The Linkages and the Transmission Mechanism between Financial Stability, Monetary Stability and Growth

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“Financial stability is an important goal of policy, but the relation of financial stability to economic performance and even the meaning of the term itself are poorly understood”
(Ben S. Bernanke, Mark L. Gertler, 1987)

ABSTRACT

"The Linkages and the Transmission Mechanism between Financial Stability, Monetary Stability and Growth"

This thesis aims to give a closer look on financial stability which has gained importance over the last two decades, especially after the last crisis that has been characterized as a banking one. Although, monetary stability is well defined, being the stability in the general level of prices or the absence of inflation or deflation, financial stability does not have as easy or universally accepted a definition. Nevertheless, there seems to be a broad consensus that financial stability refers to the smooth functioning of the key elements that make up the financial system. Our main target is to search for the linkages and the transmission mechanism between financial stability, monetary stability and growth. We begin this thesis with the literature review of our key definitions on financial stability and we continue with the theoretical models and the empirical research that have been exploited in this area. We find that, among others, an appropriate measure for financial stability can be either the probability of default or a financial stress index. After the literature review of the macroeconomic models and the empirical research we proceed to the empirical analysis. The implementation of the analysis includes a Vector Autoregressive (VAR) model by employing three proxy variables, a financial stress index as a proxy variable for financial stability and two macroeconomic variables as a measure of growth and inflation. Our intention is to search for the interactions and the dynamics in the VAR and test how a shock to the macroeconomic variables affects financial stability and vice versa, employing impulse responses and variance decompositions. Through the investigation of the dynamic characteristic of our model we have checked the interactions between our series. The model has been estimated for nine developed countries and our results have found evidence that there is a link between financial stability, monetary stability and growth. Positive innovations to our macroeconomic variables have a considerable effect on financial stability and vice versa. Overall, the empirical findings of the present study imply that in most cases financial stability seems to be positively affected after an improvement in financial conditions while, in all cases, it is negatively affected by an increase in the price level. Additionally, for most cases, an improvement in financial conditions will have a positive impact on growth.

Keywords: financial stability, monetary stability, financial crisis, VAR models

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LIST OF ABBREVIATIONS

1. ECB European Central Bank
2. ADF Augmented Dickey-Fuller
3. AIC Akaike's Information Criterion
4. AR Autoregression
5. ARCH Autoregressive Conditional Heteroskedasticity
6. CPI Consumer Price Index
7. DSGE Dynamic Stochastic General Equilibrium
8. ECB European Central Bank
9. ECM Error Correction Model
10. EDF Expected Default Frequency
11. FHGE Finite Horizon General Equilibrium
12. FSAP Financial Sector Assessment Program
13. FSCI Financial Stability Conditions Index
14. FSF Financial Stability Forum
15. FSI Financial Stress Index
16. FSIn Financial Stability Institute
17. FSIs Financial Soundness Indicators
18. GARCH Generalized Autoregressive Conditional Heteroskedasticity
19. GVAR Global Vector Autoregressive
20. IFS International Financial Statistics

21.	IFSI	Inverse FSI
22.	IMF	International Monetary Fund
23.	LR	Likelihood Ratio
24.	NP	Ratio of Non-Performing Loans to Total Portfolio
25.	OECD	Organization For Economic Cooperation And Development
26.	OLG	Overlapping Generation Models
27.	OLS	Ordinary Least Squares
28.	PoD	Probability of Default
29.	PP	Phillips – Perron
30.	p-value	Probability
31.	RBC	Real Business Cycle Models
32.	ROA	Return on Assets
33.	ROE	Return on Equity
34.	s.e.	Standard Error
35.	SC	Schwartz Information Criteria
36.	SVAR	Structural Vector Autoregressive
37.	VAR	Vector Autoregression
38.	VARMA	Vector ARMA
39.	VECM	Vector Error Correction Model
40.	WB	World Bank

1. INTRODUCTION

In general, the objective of financial stability has gained importance over the last two decades, especially after the last crisis that has been characterized as a banking one. Monetary stability is defined as stability in the general level of prices, or as an absence of inflation or deflation. In contrast, financial stability does not have as easy or universally accepted a definition. Nevertheless, there seems to be a broad consensus that financial stability refers to the smooth functioning of the key elements that make up the financial system. The motivation of this paper was the imbalances in the financial sector of 2007 that begun with the collapse of Lehman Brothers and evolved rapidly to global turmoil, followed by the recession in the late 2000s and the 2010 European sovereign debt crisis. Many central banks moved in the direction of stabilizing their economies in order to prevent a deeper downturn bolstering their banking sector. Our principal objective is to find the linkages and the transmission mechanisms between financial stability, monetary stability and growth.

We begin this thesis with a brief description of the financial system and the financial system components. It is, in this context, necessary to try to understand the relationship among the most important actors of the system as well as the factors affecting the smooth operation of the financial system. We continue with the key definitions of financial stability and the literature review of the theoretical macroeconomic models that have been exploited in this area. After the literature review, the presentation of the macroeconomic models and the research that has been done until now, we continue on to Chapter 3 and the empirical analysis of our model. The analysis consists of a VAR model by employing 3 proxy time series in nine developed countries. Finally, the last part of this thesis discusses the outcome of the analysis and also derives a conclusion from them.

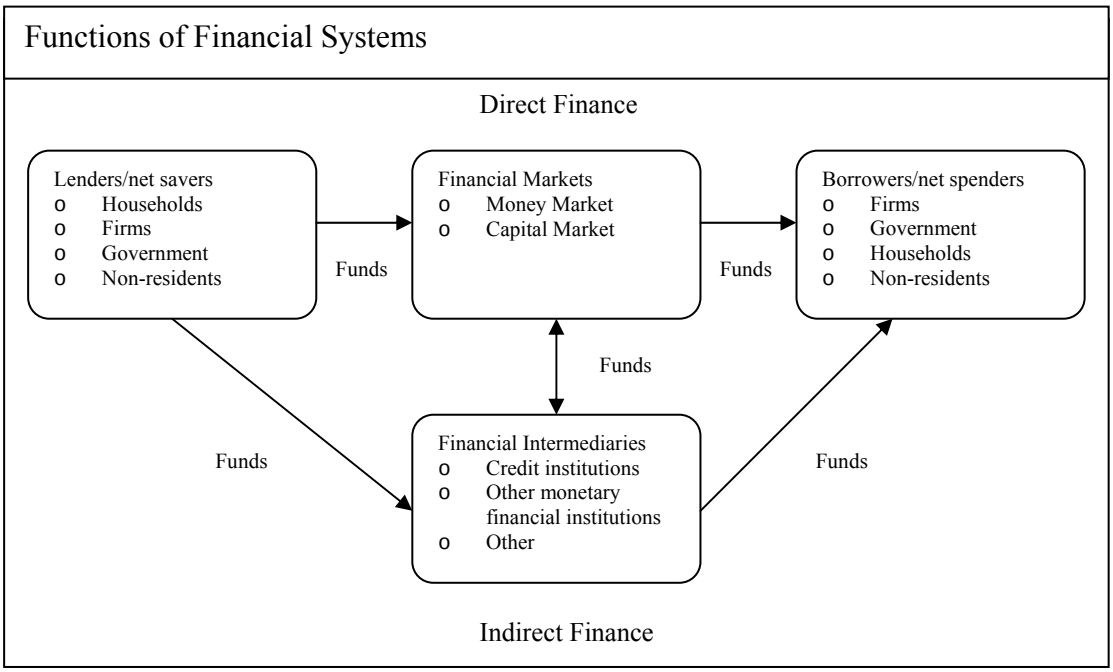
CHAPTER 2: Literature Review

2.1. The financial system components

It is necessary to give a brief description of the financial system and what it is consist of. The financial system is comprised of three separable but closely related components. First there are *financial intermediaries* that pool funds and risks and then allocate them to their competing uses. Increasingly, financial institutions provide a range of services and not just traditional banking services of taking deposits and making loans. Institutions such as insurance companies, pension funds, hedge funds, and financial non financial hybrids supply a range of financial services. Second, there are *financial markets* that directly match savers and investors, for example, through the issuance and sale of bonds or equities directly to investors. Third, there is the *financial infrastructure*, comprised of both privately-and publicly-owned and operated institutions such as clearance, payment, and settlements systems for financial transactions as well as monetary, legal, accounting, regulatory, supervisory, and surveillance infrastructures. Notably, both private and public persons participate in financial markets and in vital components of the financial infrastructure. Governments borrow in markets, hedge risks, operate through markets to conduct monetary policy and maintain monetary stability, and own and operate payments and settlement systems. Accordingly, the term financial system encompasses both the monetary system with its official understandings, agreements, conventions, and institutions as well as the processes, institutions, and conventions of private financial activities.

To shield the financial system and guarantee financial stability, the main sources of risk and vulnerability must be identified and all relevant parties, such as financial institutions and supervisors, be made aware of the risks. Financial system face endogenous and exogenous risks. Endogenous risks may arise in any of the financial system's three main components while exogenous risks stem from problems outside the financial system. Financial institution, market and infrastructure-based

Figure 2.1: The functions of the financial system, Source ECB.



vulnerabilities are source of endogenous risks. As Houben et al. (2004) state, traditional financial risks are related to credit, market, liquidity, interest rates and foreign currency exposures. Financial markets are also the source of endogenous risks. Such as counterparty risk and asset price misalignments. Financial markets can also be vulnerable to runs and contagion. The financial system has become more market-oriented in the past decade, including through an increase in financial institutions' market activities and exposures, as well as through greater participation by non-financial corporations and households in markets. Hence, market-based risks are becoming more relevant for financial stability. Infrastructure-based vulnerabilities are a third source of risk. In payment systems, several risks may develop related to clearing and settlement. These often originate in the financial institutions participating in the system, and are in that sense related to institutions based vulnerabilities. Finally, vulnerabilities may be exogenous, i.e., originate outside the financial system. For instance, disturbances may arise at the macroeconomic level, such as oil price shocks, technological innovations and policy imbalances. In particular, a balanced monetary and fiscal policy mix may be considered critical for financial stability. Furthermore, microeconomic events, such as a failure of a large company, may

undermine market confidence and create imbalances that affect the whole financial system. Other examples of exogenous disturbances are a sudden introduction or withdrawal of trade restrictions, political events and natural disasters.

In a financial crisis, trust and confidence breaks down and there is usually a rush to obtain liquidity, which could result in a contraction of bank credit that sequentially could lead to a decline in economic activity. The costs of a systemic failure have been estimated to be large. Hoggarth et al. (2002) studied the cost of 33 systemic banking crises over the past 25 years. They first consider the direct resolution costs to the government and then the broader costs to the welfare of the economy proxied by losses in GDP. They find that the cumulative output losses incurred during crisis periods are large, roughly 15-20%, on average, of annual GDP. In addition to previous research, they have estimated that output losses incurred during crises in developed countries are as high, or higher, on average, than those in emerging-market economies. Moreover, output losses during crisis periods in developed countries also appear to be significantly larger 10%-15% than in neighbouring countries that did not at the time experience severe banking problem.

Table 2.1: Sources of Risk to Financial Stability, Source Houben et al. (2004)

Endogenous	**Exogenous**
Institutions-based: • Financial risks o Credit o Market o Liquidity o Interest rate o Currency • Operational risk • Information technology weaknesses • Legal/integrity risk • Reputation risk • Business strategy risk • Concentration risk • Capital adequacy risk Market-based: • Counterparty risk • Asset price misalignment • Run on markets o Credit o Liquidity • Contagion Infrastructure-based : • Clearance, payment and settlement system risk • Infrastructure fragilities o Legal o Regulatory o Accounting o Supervisory • Collapse of confidence leading to runs • Domino effects	Macroeconomic disturbances: • Economic-environment risk • Policy imbalances Event risk • Natural disaster • Political events • Large business failures

2.2. *Financial Stability Definition*

In recent years, and even more after the last financial crisis of 2007 governments are taking measures to the direction of strengthening the financial stability of their economies. In many cases, central banks have the responsibility of monitoring and securing financial stability while they publish financial stability reports without following an exact framework. Usually, in these reports we find general descriptions of the financial conditions and the economic situation in the economy. Also observations on some key macroeconomic variables and some financial soundness indicators are included that portray the strength of the banking system. The absence of a single acceptable definition of financial stability, like there is for monetary stability, creates difficulties on establishment of a unique framework.

Defining financial stability is important for the development of relevant analytical tools as well as for the design of policy and operational frameworks (Issing, 2003). In addition, there is as yet no widespread agreement on a useful working definition of financial stability. In the literature we noticed the wide use of the terms financial stability and financial instability. The term financial stability broadly describes a steady state in which the financial system efficiently performs its key economic functions, such as allocating resources and spreading risk as well as settling payments, and is able to do so even in the event of shocks, stress situations and periods of profound structural change.

To begin with one definition that refer to instability rather than to stability, Anna Schwartz (1986) gives a description on financial crisis, “A financial crisis is fueled by fears that the means of payment will be unobtainable at any price and in a fractional reserve banking system leads to a scramble for high-powered money. It is precipitated by actions of the public that suddenly squeeze the reserves of the banking system ... The essence of a financial crisis is that it is short-lived, ending with a slackening of the public’s demand for additional currency.” In Schwartz’s definition we can notice doubts that means of payment may be unavailable at any price. Schwartz makes the distinction between real and pseudo financial crises. The former is a banking panic or stock market crash leading to a scramble for currency or central bank liabilities (high-powered money) where the latter refers to all other events.

Pseudo crises are marked by significant loss of wealth but no connection to the money supply or payments system. Schwartz contends that a monetary regime that limits fluctuations in the inflation rate also will tend to limit financial instability by lessening the information problems associated with evaluating the quality of alternative investments. Subsequently, the Schwartz Hypothesis is not a theory of financial crisis, but rather an explanation of how price level instability can lead to or exacerbate financial distress and possibly lead to a crisis. Moreover, the mechanism Schwartz describes is compatible with a variety of explanations of why crises occur.

Moreover, one can classify on instability definitions Minsky's (1978), "Financial Instability Hypothesis" that the inherent financial instability of financial markets is based on the overoptimistic behaviour of economic agents. In this hypothesis, as an economy enters into an upswing, risk premia are gradually eroded as managers of firms and banks discover that the majority of conservatively financed projects are succeeding. Gradually, two characteristics emerge: "Existing debts are easily validated and units that were heavily in debt prospered: it pays to lever". As a result, prevailing risk premia begin to be considered as excessive. Lenders and borrowers begin to take on greater risks and, fuelled by credit and optimism about future profits, this sets off both growth in investment and exponential increases in asset prices. At some point, excesses occur, and the conditions that underpinned the boom eventually trigger its collapse.

Financial stability can be viewed as an absence of instability. The definition of instability that Crockett employs for the purpose of his paper is a situation in which economic performance is potentially impaired by fluctuations in the price of financial assets or by an inability of financial institutions to meet their contractual obligations. Crockett (1997) "...define financial stability as an absence of instability....a situation in which economic performance is potentially impaired by fluctuations in the price of financial assets or by an inability of financial institutions to meet their contractual obligations".

Regarding financial instability, Mishkin (1999) states that financial instability "occurs when shocks to the financial system interfere with information flow so that the financial system can no longer do its job of channelling funds to those with

productive investment opportunities". Mishkin gives emphasis on the role of asymmetric information in financial crises.

Davis (2002) defines systemic risk and financial instability as "a heightened risk of a financial crisis". A financial crisis is then described as "a major collapse of the financial system, entailing inability to provide payments services or to allocate credit to productive investment opportunities. Davis (2002) analyzes three principal types of financial instability. One generic type of instability is centred on bank failures, typically following loan or trading losses (Davis 1995a, 2001a). A second type of financial disorder involves extreme market price volatility after a shift in expectations (Davis 1995b). A third type of turbulence, which is linked to the second, involves protracted collapses of market liquidity and issuance (Davis 1994).

Chant (2003) considers how financial instability differs from other kinds of instability, how it is different from the volatility normally associated with a well functioning financial system, and how instability can be propagated within the financial system and to the real economy. He defines financial instability as "…conditions in financial markets that harm or threaten to harm an economy's performance through their impact on the working of the financial system".

Ferguson (2003) describes financial instability as "a situation characterized by …three basic criteria:

1. some important set of financial asset prices seem to have diverged sharply from fundamentals; and/or
2. market functioning and credit availability, domestically and perhaps internationally, have been significantly distorted; with the result that,
3. aggregate spending deviates (or is likely to deviate) significantly, either above or below, from the economy's ability to produce".

Ferguson incorporates the distortion of asset prices into his definition of financial instability and simultaneously there is explicit coverage of the ultimate impact of financial instability on the macroeconomy, in terms of the impact on aggregate spending.

Tommaso Padoa-Schioppa (2003) contents that"...[financial stability is] a condition where the financial system is able to withstand shocks without giving way

to cumulative processes which impairs the allocation of savings to investment opportunities and the processing of payments in the economy.

According to Foot (2003), "…we have financial stability where there is:

a) monetary stability,

b) employment levels close to the economy's natural rate,

c) confidence in the operation of the generality of key financial institutions and markets in the economy,

d) there are no relative price movements of either real or financial assets within the economy that will undermine a or b".

This is one of the few definitions which mention monetary stability as an essential part of financial stability. So, this definition explicitly incorporates monetary stability.

Large, (2003) like Crockett (1997) and Foot (2003), refers to financial stability as entailing confidence in the financial system "In a broad sense.....think of financial stability in terms of maintaining confidence in the financial system. Threats to that stability can come from shocks of one sort or another. These can spread through contagion, so that liquidity or the honoring of contracts becomes questioned. And symptoms of financial instability can include volatile and unpredictable changes in prices. Preventing this from happening is the real challenge."

Moreover, Haldane et al. (2004) give a definition that refer to deviations from optimal savings/investment plan begin by defining financial instability. Their proposed definition of the latter is summarised as follows: "financial instability could be defined as any deviation from the optimal saving–investment plan of the economy that is due to imperfections in the financial sector."

Schinasi (2004b) proposes and analyses a definition of financial stability that has three important characteristics. First, the financial system is efficiently and smoothly facilitating the intertemporal allocation of resources from savers to investors and the allocation of economic resources generally. Second, forward-looking financial risks are being assessed and priced reasonably accurately and they are also being relatively well managed. Third, the financial system is in such condition that it can comfortably if not smoothly absorb financial and real economic surprises and shocks. If any one or a combination of these characteristics is not being maintained, then it is likely that the financial system is moving in the direction of becoming less stable, and

at some point might exhibit instability. Moreover Schinasi states that, "A financial system is in a range of stability whenever it is capable of facilitating (rather than impeding) the performance of an economy and of dissipating financial imbalances that arise endogenously or as a result of significant adverse and unanticipated events" (Schinasi, 2004). So we can declare that Schinasi's definition stands out in its view of financial stability as a continuum.

Regarding definitions of financial stability that are comprised with the term instability, Allen & Wood (2006), refer to financial instability as "episodes in which a large number of parties, whether they are households, companies or (individual) governments, experience financial crises which are not warranted by their previous behaviour and where these crises collectively have seriously adverse macroeconomic effects". Allen and Wood offer a definition which includes the non-financial sector in this definition, explaining that financial institutions are not the only entities which experience financial stress.

Moreover, many definitions recognize explicitly, the possible impact of financial instability on the economy at large. There is recognition that instability often arise from unforeseen shocks impacting the financial system. Some of the above definitions suggest that financial stability is related to the financial condition of financial companies but not of non-financial companies, or in other words, that financial instability can arise only from financial problems of financial institutions. Examples include Mishkin (1991), Padoa-Schioppa (2002), Schinasi (2003) and Foot (2003). Crockett (1997) and Davis (2002) identify financial stability in terms of instability and describe a situation in which financial instability impairs the real economy. In addition Mishkin (1991) offers a description of instability when information problems undermine the financial system's ability to allocate funds to productive investment opportunities. A similar approach is taken by writers focusing on systemic risk specifically in terms of financial problems that stem from linkages between financial institutions or markets and that have a potentially large adverse impact on the real economy (De Bandt & Hartmann, 2003). Haldane et al. (2004) defines financial stability in terms of a simple model in which asset prices serve to secure the optimal level of savings and investment. Others take a macro prudential

viewpoint and specify financial stability in terms of limiting risks of significant real output losses associated with episodes of financial system-wide distress (Borio, 2003).

In conclusion, we find that at the reviewed literature, there is reference to financial stability as entailing confidence in the financial system. Thus, we can take financial stability as a situation in which the financial system is capable of allocating resources efficiently between activities and across time, assessing and managing financial risks, and absorbing shocks.

2.3. Central Banks, Monetary and Financial Stability

Monetary and financial stability are closely related, if not inextricably intertwined, even though there is no consensus on why this is so. The financial stability challenge can be characterized as maintaining the smooth functioning of the financial system and its ability to facilitate and support the efficient functioning and performance of the economy. While monetary stability seems to be less a source of worry than in previous decades, financial stability is an increasing concern of central bankers (De Graeve et al., 2007). A key challenge therefore for central banks is to maintain monetary and financial stability simultaneously. For Borio & Lowe (2002) and Borio et al. (2003), the achievement of low inflation has created a "new environment", in the context of which the relation between monetary stability and financial stability has to be reconsidered. The success in controlling inflation, underpinning and enhancing central bank credibility at the same time, can conceal imbalances that ultimately lead to higher asset price volatility with serious macroeconomic consequences. Borio (2006) refers to this as a "paradox of credibility." In other words, policymakers' decisions to manage liquidity can result in unsuccessful monetary policy. Decreasing interest rates in order to increase liquidity it can lead to an increase to inflation. Although, the concept of financial stability is relatively new and there is no widely accepted definition or model or analytical framework for assessing the stability of the financial system the last years has attracted the attention of the research community. De Graeve et al. (2007) connect financial stability and the concept of the banking distress and define it as "a bank's probability of distress according to the supervisor's definition of problem banks used for supervisory policy". Furthermore, they find the existence of a trade off between

monetary and financial stability, suggesting that an unexpected tightening of monetary policy increases the mean probability of distress.

A growing number of central banks around the world are making financial stability assessments and publishing financial stability reports, many of them based on a broad conception of financial stability. As many central banks established financial stability departments and began publishing Financial Stability Reports, they have also adopted specific definitions in order to provide some guidance to their objective of safeguarding financial stability. Based on the survey of the available financial stability reports and benchmarks, Čihák (2006) provide useful insights into how central banks analyze financial stability. Some central banks reports include under the heading of instability those situations when a system is subject to significant shocks, even though it does not seem to have major exposures. Other reports include financial stability as the situation when the efficiency of financial intermediation between ultimate borrowers and ultimate lenders is not subject to significant adverse shocks. Čihák survey results suggest that there is no unambiguous definition of financial stability or systemic risk, and that, generally, the responsibility for financial stability is not explicitly formulated in laws.

Nevertheless, is interesting to see how central banks define financial stability and how it is been depicted to Financial stability reports. The European Central Bank (ECB) in its financial stability review presents the following definition. “Financial stability can be defined as a condition in which the financial system - comprising of financial intermediaries, markets and market infrastructures - is capable of withstanding shocks and the unravelling of financial imbalances, thereby mitigating the likelihood of disruptions in the financial intermediation process which are severe enough to significantly impair the allocation of savings to profitable investment opportunities”. We notice that there is emphasis on shocks that disrupt the functioning of the financial system and by extension, on the resilience of the financial system to these shocks while it give emphasis on the key function of the financial system which is the efficient allocation of resources from savers to investors.

