	0.004 ***
Germany	0.388	0.286	0.171	0.075 *		0.329	0.914	0.141	0.843	0.869	0.271
Greece	0.308	0.585	0.781	0.958	0.235		0.192	0.620	0.538	0.390	0.113
Ireland	0.483	0.848	0.256	0.003 ***	0.180	0.504		0.019 **	0.824	0.067 *	0.435
Italy	0.511	0.341	0.328	0.289	0.031 **	0.055 *	0.440		0.042 **	0.155	0.270
Netherlands	0.018 **	0.676	0.517	0.924	0.025 **	0.239	0.175	0.134		0.969	0.329
Portugal	0.595	0.131	0.124	0.065 *	0.472	0.745	0.004 ***	0.018 **	0.810		0.180
Spain	0.955	0.503	0.739	0.119	0.086 *	0.006 ***	0.775	0.176	0.018 **	0.484	

*, ** and *** denote significance at 10%, 5% and 1%, respectively

the numbers represent the corresponding p-values

each element of the matrix examines whether the variable of each row Granger cause the variable of each column

Table A.10:Block Exogeneity Wald Tests for Equity Markets Stress Indices (variable of each row do not Granger Cause variable of each column)

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria		0.587	0.857	0.930	0.584	0.469	0.322	0.683	0.379	0.744	0.481
Belgium	0.004 ***		0.036 **	0.165	0.015 **	0.290	0.237	0.340	0.487	0.117	0.270
Finland	0.056 *	0.629		0.969	0.759	0.407	0.722	0.716	0.676	0.864	0.939
France	0.675	0.395	0.531		0.526	0.951	0.486	0.506	0.712	0.829	0.570
Germany	0.206	0.236	0.221	0.937		0.155	0.808	0.595	0.837	0.723	0.407
Greece	0.843	0.541	0.778	0.399	0.215		0.698	0.744	0.256	0.463	0.282
Ireland	0.181	0.000 ***	0.013 **	0.012 **	0.010 ***	0.001 ***		0.005 ***	0.002 ***	0.002 ***	0.308
Italy	0.000 ***	0.000 ***	0.001 ***	0.000 ***	0.000 ***	0.004 ***	0.008 ***		0.001 ***	0.000 ***	0.032 **
Netherlands	0.259	0.113	0.200	0.530	0.735	0.981	0.655	0.593		0.237	0.491
Portugal	0.938	0.398	0.316	0.824	0.668	0.743	0.519	0.841	0.853		0.218
Spain	0.661	0.579	0.884	0.976	0.699	0.783	0.429	0.740	0.764	0.303	

*, ** and *** denote significance at 10%, 5% and 1%, respectively

the numbers represent the corresponding p-values

each element of the matrix examines whether the variable of each row Granger cause the variable of each column

Table A.11: Block Exogeneity Wald Tests for Bond Markes Stress Indices (variable of each row do not Granger Cause variable of each column)

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Au Austria		0.863	0.206	0.497	0.777	0.835	0.583	0.984	0.344	0.625	0.700
Be Belgium	0.012 **		0.060 *	0.532	0.709	0.928	0.374	0.195	0.145	0.396	0.977
Fi Finland	0.006 ***	0.110		0.007 ***	0.054 *	0.520	0.934	0.036 **	0.042 **	0.161	0.167
Fr France	0.928	0.357	0.946		0.009 ***	0.578	0.571	0.032 **	0.421	0.839	0.284
Ge Germany	0.530	0.516	0.096 *	0.001 ***		0.509	0.925	0.087 *	0.054 *	0.642	0.964
Gr Greece	0.298	0.533	0.424	0.605	0.030 **		0.728	0.975	0.188	0.435	0.378
Ire Ireland	0.804	0.785	0.337	0.413	0.292	0.969		0.815	0.717	0.465	0.874
Ita Italy	0.374	0.032 **	0.342	0.053 *	0.474	0.109	0.126		0.432	0.196	0.500 **
Ne Netherlands	0.995	0.251	0.516	0.003 ***	0.049 **	0.714	0.460	0.339		0.735	0.573
Po Portugal	0.185	0.344	0.005 ***	0.905	0.324	0.713	0.918	0.967	0.405		0.483
Sp Spain	0.000 ***	0.000 ***	0.007 ***	0.001 ***	0.002 ***	0.186	0.136	0.001 ***	0.000 ***	0.107	

*, *, ** and *** denote significance at 10%, 5% and 1%, respectively

th the numbers represent the corresponding p-values

ea each element of the matrix examines whether the variable of each row Granger cause the variable of each column

Graph A50: Generalized Impulse Responses for Eurozone Countries - First Principal Component Based FSI

Graph A51: Generalized Impulse Responses for Eurozone Banking Sectors - First Principal Component Based FSI

Graph A52: Generalized Impulse Responses for Eurozone Money Markets - First Principal Component Based FSI

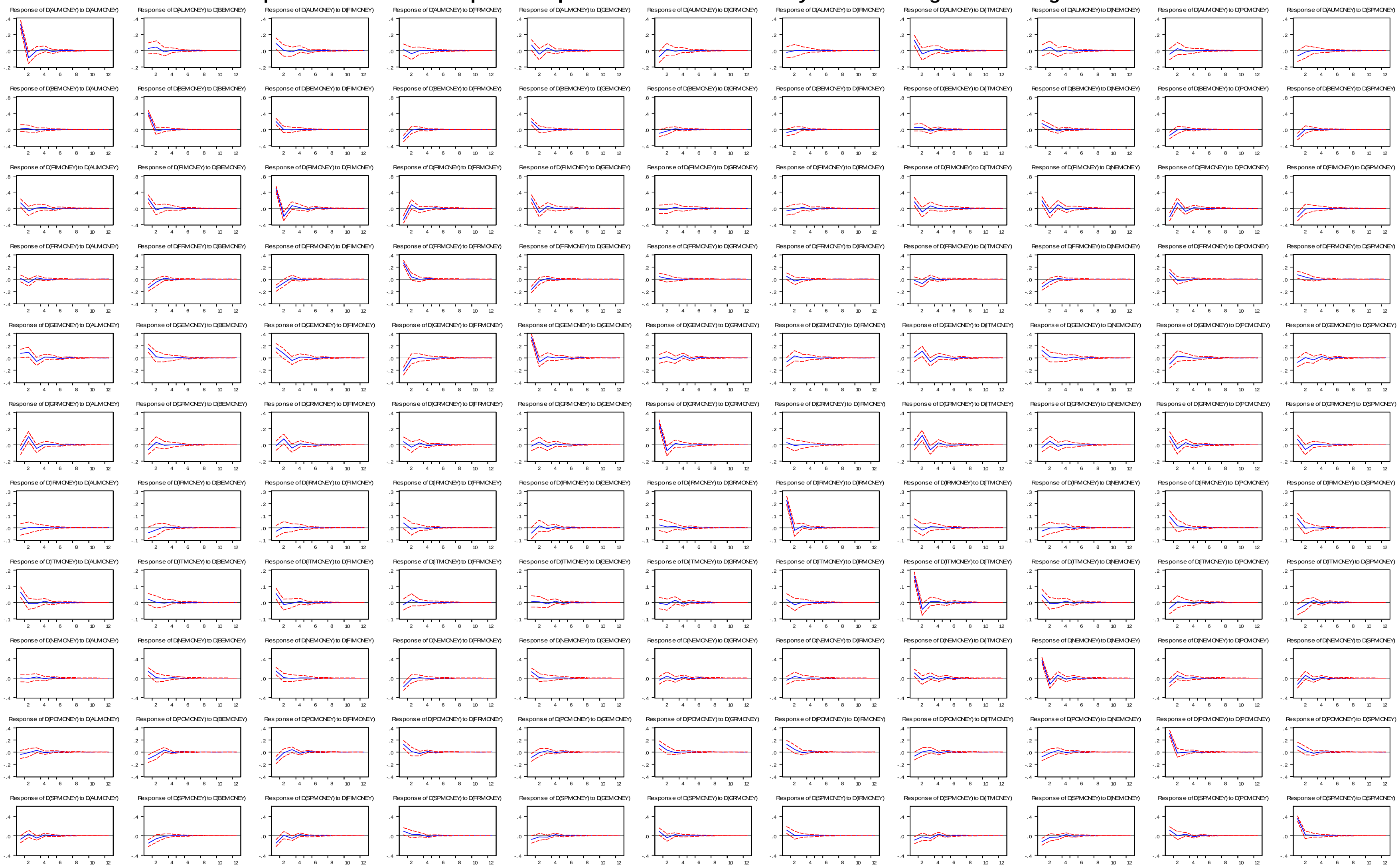
Graph A53: Generalized Impulse Responses for Eurozone Equity Markets - First Principal Component Based FSI

Graph A54: Generalized Impulse Responses for Eurozone Bond Markets - First Principal Component Based FSI

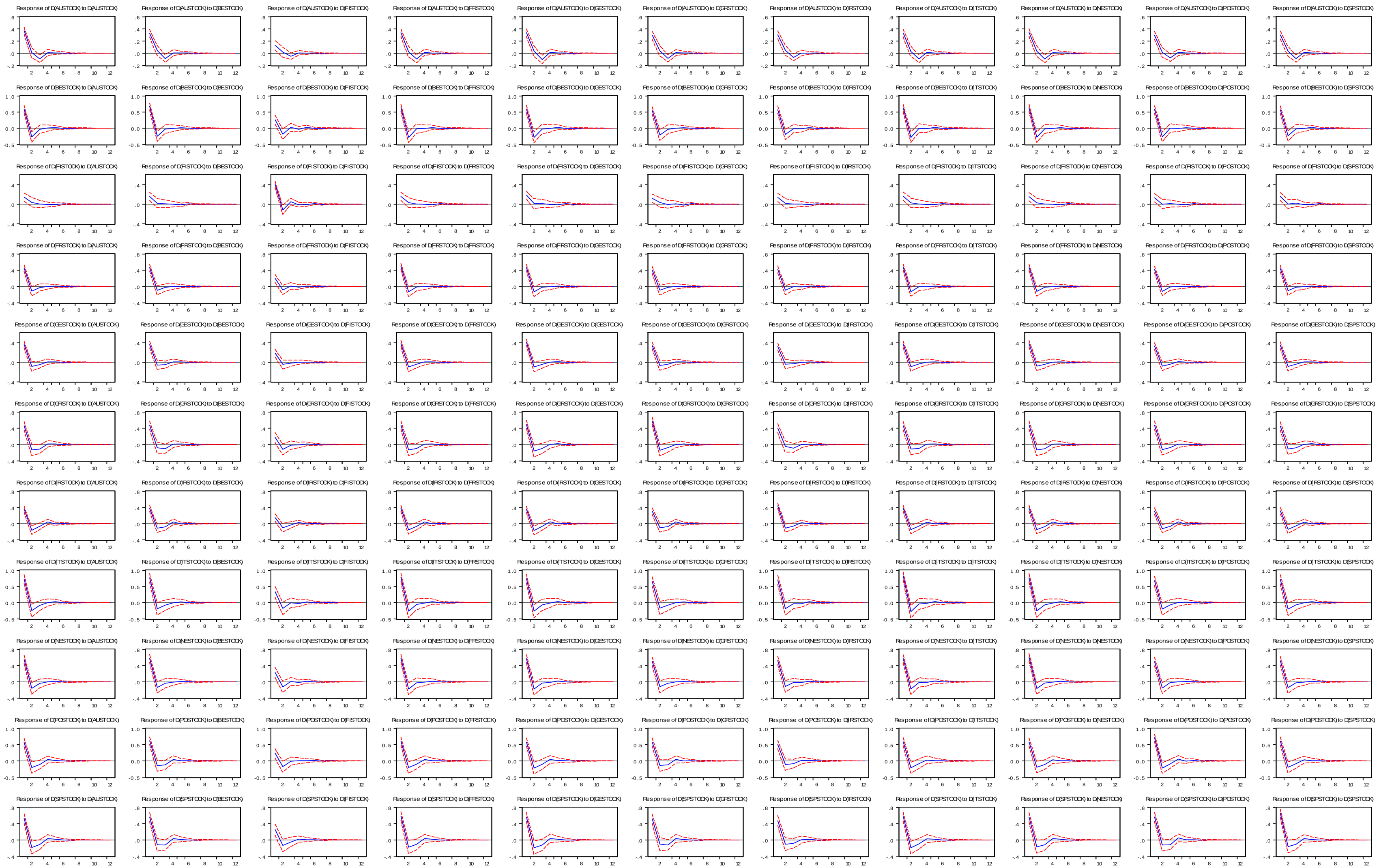
Graph A55: Generalized Impulse Responses for Eurozone Countries - Weighted Loadings Based FSI

Graph A56: Generalized Impulse Responses for Eurozone Banking Sectors - Weighted Loadings Based FSI

Graph A57: Generalized Impulse Responses for Eurozone Money Markets - Weighted Loadings Based FSI



Graph A58: Generalized Impulse Responses for Eurozone Equity Markets - Weighted Loadings Based FSI



Graph A59: Generalized Impulse Responses for Eurozone Bond Markets - Weighted Loadings Based FSI

