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Financial Stability and Policy Measures

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“The introduction of a substantial government transfer tax on all transactions might prove the most serviceable reform available, with a view to mitigating the predominance of speculation over enterprise in the United States”

(John Maynard Keynes (1936))

ABSTRACT

“Financial Stability and Policy Measures”

Financial stability has gain great importance after the last financial crisis and the need of policy measures oriented to safeguarding and strengthen the financial system motivated us to this research. This Thesis examines the interaction between financial stability growth and monetary policy and provides an assessment of two different financial stress indexes (FSIs) as a measure of financial stability using a Vector Autoregressive Model (VAR). Our principal objective is to search for evidence of the relation of financial stability with the key macroeconomic variables. The results indicate the interaction of financial stability to the real economy and therefore the necessity of policy measures proposals for strengthening the financial stability. Finally, we describe the need for a new regulatory structure for the financial system and policy measures towards to bolstering the resilience of the international financial system in order to encounter the moral hazard risks that the recent crisis brought to surface.

Keywords: financial stability, financial crisis, Policy Measures, Financial Transaction Tax

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LIST OF ABBREVIATIONS

1. ADF Augmented Dickey-Fuller
2. AIC Akaike’s Information Criterion
3. AR Autoregression
4. ARCH AutoRegressive Conditional Heteroskedasticity
5. CCA Contingent claims analysis
6. CDO Collateralized debt obligations
7. CFNAI Chicago Fed National Activity Index
8. CPI Consumer Price Index

9. CSD Cross-section dispersion
10. DD Distance to default
11. DSGE Dynamic stochastic general equilibrium
12. ECB European Central Bank
13. ECM Error Correction Model
14. EDF Expected Default Frequency
15. FSF Financial Stability Forum
16. FSI Financial stress index
17. FSIs Financial soundness indicators
18. FTT Financial Transactions Tax
19. GARCH Generalized Autoregressive Conditional Heteroskedasticity
20. GDP Gross Domestic Product
21. GVAR Global Vector Autoregressive
22. IFS International Financial Statistics
23. IFSI Inversed FSI
24. IMF International Monetary Fund
25. IMFFSI IMF Financial Stress Index
26. IVOL Idiosyncratic volatility
27. KCFSI Kancas City Financial Stress Index
28. LIBOR London Interbank Offered Rate
29. LR Likelihood Ratio
30. MBS Mortgage-backed securities
31. OECD Organization for Economic Cooperation and Development
32. OLS Ordinary Least Squares
33. PoD Probability of default
34. PP Phillips – Perron
35. p-value Probability
36. RBC Real business cycle models
37. s.e. Standard Error
38. SC Schwartz information criteria
39. SVAR Structural vector autoregressive
40. VAR Vector Autoregression

41. VECM Vector Error Correction Model

42. VIX   Volatility Index

1. Introduction

Financial stability analyses are complicated by the lack of a clear and consensus definition of financial stability and in this paper we give a full description of the alternative definitions. Although is still not exist an unique acceptable definition for financial stability as there is for monetary stability, we can take financial stability as a situation in which the financial system is capable of smoothly and efficiently allocate economic resources between activities and across time, assessing accurately and managing well financial risks, and finally can absorb financial and real economic surprises and shocks (Schinasi, 2004b). The definition of financial stability is essential for the development of relevant analytical tools as well as for the design of policy and operational frameworks (Issing, 2003). Furthermore, since assessment of financial stability in general is based on a wide range of risk factors, one can not expect one single model or a single measure to satisfactorily capture all the risk factors. Searching for an appropriate financial stability measure, we investigate the use of two different FSIs. We employ the FSIs in two different VAR models in order to search if there is a trade off, mainly, between financial stability and growth. The results of our models indicate the need for policy measures that will safeguard and strengthen financial stability.

In recent years, and even more after the last global financial crisis, governments are taking measures towards of strengthening the financial stability of their economies. The financial turmoil has pushed forward to a new regulatory framework facing the danger of high systemic risk and the imbalanced in the financial markets. After the high cost rescue of financial institutions exposed to toxics bonds, the rise of fiscal debt came to cut off the sluggish recovery and introduce a new cycle of financial instability. 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.

We begin this thesis with the key definitions of financial stability and the literature review has been exploited in this area. The objective of this paper is to study the dynamic relationship between financial stability, measured by two alternative proxy variables, growth and inflation. The empirical analysis consists of a VAR model by employing 3 proxy time series in a single country case study: USA. The results of our models indicate the need for policy measures that will safeguard and strengthen financial stability. Secondly, the assessment of the two FSIs reached to similar empirical evidence. Finally, the last part of this thesis aims to give alternative policy measures. Some believe that the financial system deregulation contributed to the U.S. financial crisis of 2007-2009 and the global financial crisis of 2008-2009. A discussion is open about the necessity of institutional changes and establishment of a new regulatory framework. Under the present circumstances of a fragile global recovery policy steps towards financial stability are more necessary than ever.

2. Definining Financial Stability

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.

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 channeling 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 centered 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.

2.1. 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.

2.2. Measurements of 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:

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

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 (PoD_t) is obtained using the DD_t 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 is calculated on an internationally harmonized basis, and is released quarterly by most countries. 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 direction 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.

3. Empirical Analysis: USA Case Study using two different FSIs

3.1. Selected Variables and Data Description

There are several financial stress indexes that include different variables and are combined into a single measure with different ways. Illing and Liu explored several different ways of combining financial variables into a composite index, one of which was principal components. They test three different weighting methods: The first method is the factor analysis approach in this paper is motivated by the Chicago Fed National Activity Index (CFNAI) which in turn is based on the techniques of Stock and Watson (1989, 1999). The Kansas City Financial stress index (KCFSI) is constructed in a similar way to the CFNAI. A second approach weights the variables by the relative size of each market to which they pertain. The larger the market as a share of total credit in the economy, the higher the weight assigned to the variable proxying stress in that market. A third approach is the variance-equal weighting method generates an index that gives equal importance to each variable. It is the most common weighting method used in the literature.

Illing and Liu index includes a number of variables such as a corporate bond spread, a measure of liquidity in the Treasury market and a measure of volatility in the overall stock market. It includes some variables, such as exchange rate volatility, that are more important for a small open economy like Canada's than for the United States. Another composite index of financial stress that has attracted widespread attention is one developed by economists at the International Monetary Fund (IMF). In contrast to the Kansas City Fed and Bank of Canada indexes, the IMF index does not use principal components to determine the coefficients on the variables. Instead, the variables are standardized and assigned equal weights. The IMF index uses a somewhat smaller set of variables than the Kansas City Fed and Bank of Canada indexes, because the goal of the project was to construct an index that could be used for 17 different countries. Most of the variables in the IMF index closely resemble those in the Bank of Canada index. However, the IMF index differs by including a measure of stress in the interbank lending market and omitting any measure of liquidity in the government securities market. Though useful for international comparisons, the limited number of variables in the IMF index means that it may be less suited than the KCFSI for detecting financial stress in the United States. In order to test for the financial stability we use two different models with two alternative financial stress indexes. The Kansas City stress index (KC-FSI) and the IMF financial stress index (IMF-FSI).

For the purpose of our analysis the VAR model is consist of a single module measure of financial stability, the financial stress index (FSI), a growth index and an inflation index. Next we test an augmented VAR model with more than three variables. The macroeconomic variables are from IMF statistics data base (IFS) and are on quarterly basis. Our data set includes the USA case study over the period 1990 Q1 till 2009 Q1. The two models include the FSI[1] for measuring financial stability, GDP for measuring growth and the consumer price index as a measure for inflation. 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 financial stress index, inversed (FSI) i.e. we have multiplied the FSI by -1 so that a drop in the index registers with a decrease of financial stability.

FSI =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 FSI has a mean of zero and a standard deviation of one. Therefore, when the FSI 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

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

of financial stress such as PoD and expected default frequency (EDF) were not easy accessible or were confidential corporate data (see Moody's KMV Credit Monitor)[2].

The purpose of this study is to examine whether financial stability, measured as described by either the IMF FSI or the Kansas City FSI, would have an impact on economic welfare, on monetary stability and vice versa. For that purpose we use GDP Vol. for measuring the GDP change yearly as a measure for growth. Inflation is defined as the % change in the CPI index. 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 Kansas City Financial Stress Index

The first of the two financial stress indexes that we use in our model is the Kansas City Financial Stress Index (KCFSI). The KCFSI is a monthly measure of stress in the U.S. financial system based on 11 financial market variables. A positive value indicates that financial stress is above the long-run average, while a negative value signifies that financial stress is below the long-run average. Another useful way to assess the current level of financial stress is to compare the index to its value during past, widely recognized episodes of financial stress. These variables fall into two broad categories: average yield spreads, and measures based on the actual or expected behavior of asset prices. The index is calculated using the principal components procedure. Under this procedure, the coefficients of the 11 variables are chosen so that the index explains the maximum possible amount of total variation in the variables from February 1990 through the current month.

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

Table 3.1: Kansas City Financial Stress index

Index Variables
A. Yield spreads
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
B. Behavior of asset prices
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
The contribution of each variable equals the change in the standardized value of the varia-ble times the coefficient of the variable in the index.

Several criteria were used in selecting variables for the KCFSI. First, each variable had to represent one or more of the five features of financial stress. Second, each variable had to reflect prices or yields on financial markets, on the grounds that market prices and yields embody the largest amount of information and are the quickest to reflect changes in financial conditions. Third, each variable had to be available on at least a monthly basis, so that a monthly financial stress index could be constructed. And finally, each variable had to be available at least since 1990, in order to assess the ability of the KCFSI to identify past episodes of financial stress. These criteria led to the selection of 11 variables, each of which is explained below. Table 3.1 summarizes the key features of financial stress captured by the variables.

3.2.1 KCFSI Chosen Variables

The first six variables are concerning the yields spreads and the rest to the end the behavior of asset prices. Next it follows a brief description of each selected variable in the KCFSI.

1. Three month LIBOR/T-Bill spread (TED spread)

The three month London Interbank Offered Rate (LIBOR) is a measure of the cost to banks of lending to each other over the short term. Each day, a panel of 16 large banks reports the rate at which they believe they could borrow unsecured, dollar-denominated funds on the interbank market. This rate could exceed the rate on a Treasury bill of the same maturity for two possible reasons: Lending banks fear the loan may not be repaid (default risk), or because banks worry they will experience an unexpected need for funds before the loan comes due (liquidity risk). If lending banks have difficulty determining which borrowing banks are good risks and which are bad risks, a problem of adverse selection can also arise, further increasing the LIBOR/T-bill spread. Thus, the LIBOR/T-bill spread captures three distinct aspects of financial stress, flight to quality, flight to liquidity, and asymmetry of information between buyers and sellers of financial assets.