2.4. Financial Stability Institutions.

Financial stability issues have been receiving priority attention from policy makers around the world. The catalyst for this trend was the liberalisation of the financial system and the financial crises that were bigger and for often. Following the necessity for measures, the World Bank (WB) and the International Monetary Fund (IMF) introduced the Financial Sector Assessment Program (FSAP) in 1999, aimed at assessing regularly the strengths and weaknesses of financial systems in their member countries. FSAP seeks to identify the strengths and vulnerabilities of a country's financial system and to determine how key sources of risk are being managed.

In addition, several international forums devoted to financial stability issues have emerged or become more active, including bodies such as the Financial Stability Forum, which was The Financial Stability Forum (FSF), was a group consisting of major national financial authorities such as finance ministries, central bankers, and international financial bodies. The Forum was founded in 1999 to promote international financial stability. The Financial Stability Board was established in April 2009 as the successor to the Financial Stability Forum (FSF). The FSB has been established to coordinate at the international level the work of national financial authorities and international standard setting bodies and to develop and promote the implementation of effective regulatory, supervisory and other financial sector policies. Furthermore, Basel Committee on Banking Supervision provides a forum for regular cooperation on banking supervisory matters. Its objective is to enhance understanding of key supervisory issues and improve the quality of banking supervision worldwide.

As a response to the East Asian financial crisis of 1997, the Bank for International Settlements (BIS) and the Basel Committee on Banking Supervision jointly created the Financial Stability Institute (FSIn) in 1999 to assist financial sector supervisors around the world in improving and strengthening their financial systems. Its primary role is to improve the coordination between national Bank Regulators.

There are several others international organisms and institutions that contributes to the maintenance of the financial stability such as, Committee on the Global Financial System, Committee on Payment and Settlement Systems, International Association of Insurance Supervisors , International Accounting

Standards Board , International Organization of Securities Commissions and the International Association of Deposit Insurers. There is also the Counterparty Risk Management Policy Group, a private sector organization devoted to fostering financial stability.

2.5. Macroeconomic Models on Financial Stability

Alternative macroeconomic models are available for policy analyses and Bårdsen et al. (2006) evaluate the usefulness of some models from the perspective of financial stability. As we can observe in Table 3.1 they have categorized macroeconomic models regarding to financial stability in six categories. As financial stability is based on a wide range of risk factors, they assume that one can not expect one single model to satisfactorily capture all the risk factors and for that reason a suite of models is needed.

Table 2.2: Macroeconomic models regarding financial stability, Source Gunnar Bårdsen et al. (2006).

1.	Real business cycle (RBC) models. Infinite horizon, representative agent, calibrated.
2.	• Dynamic stochastic general equilibrium (DSGE) models. Infinite horizon, representative agent, calibrated or estimated.
3.	• Overlapping generation (OLG) models. Infinite horizon, calibrated.
4.	• Finite horizon general equilibrium (FHGE) models. Heterogeneous agents, calibrated. Endogenous default and liquidity constraints.
5.	• Dynamic aggregative estimated (DAE) models. Large and small scale, reduced form. (Cowles commission type of models.)
6.	• Structural vector autoregressive (SVAR) models. Estimated.

The RBC models approach is a flexible framework for quantitative business cycle analysis which owes much to the pioneering work by Kydland & Prescott (1982). Their theoretical framework was based on the idea that the neoclassical growth model could be used to study business cycles, with the use of stochastic

technology and rational expectations. The main emphasis is on having very strong microeconomic foundations, usually in the form of forward looking agents engaging in optimal path allocations of resources and as a result they produced a model that adhered to the Lucas micro-foundations research agenda. Their approach to business cycle empirics became known as calibration. This involves choosing parameters on the basis of long-run data properties and judgment. Prescott challenged the dominant view that business cycles are caused by monetary and financial disturbances. According to that view, upswings in economic activity result from unexpectedly rapid increases in the supply of money, while downswings result from slow growth or a fall in the money supply. In contrast, Prescott and his collaborators presented evidence that business cycles of the sort seen during the postwar era would occur even if there were no monetary or financial disturbances.

In addition, the DSGE models are dynamic, as they studying how the economy evolves over time and they trace the path of variables over time, stochastic, as they taking into account the fact that the economy is affected by random shocks such as technological change, fluctuations in the price of oil, or errors in macroeconomic policy-making and they incorporate the inherent randomness of economic life. Finally these models are general equilibrium as they take into account the fact that everything depends on everything else. In many DSGEs models we notice the absence of an appropriate way of modeling financial markets. The relevance of the financial structure of the economy is well known as reflected by the repetitive waves of financial crises across the world (1930s Great Depression, 1980s-90s Japanese crisis, 1980s Latin American crisis, 1994 Tequila crisis, 1997 Asian crises and the crisis of 2008 which has been characterized as a banking one). Therefore, by excluding a formal modeling of financial markets or financial frictions, the current benchmark DSGE model fails to explain important regularities of the business cycle and also excludes any possible analysis of other key policy issues of concern for central banks, such as financial vulnerabilities, illiquidity or the financial systems' procyclicality. In fact, the weak modeling of financial markets in these models also limits their use for stress testing in financial stability exercises.

Overlapping generation (OLG) models are overlapping generation models with asymmetric information. Their main contribution is that economies with

different initial levels of aggregate wealth may converge to steady states characterised by either a low or high level of capital accumulation and by different financial systems. This class of models analyses the effects of moral hazard arising from asymmetric information in the credit market on both short-run (business cycle) and long-run (growth) macroeconomic phenomena.

In their model, Azariadis & Smith (1993), the main representatives of the overlapping generation (OLG) models, include production, which implies that the relationship between credit markets and output growth can be analysed. They find that adverse selection in financial markets may reduce the rate of return at the inside-money steady state. Hence, an economy that would not generate monetary equilibria under full information may generate these equilibria in the asymmetric information case. The intuition behind this result is that the equilibrium credit rationing induced by adverse selection will force agents to save more than in the full information case and this will lower the autarkic interest rate.

Bernanke, Gertler & Gilchrist (1999), develop a new Keynesian model. The authors need both a real and a nominal rigidity to get a relationship between a financial variable (firms' net worth) and investment. They incorporate a partial equilibrium model of the credit market into a standard dynamic new Keynesian framework with monopolistic competition and price stickiness. The model includes a government sector, whose monetary policy rule sets the current nominal short-term interest rate. Monetary policy has an impact on the real economy through the balance sheets of the borrowers, through a financial accelerator mechanism.

A recent model by Goodhart et al. (2006) which is distinct from, but complementary to the role of the "financial accelerator" in macroeconomic performance, in a finite horizon general equilibrium (FHGE) framework, use a micro-founded general equilibrium model with endogenous default and heterogeneous agents in order to analyze financial fragility, based on earlier work by Tsomocos (2003a and b). The main contribution of this finite horizon general equilibrium (FHGE) model is that financial fragility emerges as an equilibrium phenomenon, and therefore there is a role for active policy for crisis prevention and management. In addition, since a monetary sector is incorporated, the interaction of both monetary and regulatory policies can be assessed. In their model, when deposit and loan rates

increase, borrowing activity declines as banks move close to violating their capital adequacy requirements.

2.6. The Financial Accelerator

The financial accelerator has been the most common approach to incorporate financial frictions into a DSGE framework. Financial frictions allow for a role of balance sheet variables and risk premia in influencing economic outcomes. In this way, they provide a channel through which changes in variables like financial depth and attitudes toward risk affect economic activity. Some financial frictions have been integrated into general equilibrium models and shown to enhance the persistence of shocks (Bernanke et al., 1999).

The financial accelerator in macroeconomics refers to the idea that adverse shocks to the economy may be amplified by worsening financial market conditions. More broadly, adverse conditions in the real economy and in financial markets mutually reinforce each other, leading to a feedback loop that propagates the financial and macroeconomic downturn. The link between the real economy and financial markets stems from firms' need for external finance to engage in profitable investment opportunities. On the other hand, firms' ability to borrow largely depends on the market value of their financial and tangible assets (net of their liabilities), in other words their net worth. The reason for this is the familiar story of asymmetric information. Since lenders are likely to have little information about the creditworthiness of a borrower, they often require borrowers to set forth their ability to repay, which may take the form of collateralizing their assets. Thus, a fall in asset prices that is induced by an initial shock deteriorates the balance sheets of the firms in the sense that their net worth worsens and their ability to borrow declines. Tightening financing conditions limit their investment, which in turn reduces their economic activity or output. Finally, the decreased economic activity further cuts the asset prices down which leads to a feedback cycle of falling asset prices, deteriorating balance sheets, tightening financing conditions and declining economic activity. This vicious cycle is called a financial accelerator, a financial feedback loop or a loan-credit cycle.

Although, such framework has been employed to capture firm's balance sheet effects on investment by relying on a one-period stochastic optimal debt contract with costly- state verification, this approach has its limitations. The key aspect is that such setting allows endogenously determining an external finance premium above the risk-free interest rate. For the most part, however, the quantitative effects of the frictions are small. One critic is that these models are not able to generate the sizeable boom-bust cycles that are increasingly the focus of policymakers.

Another way of rationalizing a financial accelerator theoretically focusing on principal-agent problems in credit markets is the Kiyotaki–Moore model of credit cycles (Kiyotaki & Moore, 1997). It is an economic model developed that shows how small shocks to the economy might be amplified by credit restrictions, giving rise to large output fluctuations. The model assumes that borrowers cannot be forced to repay their debts. Therefore, in equilibrium, lending occurs only if it is collateralized. That is, borrowers must own a sufficient quantity of capital that can be confiscated in case they fail to repay. This collateral requirement amplifies business cycle fluctuations because in a recession, the income from capital falls, causing the price of capital to fall, which makes capital less valuable as collateral, which limits firms' investment by forcing them to reduce their borrowing, and thereby worsens the recession.

2.7. The transmission of financial distress

Credit has played a key role in the transmission of financial distress to the broader economy, consistent with evidence from the literature. Indeed, studies by Gilchrist et al. (2009), Jacobson et al, (2005), and Carlson et al. (2008) indicate the credit channel as the main channel of transmission of financial distress, the strength of which hinges on that of the financial accelerator (Bernanke, Gertler & Gilchrist, 1999; and Kiyotaki & Moore, 1997).

The evidence on the transmission of financial distress has mostly been limited to advanced economies and seldom uses a framework that integrates macroeconomic, financial and (nonfinancial) corporate sector variables. Recent papers (Carlson et al, 2008; and Pesaran et al, 2004) examine the spillover effects of credit risk shocks in a multi-country context with the credit risk been modeled separately from

macroeconomic variables. Financial distress in these papers is measured as bank capital or borrowers' default risk, proxied by corporate bond spreads, credit default swap spreads or data on actual defaults.

2.8. The Empirical Evidence on Financial Stability

One difficulty that many researchers faces is the quantification of financial stability or in other words to find an appropriate measure for it. In general, we find two different approaches. The first one, uses as a measure a financial stress index (FSI) which contains several variables in order to measure the financial stress in the economy. The compilation of such an index have been proposed by, Illing & Liu (2003), Hanschel & Monnin (2004), Van den End, (2006) and Davig & Hakkio (2010). The second approach that is commonly used in literature, uses a single measure such as probability of default (PoD) which is a function of distance to default (DD) and its calculation is based on the modern theory and practice of contingent claims analysis (CCA) and the Merton Model. The DD indicator is computed as the sum of the ratio of the estimated current value of assets to debt and the return on the market value of assets, divided by the volatility of assets. The formula is given by:

$$DD_t = \frac{\ln(V_{A,t}/D_t)+(\mu-\frac{1}{2}\sigma^2{}_A)T}{\sigma_A\sqrt{T}} \qquad (2.1)$$

Using market data of equity and annual accounting data, the market value V_A and the volatility of assets σ_A are typically estimated using Black & Scholes (1973) and Merton (1974) options pricing model. The theoretical probability of default (PoDt) is obtained using the DDt as: PoD_t=N (-DD_t),

where N is the cumulative probability distribution function (cdf) for a variable that is normally distributed with a mean zero and a standard deviation of 1 and μ measures the mean growth of VA. With a similar approach Moody's MKMV has implemented the Vasicek-Kealhofer (VK) an extension of the Black-Scholes-Merton framework model to calculate an Expected Default Frequency (EDF).

Additionally, the International Monetary Fund (IMF) has developed a set of "financial soundness indicators" (FSIs) that it calculated on an internationally harmonized basis, and be released quarterly by most countries (See Appendix). The analysis of financial stability requires a broad set of indicators, such as balance sheet

data reflecting sector financial positions, ratios between net debt and income, measures of counter party risk (such as credit spreads) and of liquidity and asset quality (such as non-performing loans), open foreign exchange positions, and exposures per sector with special attention to measures of concentration. Financial stability analysis needs to cover all of the above sources of risks and vulnerabilities which require systematic monitoring of individual parts of the financial system, as well as their relationships, and the real economy.

Hoggarth & Sapporta (2002), attempt to account for the dynamics between banks' write-off to loan ratio and key macroeconomic variables using VAR model and estimate the cost of 33 systemic banking crises over the past 25 years. They first consider the direct resolution costs to the government and then the broader costs to the welfare of the economy proxied by losses in GDP. They carried out the analysis for the United Kingdom using a single module measure VAR. The VAR consists of the financial stress index, the output gap the annual rate of change in retail prices and the nominal bank short-term interest rate. As FSI they use bank write-offs which are the losses (net of recoveries) made by UK-owned banks on loans initiated from their UK-resident banking operations. As result they found some effect of growth on their measure of financial stability (write offs) but no effect in the opposite direction.

Illing & Liu (2003) provide a good description of how one might attempt to build a composite indicator of financial stability. To begin with, relevant variables need to be selected. The choice is most often based on the early warning indicators literature and typically covers the banking system, the foreign exchange market and the equity market. Then, the single aggregate measure is calculated as a weighted average of the variables previously identified each with a suitable lag. One important aspect of the weighted average construction is the weights. The variance-equal method is the most commonly used in the literature and consists of normalizing each variable and then assigning equal weights. The FSI provides an ordinal measure of stress in the financial system. Changes in the FSI are useful in evaluating whether stress is rising or falling, and in establishing time frames for extreme events but also it can be used to explain changes in real economic variables, such as GDP and investment. Extremely high levels of financial stress impair not only the financial

system but also result in significant losses in the real economy. Alternative, lower levels of stress may also affect the real economy to a lesser extent: for example, they could result in tight liquidity conditions and asset-price instability, both of which could lead to an increase in the cost of capital and reduce private investment and consumption.

Hanschel & Monnin (2004) use a composite stress index, choosing the variance equal weight method to compute it. They focus on the banking sector, and propose an index that can be used to measure stress in the Swiss banking sector. They use market price data, balance sheet data and other non public data of banks that are under special scrutiny to compile the FSI and use macroeconomic variables to test on macroeconomic imbalances. They estimate whether the values of the index can be predicted by the set of macroeconomic variables. They forecast the Swiss financial index running a regression using as explanatory variables the gaps the share price index, housing price index, the GDP, the credit to GDP ratio and the investment to GDP ratio. They found that a significant link exists between the macroeconomic environment and the banking sector's condition and that the macroeconomic imbalances generally build up years before the stress rises in the banking sector

Jacobson et al. (2005), make use of multiple module approach in order to assess macroeconomic feedbacks. They propose a reduced form approach for Sweden consisting of an aggregate VAR model that includes the average default frequency of companies as a measure of financial stability, a model linking macro and balance sheet specific factors to defaults of companies, and a module linking the evolution of balance sheets in response to macro factors. By integrating these three building blocks they show that there are significant feedback effects from financial stability back to the real economy. They find that the aggregate default frequency is a significantly and quantitatively important link from the financial to the real side of the economy. Their empirical model implies that the effects of monetary policy on the default frequency and the inflation rate are state dependent: monetary policy appears to be more potent under recessions than during booms.

An alternative method to construct a FSI has been proposed by Van den End, (2006). The "financial stability conditions index" was built based on indicators characterizing monetary conditions, namely: interest rates, effective exchange rate,

real estate prices, stock prices, solvency of financial institutions and volatility of financial institutions stock index. The innovation of this index resides in the introduction of some upper and lower critical limits to take into account the potential non-linear effects. For estimating the weights at the FSCI he used a VAR model. For a financial stability indicator, the interaction between financial market prices, the economy and the financial sector has particular relevance. The VARs are estimated with six lags, which is the maximum number given the necessary degrees of freedom. Critical states have been defined as an upper (imbalances) and a lower (instability) boundary of the FSCI. Movements of the index towards these boundaries provide relevant signals since they might point to the development of a boom/bust cycle. The application of the FSCI to the Netherlands and six other OECD countries shows that the index indeed reflects the typical boom/bust cycle which might be a harbinger of financial crises.

Aspachs et al. (2006) main objective, have been to refute the opening quote, and to find a metric for measuring financial stability. Their paper follows the same route such as Hanschel & Monnin (2004) and Illing & Liu (2003) with the difference that the variables in their financial stress index are not derived from any structural model and their estimates are limited to single countries (Switzerland and Canada respectively). In order to measure the financial stability they obtain their key variables from Goodhart et al. (2006), general equilibrium model on seven countries.
Aspachs et al. (2006) use a VAR model with macroeconomic variables and a two factor model, profitability and probability of default (PoD) in order to measure financial stability. Their data set included seven advanced economies over the period 1990 Q4 till 2004 Q4. As macroeconomic variables they use GDP, CPI, short term interest rates and residential property prices. Analyzing impulse response functions they estimate that the response of GDP growth to pod is negative and significant Thus, an increase of the default probability of the banking sector induces a decrease in the growth rate of GDP. In addition, the response of GDP growth to a shock to the banking sector equity index is positive and significant.
Alves (2005), Pesaran et al. (2006), and Castren et al. (2007) use models that allow for influence from explanatory economic variables on default probabilities, but not the other way around. They use VAR models for forecasting the development of the

macroeconomic variables. Alves (2005) takes into account that the likelihood of defaults and the macroeconomic variables display common trends.

Pesaran et al. (2006) adopt the Global Vector Autoregressive (GVAR) model to generate conditional loss distributions of a credit portfolio of a large number of firms in various regions of the world. Castren et al. (2007) using the (GVAR) model and constructing a linking satellite equation for the firm-level Expected Default Frequencies (EDFs), show how to analyse the euro area corporate sector probability of default under a wide range of domestic and foreign macroeconomic shocks. The results show that, at the euro area aggregate level, the median EDFs react most to shocks to the GDP, exchange rate, oil prices and equity prices. In Pesaran et al. (2006) the VAR includes GDP, consumer prices, the nominal money supply, equity prices, exchange rates vis-à-vis the dollar and nominal interest rates for eleven countries/regions over the 1979-99 period of time. The global VAR is used as an input into simulations for firms' equity returns, which are then linked to the loss distribution of a corporate loan portfolio. A clear advantage of this approach is that it links the credit risk of internationally diversified loan portfolios in a detailed macroeconomic model that allows for differences across country and region.

Cihak (2007) proposes a measure of financial stability that can be used in practice. He argues that a good measure of systemic stability needs to incorporate three elements: probabilities of failure in individual financial institutions, loss given default in the financial institutions, and correlation of defaults across the institutions. He evaluates the existing measures of financial stability concentrating in studies that use PoD as a measure for financial stability and he founds that they generally come up short because tend to overlook the fact that "size matters".

Carlson at al. (2008) develop an index of financial sector health using a distance-to-default measure based on a Merton-style option pricing model. Their index spans over three decades and appears to capture periods when financial sector institutions were strong and when they were weak. They find that the health of the financial sector does indeed have an impact on macroeconomic variables. A typical negative shock to our index results in a cumulative decrease in investment of about 2 percent over the subsequent two years. Further, they find that the impact of shocks to the profitability of nonfinancial firms on investment is magnified by the inclusion of

financial variables in the VAR. This effect occurs because declines in firm profitability decrease the health of the financial sector which in turn have their own impact on investment, an amplification mechanism reminiscent of the mechanisms in the financial-accelerator literature

Asberg Sommar & Shahnazarian (2008), incorporate expected default frequency(EDF) data in cointegrated closed-economy VAR models and find cointegration relationships between the macro and EDF variables and identify significant relationships between EDFs on the one hand and short-term interest rates, GDP and inflation on the other hand. They use a vector error-correction model to study interdependencies between the aggregate EDF and the macroeconomic development. Forecasts indicate that a lower short-term interest rate reduces the EDF and, in turn, risk premiums. This reduces the marginal cost for corporate investments and household consumption and stimulates growth through these two components of aggregate demand. At the same time, it imposes a downward pressure on the product prices of firms and thereby on inflation.

Gilchrist et al. (2009) research estimates that that credit market shocks have contributed significantly to U.S. economic fluctuations during the 1990-2008 period. According to impulse responses from a structural factor-augmented vector autoregression, unexpected increases in bond spreads cause large and persistent contractions in economic activity.

Chen et al. (2009) examine how distress in banks and corporates affects domestic economies and gets transmitted to other economies following the methodology of Pesaran et al. (2006). The GVAR model includes the EDFs and macroeconomic variables, such as industrial production, real short-term interest rates, real effective exchange rates and real stock prices. Their analysis which is based on a GVAR model for 30 advanced and emerging economies for the period from January 1996 to December 2008, confirms strong macro-financial linkages within domestic economies and globally. The results point to two-way causality between bank and corporate distress and to significant global macroeconomic and financial spillovers from either type of distress when it originates in a systemic economy. They found that growth in emerging economies is more sensitive to corporate than bank distress, while

the opposite is true for advanced economies. This finding may reflect a lower level of financial development of emerging economies compared to advanced economies.

Misina & Tkacz (2009) use also the Illing and Liu (2003) stress index in order to estimate the role of credit and asset prices as early-warning indicators of vulnerability in the financial system. They find that some combinations of credit and asset price variables are important predictors of financial stress.

Cardarelli et al. (2009) and Balakrishnanin et al. (2009) compile a composite stress index following the methodology as it has been proposed by Illing and Liu (2003). Cardarelli et al. (2009) examines why some financial stress episodes lead to economic downturns using a financial stress index (FSI) and proposes an analytical framework to assess the impact of financial stress on the real economy. They estimate that financial stress is often, but not always a precursor to an economic slowdown or recession. Also, when a slowdown or recession is preceded by financial stress typically it is substantially more severe than slowdowns or recessions not preceded by financial stress. In particular, slowdowns or recessions preceded by banking-related stress tend to involve two to three times greater cumulative output losses and tend to endure two to four times as long. Furthermore they note that over a 40 year period in 17 advanced countries have been 113 financial stress episodes and 29 of them have been followed by recession. From the 113 episodes the 43 have been caused by the banking sector, 50 by the securities market and 20 by the foreign exchange markets.

Balakrishnanin et al. (2009) study how financial stress, defined as periods of impaired financial intermediation, is transmitted from advanced to emerging economies using a FSI for emerging economies. They estimate that the financial linkages appear more important than trade linkages as determinants of stress transmission. Thus, emerging economies with higher foreign liabilities to advanced economies have been more affected by financial stress in advanced economies than emerging economies that are less linked.

Davig & Hakkio (2009) explore the theoretical links between financial stress and economic activity and test a FSI (KCFSI) in order to find direct evidence on the link between the index and economic activity using impulse response functions. They support the view that financial stress can slow economic activity through some

combination of increased uncertainty, increased cost of finance, and tighter credit standards.