Chapter 4

Figure A.1: Euro Area Countries FSIs

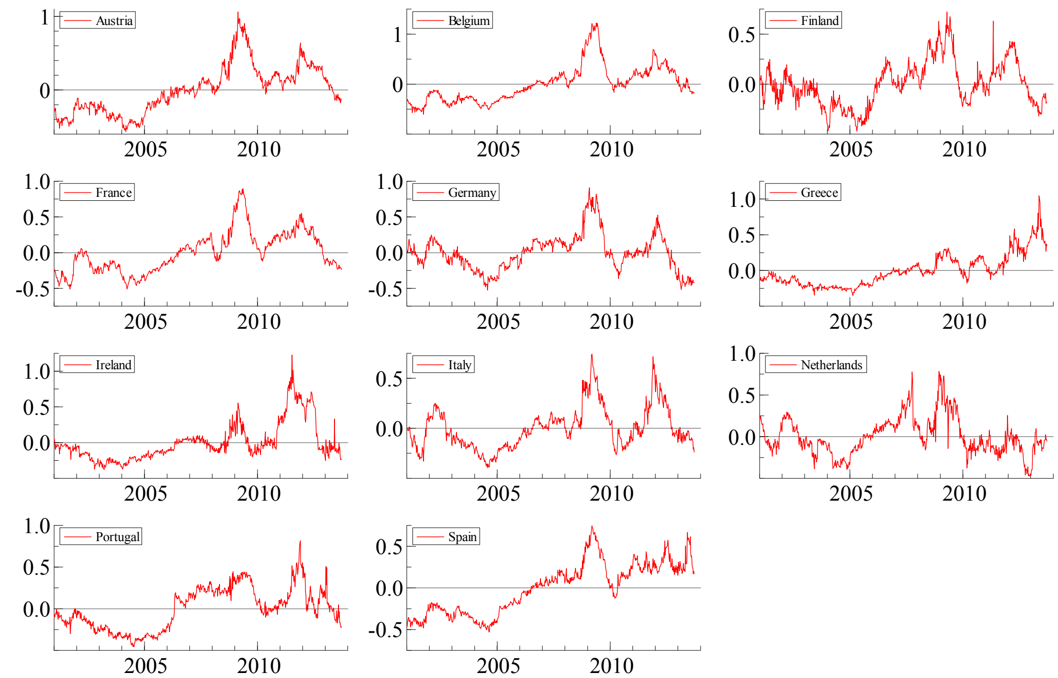


Figure A.2: Euro Area Countries FSIs Returns

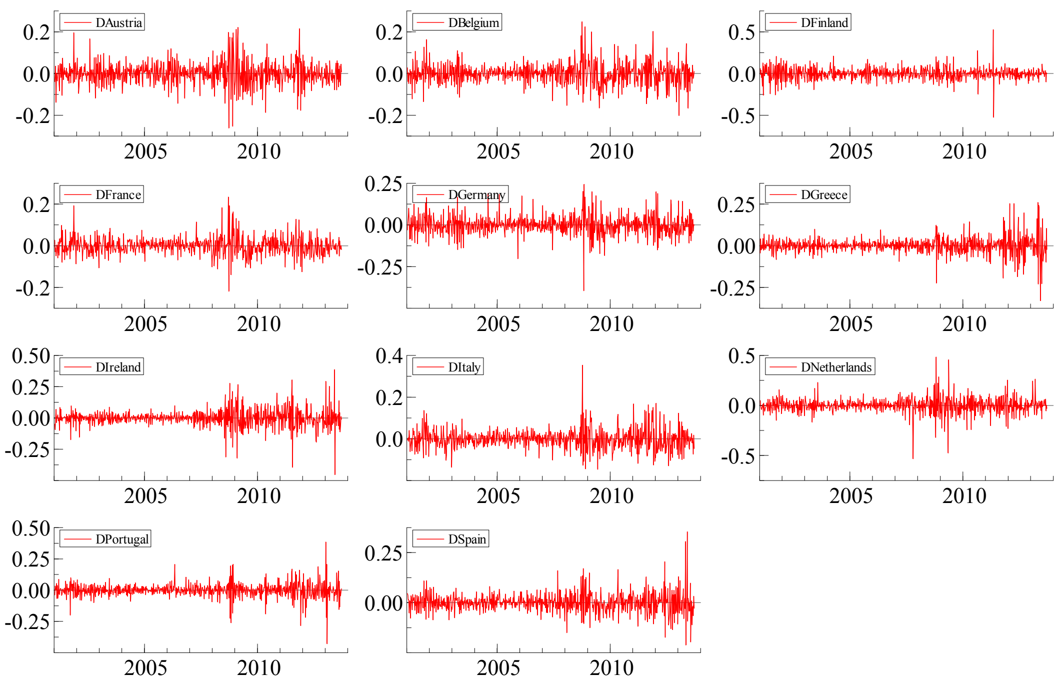


Figure A.3: Euro Area Banking FSIs

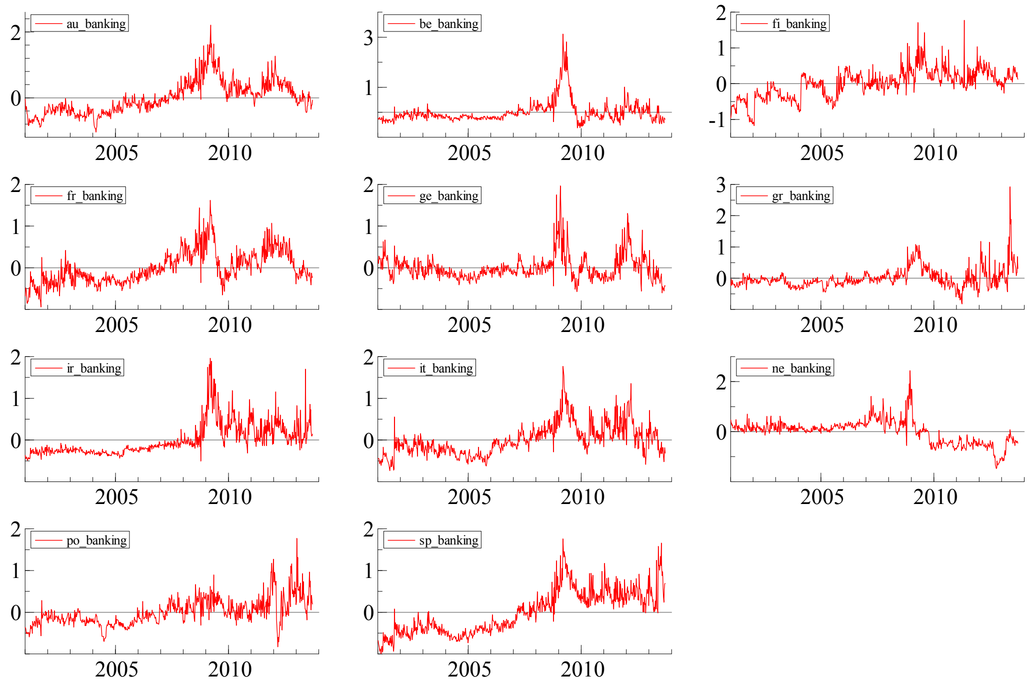


Figure A.4: Euro Area Banking FSIs Returns

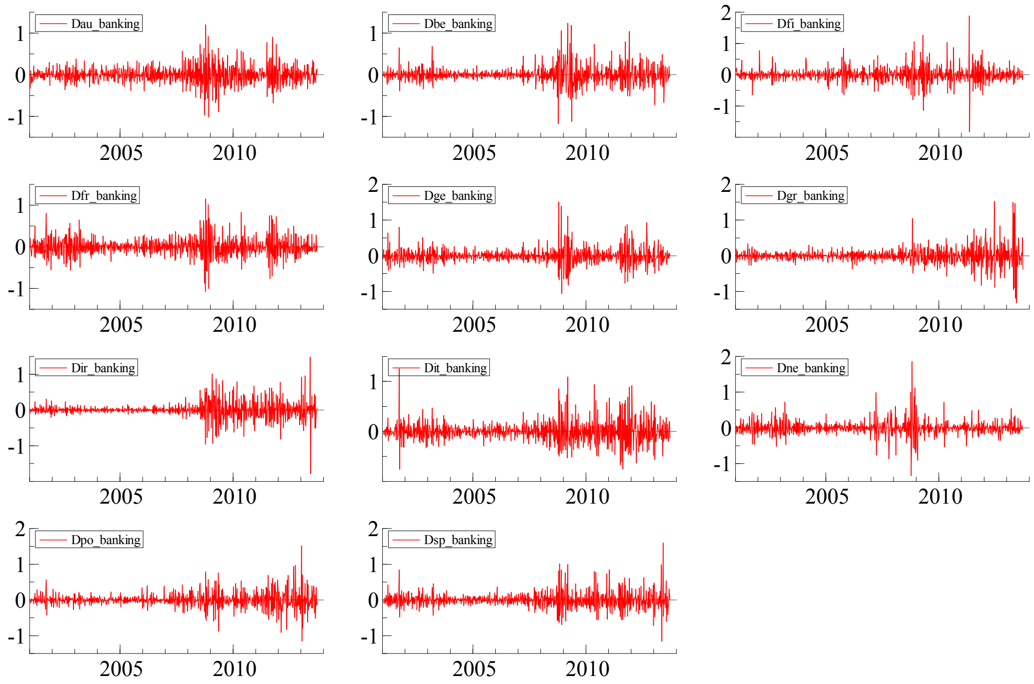


Figure A.5: Euro Area Money FSIs

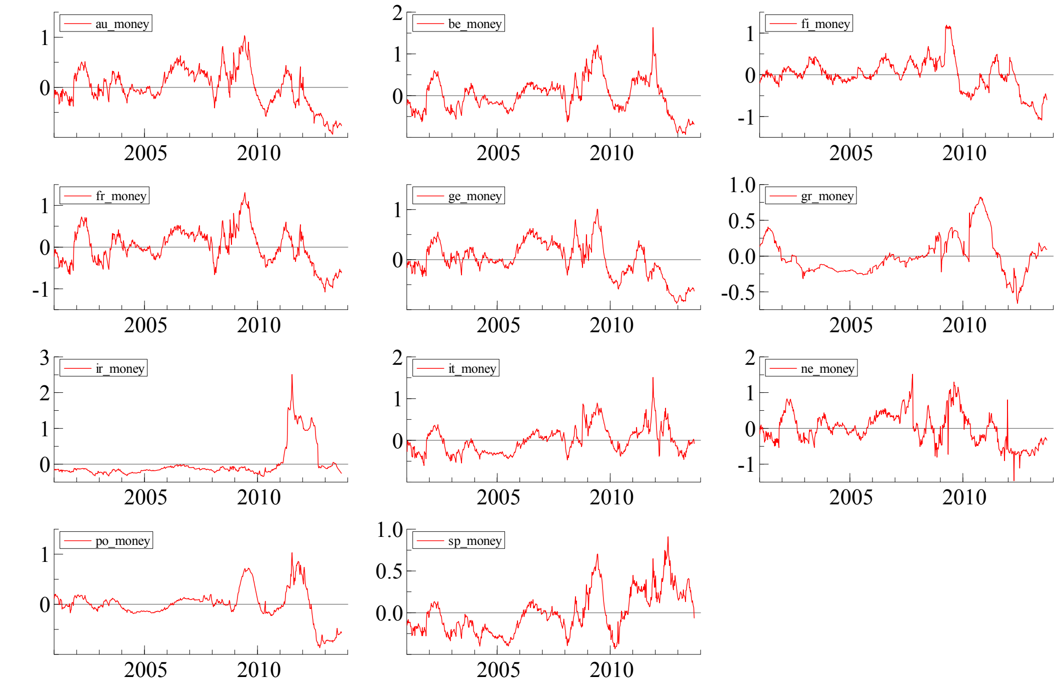


Figure A.6: Euro Area Money FSIs Returns

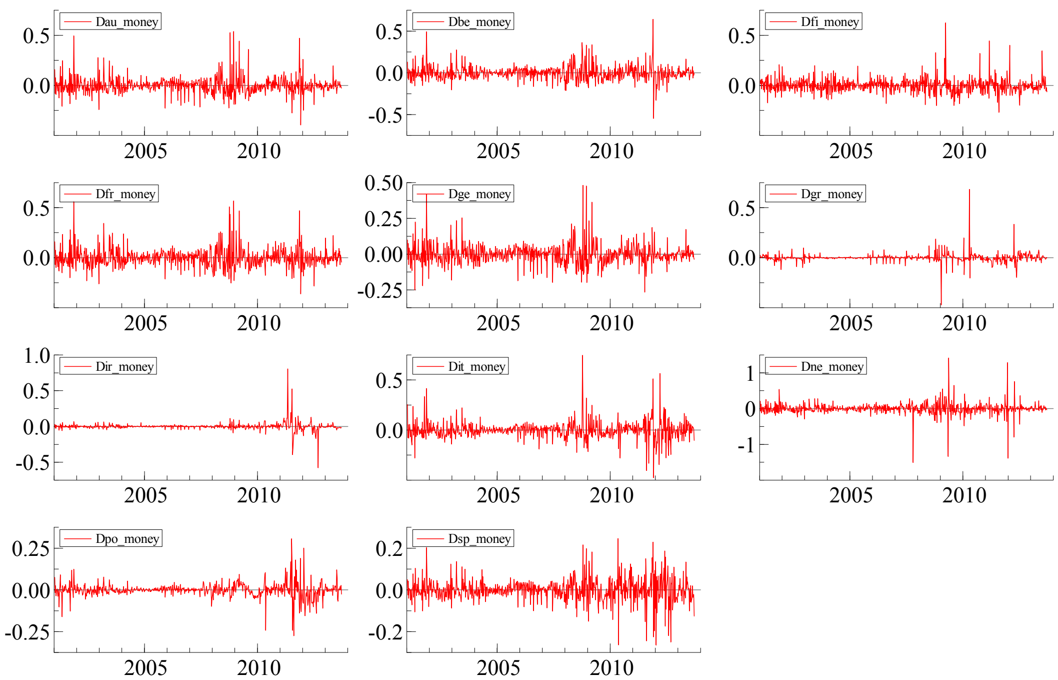


Figure A.7: Euro Area Equity FSIs

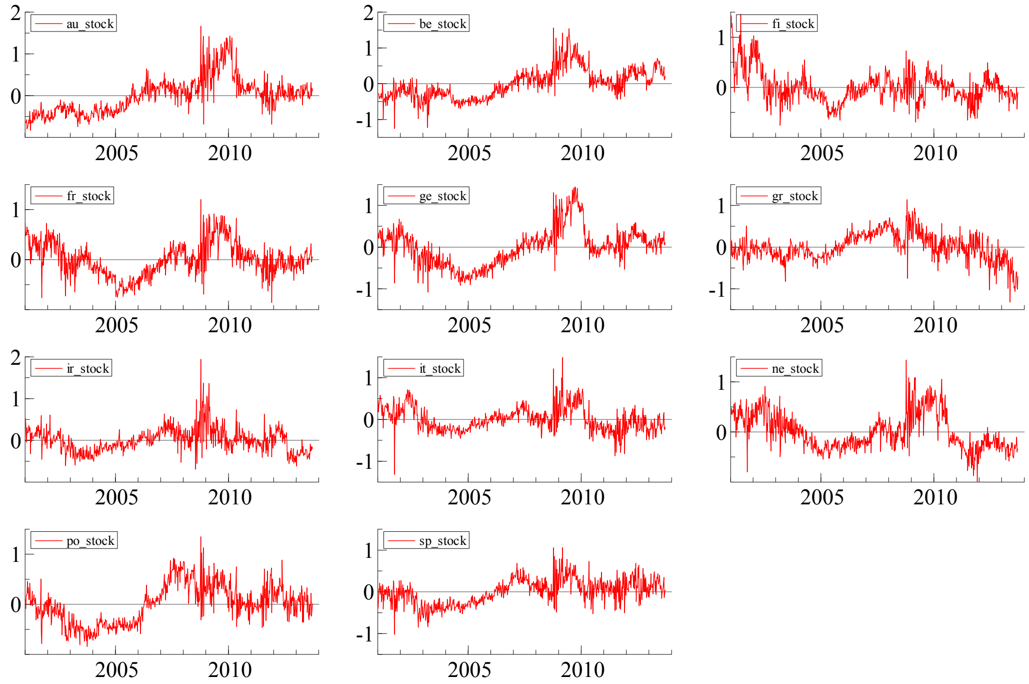


Figure A.8: Euro Area Equity FSIs Returns

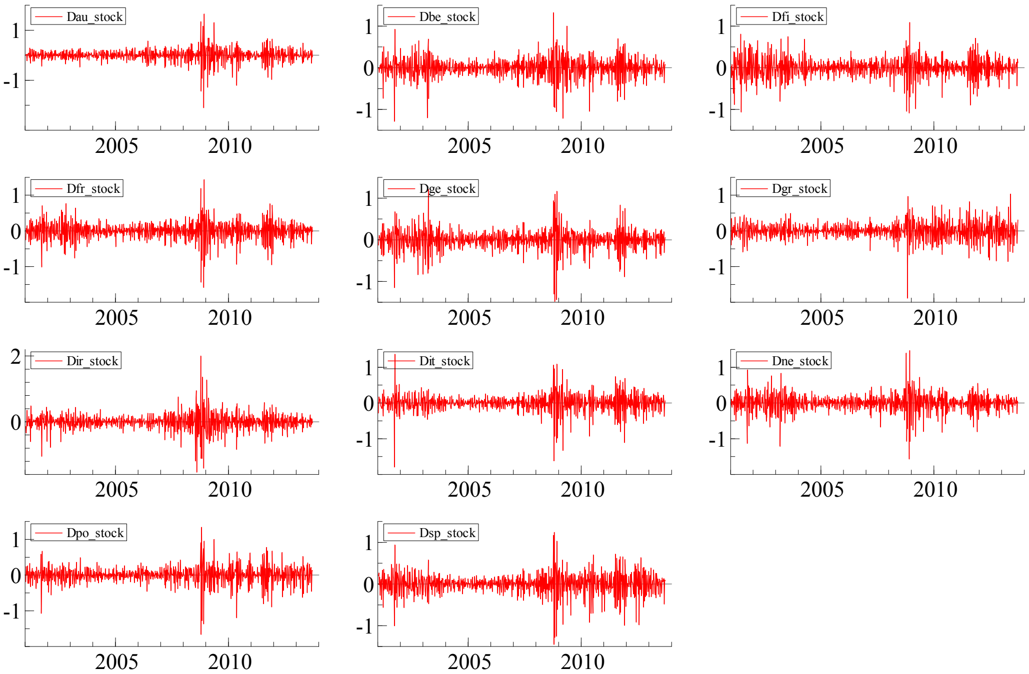


Figure A.9: Euro Area Bond FSIs

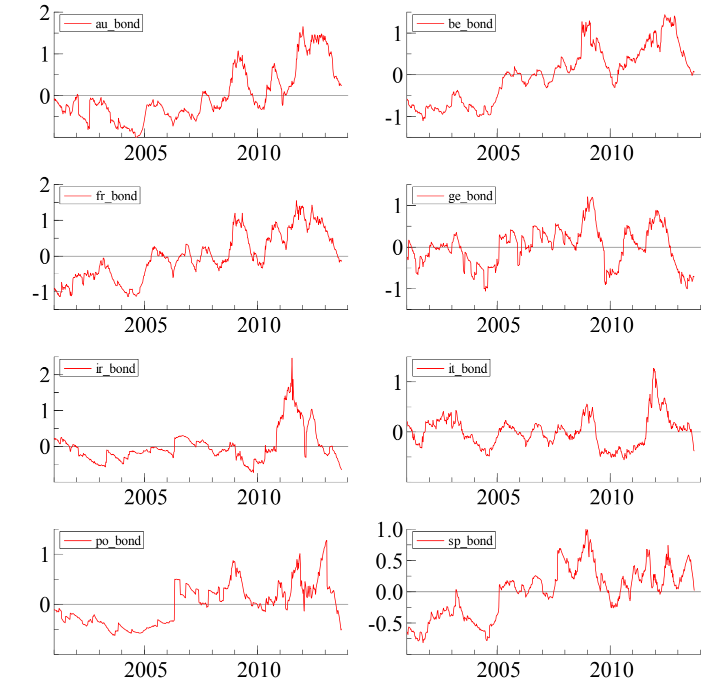


Figure A.10: Euro Area Bond FSIs Returns

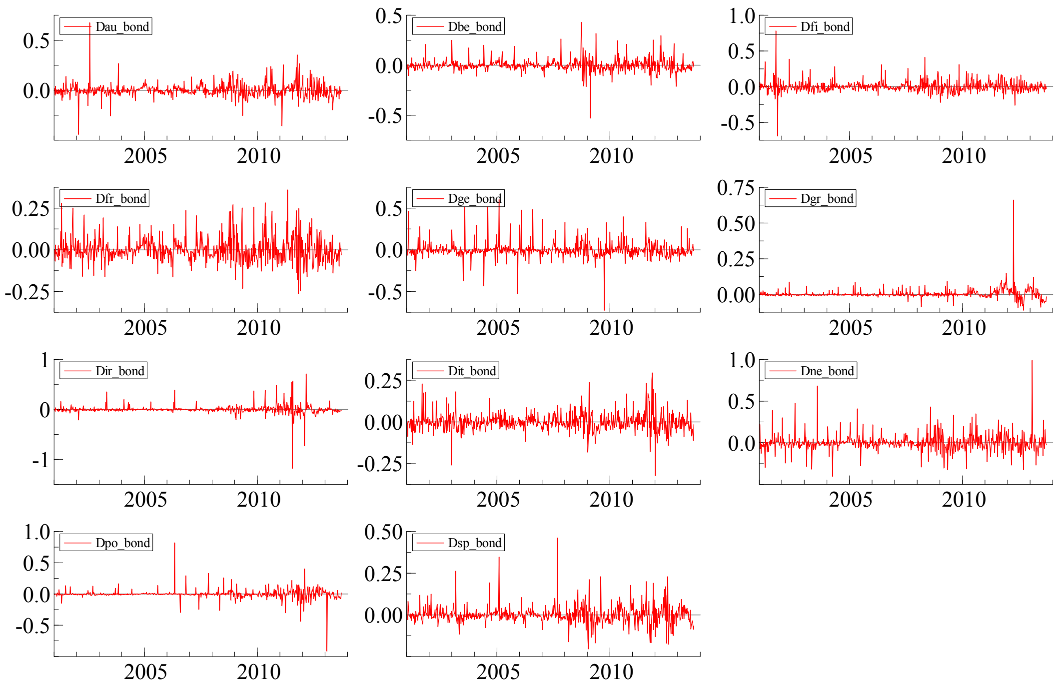


Table A.1: Euro Area Countries FSIs Correlation Matrix

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria	1										
Belgium	0.314	1									
Finland	0.178	0.219	1								
France	0.546	0.484	0.261	1							
Germany	0.279	0.405	0.245	0.396	1						
Greece	0.234	0.177	0.099	0.168	0.166	1					
Ireland	0.143	0.235	0.084	0.191	0.180	0.175	1				
Italy	0.454	0.465	0.230	0.506	0.376	0.229	0.297	1			
Netherlands	0.385	0.363	0.213	0.386	0.294	0.169	0.115	0.372	1		
Portugal	0.224	0.316	0.170	0.230	0.304	0.169	0.247	0.407	0.249	1	
Spain	0.316	0.406	0.271	0.460	0.352	0.113	0.347	0.533	0.358	0.250	1

Table A.2: Euro Area Banking FSIs Correlation Matrix

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria	1										
Belgium	0.561	1									
Finland	0.423	0.478	1								
France	0.581	0.691	0.490	1							
Germany	0.502	0.623	0.388	0.698	1						
Greece	0.333	0.323	0.206	0.306	0.289	1					
Ireland	0.399	0.399	0.283	0.443	0.338	0.235	1				
Italy	0.553	0.658	0.461	0.726	0.647	0.351	0.445	1			
Netherlands	0.219	0.447	0.211	0.420	0.284	0.156	0.207	0.294	1		
Portugal	0.426	0.538	0.367	0.455	0.474	0.303	0.362	0.550	0.181	1	
Spain	0.510	0.580	0.431	0.697	0.621	0.260	0.529	0.743	0.270	0.467	1

Table A.3: Euro Area Money FSIs Correlation Matrix

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria	1										
Belgium	0.733	1									
Finland	0.355	0.277	1								
France	0.886	0.747	0.305	1							
Germany	0.885	0.636	0.478	0.837	1						
Greece	0.259	0.147	0.220	0.246	0.267	1					
Ireland	0.181	0.186	0.100	0.150	0.176	-0.033	1				
Italy	0.537	0.660	0.129	0.496	0.438	0.030	0.305	1			
Netherlands	0.529	0.395	0.155	0.460	0.511	0.096	0.057	0.221	1		
Portugal	0.250	0.355	0.220	0.260	0.259	-0.042	0.407	0.409	0.172	1	
Spain	0.599	0.624	0.270	0.529	0.540	0.110	0.326	0.610	0.298	0.397	1

Table A.4: Euro Area Equity FSIs Correlation Matrix

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria	1										
Belgium	0.670	1									
Finland	0.589	0.685	1								
France	0.715	0.867	0.774	1							
Germany	0.641	0.800	0.728	0.907	1						
Greece	0.492	0.486	0.406	0.517	0.502	1					
Ireland	0.609	0.661	0.531	0.703	0.661	0.459	1				
Italy	0.717	0.817	0.697	0.889	0.823	0.510	0.648	1			
Netherlands	0.684	0.859	0.752	0.926	0.865	0.489	0.686	0.838	1		
Portugal	0.667	0.648	0.576	0.693	0.666	0.515	0.550	0.707	0.647	1	
Spain	0.687	0.783	0.690	0.850	0.801	0.494	0.612	0.871	0.783	0.732	1

Table A.5: Euro Area Bond FSIs Correlation Matrix

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
Austria	1										
Belgium	0.338	1									
Finland	0.373	0.304	1								
France	0.499	0.490	0.377	1							
Germany	0.263	0.150	0.244	0.318	1						
Greece	0.167	0.202	0.108	0.177	0.067	1					
Ireland	0.159	0.165	0.147	0.246	0.085	0.107	1				
Italy	0.310	0.306	0.325	0.446	0.230	0.153	0.075	1			
Netherlands	0.474	0.295	0.269	0.400	0.269	0.087	0.081	0.279	1		
Portugal	0.092	0.025	0.013	0.155	0.101	0.007	0.061	0.066	-0.077	1	
Spain	0.187	0.271	0.208	0.402	0.271	0.075	0.110	0.531	0.267	0.059	1

Table A.6: "News Effect" Coefficients from the Intra-Market GARCH-BEKK (1,1) Models