2. Two year swap spread

In an interest rate swap, one party agrees to pay another party a stream of fixed-rate payments in return for a stream of floating-rate payments. The floating-rate payments are usually based on a short-term LIBOR rate. The fixed rate is often expressed as the yield on a Treasury security of the same maturity plus a spread over that yield. This spread is positive for two reasons. First, as noted above, the LIBOR rate on which the floating-rate payments are based will generally exceed the comparable short-term Treasury yield, so that interbank lenders are compensated for the default and liquidity risk of interbank loans. As a result, an investor will agree to make floating-rate payments in return for fixed-rate payments only if he earns more than the comparable long-term Treasury yield on the fixed-rate payments. The second reason the swap spread is positive is that the claim to the fixed-rate payments is considerably less liquid than a Treasury security of the same maturity, which can always be sold on short notice on secondary markets. These explanations for the positive spread on interest rate swaps suggest that increases in the 2-year swap spread can reflect two different features of financial stress: flight to quality (fear that increased default risk in the interbank lending market will drive up LIBOR), or flight to liquidity (fear that funds will be needed before the swap expires, or fear that increased liquidity risk in the interbank market will drive up LIBOR).

3. Off-the-run/on-the-run 10-year Treasury spread

For a particular maturity, the on-the-run Treasury security is the most recently issued security of that maturity. Off-the-run Treasury securities are previously issued securities of the same maturity. The market for an off-the-run Treasury security is generally not as deep as the market for the on the run security of the same maturity. As a result, an investor holding the off-the-run security faces more risk of having to sell the security at a discount if he needs cash in a hurry. To compensate for this liquidity risk, the yield on the off-the-run security must exceed the yield on the on-the-run security. The spread between the off-the-run and on-the run yields tends to increase when investors become more concerned about the risk of an unexpected need for cash. Thus, the spread provides a good measure of the flight to liquidity that often occurs during periods of financial stress.

4. Aaa/10-year Treasury spread.

Although corporate bonds rated Aaa by Moody's are supposed to have little or no default risk, their yields are generally higher than those on Treasury securities of similar maturity. One reason Aaa bond yields can exceed comparable Treasury yields is that many of the bonds are callable, which means that the company that issued the debt can prepay the loan if a decline in interest rates makes refinancing attractive. However, another important reason for the difference in yields is that even the highest-rated corporate bonds tend to be less liquid than Treasury securities. As a result, increases in the spread between Moody's Aaa bond index and the 10-year Treasury yield provides another measure of the flight to liquidity during periods of financial stress.

5. Baa/Aaa spread

Baa-rated corporate bonds are the lowest-rated bonds classified by Moody's as investment-grade. During economic expansions, the yield on these bonds may exceed the yield on Aaa bonds by only a small margin, because investors perceive the risk of default to be almost as low on Baa bonds as Aaa bonds. However, if investors become concerned about the state of the economy or the financial health of lower-rated corporations, they will assign a higher probability of default to Baa bonds. In such circumstances, the Baa yield will rise further above the Aaa yield to compensate investors for the higher perceived risk of Baa bonds. Such an increase in the Baa/Aaa spread need not be a sign of financial stress if investors' changed beliefs about default risk are well founded. But in some cases, the increased pessimism of investors may represent an over-reaction to a prolonged period of excessive optimism. And in other cases, investors may demand a higher yield on Baa bonds, not because of an increase in the perceived risk of Baa bonds, but because of a decreased willingness to bear such risk. Either way, the increase in the Baa/Aaa spread will reflect a flight to quality. During such periods, investors may also start to worry that some Baa bonds are riskier than others. If so, a problem of adverse selection may arise, causing the Baa rate to move even further above the Aaa yield. Thus, the Baa/Aaa spread may also capture increases in information asymmetries.

6. High-yield bond/Baa spread

High-yield bonds, also known as "junk bonds," are corporate bonds with too low a rating to be considered investment-grade. The difference in default risk between high yield bonds and Baa bonds is even greater than that between Aaa bonds and Baa bonds. As a result, there should be an even greater tendency for the high-yield/Baa spread to increase in response to a flight to quality or an increase in information asymmetry. The high yield/Baa spread may also capture flights to liquidity. High-yield bonds tend to have thinner markets than investment-grade bonds, partly because they are issued in smaller quantities and partly because institutional investors such as pension funds are prohibited from investing in them. Thus, when investors become more worried about unexpected cash needs, the high-yield bond yield tends to rise further above the Baa yield to compensate investors for holding the less-liquid asset.

7. Consumer ABS/5-year Treasury spread

Consumer asset-backed securities are securities backed by pools of credit card loans, auto loans, or student loans. Like mortgage-backed securities, these securities are typically issued in tranches, with the senior tranche receiving the highest rating because it has first lien on the underlying loans. During normal times, the senior tranches are considered to have low risk because the underlying loans are geographically diversified and thus unlikely to default at the same time. As a result, the spread over Treasury securities of comparable maturity is low. During flights to quality, however, investors may become more concerned about the risk of default by consumers and require higher compensation to hold the securities, just as in the case of high-yield bonds. Asset-backed securities are also susceptible to increases in the asymmetry of information between the buyers and sellers of financial assets. Issuers of consumer asset-backed securities have an incentive to securitize only high-quality loans to preserve their long-run reputation. During periods of financial stress, however, some issuers may be tempted to retain the higher-quality loans on their balance sheets and securitize the lower-quality loans. Suspecting such behavior, investors may demand sharply higher yields on the asset-based securities.

8. Correlation between returns on stocks and Treasury bonds

In normal times, the returns on stocks and government bonds are either unrelated or move together in response to changes in the risk-free discount rate. In times of financial stress, however, investors may view stocks as much riskier than government bonds. If so, they will shift out of stocks into bonds, causing the returns on the two assets to move in opposite directions. A number of studies, some for the United States and some for other countries, confirm that the correlation between stock returns and government bond returns tends to turn negative during financial crises. Thus, the stock-bond correlation provides an additional measure of the flight to quality during periods of financial stress. This correlation is computed over rolling three-month periods using the S&P 500 and a 2-year Treasury bond index. Also, the negative value of the correlation is used in the KCFSI, so that increases in the measure correspond to increases in financial stress.

9. Implied volatility of overall stock prices (VIX)

The CBOE Volatility Index (VIX) is a measure of the expected volatility in the S&P 500 based on the market prices of options. Options to buy or sell a stock are more valuable when the stock's market price is expected to fluctuate widely, because the option has a greater likelihood of ending up "in the money." For options to buy a stock, there will be a greater chance that the market price exceeds the strike price. And for options to sell the stock there will be a greater chance that the market price falls below the strike price. The VIX exploits this relationship between volatility and options prices to compute the expected upward or downward movement in the index over the next month. As a measure of overall volatility in stock prices, it captures both uncertainty about the fundamental values of assets and uncertainty about the behavior of other investors.

10. Idiosyncratic volatility of bank stock prices

Commercial banks play a key role in the financial system as sources of credit and liquidity to their customers. Thus, in measuring financial stress, it is useful to take into account volatility in bank stock prices as well as volatility in overall stock prices. The idiosyncratic volatility of bank stock prices is the volatility of the unexpected return to bank stocks, the portion of the return that cannot be explained by movements in the overall stock market. This measure is expressed as the standard deviation of unexpected daily returns during the month and is calculated from a bank

11. Stock index and the S&P 500

The measure is designed to capture the same features of financial stress as the VIX, but for the banking industry rather than the corporate sector as a whole. Cross-section dispersion of bank stock returns. If investors become more uncertain about the relative quality of banks but each bank knows its own quality, the asymmetry of information between investors and banks will increase. One measure of investors' uncertainty about relative quality is the cross-section dispersion in unexpected bank stock returns, the portion of each bank's stock return that cannot be explained by movements in the overall market. The specific measure of dispersion used is the interquartile range of unexpected returns of the 100 largest commercial banks. This measure is calculated using daily data on the S&P 500 and the stock prices of the 100 largest commercial banks.

Financial stress is assumed to be the factor most responsible for the co-movement of the variables. This factor is then identified by the method of principal components. The first step is to express each of the 11 variables in the same units by subtracting the sample mean and dividing by the standard deviation. The next step is to calculate the coefficients of these variables in the index. These coefficients are chosen so that the index explains the maximum possible amount of the total variation in the 11 variables. The coefficients are also scaled so that the standard deviation of the index equals one. The procedure may be described formally as follows. Let X_{it} be the value of the i^{th} standardized variable in month t; let $a_1....a_{11}$ be a set of coefficients for the 11 variables; let FSI_t be the value of the financial stress index in month t; and let T be the number of months. The values $\{FSI_t\}$ and the coefficients $\{a_K\}$ are chosen to minimize the sum of squared errors, $SSE = \sum_K \sum_t (X_{Kt} - a_K FSI_t)^2$ subject to the constraint $\sum_t FSI_t^2 / T - 1 = 1$. The values of $a_1....a_{11}$ solving this problem are the elements of the first eigenvector of the sample correlation matrix of the 11 variables. Also, $FSI_t = (a_1/\lambda) X_{1t} + ... + (a_{11}/\lambda) X_{11t}$ for all t, where λ is the first eigenvalue for the sample correlation matrix.

Table 3.2. Estimated Coefficients on KCFSI Variables February 1990 to March 2009

Variable	**Coefficient in KCFSI**
TED spread	0.099
2-year swap spread	0.116
Off-the-run/on-the-run-Treasury spread	0.107
Aaa/Treasury spread	0.107
Baa/Aaa spread	0.125
High-yield bond/Baa spread	0.124
Consumer ABS/Treasury spread	0.130
Stock-bond correlation	0.081
Stock market volatility (VIX)	0.129
Idiosyncratic volatility (IVOL) of banking	0.130

industry	
Cross-section dispersion (CSD) of bank stock returns	0.116
Memo: Percent of total variation of variables explained by KCFSI	**61.4**

Note: Each coefficient represents the effect of a one-standard-deviation change in the variable on the KCFSI

Table 3.2 shows the coefficients obtained by this method using data from February 1990 to March 2009. Since the variables have been standardized, the coefficient on each variable represents the effect on the index of a one-standard-deviation change in that variable. The coefficients range from a low of 0.081 for the stock-bond correlation to 0.130 for the VIX and consumer ABS spread. These differences may seem small, but they are economically important. They imply, for example, that a one-standard-deviation change in VIX has one-and-a-half times as big an effect on the financial stress index as a one-standard deviation change in the stock-bond correlation. The last row in the table shows that 61.4 percent of the total variation in the 11 variables over the sample period is explained by the index. This number measures the tendency for the 11 variables to move together, a tendency that is assumed to result from each variable capturing a key feature of financial stress. The number in the last row of Table 3.2 is 1– SSE/SST, where SST is the total sum of squares $\sum_K \sum_t X_{Kt}^2$.

3.*3. The IMF Financial Stress Index*

After the presentation of the Kansas City stress index we proceed to the IMF financial stress index which its compilation is different and easier than the first one.

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

Table 3.3: IMF - 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**
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

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

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 IMF-FSI makes use of one variable for the stock market returns. 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 IMF- FSI contains one variable for taking in consideration the foreign exchange market. 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:

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

IMF-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 summary statistics of the inputs data which cover the period 1990 – 2009 are given in Table 3.4. This table shows descriptive statistics for the inputs of the VAR model. Mean is the average value of the series, obtained by adding up the series and dividing by the number of observations (77). Max and Min are the maximum and minimum values of the series in the current sample and std. dev. (standard deviation) is a measure of dispersion or spread in the series. We focus mainly at the differences between the KCFSI and the IMFSI where we observe that the later presents higher standard deviation and higher extreme values. Moreover the mean of the IMF FSI is quite higher than the KCFSI. The average KCFSI value is 0.049 with a standart deviation of around 1. This means that most KCFSI values (about 68%, assuming a normal distribution) have a value within one standard deviation (-0.931 - 1.47) and almost all KCFSI values (about 95%) have a value within two standard deviations (-1.47 - 2.45). The average IMF FSI value is 0.65 with a standart deviation of around 3.5. This means that 99.7% of the IMFFSI values have a value within 3 standard deviations (-9.76 – 11.06). The differences between these two stress indexes reflect also the different weighting method in their construction. All the variables in the IMF FSI are standardised using a variance-equal weighting, instead of the factor analysis approach that have been used for the construction of the KCFSI.