Li & St-Amant (2010) using a financial stress index examine empirically the impact of financial stress on the transmission of monetary policy shocks in Canada. The model used is a threshold VAR in which a regime change occurs if financial stress conditions cross a critical threshold. In the TVAR take a sample period 1981Q4 to 2006Q4 of real GDP growth rate, core inflation rate, real overnight rate, and FSI.

Finally, following a different method to compile an FSI, Morales & Estradaper (2010) form forecast for the FSI index taking into account the behavior of some macroeconomics variables. The FSI index is composed by nine variables: return on assets (ROA), return on equity (ROE), ratio of non-performing loans to total portfolio (NP), ratio of net loan losses to total loan portfolio (LP), intermediation spread (IS), ratio of liquid liabilities to liquid assets (LL), ratio of interbank funds to liquid assets (IF), uncovered liabilities ratio (ULR) and the number of financial institutions with high stress level (Stress) per period. These variables were composed to a single index using the variance-equal weight method. They perform forecast for the FSI index taking into account the behavior of some macroeconomics variables. The variables that have been considered in the VECM are the inflation rate and unemployment rate, the Colombian monthly economic activity index (IMACO), and the home price index (IPVN). The results suggest that if the economy registers a lower inflation rate or a lower unemployment rate, additional to a high growth of new homes prices accompanied by a less negatives economic activity growth rates, then the financial stress level will be lower.

CHAPTER 3: Empirical Analysis

3.1. Selected Variables and Data Description

For the purpose of our analysis the VAR model is consist of three variables: a single module measure of financial stability, the financial stress index (FSI), a growth index and an inflation index. The macroeconomic variables are from the IMF statistics data base (IFS) and are on quarterly basis. Our data set includes 9 advanced OECD countries over the period 1984 Q1 till 2009 Q4. Cardarelli et al. (2009) and Balakrishnanin et al. (2009) have developed a FSI for seventeen advanced countries by comprising seven sub indices related to banking sectors, securities markets and foreign exchange volatility. In essence, this index is a weighted sum of market based indicators for the banking sector, debt markets, equity markets and liquidity measures. Our model includes the FSI[1] for measuring financial stability, a growth measure (GDP) and an inflation measure (CPI) for the nine case studies.

Given that the FSI is built up to capture the evolution of the financial stress, we switch its sign to obtain a measure of financial stability. For the purpose of our analysis and in order to describe financial stability we use the inversed financial stress index (IFSI), i.e. we have multiplied the FSI variable by -1 so that a drop in the index registers with a decrease of financial stability.

IFSI =FSI * (-1) (3)

Thus, we have a normalize indicator of stability whose positive (negative) realizations indicate a degree of financial soundness above (below) its long term average. The IFSI has a mean of zero and a standard deviation of one. Therefore, when the IFSI exceeds zero, financial conditions are more stable than average. We use the FSI as the most appropriate measure indicating the financial stress in an economy and after we have rejected alternative measures. Financial stability indicators such as IMF soundness indicators are provided only for the years 2008 and 2009 and are on yearly basis. Moreover, was difficult to abstract the accurate information from corporate balance sheets and this method gives low frequency panel data. Using other measures of financial stress such as PoD and expected default

[1] FSI, http://www.imf.org/external/np/mcm/financialstability/papers.htm#gen, Balakrishnanin et al. (2009)

frequency (EDF) were not easy accessible or were confidential corporate data (see Moody's KMV Credit Monitor)[2].

One of our purposes in this study is to examine whether financial stability, measured as described already by the IFSI, would have an impact on economic welfare, on monetary stability and vice versa. For that reason we use in our model two proxy variables: GDP Volume as the yearly % GDP change as a measure for growth and in the CPI index as the yearly % change in the price level as a measure for the inflation. The nine case studies are: Belgium, France, Germany, Netherlands, Italy, Japan, Spain, USA and the UK. GDP Volume measures data are derived from IFS data bases from those series reported in lines 99bvp and 99bvr in the country tables. The data of Consumer Prices are those prices reported in lines 64 in the country tables. The percent changes are calculated from the index number series. Indices shown for Consumer Prices are the most frequently used indicators of inflation and reflect changes in the cost of acquiring a fixed basket of goods and services by the average consumer.

3.2. The Financial Stress Index

The FSI is an equal-variance weighted average of seven variables, grouped into three categories, Banking Sector, Securities Market and Foreign Exchange.

Table 3.1: FSI Index

FSI Variables	
A.	**Banking sector**
1.	Banking sector beta
2.	TED spread
3.	Inverted term spread
B.	**Securities market**
4.	Corporate bond spread
5.	Stock market returns
6.	Stock market volatility (GARCH1.1)
C.	**Foreign exchange market**

[2] KMV, 2001, "Modeling Default Risk," KMV Corp.

7. Exchange market volatility (GARCH1.1)

The banking sector includes tree variables, the beta of banking sector, the TED or interbank spread and Inverted term Spread

$$\beta_{it} = \frac{COV\left(r^{B}_{i,t}\ r^{M}_{i,t}\right)}{\sigma^{2}_{i,t^{M}}}, \quad \begin{cases} t = 1,.....T; T = 104 \\ i = 1,.....I; I = 9 \end{cases} \qquad (3.1)$$

where r_{it}^{B} is the year-over-year banking returns for the country i and for the period of time t, r_{it}^{M} is the year-over-year market returns for the country i and for the period of time t and the $\sigma^{2}{}_{i}{}^{M}$ is the variance of the overall market for the county i.

i.e. for obtaining the USA banking sector beta, was used the covariance of the annual return of the NYSE Composite Index (market) and the annual return of NYSE Financial Stock Price Index (banks), divided by the variance of the annual return of the NYSE Composite Index.

If $\beta_{it}>1$ it signifies that the banking sector stocks are more volatile than the market. If $0<\beta_{it}<1$ it signifies that the banking stocks are less volatile or less risky than the market. If $\beta_{it}<0$ it signifies that the stock is in reverse harmony with the market. If the market is returning positive results, the stock will return negative.

The TED spread is calculated as the difference between the three-month short-term government debt (T-bill) interest rate and three-month Inter bank offered rate. The TED spread is an indicator of perceived credit risk in the general economy. This is because T-bills are considered risk-free while interbank interest rate reflects the credit risk of lending to commercial banks. When the TED spread increases that is a sign that lenders believe the risk of default on interbank loans is increasing. Interbank lenders therefore demand a higher rate of interest, or accept lower returns on safe investments such as T-bills.

The third variable of the banking sector is the inverted term spread. The slope of the yield curve, which is measured as the difference between the short term rate and long term yields on government issued securities.

The securities market is compiled with corporate bond spreads, stock market returns and stock market volatility. The corporate bond spreads are the corporate bond yield minus the long term government bond yield. Moreover, the stock market returns

are measured as the month over month change in the stock index, but multiplied by -1, so that a sharp drop in stock prices registers as an increase in the index. A third variable for measuring the securities market is the measure of the stock market volatility. In order to measure the volatility of stock market was used the GARCH (1.1) approach.

Finally, the foreign exchange market is measured by the exchange market volatility. In order to measure the time-varying volatility of monthly changes in the nominal effective exchange rate we use also use a GARCH (1.1) approach. The autoregressive conditional heteroskedasticity (ARCH) models introduced by Engle (1982) and its extension, the GARCH models (Bollerslev, 1986) have been the most commonly employed class of time series models in the recent finance literature for studying volatility. The appeal of the models is that it captures both volatility clustering and unconditional return distributions with heavy tails. The estimation of GARCH model involves the joint estimation of a mean and a conditional variance equation. The GARCH (1,1) model which is stated as follows: $Y_t = x_t'\theta + u_t$ (3.2), where the above is the conditional mean equation with x_t being the vector of exogenous variables. The conditional variance, σ^2_t, can be stated as follows:

$$\sigma^2_t = \alpha_0 + \alpha u^2_{t-1} + \beta\sigma^2_{t-1} \qquad (3.3)$$

where α_0 is a constant term, αu^2_{t-1} is the ARCH term and $\beta\sigma^2_{t-1}$ is the GARCH term.

The variables that are included in the FSI are on monthly basis and their sources are,

- Banking sector β: DataStream, Haver Analytics, and the Organization for Economic Cooperation and Development (OECD)
- TED spread: Haver Analytics
- Inverted term spread: DataStream and Haver Analytics
- Corporate debt spread: DataStream and Haver Analytics
- Stock market returns: OECD
- Stock market volatility: OECD
- Exchange market volatility: Source: IMF

To yield the aggregate financial stress index for an individual country the seven components are standardized and summed up:

FSI_t = b + TED spread + Inverted term spread + Corporate dept spread + Stock market returns + Stock market volatility + Exchange market volatility.

All the variables in the FSI are standardised using a variance-equal weighting method which generates an index that gives equal importance to each variable. This method is the most common weighting method used in the literature. Since each variable in the FSI is standardized, the level of stress for a current event can be compared only with that of an historical event in terms of their deviations from the mean. The mean is subtracted from each variable before it is divided by its standard deviation. The formula for the index is presented in Eq. 1.

$$FSI_t = \sum_{i=1}^{k} \omega_i \frac{X_{it} - \overline{X}_{it}}{\sigma_i}, \qquad (3.4)$$

where k is the number of variables that compose the index, $\overline{X_i}$ is the average of the variable X_i, σ_i its standard deviation and ω_i is the equal weight on each variable. Therefore, the dataset refer to seven industrial countries, cover the period 1984 – 2009 and the precise sample period are given in Table 3.2

Table 3.2: Summary Statistics

Variable	*Sample*	*Mean*	*Min*	*max*	*std dev*
IFSI					
USA	(1984-2009)	0.27	-15.06	4.15	3.28
UK	(1984-2009)	0.08	-15.48	4.98	3.34
Japan	(1984-2009)	-0.29	-11.33	3.96	2.63
Italy	(1984-2009)	0.37	-7.02	4.69	2.46
Spain	(1984-2009)	0.25	-8.13	3.84	2.35
Germany	(1984-2009)	-0.01	-10.85	5.28	3.28
France	(1984-2009)	0.68	-4.64	5.10	2.25
Netherlands	(1984-2009)	0.02	-17.59	5.18	3.31
Belgium	(1984-2009)	0.42	-14.87	4.36	2.83

Variable	*Sample*	*Mean*	*Min*	*max*	*std dev*
GDP					
USA	(1984-2009)	2.74	-4.11	5.37	1.84
UK	(1984-2009)	2.44	-5.89	6.89	2.35
Japan	(1984-2009)	2.02	-8.67	9.36	2.91
Italy	(1984-2009)	1.51	-6.51	6.31	2.17
Spain	(1984-2009)	3.06	-4.44	8.37	2.37
Germany	(1984-2009)	2.18	-6.61	16.15	3.07
France	(1984-2009)	1.84	-3.88	5.69	1.59
Netherlands	(1984-2009)	2.37	-5.05	5.86	1.93
Belgium	(1984-2009)	2.11	-4.31	5.94	1.84
CPI					
USA	(1984-2009)	2.95	-1.62	6.22	1.27
UK	(1984-2009)	3.53	-1.38	10.43	2.10
Japan	(1984-2009)	0.70	-2.24	3.73	1.27
Italy	(1984-2009)	3.80	0.12	9.42	2.03
Spain	(1984-2009)	4.25	-1.11	9.66	2.14
Germany	(1992-2009)	1.93	-0.24	6.12	1.24
France	(1984-2009)	2.37	-0.42	8.83	1.58
Netherlands	(1984-2009)	2.02	-1.23	4.40	1.09
Belgium	(1984-2009)	2.35	-1.21	7.14	1.40

3.3. Time Series Properties

We first test for stationarity properties of our data using the augmented Dickey Fuller and Phillips Perron Tests. We continue testing for cointegration relation before we proceed to the VAR analysis. A strictly stationary process is one where, for any t_1, $t_2,\ldots,t_T \in Z$, any $k \in Z$ and $T = 1, 2, \ldots$

$$Fy_{t1}, y_{t2}, \ldots, y_{tT}(y_1, \ldots, y_T) = Fy_{t1+k}, y_{t2+k}, \ldots, y_{tT+k}(y_1, \ldots, y_T) \quad (3.5)$$

where F denotes the joint distribution function of the set of random variables. A series is strictly stationary if the distribution of its values remains the same as time progresses, implying that the probability that y falls within a particular interval is the same now as at any time in the past or the future. In order series to be weakly stationary should be satisfied the equations:

$$E(y_t) = \mu \quad (3.6)$$

$$E(y_t - \mu)(y_t - \mu) = \sigma^2 < \infty \quad (3.7)$$

$$E(yt_1 - \mu)(yt_2 - \mu) = \gamma_{t2-t1} \quad \forall\, t_1, t_2 \quad (3.8)$$

Where the moment $E(y_t - E(y_t))(y_{t-s} - E(y_{t-s})) = \gamma_s$, s = 0, 1, 2, . . . is known as the autocovariance function. These three equations state that a stationary process should have a constant mean, a constant variance and a constant autocovariance structure, respectively. A white noise process is one with no discernible structure. A definition of a white noise process is:

$E(y_t) = \mu$ (3.9)

$var(y_t) = \sigma^2$ (3.10)

$$\gamma_{t-r} = \begin{cases} \sigma^2 & \text{if } t = r \\ 0 & \text{if } t \neq r \end{cases} \quad (3.11)$$

Thus, a white noise process has constant mean and variance, and zero autocovariances, except at lag zero.

Stationary test

It is very important to test for the stationary of our variables. In the econometric literature AR (p) models are often used to verify the existence of a unit root. Suppose that y_t follows an AR (1) process:

$y_t = \varphi y_{t-1} + u_t$ (3.12) or equivalent $\Delta y_t = \psi y_{t-1} + u_t$ (3.13) where φ-1 = ψ

The basic objective of the test is to examine the null hypothesis that

$\psi = 0$ against the one-sided alternative $\psi < 0$.

H_0: series contains a unit root versus

H_1: series is stationary.

As a preliminarily first step the correlogram was used as an informal test for testing for stationary. If the correlation coefficient begin with high values for lag 1 and degreases with a slow rate as we add lags, then is an indication for non stationary series. Dickey Fuller (DF) tests are also known as τ -tests, and can be conducted allowing for an intercept, or an intercept and deterministic trend, or neither, in the test regression. One assumption to the DF test is that u_t is white noise, i.e. assumed not to be autocorrelated but this is not always the case. The solution to the strong evidence of autocorrelation in first differences is to 'augment' the test using p lags of the dependent variable. The alternative model to eq (3.13) is now written:

$$\Delta y_t = \psi_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t \qquad \text{(ADF) (3.14)}$$

In order to determine the optimal number of lags of the dependent variable we check the Akaike Information Criterion (AIC). In most cases, choosing an alternative information criterion, such us Swarch criterion, doesn't change the acceptance or rejection decision of the null hypothesis. Furthermore changing the number of lags gives us approximately the same results and also it doesn't change our decision whether the variables are stationary or not.

Phillips & Perron (PP) have developed a more comprehensive theory of unit root non-stationarity. The tests are similar to ADF tests, but they incorporate an automatic correction to the DF procedure to allow for autocorrelated residuals. The PP method estimates the non-augmented DF test equation and modifies the ratio of the coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic.

The results presented in Tables 3.3 & 3.4 indicate that the GDP time series for the most countries seem to be non stationary. There is a strong evidence that follow an I(1) process (non stationary at 5% level). Exception are the cases of Germany and Belgium when we use the constant term model, which are stationary at a 5% significant level, while we don't reject the null hypothesis at a significant level of 1% (non stationary at 1% level).

The CPI series seem to be stationary only for a single case, Italy. Furthermore, there is evidence of stationary at a significant level of 5% when the model includes only constant term for Belgium, Spain and Germany. Respect to the rest of the countries, U.K, Netherlands, and USA prove to be stationary at a significant level of 10% and France at a significant level of 5%

As well, the results indicate that there is also evidence of stationary for the IFSI time series for the most countries as we reject the null hypothesis at a significant level of 5% except for the case of UK (non stationary at 5% level).

We perform again the ADF and PP test taking the variables in 1st difference instead of taking them in level. In 1st differences the variables are stationary both with ADF and PP tests i.e. follow an I(0) process at a significant level of 5%.

Table 3.3: Unit root tests: Model with Constant and Trend

ADF and P-P Unit Root Tests				
Constand & Trend	*Augmented Dickey Fuller*		*Phillips-Perron*	
variables	*Statistic*	*(probability)*	*Statistic*	*(probability)*
ifsi_ger	-3.492	0.0454	-3.498	0.0447
ifsi_fr	-3.734	0.0243	-3.740	0.0239
ifsi_be	-4.084	0.0090	-3.547	0.0396
ifsi_it	-3.912	0.0148	-4.041	0.0102
ifsi_sp	-4.488	0.0025	-4.508	0.0024
ifsi_uk	-2.766	0.2134**	-2.901	0.1666**
ifsi_ne	-4.313	0.0044	-3.555	0.0388
ifsi_us	-3.853	0.0676*	-3.494	0.0452
gdp_ger	-3.271	0.0769*	-3.456	0.0497
gdp_fr	-2.360	0.3981**	-2.690	0.2427**
gdp_be	-3.262	0.0784*	-3.221	0.0859*
gdp_it	-2.731	0.2263**	-3.114	0.1084**
gdp_sp	-1.679	0.7536**	-2.804	0.1991**
gdp_uk	-2.507	0.3240**	-2.149	0.5119**
gdp_ne	-2.408	0.3729**	-2.970	0.1456**
gdp_us	-5.160	0.0002	-2.867	0.1774**
cpi_ger	-3.232	0.0870*	-3.064	0.1228**
cpi_fr	-3.132	0.1038**	-2.860	0.1794**
cpi_be	-3.357	0.0629*	-3.167	0.0967*
cpi_it	-3.876	0.0164	-3.777	0.0216
cpi_sp	-3.386	0.0588*	-3.140	0.1025**
cpi_uk	-2.734	0.2252**	-2.501	0.3270**
cpi_ne	-2.504	0.3255**	-2.170	0.5003**
cpi_us	-2.359	0.3983**	-2.971	0.1454**

**(**) denotes acceptance of the null hypothesis at the 5% (10%) level*

MacKinnon (1996) one-sided p-values, where $p(|t| \leq t_{a/2}$

Table 3.4: Unit root tests: Model with Constant

MacKinnon (1996) one-sided p-values.

Constand	*Augmented Dickey Fuller*		*Phillips-Perron*	
variables	*Statistic*	*(probability)*	*Statistic*	*(probability)*
ifsi_ger	-3.428	0.0121	-3.419	0.0124
ifsi_fr	-3.323	0.0163	-3.246	0.0201
ifsi_be	-3.250	0.0199	-3.360	0.0147
ifsi_it	-4.108	0.0014	-4.180	0.0011
ifsi_sp	-3.829	0.0036	-3.776	0.0043
ifsi_uk	-2.781	0.0647*	-2.920	0.0466
ifsi_ne	-4.195	0.0011	-3.512	0.0095
ifsi_us	-3.862	0.0153	-3.535	0.0091
gdp_ger	-2.915	0.0469	-3.083	0.0309
gdp_fr	-2.280	0.1801**	-2.650	0.0863*
gdp_be	-3.132	0.0272	-3.176	0.0243
gdp_it	-2.037	0.2708**	-2.566	0.1033**
gdp_sp	-2.182	0.2139**	-2.749	0.0693*
gdp_uk	-2.413	0.1406**	-1.818	0.3700**
gdp_ne	-2.334	0.1632**	-2.805	0.0609*
gdp_us	-2.336	0.1627**	-2.695	0.0781*
cpi_ger	-3.382	0.0152	-3.781	0.0050
cpi_fr	-4.071	0.0518*	-3.507	0.0516*
cpi_be	-3.674	0.0058	-3.108	0.0289
cpi_it	-3.396	0.0132	-3.309	0.0169
cpi_sp	-3.181	0.0239	-2.482	0.1227**
cpi_uk	-1.994	0.2888**	-1.795	0.3809**
cpi_ne	-2.478	0.1237**	-2.182	0.2139**
cpi_us	-1.994	0.2888**	-2.655	0.0854*

Significant at 10% level (**); at 5% level (*)

MacKinnon (1996) one-sided p-values, where $p(|t| \leq t_{a/2}$

ifsi_ger	*IFSI Germany*	*gdp_ge*	*GDP Germany*	*cpi_ger*	*CPI Germany*
ifsi_fr	*IFSI France*	*gdp_fr*	*GDP France*	*cpi_fr*	*CPI France*
ifsi_be	*IFSI Belgium*	*gdp_be*	*GDP Belgium*	*cpi_be*	*CPI Belgium*
ifsi_it	*IFSI Italy*	*gdp_it*	*GDP Italy*	*cpi_it*	*CPI Italy*
ifsi_sp	*IFSI Spain*	*gdp_sp*	*GDP Spain*	*cpi_sp*	*CPI Spain*
ifsi_uk	*IFSI UK*	*gdp_uk*	*GDP UK*	*cpi_uk*	*CPI UK*
ifsi_us	*IFSI USA*	*gdp_us*	*GDP USA*	*cpi_us*	*CPI USA*
ifsi_ne	*IFSI Netherlands*	*gdp_ne*	*GDP Netherlands*	*cpi_ne*	*CPI Netherlands*

Cointegration test

The next step in our analysis is to test for cointegration by employing the multivariate cointegration technique as it has been proposed by Johansen. In cointegration a linear combination of two or more integrated variables y and x can result in a stationary error term z. In general, if variables with differing orders of integration are combined, the combination will have an order of integration equal to the largest i.e. if two variables that are I(1) are linearly combined, then this combination will also be I(1).

Cointegration can be viewed as the statistical expression of the nature of long-run equilibrium relationships. If y and x are linked by some long-run relationship, from which they can deviate in the short run but must return to in the long run, residuals will be stationary. If variables diverge without bound meaning that we have non-stationary residuals we must assume no equilibrium relationship exists. It is significant to test for cointegration because it always implies for an error-correction model (ECM). For three cointegrated variables a possible error correction model would be:

$$\Delta y_t = \Delta y_t = \beta_1 \Delta x_t + \beta_2 \Delta w_t + \beta_3 (y_{t-1} - \gamma_1 x_{t-1} - \gamma_2 w_{t-1}) + u_t \quad (3.15)$$

The ECM is superior regarding modeling integrated data in first differences or in levels. Since the included macroeconomic series in the analysis are in most cases non-stationary the question arises whether one should take differences of the variables in order to eliminate the stochastic trend. With I(1) variables, using a VAR in levels or in 1st differences makes no difference asymptotically (e.g. Sims, Stock, Watson, 1990), but using 1st differences is better in small samples (Hamilton, 1994). Sims et al. (1990) show that OLS estimates of VAR coefficients are consistent under a broad range of circumstances, even if the variables are non-stationary and are used in levels. Estimating VAR in levels does not pose problems, if all variables are stationary. However, if two or more variables are I(1) and also are cointegrated, 1st difference estimates are biased because ECM is omitted. Levels estimates implicitly incorporate cointegration relationship but standard errors are unreliable, inefficient and thus we should choose a VECM model.

Johansen (1988) developed a maximum likelihood estimation procedure, which also allows one to test for the number of cointegrating relations.[3]

Consider a VEC model of order p: $\Delta Y_t = c + \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \ldots + \Gamma_{\rho-1} \Delta Y_{t-\rho+1} + e_t$, (3.16)

Where $\Pi = (\sum_{i=1}^{p} \Phi_i) - I_g \;\&\; \Gamma i = (\sum_{j=1}^{i} \Phi_j) - I_g$

If all elements in Y_t are integrated of order one and no cointegrating relationships exist, it must be the case that $\Pi = 0$. If all elements in Y_t are stationary I (0) variables, the matrix Π must be of full rank. If Π has reduced rank of $r \leq k - 1$, this means that there are r independent linear combinations of the k elements in Y_t that are stationary and this can be written as the product of a $k \times r$ matrix γ and an $r \times k$ matrix β' that both have rank r.