α_{ij}		Austria					Belgium					Finland					France					Germany					Greece					Ireland					Italy					Netherlands					Portugal					Spain				
		ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T
Austria	ba		-0.05854	0.005057	0.241013	-0.02476	0.07128	0.028061	-0.08504	-0.00525	-0.04359	-0.01691	0.014322	-0.01311	-0.03306	-0.02355	0.055799	-0.02059	-0.00213	0.040543	-0.00153	0.036426	-0.06783	0.023466	-0.00078	-0.00305	0.007933	0.021687	0.082712	0.016862	0.017015	0.178675	-0.1098	0.00987	-0.32832	-0.06724	0.128439	0.168922	0.002886	-0.01954	0.023275	0.028661	-0.11275	0.009745	-0.05758	-0.07927	-0.05069	-0.03487	-0.04859	0.011621	-0.0067	0.014764	-0.03024	0.020154	-0.02164	0.037362
	bo	0.106293		-0.09149	0.000462	-0.02484	0.02613	0.093453	0.018875	-0.26192	0.032533	0.031388	0.013477	-0.34441	0.003189	0.009001	0.175995	-0.05149	0.031186	-0.02247	-0.00495	0.008846	-0.02633	-0.02016	-0.01184	-0.00104	-0.15653	-0.02084	0.072288	-0.12638	-0.00799	0.204203	0.196831	-0.00698	-0.07298	-0.02256	0.027246	-0.07062	-0.06052	0.079277	0.195895	-0.22267	-0.09584	0.00194	-0.00453	-0.01964	-0.0517	0.205074	0.116352	-0.01428	-0.00141	-0.02353	0.176132	0.027263	-0.25102	-0.03382
	mo	-0.10114	0.102221		-0.00868	-0.03377	-0.05738	-0.07477	0.014675	0.08317	0.150083	0.006327	0.019721	-0.06444	-0.09469	0.031577	-0.01245	-0.05477	0.047982	-0.10892	-0.03131	0.08133	-0.00208	0.142944	0.001377	0.058894	0.048493	-0.00578	0.036566	0.132414	0.032086	0.031246	0.020139	-0.02669	0.049967	0.056842	-0.1041	0.005899	-0.19932	0.009316	0.083927	0.028118	0.111429	0.10163	-0.03645	-0.09322	0.027512	0.059585	-0.07488	-0.00795	0.002353	0.049414	0.022988	0.046036	-0.22949	0.039916
	eq	-0.22346	-0.15715	0.006997		-0.02206	-0.03089	0.025643	-0.00267	0.023506	-8.43E-05	0.000933	-0.06443	0.019296	0.005995	0.024255	-0.01925	0.003667	-0.01248	0.031712	-0.04218	-0.08338	-0.08388	0.096535	0.011544	-0.0287	-0.10001	0.005014	-0.10888	-0.01931	8.08E-05	0.030739	-0.00966	-0.03608	0.018436	-0.00974	-0.00257	-0.04071	0.135527	0.134642	-0.0228	-0.03003	-0.08978	0.029707	0.014151	-0.00788	-0.00212	-0.00687	-0.00919	0.021653	-0.0168	0.0046	0.032872	0.006797	0.056786	-0.01757
	T	-0.01913	-0.06886	0.026456	-0.00797		-0.04723	-0.00399	0.177395	0.018203	-0.07051	-0.00749	-0.0187	0.038561	-0.04025	-0.012	-0.00045	0.032511	0.069539	0.001243	-0.00164	-0.00836	-0.12365	0.072186	0.019455	-0.03572	-0.05763	-0.02507	0.011838	0.137125	-0.01641	-0.02394	-0.02209	0.11574	0.089264	0.000609	-0.02308	0.027969	0.107687	-0.0028	0.016624	-0.03532	0.151615	-0.08311	0.100398	0.020306	-0.02224	-0.04777	-0.00354	0.120581	0.011506	-0.01463	0.012668	-0.01047	0.006767	-0.0865
Belgium	ba	0.28287	-0.05595	-0.00923	-0.08358	-0.04541		-0.09849	-0.2086	-0.05184	0.049163	0.00085	-0.01805	0.054963	-0.05096	-0.01943	-0.02218	0.089533	-0.12836	0.039523	-0.00852	0.020242	-0.17777	-0.0482	-0.01543	-0.00424	0.237618	-0.01416	-0.02367	0.024158	0.041594	0.044059	0.114994	0.05876	0.02532	0.008587	0.057671	-0.007	0.014903	-0.09867	-0.06098	0.072334	0.243745	-0.06587	-0.14888	-0.40422	-0.0924	-0.11886	0.026625	0.129589	-0.0311	-0.14089	-0.0121	0.004161	0.0184	0.054314
	bo	-0.0231	0.108324	0.167228	-0.01855	0.039936	-0.10714		0.057791	-6.49E-05	0.047328	-0.03897	0.009385	-0.10553	5.62E-05	0.063629	-0.00227	-0.12418	0.252238	0.063518	0.005454	-0.08299	0.099908	0.102469	0.0676	-0.06973	0.186259	-0.04739	0.095921	-0.0023	-0.15051	-0.03359	-0.01939	0.035512	-0.06865	0.073931	-0.26167	-0.07249	-0.13572	0.047383	0.033953	0.018108	0.006836	-0.17131	0.012083	0.151755	0.055935	0.043835	0.042684	0.011757	0.106883	-0.0261	0.024677	-0.0016	0.096932	0.061173
	mo	0.110037	0.031974	-0.06222	0.020593	0.001545	-0.05497	-0.07315		-0.00202	-0.08916	-0.00786	-0.08879	-0.00416	-0.0343	-0.03451	-0.08304	-0.00892	-0.03089	0.042884	0.078194	0.018291	-0.04508	-0.1565	0.006182	0.024784	-0.11432	0.025086	0.006195	-0.0355	0.177456	-0.07467	-0.04356	-0.0555	-0.02901	0.031247	-0.02914	0.138914	-0.09353	0.135024	0.059301	0.20308	0.099506	-0.01329	-0.0078	-0.09837	-0.03357	0.098352	0.109116	0.046118	0.016852	0.168658	-0.00883	-0.09487	-0.05644	-0.03322
	eq	-0.0668	0.04998	-0.06695	0.005938	0.039567	0.126286	-0.03225	0.010228		0.002015	-0.00144	-0.0637	0.137407	0.192953	-0.02187	0.052331	0.006267	-0.07515	0.002817	0.050827	-0.04143	-0.02121	-0.16842	0.00557	-0.01121	0.090985	0.006302	0.088024	-0.05149	0.000765	-0.02238	0.002453	-0.00444	-0.02534	-0.02846	-0.06463	-0.03103	0.062766	0.247757	0.087871	-0.00323	0.007816	-0.01488	0.141491	-0.02072	0.011493	-0.00783	0.031334	-0.00395	0.035384	0.059909	-0.0053	-0.01464	0.046748	-0.04899
	T	-0.23897	0.04139	-0.05848	0.070228	0.133006	-0.12368	-0.10734	0.022676	-0.0462		0.054755	-0.00306	-0.017	0.169183	0.056318	0.008309	0.153175	-0.16712	0.048067	-0.00066	0.18607	-0.00555	0.007181	0.103379	-0.10592	-0.11001	0.01795	-0.01368	0.047263	-0.00755	0.008235	0.039795	-0.00618	-0.11795	0.003638	-0.02738	-0.00906	0.11404	-0.53965	0.098001	0.02903	0.25232	0.171613	-0.08093	0.043927	-0.02768	-0.03564	0.129573	0.026735	-0.03185	0.076238	-0.01577	-0.06887	-0.0298	-0.05716
Finland	ba	0.011293	-0.00112	0.01912	-0.00136	-0.00611	0.076082	-0.00361	0.004814	-0.00336	-0.18256		-0.00851	0.036762	-0.00355	-0.00777	0.02468	-0.04704	0.086705	-0.01444	0.003904	0.008073	0.015367	0.013612	-0.02095	0.00362	0.329564	-0.03763	0.043829	0.046734	-0.00515	-0.20687	-0.01958	0.014972	-0.00018	0.043652	0.010247	0.016536	-0.08687	-0.01526	-0.0097	0.017674	0.004585	0.022319	-0.00951	0.005558	-0.02727	-0.015	-0.008	-0.01869	-0.01592	0.119915	-0.00018	-0.03627	-0.02778	-0.01623
	bo	0.012103	-0.00524	-0.01399	0.113077	-0.00778	0.102225	0.000192	0.147978	0.034532	-0.0155	0.16846		0.126132	0.011939	0.089456	-0.01542	-0.10607	-0.00118	-0.0139	-0.07809	0.003938	-0.09658	-0.00354	-0.01726	0.003076	0.037811	-0.01897	-0.21771	0.017103	0.007885	0.198006	0.013353	-0.02731	0.046613	0.003475	-0.00347	-0.07511	-0.00258	-0.09841	-0.0297	-0.00089	0.109588	-0.07107	0.014619	-0.06997	-0.08488	0.098196	-0.0742	0.068718	0.057895	-0.05051	6.86E-05	0.002051	0.076625	0.236582
	mo	-0.0286	-0.00554	0.104872	-0.0635	-0.1561	-0.13558	-0.15029	-0.01476	0.004407	0.077846	-0.05377	0.153448		0.01104	-0.00665	0.01645	-0.09876	0.005853	-0.01338	-0.04301	-0.00455	0.009481	-0.04493	0.00155	-0.15454	0.015597	-0.17172	-0.14683	0.038455	-0.17792	0.061423	-0.09186	0.00435	-0.21847	0.010942	0.189289	-0.05559	0.185811	-0.12101	-0.01277	-0.1326	0.085117	-0.05858	0.040605	0.080152	-0.13143	-0.09938	0.006777	-0.20943	-0.1452	-0.00438	-0.03795	0.044782	-0.21523	-0.08742
	eq	-0.10714	0.024288	0.073667	-0.01086	0.002547	0.003681	0.034366	0.06792	-0.16016	-0.02543	0.002215	0.042705	-0.02364		0.062449	0.04045	0.023688	-0.12842	-0.01521	0.015348	-0.05107	-0.01075	-0.00067	-0.06041	-8.68E-05	0.121563	-0.00434	0.028642	-0.29068	-0.03647	-0.01151	-0.03059	-0.01379	-0.02655	-0.00542	-0.0433	0.002216	0.004629	-0.00878	-0.00072	-0.0034	0.012292	0.05944	0.000735	0.01116	0.007932	0.00613	-0.04971	-0.02389	0.023725	-0.02247	-0.00273	0.037368	0.074957	0.011526
	T	0.020681	0.011508	0.047555	0.031728	0.003211	0.064781	0.033655	0.047912	0.008374	0.05911	-0.00286	-0.01215	0.031303	-0.04724		0.049584	-0.10742	0.006361	-0.25226	-0.43056	-0.10492	0.05486	0.032671	-0.10144	-0.03318	-0.99998	0.031034	-0.03117	-0.00286	0.002646	-0.25463	-0.01464	-0.00294	0.044864	-0.1718	0.048962	-0.00521	-0.01187	-0.03849	0.002247	-0.04138	0.024608	-0.09576	0.006032	-0.0063	-0.00486	0.051982	0.053181	-0.01823	-0.04611	-0.17416	-0.00678	0.022697	-0.05762	0.154404
France	ba	0.004038	-0.02535	0.119081	0.027374	-0.01701	-0.07302	-0.05345	-0.04363	-0.0277	-0.1173	-0.02296	-0.00015	-0.00087	-0.05738	-0.01514		-0.05483	0.063718	-0.01028	-0.01839	0.095803	-0.06549	0.048134	0.000247	-0.01141	-0.07109	0.02062	0.001808	0.001737	-0.01303	0.039689	0.025095	0.0204	-0.0016	-0.03041	-0.05986	0.041259	-0.08195	0.366677	-0.01388	0.049119	-0.00896	-0.04188	0.003637	-0.00105	-0.01467	0.004478	-0.02872	0.025676	-0.03604	0.101566	0.012882	0.034471	-0.02578	0.027534
	bo	0.074262	0.007843	-0.00553	-0.00655	0.032958	-0.02504	0.200101	-0.08184	0.002861	0.056541	3.82E-05	0.221718	0.069675	0.147134	0.076931	-0.29709		-0.01223	0.090111	-0.01668	0.270818	0.110202	0.00971	-0.0405	0.042111	-0.00755	-0.0165	0.011843	-0.01133	0.004428	0.158861	0.068592	0.035657	0.109122	0.04518	0.132089	0.003552	0.012313	-0.22403	0.022381	0.004541	-0.16131	-0.11986	0.011119	-0.23098	0.066846	0.035169	0.05572	-0.18562	0.22336	0.001763	0.005378	-0.03692	-0.13399	-0.00604
	mo	0.042342	-0.11647	-0.05746	-0.08284	0.028789	0.001681	-0.14164	-0.06274	-0.01309	0.00566	-0.02148	-0.07264	-0.00299	0.014625	-0.02014	0.091212	-0.12779		-0.01254	-0.06991	-0.01084	-0.05645	-0.05485	-0.32241	0.063252	0.018548	0.06569	0.070115	0.009655	-0.03377	0.009552	-0.03921	0.002193	-0.07384	-0.05083	0.019232	0.002321	-0.09453	0.015535	0.046531	0.178297	-0.10102	-0.22544	-0.34082	-6.38E-05	-0.03646	0.128195	-0.23968	-0.05157	-0.10534	-0.00241	-0.00653	-0.29561	0.017409	-0.00093
	eq	-0.03717	0.139178	-0.07066	-0.00325	0.05054	-0.02639	0.004903	-0.03881	-0.00225	-0.02362	0.054421	-0.00069	-0.0358	0.006448	0.053101	-0.02291	-0.01013	0.000125		0.001311	-0.02047	-0.03242	0.04464	-0.0068	-0.00833	-0.03979	-0.01523	0.160869	-0.10058	-0.0176	-0.01021	-0.05498	-0.05109	-0.03337	0.032708	-0.00131	0.000313	0.103867	-0.08034	-0.00111	-0.03555	0.085549	-0.01469	0.00131	0.00251	0.003539	-0.02174	-0.00528	-0.02775	0.001273	-0.09598	0.031924	0.003553	0.052149	-0.01
	T	0.057965	0.082262	0.258952	0.10528	0.22823	0.134875	-0.08803	-0.52759	-0.07394	0.061017	0.050017	0.090039	-0.01681	0.002093	0.051271	-0.0497	-0.16505	0.060977	-0.01735		0.046464	0.060395	-0.15174	-0.00518	0.00366	0.081832	0.009774	-0.24955	-0.02466	-0.11278	0.170088	0.067049	-0.10896	0.111688	0.118479	0.11731	-0.0011	-0.1521	0.309023	-0.06203	0.010622	-0.11456	-0.01314	-0.2998	0.205894	-0.32973	0.060591	0.046126	-0.14795	0.072682	0.171746	0.008434	0.353842	0.070869	-0.01395
Germany	ba	-0.03586	-0.06729	-0.15638	0.028743	-0.01808	-0.12906	-0.07191	0.058046	-0.02038	-0.04034	-0.00061	-0.03184	0.007394	-0.11455	0.141912	-0.0459	-0.00566	-0.15833	0.003361	-0.06133		-0.05514	0.004009	0.045961	0.009485	0.019615	-0.00257	-0.13889	0.006512	-0.05323	-0.12324	0.1327	0.012861	0.001808	0.24174	0.086984	0.021187	0.00655	0.010953	0.039245	0.001403	-0.00027	0.005884	-0.02991	0.000424	-0.02135	0.128811	-0.01243	0.043736	-0.01846	-0.01942	-0.00215	0.002568	-0.00153	0.007508
	bo	0.083494	0.074284	0.001829	0.167264	0.029212	0.025658	-0.09846	0.125689	-0.09793	-0.00457	0.110193	0.00816	-0.04135	-0.02654	0.034075	-0.06156	0.015304	-0.01844	0.017953	-0.01876	0.098018		-0.03585	0.134645	-0.02945	-0.01061	0.040724	-0.0259	-0.00979	-0.01684	0.358063	0.21578	0.016457	-0.00568	0.0568	0.051281	0.019963	-0.02601	0.154775	-0.00343	0.008161	0.026793	-0.0457	0.015815	0.006225	-0.22274	-0.18379	0.045431	-0.16511	-0.3533	0.120664	-0.00436	0.016341	-0.01195	0.006306
	mo	0.022915	0.013315	-0.02138	-0.11402	0.058713	0.430349	-0.14703	-0.00915	-0.0004	-0.04528	0.223902	-0.01093	0.025353	-0.06174	-0.02282	0.04116	0.005845	-0.00672	-0.0237	-0.00767	0.062759	0.06646		0.114541	0.033691	-0.03314	-0.06228	0.045866	-0.11542	-0.0527	-0.01816	-0.05385	0.005141	-0.2525	-0.00135	0.05272	0.056465	-0.00219	0.153983	0.015424	0.022524	-0.02903	-0.06518	-0.02111	0.095054	-0.02299	-0.291	-0.03318	-0.17852	-0.00973	0.374274	0.024365	-0.002	0.045531	0.051843
	eq	0.01243	-0.00181	0.074307	-0.00097	0.01574	0.00055	-0.05265	-0.00236	0.00944	-0.00512	0.026771	0.015111	0.00658	-0.07858	0.023049	0.012733	0.01955	0.036257	-0.01091	0.020087	-0.05534	0.013512	0.006232		-0.00934	-0.0085	0.088771	-0.02309	0.013045	-0.01304	0.030871	-0.00419	-0.12344	-0.00989	-0.01144	0.044259	-0.01347	-0.01194	0.008852	0.009066	-0.02288	-0.00376	-0.07609	0.009495	0.008815	-0.00229	-0.00107	-0.00505	0.017167	-0.00703	-0.0189	0.006518	0.036879	0.007469	-0.03026
	T	-0.00513	0.027579	-0.08236	0.100238	0.062337	-0.02725	0.121734	-0.00327	0.003358	0.00907	0.00773	-0.01668	0.101083	-0.00872	-0.06394	-0.03525	-0.07206	-0.02411	-0.01194	0.002697	-0.0029	-0.16774	-0.0277	-0.00463		-0.14642	0.004786	0.01205	-0.00135	0.017393	-0.14612	-0.13219	0.015704	0.021482	-0.00462	0.113436	-0.00709	0.049803	-0.00668	0.007448	0.000857	0.067436	-0.10071	0.025791	0.056283	0.014116	-0.13195	0.05159	-0.00023	0.047714	0.083691	0.001567	0.000803	0.097889	0.131613
Greece	ba	-0.16105	0.057733	-0.06207	-0.11059	0.080044	-0.12534	0.029159	-0.01426	-0.02419	-0.04347	-0.0596	-0.02563	-0.01	-0.04078	0.011828	0.059452	-0.02138	-0.06861	0.049926	-0.01059	0.001202	0.246719	-0.09093	-0.01784	-0.04616		0.124332	-0.07049	-0.05099	-0.00893	0.130387	-0.03703	-0.04898	0.003242	-0.23268	0.00336	-0.05905	0.003162	0.004397	-0.0028	0.116632	-0.05025	-0.0526	0.009867	-0.31126	-0.01312	0.008699	-0.01628	0.004421	0.055502	0.002004	-0.00461	-0.20026	-0.06738	0.024292
	bo	0.018279	0.092619	-0.06302	0.418705	0.064773	0.095822	0.29035	0.220195	0.066607	0.09344	0.117142	0.030309	0.163052	-0.1059	0.020822	-0.40845	0.14553	-0.09772	0.058377	0.051415	0.055272	-0.02776	0.037868	-0.08795	0.015456	0.105939		0.00768	-0.12765	-0.00016	-0.10748	0.143632	0.056288	0.283007	-0.03334	0.059251	-0.06712	-0.06865	0.108201	-0.07772	0.07784	0.030861	-0.31932	-0.05592	0.241757	-0.00989	0.144101	0.200084	-0.20072	-0.06954	0.006371	0.006855	0.029522	-0.14938	0.025362