Table 3.4: Summary Statistics, USA Case Study

Variable	*Sample (n=77)*	*Mean*	*Min*	*max*	*std. dev*
KCFSI	(1991-2009)	0.049	-4.906	1.02	0.98
IMFFSI	(1991-2009)	0.650	-15.06	4.16	3.47
GDP	(1991-2009)	2.686	-3.797	5.38	1.73
CPI	(1991-2009)	2.914	-0.040	6.22	1.08

KCFSI= Inversed Kancas City Financial Stress Index

IMFFSI=Inversed IMFFinancial Stress Index

GDP= yearly GDP change

CPI= yearly CPI change

3.4 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 stationarity. 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. In order to test for stationarity we use two different tests, Augmented Dickey Fuller and Phillips & Perron (PP). 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. 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. In order to determine the optimal number of lags of the dependent variable we check the Akaike Information Criterion (AIC).

The results presented in Tables 3.5, 3.6 & 3.7 indicate that our time series are non stationary for a significance level of 5%. This means that both ADF and PP tests do not reject the null hypothesis of existence of unit root for the 4 series for null at conventional test sizes. For example the ADF one size p value with constant and trend for the KCFSI series is 0.9916 and the PP p value is 0.9952. Both indicate that we can not reject the null hypothesis at 5% and therefore the KCFSI series is non stationary. Next, we perform again the ADF and PP test taking the variables in 1st difference instead of taking them in levels. 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 3.5: 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)*
KCFSI	-0.214741	0.9916**	-0.031260	0.9952**
IMFFSI	-0.147172	0.9932**	-0.279080	0.9900**
GDP	-1.778585	0.7056**	-1.339423	0.8704**
CPI	-2.088479	0.5437**	-2.936681	0.1571**

Table 3.6: Unit root tests: Model with Constant

Constand	*Augmented Dickey Fuller*		*Phillips-Perron*	
variables	*Statistic*	*(probability)*	*Statistic*	*(probability)*
KCFSI	0.378450	0.9808**	0.403730	0.9819**
IMFFSI	0.213037	0.9718**	0.213037	0.9718**
GDP	-1.671204	0.4417**	-1.255398	0.6463**
CPI	-1.907874	0.3271**	-2.715551	0.0760*

Table 3.7: Unit root tests: Model with No Constant and Trend

None	*Augmented Dickey Fuller*		*Phillips-Perron*	
variables	*Statistic*	*(probability)*	*Statistic*	*(probability)*
KCFSI	0.246093	0.7550**	0.129380	0.7205**
IMFFSI	-0.026899	0.6707**	-0.026899	0.6707**
GDP	-1.328753	0.1688**	-1.268900	0.1868**
CPI	-1.320635	0.1712**	-1.549258	0.1133**

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

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

KCFSI & IMFFSI: the inversed Kansas City and IMF Stress indexes

3.5 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:

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

Since the included macroeconomic series in the analysis are 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 and not cointegrated. However, if two or more variables are I(1) and also are cointegrated, 1st difference estimates are biased because ECM is omitted.

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

[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.

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 $\beta' Y_t$.

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, we say that 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.

Tables 3.8 & 3.9 show the Johansen third case of trend in data and intercept in cointegration equation. The results between the trace statistic and the Max-Eigen Statistic are indicating that our series are not cointegrated. The trace statistic and the Max-Eigen Statistic reject the existence of at least one cointegration relation for a 5% level of significance. Looking at the first row under the heading at Table 3.8, it can be seen that the trace statistic is smaller than the critical value($1.45<2.11$), so the null hypothesis that $r = 0$ cannot be rejected, at the 5% level. It is thus not necessary to look at the remaining rows of the table. The same the Max-Eigen Statistic does not reject the null hypothesis of no cointegration relationship at 5% level(p value 0.31>

0.05) . Hence, reassuringly, the conclusion from this analysis is the same as that there are no cointegrating vectors. In Table 3.9 the results indicate to the same conclusions of no cointegration as the null hypothesis of r=0 is not rejected for both of the tests. In order to examine the sensitivity of our tests, we summarize the Johansen five sets assumptions. The summarization results of the Johansen cointegration test for the 5 sub models are reported in Tables 3.10 & 3.11 and indicate the absence of cointegration for both model 1 and 2.

Table 3.8: Model 1 with the KCFSI, Johansen tests for cointegration

lags	*Cointegrating Vectors**	*Trace Statistic*	*0.05 Critical Value*	*Prob***	*Cointegrating Vectors**	*Max-Eigen Statistic*	*LR Statistic*	*Prob***
5	None	1.456.530	2.113.162	0.3205	None	1.461.275	2.113.162	0.3170
	At most 1	6.763.238	1.426.460	0.5175	At most 1	7.966.021	1.426.460	0.3822
	At most 2	0.519029	3.841.466	0.4713	At most 2	0.063523	3.841.466	0.8010

Table 3.9: Model 2 with the IMFFSI, Johansen tests for cointegration

lags	*Cointegrating Vectors**	*Trace Statistic*	*0.05 Critical Value*	*Prob***	*Cointegrating Vectors**	*Max-Eigen Statistic*	*LR Statistic*	*Prob***
5	None	2.264.229	2.979.707	0.2641	None	1.461.275	2.113.162	0.3170
	At most 1	8.029.544	1.549.471	0.4623	At most 1	7.966.021	1.426.460	0.3822
	At most 2	0.063523	3.841.466	0.8010	At most 2	0.063523	3.841.466	0.8010

Max-eigenvalue test indicates no cointegration at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level*
***MacKinnon-Haug-Michelis (1999) p-values*

Table 3.10: Model 1with the KCFSI, Summarization of 5 set assumption

Sample: 1990Q1 2009Q1
Included observations: 71
Series: IKCFSI GDP CPI
Lags interval: 1 to 5

Selected (0.05 level*) Number of Cointegrating Relations by Model 3

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	0	0	0	0	0
Max-Eig	0	0	0	0	0

**Critical values based on MacKinnon-Haug-Michelis (1999)*

Table 3.11: Model 2 with the IMF-FSI, Summarization of 5 set assumption

Sample: 1990Q1 2009Q1					
Included observations: 77					
Series: IMF-FSI GDP CPI					
Lags interval: 1 to 5					
Selected (0.05 level*) Number of Cointegrating Relations by Model 3					
Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	0	0	0	0	0
Max-Eig	0	0	0	0	0
**Critical values based on MacKinnon-Haug-Michelis (1999)*					

As a conclusion to Johansen cointegration test and according both of Trace Statistic and the Max - Eigenvalue Statistic results, we decide to use the VAR model in first differences following Hamilton and Sims for the two cases. This decision is based to the fact that the series are not cointegrated. 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.

3.6. 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,

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

In matrix notation the 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 $(FSI_t, GDP_t, CPI_t)'$ 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.

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

In case of existence of cointegration the vector error correction model VECM that we will use 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. In our case, although our series are I(1) we have no cointegration vector and thus the appropriate way to follow is the VAR model with the series not in levels but in first difference in order to be stationary.

3.7. 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 (AIC) and the Schwartz information criteria (SC). Furthermore, the likelihood ratio (LR) test was also used in the selection of the appropriate lag for the 2 case studies. 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 or 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 normal distributed. Furthermore, we test the specification of each of the VAR models in order to confirm robustness. The best lag order for our two models is 4 even if the SC test at the model 1 indicates best lag 1 and at model 2 no lags. That is because 4 lags minimize the residual autocorrelation while using 1 lag is not.

Table 3.12: Model 1, Lag Order Selection Criteria

VAR Lag Order Selection Criteria
Endogenous variables: DIKCFSI DGDP DCPI
Exogenous variables: C
Sample: 1990Q1 2009Q1
Included observations: 69

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1.824.209	NA	0.043322	5.374.519	5.471.654	5.413.056
1	-1.611.537	4.006.859	0.030370	5.018.949	5.407489*	5.173096*
2	-1.523.187	1.587.742	0.030568	5.023.731	5.703.677	5.293.488
3	-1.452.883	1.202.308	0.032496	5.080.820	6.052.170	5.466.187
4	-1.233.860	35.55145*	0.022525*	4.706842*	5.969.598	5.207.819
5	-1.202.874	4.760.293	0.027053	4.877.895	6.432.056	5.494.482
6	-1.118.661	1.220.467	0.028010	4.894.671	6.740.237	5.626.869
7	-1.029.502	1.214.630	0.028799	4.897.108	7.034.080	5.744.916

** 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

Table 3.13: Model 2, Lag Order Selection Criteria

VAR Lag Order Selection Criteria
Endogenous variables: DIMF-FSI DGDP DCPI
Exogenous variables: C
Sample: 1990Q1 2009Q1
Included observations: 77

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-3.118.628	NA	0.715072	8.178.255	8.269572*	8.214.781
1	-2.954.695	3.108.345	0.590297	7.986.220	8.351.489	8.132.324
2	-2.834.808	2.179.754	0.546879	7.908.593	8.547.813	8.164.275
3	-2.737.888	1.686.666	0.538705	7.890.618	8.803.789	8.255.878
4	-2.544.318	32.17790*	0.413857*	7.621605*	8.808.727	8.096443*
5	-2.505.258	6.188.749	0.476498	7.753.916	9.214.989	8.338.332
6	-2.425.958	1.194.644	0.496225	7.781.709	9.516.734	8.475.704
7	-2.327.149	1.411.562	0.493748	7.758.828	9.767.804	8.562.401

** 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

3.8. 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 results 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 3.14: Model 1 Portmanteau Residual Tests and LM correlation test

VAR Residual Portmanteau Tests for Autocorrelations H0: no residual autocorrelations up to lag h Sample: 1990Q1 2009Q1						*VAR Residual Serial Correlation LM Tests H0: no serial correlation at lag order h Sample: 1990Q1 2009Q1*		
Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df	Lags	LM-Stat	Prob
1	0.764547	NA*	0.775315	NA*	NA*	1	4.788.299	0.8524
2	4.917.157	NA*	5.046.571	NA*	NA*	2	1.184.666	0.2221
3	7.362.021	NA*	7.597.734	NA*	NA*	3	6.730.163	0.6652
4	9.959.217	NA*	1.034.771	NA*	NA*	4	4.965.875	0.8373
5	1.725.791	0.0448	1.819.108	0.0330	9	5	1.233.401	0.1951
6	2.874.521	0.0516	3.072.268	0.0310	18	6	2.049.213	0.0151
7	3.594.534	0.1165	3.869.821	0.0675	27	7	1.388.538	0.1265
8	4.757.616	0.0939	5.178.288	0.0429	36	8	1.512.276	0.0876
9	5.835.947	0.0873	6.410.666	0.0320	45	9	1.309.116	0.1585
10	6.173.913	0.2191	6.803.143	0.0949	54	10	5.049.869	0.8299
11	6.270.117	0.4869	6.916.695	0.2771	63	11	1.463.295	0.9974
12	7.593.514	0.3529	8.504.772	0.1395	72	12	1.686.098	0.0509
**The test is valid only for lags larger than the VAR lag order.*						*Probs from chi-square with 9 df.*		