$\Pi = \gamma\beta'$,

where β denotes the matrix of cointegrating vectors, while γ represents the matrix of weights with which each cointegrating vector enters each of the ΔY_t equations. Matrix β contains the long run relationships between variables in Y_t and γ contains the short run adjusting parameters towards the long run steady state relationship $\beta' Y_t$.

The first step in the Johansen approach involves testing hypotheses about the rank of the long-run matrix. We can use the estimated eigenvalues,

say $\hat{\lambda}_1 \succ \hat{\lambda}_2 \succ \ldots \hat{\lambda}_k$, to test hypotheses about the rank of Π. The trace test checks whether the smallest $k - r_0$

eigenvalues are significantly different from zero. The hypothesis H_0: $r \leq r_0$ versus the alternative H_1: $r_0 < r \leq k$, can be tested using the statistic: $\lambda_{trace}(r_0) = -T \sum_{j=r_0+1}^{\kappa} \log(1-\hat{\lambda}_j)$

An alternative test is the maximum eigenvalue test, as it is based on the estimated $(r_0 + 1)^{th}$ largest eigenvalue.

H_0: $r \leq r_0$ versus the more restrictive alternative H_1: $r = r_0 + 1$

$\lambda_{\max}(r_0) = -T \log(1 - \hat{\lambda}_{r0+1})$

Subsequently we perform cointegration analysis using Johansen Cointegration Test.

[3] Verbeek, Marno, "A guide to modern econometrics" 2nd ed, John Wiley & Sons Ltd, The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ, England, 2004.

As it has been considered by Johansen we have the following five deterministic trend cases:

1. The level data have no deterministic trends and the cointegrating equations do not have intercepts:
2. The level data have no deterministic trends and the cointegrating equations have intercepts:
3. The level data have linear trends but the cointegrating equations have only intercepts
4. The level data and the cointegrating equations have linear trends
5. The level data have quadratic trends and the cointegrating equations have linear trends

Since there are three variables in the system, there can be at most two linearly independent cointegrating vectors, i.e., $r \leq 3$. We perform the Johansen cointegration test with 5 lags and the choice of deterministic trend in the data and intercept without trend in the cointegration equation. If we get one or more than one cointegrated vector (error terms) in the model, there exists a long run relationship among the variables. The cointegration is tested in non-stationary data only. The Johansen approach weaknesses are that it is sensitive to variables selection and number of lags included and secondly does not perform very well in small samples.

The ECM would be the appropriate model rather than a model in pure first difference form because it would enable us to capture the long-run relationship between the series as well as the short-run one. The main feature of the ECM is its capability to correct for any disequilibrium that may shock the system from time to time. The error correction term picks up such disequilibrium and guides the variables of the system back to equilibrium.

Table 3.5: Johansen tests for cointegration, sub model 3

Country	*lags*	*Cointegrating Vectors**	*Trace Statistic*	*0.05 Critical Value*	*Prob***	*Cointegrating Vectors**	*Max-Eigen Statistic*	*LR Statistic*	*Prob***
USA	5	r=0	2.036.843	2.979.707	0.3981	r=0	1.244.175	2.113.162	0.5047
USA	5	r≤1	7.926.684	1.549.471	0.4733	r≤1	7.611.214	1.426.460	0.4196
USA	5	r≤2	0.315469	3.841.466	0.5743	r≤2	0.315469	3.841.466	0.5743
UK	5	r=0	2.125.446	2.979.707	0.3420	r=0	1.050.016	2.113.162	0.6968

UK	5	r≤1	1.075.430	1.549.471	0.2271	r≤1	8.635.147	1.426.460	0.3178
UK	5	r≤2	2.119.151	3.841.466	0.1455	r≤2	2.119.151	3.841.466	0.1455
Japan	5	r=0***	3.312.854	2.979.707	0.0199	r=0	2.011.335	2.113.162	0.0689
Japan	5	r≤1	1.301.519	1.549.471	0.1143	r≤1	1.113.141	1.426.460	0.1477
Japan	5	r≤2	1.883.771	3.841.466	0.1699	r≤2	1.883.771	3.841.466	0.1699
Italy	5	r=0	2.484.749	2.979.707	0.1670	r=0	1.254.635	2.113.162	0.4947
Italy	5	r≤1	1.230.114	1.549.471	0.1431	r≤1	8.057.123	1.426.460	0.3730
Italy	5	r≤2***	4.244.014	3.841.466	0.0394	r≤2***	4.244.014	3.841.466	0.0394
Spain	5	r=0	2.629.081	2.979.707	0.1202	r=0	1.689.341	2.113.162	0.1771
Spain	5	r≤1	*9,40E+06*	*1,55E+06*	0.3299	r≤1	9.035.151	1.426.460	0.2832
Spain	5	r≤2	0.362242	3.841.466	0.5473	r≤2	0.362242	3.841.466	0.5473
Germany	5	r=0***	3.200.089	2.979.707	0.0274	r=0	1.892.488	2.113.162	0.0991
Germany	5	r≤1	1.307.601	1.549.471	0.1120	r≤1	9.155.622	1.426.460	0.2734
Germany	5	r≤2***	3.920.390	3.841.466	0.0477	r≤2	3.920.390	3.841.466	0.0477
France	5	r=0***	4.499.876	2.979.707	0.0004	r=0***	3.371.076	2.113.162	0.0005
France	5	r≤1	1.128.800	1.549.471	0.1944	r≤1	7.620.959	1.426.460	0.4185
France	5	r≤2	3.667.041	3.841.466	0.0555	r≤2	3.667.041	3.841.466	0.0555
Netherlands	5	r=0***	3.540.346	2.979.707	0.0102	r=0	1.961.550	2.113.162	0.0804
Netherlands	5	r≤1***	1.578.796	1.549.471	0.0452	r≤1	1.205.640	1.426.460	0.1085
Netherlands	5	r≤2	3.731.564	3.841.466	0.0534	r≤2	3.731.564	3.841.466	0.0534
Belgium	5	r=0***	4.022.326	2.979.707	0.0022	r=0	2.078.546	2.113.162	0.0558
Belgium	5	r≤1***	1.943.780	1.549.471	0.0121	r≤1	1.276.117	1.426.460	0.0852
Belgium	5	r≤2***	6.676.622	3.841.466	0.0098	r≤2***	6.676.622	3.841.466	0.0098

**Cointegration Sub-model 3*

**MacKinnon-Haug-Michelis (1999) p-values

***denotes rejection of the hypothesis at the 0.05 level

In order to examine the sensitivity of the cointegration tests to the type of the specification we used, we summarize the Johansen five sets assumptions and we present them in Table 3.6. Table 3.5 shows the Johansen third case of trend in data and intercept in cointegration equation. The results of the Johansen cointegration test indicate a single cointegration vector only for the case of France taking in consideration both the Max- Eigenvalue Statistic and the Trace statistic using the Johansen's third cointegration sub model. Trace statistic indicates that Japan and Germany have one cointegration vector, Netherlands has two cointegration vectors, Belgium has three cointegration vectors, which comes in contradiction with the max Eigenvalue Statistic results where only the French model has one cointegration vector.

As we can observe at Table 3.6 the results are confirmed for the case of Netherlands where the trace test does not reject the hypothesis of existence at least two cointegration vectors. On the other side, Max - Eigenvalue test accepts the null

hypothesis of no cointegration vector. Similar to the Netherlands case are the cases of Japan and Germany where the Trace Test indicates one cointegration vector and the Max - Eigenvalue test indicates for none. For the case of Belgium, Trace statistic indicates that the hypothesis of no cointegration vector is rejected, the null hypothesis of at least one or at least two cointegration vectors is rejected as well. The null hypothesis of no cointegration vector is accepted when we consider the Max – Eigenvalue test. As a conclusion to Johansen cointegration test and according both of Trace Statistic and the Max - Eigenvalue Statistic results, we decide to use the VEC model only for the singe case of France.

In addition, for all the cases we use a VAR model in first differences, although according to Sims et al. (1993) we can take VAR in levels because our series are not cointegrating and at least two time series, GDP and CPI in most of the cases follow an I(1) process. In fact, the Johansen test can be affected by the lag length employed in the VECM, and so it is useful to select the lag length optimally using the information criteria.

Table 3.6: Cointegration Test, summarization of 5 set of assumptions

	Data Trend:	*None*	*None*	*Linear*	*Linear*	*Quadratic*
	Test Type	*No Intercept*	*Intercept*	*Intercept*	*Intercept*	*Intercept*
Model	*Trace*	*No Trend*	*No Trend*	*No Trend*	*Trend*	*Trend*
USA		0	0	0	0	1
UK		0	0	0	0	0
Japan		2	0	1	1	0
Italy		0	0	0	0	0
Spain		1	0	0	0	0
Germany		1	0	1	0	0
France		1	1	1	1	0
Netherlands		2	1	2	0	1
Belgium		1	1	3	1	3

	Data Trend:	*None*	*None*	*Linear*	*Linear*	*Quadratic*
	Test Type	*No Intercept*	*Intercept*	*Intercept*	*Intercept*	*Intercept*
Model	*Max-Eig*	*No Trend*	*No Trend*	*No Trend*	*Trend*	*Trend*
USA		0	0	0	0	0
UK		0	0	0	0	0
Japan		1	0	0	0	0
Italy		0	0	0	0	0
Spain		1	0	0	0	0
Germany		0	0	0	0	0
France		1	1	1	1	1
Netherlands		0	0	0	0	0

Belgium	1	0	0	0	0

3.4. The VAR Model

In contrast with calibrated models that emphasize theory replication, vector autoregressive (VARs) models emphasize data replication. VARs were introduced by Sims (1980) to overcome "incredible" restrictions, and became very popular, in particular in forecasting, but they are also used for policy analysis. However, the need for structure soon prompted the need for restricted versions, structural VARs (sVAR), where restrictions are put on the distribution of the residuals of the system to identify shocks and their transmission mechanisms in the form of impulse responses. A p-lag VAR(p) with three variables (k=3) would be given by the equations,

$$\begin{pmatrix} IFSI_t \\ GDP_t \\ CPI_t \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} + \begin{pmatrix} \phi^1_{11} & \phi^1_{12} & \phi^1_{13} \\ \phi^1_{21} & \phi^1_{22} & \phi^1_{23} \\ \phi^1_{31} & \phi^1_{32} & \phi^1_{33} \end{pmatrix} \begin{pmatrix} IFSI_{t-1} \\ GDP_{t-1} \\ CPI_{t-1} \end{pmatrix} + \ldots + \begin{pmatrix} \phi^p_{11} & \phi^p_{12} & \phi^p_{13} \\ \phi^p_{21} & \phi^p_{22} & \phi^p_{23} \\ \phi^p_{31} & \phi^p_{32} & \phi^p_{33} \end{pmatrix} \begin{pmatrix} IFSI_{t-p} \\ GDP_{t-p} \\ CPI_{t-p} \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix}$$

(3.17)

Or in matrix notation the above system can be written as:

$Y_t = c + \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} + e_t$, (3.18)

where Y_t is the endogenous vector ($IFSI_t$, GDP_t, CPI_t)′and the disturbance term et (e_{1t}, e_{2t}, e_{3t})′ is iid~N(0, σ2).

which can be further simplified by adopting the matric form of a lag polynomial

$\Phi(L) = In - \Phi_1 L - \ldots - \Phi_p L^p$ (3.19)

Thus finally we get

$\Phi(L)Y_t = c + e_t$ (3.20)

A basic assumption in the above model is that the residual vector follows a multivariate white noise, i.e.

$E(e_t) = 0$

$$E(e_t\, e'_s) = \begin{cases} \hat{\Sigma} & \text{if } t = s \\ 0 & \text{if } t\ t \neq s \end{cases}$$

The coefficient matrices must satisfy certain constraints in order that the VAR-model is stationary. They are just analogies with the univariate case, but in matrix terms. It is required that roots of $|I - \Phi_{1z} - \Phi_{2z}^2 - \ldots - \Phi_{pz}^p| = 0$ lie outside the unit circle or, equivalently, if the eigenvalues of the companion matrix have modulus less than one.

$$F = \begin{pmatrix} \Phi_1 & \Phi_2 & \ldots. & \Phi_n \\ I_n & 0 & \ldots. & 0 \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & I_n & 0 \end{pmatrix}$$

The vector error correction model VECM that we use in case France is a transformation of the above VAR and we have presented at the Johansen cointegration test (3.16) with three variables (g=3) and p lags:

$\Delta Y_t = c + \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \ldots.. + \Gamma_\rho \Delta Y_{t-\rho} + e_t,$

Where $\Pi = (\sum_{i=1}^{p} \Phi_i) - I_g \;\&\; \Gamma i = (\sum_{j=1}^{i} \Phi_j) - I_g$

The VECM would be the appropriate model rather than a model in pure first difference form because it would enable us to capture the long-run relationship between the series as well as the short-run one. The error correction term corrects disequilibrium that may shock the system from time to time, picks up such disequilibrium and guides the variables of the system back to equilibrium. The estimated French model is presented in the Appendix B. The normalized cointegrated coefficients are statistical significant for the CPI and GDP variables. The normalized cointegrating vector is given in the second column and corresponds to:

$$IFSI_t = 9.931GDP_t - 9.745CPI_t.$$

The adjustment coefficients are also significant for the CPI and GDP variables but as we can observe, the speed of adjustment to equilibrium is relative slow meaning that our model converges to equilibrium with a very low speed rate (0.01%).

Imposing restrictions on the cointegrating vector we set the parameters of a single variable to be zero. In order to set the restriction that the IFSI variable does not appear in the cointegrating equation we set B(1,1) = 0 referring to the (1,1)-th element of the transpose of the β matrix. In this case the p-value is 0.59, therefore the

restriction is supported by the data and consequently the IFSI variable should not be included in the cointegrating relationship (Table 3.7). Furthermore, in $\Pi=\alpha\beta'$ the matrix α represents the speed of adjustment to the disequilibrium. If all α_{ij} in row i of α are equal to zero, then the corresponding cointegration vector does not enter the equation determining the ith element of Δx_t. In this case the variable is said to be weakly exogenous with respect to the β parameters. In order to test the null hypothesis that the equation for the IFSI variable does not include the first cointegrating vector we set A(1,1)= 0 (Table 3.8). Thus, we test the null hypothesis that the equation for the first variable in the order that they were listed in the original specification (IFSI) does not include the first cointegrating vector. The results indicate that the restriction is being supported by the data, as the null hypothesis is not rejected. In each case, there is one restriction, so that the test statistic follows a χ^2 distribution with 1 degree of freedom.

Table 3.7: Vector Error Correction Estimates with Restrictions

Cointegration Restrictions: B(1,1)=0			
Convergence achieved after 4 iterations.			
Not all cointegrating vectors are identified			
LR test for binding restrictions (rank = 1):			
Chi-square(1)	0.275939		
Probability	0.599376		
Cointegrating Eq:	CointEq1		
IFSI(-1)	0.000000		
GDP(-1)	-0.541369		
CPI(-1)	0.523989		
C	-0.426056		
Error Correction:	D(IFSI)	D(GDP)	D(CPI)
CointEq1	0.152610	-0.101592	-0.174277
	(0.13943)	(0.05884)	(0.03227)
	[1.09452]	[-1.72669]	[-5.40048]

Table 3.8: Vector Error Correction Estimates with Restrictions

Cointegration Restrictions: A(1,1)=0

Convergence achieved after 6 iterations.			
Not all cointegrating vectors are identified			
LR test for binding restrictions (rank = 1):			
Chi-square(1)	1.620.035		
Probability	0.203087		
Cointegrating Eq:	CointEq1		
IFSI(-1)	0.015634		
GDP(-1)	-0.556113		
CPI(-1)	0.536161		
C	-0.439254		
Error Correction:	D(IFSI)	D(GDP)	D(CPI)
CointEq1	0.000000	-0.087789	-0.179795
	(0.00000)	(0.05765)	(0.03142)
	[NA]	[-1.52284]	[-5.72228]

Lag order Selection

The general approach for lag selection is to fit VAR(p) models with orders p = 0, ..., p_{max} (p is the lag, p_{max} is the maximum lag) and choose the value of p which minimizes some model selection criteria. The two most popular are the Akaike's (AIC) and the Schwartz information criteria (SC). Furthermore, the likelihood ratio (LR) test is also used in the selection of the appropriate lag for the 9 cases. The multivariate versions are given by:

$$AIC = \log\left|\hat{\Sigma}\right| + 2k'/\mathrm{T} \quad (3.21)$$

$$SC = \log\left|\hat{\Sigma}\right| + \frac{k'}{\mathrm{T}}\log(\mathrm{T}) \quad (3.22)$$

where $\hat{\Sigma}$ is the variance-covariance matrix of residuals, T is the number of observations and k is the total number of regressors in all equations. The AIC and SC criterion minimizes the error term corrected for a penalty function. The best fitting model is the one that minimizes the criterion function. The likelihood ratio test (LR) can be also used in determining the order of a VAR. The test is generally of the form LR = T(log $|\hat{\Sigma}_k|$ − log $|\hat{\Sigma}_p|$), where T is the sample size, $\hat{\Sigma}_k$ denotes the maximum likelihood estimate of the residual covariance matrix of VAR(k) and $\hat{\Sigma}_p$ the estimate

of VAR(p) (p >k) residual covariance matrix (Lütkepohl 1991, p. 125–126). The LR method minimizes the log determinant of the residual covariance matrix.

The best fitting model is the one that maximizes the LR, or minimizes the FPE criterion function, AIC, SIC or HQ. Alternative criteria imply different tradeoffs between better and loss of degrees of freedom. We begin with a VAR of 10 lags on all endogenous variables and we check the two information criteria and the LR test. These information criteria can be used for model selection such as determining the lag length of the VAR model, with smaller values of the information criterion being preferred. Additional requirement is that VAR residuals are not autocorrelated, are homoskedastic and are normal distributed. Furthermore, we test the specification of each of the VAR models in order to confirm robustness.

Table 3.9: Lag Order Selection Criteria

VAR Lag Order Selection Criteria
Endogenous variables: DIFSI DGDP DCPI
Exogenous variables: C

Country	*Lag*	*LogL*	*LR*	*FPE*	*AIC*	*SC*	*HQ*
USA	4	-3.536	69.42*	0.518*	7.852*	8.868*	8.263*
UK	5	-3.125	25.79*	0.472*	7.753*	9.060	8.281
Japan	4	-3.828	40.26*	2.146*	9.271*	1.034	9.705
Italy	5	-3.013	3.43	0.218	6.986*	8.236*	7.492*
Spain	4	-3.971	5.12	1.961*	9.182*	1.023	9.605
Germany	3	-2.385	20.36*	0.783	8.263*	9.265	8.657
France	4	-3.012	7.09	0.139*	6.543	7.534*	6.945*
Netherlands	4	-3.863	30.41*	0.718*	8.178*	9.170	8.580
Belgium	4	-4.090	4.73	1.113*	8.616*	9.608	9.018*

** indicates lag order selected by the criterion*
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Residual Tests

We perform a number of tests to ensure the model fits the data well. We check if the determinant residual covariance is near to zero in order our estimates to be efficient.

$\left|\hat{\Sigma}\right| = \det\left(\frac{1}{T-p}\sum_t \hat{e}_t\hat{e}_t'\right)$ (3.23) with p parameters per equation in the VAR.

The VAR estimations indicate that the determinant residual covariance is near to zero and thus our estimates are efficient. In addition, the usual diagnostic checks need to be made, to ensure that our model is well specified. In order to investigate whether the VAR residuals are White Noise, the hypothesis to be tested is H_0: $Y_1 = \ldots.. = Y_h = 0$ where $Y_k = (\rho_{ij}(k))$ is the autocorrelation matrix of the residual series with $\rho_{ij}(k)$ the cross autocorrelation of order k of the residuals series i and j. For this purpose we use portmanteau test and the Q-statistic up to lag h, $Q_h = T\sum_{k=1}^{h} tr(\hat{r}'_k\hat{r}_0^{-1}\hat{r}_k\hat{r}_0^{-1})$ [4] (Lükepohl, 1993) where $\hat{r}_k = (\hat{\rho}_{ij}(k))$ are the estimated residual autocorrelations, and the $\hat{\rho}_0$ contemporaneous correlations of the residuals. If there is evidence of autocorrelation, more lags need to be added until the autocorrelation has been removed.

Table 3.10: Portmanteau Residual Tests

VAR Residual Portmanteau Tests for Autocorrelations
H0: no residual autocorrelations up to lag h

Country	*USA*		*UK*		*Japan*		*Italy*	
Lags	*Q-Stat*	*Prob.*	*Q-Stat*	*Prob.*	*Q-Stat*	*Prob.*	*Q-Stat*	*Prob.*
1	1.885	NA*	1.225	NA*	Q-Stat	Prob.	1.616	NA*
2	7.840	NA*	2.770	NA*	1.702	NA*	3.469	NA*
3	12.05	NA*	4.536	NA*	3.532	NA*	6.957	NA*
4	18.55	NA*	7.463	NA*	6.107	NA*	14.47	NA*
5	24.61	0.0134	12.00	NA*	12.09	NA*	26.17	0.1119
6	34.34	0.1114	14.45	0.1071	16.00	0.1668	33.38	0.1150
7	39.74	0.1541	22.52	0.2094	21.77	0.2421	43.91	0.1211
8	52.55	0.1368	34.03	0.1651	28.10	0.4054	58.63	0.1100
9	64.38	0.1304	36.90	0.4269	45.04	0.1435	62.48	0.1431
10	68.68	0.1862	37.75	0.7697	53.18	0.1882	74.34	0.1346
11	76.12	0.1241	41.79	0.8872	56.27	0.3896	80.30	0.1697
12	83.45	0.1678	56.91	0.6916	65.82	0.3792	83.92	0.1591

Country	*Spain*		*Germany*		*France*		*Netherlands*	
Lags	*Q-Stat*	*Prob.*	*Q-Stat*	*Prob.*	*Q-Stat*	*Prob.*	*Q-Stat*	*Prob.*

[4] Lutkepohl, Helmut (1993), Introduction to Multiple Time Series, 2nd Ed., Ch. 4.4

1	1.949	NA*	0.328	NA*	2.221	NA*	0.167	NA*
2	8.347	NA*	0.804	NA*	6.464	NA*	0.978	NA*
3	11.69	NA*	4.448	NA*	8.173	NA*	1.897	NA*
4	16.43	NA*	9.373	NA*	1.4.51	NA*	4.339	NA*
5	24.33	0.0038	12.71	NA*	20.40	0.0156	5.301	NA*
6	30.12	0.0363	22.61	0.0071	25.37	0.1150	11.04	0.2729
7	34.07	0.1638	26.34	0.0922	32.65	0.2086	13.81	0.7411
8	46.15	0.1197	39.45	0.0975	48.29	0.0827	32.99	0.1973
9	54.00	0.1682	45.37	0.1360	5.453	0.1560	42.25	0.2190
10	60.12	0.2637	49.26	0.3063	6.342	0.1783	49.58	0.2955
11	64.48	0.4245	50.60	0.6062	7.226	0.1985	59.03	0.2967
12	75.85	0.3553	59.73	0.5935	8.397	0.1581	66.06	0.3715

Country	*Belgium*				
Lags	*Q-Stat*	*Prob.*	*Lags*	*Q-Stat*	*Prob.*
1	0.849	NA*	7	26.72	0.1844
2	3.372	NA*	8	48.33	0.1151
3	4.309	NA*	9	53.36	0.1312
4	8.375	NA*	10	60.62	0.2598
5	10.97	NA*	11	66.66	0.3156
6	21.31	0.0113	12	70.19	0.2238

As we can observe from Table 3.10, the residuals are not serially correlated as the no - autocorrelation hypothesis is strongly accepted. The result of no autocorrelation is reinforced by the LM Test which reports the multivariate LM test statistics for residual serial correlation up to the specified order. (Appendix B)

Accordingly, the heteroskedasticity test with no cross terms indicates that the model is not misspecified. Table 3.11 left column indicates that residuals are homeskedastic at a significant level of 5%. Moreover, in Table 3.11 right column, normality is rejected for the most of the cases at a significance level of 5% except from UK, Germany, Italy and France. As the Jarque-Bera test indicates, in case of Japan normality is rejected due to excess kurtosis rather than to skewness. In principle, rejection of normal distribution invalidates the test statistics. Nevertheless measures of skewness are found to be not informative in small samples. Thus, the rejection of normality may not affect our results. However as a different solution to normality problem is the use of alternative distributions to normal. Furthermore we choose the Cholesky factorization method in order to orthogonalize the residuals. The

factorization matrix is the inverse of the lower triangular Cholesky factor of the residual covariance matrix.