	mo	-0.04902	-0.08485	-0.0017	0.173557	0.000455	-0.02602	-0.03527	0.020038	0.125369	-0.03486	-0.60321	-0.02764	0.122377	-0.05025	0.234875	0.000943	-0.09751	-0.13816	-0.0626	0.016675	0.00936	0.019465	-0.0315	-0.08896	0.013292	0.293152	-0.03572		0.013009	0.042481	0.004795	-0.24154	-0.15625	0.093389	-0.0158	0.188339	-0.05544	-0.04467	-0.20048	0.146057	0.041072	-0.10354	0.053801	-0.02743	0.075971	0.035876	0.13696	0.003179	-0.17013	-0.1074	0.097116	-0.154	0.256246	0.032894	-0.01783
	eq	-0.05586	0.114406	-0.04301	0.019508	-0.00131	-0.0244	-0.08314	0.02579	0.055925	0.013196	0.02678	-0.00572	-0.11998	0.047911	-0.0005	-0.04836	-0.01516	-0.02751	0.056936	0.044817	-0.00371	-0.00925	0.026544	0.136945	0.003245	-0.10458	-0.00452	-0.0083		-0.01312	-0.11957	0.030323	0.044616	0.001508	0.136841	-0.0567	-0.01331	0.012591	0.24732	-0.0355	0.00187	-0.0069	0.038338	0.178145	0.065796	-0.05899	0.422251	-0.02998	0.002156	0.022243	-0.13742	-0.00914	0.035154	0.008964	0.000417
	T	-0.0362	0.005698	0.068282	0.117815	0.001549	0.145276	0.240517	-0.04034	-0.04512	-0.03692	0.09119	-0.02226	0.029655	0.016476	-0.04622	-0.01545	-0.02261	-0.00091	0.001285	0.166736	-0.11511	-0.05955	0.122916	0.018314	0.017343	-0.039	-0.01365	0.196801	0.128066		0.012289	0.030169	-0.18206	0.001508	0.084746	-0.0504	-0.0079	-0.00083	0.284739	0.044531	-0.0642	-0.06096	0.015077	0.019634	-0.12287	-0.33167	0.003688	-0.06201	0.019875	-0.07883	-0.09729	-0.01623	-0.04361	0.12159	0.007218
Ireland	ba	-0.02547	0.103235	-0.16885	0.081098	0.025555	-0.04734	0.063214	-0.08268	-0.02455	-0.18534	-0.0248	-0.01964	0.194133	-0.07174	0.03145	0.065485	0.13484	-0.08851	-0.02876	0.207106	-0.08569	-0.11746	0.091404	-0.11219	-0.01239	0.048038	0.142622	-0.024	-0.00183	-0.01052		-0.04611	0.000774	-0.01503	0.051371	0.112614	-0.01592	-0.0829	-0.09686	-0.03535	-0.09545	0.229226	-0.07512	0.013007	0.122195	-0.30869	0.010621	-0.03081	-0.00603	0.030285	-0.08548	0.013345	-0.09492	0.006832	0.018346
	bo	-0.09048	-0.16948	0.052779	0.007053	0.012299	-0.02756	0.017115	0.072658	-0.00244	0.022052	0.042596	0.07796	0.042817	0.074074	0.010331	0.002093	-0.02195	0.083618	-0.01945	-0.01178	0.010217	-0.04756	0.042869	-0.0011	-0.00423	0.045114	-0.01822	0.046082	0.127301	-0.04067	-0.00019		0.005031	-0.01221	-0.073	0.116262	-0.03953	-0.08201	-0.02182	-0.0005	0.005512	-0.00304	0.011039	-0.0074	0.003669	-0.3149	-0.05232	0.031755	0.028386	-0.04904	0.026495	-0.00025	0.008838	0.028599	0.025138
	mo	0.020668	-0.07955	0.008801	0.067802	-0.03232	-0.01812	0.017836	0.10777	0.007319	-0.00059	0.210652	-0.00508	-0.10967	0.066194	0.006808	0.009802	-0.02461	0.039368	0.015063	-0.03226	-0.08967	0.002329	-0.01236	-0.01958	-0.03743	-0.00912	-0.05192	0.07027	0.038667	-0.03031	-0.03604	-0.05707		0.009526	0.054557	-0.0012	-0.05151	-0.01992	0.096021	0.092609	0.007163	0.13208	-0.05197	0.076039	0.144441	0.081846	-0.13125	0.004199	0.004787	0.152009	0.041633	0.124193	-0.00228	-0.08519	0.224493
	eq	-0.02313	0.249393	-0.02408	-0.01049	-0.04705	0.104477	0.13777	0.003006	0.006624	0.063168	-0.00071	-0.00468	-0.02333	-0.01594	0.015957	-0.00588	-0.02457	-0.07814	0.015664	-0.04584	-0.02552	-0.18022	-0.07314	-0.00114	-0.00969	0.013596	0.001507	-0.00531	-0.03876	-0.03961	0.02687	-0.00871	-0.0056		0.163927	-0.03576	0.002144	0.04585	0.044138	0.021641	-0.02682	-0.01578	0.039884	0.038754	-0.01934	0.019058	0.00323	-0.02597	0.106635	0.01427	0.037017	0.024768	-0.02011	-0.0361	-0.0271
	T	0.033946	0.024521	-0.04092	0.044708	0.079586	-0.00445	0.048165	-0.0862	0.18433	0.030931	-0.52072	-0.02072	0.003043	-0.00248	0.008178	-0.0276	0.076763	0.145381	-0.16514	-0.00205	-0.11669	0.054105	-0.05751	-0.09625	-0.07947	0.044352	-0.00537	0.031723	-0.09781	0.003098	0.04343	0.020848	0.071604	-0.18589		0.029353	-0.04416	-0.03799	0.057197	0.048103	-0.01171	0.102565	0.464957	-0.01284	0.054427	-0.15892	-0.00288	0.050838	-0.04667	0.016255	-0.00019	0.036226	-0.02412	-0.00489	-0.01312
Italy	ba	-0.04927	0.002111	0.007138	-0.02284	0.030011	-0.03389	-0.04078	-0.00928	-0.04427	-0.03994	0.018482	-0.06731	-0.0264	-0.0091	0.006098	0.021805	0.083926	-0.03668	-0.00011	0.008568	-0.04957	0.045011	0.039794	-0.00016	-0.04665	0.15453	-0.08136	-0.03959	0.002164	-0.00564	-0.06754	-0.04241	0.003494	0.126642	-0.04138		0.040634	-0.01403	-0.02581	-0.02927	0.000421	-0.01398	-0.06318	-0.07179	-0.02144	0.070796	0.024108	-0.01901	0.002872	0.010325	-0.02779	0.017359	-0.04187	0.032086	0.022108
	bo	-0.14089	0.059543	-0.12485	-0.07521	-0.03727	-0.00302	0.080898	-0.05893	-0.01567	-0.0764	-0.05558	-0.00357	-0.01796	0.151994	0.077207	-0.58184	-0.12515	-0.00047	0.064863	-0.03936	0.080807	-0.08071	-0.00154	-0.01656	0.075013	-0.05939	0.001427	-0.00896	0.013543	0.036802	-0.05144	0.020407	0.005172	-0.02251	0.08819	-0.07054		0.44104	-0.10284	0.114485	0.009423	0.211808	-0.04835	-0.0091	-0.00824	0.10766	-0.00886	0.052643	0.03007	-0.00167	-0.0064	0.00407	-0.01534	0.128139	0.357653
	mo	-0.09821	-0.05321	-0.04341	-0.02967	0.079738	-0.21588	-0.06355	0.126186	-0.02089	-0.03324	-0.01577	0.031637	0.138208	0.099186	-0.00179	0.037457	-0.11066	-0.00693	0.089424	-0.10347	-0.00971	0.225478	0.00233	-0.0224	0.031589	-0.10925	0.028295	-0.00088	-0.02877	0.001998	0.229564	0.273366	0.074929	-0.13645	-0.02525	0.08689	-0.18607		-0.04162	-0.04572	-0.00195	-0.03173	-0.00392	0.011579	0.050107	0.233951	0.034986	-0.06356	0.012504	0.023643	0.018924	-0.03837	-0.03689	-0.07465	0.297718
	eq	0.038789	0.007818	-0.0611	-0.02416	-0.00335	0.064697	0.042878	-0.05494	-0.0183	0.032838	-0.00272	0.031125	0.046617	0.000916	0.022164	-0.38838	0.012551	-0.03258	0.099461	-0.0669	-0.0353	-0.14424	-0.07893	0.001025	-0.0255	0.047463	0.018064	0.022974	0.006737	-0.00046	0.03557	-0.01407	-0.07336	-0.01326	-0.0012	0.0435	0.000115	0.01412		-0.01045	0.008193	-0.02742	-0.01877	0.011082	0.002653	0.089767	-0.08546	0.003649	0.005635	0.038526	-0.01577	0.010278	9.16E-05	-0.00436	0.044577
	T	-0.27012	0.044862	-0.10403	0.061041	-0.07913	0.139378	-0.16676	-0.00941	0.034016	-0.17418	-0.15498	0.185227	-0.14235	0.143676	-0.06126	-0.0376	-0.02322	-0.00021	0.005812	0.023721	-0.38063	-0.00772	-0.12627	0.001195	-0.02194	-0.05697	-0.16281	-0.10968	0.031087	-0.16662	0.000892	0.006151	-0.12351	0.041039	-0.00562	-0.08192	-0.11921	0.153206	0.610579		-0.01597	0.105041	0.026741	0.054047	0.069206	0.074794	0.111796	-0.16471	0.094235	0.071567	-0.07659	0.081205	-0.07972	0.137556	-0.00834
Netherlands	ba	-0.02768	0.059619	0.007832	0.01948	0.025291	-0.02234	-0.14588	0.001751	0.001222	-0.01575	-0.01415	0.035054	0.00142	-0.0013	0.022533	-0.01147	0.015008	-0.02143	0.06245	-0.00161	-0.00517	0.083928	-0.0073	-0.01109	-0.00544	-0.13029	-0.10404	0.138393	0.042912	0.031524	0.055449	-0.00344	-0.05446	0.017102	-0.00456	-0.07491	-0.02975	-0.08174	-0.00999	-0.00541		-0.01051	0.024439	-0.02139	-0.0019	-0.00142	0.012875	-0.04413	-0.14411	-0.03367	-0.0209	-0.01389	-0.06197	0.003519	1.08E-05
	bo	0.079339	0.100705	-0.13667	0.005437	-0.09482	0.016313	0.009561	0.098339	-0.07379	0.074479	0.02783	0.110946	-0.00844	-0.06672	0.079028	-0.16474	0.072208	0.15238	-0.15696	-0.00322	-0.39493	0.078791	0.036669	0.001073	0.121239	0.001217	-0.29064	-0.05937	0.056286	-0.0121	0.091981	-0.00746	-0.00912	0.059044	0.02884	0.199002	-0.00163	0.117916	0.039266	0.135666	0.095565		-0.02876	-0.03047	0.038716	0.023109	0.023512	0.116997	0.102347	0.055982	-0.17599	-0.0359	0.021943	-0.00333	0.058517
	mo	-0.0954	-0.05946	-0.1184	-0.00236	0.008411	0.015937	0.031981	-0.01464	0.022202	-0.00981	0.060523	-0.02896	-0.00703	0.005609	-0.01559	-0.045	0.015964	0.040558	0.003198	-0.15793	0.017314	0.034147	-0.00584	0.084151	0.008356	0.010862	-0.00482	-0.07961	0.038583	0.007908	0.093278	0.023434	0.01604	0.037072	-0.0633	0.080886	0.032475	-0.02602	0.001762	-0.01054	0.021944	-0.06279		0.064449	0.022179	-0.01782	-0.03955	-0.02049	0.014215	-0.04813	0.036132	-0.02623	-0.01451	0.010752	0.008665
	eq	-0.00378	0.156629	-0.03685	0.008798	-0.0061	0.00345	0.050015	-0.03415	0.041727	0.098831	0.005123	0.030504	-0.02088	0.016621	0.030711	0.052274	0.013697	-0.00904	0.008357	0.125592	-0.00674	0.074619	0.064796	-0.00924	-0.00721	0.002446	-0.0156	0.047626	-0.03903	-0.02205	-0.017	-0.00096	-0.04271	-0.00718	-0.04868	-0.05715	0.046543	0.057864	0.000127	-0.00637	0.00429	0.172052	-0.0322		0.019091	0.080148	-0.03133	0.012149	-0.00974	0.021802	0.00293	-0.00116	-0.02709	-0.02719	-0.05029
	T	-0.08705	0.026809	0.034482	0.022881	-0.02513	0.00704	-0.06716	-0.01179	-0.01333	-0.0016	0.007212	0.028002	-0.07479	0.014319	0.042463	-0.03931	-0.00844	-0.00226	-0.04307	-0.0494	-0.01851	-0.00282	-0.14186	-0.03891	-0.01917	0.025188	-0.10037	-0.0664	-0.13008	0.056694	-0.02413	-0.07758	-0.04249	-0.10646	0.05844	0.080379	-0.06607	-0.01061	0.009277	-0.20364	0.010856	-0.12562	-0.00793	0.065985		0.008193	0.183214	-0.00138	0.315561	-0.04064	-0.05716	0.040838	-0.8458	0.012571	-0.05486
Portugal	ba	-0.21671	0.229043	0.032775	-0.0583	-0.01203	0.185952	-0.00474	0.117615	-0.06407	-0.01932	0.052335	0.016327	0.033045	-8.47E-05	-0.00192	0.000398	-0.32813	0.075559	-0.04293	-0.01121	0.113665	0.012771	0.029486	-0.03082	0.00862	0.115074	0.001949	-0.1645	0.198431	0.016441	0.010566	0.061513	0.003762	-0.17827	-0.05276	-0.00663	-0.00656	-0.07194	-0.04294	-0.03725	0.024301	-0.05873	0.055333	0.000791	-0.05812		-0.02648	-0.01487	-0.00089	-0.01614	0.015248	0.023268	0.048673	0.021951	-0.11162
	bo	0.011829	-0.10591	-0.04511	-0.08755	0.112761	0.028028	0.182667	0.051037	0.142482	0.148067	0.084712	-0.04964	0.00973	-0.06396	0.003382	0.109193	0.038856	-0.11108	0.285511	-0.00113	-0.11303	0.088129	-0.01223	0.002366	-0.05722	-0.00261	0.007583	-0.0621	0.100558	0.108563	-5.94E-05	0.120478	0.033257	0.052796	0.050547	-0.09548	0.267541	0.089224	0.138757	0.048036	0.011084	-0.02427	-0.05377	0.182091	-0.00111	0.046237		0.012099	-0.04233	-0.02791	-0.13925	-0.03074	-0.14802	-0.0065	-0.07505
	mo	0.021796	0.039941	-0.01758	0.073482	-0.06722	-0.10085	0.000755	-0.26737	-0.10081	0.122555	-0.34419	0.059026	0.000349	0.00057	-0.07168	0.016505	-0.16358	-0.0241	0.022241	0.078783	0.050033	-0.06424	0.108468	-0.04009	-0.05383	-0.44704	-0.24928	-0.02291	0.078512	0.070331	0.078554	0.047262	0.042852	0.002179	-0.08618	0.024348	-0.21118	0.031725	0.797527	0.090797	-0.00569	-0.01931	0.077208	0.100424	0.001537	-0.00062	-0.07327		0.062117	0.045352	-0.01739	-0.03587	-0.01352	-0.0224	0.000812
	eq	-0.01473	0.009795	0.006603	-0.01231	0.021076	0.065838	0.042473	-0.02365	0.023047	0.047981	-0.1452	0.016835	-0.03573	0.01283	0.046041	-0.06739	0.058931	0.028873	0.056288	0.018874	0.017512	0.042779	0.015947	0.11227	-0.00456	0.164874	0.002264	0.107515	-6.92E-05	-0.04365	0.003487	0.026455	-0.0849	-0.00631	0.036804	-0.01199	0.038874	0.105864	0.033307	-0.04567	-0.06902	0.0903	0.056567	0.003436	0.005904	0.000331	0.003861	0.007658		0.013747	0.125628	0.035634	0.042973	0.178811	0.034251
	T	-0.03934	-0.00676	-0.00196	0.094335	0.003806	0.150283	-0.05471	-0.04581	-0.03017	-0.00323	0.006975	0.03368	0.040492	0.003856	0.002064	0.013459	-0.01831	0.167375	-0.06072	-0.03157	-0.03996	-0.00955	-0.01386	0.002197	-0.026	-0.29637	0.094221	0.086088	-0.03034	0.044638	0.18599	0.026976	-0.00177	-0.00551	0.035696	-0.04352	0.012936	0.028434	-0.02154	-0.21943	-0.03011	0.06025	0.047333	-0.04198	0.006045	-0.05774	0.00084	-0.0468	0.11105		0.016914	0.000271	0.019214	0.018768	-0.06548
Spain	ba	0.032565	-0.00256	-0.02406	-0.01667	-0.01188	0.097388	0.010543	0.033638	-0.00419	-0.01412	0.039729	0.002246	0.013345	-0.00988	0.185828	-0.00669	-0.03957	-0.25695	0.05611	-0.1431	0.033258	-0.14297	-0.02294	0.146789	-0.04185	-0.02015	0.033828	-0.06445	-0.0987	0.019683	0.085063	0.02481	-0.02011	-0.03836	-0.02011	0.0119	0.002032	-0.043	-0.10548	0.076159	-0.00246	0.03747	0.007802	-0.01524	0.014153	0.008946	0.070235	-0.08415	-0.01812	-0.00336		0.009483	0.046802	-0.101	-0.05939
	bo	-0.44871	0.028776	-0.01192	-0.00059	-0.00785	0.003941	0.046977	6.16E-05	-0.01016	-0.00396	0.004635	0.000784	0.146771	0.0041	-0.00895	0.335737	0.001421	0.000804	0.06777	-0.0883	0.005662	-0.0057	-0.06059	-0.0002	0.051485	-0.09214	-0.059	0.075246	-0.01107	0.012846	-0.03851	0.004389	-0.11307	0.154577	0.056468	-0.11267	0.015297	0.010916	-0.01761	0.059515	-0.01897	-0.09303	-0.47396	-0.00965	-0.03512	-0.07339	0.022238	0.016949	0.039988	-0.00103	0.085118		0.0069	0.021114	0.024686
	mo	0.022143	-0.04361	0.00812	0.054007	0.005593	-0.26407	0.081441	0.095715	0.051627	0.015261	0.038039	0.140103	-0.06536	-0.0056	-0.04321	0.086091	0.094088	-0.05685	-0.04321	-0.10503	0.006397	0.015184	-0.01346	-0.00048	6.00E-05	0.009329	-0.0029	-0.08042	-0.1645	0.046363	0.273862	0.030184	0.026584	-0.21601	0.105211	0.155703	-0.14583	0.171433	-0.00107	-0.07624	-0.05693	-0.03099	-5.55E-05	-0.03165	-0.09189	0.052699	0.076872	0.009895	-0.13824	0.003194	0.069574	-0.16936		-0.00253	-0.03631
	eq	-0.12758	0.01958	0.006751	0.047986	0.012256	0.000623	-0.09037	-0.04386	0.01294	0.004002	-0.00947	0.012304	0.015031	0.068872	0.007042	-0.07737	0.153775	-0.02315	0.034327	0.090717	-0.0975	0.005218	-0.05056	0.011316	-0.01079	-0.12103	0.010481	-0.16045	-0.09429	-0.01413	-0.01691	-0.02449	-0.06444	-0.02307	-0.07631	-0.1956	-0.00576	0.083909	0.012141	-0.01523	-0.01333	-0.01525	-0.03005	0.074737	-0.08182	0.029173	-0.09504	0.035528	0.037414	0.042432	-0.06449	0.015952	0.034784		-0.06077
	T	0.037967	-0.06821	-0.07799	0.140417	0.105645	0.057477	-0.05759	0.133554	0.089869	-0.07189	0.004891	-0.04551	-0.14494	-0.01464	-0.03899	-0.1045	0.072116	-0.19372	0.014323	-0.12276	-0.05896	-0.07037	-0.08875	0.009446	-0.02128	-0.21706	0.178113	0.263283	-0.00169	-0.04192	0.235292	-0.03333	-0.00077	0.220217	0.184355	-0.04266	0.001552	-0.01387	0.197305	0.140139	0.000721	0.006866	-0.02673	0.0097	0.228165	0.119062	0.034145	-0.02041	0.284511	0.04266	0.027554	0.011623	0.037667	0.040916	