Table 3.15: Model 2 Portmanteau Residual Tests and LM correlation test

VAR Residual Portmanteau Tests for Autocorrelations H0: no residual autocorrelations up to lag h Sample: 1990Q1 2009Q1						*VAR Residual Serial Correlation LM Tests H0: no serial correlation at lag order h Sample: 1990Q1 2009Q1*		
Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df	Lags	LM-Stat	Prob
1	1.452.664	NA*	1.471.778	NA*	NA*	1	1.165.748	0.2333
2	5.767.812	NA*	5.901.996	NA*	NA*	2	1.141.942	0.2481
3	1.030.824	NA*	1.062.649	NA*	NA*	3	1.389.617	0.1261
4	1.572.689	NA*	1.634.206	NA*	NA*	4	1.319.818	0.1538

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

5	2.147.265	0.0107	2.248.683	0.0075	9	5	7.718.975	0.5627
6	3.101.803	0.0286	3.283.887	0.0175	18	6	1.704.093	0.0481
7	3.927.129	0.0598	4.191.744	0.0335	27	7	1.450.407	0.1055
8	4.764.115	0.0928	5.125.773	0.0476	36	8	1.207.513	0.2091
9	5.830.499	0.0881	6.333.296	0.0370	45	9	1.276.605	0.1735
10	6.020.823	0.2612	6.552.026	0.1354	54	10	3.675.847	0.9314
11	6.571.133	0.3831	7.194.054	0.2060	63	11	8.005.069	0.5336
12	7.711.352	0.3186	8.544.775	0.1330	72	12	1.306.149	0.1598

**The test is valid only for lags larger than the VAR lag order. Probs from chi-quare with 9 df.*
df is degrees of freedom for (approximate) chi-square distribution

As we can observe from Tables 3.14 and 3.15 the residual Portmanteau Tests for autocorrelations 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. (Table 3.15 right column)

Accordingly, the heteroskedasticity test with no cross terms indicates that the model is not misspecified. Table 3.16 at the right column indicates that residuals are homeskedastic at a significant level of 5%. Moreover, Table 3.16 at left column indicates that normality is rejected for the two models at a significance level of 5%. In principle rejection of normal distribution invalidates the test statistics. The problem of non normality is due to skewness and kurtosis. 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 3.16: Model 1, White Heteroskedasticity Tests & Multivariate Normality Tests

VAR Residual Normality Tests *Orthogonalization: Cholesky (Lutkepohl)* *H0: residuals are multivariate normal* *Sample: 1990Q1 2009Q1* *Included observations: 72*	*VAR Residual Heteroskedasticity Tests:* *No Cross Terms (only levels and squares)* *Sample: 1990Q1 2009Q1* *Included observations: 72*
Component Skewness Chi-sq df Prob.	Joint test:

1	-1.490.330	2.665.301	1	0.0000*	Chi-sq	df	Prob.
2	0.236091	0.668868	1	0.4134	167.3992	144	0.0886
3	-0.232651	0.649515	1	0.4203			
Joint		2.797.140	3	0.0000*			
Component	Kurtosis	Chi-sq	df	Prob.			
1	7.869.937	7.114.885	1	0.0000			
2	2.207.392	1.884.682	1	0.1698			
3	2.025.595	2.848.396	1	0.0915			
Joint		7.588.193	3	0.0000*			
Component	Jarque-Bera	df	Prob.				
1	9.780.186	2	0.0000				
2	2.553.550	2	0.2789				
3	3.497.911	2	0.1740				
Joint	1.038.533	6	0.0000*				

Table 3.17: Model 2, White Heteroskedasticity Tests & Multivariate Normality Tests

VAR Residual Normality Tests *Orthogonalization: Cholesky (Lutkepohl)* *H0: residuals are multivariate normal* *Sample: 1990Q1 2009Q1* *Included observations: 77*					*VAR Residual Heteroskedasticity Tests:* *No Cross Terms (only levels and squares)* *Sample: 1990Q1 2009Q1* *Included observations: 77*		
Component	Skewness	Chi-sq	df	Prob.	Joint test:		
1	-1.054.726	1.427.641	1	0.0002	Chi-sq	df	Prob.
2	0.125790	0.2030651	1	0.6523			
3	-0.184796	0.4382551	1	0.5080	162.6825	144	0.1367
Joint		1.491.773	3	0.0019*			
Component	Kurtosis	Chi-sq	df	Prob.			
1	6.522.132	3.980.070	1	0.0000			
2	1.841.731	4.304.258	1	0.0380			
3	2.326.457	1.455.493	1	0.2276			
Joint		4.556.045	3	0.0000*			
Component	Jarque-Bera	df	Prob.				
1	5.407.711	2	0.0000				
2	4.507.323	2	0.1050				
3	1.893.748	2	0.3880				
Joint	6.047.818	6	0.0000*				

** Rejection of the null hypothesis*

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 financial variables like interest rates were 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: IMF-FSI, 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 FSI reflecting priors that the economic cycle affects financial stress only after a lag.

3.9. 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 $\Sigma = PP'$. 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 $E(w_t w_t') = I$

3.10. USA Model 1 Results using the Kansas City FSI

We test the first model using the KCFSI. Figure 3.1 shows that the Inversed Kansas City Financial Stress Index KCFSI has reached low levels during three separate periods, the 1990-91 recession, the extended period from fall 1998 to fall 2002, and the credit crisis that began in the summer of 2007. The first dip in the KCFSI occurred in December 1990-January 1991, during the late stages of the 1990-91 recession. The constructors of the index point 6 low points within a relatively short time span between the period from October 1998 to October 2002. Not surprisingly, the biggest decreases in the KCFSI have occurred during the current crisis. The first signal from the KCFSI of increased financial stress was in August 2007.

The KCFSI 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. While there is clearly a positive relationship between these KCFSI and GDP, it is not easy to tell whether one variable provides information about future values of the other variable. Thus, each variable is regressed on lagged values of itself and lagged values of the other variable. Not surprisingly, the biggest decreases in the

KCFSI have occurred during the 2007 credit crisis where the financial stability is at its lowest levels. The KCFSI index reached two several low points in 2000 with the September (9/11) attacks on the United States and the Enron scandal. Earlier the KCFSI index had several low points from 1987 until the 1990-91 recession.

The KCFSI and the GDP series have a strong correlation, moving in same directions throughout the period. This positive relationship is especially pronounced in late 2008, when financial stress spiked and the recession deepened. But even before then, however, the two variables show a strong tendency to move in the same directions. Specifically, the contemporaneous correlation between KCFSI and GDP is 0.589 for the period ending in August 2009.

Table 3.18: Correlation Matrix

	KCFSI	*GDP*	*CPI*
KCFSI	1	0.589	-0.098
GDP	0.589	1	-0.157
CPI	-0.098	-0.157	1

One fundamental weakness of the VAR approach to modeling is that it’s a theoretical nature and the large number of parameters involved makes 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.

FIGURE 3.1:KCFSI, GDP, CPI Series in Levels

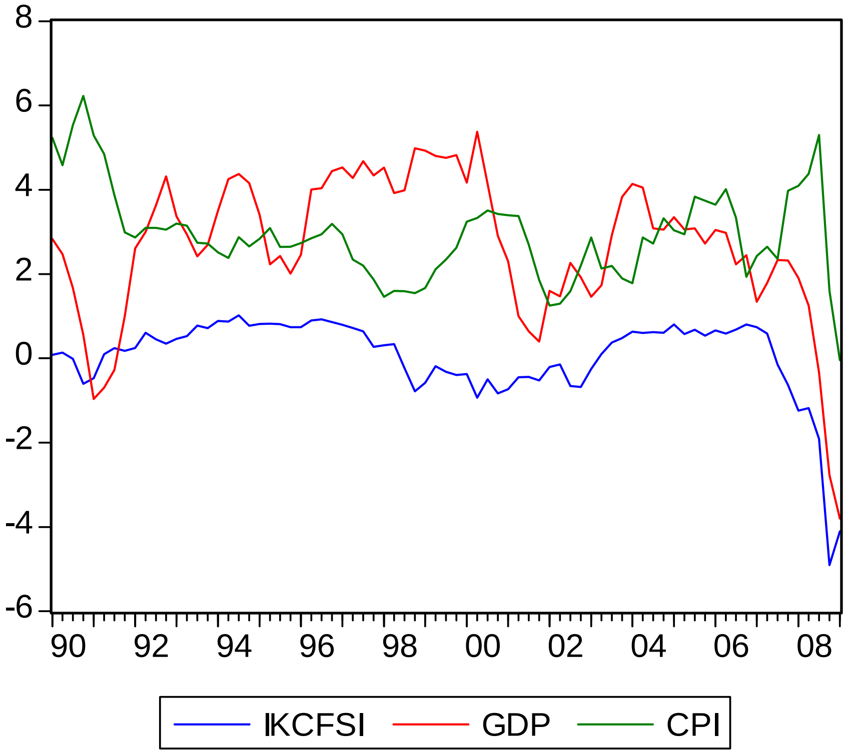
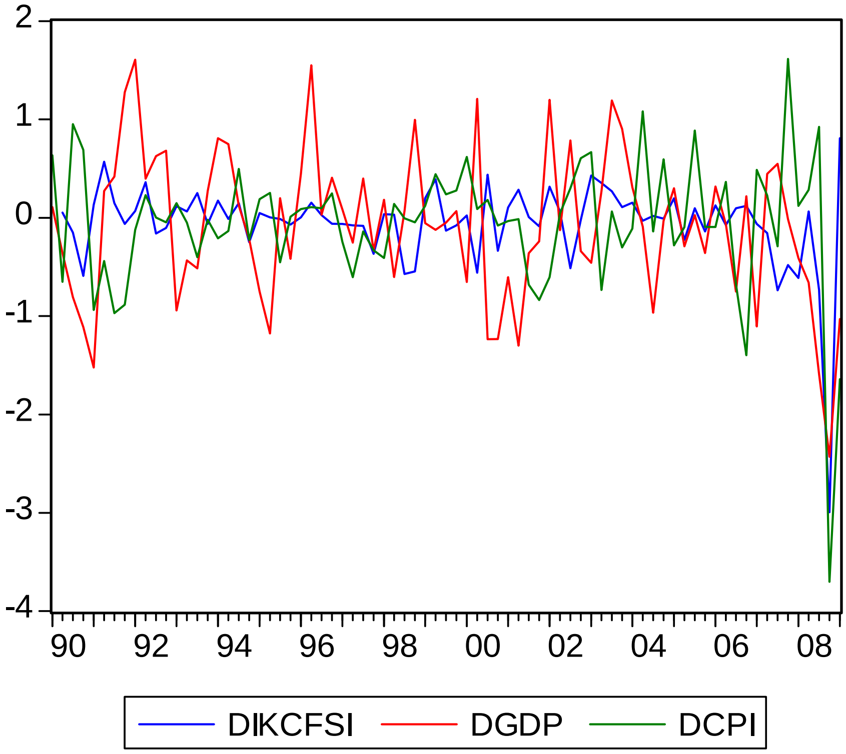


FIGURE 3.2:KCFSI, GDP, CPI Series in 1st difference



3.11. 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 $(LR = (T - p)(\ln|\hat{\Sigma}_r| - \ln|\hat{\Sigma}_u|) \sim \chi^2(mkp))$ 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 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 × 3var) = 15 variables in each equation, implying that we have 62 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 3.19.