Table 3.11: White Heteroskedasticity Tests & Multivariate Normality Tests

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)			*VAR Residual Normality Tests Orthogonalization: Cholesky (Lutkepohl) H0: residuals are multivariate normal*		
Country	*hi-sq*	*Prob.*	*Component*	*Jarque-Bera*	*Prob.*
USA	147.835	0.0891	Joint	3.483.394	0.0000
UK	576.267	0.2067	Joint	8.084.366	0.2320
Japan	143.689	0.0907	Joint	1.360.535	0.0344
Italy	475.995	0.4015	Joint	2.710.654	0.2688
Spain	117.126	0.0830	Joint	2.045.134	0.0023
Germany	942.614	0.2214	Joint	1.090.641	0.0914
France	896.569	0.2683	Joint	7.601.425	0.2731
Netherlands	938.659	0.0806	Joint	5.939.387	0.0000
Belgium	573.728	0.1284	Joint	2.355.232	0.0006

Since the variance-covariance matrix of the VAR residuals/shocks is unlikely to be diagonal, the residuals need to be orthogonalised. A common procedure is to apply a Cholesky decomposition, which is equivalent to adopting a particular ordering of the variables and allocating any correlation between the residuals of any two elements to the variable that is ordered first.

By changing the order of the variables a different structure on the model is imposed. Since similar results are obtained when doing this suggests that the analysis is not sensitive to the precise identification scheme. Thus, following an empirical method, variables in the model were initially ordered in ascendance according to the likely speed of reaction to any particular shock. Variables at the front end of the VAR are assumed to affect the following variables contemporaneously but only to be affected themselves by shocks to the other variables after a lag. Variables at the bottom of the VAR, on the other hand, only affect the preceding variables after a lag but are affected themselves immediately. The CPI was ordered at the bottom of the VAR implying that they react instantaneously to shocks in the real side variables whereas the other variables like GDP and FSI react only after a lag following shocks to the financial variables. Thus, the variables ordering in the VAR is: IFSI, GDP, CPI

Sims (1981) has made the following suggestions as to how variables should be ordered in order to obtain the impulses.

1. Variables that are not expected to have any predictive value for other variables should be put last.
2. The first variable in the ordering explains 100% of its first step variance.

The GDP was ordered after IFSI reflecting priors that the economic cycle affects financial stress only after a lag.

3.5. Impulse response functions and variance decompositions

Impulse response functions and variance decompositions offer method for examining VAR system dynamics. Impulse responses trace out the responsiveness of the dependent variables in the VAR to shocks to each of the variables.

The impulse response functions can be used to produce the time path of the dependent variables in the VAR, to shocks from all the explanatory variables. If the system of equations is stable any shock should decline to zero, an unstable system would produce an explosive time path. This technique determines how much of the forecast error variance for any variable in a system, is explained by innovations to each explanatory variable, over a series of time horizons.

$$Y_t = \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} + e_t, \qquad (3.24)$$

$$Y_t = \Phi_1 (L)\, e_t = \sum_{i=o}^{\infty} \Phi_i e_{t-i} \qquad (3.25)$$

where Φ_i is the MA coefficients measuring the impulse response. The error terms et represent shocks in the system. More specifically, $\Phi_{jk,i}$ represents the response of variable j to an unit impulse in variable k occurring i-th period ago. The response of y_i to a unit shock in y_j is given the sequence, known as the impulse multiplier function, $\Phi_{ij,1}$, $\Phi_{ij,2}$, $\Phi_{ij,3}$, . . .,where $\Phi_{ij,k}$ is the ijth element of the matrix Φ_k (i, j = 1, . . . , m).

Variance decompositions give the proportion of the movements in the dependent variables that are due to their own shocks, versus shocks to the other

variables. In other words variance decomposition determines how much of the forecast error variance of each of the variable can be explained by exogenous shocks to the other variables. This is an alternative method to the impulse response functions for examining the effects of shocks to the dependent variables. Usually own series shocks explain most of the error variance, although the shock will also affect other variables in the system. While impulse response functions trace the effects of a shock to one endogenous variable on to the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. The components of this error variance accounted for by innovations to yj is given by $\sum_{\kappa=0}^{s} \Phi_{ij,k}^{2}$. Comparing this to the sum of innovation responses we get a relative measure how important variable js innovations are in the explaining the variation in variable i at different step-ahead forecasts.

It is important to consider the ordering of the variables when conducting these tests, as in practice the error terms of the equations in the VAR will be correlated, so the result will be dependent on the order in which the equations are estimated in the model. Thus, impulse responses and variance decompositions are sensitive to the variables ordering in the system. As a robustness check, different orderings of the variables were considered and the impulse responses computed using the Cholesky decomposition instead of the 'generalised impulse' function as it is described in Pesaran and Shin (1998). The first method constructs an orthogonal set of shocks that depend on the variable ordering. Cholesky uses the inverse of the Cholesky factor of the residual covariance matrix to orthogonalize the impulses. This option imposes an ordering of the variables in the VAR and attributes all of the effect of any common component to the variable that comes first in the VAR system.

As Σ matrix is usually non-diagonal, it is impossible to shock one variable with other variables fixed. In order to single out the individual effects the residuals must be first orthogonalized, such that they become contemporaneously uncorrelated. Choleski decomposition is the most popular one which we shall turn to now. Let P be a lower triangular matrix such that Σ = PP′. then eq. (1) can be rewritten as:

$$Y_t = \Phi_1(L)e_t = \sum_{i=o}^{\infty} \Theta_i w_{t-i} \qquad (3.26)$$

where $\Theta_i = \Phi_i P$, $w_t = P^{-1}e_t$, and $E(w_t w_t') = I$

3.6. USA Model Results

As one may observe in Figure 4.1 the financial stability index identifies major financial stress episodes such as the recent financial crisis (2007), the September (9/11) attacks on the United States (2001, the Enron scandal (2001) and the '90s recession in USA. The IFSI and the GDP series indicate a strong positive correlation, moving in the same directions throughout the period. The positive relationship is especially pronounced in late 2008, when financial stress spiked and the recession deepened. Even before then, however, the two variables show a strong tendency to move in the same directions. Not surprisingly, the biggest decreases in the IFSI have occurred during the 2007 credit crisis where the financial stability is at its lowest levels. The IFSI index reached two several low points in 2000 with the September (9/11) attacks on the United States and the Enron scandal. Earlier the IFSI index had several low points from 1987 until the 1990-91 recession. While there is clearly a positive relationship between these IFSI and GDP, it is not easy to tell whether one variable provides information about future values of the other variable.

One fundamental weakness of the VAR approach to modeling is that its a theoretical nature and the large number of parameters involved make the estimated models difficult to interpret. In particular, some lagged variables may have coefficients which change sign across the lags, and this, together with the interconnectivity of the equations, could render it difficult to see what effect a given change in a variable would have upon the future values of the variables in the system. In order to partially alleviate this problem, three sets of statistics are usually constructed for an estimated VAR model: block significance tests, impulse responses and variance decompositions.

It is difficult to predetermine theoretically the appropriate coefficients sign of our three variables. The models in the neoclassical framework can yield very different results with regard to inflation and growth. An increase in inflation can result in higher output (Tobin Effect) or lower output (Stockman Effect) or no change in output (Sidrauski). Under the Keynesian model, there is a short-run trade-off between

output and the change in inflation, but no permanent trade-off between output and inflation.

The VAR estimated coefficients are presented in Appendix B. As someone may observe, in the IFSI equation all the estimated variables coefficients are statistically non significant, in the GDP equation the coefficients of the $ifsi_{t-1}$ $ifsi_{t-2}$ $ifsi_{t-3}$ gdp_{t-2} gdp_{t-4} variables are statistical significant and in the CPI equation only the coefficients of cpi_{t-1} cpi_{t-3} cpi_{t-4} variables are statistical significant. The above results indicate that we need an improved VAR model as the impulse responses and the variance decompositions may be questioned.

Granger Causality/Block Exogeneity Tests

If the history of x does not help to predict the future values of y, we say that x does not Granger-cause y[5]. In a two-variable VAR(p) the process x_t does not Granger cause y_t if all coefficients in $\Phi_{12}(L) = 0$ (or a joint test $\varphi_{21}(1) = \varphi_{21}(2) = ... = \varphi_{21}(p) = 0$ at all lags is not rejected). This concept involves the effect of past values of x on the current value of y. Thus, it answers the question whether past and current values of x help predict the future value of y. In a n-variable VAR(p), block-exogeneity test looks at whether the lags of any variables Granger-cause any other variable in the system. This can be done with the likelihood ratio test $(LR = (T-p)(\ln\left|\hat{\Sigma}_r\right| - \ln\left|\hat{\Sigma}_u\right|) \sim \chi^2(mkp))$ by estimating with OLS the restricted and non-restricted regressions, and calculating the respective residual covariance matrices. The restricted regression, perform OLS regressions of each of the elements in y on a constant, p lags of the elements of x and p lags of the elements of y and the non restricted regression, perform OLS regressions of each of the elements in y on a constant and p lags of the elements of y.

Granger causality really implies a correlation between the current value of one variable and the past values of others, it does not mean changes in one variable cause changes in another. By using an F-test to jointly test for the significance of the lags on the explanatory variables, this in effect tests for Granger causality between these variables. The Granger causality test can also be used as a test for whether a variable

[5] Granger, C.W. (1969). Econometrica 37, 424–438. Sims, C.A. (1972). *American Economic Review*, 62, 540–552.

is exogenous. i.e. if no variables in a model affect a particular variable it can be viewed as exogenous. Therefore, in order to see which sets of variables have significant effects on each dependent variable and which do not we proceed to Block F-tests and an examination of causality in a VAR will suggest which of the variables in the model have statistically significant impacts on the future values of each of the variables in the system. In our case there are (1 + 4lags × 3 variables) = 15 variables in each equation, implying that we have 89 degrees of freedom. F-tests for the null hypothesis that all of the lags of a given variable are jointly insignificant in a given equation are presented in Table 3.12.

Table 3.12: USA Model, Causality Tests, Marginal significance levels associated with joint F-tests

	Lags of variable		
Dependent variable	DIFSI	DCPI	DGDP
DIFSI	0.0153	0.0177	0.2526
DCPI	0.0046	0.0000	0.0535
DGDP	0.0021	0.0034	0.0002

Null Hypothesis: All 4 lags have no explanatory power for that particular equation in the VAR

Of all the lagged variables in the DIFSI equation, only the lags of the DIFSI and DCPI variable are quite significant at the 5% level. In addition for the DIFSI equation the DGDP variable is almost significant at the 25% level. It appears, however, that lagged values of the DIFSI variable have explanatory power for some other variables in the system. These results are shown in the first column of table 3.10. The DIFSI appears to help in explaining variations in the other two variables the DCPI and the DGDP at a significant level of 5%. In the Appendix B are presented the Block exogeneity tests for the 9 case studies. Since we have estimated a tri-variate VAR, three panels are displayed, with one for each dependent variable in the system. The results, in many cases, show very little evidence of lead lag interactions between the series. For the case of Japan, none of the results shows any causality that is significant at the 5% level. Furthermore, the results indicate that the interactions are not as many as we expected.

Figure 3.1: IFSI, GDP, CPI Series in Levels

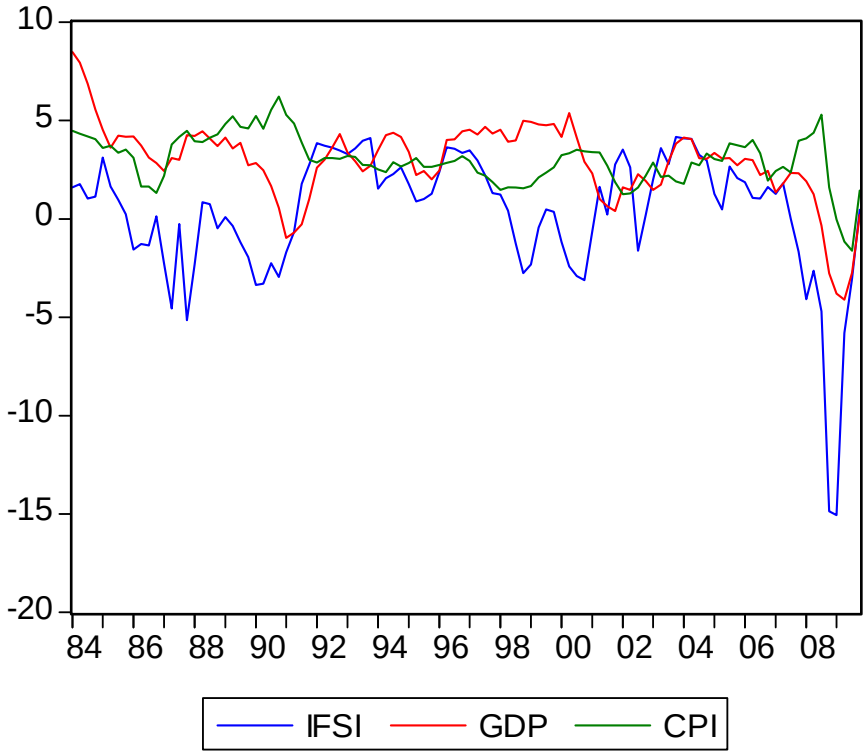
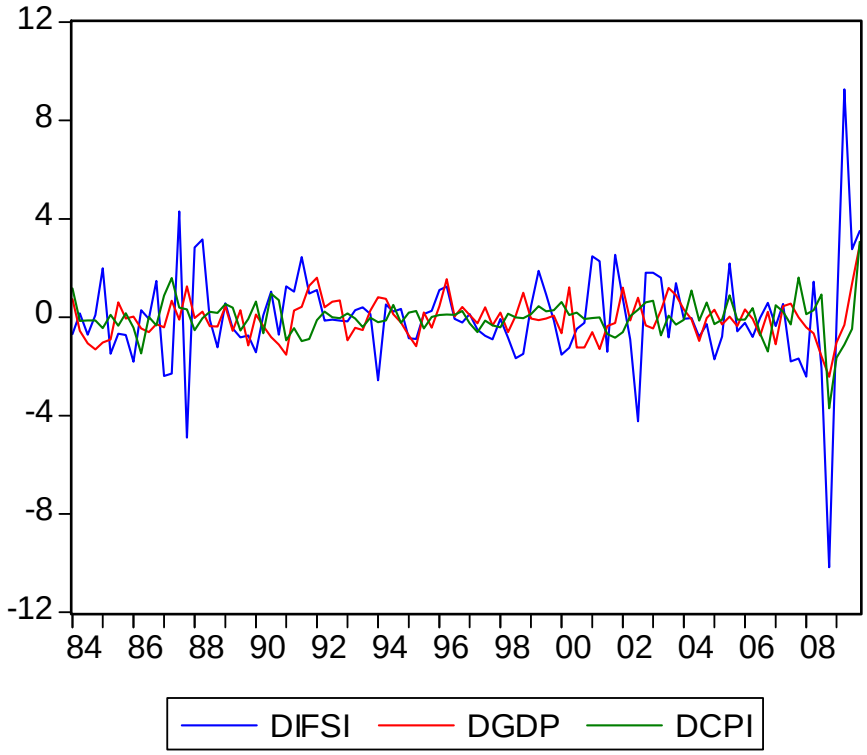


Figure 3.2: IFSI, GDP, CPI Series in 1st difference



3.7. Description of Impulse Response Functions & Variance Decompositions, USA Case study

From the estimated VAR, the orthogonalized impulse response functions are performed for 10 period times. The impulse response is the estimated change in DIFSI following a one-standard-deviation shock to DGDP and to DCPI, based on the VAR model with 4 lags. Figure 3.3 plots the impulse responses for the USA case study.

The first row in the Figure 3.3 shows the response of the stability index to a one standard deviation shock to the other variables of the model. As indicated by the solid line, a shock to DCPI leads to an decrease in DFSI of 0,8 standard deviation within the first 3 time periods. After that point, the IFSI response continues to be negative to the CPI shock until the period 6. Thus, an increase of the inflation index induces a decrease in the stability index. In addition, the response of DIFSI to a shock to DGDP is positive but not very significant (up to 0.4 s.d) for two periods and after it declines before it fade out to zero. Put in a different way, maintaining all other variables constant, a positive shock to the growth has a positive impact on stability while a positive shock to CPI value has a negative impact on stability. Furthermore, the first column in the figure shows the response of growth and inflation to a one standard deviation shock to the stability index of the model. In both cases a positive shock of IFSI leads to a positive impact on inflation and to growth for at least 4 time periods.

In our empirical analysis we have also included a variance decomposition analysis. Table 3.13 reports the results of the USA VAR model. Variance decomposition gives as the opportunity to investigate which part of the forecast error variance is caused by which variable. The first panel shows that forecast errors in DIFSI are mainly duo to itself. The second and the third panel indicate how much of the variation in the DIFSI equation can be explained by a shock to DGDP and DCPI. The findings of the variance decomposition are that the shocks to the DCPI and DGDP together account only for over a 20% of the variation in the financial stability. Moreover Figure 3.4 plots the variance decompositions of the three variables. Financial stability explains a 20% and a 15% of the variation of the Growth and Inflation accordingly.

Figure 3.3: Impulse responses for 10 lags, Response Standard errors: Monde Carlo with 100 Repetitions

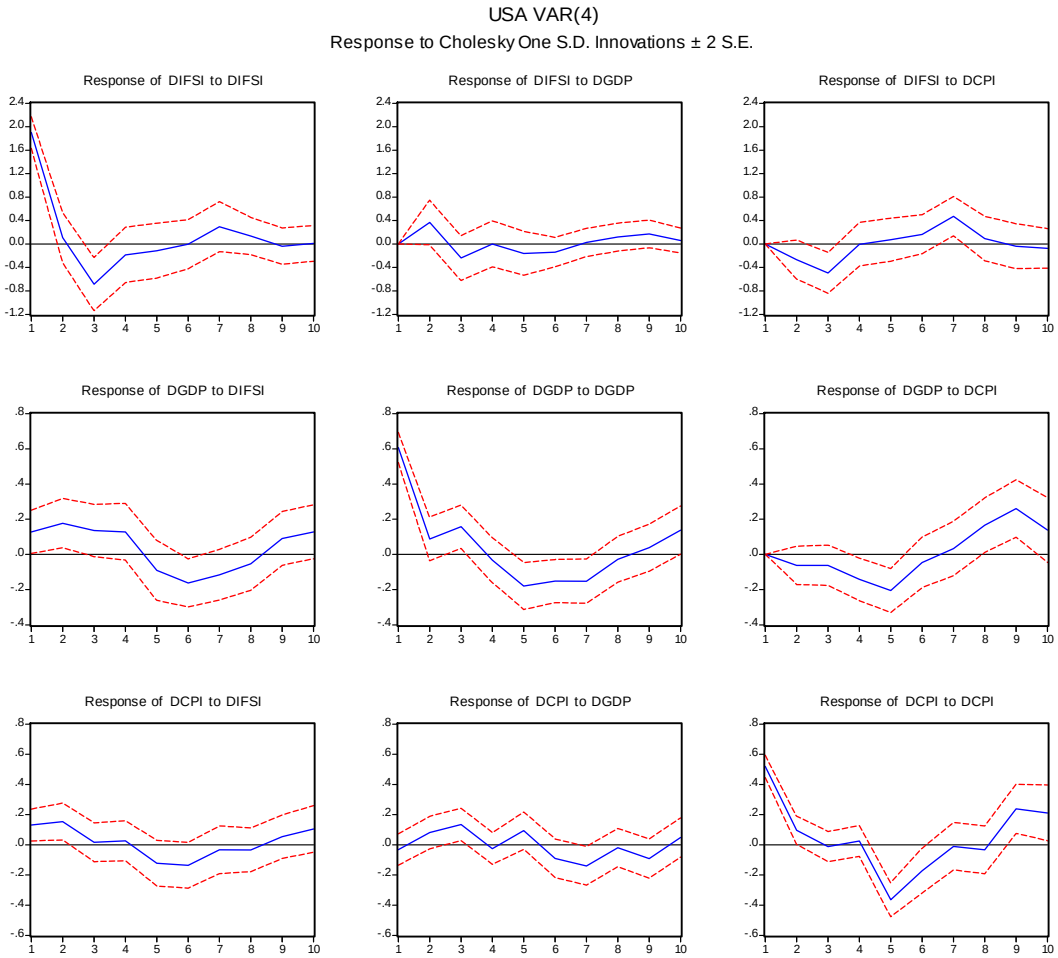


Table 3.13: USA Variance Decomposition: 12 Periods

	Variance Decomposition of DIFSI:			
Period	*S.E.*	*DIFSI*	*DGDP*	*DCPI*
1	2.080719	100.0000	0.000000	0.000000
2	2.227990	94.43562	3.975141	1.589235
3	2.348240	85.26894	4.591076	10.13999
4	2.420647	82.82073	4.418518	12.76076
5	2.495861	82.30418	4.725641	12.97018
6	2.595027	83.55774	4.441370	12.00089
7	2.723964	84.14510	4.467854	11.38704
8	2.800767	82.94772	4.704581	12.34770
9	2.867995	81.79261	4.644938	13.56246
10	2.940522	81.00433	4.473316	14.52236
11	3.008025	79.53514	4.305006	16.15985
12	3.065029	80.04244	4.387023	15.57054

Figure 3.4: USA Variance Decomposition

3.8. Results of the Other Countries: Impulse Responses

Impulse responses for the rest of the eight countries of our analysis are presented in Figure 3.5. The results are often contradictory in respect of the response of the financial stability indicator to a positive shock to DGDP and DCPI variables. For instance, UK and Belgium IFSI seems to have the opposite responses when DGDP has a positive innovation. A positive shock to Growth at 7 out of 9 cases indicates a positive response of the IFSI. Further, a positive shock to inflation will have a negative effect in the financial stability conditions. As one may observe in Figure 3.5, one deviation increase in CPI will have a significant negative effect for all the countries. As a result, an increase in price levels it will deteriorate financial stability conditions.