Notes: These are the estimated "news effect" coefficients from the bivariate GARCH-BEEK(1,1) models for the case of cross-markets analysis. Markets FSIs are represented as: ba (banking sector), bo (bond market), mo (money market), eq (equity market) and T (country). The table is read row by row, with the direction of effect to be towards each one of the columns. For instance, the estimated coefficient for the relation of Austrian bond market with banking sector is 0.106293.

Table A.7: Probability Values for the "News Effect" Coefficients from the Intra-Market GARCH-BEKK (1,1) Models

p-values for α_{ij}		Austria					Belgium					Finland					France					Germany					Greece					Ireland					Italy					Netherlands					Portugal					Spain				
		ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T
Austria	ba		0.000	0.991	0.103	0.435	0.851	0.268	0.270	0.968	0.112	0.900	0.132	0.913	0.714	0.099	0.396	0.324	0.979	0.653	0.957	0.287	0.000	0.234	0.913	0.788	0.888	0.011	0.000	0.172	0.757	0.128	0.020	0.948	0.000	0.027	0.000	0.000	0.010	0.948	0.618	0.829	0.000	0.955	0.260	0.001	0.000	0.991	0.315	0.844	0.921	0.520	0.004	0.117	0.780	0.000
	bo	0.104		0.000	0.889	0.582	0.129	0.000	0.953	0.681	0.656	0.006	0.960	0.018	0.844	0.990	0.561	0.620	0.608	0.987	0.950	0.967	0.759	0.673	0.991	0.000	0.323	0.000	0.000	0.678	0.000	0.000	0.213	0.847	0.000	0.875	0.000	0.000	0.805	0.066	0.952	0.895	0.841	0.928	0.000	0.000	0.000	0.005	0.014	0.830	0.916	0.848	0.000	0.791	0.277	0.772
	mo	0.937	0.000		0.980	0.766	0.420	0.645	0.821	0.540	0.160	0.960	0.876	0.541	0.005	0.864	0.825	0.344	0.277	0.788	0.436	0.277	0.939	0.815	0.770	0.309	0.000	0.920	0.616	0.000	0.790	0.403	0.928	0.774	0.492	0.864	0.558	0.894	0.375	0.892	0.274	0.945	0.000	0.930	0.907	0.957	0.946	0.000	0.215	0.853	0.839	0.912	0.967	0.240		0.645
	eq	0.007	0.000	0.756		0.980	0.591	0.758	0.989	0.990	0.593	0.995	0.334	0.175	0.912	0.015	0.918	0.988	0.526	0.953	0.351	0.287	0.000	0.000	0.904	0.163	0.000	0.054	0.788	0.971	0.952	0.711	0.793	0.000	0.951	0.719	0.993	0.170	0.000	0.931	0.707	0.435	0.002	0.819	0.925	0.937	0.978	0.000	0.849	0.935	0.947	0.990	0.201	0.361	0.420	0.087
	T	0.980	0.247	0.919	1.000		0.913	0.866	0.036	0.996	0.305	0.945	0.899	0.005	0.902	0.965	0.695	0.919	0.540	0.602	0.549	0.855	0.030	0.745	0.913	0.904	0.916	0.026	0.000	0.724	0.801	0.878	0.969	0.875	0.000	0.665	0.990	0.717	0.066	0.944	0.701	0.894	0.000	0.316	0.753	0.899	0.967	0.705	0.899	0.997	0.124	0.999	0.975	0.914	0.996	0.240
Belgium	ba	0.690	0.000	0.804	0.835	0.188		0.019	0.000	0.845	0.002	0.000	0.922	0.000	0.813	0.382	0.780	0.000	0.000	0.792	0.814	0.994	0.000	0.083	0.885	0.971	0.403	0.117	0.740	0.035	0.288	0.433	0.010	0.871	0.229	0.419	0.962	0.747	0.000	0.897	0.030	0.192	0.000	0.584	0.248	0.000	0.000	0.000	0.503	0.533	0.243	0.003	0.724	0.350	0.861	0.998
	bo	0.769	0.000	0.688	0.850	0.011	0.497		0.582	0.957	0.000	0.872	0.749	0.237	0.954	0.623	0.861	0.035	0.628	0.937	0.780	0.957	0.227	0.030	0.822	0.924	0.169	0.180	0.000	0.363	0.115		0.641	0.317	0.122		0.624	0.338	0.439	0.948	0.879	0.913	0.856	0.866	0.988	0.000	0.000	0.984	0.000	0.997	0.241	0.000	0.828	0.962	0.991	0.011
	mo	0.029	0.655	0.338	0.965	0.973	0.631	0.497		0.991		0.886	0.618	0.832	0.910	0.633	0.978	0.943	0.798	0.000	0.763	0.967	0.022		0.979	0.551	0.612	0.201	0.938	0.994	0.000	0.922	0.699	0.208	0.969	0.612	0.993	0.091	0.377	0.955	0.265	0.391	0.595	0.992	0.988	0.004	0.379	0.227	0.521	0.974	0.764	0.290	0.860	0.481	0.484	0.249
	eq	0.745	0.051	0.221	0.981	0.552	0.097	0.737	0.826		0.869	0.962	0.539	0.000	0.005	0.162	0.840	0.802	0.240	0.893	0.858	0.903	0.020	0.000	0.969	0.545	0.000	0.851	0.094	0.733	0.908	0.475	0.938	0.607	0.974	0.103	0.991	0.176	0.865	0.934	0.000	0.982	0.032	0.999	0.898	0.191	0.969	0.000	0.599	0.991	0.414	0.000	0.933	0.436	0.940	0.301
	T	0.364	0.801	0.257	0.519	0.547	0.723	0.000		0.886		0.000	0.991	0.471	0.266	0.582	0.994	0.482	0.000	0.000	0.753	0.774	0.997	0.870	0.775	0.091	0.001	0.823	0.716	0.875	0.837	0.914	0.897	0.908	0.780	0.725	0.963	0.526	0.733	0.897	0.241	0.711	0.595	0.701	0.000	0.987	0.902	0.329	0.150	0.864	0.993	0.966	0.895	0.584	0.949	0.809
Finland	ba	0.920	0.527	0.310	0.992	0.596	0.000	0.585	0.990	0.953	0.000		0.991	0.305	0.989	0.851	0.494	0.529	0.000	0.475	0.863	0.797	0.280	0.643	0.368	0.991	0.000	0.000	0.685	0.212	0.800	0.000	0.985	0.387	0.969	0.000	0.992	0.211	0.000	0.623	0.188	0.457	0.266	0.868	0.991	0.706	0.000	0.107	0.174	0.562	0.076	0.003	0.940	0.000	0.535	0.212
	bo	0.915	0.959	0.893	0.324	0.960	0.942	0.878	0.115	0.944	0.973	0.991		0.159	0.980	0.493	0.981	0.174	0.917	0.993	0.421	0.981	0.000	0.940	0.996	0.890	0.000	0.594	0.000	0.972	0.862	0.000	0.669	0.923	0.912	0.919	0.905	0.279	0.787	0.732	0.878	0.043	0.001	0.520	0.994	0.630	0.752	0.240	0.423	0.940	0.414	0.934	0.960	0.992	0.758	0.000
	mo	0.808	0.591	0.329	0.770	0.000	0.011	0.070	0.620	0.000	0.217	0.907	0.082		0.919	0.409	0.038	0.003	0.782	0.000	0.342	0.842	0.987	0.690	0.726	0.002	0.980	0.117	0.121	0.785	0.000	0.096	0.435	0.310	0.322	0.828	0.031	0.291	0.056	0.182	0.784	0.903	0.013	0.981	0.949	0.000	0.217	0.000	0.000	0.759	0.925	0.751	0.419	0.000	0.000	0.421
	eq	0.011	0.115	0.000	0.893	0.898	0.981	0.458	0.313	0.065	0.487	0.981	0.841	0.197		0.009	0.274	0.728	0.000	0.934	0.580	0.625	0.948	0.994	0.438	0.877	0.448	0.436	0.000	0.055	0.957	0.978	0.436	0.177	0.862	0.597	0.581	0.987	0.849	0.941	0.916	0.953	0.752	0.601	0.988	0.785	0.933	0.959	0.457	0.727	0.232	0.962	0.844	0.438	0.790	0.365
	T	0.969	0.963	0.798	0.781	0.979	0.883	0.451	0.498	0.890	0.342	0.806	0.947	0.502	0.592		0.722	0.658	0.843	0.058	0.244	0.092	0.412	0.837	0.478	0.499	0.000	0.662	0.232	0.973	0.002	0.753	0.845	0.931	0.798	0.183	0.823	0.635	0.870	0.909	0.620	0.898	0.939	0.055	0.947	0.978	0.836	0.000	0.006	0.888	0.614	0.241	0.943	0.445	0.372	0.016
France	ba	0.926	0.297	0.000	0.871	0.679	0.741	0.097	0.843	0.909	0.211	0.708	0.988	0.523	0.298	0.400		0.025	0.001	0.810	0.000	0.541	0.000	0.165	0.984	0.809	0.000	0.000	0.518	0.996	0.497	0.488	0.559	0.983	0.993	0.150	0.924	0.299	0.117	0.193	0.295	0.949	0.963	0.413	0.986	0.998	0.761	0.044	0.346	0.895	0.062	0.783	0.502	0.015	0.950	0.000
	bo	0.036	0.934	0.890	0.998	0.918	0.803	0.005	0.218	0.949	0.221	0.879	0.053	0.244	0.960	0.687	0.048		0.931	0.853	0.001	0.320	0.565	0.866	0.892	0.871	0.899	0.290	0.938	0.823	0.862	0.449	0.062	0.842	0.595	0.086	0.002	0.890	0.000	0.909	0.176	0.990	0.066	0.785	0.963	0.000	0.925	0.130	0.801	0.026	0.039	0.000	0.846	0.469	0.136	0.811
	mo	0.920	0.204	0.110	0.568	0.592	0.340	0.335	0.651	0.928	0.687	0.874	0.394	0.985	0.912	0.632	0.055	0.009		0.986	0.025	0.949	0.605	0.949	0.974	0.154	0.898	0.089	0.032	0.925	0.124	0.953	0.787	0.991	0.403	0.895	0.985	0.919	0.991	0.991	0.202	0.305	0.000		0.125	0.876	0.035	0.221	0.009	0.785	0.000	0.975	0.971	0.000	0.843	0.910
	eq	0.934	0.131	0.066	0.948	0.001	0.700	0.984	0.000	0.799	0.000	0.352	0.984	0.000	0.967	0.001	0.721	0.607	0.912		0.865	0.762	0.058	0.046	0.989	0.774	0.896	0.103	0.000	0.641	0.394	0.880	0.013	0.000	0.971	0.442	0.697	0.924	0.000	0.792	0.927	0.339	0.000	0.945	0.869	0.899	0.917	0.000	0.292	0.838	0.981	0.950	0.453	0.731	0.820	0.983
	T	0.939	0.839	0.058	0.623	0.206	0.656	0.211	0.199	0.905	0.521	0.966	0.742	0.876	0.834	0.735	0.088	0.319	0.640	0.925		0.998	0.975	0.420	0.334	0.676	0.580	0.802	0.665	0.680	0.000	0.000	0.995	0.814	0.557	0.218	0.728	0.924	0.000	0.000	0.451	0.971	0.567	0.002	0.521	0.184	0.967	0.785	0.683	0.000	0.901	0.032	0.874	0.000	0.048	0.653
Germany	ba	0.236	0.554	0.022	0.839	0.673	0.975	0.525	0.181	0.916	0.042	0.791	0.859	0.794	0.321	0.069	0.758	0.890	0.000	0.948	0.967		0.705	0.972	0.725	0.863	0.904	0.683	0.000	0.946	0.045	0.136	0.437	0.288	0.954	0.000	0.348	0.958	0.863	0.963	0.887	0.977	0.907	0.935	0.852	0.881	0.993	0.000	0.973	0.982	0.226	0.950	0.825	0.943	0.943	0.934
	bo	0.000	0.002	0.682	0.000	0.295	0.266	0.065	0.106	0.014	0.998	0.004	0.000	0.604	0.837	0.560	0.000	0.720	0.702	0.000	0.988	0.740		0.000	0.171	0.012	0.156	0.006	0.020	0.853	0.478	0.106	0.146	0.338	0.672	0.000	0.709	0.345	0.525	0.012	0.457	0.919	0.340	0.067	0.967	0.957	0.000	0.125	0.152	0.230	0.002	0.000	0.000	0.000	0.018	0.666
	mo	0.970	0.873	0.984	0.000	0.200	0.003	0.000		0.874	0.330	0.672	0.962	0.193	0.894	0.626	0.718	0.929	0.997	0.958	0.948	0.965	0.000		0.927	0.040	0.797	0.001	0.151	0.024	0.000	0.928	0.801	0.953	0.537	0.561	0.848	0.740	0.928	0.809	0.983	0.918	0.667	0.974	0.956	0.194	0.933	0.486	0.912	0.000	0.906	0.000	0.786	0.431	0.873	0.096
	eq	0.720	0.992	0.000	0.813	0.567	0.889	0.004	0.943	0.946	0.780	0.607	0.938	0.774	0.528	0.571	0.892	0.556	0.764	0.963	0.008	0.827	0.371	0.819		0.704	0.973	0.000	0.325	0.946	0.602	0.252	0.847	0.000	0.967	0.799	0.992	0.582	0.700	0.976	0.133	0.748	0.852	0.907	0.968	0.843	0.916	0.996	0.848	0.840	0.773	0.331	0.718	0.019	0.986	0.000
	T	0.928	0.000	0.570	0.696	0.198	0.888	0.903	0.565	0.967	0.330	0.972	0.764	0.199	0.836	0.390	0.941	0.654	0.890	0.893	0.616	0.927	0.063	0.863	0.948		0.000	0.941	0.970	0.914	0.820	0.491	0.001	0.782	0.938	0.888	0.258	0.941	0.991	0.882	0.929	0.996	0.034	0.691	0.944	0.944	0.937	0.000	0.137	0.946	0.473	0.724	0.983	0.000	0.887	0.004
Greece	ba	0.002	0.507	0.000	0.000	0.323	0.689	0.104	0.001	0.040	0.000	0.001	0.000	0.907	0.766	0.345	0.344	0.174	0.303	0.735	0.107	0.993	0.369	0.522	0.672	0.000		0.000	0.000	0.120	0.969	0.955	0.769	0.682	0.955	0.000	0.999	0.001	0.967	0.989	0.654	0.938	0.000	0.433	0.503	0.000	0.000	0.475	0.009	0.866	0.217	0.809	0.561	0.004	0.418	0.037
	bo	0.927	0.000	0.158	0.807	0.373	0.629	0.152	0.139	0.879	0.937	0.000	0.988	0.271	0.823	0.923	0.004	0.319	0.595	0.512	0.767	0.912	0.597	0.000	0.889	0.977	0.200		0.000	0.998	0.944	0.000	0.021	0.961	0.906	0.194	0.989	0.136	0.647	0.957	0.878	0.797	0.009	0.639	0.995	0.895	0.958	0.711	0.000	0.821	0.349	0.075	0.920	0.857	0.510	0.729
	mo	0.142	0.017	0.938	0.881	0.000	0.777	0.000	0.975	0.319	0.663	0.961	0.037	0.015	0.947	0.859	0.671	0.945	0.037	0.544	0.566	0.533	0.905	0.322	0.957	0.970	0.002	0.000		0.805	0.937	0.399	0.085	0.353	0.502	0.000	0.539	0.000	0.363	0.377	0.443	0.001	0.417	0.825	0.932	0.143	0.007	0.419	0.005	0.000	0.967	0.839	0.845	0.000	0.073	0.803
	eq	0.000	0.000	0.000	0.946	0.924	0.000	0.000	0.982	0.784	0.639	0.606	0.932	0.289	0.489	0.971	0.893	0.000	0.225	0.345	0.197	0.978	0.738	0.109	0.038	0.945	0.144	0.999	0.171		0.954	0.140	0.994	0.001	0.935	0.532	0.415	0.466	0.527	0.027	0.000	0.872	0.030	0.620	0.006	0.826	0.000	0.018	0.037	0.938	0.513	0.868	0.733	0.906	0.970	0.896
	T	0.981	0.000	0.688	0.834	0.749	0.858	0.000	0.000	0.815	0.405	0.822	0.640	0.000	1.000	0.000	0.953	0.794	0.821	0.242	0.000	0.475	0.576	0.000	0.894	0.937	0.973	0.986	0.155	0.981		0.986	0.560	0.784	0.849	0.000	0.348	0.901	0.902	0.410	0.817	0.744	0.777	0.962	0.959	0.021	0.407	0.885	0.471	0.821	0.017	0.740	0.569	0.000	0.661	0.000
Ireland	ba	0.574	0.000	0.143	0.765	0.597	0.356		0.414	0.548	0.007	0.000	0.000	0.000	0.712	0.490	0.404	0.014	0.013	0.772	0.752	0.167	0.019	0.150	0.057	0.839	0.971	0.000	0.029	0.855	0.883		0.127	0.998	0.889	0.082	0.014	0.367	0.335	0.888	0.000	0.709	0.517	0.002	0.000	0.000	0.000	0.000	0.010	0.939	0.914	0.902	0.072	0.000	0.945	0.871
	bo	0.660	0.000	0.744	0.976	0.918	0.834	0.606	0.001	0.891	0.783	0.994	0.532	0.813	0.713	0.968	0.634	0.771	0.007	0.848	0.990	0.994	0.650	0.299	0.612	0.788	0.878	0.322	0.161	0.993	0.128	0.818		0.992	0.966	0.580	0.944	0.158	0.470	0.968	0.709	0.941	0.931	0.941	0.938	0.991	0.154	0.127	0.528	0.875	0.981	0.911	0.934	0.901	0.899	0.157
	mo	0.950	0.321	0.861	0.221	0.855	0.999	0.931	0.164	0.988	0.881	0.473	0.980	0.152	0.770	0.918	0.991	0.930	0.895	0.280	0.919	0.703	0.728	0.941	0.969	0.793	0.990	0.746	0.669	0.966	0.722	0.997	0.967		0.782	0.608	0.915	0.992	0.227	0.806	0.823	0.677	0.587	0.801	0.751	0.908	0.804	0.726	0.983	0.931	0.959	0.000	0.342	0.947	0.833	0.320
	eq	0.084	0.000	0.064	0.943	0.000	0.000	0.401	0.924	0.960	0.000	0.978	0.983	0.087	0.965	0.156	0.997	0.201	0.006	0.978	0.403	0.593	0.009	0.167	0.958	0.567	0.764	0.552	0.696	0.604	0.000	0.823	0.688	0.163		0.000	0.280	0.904	0.375	0.643	0.616	0.900	0.006	0.553	0.719	0.726	0.859	0.291	0.000	0.000	0.108	0.084	0.060	0.017	0.869	0.833
	T	0.845	0.484	0.875	0.926	0.143	0.959		0.327	0.582	0.975	0.000	0.927	0.944	0.709	0.440	0.745	0.303	0.402	0.757	0.888	0.006	0.593	0.003	0.824	0.004	0.011	0.875	0.000	0.776	0.002	0.776	0.005	0.486	0.289		0.000	0.021	0.121	0.905	0.837	0.976	0.594	0.000	0.898	0.741	0.256	0.686	0.450	0.826	0.799	0.803	0.837	0.747	0.826	0.000
Italy	ba	0.000	0.000	0.833	0.885	0.898	0.963	0.789	0.962	0.977	0.331	0.953	0.303	0.000	0.965	0.852	0.925	0.000	0.215	0.874	0.539	0.654	0.682	0.024	0.995	0.236	0.811	0.825	0.100	0.956	0.018	0.015	0.478	0.883	0.167	0.000		0.205	0.768	0.862	0.437	0.804	0.774	0.286	0.023	0.729	0.000	0.065	0.699	0.969	0.964	0.865	0.127	0.001	0.692	0.987
	bo	0.531	0.000	0.365	0.940	0.644	0.745	0.382	0.669	0.711	0.539	0.789	0.959	0.884	0.973	0.527	0.381	0.350	0.562	0.896	0.141	0.975	0.277	0.647	0.885	0.711	0.296	0.954	0.000	0.909	0.466	0.001	0.896	0.977	0.983	0.087	0.837		0.001	0.849	1.000	0.699	0.000	0.398	0.993	1.000	0.417	0.920	0.305	0.978	0.871	0.973	0.958	0.904	0.000	0.000
	mo	0.000	0.787	0.882	0.782	0.118	0.000	0.385	0.413	0.928	0.798	0.401	0.000	0.619	0.163	0.964	0.981	0.000	1.000	0.400	0.000	0.953	0.000	0.956	0.969	0.988	0.000	0.168	0.993	0.943	0.601	0.377	0.368	0.241	0.750	0.628	0.754	0.000		0.677	0.668	0.997	0.669	0.995	0.994	0.430	0.200	0.000	0.000	0.974	0.721	0.876	0.910	0.165	0.891	0.000
	eq	0.775	0.200	0.001	0.974	0.931	0.919	0.178	0.651	0.949	0.876	0.971	0.670	0.086	0.964	0.777	0.042	0.651	0.943	0.688	0.000	0.939	0.000	0.261	0.775	0.447	0.903	0.000	0.000	0.872	0.984	0.751	0.832	0.001	0.939	0.915	0.822	0.793	0.530		0.791	0.935	0.903	0.857	0.891	0.839	0.074	0.000	0.495	0.986	0.263	0.748	0.079	0.410	0.966	0.492
	T	0.269	0.957	0.374	0.948	0.079	0.650	0.686	0.793	0.541	0.263	0.800	0.683	0.363	0.907	0.507	0.921	0.033	0.713	0.924	0.475	0.904	0.000	0.950	0.800	0.815	0.953	0.014	0.176	0.940	0.011	0.973	0.937	0.508	0.972	0.985	0.900	1.000	0.039	0.664		0.977	0.531	0.958	0.957	0.675	0.685	0.000	0.000	0.955	0.000	0.421	0.438	0.790	0.026	0.000
Netherlands	ba	0.929	0.578	0.895	0.980	0.591	0.847	0.000	0.943	0.990	0.007	0.918	0.675	0.992	0.977	0.881	0.979	0.832	0.788	0.545	0.957	0.960	0.173	0.794	0.966	0.926	0.002	0.000	0.000	0.673	0.162	0.930	0.751	0.363	0.878	0.388	0.159	0.208	0.952	0.968	0.931		0.731	0.763	0.974	0.976	0.984	0.698	0.154	0.434	0.089	0.778	0.530	0.000	0.993	0.158
	bo	0.000	0.481	0.000	0.995	0.000	0.000	0.284	0.179	0.000	0.775	0.240	0.002	0.675	0.807	0.363	0.873	0.014	0.000	0.000	0.940	0.334	0.139	0.773	0.891	0.000	0.000	0.000	0.343	0.021	0.477	0.786	0.914	0.930	0.000	0.947	0.504	0.836	0.869	0.922	0.184	0.874		0.952	0.907	0.562	0.443	0.000	0.614	0.002	0.881	0.021	0.195	0.399	0.219	0.367
	mo	0.304	0.000	0.812	0.972	0.214	0.853	0.791	0.964	0.998	0.909	0.832	0.065	0.958	0.969	0.135	0.688	0.916		0.941	0.000	0.940	0.391	0.972	0.668	0.403	0.946	0.651	0.008	0.726	0.922	0.022	0.647	0.482	0.747	0.000	0.870	0.000	0.994	0.997	0.663	0.788	0.791		0.922	0.077	0.835	0.126	0.492	0.902	0.085	0.970	0.045	0.699	0.749	0.775
	eq	0.918	0.000	0.506	0.952	0.869	0.948	0.403	0.659	0.975	0.000	0.984	0.822	0.603	0.908	0.007	0.945	0.800	0.704	0.948	0.000	0.971	0.002	0.000	0.945	0.868	0.914	0.869	0.000	0.769	0.296	0.000	0.899	0.079	0.995	0.000	0.138	0.975	0.839	0.936	0.714	0.993	0.007	0.744		0.913	0.318	0.724	0.116	0.956	0.046	0.975	0.817	0.072	0.847	0.000
	T	0.689	0.021	0.993	0.985	0.795	0.000	0.012	0.929	0.767	0.986	0.558	0.731	0.000	0.928	0.863	0.994	0.377	0.755	0.888	0.185	0.964	0.752	0.357	0.946	0.986	0.000	0.766	0.000	0.921	0.005	0.000	0.906	0.701	0.661	0.388	0.892	0.999	0.965	0.847	0.050	0.952	0.112	0.769	0.984		0.949	0.000	0.956	0.471	0.490	0.830	0.724	0.000	0.934	0.030
Portugal	ba	0.000	0.000	0.416	0.368	0.582	0.000	0.269	0.000	0.874	0.437	0.172	0.803	0.132	1.000	0.983	0.976	0.015	0.559	0.482	0.517	0.990	0.008	0.007	0.439	0.663	0.000	0.846	0.000	0.006	0.584	0.016	0.090	0.581	0.466	0.005	0.000	0.536	0.001	0.042	0.101	0.683	0.000	0.690	0.750	0.022		0.565	0.700	0.864	0.776	0.279	0.498	0.601	0.825	0.077
	bo	0.977	0.087	0.000	0.000	0.458	0.717	0.950	0.726	0.028	0.298	0.000	0.444	0.021	0.948	0.395	0.024	0.687	0.806	0.000	0.188	0.000	0.591	0.951	0.992	0.000	0.820	0.173	0.765	0.004	0.000	0.000	0.000	0.107	0.964	0.451	0.504	0.068	0.000	0.000	0.000	0.818	0.000	0.875	0.416	0.000	0.670		0.817	0.903	0.000	0.752	0.435	0.058	0.104	0.000
	mo	0.592	0.869	0.883	0.935	0.394	0.870	0.507	0.611	0.914	0.282	0.348	0.901	0.000	0.879	0.121	0.775	0.947	0.771	0.916	0.587	0.995	0.204	0.918	0.987	0.013	0.137	0.000	0.000	0.959	0.134	0.561	0.839	0.951	0.937	0.717	0.960	0.186	0.000	0.005	0.000	0.942	0.831	0.772	0.997	0.917	0.976	0.794		0.786	0.619	0.709	0.798	0.128	0.882	0.460
	eq	0.756	0.505	0.913	0.983	0.994	0.764	0.255	0.928	0.931	0.113	0.929	0.862	0.191	0.890	0.003	0.475	0.003	0.265	0.304	0.000	0.965	0.273	0.000	0.235	0.890	0.402	0.879	0.000	0.902	0.016	0.798	0.343	0.171	0.225	0.254	0.949	0.823	0.744	0.938	0.168	0.125	0.012	0.276	0.987	0.891	0.919	0.842	0.483			0.000	0.105	0.801	0.791	0.002
	T	0.963	0.697	0.856	0.979	0.651	0.732	0.779	0.662	0.912	0.994	0.880	0.730	0.833	0.917	0.983	0.851	0.840	0.000	0.993	0.490	0.884	0.406	0.899	0.933	0.688	0.004	0.000	0.183	0.904	0.332	0.094	0.978	0.999	0.986	0.060	0.983	0.914	0.848	0.783	0.000	0.943	0.778	0.582	0.797	0.958	0.882	0.000	0.133			0.909	0.890	0.883	0.987	0.000
Spain	ba	0.759	0.945	0.413	0.945	0.926	0.516	0.000	0.059	0.000	0.881	0.146	0.858	0.516	0.986	0.000	0.832	0.000	0.000	0.936	0.000	0.786	0.000	0.000	0.007	0.019	0.981	0.000	0.002	0.926	0.085	0.246	0.705	0.000	0.357	0.431	0.929	0.987	0.029	0.409	0.000	0.922	0.058	0.998	0.966	0.803	0.387	0.661	0.000	0.015	0.941		0.606	0.726	0.588	0.173
	bo	0.046	0.269	0.992	0.975	0.954	0.966	0.614	0.939	0.987	0.938	0.937	0.963	0.254	0.649	0.957	0.474	0.080	0.918	0.718	0.534	0.958	0.129	0.518	0.665	0.888	0.452	0.193	0.944	0.989	0.913	0.674	0.976	0.452	0.306	0.933	0.590	0.952	0.987	0.653	0.260	0.943	0.606	0.028	0.938	0.001	0.577	0.502	0.044	0.942	0.926	0.626		0.965	0.832	0.795
	mo	0.924	0.757	0.795	0.906	0.488	0.003	0.326	0.739	0.865	0.888	0.072	0.804	0.000	0.883	0.554	0.820	0.533	0.000	0.866	0.060	0.955	0.000	0.003	0.920	0.000	0.804	0.757	0.361	0.958	0.000	0.000	0.874	0.433	0.366	0.248	0.083	0.484	0.331	0.760	0.413	0.836	0.133	0.896	0.921	0.149	0.967	0.476	0.823	0.731	0.979	0.948	0.003		0.881	
	eq	0.315	0.236		0.517	0.660	0.887	0.977	0.000	0.950	0.762	0.955	0.512	0.064	0.680	0.502	0.740	0.000	0.293	0.793	0.000	0.618	0.013	0.294	0.993	0.725	0.109	0.000	0.000	0.396	0.795	0.808	0.323	0.389	0.922	0.050	0.010	0.000	0.004	0.928	0.119	0.854	0.528	0.686	0.574	0.000	0.174	0.001	0.024	0.926	0.883	0.240	0.428	0.033		0.003
	T	0.885	0.472	0.861	0.944	0.302	0.993	0.053	0.337	0.736	0.504	0.925	0.000	0.784	0.729	0.711	0.762	0.060	0.798	0.997	0.030	0.967	0.134	0.252	0.000	0.707	0.847	0.156	0.141	0.864	0.000	0.895	0.946	0.977	0.924	0.000	0.995	0.682	0.000	0.909	0.000	0.705	0.316	0.886	0.597	0.024	0.352	0.376	0.632	0.364	0.000	0.788	0.880		0.902	

Notes: These are the p-values of the estimated "news effect" coefficients from the bivariate GARCH-BEEK(1,1) models for the case of cross-markets analysis. Markets FSIs are represented as: ba (banking sector), bo (bond market), mo (money market), eq (equity market) and T (country). The table is read row by row, with the direction of effect to be towards each one of the columns. For instance, the p-value for the estimated coefficient representing the relation of Austrian bond market with banking sector is 0.104.