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

Table 3.19: USA Model 1, Causality Tests, Marginal significance levels associated with joint F-tests

	Lags of variable		
Dependent variable	*DKCFSI*	*DGDP*	*DCPI*
DKCFSI	0.0151	0.8850	0.0002
DGDP	0.0149	0.0158	0.2467
DCPI	0.4114	0.4207	0.2255

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

Of all the lagged variables in the DKCFSI equation, only the lags of the DKCFSI and the DCPI variables are quite significant at the 5% level. In addition, in the DKCFSI equation the DGDP variable has very low significancy. It appears, however, that lagged values of the DKCFSI variable have explanatory power for some other variables in the system. These results are shown in the first column of table 3.19. The DKCFSI appears to help in explaining variations in the other two variables: DGDP at a significant level of 5% and the DCPI at a significant level of almost 40%.

Table 3.20: VAR(4) 1 model estimation with KCFSI

Vector Autoregression Estimates
Sample (adjusted): 1991Q1 2009Q1
Standard errors in ( ) & t-statistics in [ ]

	DKCFSI	DGDP	DCPI
DKCFSI(-1)	0.272128*	0.350775	0.136852
	(0.13822)	(0.21406)	(0.18838)
	[1.96876]	[1.63870]	[0.72645]
DKCFSI(-2)	-0.240770	0.827724*	-0.093765
	(0.20106)	(0.31137)	(0.27403)
	[-1.19747]	[2.65829]	[-0.34217]
DKCFSI(-3)	0.257350	0.281663	0.069151*
	(0.21093)	(0.32665)	(0.28747)
	[1.22009]	[0.86228]	[0.24055]
DKCFSI(-4)	0.480209*	0.074986*	0.191453
	(0.20409)	(0.31607)	(0.27816)
	[2.35287]	[0.23725]	[0.68828]

DGDP(-1)	0.077840	0.065584	0.172608
	(0.07617)	(0.11795)	(0.10381)
	[1.02198]	[0.55602]	[1.66279]
DGDP(-2)	-0.060709	0.126882	0.159252
	(0.08059)	(0.12480)	(0.10983)
	[-0.75333]	[1.01668]	[1.44995]
DGDP(-3)	0.085406	-0.120458	-0.018127
	(0.08114)	(0.12565)	(0.11058)
	[1.05262]	[-0.95868]	[-0.16393]
DGDP(-4)	0.008593	-0.394263*	0.005487
	(0.07872)	(0.12191)	(0.10729)
	[0.10915]	[-3.23395]	[0.05114]
DCPI(-1)	-0.382839	-0.118632	0.122800
	(0.09180)	(0.14217)	(0.12512)
	[-4.17020]	[-0.83444]	[0.98147]
DCPI(-2)	0.116828	0.156631	0.054565
	(0.11349)	(0.17575)	(0.15468)
	[1.02941]	[0.89119]	[0.35277]
DCPI(-3)	0.100966	-0.157898	0.339401*
	(0.10879)	(0.16848)	(0.14827)
	[0.92808]	[-0.93721]	[2.28906]
DCPI(-4)	-0.026647	-0.361324*	-0.646462*
	(0.10881)	(0.16851)	(0.14830)
	[-0.24489]	[-2.14424]	[-4.35917]
C	-0.047764	-0.003802	-0.052493
	(0.04712)	(0.07298)	(0.06422)
	[-1.01361]	[-0.05210]	[-0.81735]
R-squared	0.377665	0.462985	0.480718
Adj. R-squared	0.251089	0.353761	0.375101
Sum sq. resids	9.065.270	2.174.081	1.683.869
S.E. equation	0.391980	0.607032	0.534230
F-statistic	2.983.688	4.238.878	4.551.531
Log likelihood	-2.756.381	-5.905.448	-4.985.604
Akaike AIC	1.126.773	2.001.513	1.746.001
Schwarz SC	1.537.837	2.412.578	2.157.066
Mean dependent	-0.050370	-0.039339	-0.073963
S.D. dependent	0.452949	0.755119	0.675808
Determinant resid covariance (dof adj.)		0.012786	
Determinant resid covariance		0.007036	

Log likelihood	-1.280.467
Akaike information criterion	4.640.186
Schwarz criterion	5.873.380

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 Table 3.18. As someone may observe, in the IMF-FSI equation only the $KCFSI_{t-1}$ and the $KCFSI_{t-4}$ coefficients are statistically significant. In the GDP equation the coefficients of the $KCFSI_{t-2,}$ $KCFSI_{t-4,}$ GDP_{t-4} CPI_{t-4} variables are statistical significant and in the CPI equation only the coefficients of $KCFSI_{t-3,}$ $CPI_{t-3,}$ 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.

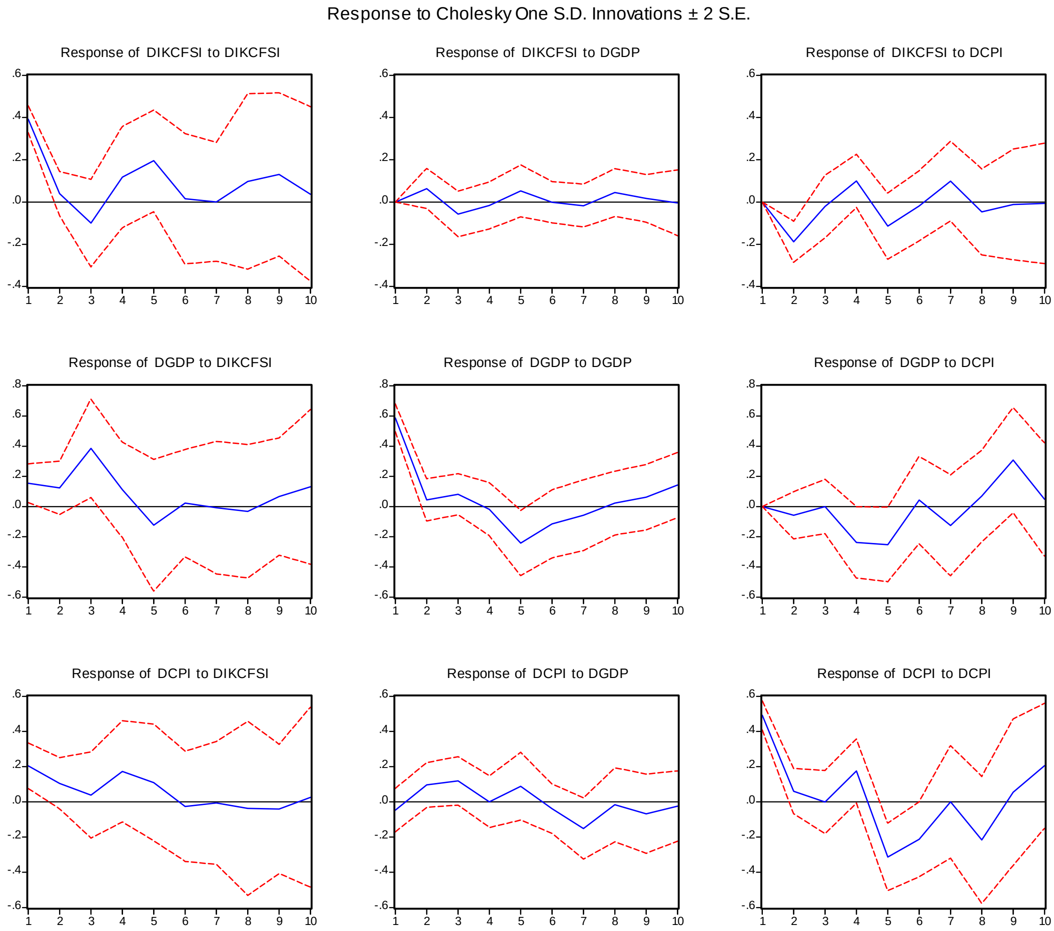
3.12. Description of Impulse Response Functions & Variance Decompositions, USA Case study model 1 using the Kansas City FSI

The variance decompositions and impulse responses for the VAR are given in Figures 3.3 and 3.4, respectively. From the estimated VAR the orthogonalized impulse response functions are performed for 10 period times. The impulse response is the estimated change in DKCFSI following a one-standard-deviation shock to DGDP and to DCPI, based on the VAR model for 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 DKCFSI of 0,2 standard deviation within the first 2 time periods. After that point, the DKCFSI response continues to be negative to the CPI shock until 3 quarters. Thus, an increase of the inflation index induces a decrease in the stability index at short time before it fades out. In addition, the response of DKCFSI to a shock to DGDP is positive but not very significant (up to 0.2 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 KCFSI leads to a positive impact on inflation and to growth for at least 5 time periods. The response GDP is 0.4 deviations after 3 periods and the response of CPI reaches at 0.2 points.

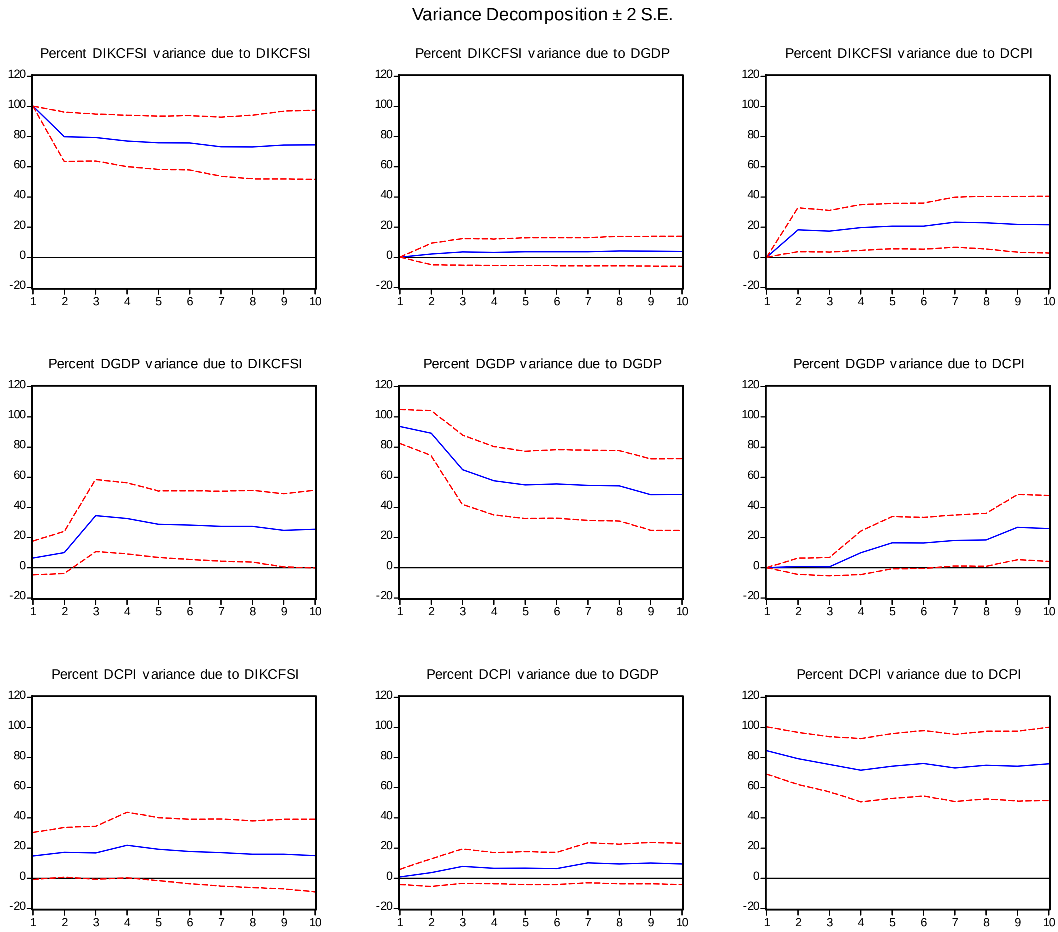
In our empirical analysis we have also included a variance decomposition analysis. Table 3.21, reports the results of the Variance Decomposition of DKCFSI variable which is the main focusing our analysis. Variance decomposition gives as the opportunity to investigate which part of the forecast error variance is caused by which variable. The first panel shows that forecast errors in DKCFSI are mainly duo to itself. The second and the third panel indicate how much of the variation in the DKCFSI 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 25% of the variation in the financial stability. Moreover Figure 3.4 plots the variance decompositions for the three series and Figure 3.5 presents the combined results. Financial stability explains a 30% and a 20% of the variation of the growth and inflation accordingly.