Accordingly, a positive shock to IFSI has a positive shock to Growth for Italy, Spain, France, Germany and Netherlands, USA and Belgium. The response of GDP to a positive shock to the financial stability index at 7 out of 9 cases seems to be positive at least for the first periods. Thus, in most cases when the financial activity in the economy increases financial conditions are improving and we have a positive effect to Growth. This result can be interpreted using the financial accelerator. A decrease in financial stress that is, an improvement of financial conditions affects the real economy by directly tying the cost of borrowing to the financial condition of firms. In this setting, a “financial accelerator” arises through which an improvement in the financial condition of firms lowers their cost of borrowing funds and thus leads to an increase to investment. In turn, an increase in investment will raise profits and further improve the financial condition of firms. The financial accelerator indicates that lower financial stress, as reflected primarily through heightened uncertainty, is associated with higher economic activity.

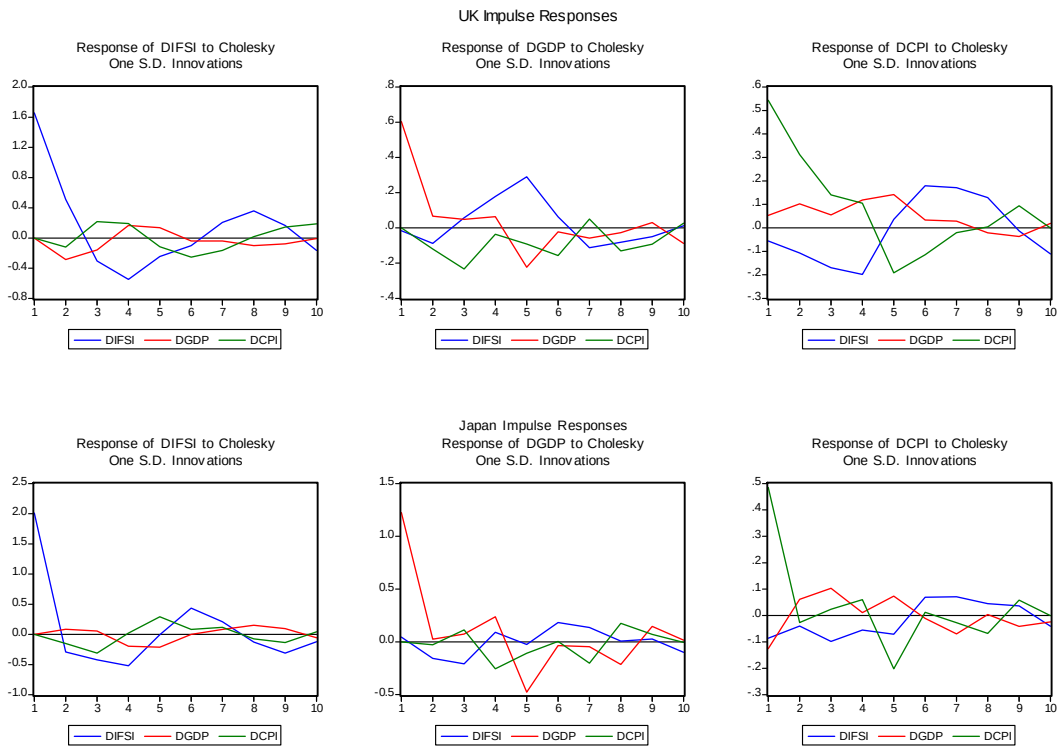
We assume that a positive shock to financial stability has negative effect to the price level. As we see in Figure 3.5 a positive innovation to IFSI gives contradictory results among the case studies. For UK, Japan and Netherlands the CPI is affected negatively for the first 4 to 6 periods of time. In contrast, for Italy, Spain, Germany, France and Belgium inflation seems to be affected positively and significant. The main observation of the impulse responses is that the responses are not very intense

and the highest standard deviation is up to 0.5 in most of the cases. The accumulative results for the 9 case studies are presented in Table 3.14.

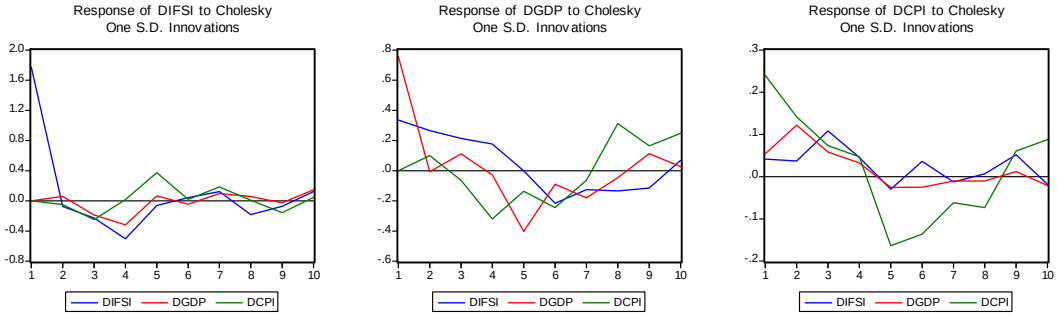
Table 3.14: Cumulative Results of the 9 cases

Response of financial stability indicator to a positive shock to the other variables:
A positive shock to Growth: 7 out of 9 cases positive response of IFSI
A positive shock to Inflation: 9 out of 9 cases negative response of IFSI
Responses of GDP and CPI to a positive shock to the financial stability indicator:
GDP Response, positive effect 7 out of 9 cases
CPI Response, negative effect for 3 cases and positive for 6 cases

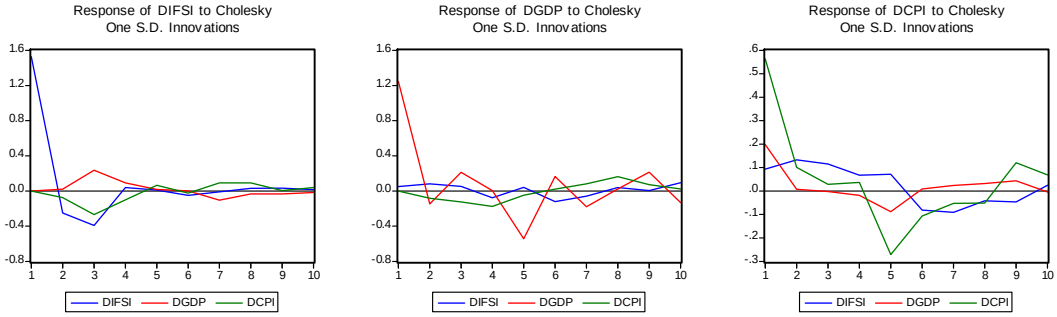
Figure 3.5: Impulse Responses of UK, Japan, Italy, Spain, Germany, France, Netherlands, Belgium



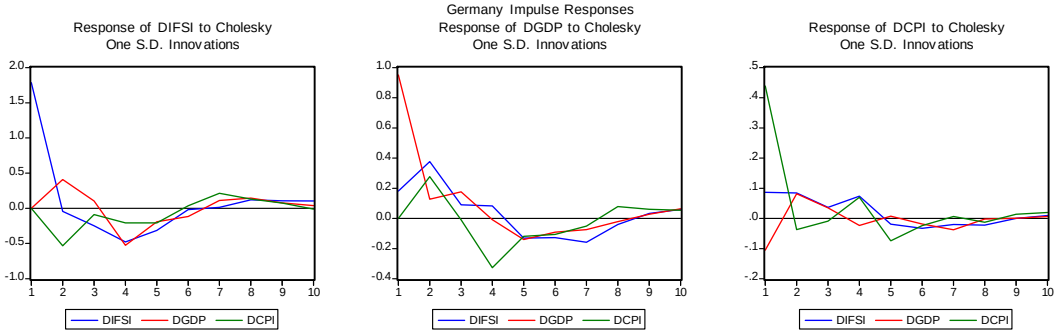
Italy Impulse Responses



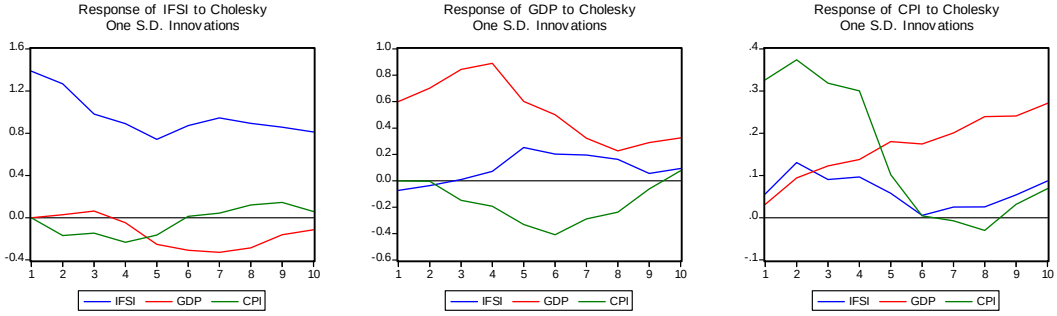
Spain Impulse Responses

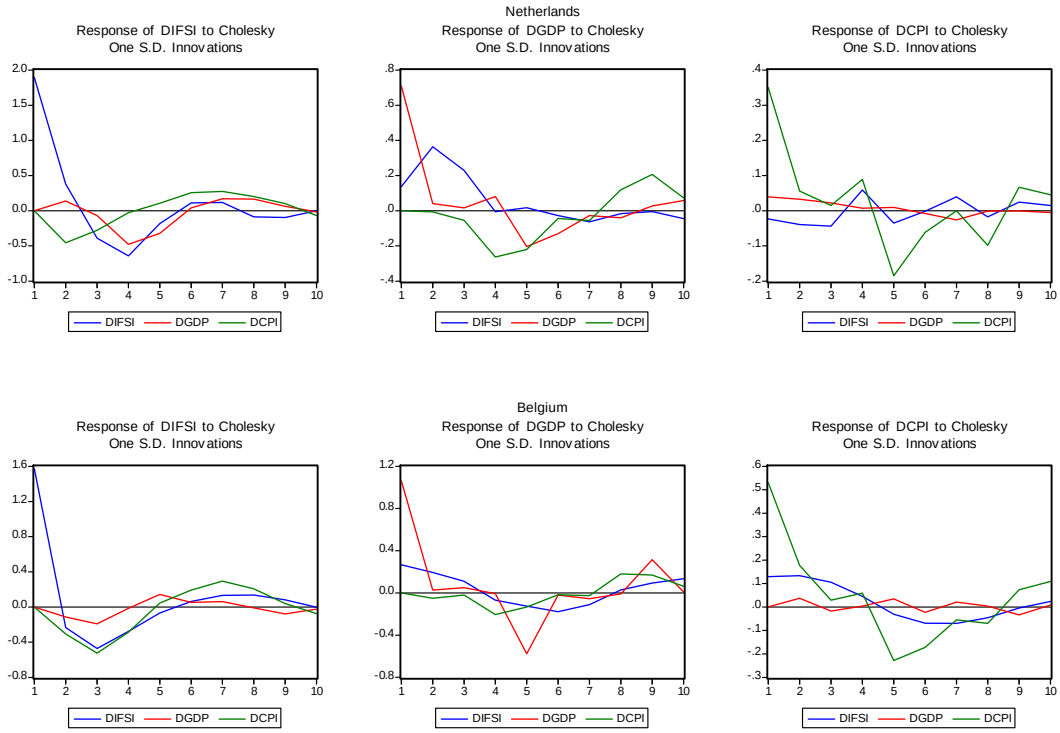


Germany Impulse Responses



France Impulse Responses VECM(4)





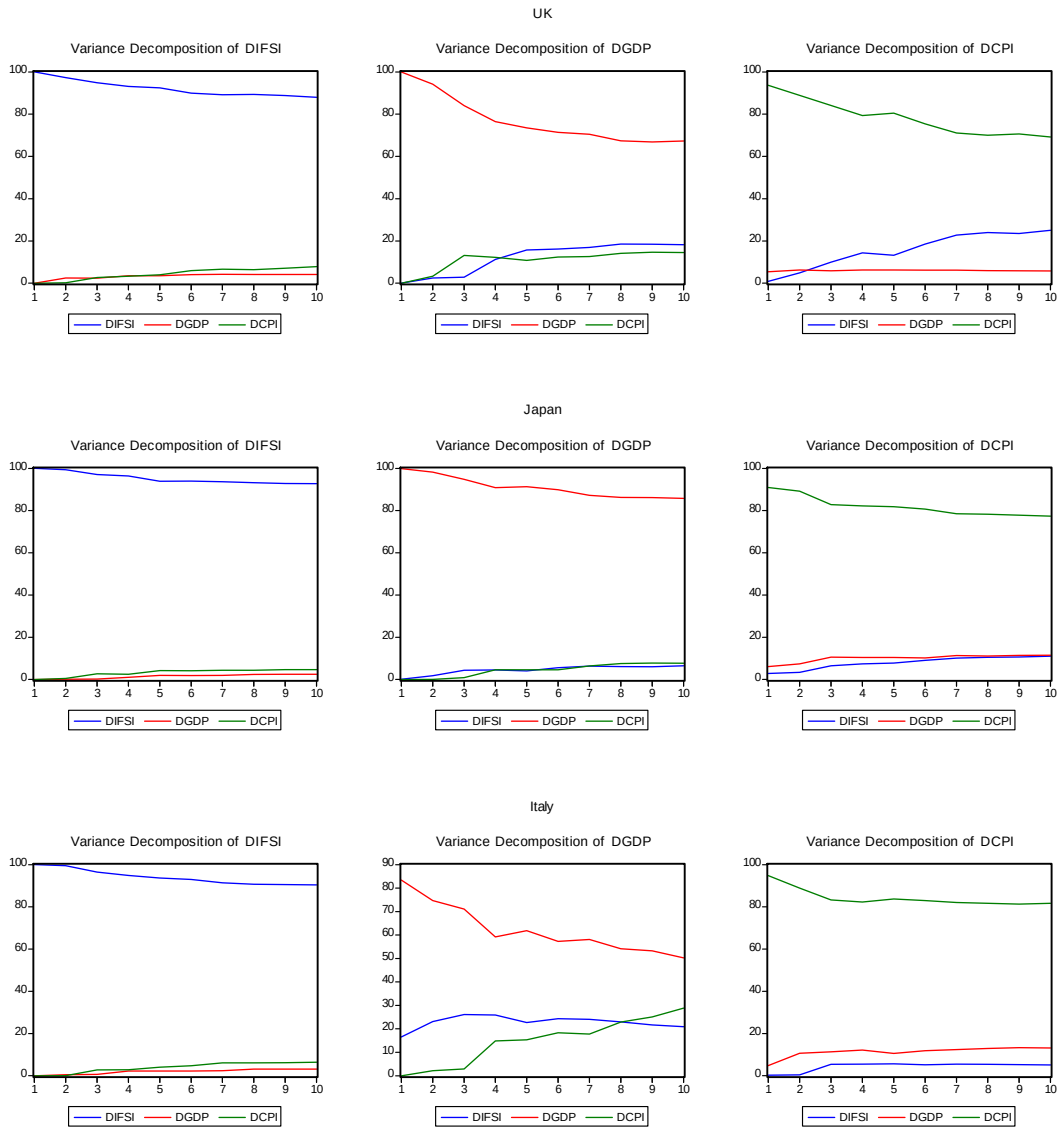
3.9. Variance Decompositions of the other 9 countries

For the purpose of or analysis we have also conducted a variance decomposition analysis for the 9 cases. The variance decompositions of the financial stability variable indicate that at most a 80% of the variation is explained by its own variance while only a pure proportion of the variance of the financial stability (20%) is explained after 10 periods by DGDP and DCPI. Shocks in financial stability and in price level have a little effect for the most countries on the variance of the growth. However, as we can observe in Figure 3.6 for Italy and Netherlands a significant proportion over a 20% of the variation of the DGDP is due to shocks to DIFSI and to DCPI.

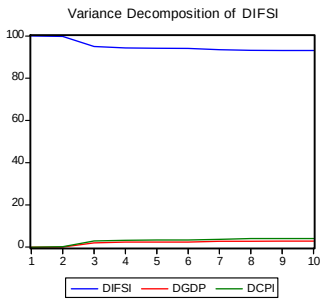
Furthermore, innovations in financial stability and to growth have, for some countries, noticeable contribution to the variance of inflation. For UK model, DIFSI explains the 25% of the variance in the DCPI after 10 periods while for France a significant proportion of the variation of DCPI is accounted for by innovations in DGDP, over 40% after 10 periods. In conclusion, we have found that financial

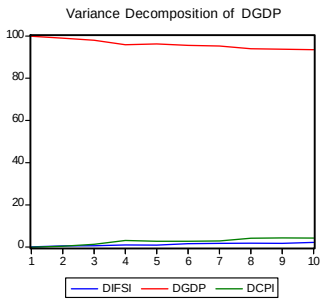
stability shocks account for only a small proportion of the total variation in the data set.

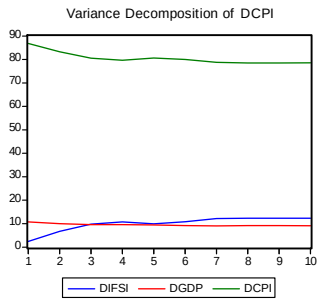
Figure 3.6: Variance Decompositions of UK, Japan, Italy, Spain, Germany, France, Netherlands, Belgium



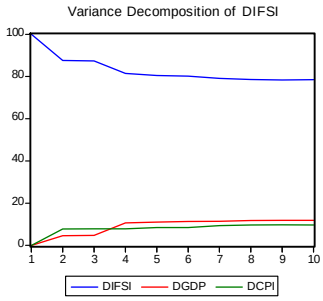
Spain

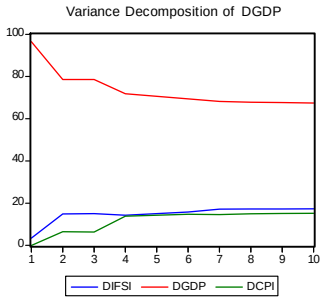


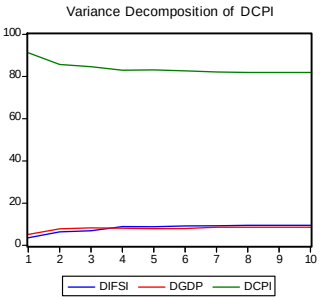




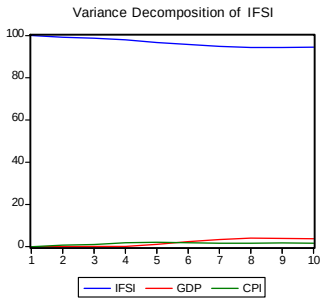
Germany

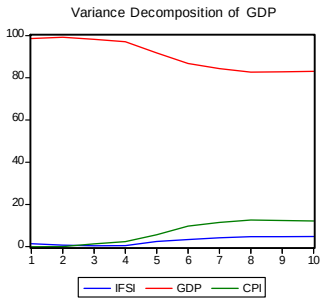


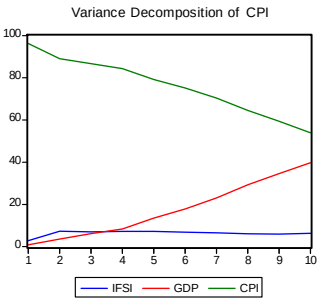




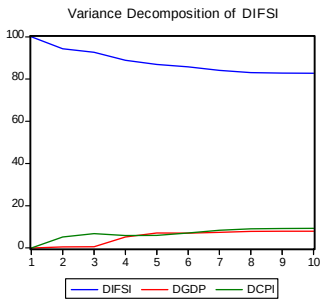
France

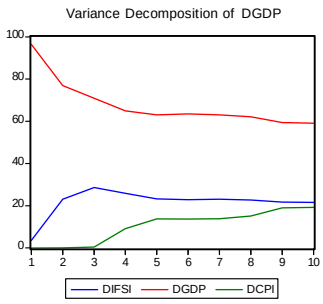


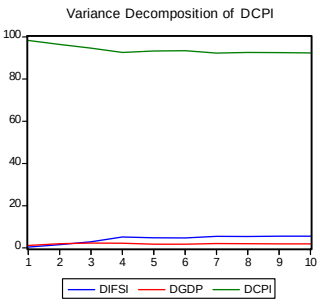


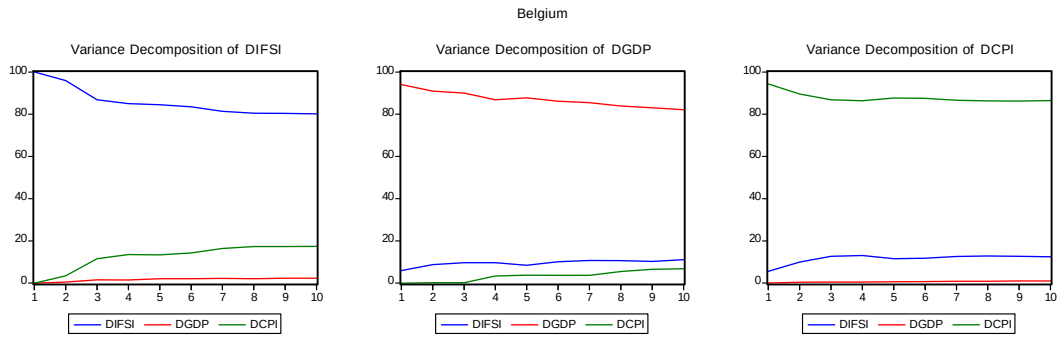


Netherlands









3.10. Robustness Test - Sensitivity Analysis

Robustness analysis defines the ability of an economic model to remain valid under different assumptions, parameters and initial conditions. The results have been checked for robustness changes in the changes in the sample and changes in the number of the variables. We have found that our result is robust to such changes. In order to check the effect of the property market and to interest rate to financial stability we add an index of property prices and a short run interest rate. We run an augmented VAR model with the next order: IFSI CPI GDP ShInter, Prop. Property prices index was taken from Bank for International Settlements (BIS) and it is available for all the countries we are interesting except for Japan and Netherlands. In our model Property variable (Prop) represents the yearly percent change to the property prices. Moreover, we add a fifth variable to our model, the short interest rate (ShInt) which was taken from the IFS data base. Both these variables are I(1) and therefore we took the first difference in order to become stationary.

In the appendix B is presented the VEC(5) USA model with one cointegration vector. In general, our results indicate that a positive innovation of property prices has a positive effect on financial stability for three countries and negative effect for four countries. Furthermore, the results are indicating that a positive shock to the interest rate has a significant negative effect to financial stability and it is in line with the theory i.e. an increase to the interest it will raise the cost to investment and will increase the financial stress to businesses. Variance decomposition results indicate that the two variables explain less than 10% of the forecast variation of financial stability. In addition, a positive innovation of financial stability will have negative

effect to interest rate at 5 of 8 of our cases (US, UK, Japan, Italy, France) and a positive effect to property prices at 5 of 7 of our cases (Japan wasn't included as lack of availability of property time series).

We have serious doubts for the estimated augmented VAR with the five variables because the data don't fit well to the model. The Q-test indicates autocorrelation problem. Thus, in the augmented VAR the residuals don't pass the white noise test. More precisely, a serial autocorrelation problem to the residuals indicates that our results with the VAR model of 5 variables are serious questioned. Autocorrelation problem suggest that there is some missing variable or VAR is not specified perfectly. Adding more lags doesn't soaks up autocorrelation problem.