Table A.8: "Volatility Spillover" Coefficients from the Intra-Market GARCH-BEKK (1,1) Models

β_j		Austria					Belgium					Finland					France					Germany					Greece					Ireland					Italy					Netherlands					Portugal					Spain				
		ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T
Austria	ba		0.02022	0.012548	-0.09527	0.007168	0.002893	-0.06297	0.050115	0.034571	0.02323	0.001002	-0.00658	-0.00727	0.004972	0.011194	0.017643	-0.04194	-0.0047	0.000337	-0.00204	-0.00322	-0.01301	-0.00486	-0.01877	-0.00772	0.000579	0.019662	0.007139	0.155049	-0.00421	0.036206	0.099051	0.002353	0.038248	-0.00641	0.030919	-0.10509	0.003542	-0.01192	-0.01002	0.005153	0.005008	0.001144	0.000311	-0.00095	0.02104	0.057338	0.005953	0.002363	-0.00027	0.002139	0.023763	-0.01302	-0.00082	-0.00831
	bo	-0.0176		-0.00975	0.000548	0.069612	0.154122	0.006841	-0.23847	0.063723	0.011233	0.15611	-0.0049	0.0382	0.004639	-0.01543	0.020096	0.146783	-0.0387	-0.00256	-0.00028	0.017354	-0.03279	-0.00171	-0.16231	0.017697	-0.03306	0.001714	0.012735	0.031243	-0.05043	0.061485	-0.051	-0.01884	0.00177	-0.02742	-0.01712	0.030876	0.003632	0.139954	-0.05541	0.043567	-0.00029	0.007002	0.006043	0.000447	-0.01623	-0.04484	-0.13252	-0.09527	-0.01532	-0.06635	-0.02813	-0.00469	0.1825	0.046375
	mo	-0.11277	0.020595		0.000414	-0.03707	-0.10199	-0.0187	-0.00136	0.239259	0.127211	-0.0115	-0.00948	0.01538	0.012104	-0.03152	0.001816	0.026354	-0.00097	0.770255	0.00465	0.031738	-0.00356	-0.0266	0.059658	-0.02163	0.028336	-0.05143	0.038749	0.133169	-0.02478	-0.02429	-0.05108	0.003782	0.183524	-0.01185	0.044248	0.052922	-0.02756	0.038326	0.07504	-0.02627	0.001028	0.01438	0.01263	0.058461	-0.10363	0.003477	0.021489	0.011387	0.002457	0.059198	-0.00265	0.030915	0.191226	-0.00082
	eq	0.074413	-0.01451	-0.00221		-0.02043	-0.00048	-0.02954	0.006426	-0.02826	-0.02818	-0.00032	0.014364	-0.02106	-0.03651	-0.01091	-0.01456	0.001491	0.006168	-0.02001	0.02285	0.017976	-0.04909	-0.05447	-0.03282	0.015077	-0.11412	-0.00647	0.092287	0.023653	-0.0038	0.019872	-0.00082	0.10954	-0.01878	-0.02575	-0.00462	0.040084	0.026695	-0.06041	-0.0225	0.013248	0.082111	-0.0433	0.008511	0.028502	-0.01871	0.007539	0.009207	-0.02737	0.014994	-0.02138	0.018659	0.000583	-0.02592	0.02051
	T	-0.06401	-0.06857	0.028711	0.016487		0.019358	0.00031	-0.02261	-0.00499	0.038966	-0.02803	0.008365	-0.00778	-0.03	-0.02125	-0.00241	-0.00513	0.00542	0.00408	0.011553	0.051689	0.02572	-0.00062	-0.00076	-0.04847	0.024206	0.017222	-0.00012	-0.04513	0.023632	0.001289	-0.03123	-0.02627	0.053402	0.003722	0.001623	-0.00263	-0.0374	0.087352	0.008125	-0.01071	-0.04045	-0.00499	-0.00822	0.041206	-0.10465	0.01214	0.041156	-0.04903	-0.0347	-0.00715	0.01247	0.251592	-1.60E-05	0.054932
Belgium	ba	-0.07991	-0.01409	0.051207	0.046637	0.013413		-0.01122	0.174296	0.01693	-0.01866	-0.01358	-0.01219	0.001981	0.01805	0.084622	0.052266	-0.06229	0.105876	-0.03066	-0.00462	-0.01485	0.025489	0.011355	0.009036	0.002363	0.50038	0.003314	-0.03784	0.043236	-0.02653	0.013301	-0.07456	-0.04952	-0.00281	-0.007	-0.0086	0.001778	0.009171	0.067989	0.013053	-0.00397	-0.14522	0.026991	0.027438	0.130466	0.011859	0.022447	0.029865	-0.13014	0.008819	0.062998	0.009136	-0.02019	-0.00239	0.00346
	bo	-0.00438	-0.01093	-0.0252	0.01406	0.06651	0.052031		0.000415	-0.01626	0.045514	0.061609	0.001105	-0.03291	0.001778	-0.09344	0.001685	-0.0263	-0.06491	-0.04287	0.002514	-0.04958	-0.03112	-0.00937	0.020516	0.000486	-0.07552	0.00192	0.130938	0.000522	0.0371	-0.0224	0.002406	-6.17E-05	-0.0126	0.129917	0.018908	-0.01146	-0.14638	-0.02247	-0.01609	-0.0138	-0.02112	0.093152	0.006967	0.007354	-0.14628	0.011687	0.083511	-0.05347	-0.03949	-0.40623	0.014365	0.06609	0.044868	0.062918
	mo	-0.09232	0.006712	0.013262	-0.07922	-0.00268	-0.05809	0.00195		-0.00225	0.090962	-0.00324	0.09161	0.005471	0.012473	-0.02785	-0.10505	0.09453	-0.00434	-0.03472	-0.01251	0.03429	0.024816	0.089173	0.013751	0.000194	0.003469	-0.01011	-0.00213	0.020391	-0.01541	-0.04488	0.054276	0.020143	0.011105	0.005519	-0.01619	0.123909	-0.02644	-0.17296	0.097831	0.044086	0.010573	-0.08953	0.001157	-0.00205	0.030989	-0.09112	0.023777	0.032283	0.07157	-0.09927	-0.00022	-0.01819	-0.06684	0.00144
	eq	0.010653	-0.0264	-0.00137	-0.00201	-0.03151	-0.04381	0.020616	-0.002		0.00952	0.004647	-0.01126	0.042161	-0.04526	0.071571	0.046143	0.011916	0.055481	-0.00013	-0.00509	0.001781	0.011692	-0.03601	0.008962	-0.00058	-0.01679	0.004378	-0.05707	0.052244	-0.01836	0.004183	-0.01388	-0.00056	0.038029	0.015137	-0.00546	-0.08723	0.009831	-0.26541	0.044095	0.00107	0.00069	-0.07599	0.115019	0.029431	-0.0142	-0.00094	-0.00689	-0.01184	-0.03447	-0.0623	-0.00464	0.021642	0.006202	0.013995
	T	-0.16221	-0.032	-0.00274	0.024586	-0.04842	0.174782	-0.14092	-0.04305	-0.04184		0.011992	0.000333	-0.00028	0.01563	0.006677	-0.00388	-0.02921	-0.05971	0.062499	0.06069	-0.07099	-0.00069	-0.01482	-0.0501	-0.00435	-0.02503	0.021387	0.064472	0.025297	-0.03025	0.034129	-0.06373	-0.00162	0.020614	0.124711	-0.03371	0.004347	0.135217	0.641063	0.007228	0.10208	-0.25011	-0.01622	0.048925	0.058208	-0.02189	0.002852	0.01663	-0.08445	-0.00531	0.056109	-0.01458	-0.01758	0.120959	0.036756
Finland	ba	0.017912	-0.00015	0.003443	-0.00226	0.013299	0.058818	-0.00087	0.093996	-0.00578	-0.00962		0.022052	-0.00487	-0.01133	-0.00806	0.011989	0.012015	-0.03921	-0.06693	-0.01044	0.012912	-0.00846	-0.00122	-0.02644	0.007263	0.008046	0.022478	-0.003	-0.08654	-0.02209	-0.0433	0.025844	-0.00539	0.00183	0.000729	0.059677	-0.01109	0.010248	-0.01611	0.01278	0.013184	9.14E-05	0.064782	-0.0227	-0.01957	0.000928	0.013269	0.041956	-0.02395	0.011102	0.058191	-0.00651	-0.0029	-0.03309	-0.00857
	bo	0.014663	0.000302	0.065687	-0.02468	-0.01275	-0.04409	-0.004	-0.11936	-0.00634	0.002781	-0.33943		0.024763	0.006887	0.107215	-0.10474	0.005452	-0.00424	0.010245	0.026283	-0.00906	0.102135	0.00732	0.011166	0.000893	0.015193	0.026397	-0.15805	0.161927	0.004968	-0.19844	-0.03743	-0.01458	0.008303	0.000224	-0.02999	-0.03413	0.010684	-0.08152	-0.01511	-0.22069	0.01827	-0.00318	-0.00032	0.020448	0.031808	-0.04626	0.087117	-0.00944	-0.06597	-0.15253	0.002008	-0.00079	-0.01459	-0.04717
	mo	0.127107	-0.00771	-0.00546	0.210545	0.023679	0.002811	0.020214	0.00945	-0.00986	0.273454	-0.01158	-0.00469		0.005514	-0.00088	0.142972	-0.00975	0.013048	-0.08804	-0.02496	0.006952	-0.00053	-0.03486	0.003466	-0.05157	0.002864	-0.06727	0.0295	-0.01119	0.083058	-0.00703	-0.05157	-0.00583	-0.00016	-0.02569	-0.10152	-0.04983	0.053237	-0.0628	0.016126	0.013512	-0.06142	0.005606	-0.05361	0.026158	-0.01488	0.008012	0.00086	0.338111	0.013236	0.171628	-0.01549	-0.00213	0.003531	-0.01039
	eq	0.029817	-0.268	-0.00719	0.028153	0.002376	-0.02195	-0.00427	-0.04315	0.040054	-0.07286	-0.00116	-0.03686	-0.00047		0.004707	0.00614	-0.01706	0.001609	-0.00539	-0.00393	0.044247	-0.00405	-0.00591	0.030379	-0.00761	-0.02814	0.007049	-0.00994	0.11114	0.010608	-0.13896	0.014351	0.005232	-0.01252	0.009262	-0.03344	-0.02343	-0.04073	0.003107	0.018107	0.001187	-0.02059	-0.05746	-0.00263	-0.00702	-0.00457	-0.00169	-0.24147	0.007513	-0.00055	0.019997	-0.00847	-0.09245	0.011797	0.005222
	T	0.00696	0.04773	0.049909	0.006093	0.037677	-0.18381	0.032298	0.060598	-0.11183	-0.02234	-0.00024	-0.22394	-0.208	-0.02559		0.005483	0.014804	0.055726	-0.00623	-0.02242	0.024659	0.163906	0.018106	-0.05312	0.097638	-0.13027	0.067075	0.00041	0.001597	0.021496	0.038301	-0.02526	0.002413	-0.01207	0.157481	-0.01714	0.090375	0.077777	0.0052	0.043213	-0.04905	-0.04596	0.037231	-0.01236	0.046356	-0.01699	-0.02446	0.017342	-0.01735	0.074116	0.000227	0.030074	0.010125	-0.07005	-0.07632
France	ba	-0.00179	0.052332	-0.0193	-0.0069	0.016355	0.001125	0.000833	0.058184	-0.00123	0.03339	0.019752	0.003517	-0.03963	-0.011	0.001075		0.084697	0.03757	0.00733	0.01058	-0.02156	-0.0733	-0.00047	-0.00354	0.020442	-0.01394	0.00209	0.004717	0.133147	0.016546	0.020266	-0.01211	-0.01223	-0.04011	0.008561	-0.00388	0.003389	-0.00232	-0.0891	0.018301	-0.03242	-0.03748	0.06764	-0.00101	0.039614	0.065159	-0.00232	0.001023	0.027864	0.018314	0.042454	-0.0138	-0.00842	-0.03375	-0.00383
	bo	0.001962	-0.00041	-0.12415	-0.00126	-0.01955	0.584713	0.040715	-0.0366	-0.01959	0.009366	-0.01684	-0.14266	-0.00712	0.00632	0.066221	-0.52347		-0.04966	-0.01716	-0.00886	-0.26494	-0.01576	9.29E-05	0.23613	-0.11856	-0.40362	0.013308	0.003999	-0.00752	-0.02568	0.375611	0.017703	-0.00282	-0.00545	0.009704	-0.00882	0.076008	-0.00247	-0.01358	0.031108	-0.00508	-0.02676	-0.0251	-0.01128	0.158077	-0.09977	0.073656	-0.02569	-0.04065	-0.03192	-9.40E-05	0.003151	0.106454	-0.0069	0.002127
	mo	0.037821	0.0747	0.001544	-0.06076	-0.03805	-0.08564	0.030709	0.02111	-0.28046	9.54E-05	0.036856	0.101824	-0.00017	-5.05E-05	0.000514	-0.06908	0.058331		-0.0113	0.023617	0.007041	-0.0492	0.015256	0.185487	0.012623	0.375047	0.003508	-0.04848	-0.02412	-0.05533	0.052205	0.020046	0.014297	0.137677	-0.0549	-0.01475	0.047848	0.002746	0.065047	-0.05296	0.051221	-0.00738	0.002061	-0.11954	0.150433	-0.00691	-0.05749	-0.09075	0.005719	0.049602	-0.00155	0.025953	0.114616	-0.0102	0.000257
	eq	0.014655	0.006388	-0.04707	0.010711	-0.02678	0.01493	0.019982	0.044436	-0.00237	-0.03077	-0.02782	-0.01405	0.022605	0.024213	-0.01734	0.002084	0.012603	-0.02101		-0.00427	0.057338	-0.0408	-0.01539	0.001896	-0.00459	0.045665	0.026148	-0.04897	0.006238	0.005945	-0.01507	0.049026	-0.00205	0.030329	-0.00402	0.121644	-0.02064	0.038503	0.014156	-0.00752	0.004318	-0.02993	-0.04166	0.021048	-0.00907	-0.0545	0.00599	-0.00127	-0.02562	0.043222	0.024958	-0.02226	0.033166	0.01439	0.003959
	T	0.018246	-0.06437	-0.02826	-0.05192	-0.10566	0.017107	-0.07407	0.058117	0.048946	-0.13127	0.095342	-0.00372	0.006913	0.003925	-0.00042	0.007341	0.163039	-0.01045	0.089609		0.018493	-0.04683	-0.07983	0.009318	-0.05101	-0.05982	0.014506	-0.22498	-0.02253	0.181587	-0.05339	0.12163	-0.02184	-0.15767	0.035592	0.005887	0.057624	0.09492	0.055273	-0.02544	0.001056	0.108846	0.006753	0.055395	-0.0478	0.011938	0.021842	-0.07718	-0.07266	-0.06398	-0.016	0.040712	-0.16543	0.025094	0.013942
Germany	ba	-0.01964	-0.01381	-0.08616	-0.00958	-0.00736	-0.03754	0.049085	-0.03959	0.068945	0.031529	-0.0001	0.024093	-0.00842	0.048374	-0.11693	0.008183	0.002407	0.023997	-0.02089	0.008924		0.030466	-0.00207	0.035161	0.002037	0.028298	-0.00544	0.018647	-0.00377	0.00939	0.032569	0.001361	0.024729	-0.00227	-0.04944	-0.10029	0.004304	0.000592	0.012343	-0.00121	-0.0006	0.029334	-0.00306	0.008499	0.017533	0.020318	0.066893	-0.00704	0.057355	0.028808	0.011283	-2.02E-05	-0.00072	-4.41E-05	0.005831
	bo	0.011771	0.021284	0.015889	0.082151	-0.01608	-0.00454	0.025981	0.006875	-0.08947	0.002738	0.099283	-0.01066	0.040051	0.031823	-0.05392	0.018245	0.010698	0.023604	0.010066	0.01165	-0.10292		0.010289	0.046883	0.033822	-0.00666	0.04699	0.00608	-0.07356	0.032544	0.039916	0.044824	0.002997	-0.00135	-0.00283	-0.04803	0.025425	-0.03819	-0.04164	-0.21904	0.041041	0.034269	0.111893	0.014907	0.0218	-0.13775	0.064204	-0.04328	-0.09562	0.084708	0.240247	8.04E-05	-0.00887	0.007467	-0.00681
	mo	0.004457	-0.00965	0.003667	0.060352	-0.04836	-0.0653	0.015011	-0.00095	0.002882	0.019988	-0.11814	0.004911	0.001482	0.039251	-0.00205	-0.00528	0.064703	0.002464	0.040568	0.001684	-0.01373	0.058502		0.068866	0.04121	-0.00449	0.020266	0.044943	0.000344	7.20E-05	0.027679	-0.00654	-0.0001	-0.10793	-0.00376	-0.01649	-0.03614	0.02493	0.237852	-0.00567	0.043653	-0.07564	0.028733	-0.02517	-0.08399	-0.22049	-0.04038	0.022666	0.092855	0.0032	0.012886	-0.0066	0.007437	0.003147	8.18E-05
	eq	0.019588	0.007729	-0.08107	0.023567	-0.04903	-0.03679	0.008706	-0.04829	-0.00685	0.025862	-0.00873	-0.01039	-0.01797	0.05823	0.020784	-0.03469	-0.01249	-0.04083	0.039478	-0.00969	-0.00246	-0.01343	-0.00961		-0.00791	-0.04592	0.002526	0.019712	-0.03656	0.002293	0.000271	-0.0229	-0.01745	0.02678	0.011402	-0.0552	-0.02932	0.040248	0.009052	-0.01056	0.012	0.042539	-0.06473	-0.00463	-0.01233	0.008224	-0.00125	-0.00648	-0.00525	-0.00626	-0.00679	-0.00535	-0.01015	0.018992	-0.02932
	T	0.001675	-0.12235	0.095047	-0.05852	0.034197	0.013993	-0.00248	-0.01111	0.024341	0.014629	-0.01509	-0.03763	0.150135	0.009456	-0.01362	0.020438	0.307095	-0.01612	0.006695	0.004906	0.000462	-0.08277	-0.03891	0.004793		0.042288	0.025779	0.027713	-0.00385	0.022913	0.096504	0.107322	0.010752	-0.07638	0.006386	0.035923	-0.00885	0.019461	0.004044	0.007214	-0.00044	-0.01129	0.014668	-0.02702	-0.03118	-0.01105	0.00177	-0.0037	-0.00025	0.000723	0.046841	-0.00193	0.000975	0.037275	0.103503
Greece	ba	0.023895	-0.00313	-0.01655	0.042396	-0.01318	-0.03225	0.008385	0.00757	0.017814	0.010173	0.001815	-0.01254	0.001601	0.005188	0.001193	0.006436	0.007567	-0.03543	-0.02548	0.001822	-0.02393	0.017283	0.03241	0.030399	-0.02071		0.013473	0.015945	0.009033	0.005307	-0.00112	0.006596	0.019484	-0.01773	-0.12254	-0.00053	-0.00208	0.0643	0.013134	0.00325	0.023543	0.003911	-0.05962	-0.00104	0.069366	-0.12259	-0.03202	0.021903	-0.03577	0.001672	0.003449	0.04749	0.089067	0.061456	-0.00477
	bo	-0.00138	-0.01232	0.149681	0.018819	-0.02977	0.002179	-0.03928	0.357086	-0.12687	-0.05005	0.05274	-0.02148	0.064059	0.023625	-0.13176	0.063331	-0.03962	-0.04855	-0.08443	-0.01199	0.057576	-0.08775	-0.01357	-0.01287	-0.05247	-0.23093		-0.05702	0.032851	0.000661	-0.01205	-0.02462	-0.01114	-0.47485	-0.06694	0.081843	-0.05205	-0.04223	0.17297	-0.30985	0.045175	-0.00577	0.039401	0.033091	-0.31538	0.006818	-0.02152	0.02905	0.080557	-0.00888	0.003592	0.089121	-0.02009	0.06627	-0.00411