FIGURE 3.3: USA Model 1, Impulse responses for 10 lags



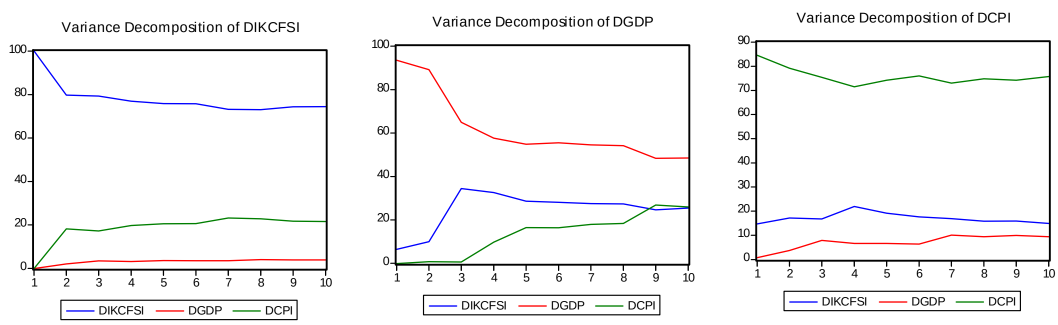
DIKCFSI = Inversed KCFSI in First Difference
DGDP= GDP in First Difference
DCPI= CPI in First Difference

FIGURE 3.4: USA Variance Decompositions



Mode Carlo 100 repetitions

FIGURE 3.5: USA Variance Decomposition Combined Graph: 10 Periods



In first row in Figure 3.4 we present the variance decomposition of the DKCFSI variable due to a shock to the other variables. We can observe that the variance is mainly due to its own shock. It starts from around 80% and falls after 10 quarters to

74%. The DGDP has little to explain in the movement of DKCFSI series as it has a proportion of 5% but the DCPI after first quarter and till the end explains 21% of the DKCFSI movement. The second row presents the variance decomposition of DGDP and the third the variance decomposition of DCPI. That is, little of the movement of the DGDP and DCPI series can be explained by movements other than their own. In Figure 3.5 in the middle we see that at 10th quarter DCPI and DKCFSI explain around 25% each of the DGDP movement which is a high proportion. The DGDP seems particularly influenced by other series shocks. At the same Figure in right we see that DKCFSI explain around 15% and DGDP a 10% of the DCPI movement.

Table 3.21: USA model 1 Variance Decomposition

Variance Decomposition of DIKCFSI:				
Period	*S.E.*	*DIKCFSI*	*DGDP*	*DCPI*
1	0.391980	1.000.000	0.000000	0.000000
2	0.441252	79.75.019	2.080.818	1.816.899
3	0.456425	79.29.595	3.502.687	17.20.137
4	0.482222	77.01.736	3.250.425	19.73.222
5	0.535134	75.84.522	3.610.102	20.54.468
6	0.535662	75.77.940	3.603.196	20.61.740
7	0.544975	73.21.164	3.580.848	23.20.751
8	0.557476	73.03.245	4.082.700	22.88.485
9	0.573002	74.34.122	3.955.450	21.70.333
10	0.574279	74.43.851	3.942.162	21.61.933

Variance Decomposition of DGDP:				
Period	*S.E.*	*DIKCFSI*	*DGDP*	*DCPI*
1	0.607032	6.434.565	93.56.544	0.000000
2	0.623729	10.00.438	89.12.247	0.873144
3	0.737851	34.48.424	64.89.183	0.623936
4	0.783563	32.58.074	57.59.929	9.819.977
5	0.867077	28.67.406	54.84.347	16.48.247
6	0.876006	28.15.444	55.46.595	16.37.961
7	0.886851	27.47.863	54.54.407	17.97.730
8	0.890463	27.39.002	54.16.748	18.44.250
9	0.946190	24.73.462	48.39.447	26.87.092
10	0.966698	25.50.433	48.51.073	25.98.494

3.13. USA Model 2 Results using the IMF- FSI

We test the second model using the IMF FSI. In Figure 3.6 the IMF financial stability index is more intensive than the KCFSI following strongest peaks and valleys as result of grater standard deviations. The IMF FSI and the GDP series, as the KCFSI, have a strong correlation, moving in same directions throughout the period. Specifically, the contemporaneous correlation between IMF-FSI and GDP is -0.52 for the period ending in August 2010. If we want to compare the correlations of the two FSIs we can say that they have the same signs as it is expected. The correlation of the KCFSI and the GDP is 0.58 similar to the IMFFSI. In addition, the Kansas City index proved to be closely related to the CPI with -0.098 instead of -0.05 of the FSI.

Table 3.22: Correlation Matrix

	IMF-FSI	*GDP*	*CPI*
IMF-FSI	1	0.521	-0.005
GDP	0.521	1	-0.157
CPI	-0.005	-0.157	1

FIGURE 3.6:IMF - FSI, GDP, CPI, Series in Levels

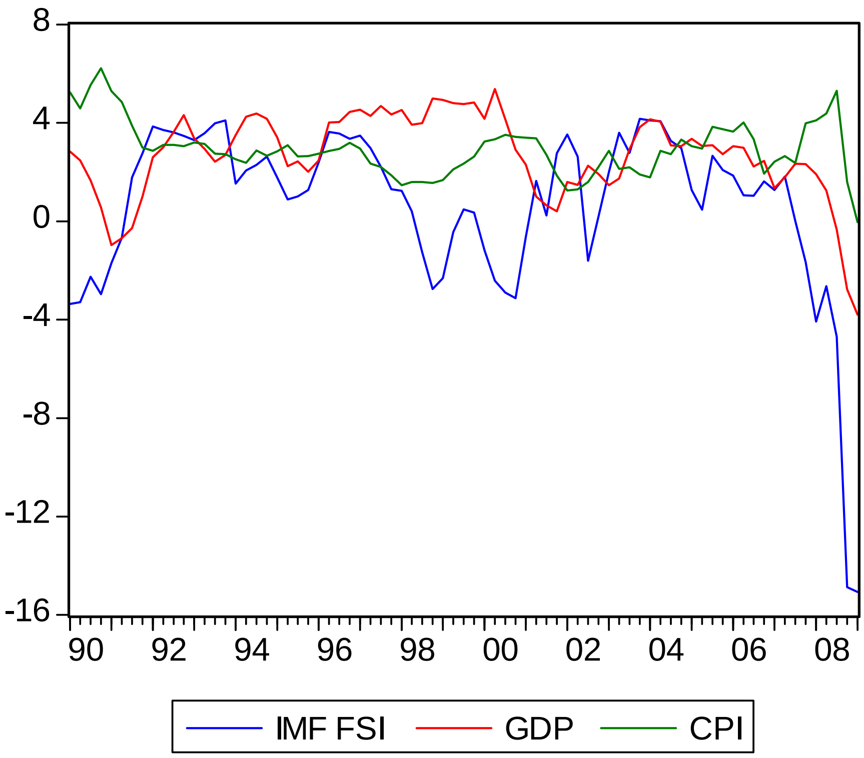
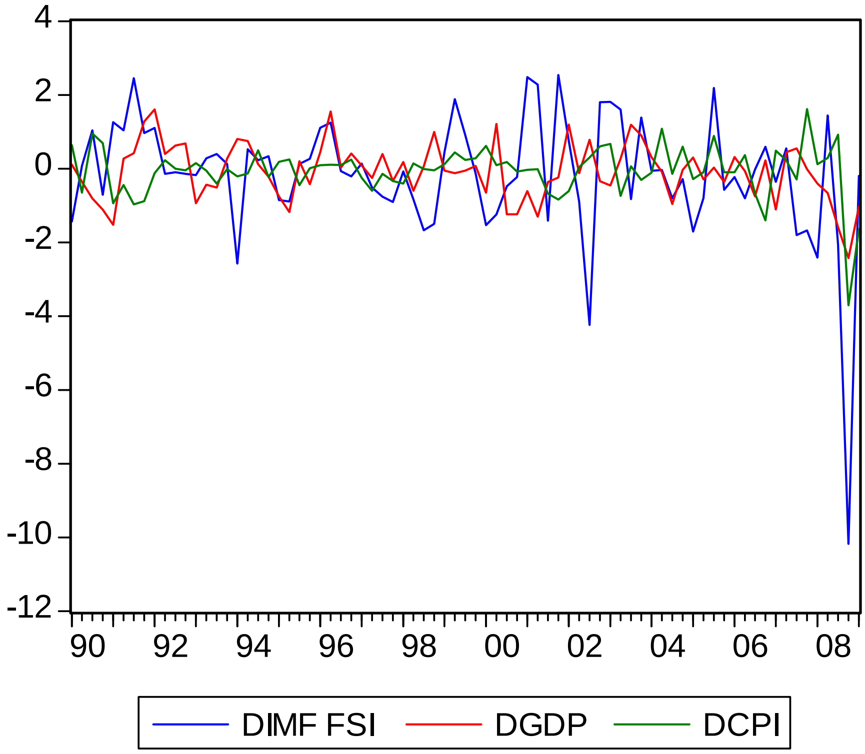


FIGURE 3.7:IMF - FSI, GDP, CPI, Series in 1st difference



IMF FSI = Inversed IMF Financial stress index in levels

DIMF FSI= Inversed IMF Financial stress index in 1st difference

Table 3.23: USA Model 2, Causality Tests, Marginal significance levels associated with joint F-tests

Dependent variable	*Lags of variable* DIMF-FSI	*DGDP*	*DCPI*
DIMF-FSI	0.2079	0.5460	0.1638
DGDP	0.0419	0.0339	0.4269
DCPI	0.4176	0.0854	0.1429

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

Block exogeneity test and the causality test for the case study with the IMFFSI are presented in the above table 3.20. Of all the lagged variables in the DKCFSI equation, we have no lags of variable that are significant at the 5% level. In addition for the DIMF-FSI equation the DIMF-FSI variable is almost significant at the 20% level, the DGDP at 50% level and the DCPI at 16 percent level. It appears, however, that lagged values of the DKCFSI variable have explanatory power for some other variables in the system. These results are shown in the first column of table 3.10. The DKCFSI appears to help in explaining variations of the DGDP at a significant level of 5%.