Alternatively, in order to enchase the robustness, we use the Kansas City Financial Stress index instead of the IMF stress index. The KCFSI is a monthly index which combines 11 variables that provide a range of economic signals of financial stress and is available only for the USA. The variables fall into two broad categories: credit and liquidity spreads and measures based on the actual or expected behavior of asset prices. The KCFSI has a mean of zero and a standard deviation of one. Thus, when the KCFSI exceeds zero, financial conditions are more stressed than average. Like with the FSI, in order to have a measure of financial stability instead of financial stress we invert the KCFSI.

Table 3.15: Kansas City Financial Stress index

KCFSI: Variable
1. TED spread
2. 2-year swap spread
3. Off-the-run/on-the-run-Treasury spread
4. Aaa/Treasury spread
5. Baa/Aaa spread
6. High-yield bond/Baa spread
7. Consumer ABS/Treasury spread
8. Stock-bond correlation
9. Stock market volatility (VIX)
10. Idiosyncratic volatility (IVOL) of banking industry

11. Cross-section dispersion (CSD) of bank stock returns

In contrast to the IFSI that we have used in our analysis and contains seven variables that are standardized and assigned equal weights, the Kansas City Fed Index use principal components to determine the coefficients on the variables. These coefficients are chosen so that the index explains the maximum possible amount of the total variation in the 11 variables. Furthermore, the IFSI index differs by including a measure of stress in the interbank lending market and omitting any measure of liquidity in the government securities market (Haiko, 2009). The results are similar to our findings and bolster the robustness of our model. The impulse responses of USA model follow the same direction as with the first model with the difference that in case of a positive shock to GDP and the CPI variable the responses of the financial stability variable are more intense. The result of the variance decompositions is keeping in line with our earlier findings. DCPI explains at most 20% of the variance of DIFSI while DGDP has only a little effect.

Figure 3.7: Impulse responses to USA VAR (4) Model using IKFCI as stability index.

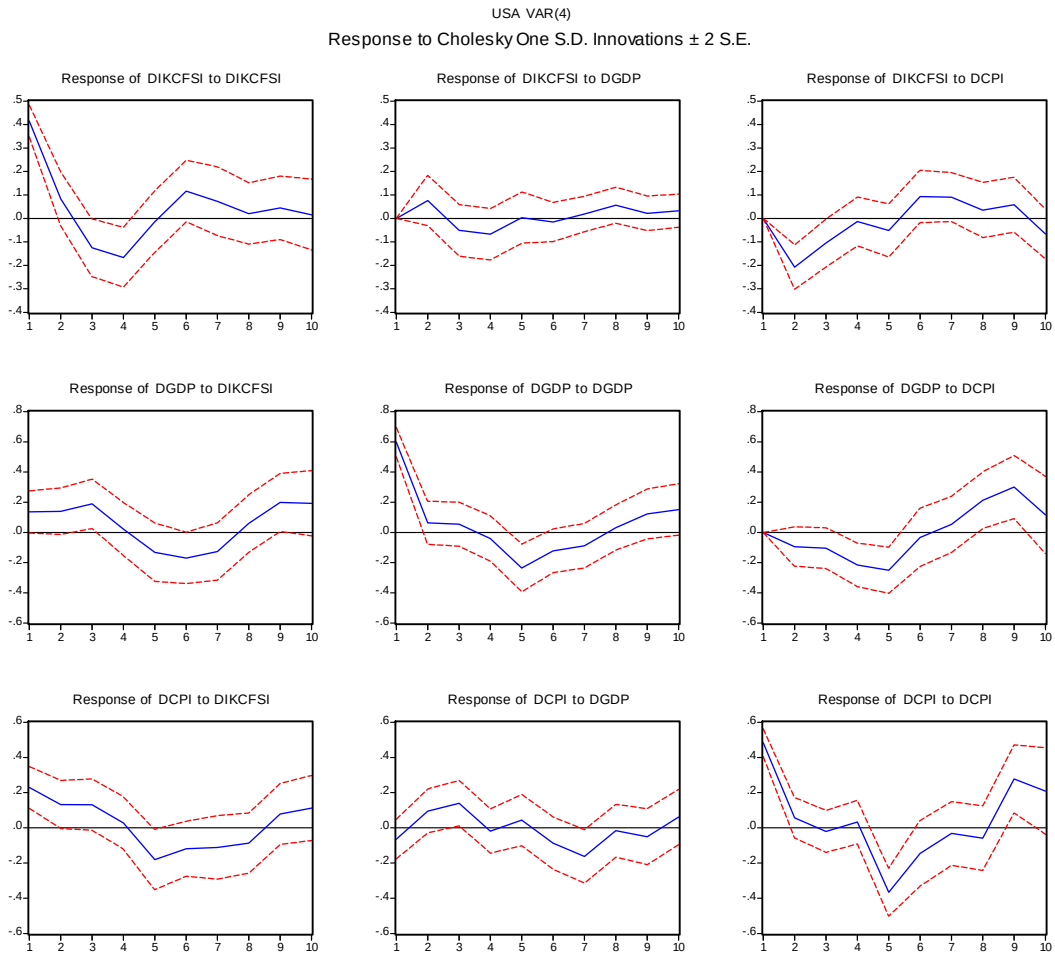
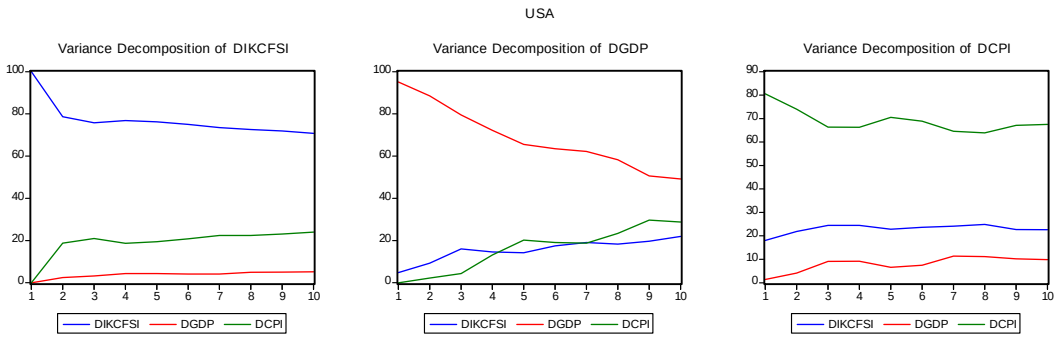


Figure 3.8: Variance decompositions



4. Discussion and Conclusions

The aim of the present thesis has been to examine whether financial stability, measured as described by the inversed stress index, would have an impact on economic welfare, on monetary stability and vice versa. We sought to test how the financial stability is affected by the growth and inflation using two proxy variables: GDP Volume for measuring the yearly GDP change as a measure for growth and in the CPI index as the yearly % change in the price level. Our data set included 9 advanced countries of OECD: Belgium, France, Germany, Netherlands, Italy, Japan, Spain, US and the UK over the period 1984 Q1 till 2009 Q1.

The first part of this thesis reviews the theoretical and the empirical literature on financial stability while the second part encloses the empirical analysis. In the theoretical review we examined the theoretical models of financial stability giving mainly emphasis on the financial accelerator while in the empirical findings we searched for an appropriate measure of financial stability. In the empirical analysis we tried to examine the linkages and the dynamics between financial stability, monetary stability and growth. We used a primal VAR model with three proxies variables that allows the investigation of the financial stability effects to economic activity, to price levels and vice versa. Furthermore, in the empirical analysis we examined an augmented VAR model with two additional variables the interest rate and the property prices.

In particular, after the brief introduction, we continued in chapter 2 where we presented the literature review on financial stability. In subchapter 2.1 we made a concise reference to the financial system and to the financial system components (financial intermediaries, financial markets, financial infrastructure) while we made a short reference to the endogenous and exogenous vulnerabilities of the financial system. In subchapter 2.2 we examined the definitions that encompass the term “financial stability”. Although there is not a single acceptable definition and there is a little confuse of what financial stability should include, in general we can take financial stability as a situation in which the financial system is capable of allocating resources efficiently between activities and across time, assessing and managing financial risks, and absorbing shocks. In subchapters 2.3 and 2.4 we examined the key

role of the central banks and we presented institutions with main purpose the consolidation of financial stability in financial markets. A growing number of central banks around the world are making financial stability assessments and publishing financial stability reports, many of them based on a broad conception of financial stability while several international institutions are devoted to financial stability issues. Next, we presented the theoretical models on financial stability while we gave emphasis on financial accelerator and the credit as the main channel of financial distress (2.5, 2.6, and 2.7). We have distinguished two basic theories. First, the financial accelerator has been the most common approach to incorporate financial frictions into a DSGE framework (Bernanke et al., 1999) and second, a recent model by Goodhart et al. (2006) which is distinct from, but complementary to the role of the financial accelerator in macroeconomic performance, in a finite horizon general equilibrium framework. Chapter 2 closes with subchapter 2.8 where we presented an appropriate measure of financial stability and also we presented empirical findings on this research area. Our attention estimated in two different approaches for a financial stability metric, the probability of default and the financial stress index. Moreover, the evidence in the empirical literature indicates the relationship between financial stability and economic activity and that the financial stability is an important link from the financial to the real side of the economy.

Chapter 3 is comprised by the empirical analysis employing a multivariate autoregressive model. Our principal objective was to search for evidence of the relation of financial stability with the key macroeconomic variables. The results carry noteworthy implications for policy making although it is necessary to proceed with care. In overall, the results imply that in most cases financial stability seems to be positive affected after an improvement in financial conditions while in all cases is negative affected by an increase in the price level. Additionally, for the most cases, an improvement in financial conditions will have a positive impact to growth while the results of the positive innovation of financial stability to inflation are mixed. We performed sensitivity analysis to show that our results are robust where we included an augmented VAR model with five variables but due to autocorrelation problem the results are questioned.

Even though this thesis provides important information for the financial stability, a number of issues are still remain open and require further research. The low intensity of the impulse responses and the low contributions of innovations to growth and to inflation to financial stability variance motivate us to look for an augmented model with additional variables although we have to deal with serial correlation and misspecification problem. One future research may include alternative models such panel data estimation or Vector ARMA (VARMA) models.

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APPENDIX A: IMF Core and Encouraged Set indicators

Core Set indicators, Source (IMF)

- Regulatory capital to risk-weighted assets
- Regulatory Tier I capital to risk-weighted assets
- Nonperforming loans to total gross loans
- Nonperforming loans net of provisions to capital
- Sectoral distribution of loans to total loans
- Large exposures to capital
- Return on assets
- Return on equity
- Interest margin to gross income
- Noninterest expenses to gross income
- Liquid assets to total assets (liquid asset ratio)
- Liquid assets to short-term liabilities
- Duration of assets
- Duration of liabilities
- Net open position in foreign exchange to capital

Encouraged Set, Source (IMF)

- Capital to assets
- Geographical distribution of loans to total loans
- Gross asset position in financial derivatives to capital
- Gross liability position in financial derivatives to capital
- Trading income to total income
- Personnel expenses to non interest expenses
- Spread between reference lending and deposit rates
- Spread between highest and lowest interbank rate
- Customer deposits to total (non-interbank) loans
- Foreign currency-denominated loans to total loans
- Foreign currency-denominated liabilities to total liabilities
- Net open position in equities to capital
- Average bid-ask spread in the securities market 1/
- Average daily turnover ratio in the securities market 1/
- Assets to total financial system assets
- Assets to GDP
- Total debt to equity
- Return on equity
- Earnings to interest and principal expenses
- Corporate net foreign exchange exposure to equity
- Number of applications for protection from creditors
- Household debt to GDP
- Household debt service and principal payments to income
- Real estate prices
- Residential real estate loans to total loans
- Commercial real estate loans to total loans

APPENDIX B: VAR ESTIMATES

Country	***USA***			**Japan**			**Spain**			**Netherlands**			**Belgium**		
Variable	*DIFSI*	*DGDP*	*DCPI*	*DIFSI*	*DGDP*	*DCPI*	*DIFSI*	*DGDP*	*DCPI*	*DIFSI*	*DGDP*	*DCPI*	*DIFSI*	*DGDP*	*DCPI*
DIFSI(-1)	0.034447	0.076311*	0.041073	-0.158619	-0.080410	-0.023214	-0.184537	0.091051	0.065016	0.121608	0.196914*	-0.013111	-0.082834	0.127698	0.051593
	(0.10703)	(0.03627)	(0.03146)	(0.10876)	(0.06621)	(0.02749)	(0.10891)	(0.08098)	(0.03998)	(0.10634)	(0.04855)	(0.02149)	(0.10905)	(0.07595)	(0.03786)
	[0.32183]	[2.10403]	[1.30546]	[-1.45842]	[-1.21439]	[-0.84461]	[-1.69442]	[1.12438]	[1.62607]	[1.14357]	[4.05617]	[-0.61014]	[-0.75957]	[1.68135]	[1.36286]
DIFSI(-2)	-0.172969	0.094025*	-0.075364	-0.266424*	-0.108091	-0.049965	-0.226013*	0.061374	0.096187*	-0.302455*	0.074150	-0.034346	-0.151570	0.077897	0.047703
	(0.13113)	(0.04444)	(0.03855)	(0.10659)	(0.06489)	(0.02694)	(0.11208)	(0.08334)	(0.04115)	(0.11767)	(0.05372)	(0.02378)	(0.10969)	(0.07639)	(0.03808)
	[-1.31902]	[2.11600]	[-1.95515]	[-2.49958]	[-1.66573]	[-1.85496]	[-2.01646]	[0.73643]	[2.33753]	[-2.57032]	[1.38032]	[-1.44447]	[-1.38183]	[1.01972]	[1.25280]
DIFSI(-3)	0.088542	0.141762*	0.026891	-0.360470*	-0.006139	-0.026003	-0.119706	0.041605	0.061027	-0.243531	0.113362*	-0.000575	-0.047513	0.013387	0.013141
	(0.13673)	(0.04633)	(0.04019)	(0.12117)	(0.07377)	(0.03062)	(0.11298)	(0.08401)	(0.04148)	(0.12253)	(0.05594)	(0.02476)	(0.11706)	(0.08152)	(0.04063)
	[0.64756]	[3.05971]	[0.66906]	[-2.97479]	[-0.08322]	[-0.84915]	[-1.05953]	[0.49526]	[1.47131]	[-1.98753]	[2.02659]	[-0.02324]	[-0.40590]	[0.16422]	[0.32340]
DIFSI(-4)	0.022756	0.032675	-0.031794	-0.188203	-0.045181	-0.062804*	0.005921	0.062070	0.095781*	-0.034941	0.058026	-0.013862	-0.016958	0.068350	0.011468
	(0.13759)	(0.04662)	(0.04044)	(0.12306)	(0.07492)	(0.03110)	(0.11079)	(0.08238)	(0.04068)	(0.13065)	(0.05964)	(0.02640)	(0.11240)	(0.07828)	(0.03902)
	[0.16539]	[0.70084]	[-0.78613]	[-1.52934]	[-0.60305]	[-2.01948]	[0.05345]	[0.75346]	[2.35477]	[-0.26744]	[0.97288]	[-0.52509]	[-0.15087]	[0.87313]	[0.29391]
DGDP(-1)	0.442945	0.130125	0.135982	0.038138	0.014003	0.044254	0.113287	-0.118148	-0.002017	-0.210574	-0.039390	0.094485*	-0.106156	0.025306	0.035569
	(0.28451)	(0.09641)	(0.08363)	(0.16787)	(0.10220)	(0.04242)	(0.13299)	(0.09888)	(0.04882)	(0.22020)	(0.10052)	(0.04449)	(0.13057)	(0.09093)	(0.04532)
	[1.55685]	[1.34973]	[1.62595]	[0.22719]	[0.13702]	[1.04316]	[0.85183]	[-1.19480]	[-0.04131]	[-0.95630]	[-0.39184]	[2.12353]	[-0.81305]	[0.27830]	[0.78477]
DGDP(-2)	-0.313664	0.238278*	0.082094	-0.001566	0.089384	0.092079*	0.244629	0.183942	-0.018083	0.109503	-0.021857	0.028907	-0.165227	0.064109	-0.023351
	(0.28981)	(0.09820)	(0.08519)	(0.16249)	(0.09892)	(0.04106)	(0.13005)	(0.09670)	(0.04774)	(0.21562)	(0.09843)	(0.04357)	(0.13143)	(0.09153)	(0.04562)
	[-1.08231]	[2.42637]	[0.96367]	[-0.00964]	[0.90358]	[2.24244]	[1.88108]	[1.90228]	[-0.37876]	[0.50786]	[-0.22204]	[0.66348]	[-1.25715]	[0.70039]	[-0.51180]
DGDP(-3)	0.401861	-0.073194	-0.098220	-0.092146	0.136754	0.021395	0.126555	0.069929	-0.051125	-0.217612	0.065064	-0.027892	-0.014615	0.019637	0.022979

	(0.29098)	(0.09860)	(0.08553)	(0.16690)	(0.10161)	(0.04218)	(0.13249)	(0.09851)	(0.04864)	(0.19756)	(0.09019)	(0.03992)	(0.13159)	(0.09164)	(0.04568)
	[1.38106]	[-0.74234]	[-1.14834]	[-0.55211]	[1.34590]	[0.50728]	[0.95518]	[0.70983]	[-1.05105]	[-1.10152]	[0.72143]	[-0.69871]	[-0.11107]	[0.21428]	[0.50306]
DGDP(-4)	-0.092319	-0.332192*	0.077645	-0.054516	-0.427935*	-0.007504	0.021781	-0.481392*	-0.029728	-0.060900	-0.284500*	-0.019824	0.113825	-0.518536*	0.036089
	(0.26373)	(0.08937)	(0.07752)	(0.16957)	(0.10323)	(0.04285)	(0.13162)	(0.09787)	(0.04832)	(0.18218)	(0.08317)	(0.03681)	(0.13436)	(0.09358)	(0.04664)
	[-0.35005]	[-3.71723]	[1.00158]	[-0.32149]	[-4.14527]	[-0.17511]	[0.16548]	[-4.91891]	[-0.61522]	[-0.33429]	[-3.42078]	[-0.53852]	[0.84714]	[-5.54131]	[0.77374]
DCPI(-1)	-0.446023	-0.076212	0.193679*	-0.309275	-0.058604	-0.055046	-0.335946	-0.138436	0.132321	-1.144.96*	-0.137578	0.123242	-0.575581*	-0.094376	0.334567*
	(0.30118)	(0.10206)	(0.08853)	(0.41364)	(0.25182)	(0.10453)	(0.26044)	(0.19365)	(0.09562)	(0.49903)	(0.22782)	(0.10084)	(0.28327)	(0.19728)	(0.09833)
	[-1.48093]	[-0.74677]	[2.18771]	[-0.74770]	[-0.23272]	[-0.52660]	[-1.28990]	[-0.71488]	[1.38388]	[-2.29437]	[-0.60389]	[1.22218]	[-2.03194]	[-0.47839]	[3.40240]
DCPI(-2)	-0.115178	0.062377	-0.143554	-0.707269	0.206712	0.041452	-0.390281	-0.126137	0.030795	-0.213983	0.262004	0.152014	-0.852092*	0.068168	-0.022908
	(0.36523)	(0.12376)	(0.10736)	(0.42488)	(0.25867)	(0.10737)	(0.24104)	(0.17923)	(0.08849)	(0.51676)	(0.23591)	(0.10442)	(0.30239)	(0.21060)	(0.10497)
	[-0.31535]	[0.50401]	[-1.33714]	[-1.66464]	[0.79914]	[0.38606]	[-1.61914]	[-0.70379]	[0.34799]	[-0.41408]	[1.11060]	[1.45578]	[-2.81787]	[0.32369]	[-0.21823]
DCPI(-3)	0.080875	-0.010369	0.232889*	-0.174597	-0.595132*	0.092914	-0.045608	-0.325606	0.176901	0.753188	-0.303498	0.222249*	-0.410118	-0.224795	0.178562
	(0.35978)	(0.12191)	(0.10576)	(0.43249)	(0.26330)	(0.10930)	(0.24392)	(0.18137)	(0.08955)	(0.51228)	(0.23387)	(0.10352)	(0.31227)	(0.21748)	(0.10840)
	[0.22479]	[-0.08505]	[2.20215]	[-0.40370]	[-2.26026]	[0.85012]	[-0.18698]	[-1.79531]	[1.97547]	[1.47025]	[-1.29773]	[2.14701]	[-1.31336]	[-1.03366]	[1.64726]
DCPI(-4)	0.439704	-0.213609	-0.670823*	0.401509	-0.332777	-0.442903	0.073350	0.060473	-0.510347*	-0.527860	-0.038279	-0.401532*	0.067950	-0.002672	-0.427758*
	(0.35625)	(0.12072)	(0.10472)	(0.43702)	(0.26606)	(0.11044)	(0.25857)	(0.19225)	(0.09493)	(0.51007)	(0.23286)	(0.10307)	(0.31524)	(0.21955)	(0.10943)
	[1.23425]	[-1.76950]	[-6.40593]	[0.91875]	[-1.25077]	[-4.01040]	[0.28368]	[0.31455]	[-5.37626]	[-1.03488]	[-0.16439]	[-3.89580]	[0.21555]	[-0.01217]	[-3.90885]
C	-0.146025	-0.062816	-0.019539	-0.039350	-0.122766	-0.022014	-0.010197	-0.120302	-0.114614	-0.151818	-0.024514	-0.017337	-0.163169	-0.016397	-0.040964
	(0.17941)	(0.06079)	(0.05274)	(0.20897)	(0.12722)	(0.05281)	(0.17240)	(0.12819)	(0.06329)	(0.19956)	(0.09111)	(0.04033)	(0.16000)	(0.11143)	(0.05554)
	[-0.81391]	[-1.03326]	[-0.37050]	[-0.18831]	[-0.96497]	[-0.41685]	[-0.05915]	[-0.93849]	[-1.81087]	[-0.76074]	[-0.26908]	[-0.42992]	[-1.01983]	[-0.14715]	[-0.73756]

[ ] t-statistic, ( ) St. errors

* significant at the 5% level.