	mo	-0.02044	-0.04302	-0.00302	-0.11921	-0.00485	0.038905	-0.01894	0.161295	0.059966	-0.0147	-0.10221	0.018411	-0.05053	-0.04335	-0.0286	-0.04278	-0.14136	0.139998	0.023815	0.00687	-6.53E-05	-0.01483	-0.01939	-0.04744	-0.00383	-0.03396	0.02027		-0.00425	-0.02546	-0.06822	-0.00196	0.043969	0.104996	0.117887	0.025029	-0.03174	0.012343	-0.02775	0.005648	-0.01838	0.09398	0.138419	0.174866	0.01379	-0.00688	-0.12836	0.002144	0.061737	0.053829	-0.0533	0.028801	-0.08065	-0.01803	0.005659
	eq	-0.02234	-0.03222	-0.01461	-0.0252	0.001489	-0.04207	-0.12981	-0.01471	-0.05792	-0.03334	-0.00347	-0.00415	0.009388	-0.00898	-0.01416	-0.00989	0.015809	0.000149	0.042922	-0.01049	0.017878	0.019411	-0.00666	-0.02614	0.001456	-0.01392	0.001049	0.029084		-0.00341	-0.00522	0.053824	-0.03567	-0.00058	-0.02031	-0.01487	-0.01457	0.024501	-0.11885	0.012802	0.000283	-0.01026	0.038684	0.000409	0.023595	-0.025	0.004798	-0.00359	-0.00029	0.005466	0.032417	-0.00768	-0.00514	0.005672	-0.00157
	T	0.006346	0.071982	-0.0253	0.090791	-0.00343	-0.05103	0.040893	0.002142	0.032153	0.008497	0.004139	-0.00443	-0.06957	0.036307	-0.00256	-0.04191	0.062638	0.001189	0.00129	-0.09325	0.243413	-0.01294	0.075443	0.037337	-0.05026	-0.02036	0.013437	0.063646	-0.00261		9.03E-05	-0.04304	-7.33E-05	6.70E-05	-0.0961	-0.05098	0.113866	-0.04186	0.077413	0.002819	-0.01	0.049545	0.036719	-0.05675	-0.08415	-0.22532	-0.03348	-0.02673	-0.01657	-0.11738	0.059357	-0.00247	0.003222	0.121864	-0.02982
Ireland	ba	-0.02056	-0.09171	0.04763	-0.04602	0.004949	-0.01454	0.16481	0.02354	0.007616	-0.01114	0.036925	0.012328	0.023158	0.111546	0.005185	-0.02916	-0.05164	-0.02871	0.010009	0.04916	0.005179	-0.01389	-0.03795	0.003166	0.001582	-0.01076	0.016153	0.024598	0.015235	-0.15369		0.033606	-0.0169	0.011456	-0.01459	-0.08817	0.199046	0.008048	0.05546	-0.00882	-0.18569	-0.11297	0.026568	0.109539	0.210358	0.015759	0.020127	0.018466	0.051539	-0.00871	0.0305	0.021273	0.002024	-0.0004	-0.00833
	bo	-0.01912	0.048561	-0.00185	0.018788	-0.00205	0.022191	0.021672	-0.09456	0.020893	-0.00868	-0.02189	0.122476	0.027287	-0.00787	0.021396	-0.00159	-0.03576	-0.03243	0.000583	0.001009	-0.00623	-0.00297	0.022214	0.001199	-0.00901	0.027585	0.018716	0.008972	-0.50056	0.074836	-0.18095		-0.00229	-0.00612	-0.11659	-0.11525	0.002081	0.040613	0.001361	-0.08192	-0.00375	-0.00233	-0.00268	0.015674	-0.00945	0.069341	0.040353	-0.02361	-0.002	0.030723	0.004004	0.003278	0.053393	-0.01992	-0.04852
	mo	-0.09552	0.143899	-0.00012	0.020456	-0.01036	0.030523	0.008404	-0.07017	0.008738	0.000579	0.053483	0.013145	0.012524	0.129093	-0.00742	-0.00244	-0.01484	-0.09186	0.053476	0.01758	-0.02697	-0.01416	-0.02488	0.170187	-0.09029	-0.08666	0.053278	0.01339	0.131263	0.035786	0.046905	0.053498		-0.00559	-0.21721	0.008891	-0.04586	0.021096	0.048872	-0.02149	0.024219	0.063232	0.040938	-0.02968	-0.01239	0.05521	0.056707	-0.00141	0.057186	-0.16848	-0.03837	-0.03608	-0.00228	0.001235	0.027131
	eq	0.035718	-0.00986	-0.07379	0.058739	0.01724	-0.10579	0.018297	-0.00364	-0.0044	-0.0206	0.000325	-0.00526	0.018438	0.042503	-0.01742	0.003457	0.006591	-0.01835	-0.02247	0.029328	0.035888	0.169003	0.03482	-0.00171	0.053951	-0.00656	0.002963	-0.04525	0.052377	0.002989	-0.0252	0.00921	0.008764		0.001752	-0.00581	-0.00263	0.001639	-0.00919	-0.0151	0.015283	-0.00099	-0.07319	-0.02477	0.038741	-0.05261	0.006165	0.003642	-0.00695	5.15E-05	-0.06041	-0.01402	0.011202	0.024242	0.022697
	T	-0.00061	0.028151	0.0101	-0.01544	-0.0821	0.003142	-0.13007	-0.01923	-0.02309	-0.27682	0.185959	-0.24089	0.009584	-0.00751	-0.00193	0.091443	-0.03274	0.01016	-0.01803	-0.00173	0.036508	0.071903	0.021165	-0.08111	-0.16748	0.020934	0.002227	-0.01644	0.022877	0.174715	-0.01195	0.028635	0.053639	-0.00405		-0.08063	0.01257	-0.06897	0.026541	-0.031	0.120478	-0.03182	0.623061	-0.09299	-0.02671	-0.00015	-0.01717	-0.02694	-0.01894	-0.06362	-0.00057	-0.02378	-0.03837	-0.02443	0.002008
Italy	ba	-0.09819	0.004246	0.013649	0.015475	-0.00141	0.002958	-0.002	0.018841	0.021901	0.028248	-0.01229	0.055744	0.013372	0.030115	-0.00252	0.026463	-0.01284	0.03363	-0.0009	0.001456	0.07133	0.015835	0.010105	0.00116	-0.08486	0.036002	-0.00483	-0.00703	0.001451	0.02462	0.068675	0.045223	-0.00072	0.021088	0.029025		-0.01522	0.036803	-0.15811	0.018498	-0.04274	-0.00894	0.038084	0.045854	-0.00936	0.194607	-0.00308	0.007645	0.006685	-0.02341	0.002247	0.010147	-0.01905	0.04512	0.007604
	bo	0.066202	0.004013	-0.09184	-0.06848	0.000847	-0.00192	0.00147	-0.0584	0.013183	-0.00207	0.051429	0.002533	0.069924	0.478785	-0.05248	-0.06634	-0.06556	9.64E-06	0.060945	-0.04211	-0.0696	-0.0138	0.001669	0.024906	0.021884	0.100598	7.60E-05	0.047321	-0.00096	-0.06984	-0.02873	0.013716	0.002273	0.125722	-0.10461	0.059347		-0.14082	-0.0722	0.06918	-0.00719	-0.09907	0.000116	0.03085	0.044188	-0.01997	0.013666	-0.02817	-0.00152	-0.07533	0.000338	0.000465	-0.09662	0.113765	-0.2784
	mo	-0.10383	0.036604	0.022715	-0.10391	0.007434	-0.02359	0.115286	0.035337	-0.123	-0.02051	0.005133	-0.09722	-0.04497	0.099518	-0.003	0.022068	0.04674	0.005081	-0.05703	-0.01923	-0.12328	0.110585	-0.00228	-0.00596	-0.04701	-0.0593	0.027728	-0.02622	-0.08121	0.052308	-0.04421	-0.08182	-0.12161	0.00759	0.005516	-0.03598	0.088705		0.004211	0.00789	-0.02221	0.008245	-0.02888	0.072067	-0.019	-0.13326	-0.00945	0.002714	-0.02266	-0.01647	-0.00313	0.040214	0.015275	0.00017	-0.17494
	eq	0.024941	-0.07807	-0.00834	0.014583	-0.01573	-0.05489	0.006377	0.062146	0.019579	-0.03078	0.001539	0.008552	0.121909	0.002667	-0.00674	0.087805	0.017465	-0.02015	0.095277	0.006089	0.015559	0.036053	-0.02614	-0.01134	0.002622	-0.01969	-0.01224	0.009823	0.000674	-0.01418	-0.06	0.042712	-0.02025	-0.00374	-0.00882	0.142256	3.64E-05	0.003448		-0.0141	0.005103	0.120787	-0.00787	0.011128	-3.90E-05	0.00071	0.015004	-0.0017	-0.0187	-0.02837	-0.02075	0.002006	0.078011	0.003793	-0.02625
	T	0.161719	0.006831	-0.03617	0.022687	-0.01676	0.008324	0.06075	-0.00709	-0.02678	0.000111	-0.00522	-0.04328	-0.08375	-0.07581	-0.0192	-0.01755	-0.02855	0.000658	0.000413	0.046852	0.018467	0.003171	0.06797	0.004188	-0.00816	-0.03375	0.10126	-0.01656	-0.00328	0.004452	0.021189	-0.00016	0.02874	-0.00832	0.02337	0.086307	-0.02353	-0.01778	0.371823		0.040583	-0.08033	0.007266	0.053481	0.037512	0.015295	-0.02695	0.024941	-0.02966	-0.00127	0.001906	-0.08563	0.120883	0.114257	-0.00903
Netherlands	ba	-0.02884	-0.00884	0.002204	-0.00328	-0.01282	-0.11316	-0.00672	-0.01495	0.005951	0.001134	-0.01009	0.012619	0.027191	0.001971	-0.0063	0.005391	-0.00534	-0.03905	0.002854	-0.01075	-0.016	-0.03388	0.001167	0.037892	-0.00081	-0.01967	-0.02209	0.063068	-0.00101	0.010136	0.014828	0.038706	0.009657	0.000457	-0.00718	0.064096	0.026039	0.0471	0.004487	-0.00399		-0.01803	-0.03216	0.013285	-0.00388	0.040305	-0.03412	0.023215	0.22487	0.035818	-0.0497	0.00814	0.03075	-0.00097	-0.00467
	bo	-0.0052	0.003626	-0.00153	-0.00061	0.020098	0.001465	0.018964	-0.0204	-0.06417	0.022885	0.185705	-0.04423	0.035132	0.005352	0.568956	0.156663	0.095064	0.036968	0.050851	-0.00075	-0.11456	-0.03518	0.044142	-0.015	0.030506	-0.02895	0.040152	-0.02752	0.039494	0.002876	0.055461	0.033801	-0.03124	0.00826	0.001784	0.036458	0.007663	-0.01756	-0.06594	0.046645	0.015234		-0.00444	0.012406	-0.0132	0.011574	0.020122	0.036422	-0.17577	0.011194	0.002619	-0.00807	0.067529	-0.00194	0.010296
	mo	0.029565	0.00439	0.011731	0.001395	0.00149	-0.06611	-0.01979	0.006762	0.040276	-0.01955	-0.10391	0.034149	0.005101	0.011125	-0.05193	-0.0136	0.006329	0.001007	0.006404	0.009186	0.055654	-0.03533	0.034253	-0.02016	0.008969	0.000841	0.0258	-0.01349	-0.14133	-0.0121	-0.09254	-0.04974	-0.11639	0.001149	-0.05872	-0.03947	0.003212	0.024566	-0.00013	-0.00566	0.024284	0.042986		-0.00244	0.01553	-0.1005	0.018387	-0.00077	0.060846	-0.04994	-0.04413	0.022952	-0.01571	0.011649	0.005354
	eq	0.003333	-0.0293	-0.00149	-0.00531	-0.00293	0.022627	-0.00964	0.010278	-0.09106	-0.03884	0.000909	-0.0304	0.032228	-0.00131	-0.00091	0.009618	-0.00254	0.005162	-0.00474	-0.02771	0.007631	-0.02209	0.018994	-0.01297	-0.00415	-0.00854	-0.01141	-0.0554	-0.02905	0.021364	-0.00845	-0.01636	0.013071	0.015745	-0.04288	0.000747	-0.0364	-0.0141	-8.54E-05	0.000205	0.000915	-0.08136	0.001127		-0.02069	0.041313	-0.01796	-0.01011	-0.01992	-0.00316	-0.02109	0.000396	0.01969	0.012829	0.037417
	T	-0.00594	-0.00075	-0.0389	-0.00971	-0.01102	-0.00127	-0.04825	0.011138	-0.12608	-0.0406	0.001922	-0.00807	-0.02159	-0.00179	-0.03322	-0.02652	-0.04	-0.00073	0.012181	0.018069	0.004174	-0.00772	0.051568	0.052076	0.017062	-0.00259	0.120677	-0.01806	-0.13903	0.007834	-0.02576	0.058377	0.015025	0.026376	-0.01533	0.000583	-0.02781	0.050533	0.003584	-0.12556	0.062374	0.140505	-0.00258	0.022181		0.011028	-0.02104	0.016433	-0.15203	-0.03824	0.017544	0.050876	0.999305	0.005046	0.103519
Portugal	ba	-0.13551	0.066154	0.043738	0.028936	0.007238	-0.02792	0.000209	-0.10962	0.026709	0.009132	-0.00702	-0.01389	0.02652	0.00335	0.000865	-9.21E-05	0.199609	0.020673	0.044184	0.0006	-0.09638	0.010982	0.005189	-0.00988	-9.42E-05	0.021843	-0.00902	0.011755	0.123883	0.012686	-0.00054	-0.02245	-0.00068	0.045907	0.030234	-0.03255	0.012476	0.043063	0.028993	-0.00225	-0.02778	-0.03124	0.007069	-0.0183	-0.00829		0.02939	0.012731	0.00021	0.039549	0.035113	0.012225	-0.02199	0.085965	0.117662
	bo	-0.03513	0.021621	-0.05471	-0.1248	-0.02647	-0.03449	-0.01537	0.08292	0.015556	-0.01495	-0.05061	0.020612	-0.00505	0.005922	0.05993	0.213296	-0.03483	0.006348	-0.0361	-3.07E-06	-0.07175	-0.03446	0.00631	0.00092	-0.00317	0.032757	0.001143	0.075562	-0.00331	0.038339	-0.01252	-0.00357	-0.03574	0.008252	0.043009	0.166753	-0.03574	0.009109	-0.10609	0.007215	0.021005	-0.00185	-0.09133	0.023796	0.000129	-0.03601		-0.00121	-0.1327	0.21965	-0.11422	0.028254	-0.01265	0.002356	0.008054
	mo	-0.03775	0.130512	-0.06912	-0.04807	-0.01921	0.005744	-0.00141	0.003225	0.064712	-0.05735	-0.18691	-0.07497	-0.13063	-0.00014	0.015787	-0.00277	0.114378	0.039997	0.019492	0.05123	0.072854	0.006979	-0.21993	0.020463	0.030994	-0.19236	-0.03687	-0.08994	0.091898	0.042596	-0.05442	0.046881	-0.09567	0.040788	0.089159	-0.0347	0.118254	0.009893	-0.24174	0.031244	-0.00733	0.004326	0.154542	0.05402	-0.0015	-0.04595	0.012676		0.08227	-0.02582	-0.00651	0.025062	0.002257	0.010198	0.023508
	eq	-0.00561	0.023943	-0.01798	0.003232	-0.0097	-0.08432	-0.01713	0.003819	0.01631	0.028513	-0.11569	-0.01632	-0.002	-0.00367	-0.01252	0.0048	0.000326	-0.00085	-0.00123	-0.00501	-0.01889	0.001942	-0.03701	-0.05571	0.00401	-0.02214	-0.0067	-0.03108	-0.00065	0.034669	-0.02539	-0.05607	0.020036	-0.00533	-0.02292	-0.00199	-0.05578	0.113973	0.026145	0.003439	0.00267	0.016842	-0.07659	0.012414	0.009364	-0.00185	0.01336	-0.01331		-0.02093	-0.00343	-0.03626	-0.01391	-0.046	0.005756
	T	0.016377	0.000152	-0.00163	-0.05556	0.018796	0.013703	0.050944	-0.07308	0.029377	0.002548	-0.03831	-0.00145	-0.00874	-0.01864	-0.01025	0.016666	0.001239	-0.08265	-0.01963	0.013179	0.010485	-0.00884	-0.01144	0.040211	0.007309	-0.00232	0.024974	-0.03976	-0.02029	0.022908	0.018438	-0.0212	0.031186	-0.00536	0.02151	0.013607	0.001176	0.056387	0.009191	-0.02598	-0.02285	-0.0102	-0.00168	-0.03708	0.008855	-0.00537	-0.00554	0.060241	0.03483		-0.00762	0.000333	0.080963	-0.00443	0.075801
Spain	ba	-0.02532	0.032388	-0.03868	0.018588	0.008975	-0.02091	0.015296	0.017914	0.032465	0.002871	-0.02573	0.000127	-0.02317	-0.00433	-0.01043	-0.00015	0.014698	0.127186	0.020221	0.014331	-0.02047	-0.02009	-0.10589	0.021605	-0.01481	-0.01077	-0.0349	-0.00273	0.052486	-0.00432	-0.01399	-0.01997	0.023004	0.081398	0.048209	0.078413	0.112946	0.003901	0.03516	0.048232	0.009867	0.000449	0.02204	0.027547	-0.00313	-0.12432	0.003804	0.067376	-0.00065	0.003026		0.038474	0.011961	-0.13874	0.008658
	bo	-0.37499	0.007044	-0.01737	-0.04534	-0.02506	0.032673	-0.02083	4.40E-05	0.014515	0.008464	-0.00089	-0.00068	-0.00513	0.008821	-0.03712	0.003898	-0.00079	-0.03327	-0.02213	-0.01393	-0.00248	-4.96E-05	0.013876	0.000505	-0.09513	-0.10524	-0.03524	0.000364	0.004967	0.022825	-0.04645	-0.00426	-0.00792	-0.02247	0.033062	-0.0061	0.00841	-0.03778	0.001398	0.01463	-0.0008	0.105008	-0.0423	0.009213	-0.00221	-0.05389	-0.15126	-0.01017	-0.01986	-0.00734	-0.16003		-0.03498	0.369861	-0.07244
	mo	0.024618	-0.00952	-0.00335	-0.15582	-0.00999	0.175323	-0.02931	0.07134	-0.01684	0.068045	-0.00693	0.042376	0.003677	0.001107	-0.1168	-0.01567	-0.10956	-0.02556	-0.0652	0.050129	0.014661	0.006156	-0.00686	0.00265	1.12E-05	-0.05224	0.017386	0.070733	-0.10323	0.040445	-0.01769	-0.01214	0.173289	0.02178	0.053197	0.073297	0.085513	-0.0717	-0.04222	-0.032	-0.03018	-0.00841	0.004485	0.003921	-0.00586	-0.0237	0.024892	-0.0496	0.019753	-0.03971	0.043352	0.063937		-0.00314	0.025694
	eq	0.102349	-0.02129	-0.01612	-0.01236	-0.00486	-0.03303	-0.02431	0.062627	-0.01392	-0.00108	0.011651	-0.02142	-0.00179	-0.0666	0.001849	-0.04767	0.009614	0.004325	-0.01594	-0.07844	0.080862	-0.10695	-0.00505	-0.01171	-0.00451	-0.0109	-1.94E-05	0.022758	0.01536	-0.01822	-0.01178	0.049238	0.037669	-0.01252	0.031467	-0.01089	-0.00243	8.81E-05	-0.00977	-0.01871	0.030794	0.16882	-0.02724	-0.03912	-0.00861	-0.07244	-0.10821	-0.00995	-0.01601	-0.02724	0.070568	-0.02608	-0.00016		0.018521
	T	-0.05192	-0.10204	-0.04009	-0.17034	-0.06911	-0.01425	-0.00882	0.009177	-0.02497	-0.02048	0.025496	-0.00074	0.023274	-0.00334	0.045446	0.037073	-0.01172	-0.12925	-0.03696	-0.03604	-0.10632	0.018189	-0.07785	-0.00237	-0.07167	0.026921	-0.00865	0.015299	0.000664	0.159676	0.149152	0.048661	-0.00438	-0.10731	-0.04921	-0.0095	0.025024	0.007561	0.07097	0.010601	0.000902	-0.00395	0.010702	-0.13638	-0.21634	-0.04316	-0.00312	-0.01908	-0.29169	-0.01977	-0.0015	0.005013	-0.03958	0.080746	

Notes: These are the estimated "volatility spillover" coefficients from the bivariate GARCH-BEEK(1,1) models for the case of cross-markets analysis. Markets FSIs are represented as: ba (banking sector), bo (bond market), mo (money market), eq (equity market) and T (country). The table is read row by row, with the direction of effect to be towards each one of the columns. For instance, the estimated coefficient for the relation of Austrian bond market with the Austrian banking sector is -0.0176.

Table A.9: Probability Values for the "Volatility Spillover" Coefficients from the Intra-Market GARCH-BEKK(1,1) Models

p-values for β_{ij}		Austria					Belgium					Finland					France					Germany					Greece					Ireland					Italy					Netherlands					Portugal					Spain				
		ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T	ba	bo	mo	eq	T
Austria	ba		0.000	0.913	0.506	0.639	0.971	0.019	0.000	0.938	0.081	0.971	0.680	0.843	0.896	0.691	0.657	0.000	0.762	0.992	0.543	0.712	0.045	0.739	0.500	0.137	0.974	0.157	0.000	0.000	0.874	0.008	0.001	0.978	0.000	0.031	0.000	0.000	0.000	0.975	0.615	0.960	0.147	0.892	0.903	0.812	0.000	0.931	0.649	0.959	0.996	0.412	0.005	0.222	0.921	0.000
	bo	0.340		0.000	0.746	0.004	0.067	0.008	0.047	0.460	0.798	0.000	0.964	0.727	0.000	0.786	0.799	0.000	0.347	0.967	0.478	0.935	0.019	0.873	0.795	0.000	0.537	0.000	0.000	0.099	0.000	0.000	0.441	0.004	0.594	0.757	0.000	0.000	0.945	0.000	0.836	0.969	0.940	0.884	0.001	0.672	0.000	0.138	0.015	0.271	0.129	0.785	0.034	0.939	0.049	0.000
	mo	0.949	0.000		0.980	0.536	0.001	0.848	0.858	0.022	0.032	0.899	0.852	0.576	0.000	0.622	0.858	0.000	0.920	0.009	0.825	0.000	0.860	0.990	0.050	0.599	0.000	0.000	0.450	0.000	0.806	0.830	0.548	0.924	0.000	0.868	0.713	0.402	0.905	0.000	0.026	0.937	0.908	0.976	0.973	0.953	0.866	0.338	0.325	0.874	0.876	0.612	0.988	0.138		0.973
	eq	0.165	0.593	0.870		0.990	0.958	0.736	0.699	0.986	0.537	0.921	0.670	0.214	0.000	0.135	0.909	0.975	0.653	0.970	0.468	0.682	0.000	0.000	0.665	0.113	0.000	0.376	0.703	0.952	0.909	0.390	0.974	0.000	0.962	0.002	0.973	0.188	0.035	0.994	0.025	0.932	0.292	0.450	0.929	0.095	0.650	0.000	0.895	0.804	0.923	0.940	0.015	0.950	0.435	0.013
	T	0.913	0.000	0.832	1.000		0.945	0.813	0.906	0.966	0.113	0.947	0.936	0.010	0.907	0.987	0.931	0.904	0.780	0.059	0.891	0.920	0.313	0.922	0.899	0.388	0.795	0.017	0.000	0.867	0.845	0.966	0.926	0.621	0.000	0.817	0.986	0.870	0.523	0.854	0.780	0.954	0.000	0.969	0.973	0.473	0.792	0.271	0.086	0.999	0.000	0.999	0.970	0.000	0.968	0.028
Belgium	ba	0.361	0.016	0.000	0.871	0.159		0.026	0.000	0.934	0.281	0.000	0.765	0.250	0.915	0.084	0.143	0.000	0.001	0.787	0.929	0.990	0.008	0.169	0.861	0.894	0.629	0.249	0.335	0.000	0.357	0.701	0.000	0.928	0.712	0.001	0.860	0.798	0.000	0.931	0.104	0.905	0.000	0.700	0.703	0.000	0.009	0.076	0.008	0.154	0.618	0.323	0.662	0.000	0.935	1.000
	bo	0.776	0.000	0.893	0.822	0.000	0.682		0.962	0.981	0.000	0.806	0.798	0.404	0.936	0.450	0.958	0.728	0.658	0.993	0.856	0.985	0.773	0.807	0.957	0.989	0.007	0.920	0.000	0.710	0.078		0.957	0.950	0.035		0.990	0.737	0.353	0.914	0.869	0.881	0.718	0.783	0.994	0.492	0.000	0.966	0.000	0.993	0.481	0.000	0.877	0.253	0.970	0.000
	mo	0.000	0.639	0.516	0.008	0.944	0.173	0.971		0.992		0.963	0.008	0.856	0.979	0.594	0.980	0.713	0.953	0.000	0.891	0.945	0.000		0.823	0.949	0.778	0.107	0.942	0.994	0.000	0.706	0.442	0.442	0.990	0.978	0.992	0.009	0.209	0.905	0.000	0.751	0.947	0.887	0.971	0.561	0.002	0.000	0.441	0.985	0.011	0.278	0.853	0.822	0.000	0.907
	eq	0.849	0.019	0.000	0.986	0.655	0.007	0.363	0.932		0.579	0.960	0.211	0.000	0.208	0.011	0.522	0.650	0.000	0.887	0.988	0.946	0.000	0.000	0.954	0.981	0.019	0.577	0.000	0.813	0.000	0.695	0.411	0.992	0.944	0.226	0.999	0.000	0.953	0.839	0.000	0.995	0.753	0.995	0.942	0.001	0.958	0.846	0.863	0.954	0.000	0.000	0.926	0.030	0.982	0.686
	T	0.376	0.877	0.919	0.008	0.255	0.513	0.000		0.916		0.000	0.987	0.000	0.011	0.822	0.994	0.419	0.000	0.000	0.029	0.918	0.998	0.513	0.478	0.602	0.040	0.806	0.001	0.695	0.417	0.016	0.678	0.975	0.871	0.822	0.826	0.657	0.072	0.856	0.737	0.640	0.000	0.970	0.000	0.906	0.834	0.432	0.775	0.000	0.992	0.844	0.707	0.864	0.877	0.564
Finland	ba	0.922	0.823	0.710	0.987	0.204	0.000	0.965	0.210	0.948	0.000		0.985	0.218	0.967	0.811	0.850	0.014	0.000	0.012	0.610	0.767	0.470	0.960	0.395	0.991	0.028	0.000	0.962	0.128	0.000	0.000	0.966	0.813	0.913	0.000	0.976	0.643	0.237	0.793	0.018	0.815	0.853	0.026	0.986	0.397	0.437	0.000	0.000	0.775	0.341	0.015	0.906	0.008	0.573	0.238
	bo	0.772	0.992	0.136	0.047	0.911	0.894	0.650	0.004	0.908	0.986	0.985		0.564	0.998	0.281	0.908	0.900	0.445	0.980	0.817	0.989	0.000	0.943	0.968	0.796	0.000	0.777	0.001	0.877	0.575	0.000	0.040	0.974	0.985	0.978	0.477	0.859	0.000	0.816	0.840	0.141	0.215	0.877	0.973	0.456	0.770	0.000	0.000	0.980	0.112	0.002	0.955	0.928	0.883	0.000
	mo	0.299	0.432	0.806	0.187	0.000	0.515	0.210	0.741	0.000	0.000	0.842	0.655		0.864	0.856	0.000	0.645	0.522	0.000	0.009	0.940	0.980	0.440	0.952	0.017	0.940	0.000	0.510	0.675	0.000	0.075	0.853	0.006	0.438	0.019	0.002	0.522	0.548	0.000	0.653	0.994	0.294	0.962	0.876	0.000	0.046	0.716	0.001	0.914	0.862	0.005	0.458	0.582	0.854	0.938
	eq	0.248	0.000	0.000	0.680	0.819	0.683	0.820	0.139	0.357	0.001	0.991	0.637	0.917		0.847	0.391	0.880	0.890	0.973	0.501	0.568	0.950	0.942	0.703	0.955	0.745	0.507	0.002	0.004	0.949	0.306	0.779	0.547	0.898	0.006	0.498	0.700	0.000	0.936	0.000	0.981	0.000	0.256	0.989	0.224	0.998	0.945	0.000	0.902	0.894	0.837	0.317	0.000	0.931	0.582
	T	0.988	0.662	0.504	0.847	0.944	0.040	0.459	0.158	0.884	0.418	0.911	0.112	0.742	0.911		0.979	0.970	0.445	0.912	0.000	0.085	0.424	0.588	0.904	0.629	0.000	0.000	0.890	0.983	0.000	0.501	0.841	0.960	0.918	0.000	0.904	0.006	0.270	0.966	0.021	0.958	0.944	0.004	0.963	0.908	0.929	0.000	0.007	0.685	0.955	0.812	0.765	0.069	0.160	0.000
France	ba	0.918	0.338	0.000	0.959	0.061	0.987	0.950	0.752	0.978	0.203	0.729	0.961	0.000	0.000	0.966		0.139	0.005	0.944	0.000	0.877	0.000	0.980	0.985	0.406	0.293	0.000	0.002	0.759	0.347	0.145	0.711	0.985	0.989	0.381	0.886	0.674	0.965	0.369	0.050	0.941	0.448	0.068	0.978	0.964	0.374	0.000	0.717	0.812	0.200	0.680	0.355	0.104	0.294	0.009
	bo	0.808	0.866	0.000	0.999	0.900	0.000	0.028	0.712	0.745	0.445	0.673	0.131	0.714	0.991	0.691	0.548		0.261	0.950	0.016	0.092	0.806	0.897	0.203	0.743	0.174	0.042	0.882	0.000	0.185	0.091	0.801	0.956	0.941	0.518	0.001	0.000	0.000	0.991	0.071	0.983	0.000	0.848	0.807	0.000	0.083	0.418	0.848	0.047	0.000	0.000	0.900	0.005	0.871	0.956
	mo	0.774	0.018	0.867	0.529	0.066	0.000	0.491	0.469	0.000	0.602	0.158	0.007	0.928	0.879	0.980	0.003	0.037		0.952	0.595	0.911	0.000	0.989	0.844	0.789	0.915	0.629	0.000	0.588	0.271	0.185	0.564	0.735	0.026	0.666	0.988	0.108	1.000	0.874	0.103	0.495	0.000		0.020	0.000	0.859	0.008	0.000	0.973	0.000	0.881	0.875	0.000	0.924	0.931
	eq	0.709	0.470	0.072	0.778	0.200	0.610	0.734	0.000	0.799	0.000	0.498	0.955	0.000	0.849	0.405	0.965	0.612	0.403		0.592	0.185	0.000	0.445	0.978	0.881	0.872	0.000	0.000	0.977	0.776	0.867	0.106	0.603	0.947	0.972	0.000	0.335	0.069	0.951	0.914	0.899	0.000	0.338	0.855	0.661	0.397	0.000	0.773	0.760	0.443	0.969	0.167	0.001	0.918	0.994
	T	0.962	0.344	0.691	0.901	0.568	0.889	0.000	0.587	0.983	0.015	0.731	0.867	0.882	0.925	0.178	0.000	0.010	0.926	0.651		0.787	0.937	0.646	0.647	0.347	0.364	0.549	0.000	0.920	0.000	0.000	0.984	0.636	0.004	0.065	0.680	0.192	0.000	0.136	0.758	0.891	0.057	0.314	0.691	0.511	0.059	0.564	0.000	0.000	0.098	0.179	0.632	0.257	0.000	0.030
Germany	ba	0.000	0.642	0.000	0.923	0.767	0.929	0.213	0.705	0.132	0.037	0.727	0.862	0.784	0.670	0.000	0.941	0.905	0.000	0.632	0.863		0.614	0.947	0.657	0.964	0.789	0.207	0.000	0.971	0.414	0.003	0.830	0.000	0.933	0.000	0.051	0.993	0.967	0.966	0.833	0.980	0.126	0.929	0.952	0.626	0.990	0.000	0.963	0.964	0.069	0.968	0.874	0.926	0.993	0.915
	bo	0.065	0.075	0.273	0.000	0.189	0.015	0.122	0.595	0.057	0.983	0.235	0.000	0.513	0.322	0.924	0.000	0.092	0.074	0.000	0.913	0.969		0.000	0.922	0.089	0.690	0.002	0.617	0.038	0.387	0.008	0.000	0.292	0.001	0.812	0.700	0.198	0.055	0.002	0.000	0.021	0.000	0.020	0.635	0.005	0.000	0.244	0.000	0.547	0.007	0.006	0.640	0.000	0.000	0.494
	mo	0.954	0.337	0.994	0.000	0.263	0.653	0.441		0.581	0.322	0.659	0.891	0.010	0.892	0.940	0.941	0.356	0.999	0.894	0.971	0.744	0.000		0.811	0.587	0.973	0.000	0.213	0.645	0.003	0.697	0.960	0.948	0.522	0.781	0.729	0.753	0.600	0.148	0.967	0.778	0.000	0.987	0.618	0.235	0.089	0.007	0.806	0.000	0.944	0.080	0.918	0.801	0.957	0.383
	eq	0.320	0.796	0.000	0.599	0.000	0.237	0.330	0.000	0.953	0.000	0.814	0.735	0.534	0.440	0.649	0.820	0.719	0.708	0.815	0.067	0.985	0.224	0.014		0.799	0.546	0.110	0.005	0.890	0.953	0.815	0.339	0.000	0.917	0.780	0.989	0.000	0.261	0.979	0.059	0.865	0.000	0.372	0.980	0.747	0.865	0.885	0.389	0.947	0.867	0.015	0.821	0.164	0.943	0.000
	T	0.665	0.000	0.027	0.596	0.808	0.827	0.994	0.883	0.991	0.016	0.992	0.790	0.000	0.926	0.829	0.916	0.505	0.719	0.704	0.870	0.762	0.050	0.103	0.965		0.000	0.180	0.847	0.967	0.891	0.443	0.000	0.867	0.095	0.831	0.017	0.756	0.965	0.963	0.817	0.990	0.622	0.796	0.857	0.854	0.472	0.071	0.637	0.978	0.936	0.700	0.961	0.000	0.958	0.102
Greece	ba	0.042	0.752	0.000	0.000	0.128	0.149	0.313	0.242	0.754	0.123	0.417	0.000	0.926	0.972	0.000	0.002	0.018	0.935	0.539	0.512	0.884	0.285	0.184	0.743	0.000		0.000	0.000	0.197	0.957	0.996	0.944	0.766	0.914	0.000	0.999	0.629	0.358	0.966	0.510	0.960	0.000	0.488	0.910	0.000	0.000	0.000	0.000	0.156	0.591	0.987	0.000	0.000	0.130	0.068
	bo	0.597	0.000	0.000	0.921	0.024	0.971	0.812	0.000	0.404	0.545	0.000	0.978	0.011	0.929	0.000	0.000	0.193	0.658	0.000	0.488	0.798	0.000	0.000	0.835	0.331	0.000		0.000	0.995	0.961	0.035	0.111	0.878	0.303	0.000	0.980	0.000	0.177	0.118	0.000	0.269	0.000	0.899	0.977	0.792	0.976	0.196	0.000	0.787	0.000	0.373	0.234	0.603	0.729	0.886
	mo	0.362	0.000	0.952	0.859	0.000	0.000	0.000	0.070	0.002	0.636	0.961	0.000	0.000	0.839	0.742	0.902	0.385	0.090	0.023	0.000	0.564	0.809	0.498	0.669	0.938	0.064	0.000		0.643	0.175	0.638	0.922	0.345	0.000	0.000	0.668	0.000	0.995	0.799	0.908	0.000	0.112	0.036	0.000	0.000	0.051	0.101	0.000	0.000	0.984	0.432	0.891	0.000	0.002	0.726
	eq	0.013	0.000	0.000	0.923	0.939	0.000	0.000	0.983	0.834	0.000	0.902	0.950	0.003	0.905	0.861	0.977	0.000	0.941	0.246	0.651	0.859	0.087	0.217	0.696	0.970	0.035	0.998	0.000		0.976	0.280	0.977	0.050	0.946	0.000	0.584	0.145	0.048	0.130	0.279	0.921	0.000	0.278	0.860	0.898	0.000	0.627	0.696	0.946	0.772	0.770	0.683	0.957	0.981	0.843
	T	0.928	0.000	0.713	0.951	0.836	0.957	0.098	0.000	0.791	0.684	0.923	0.856	0.000	0.998	0.000	0.767	0.305	0.927	0.425	0.000	0.118	0.781	0.000	0.794	0.768	0.964	0.964	0.243	0.985		0.968	0.049	0.704	0.963	0.000	0.000	0.005	0.584	0.860	0.948	0.796	0.407	0.890	0.916	0.000	0.036	0.688	0.000	0.972	0.001	0.842	0.847	0.000	0.004	0.000
Ireland	ba	0.520	0.000	0.143	0.734	0.567	0.725		0.257	0.647	0.278	0.000	0.000	0.000	0.682	0.804	0.380	0.001	0.211	0.834	0.000	0.766	0.096	0.081	0.921	0.924	0.969	0.000	0.001	0.856	0.000		0.143	0.957	0.845	0.172	0.000	0.000	0.059	0.380	0.005	0.748	0.324	0.006	0.000	0.000	0.157	0.000	0.005	0.007	0.950	0.831	0.014	0.000	0.989	0.368
	bo	0.815	0.209	0.934	0.010	0.987	0.747	0.009	0.037	0.797	0.946	0.994	0.209	0.819	0.906	0.966	0.731	0.871	0.034	0.877	0.997	0.959	0.833	0.310	0.900	0.001	0.926	0.003	0.300	0.981	0.077	0.002		0.988	0.980	0.511	0.707	0.929	0.717	0.984	0.000	0.949	0.924	0.918	0.897	0.984	0.382	0.000	0.103	0.684	0.947	0.891	0.858	0.641	0.881	0.073
	mo	0.887	0.000	0.879	0.000	0.990	0.973	0.951	0.281	0.983	0.942	0.824	0.900	0.853	0.502	0.941	0.999	0.956	0.837	0.459	0.943	0.758	0.332	0.736	0.514	0.589	0.979	0.646	0.940	0.824	0.528	0.978	0.844		0.837	0.009	0.940	0.984	0.000	0.754	0.851	0.806	0.024	0.221	0.809	0.880	0.929	0.402	0.943	0.869	0.375	0.000	0.732	0.407	0.980	0.462
	eq	0.000	0.000	0.000	0.861	0.000	0.000	0.428	0.952	0.952	0.001	0.992	0.970	0.048	0.856	0.375	0.973	0.351	0.237	0.960	0.112	0.354	0.000	0.123	0.993	0.000	0.821	0.710	0.000	0.475	0.510	0.339	0.458	0.608		0.468	0.684	0.124	0.944	0.928	0.259	0.890	0.186	0.143	0.869	0.003	0.767	0.684	0.022	0.039	0.922	0.000	0.004	0.097	0.841	0.852
	T	0.977	0.000	0.809	0.853	0.017	0.594		0.057	0.902	0.824	0.000	0.032	0.461	0.846	0.000	0.133	0.389	0.968	0.948	0.904	0.000	0.221	0.268	0.689	0.506	0.000	0.947	0.000	0.915	0.000	0.741	0.549	0.006	0.292		0.000	0.294	0.000	0.754	0.374	0.892	0.849	0.000	0.000	0.859	0.149	0.034	0.063	0.908	0.065	0.794	0.763	0.551	0.615	0.000
Italy	ba	0.000	0.000	0.535	0.628	0.980	0.965	0.987	0.056	0.990	0.203	0.991	0.110	0.151	0.851	0.958	0.911	0.000	0.606	0.867	0.871	0.118	0.000	0.009	0.923	0.000	0.860	0.955	0.711	0.965	0.000	0.000	0.002	0.960	0.143	0.000		0.540	0.611	0.000	0.670	0.454	0.372	0.333	0.025	0.702	0.000	0.535	0.636	0.623	0.029	0.967	0.117	0.000	0.482	0.836
	bo	0.000	0.000	0.638	0.637	0.720	0.767	0.958	0.374	0.054	0.970	0.763	0.970	0.531	0.510	0.310	0.578	0.445	0.785	0.912	0.381	0.969	0.891	0.845	0.468	0.591	0.000	0.944	0.000	0.921	0.002	0.000	0.694	0.630	0.355	0.203	0.608		0.002	0.922	1.000	0.833	0.000	0.226	0.990	0.997	0.600	0.390	0.000	0.995	0.000	0.978	0.868	0.251	0.000	0.000
	mo	0.000	0.497	0.943	0.060	0.641	0.000	0.005	0.505	0.871	0.566	0.523	0.000	0.080	0.000	0.949	0.976	0.000	0.999	0.000	0.000	0.146	0.037	0.949	0.981	0.958	0.001	0.020	0.957	0.390	0.000	0.629	0.565	0.000	0.954	0.000	0.899	0.000		0.893	0.641	0.948	0.986	0.994	0.828	0.267	0.081	0.000	0.000	0.063	0.566	0.869	0.759	0.108	0.982	0.000
	eq	0.828	0.000	0.121	0.974	0.433	0.941	0.413	0.701	0.984	0.773	0.961	0.841	0.000	0.905	0.744	0.565	0.745	0.953	0.650	0.001	0.886	0.000	0.001	0.980	0.900	0.913	0.007	0.000	0.869	0.860	0.853	0.220	0.008	0.918	0.538	0.000	0.955	0.795		0.445	0.963	0.424	0.915	0.836	0.736	0.853	0.000	0.161	0.982	0.532	0.686	0.000	0.000	0.947	0.444
	T	0.809	0.860	0.342	0.928	0.611	0.934	0.821	0.332	0.001	0.677	0.916	0.653	0.494	0.690	0.704	0.966	0.360	0.884	0.909	0.458	0.938	0.000	0.965	0.801	0.891	0.926	0.006	0.568	0.959	0.428	0.000	0.946	0.813	0.986	0.827	0.820	1.000	0.270	0.581		0.910	0.156	0.974	0.820	0.000	0.797	0.000	0.000	0.964	0.000	0.878	0.139	0.008	0.000	0.000
Netherlands	ba	0.865	0.737	0.943	0.987	0.761	0.000	0.046	0.010	0.932	0.066	0.950	0.926	0.484	0.989	0.975	0.988	0.964	0.066	0.864	0.471	0.901	0.187	0.942	0.888	0.995	0.925	0.000	0.000	0.962	0.286	0.464	0.047	0.488	0.763	0.001	0.237	0.116	0.968	0.980	0.864		0.667	0.803	0.980	0.971	0.759	0.065	0.569	0.151	0.103	0.652	0.636	0.538	0.985	0.903
	bo	0.421	0.932	0.838	0.983	0.002	0.077	0.038	0.687	0.000	0.590	0.000	0.069	0.116	0.000	0.005	0.760	0.000	0.000	0.000	0.963	0.157	0.000	0.426	0.448	0.029	0.000	0.000	0.000	0.000	0.765	0.001	0.297	0.000	0.544	0.954	0.528	0.005	0.937	0.431	0.418	0.874		0.974	0.217	0.366	0.007	0.000	0.556	0.356	0.788	0.892	0.170	0.000	0.002	0.442
	mo	0.793	0.008	0.768	0.971	0.534	0.198	0.659	0.921	0.996	0.557	0.667	0.392	0.976	0.859	0.000	0.915	0.886		0.887	0.000	0.675	0.483	0.893	0.915	0.000	0.967	0.000	0.040	0.091	0.895	0.000	0.131	0.000	0.969	0.000	0.765	0.000	0.975	0.996	0.818	0.744	0.300		0.946	0.378	0.336	0.629	0.905	0.283	0.004	0.981	0.219	0.884	0.787	0.727
	eq	0.894	0.000	0.960	0.968	0.894	0.546	0.537	0.890	0.962	0.000	0.993	0.860	0.581	0.975	0.987	0.983	0.914	0.689	0.914	0.002	0.928	0.011	0.066	0.973	0.916	0.383	0.835	0.000	0.824	0.238	0.000	0.442	0.039	0.984	0.000	0.857	0.915	0.576	0.936	0.980	0.988	0.000	0.290		0.936	0.467	0.873	0.954	0.888	0.678	0.851	0.901	0.141	0.898	0.000
	T	0.948	0.842	0.989	0.988	0.750	0.000	0.000	0.564	0.304	0.488	0.605	0.820	0.000	0.803	0.383	0.991	0.000	0.613	0.914	0.047	0.937	0.009	0.539	0.915	0.838	0.000	0.519	0.000	0.770	0.000	0.000	0.959	0.846	0.818	0.840	0.871	0.995	0.394	0.630	0.042	0.779	0.027	0.629	0.993		0.753	0.000	0.720	0.797	0.192	0.895	0.000	0.000	0.838	0.000
Portugal	ba	0.000	0.000	0.644	0.759	0.814	0.000	0.902	0.000	0.916	0.321	0.015	0.763	0.022	1.000	0.977	0.929	0.000	0.498	0.517	0.905	0.948	0.000	0.004	0.842	0.897	0.000	0.000	0.000	0.000	0.125	0.516	0.129	0.251	0.607	0.026	0.000	0.126	0.001	0.776	0.752	0.828	0.000	0.870	0.702	0.384		0.000	0.104	0.895	0.002	0.000	0.082	0.655	0.001	0.001
	bo	0.955	0.087	0.000	0.000	0.466	0.069	0.985	0.000	0.602	0.000	0.001	0.229	0.000	0.983	0.000	0.000	0.333	0.856	0.000	0.503	0.000	0.370	0.805	0.996	0.000	0.000	0.046	0.111	0.000	0.712	0.000	0.000	0.483	0.994	0.012	0.000	0.012	0.000	0.000	0.000	0.017	0.000	0.515	0.196	0.000	0.000		0.956	0.378	0.000	0.624	0.000	0.021	0.002	0.629
	mo	0.033	0.012	0.540	0.963	0.804	0.897	0.487	0.986	0.922	0.476	0.186	0.836	0.000	0.898	0.520	0.672	0.887	0.056	0.887	0.146	0.956	0.428	0.877	0.992	0.285	0.001	0.000	0.000	0.911	0.001	0.262	0.860	0.749	0.010	0.535	0.951	0.385	0.000	0.000	0.000	0.949	0.806	0.468	0.991	0.523	0.969	0.935		0.597	0.501	0.203	0.063	0.883	0.845	0.001
	eq	0.832	0.006	0.635	0.994	0.997	0.389	0.992	0.996	0.964	0.000	0.955	0.926	0.941	0.943	0.625	0.986	0.688	0.979	0.960	0.000	0.865	0.937	0.000	0.499	0.958	0.728	0.043	0.001	0.907	0.167	0.000	0.013	0.148	0.000	0.374	0.856	0.579	0.010	0.891	0.863	0.914	0.727	0.001	0.921	0.826	0.774	0.396	0.040			0.852	0.305	0.632	0.938	0.005
	T	0.994	0.860	0.848	0.980	0.000	0.959	0.302	0.142	0.903	0.997	0.826	0.836	0.945	0.924	0.976	0.703	0.319	0.000	0.856	0.418	0.948	0.368	0.873	0.865	0.905	0.964	0.000	0.983	0.919	0.001	0.000	0.891	0.969	0.984	0.008	0.980	0.815	0.716	0.858	0.000	0.963	0.945	0.697	0.831	0.856	0.960	0.000	0.083			0.121	0.576	0.558	0.986	0.000
Spain	ba	0.000	0.000	0.708	0.962	0.956	0.504	0.000	0.043	0.000	0.901	0.057	0.990	0.002	0.993	0.000	0.989	0.000	0.055	0.922	0.000	0.615	0.292	0.000	0.006	0.081	0.975	0.000	0.409	0.926	0.475	0.618	0.880	0.000	0.000	0.001	0.523	0.165	0.658	0.474	0.000	0.495	0.975	0.974	0.953	0.868	0.000	0.861	0.000	0.127	0.634		0.000	0.655	0.003	0.444
	bo	0.000	0.469	0.983	0.342	0.892	0.892	0.817	0.946	0.991	0.748	0.963	0.964	0.920	0.824	0.842	0.952	0.846	0.907	0.967	0.877	0.953	0.794	0.807	0.508	0.736	0.000	0.305	0.993	0.989	0.461	0.051	0.967	0.876	0.781	0.938	0.815	0.964	0.909	0.510	0.810	0.846	0.371	0.673	0.882	0.000	0.265	0.000	0.000	0.972	0.934	0.000		0.551	0.223	0.276
	mo	0.708	0.858	0.610	0.102	0.000	0.000	0.200	0.625	0.919	0.424	0.427	0.839	0.645	0.926	0.000	0.940	0.000	0.000	0.762	0.017	0.736	0.000	0.885	0.899	0.001	0.000	0.200	0.000	0.981	0.000	0.000	0.846	0.000	0.864	0.183	0.000	0.088	0.142	0.000	0.707	0.916	0.022	0.978	0.932	0.099	0.856	0.500	0.000	0.844	0.520	0.954	0.006		0.962	
	eq	0.009	0.014		0.754	0.893	0.569	0.956	0.000	0.975	0.936	0.855	0.035	0.817	0.290	0.597	0.738	0.024	0.858	0.843	0.000	0.851	0.000	0.345	0.995	0.835	0.433	0.000	0.000	0.731	0.132	0.654	0.283	0.062	0.944	0.372	0.796	0.000	0.985	0.811	0.000	0.773	0.000	0.142	0.805	0.101	0.000	0.000	0.241	0.947	0.941	0.000	0.183	0.969		0.009
	T	0.268	0.004	0.906	0.463	0.358	0.998	0.345	0.848	0.871	0.873	0.772	0.810	0.607	0.812	0.179	0.654	0.775	0.781	0.994	0.000	0.925	0.661	0.051	0.000	0.050	0.524	0.009	0.299	0.803	0.000	0.119	0.881	0.845	0.966	0.000	0.985	0.115	0.000	0.906	0.000	0.930	0.582	0.931	0.049	0.000	0.109	0.919	0.022	0.000	0.000	0.932	0.844		0.566	

Notes: These are the p-values for the estimated "volatility spillover" coefficients from the bivariate GARCH-BEEK(1,1) models for the case of cross-markets analysis. Markets FSIs are represented as: ba (banking sector), bo (bond market), mo (money market), eq (equity market) and T (country). The table is read row by row, with the direction of effect to be towards each one of the columns. For instance, the p-value for the estimated coefficient representing the spillover of Austrian bond market to the Austrian banking sector is 0.340.

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