Country	**UK**			**Italy**			**Germany**			
Variable	*DIFSI*	*DGDP*	*DCPI*	DIFSI	DGDP	DCPI		DIFSI	DGDP	DCPI
DIFSI(-1)	0.297479*	-0.059165	-0.044576	-0.060846	0.128505*	-0.002865	DIFSI(-1)	0.005058	0.159670*	0.043462
	(0.11348)	(0.04139)	(0.03763)	(0.11545)	(0.05827)	(0.01989)		(0.12809)	(0.06949)	(0.03294)
	[2.62135]	[-1.42940]	[-1.18472]	[-0.52703]	[2.20546]	[-0.14407]		[0.03949]	[2.29773]	[1.31957]
DIFSI(-2)	-0.298153*	0.037001	-0.047077	-0.159559	0.090315	0.037920	DIFSI(-2)	-0.131917	-0.027874	0.009190
	(0.11937)	(0.04354)	(0.03958)	(0.11763)	(0.05937)	(0.02026)		(0.13413)	(0.07276)	(0.03449)
	[-2.49781]	[0.84988]	[-1.18952]	[-1.35643]	[1.52129]	[1.87136]		[-0.98351]	[-0.38307]	[0.26645]
DIFSI(-3)	-0.171330	0.055268	-0.058922	-0.242357*	0.165291*	-0.010835	DIFSI(-3)	-0.167568	0.084049	0.038230
	(0.13024)	(0.04750)	(0.04318)	(0.11441)	(0.05774)	(0.01971)		(0.12757)	(0.06921)	(0.03280)
	[-1.31551]	[1.16347]	[-1.36452]	[-2.11824]	[2.86250]	[-0.54974]		[-1.31354]	[1.21447]	[1.16547]
DIFSI(-4)	0.012685	0.089585	0.066681	0.089771	0.100761	0.000687	DGDP(-1)	0.295970	0.203432	0.076921
	(0.13225)	(0.04824)	(0.04385)	(0.12226)	(0.06170)	(0.02106)		(0.24226)	(0.13143)	(0.06229)
	[0.09592]	[1.85725]	[1.52076]	[0.73426]	[1.63299]	[0.03264]		[1.22171]	[1.54789]	[1.23483]
DIFSI(-5)	-0.052442	-0.049865	0.014863	-0.030387*	0.048863	0.008817	DGDP(-2)	0.117996	0.046048	0.012437
	(0.13584)	(0.04955)	(0.04504)	(0.12427)	(0.06272)	(0.02141)		(0.24942)	(0.13531)	(0.06413)
	[-0.38605]	[-1.00643]	[0.33001]	[-0.24453]	[0.77911]	[0.41190]		[0.47308]	[0.34032]	[0.19392]
DGDP(-1)	-0.453688	0.130022	0.118340	-0.085134	-0.014216	0.122823*	DGDP(-3)	-0.566012*	-0.173092	-0.025218
	(0.29500)	(0.10760)	(0.09781)	(0.22951)	(0.11583)	(0.03954)		(0.21731)	(0.11789)	(0.05588)
	[-1.53793]	[1.20842]	[1.20992]	[-0.37093]	[-0.12273]	[3.10663]		[-2.60464]	[-1.46824]	[-0.45130]

France

Cointegrating Eq:	CointEq1		
IFSI(-1)	1.000.000		
GDP(-1)	9.931.685		
	-392.395		
	[2.53105]		
CPI(-1)	-9.745.515		
	-201.459		
	[-4.83746]		
C	7.709.875		
Error Correction:	D(IFSI)	D(GDP)	D(CPI)
CointEq1	-0.010368	0.007904	0.008350
	(0.00809)	(0.00335)	(0.00187)
	[-1.28186]	[2.35618]	[4.45956]
D(IFSI(-1))	-0.099102	0.052663	0.047637
	(0.10839)	(0.04495)	(0.02509)
	[-0.91429]	[1.17150]	[1.89861]
D(IFSI(-2))	-0.167208	0.062164	-0.033872
	(0.10842)	(0.04496)	(0.02510)
	[-1.54224]	[1.38251]	[-1.34966]
D(IFSI(-3))	-0.124623	0.061622	0.015782
	(0.10760)	(0.04463)	(0.02491)
	[-1.15818]	[1.38086]	[0.63362]
D(IFSI(-4))	-0.153993	0.084513	-0.018338

DGDP(-2)	-0.077327	0.100496	-0.035790	-0.077709	0.073480	-0.019448
	(0.25657)	(0.09358)	(0.08507)	(0.21126)	(0.10662)	(0.03639)
	[-0.30138]	[1.07388]	[-0.42072]	[-0.36784]	[0.68918]	[-0.53440]
DGDP(-3)	0.216481	0.129984	0.104263	-0.290018	0.078976	-0.024302
	(0.25287)	(0.09223)	(0.08384)	(0.19032)	(0.09605)	(0.03278)
	[0.85609]	[1.40932]	[1.24358]	[-1.52384]	[0.82222]	[-0.74128]
DGDP(-4)	0.074197	-0.320367*	0.099196	-0.214629	-0.364344	-0.017826
	(0.25362)	(0.09250)	(0.08409)	(0.19757)	(0.09971)	(0.03403)
	[0.29256]	[-3.46332]	[1.17967]	[-1.08635]	[-3.65401]	[-0.52378]
DGDP(-5)	-0.247427	0.216661*	0.036463	-0.121160	0.032580	0.171414*
	(0.25677)	(0.09365)	(0.08513)	(0.20578)	(0.10385)	(0.03545)
	[-0.96362]	[2.31345]	[0.42831]	[-0.58879]	[0.31371]	[4.83573]
DCPI(-1)	-0.220579	-0.221004	0.575240	0.518869	0.083400	0.685639
	(0.32952)	(0.12019)	(0.10925)	(0.52576)	(0.26534)	(0.09057)
	[-0.66940]	[-1.83885]	[5.26525]	[0.98690]	[0.31431]	[7.57055]
DCPI(-2)	0.490863	-0.286426*	-0.056856	-0.970518	-0.068974	-0.143116
	(0.33713)	(0.12296)	(0.11178)	(0.61710)	(0.31144)	(0.10630)
	[1.45600]	[-2.32935]	[-0.50866]	[-1.57272]	[-0.22147]	[-1.34633]
DCPI(-3)	-0.274274	0.265492*	0.128354	1.041.438	-0.802673	0.170496
	(0.34433)	(0.12559)	(0.11417)	(0.63099)	(0.31846)	(0.10869)
	[-0.79653]	[2.11393]	[1.12428]	[1.65047]	[-2.52052]	[1.56858]
DCPI(-4)	-0.176258	-0.105431	-0.485895*	-0.157694	0.117921	-0.624095*
	(0.35422)	(0.12920)	(0.11744)	(0.66874)	(0.33750)	(0.11520)
	[-0.49760]	[-0.81606]	[-4.13730]	[-0.23581]	[0.34939]	[-5.41766]

DCPI(-1)	-1.215.035*	0.631204	-0.084445
	(0.47402)	(0.25715)	(0.12188)
	[-2.56328]	[2.45459]	[-0.69282]
DCPI(-2)	-0.487983	0.098426	-0.023317
	(0.52912)	(0.28705)	(0.13605)
	[-0.92225]	[0.34289]	[-0.17138]
DCPI(-3)	-0.767957	-0.750203*	0.169882
	(0.52707)	(0.28593)	(0.13553)
	[-1.45704]	[-2.62369]	[1.25350]
C	-0.198966	-0.033746	-0.028429
	(0.22572)	(0.12245)	(0.05804)
	[-0.88147]	[-0.27558]	[-0.48982]

	(0.10532)	(0.04368)	(0.02438)
	[-1.46213]	[1.93483]	[-0.75218]
D(IFSI(-5))	-0.055294	0.064008	0.009883
	(0.10770)	(0.04467)	(0.02493)
	[-0.51342]	[1.43306]	[0.39642]
D(GDP(-1))	0.127569	0.091339	-0.021835
	(0.26972)	(0.11186)	(0.06243)
	[0.47298]	[0.81655]	[-0.34974]
D(GDP(-2))	0.103613	0.182537	-0.080513
	(0.21863)	(0.09067)	(0.05061)
	[0.47392]	[2.01317]	[-1.59091]
D(GDP(-3))	-0.101460	-0.047717	-0.061836
	(0.22837)	(0.09471)	(0.05286)
	[-0.44429]	[-0.50382]	[-1.16975]
D(GDP(-4))	-0.193752	-0.603819	0.026273
	(0.22661)	(0.09398)	(0.05246)
	[-0.85500]	[-6.42484]	[0.50085]
D(GDP(-5))	-0.092251	0.065250	-0.058944
	(0.26581)	(0.11024)	(0.06153)
	[-0.34706]	[0.59190]	[-0.95799]
D(CPI(-1))	-0.136816	-0.111567	0.327074
	(0.43224)	(0.17926)	(0.10006)
	[-0.31653]	[-0.62236]	[3.26891]
D(CPI(-2))	-0.094738	-0.350650	-0.135676
	(0.36585)	(0.15173)	(0.08469)
	[-0.25896]	[-2.31105]	[-1.60210]
D(CPI(-3))	-0.416833	0.045535	0.106784
	(0.36078)	(0.14963)	(0.08351)
	[-1.15535]	[0.30432]	[1.27862]
D(CPI(-4))	0.145387	-0.188794	-0.530845
	(0.36114)	(0.14978)	(0.08360)
	[0.40258]	[-1.26051]	[-6.35009]

DCPI(-5)	-0.199242	-0.333284*	0.377871*	-0.023317	-0.196631	0.363626*		D(CPI(-5))	0.040160	-0.163028	0.094448
	(0.33894)	(0.12362)	(0.11238)	(0.55804)	(0.28164)	(0.09613)			(0.38674)	(0.16039)	(0.08952)
	[-0.58784]	[-2.69596]	[3.36254]	[-0.04178]	[-0.69817]	[3.78271]			[0.10384]	[-1.01644]	[1.05502]
								C	0.062965	-0.140838	-0.118593
C	-0.097419	-0.055954	-0.025470	-0.023975	-0.131009	-0.029114			(0.16780)	(0.06959)	(0.03884)
	(0.17439)	(0.06361)	(0.05782)	(0.18141)	(0.09156)	(0.03125)			[0.37524]	[-2.02377]	[-3.05319]
	[-0.55862]	[-0.87967]	[-0.44049]	[-0.13215]	[-1.43089]	[-0.93165]					

[ ] t-statistic, ( ) St. errors
* significant at the 5% level.

VAR Granger Causality/Block Exogeneity Wald Tests

UK				Japan				Italy				Spain			
Dependent variable: DIFSI				**Dependent variable: DIFSI**				**Dependent variable: DIFSI**				**Dependent variable: DIFSI**			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
DGDP	3.290.995	5	0.6552	DGDP	0.396828	4	0.9827	DGDP	5.215.323	5	0.3902	DGDP	4.408.938	4	0.3535
DCPI	3.956.442	5	0.5557	DCPI	3.934.088	4	0.4150	DCPI	4.171.935	5	0.5249	DCPI	4.873.509	4	0.3005
All	7.505.518	10	0.6770	All	5.750.267	8	0.6752	All	1.039.242	10	0.4068	All	7.566.259	8	0.4769
Dependent variable: DGDP				**Dependent variable: DGDP**				**Dependent variable: DGDP**				**Dependent variable: DGDP**			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
DIFSI	1.342.944	5	0.0197*	DIFSI	4.121.803	4	0.3898	DIFSI	1.186.080	5	0.0367*	DIFSI	1.757.406	4	0.7803
DCPI	2.083.843	5	0.0009*	DCPI	7.601.343	4	0.1073	DCPI	1.559.926	5	0.0081*	DCPI	4.749.273	4	0.3140
All	3.584.083	10	0.0001*	All	1.102.031	8	0.2006	All	2.528.518	10	0.0048*	All	7.701.262	8	0.4632
Dependent variable: DCPI				**Dependent variable: DCPI**				**Dependent variable: DCPI**				**Dependent variable: DCPI**			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
DIFSI	1.070.962	5	0.0575*	DIFSI	5.951.149	4	0.2028	DIFSI	4.623.585	5	0.4635*	DIFSI	9.755.486	4	0.0448*
DGDP	5.684.355	5	0.3382	DGDP	6.247.056	4	0.1814	DGDP	2.541.333	5	0.0001*	DGDP	1.355.756	4	0.8518
All	1.719.435	10	0.0702*	All	1.216.069	8	0.1442	All	3.164.786	10	0.0005*	All	1.007.397	8	0.2599

* null hypothesis is rejected at a 10% significant level

Germany				France				Netherlands				Belgium			
Dependent variable: DIFSI				**Dependent variable: D(IFSI)**				**Dependent variable: DIFSI**				**Dependent variable: DIFSI**			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
DGDP	8.702.632	3	0.0335*	D(GDP)	2.052.199	4	0.7262	DGDP	2.517.597	4	0.6415	DGDP	2.958.895	4	0.5647
DCPI	1.075.024	3	0.0132*	D(CPI)	1.954.701	4	0.7441	DCPI	9.024.367	4	0.0605*	DCPI	2.423.710	4	0.0001*
All	2.172.729	6	0.0014*	All	4.512.625	8	0.8082	All	1.155.698	8	0.1721	All	2.668.812	8	0.0008*
Dependent variable: DGDP				**Dependent variable: D(GDP)**				**Dependent variable: DGDP**				**Dependent variable: DGDP**			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
DIFSI	6.458.127	3	0.0913*	D(IFSI)	6.626.765	4	0.1570	DIFSI	1.983.135	4	0.0005*	DIFSI	3.776.681	4	0.4371
DCPI	1.294.582	3	0.0048*	D(CPI)	9.583.427	4	0.0481*	DCPI	3.135.347	4	0.5354	DCPI	1.463.775	4	0.8330
All	2.602.388	6	0.0002*	All	1.588.911	8	0.0440*	All	2.413.235	8	0.0022*	All	8.105.056	8	0.4233
Dependent variable: DCPI				**Dependent variable: D(CPI)**				**Dependent variable: DCPI**				**Dependent variable: DCPI**			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
DIFSI	2.882.904	3	0.4100	D(IFSI)	8.530.942	4	0.0740*	DIFSI	2.581.889	4	0.6300	DIFSI	3.017.767	4	0.5549
DGDP	1.893.103	3	0.5949	D(GDP)	5.958.737	4	0.2023	DGDP	5.434.280	4	0.2456	DGDP	1.733.836	4	0.7846
All	8.014.426	6	0.2370	All	1.550.443	8	0.0500*	All	6.133.010	8	0.6323	All	5.082.424	8	0.7487

* null hypothesis is rejected at the 10% significant level

VAR Residual Serial Correlation LM Tests
Max lags 12

	UK		**Japan**		**Italy**		**Spain**		**USA**	
Lags	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob
1	6.586.447	0.6801	3.598.195	0.9358	1.574.332	0.0724	9.446.110	0.3972	7.197.948	0.6165
2	7.897.166	0.5445	4.711.932	0.8587	6.732.878	0.6649	1.934.259	0.0224*	1.742.452	0.0425*
3	6.700.051	0.6683	6.609.614	0.6777	1.124.935	0.2590	1.088.820	0.2835	1.099.069	0.2763
4	7.138.540	0.6227	2.167.415	0.0930	2.250.559	0.0674	1.687.298	0.0597	1.386.574	0.1272
5	9.012.219	0.4361	8.426.371	0.4918	1.066.537	0.2993	1.078.702	0.2906	9.497.348	0.3927

6	3.033.923	0.9629	1.013.030	0.3400	1.502.710	0.0902	5.508.315	0.7879	1.485.441	0.0950
7	9.619.962	0.3821	7.042.580	0.6327	1.479.730	0.0967	3.649.239	0.9329	9.434.441	0.3982
8	1.523.371	0.0847	2.449.901	0.0036*	2.237.332	0.0078*	1.608.541	0.0651	1.252.040	0.1855
9	3.311.588	0.9507	1.617.044	0.0634	1.162.819	0.2351	6.733.474	0.6648	1.371.757	0.1327
10	0.871395	0.9997	3.024.317	0.9633	1.344.939	0.1433	8.093.042	0.5248	6.515.830	0.6874
11	4.653.686	0.8634	9.223.643	0.4169	5.905.563	0.7493	5.673.331	0.7721	1.253.402	0.1848
12	1.825.042	0.0324*	4.354.803	0.8865	5.680.828	0.7714	9.671.240	0.3777	7.220.753	0.6141

	Germany		**France**		**Netherlands**		**Belgium**		
Lags	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob	
1	2.552.123	0.0024*	1.303.205	0.1612	7.540.791	0.5810	1.204.866	0.2106	
2	1.017.360	0.3366	1.742.154	0.0425*	4.769.166	0.8539	1.709.397	0.0473*	
3	7.680.222	0.5667	1.399.580	0.1225	1.321.932	0.1529	9.543.563	0.3887	
4	1.213.522	0.2058	1.181.629	0.2239	9.808.534	0.3662	1.906.783	0.0546	
5	9.426.721	0.3989	1.444.793	0.1073	4.032.902	0.9092	7.304.346	0.6055	
6	1.127.214	0.2575	4.901.592	0.8428	5.731.018	0.7665	1.372.143	0.1326	
7	5.102.685	0.8253	1.002.967	0.3481	3.614.689	0.9349	7.395.209	0.5960	
8	1.136.665	0.2514	2.844.554	0.0008*	2.351.442	0.0051*	3.693.792	0.0000*	
9	6.965.277	0.6407	1.192.239	0.2177	1.521.162	0.0853	1.988.467	0.9916	
10	2.939.539	0.9666	1.459.346	0.1027	6.870.990	0.6505	8.316.860	0.5026	
11	2.896.742	0.9682	8.271.673	0.5070	1.034.865	0.3230	8.182.534	0.5159	
12	7.540.239	0.5811	8.006.144	0.5335	8.848.621	0.4514	6.979.619	0.6392	

* null hypothesis is rejected at the 5% significant level

VEC (5) USA Residual Portmanteau Tests with 5 variables, IFSI CPI GDP ShInter, Prop

VEC Residual Portmanteau Tests for Autocorrelations
H0: no residual autocorrelations up to lag h

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	6.017.963	NA*	6.081.310	NA*	NA*
2	1.989.648	NA*	2.025.511	NA*	NA*
3	2.923.760	NA*	2.989.756	NA*	NA*
4	4.547.663	NA*	4.684.264	NA*	NA*
5	6.966.316	0.0000	7.235.809	0.0000	25
6	9.138.783	0.0003	9.553.108	0.0001	50
7	9.962.997	0.0302	1.044.215	0.0140	75
8	1.275.136	0.0331	1.348.400	0.0116	100
9	1.508.867	0.0573	1.606.310	0.0174	125
10	1.757.061	0.0742	1.883.364	0.0185	150
11	1.957.134	0.1353	2.109.328	0.0330	175
12	2.110.429	0.2825	2.284.523	0.0818	200

VEC (5) USA estimation, IFSI CPI GDP ShInter, Prop

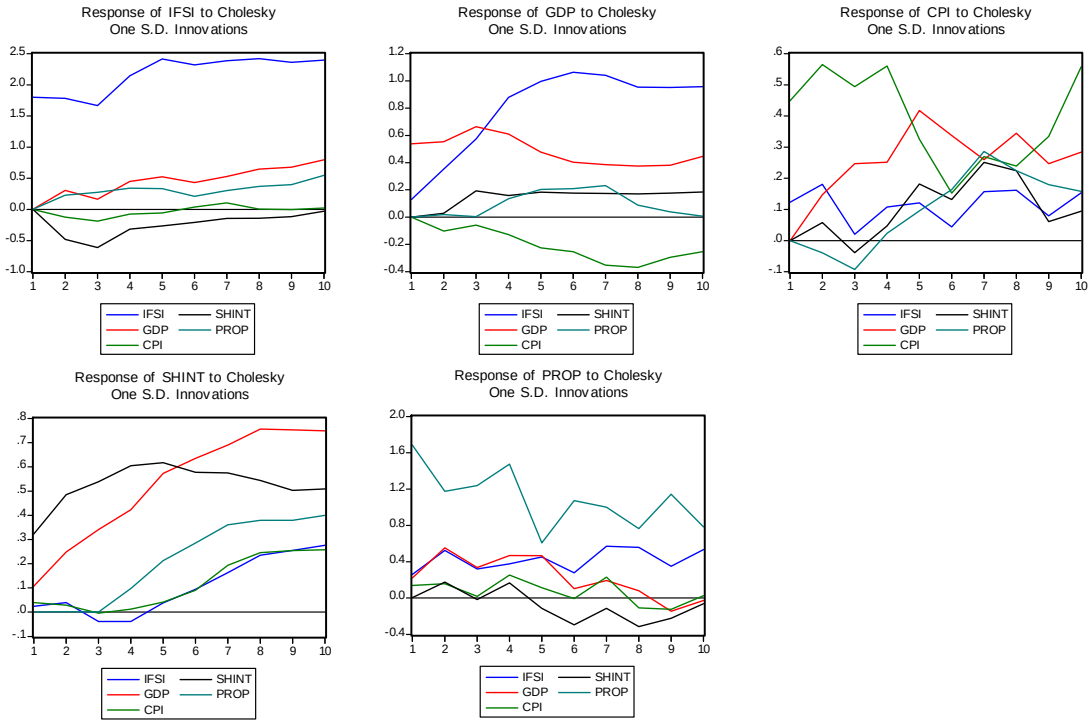
Vector Error Correction Estimates
Date: 04/04/11 Time: 19:10
Sample (adjusted): 1985Q2 2009Q1
Included observations: 96 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating
Eq: CointEq1

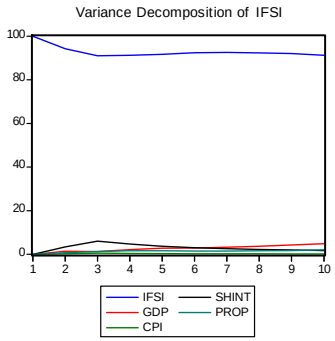
IFSI(-1)	1.000000
GDP(-1)	-2.160.183
	(0.47448)
	[-4.55269]
CPI(-1)	-2.498.971
	(0.66291)
	[-3.76967]
SHINT(-1)	1.424708
	(0.35194)
	[4.04812]
PROP(-1)	-0.605769
	(0.25449)
	[-2.38028]
C	9.079633

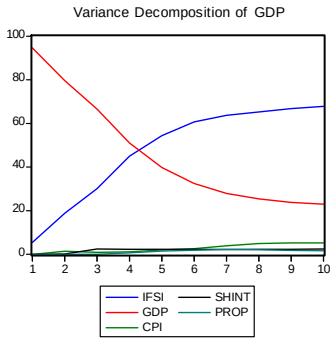
Error Correction:	D(IFSI)	D(GDP)	D(CPI)	D(SHINT)	D(PROP)
CointEq1	-0.146419	0.101810	-0.051720	-0.051882	0.010068
	(0.09845)	(0.03030)	(0.02542)	(0.01876)	(0.09422)
	[-1.48722]	[3.36022]	[-2.03433]	[-2.76520]	[0.10686]

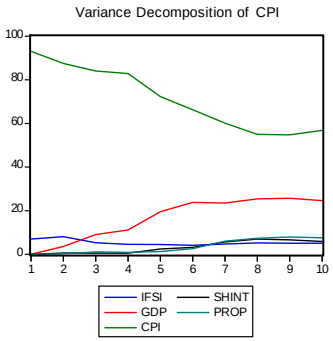
VEC (5) USA Impulse responses, IFSI CPI GDP ShInter, Prop

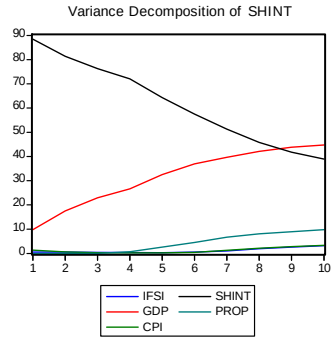


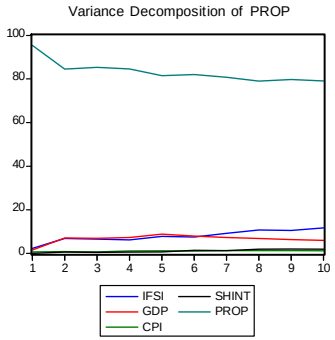
VEC (5) USA Variance Decompositions, IFSI CPI GDP ShInter, Prop


Variance Decomposition of IFSI
IFSI
SHINT
GDP
PROP
CPI


Variance Decomposition of GDP
IFSI
SHINT
GDP
PROP
CPI


Variance Decomposition of CPI
IFSI
SHINT
GDP
PROP
CPI


Variance Decomposition of SHINT
IFSI
SHINT
GDP
PROP
CPI


Variance Decomposition of PROP
IFSI
SHINT
GDP
PROP
CPI