Table 3.24: VAR(4) model estimation with IMF-FSI

Vector Autoregression Estimates
Sample: 1990Q1 2009Q1
Standard errors in ( ) & t-statistics in [ ]

	DIMF-FSI	DGDP	DCPI
DIMF-FSI(-1)	0.332218*	0.099050	0.030494
	(0.13116)	(0.04988)	(0.04145)
	[2.53293]	[1.98595]	[0.73569]
DIMF-FSI(-2)	-0.226566	0.057001	-0.105093*
	(0.16234)	(0.06173)	(0.05130)
	[-1.39567]	[0.92339]	[-2.04855]
DIMF-FSI(-3)	-0.066813	0.168323*	-0.002844
	(0.16998)	(0.06464)	(0.05372)
	[-0.39307]	[2.60416]	[-0.05294]
DIMF-FSI(-4)	0.264853	0.021347	-0.032440
	(0.17743)	(0.06747)	(0.05607)
	[1.49275]	[0.31640]	[-0.57856]
DGDP(-1)	0.091664*	0.117184	0.165409
	(0.31390)	(0.11937)	(0.09920)
	[0.29201]	[0.98172]	[1.66744]
DGDP(-2)	-0.214640	0.144312	0.216574*
	(0.31686)	(0.12049)	(0.10013)
	[-0.67740]	[1.19771]	[2.16286]
DGDP(-3)	0.321183	-0.005530	-0.056363
	(0.32470)	(0.12347)	(0.10261)
	[0.98916]	[-0.04479]	[-0.54928]
DGDP(-4)	-0.277375	-0.315396*	-0.006020
	(0.31529)	(0.11989)	(0.09964)
	[-0.87975]	[-2.63065]	[-0.06042]
DCPI(-1)	-0.883041*	-0.159719	0.145865
	(0.36043)	(0.13706)	(0.11390)
	[-2.44998]	[-1.16534]	[1.28061]

DCPI(-2)	0.361131	0.019380	-0.040476
	(0.44793)	(0.17033)	(0.14156)
	[0.80622]	[0.11377]	[-0.28594]
DCPI(-3)	-0.079871	-0.161110	0.323008*
	(0.41921)	(0.15941)	(0.13248)
	[-0.19053]	[-1.01066]	[2.43818]
DCPI(-4)	-0.169584	-0.161534	-0.667814*
	(0.43573)	(0.16569)	(0.13770)
	[-0.38920]	[-0.97491]	[-4.84984]
C	-0.148171	-0.054776	-0.033313
	(0.19278)	(0.07331)	(0.06092)
	[-0.76860]	[-0.74721]	[-0.54682]
R-squared	0.204201	0.420959	0.501830
Adj. R-squared	0.054989	0.312389	0.408423
Sum sq. resids	1.777.297	2.570.008	1.774.965
S.E. equation	1.666.441	0.633691	0.526629
F-statistic	1.368.530	3.877.296	5.372.523
Log likelihood	-1.414.619	-6.701.178	-5.276.183
Akaike AIC	4.011.998	2.078.228	1.708.100
Schwarz SC	4.407.705	2.473.935	2.103.807
Mean dependent	-0.170455	-0.084703	-0.060241
S.D. dependent	1.714.240	0.764198	0.684699
Determinant resid covariance (dof adj.)	0.259176		
Determinant resid covariance	0.148821		
Log likelihood	-2.544.318		
Akaike information criterion	7.621.605		
Schwarz criterion	8.808.727		

The VAR estimated coefficients are presented in Table 3.24. As someone may observe, in the IMF-FSI equation the IMF-FSI$_{t-1}$ the GDP$_{t-1}$ and the CPI $_{t-1}$ coefficients are statistically significant. In the GDP equation the coefficients of the IMF-FSI$_{t-3,}$ GDP$_{t-4}$ variables are statistical significant and in the CPI equation only the coefficients of IMF-FSI$_{t-2,}$ CPI$_{t-3,}$ GDP$_{t-2}$ CPI$_{t-4}$ variables are statistical significant. The above results are similar with model's 1 results and indicate that we need an improved VAR model as the impulse responses and the variance decompositions may be questioned.

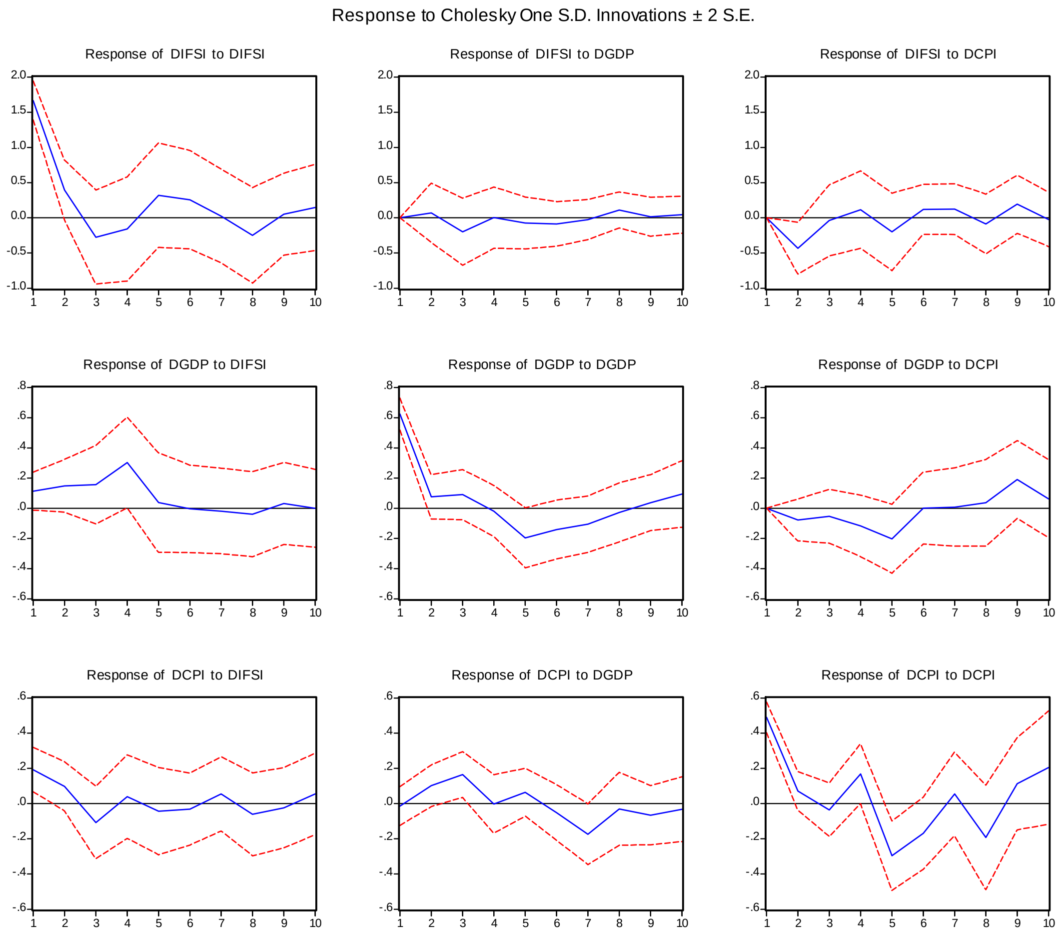
3.14. Impulse Response Functions & Variance Decompositions, USA Case study model 2 using the IMF- FSI

Impulse responses of the model 2 of our analysis are presented in Figure 3.8. The results are seems to be very similar with models 1 impulse responses. A positive shock to Growth indicates a positive response of the IMF-FSI. The difference is that the responses are less intensive than model's one. Further, a positive shock to inflation will have a negative effect in the financial stability conditions. As one may observe in Figure 3.8 one deviation increase in CPI will have a significant negative effect for both our models. As a result, an increase in price levels will deteriorate financial stability conditions.

Accordingly, a positive shock to IMF-FSI has a positive shock to Growth for both case studies. The response of GDP to a positive shock to the financial stability indicator seems to be positive for the first 5 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 interpreting 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.

As we see in Figure 3.8 a positive innovation to IMF-FSI gives a positive innovation to price level for the first 2 periods before it fade out. Although that the responses are not very intensive and the highest point of their standard deviation is up to 0.2 in most cases, we can say that an improvement in financial stability will increase prices for a short period due to the increase of economic activity and the improvement in the investment environment. This increase in inflation will not excess the natural levels.

FIGURE 3.8: Model 2, Impulse responses for 10 lags



DIFSI = Inversed IMF-FSI in First Difference
DGDP= GDP in First Difference
DCPI= CPI in First Difference

FIGURE 3.9: Model 2 USA Variance Decomposition:

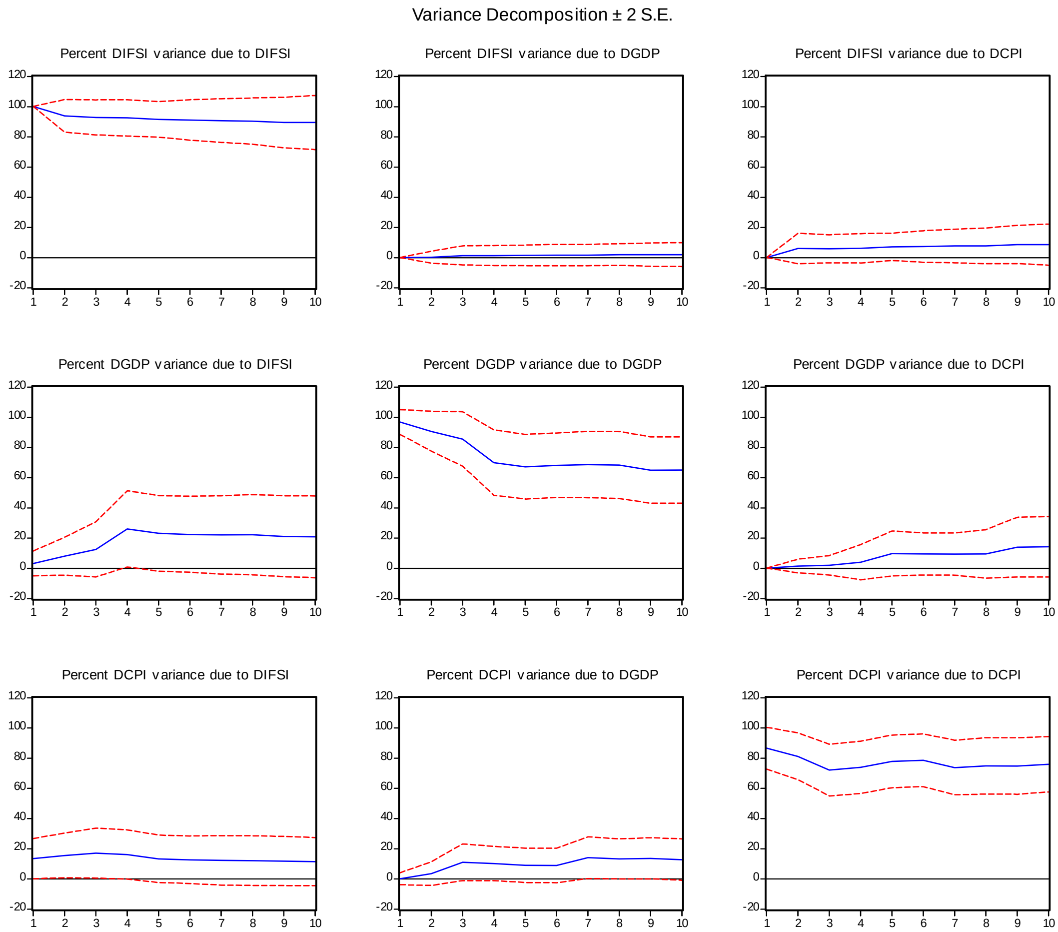
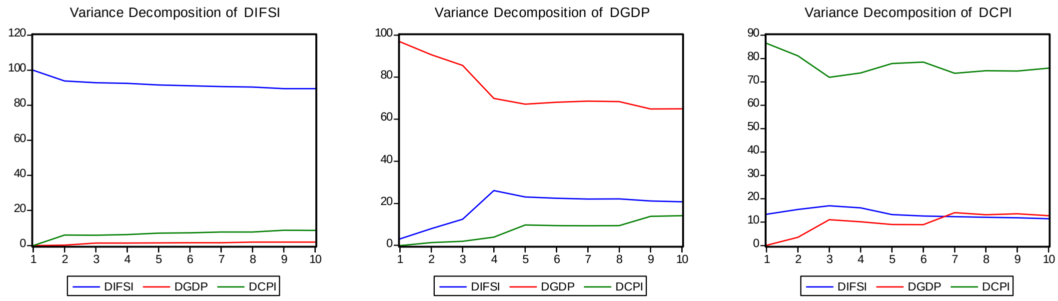


FIGURE 3.10: Model 2 USA Variance Decomposition Combined Graph: 10 Periods



For the purpose of the analysis we have also conducted a variance decomposition analysis in model 2. The variance decompositions of the financial stability variable indicating that at most a 90% of the variation is explained by its own variance while only a pure proportion of the variance of the financial stability (10%) is explained after 10 periods by DGDP and DCPI. Shocks in financial stability and in price levels explain together approximately a 30% to the variance of the growth.

Furthermore, innovations in financial stability and to growth have noteworthy contribution to the variance of inflation. The FSI explains the 10% of the variance in the DCPI after 10 periods while a not significant proportion of the variation of DCPI is accounted for by innovations in DGDP, over 10% after 10 periods. In the end, we have found that financial stability shocks account for only a small proportion of the total variation in the data set.

Table 3.25: Model 2 USA Variance Decomposition

Variance Decomposition of DIMF-FSI:				
Period	*S.E.*	*DIMF-FSI*	*DGDP*	*DCPI*
1	1.666.441	1.000.000	0.000000	0.000000
2	1.767.512	93.85.431	0.155231	5.990.458
3	1.799.946	92.81.921	1.361.859	5.818.935
4	1.810.534	9.2.49.500	1.346.194	6.158.804
5	1.850.955	91.50.596	1.443.396	7.050.649
6	1.874.557	91.09.730	1.620.461	7.282.237
7	1.878.910	90.69.162	1.632.689	7.675.695
8	1.900.639	90.34.909	1.935.407	7.715.500
9	1.911.201	89.42.766	1.920.316	8.652.023
10	1.917.508	89.42.853	1.959.924	8.611.546

Variance Decomposition of DGDP:				
Period	*S.E.*	*DIMF-IFSI*	*DGDP*	*DCPI*
1	0.633691	3.163.766	96.83.623	0.000000
2	0.659633	7.919.398	90.67.347	1.407.128
3	0.685740	12.48.293	85.59.635	1.920.718
4	0.759078	26.09.930	69.92.438	3.976.322
5	0.810730	23.08.762	67.16.265	9.749.732
6	0.823125	22.40.114	68.14.053	9.458.335
7	0.830240	22.07.331	68.62.182	9.304.872
8	0.832442	22.18.446	68.37.603	9.439.513
9	0.855238	21.14.616	64.96.414	13.88.969
10	0.862549	20.78.937	65.04.620	14.16.444

Table 3.26: Cumulative impulse responses -Results of the 2 models

Response of financial stability indicators: KCFSI – IMF FSI
A positive shock to Growth: positive response of FSI
A positive shock to Inflation: negative response of FSI
Responses of GDP and CPI to a positive shock to the financial stability indicator:
GDP Response, positive effect
CPI Response, positive effect

As a conclusion, the impulse responses of USA second model follow similar 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 (higher st. deviations). To shed more light into our analysis we proceeded to variance decompositions (VDCs), which show the percent of the variation in one variable that is explained by the shock in another variable. The result of the variance decompositions is keeping in line with our earlier findings. DCPI explains at most 20% of the variance of DKCFSI while DGDP has only little effect. Although, as expected, the variation in GDP growth 10 quarters ahead is mainly explained by GDP growth itself, Financial stress index and price index explain a significant part of its change. In both models the CPI variation is explained mainly by its own shock with financial stability index and GDP explaining together a 20% of its variation. Furthermore, it is worth mentioning that variance decompositions are similar between the two models with models one slightly explain better the variations. Exception to the similar results is that in model 1 the shock to price index has greater contribution to the variance in the stability indicator than model's 2. These results imply that causality would run from financial stability to growth and inflation. The reverse causal relationship is not refuted but evidence is weaker. Finally, from Table 3.26 we can see that both models indicate that a positive shock to GDP and to CPI give a positive and negative impulse responsive respectively to the FSI for the first quarters until it fade out through time. Also, GDP responds positively to a positive shock to financial stability index meaning that if the financial stability conditions improve this will reinforce economic growth. A positive shock to FSI will induces a positive effect to CPI which is consistent with a positive demand shock. The majority of our results clearly demonstrate that financial stability and growth are positively related and the causality runs from the former to the latter. In addition, financial stability and inflation are negatively related and the causality still runs from the former to the latter. The reverse causal relationships are not refuted, notably in case of model 1, but evidences are weaker.

4. Financial Stability and Policy Measures

The financial sector in the USA has evolved a great deal in recent decades, during which there have been some regulatory changes and the creation of new financial products such as the securitization of loan obligations of various sorts and credit default swaps. Among the most important of the regulatory changes was the Gramm-Leach-Bliley Act in 1999, which repealed the parts of the Glass–Steagall Act which had not already been repealed. This 1999 Act took down barriers to competition between traditional banks, investment banks, and insurance companies, and allowed firms to participate in all three markets in some circumstances. Some believe that this deregulation contributed to the U.S. financial crisis of 2007-2009 and the Global financial crisis of 2008-2009.

According to the theory of too big to fail, certain financial institutions are so large and so interconnected that their failure will be disastrous to an economy. Proponents of this theory believe that these institutions should become recipients of beneficial financial and economic policies from governments or central banks to keep them alive. It is thought that companies that fall into this category take positions that are high-risk, as they are able to leverage these risks based on the policy preference they receive. The term has emerged as prominent in public discourse since the 2007–2010 global financial crisis. Some have argued that the only solution is to break up all large financial institutions and that their risk-taking activities must be limited by law.

4.1. Global Tax on institutions or on Transactions

A financial transaction tax (FTT) is a tax placed on a specific type of financial transaction for a specific purpose. This term has been most commonly associated with the financial sector, as opposed to consumption taxes paid by consumers. However, it is not a taxing of the financial institutions themselves. Instead, it is charged only on the specific transactions that are designated as taxable. If an institution never carries out the taxable transaction, then it will never be taxed on that transaction. Furthermore, if it carries out only one such transaction, then it will only be taxed for that one transaction. As such, this tax is neither a financial activities tax, nor a "bank tax". This clarification is important in discussions about using a financial transaction tax as a tool to selectively discourage excessive speculation without discouraging any other activity (as Keynes originally envisioned it in 1936)

Transaction taxes can be raised on the sale of specific financial assets (such as stock, bonds or futures); can be applied to currency exchange transactions; or can be general taxes levied against a mix of different transactions. A Tobin tax, suggested by Nobel Laureate economist James Tobin, was originally defined as a tax on all spot conversions of one currency into another. The tax is intended to put a penalty on short-term financial round-trip excursions into another currency. James Tobin's purpose in developing his idea of a currency transaction tax was to find a way to manage exchange-rate volatility. In his view, currency exchanges transmit disturbances originating in international financial markets. National economies and national governments are not capable of adjusting to massive movements of funds across the foreign exchanges, without real hardship and without significant sacrifice of the objectives of national economic policy with respect to employment, output, and inflation. European Union leaders urged the IMF to consider a global tax on financial transactions in spite of opposition from the USA and doubts at the IMF itself. A (FTT) on a broad range of financial instruments including stocks, bonds, currencies and derivatives.

Instead of the financial transaction tax a financial stability contribution (FSC), or "Bank tax" is also proposed. A bank tax is a proposed tax on banks. One of the earliest modern uses of the term "bank tax" occurred in the context of the financial crisis of 2007–2010. Recently, the IMF proposed the idea of a "financial stability contribution" (FSC), which many media have referred to as a "bank tax." It was proposed as one of three possible options to deal with the crisis. FSC, a tax on financial institutions' balance sheets (most probably on their liabilities or possibly on their assets) whose proceeds would most likely be used to create an insurance fund to bail them out in any future crisis rather than making taxpayers pay for bailouts. Much of the IMF's report is devoted to the option of a levy on all major financial institutions balance sheets. Initially it could be imposed at a flat rate and later it could be refined so that the institutions with the most risky portfolios would pay more than those who took on fewer risks. Furthermore, a Financial Activities Tax or "FAT" has been proposed on bank profits and bankers' excessive remuneration packages with the proceeds going into general government revenues.

4.2. The Role of the Rating Agencies and the need for supervision

Credit rating agencies played a very important role at various stages in the subprime crisis. They have been highly criticized for understating the risk involved with new, complex securities that fueled the United States housing bubble, such as mortgage-backed securities (MBS) and collateralized debt obligations (CDO). These investments are subsequently collapsed, causing the economy to the brink of collapse. The three credit rating agencies were key enablers of the financial meltdown. The mortgage-related securities at the heart of the crisis could not have been marketed and sold without their seal of approval. Investors relied on them, often blindly. In some cases, they were obligated to use them, or regulatory capital standards were hinged on them. This crisis could not have happened without the rating agencies. Their ratings helped the market soar and their downgrades through 2007 and 2008 wreaked havoc across markets and firms.

Critics claim that conflicts of interest were involved, as rating agencies are paid by the firms that organize and sell the debt to investors, such as investment banks. There is an inherent conflict of interest when a professional firm is also publicly-traded, as the pressure to grow and increase profits is relatively stronger, which may detract from the quality of work performed. Moody's became a public firm in 2001, while Standard & Poor's is part of the publicly-traded McGraw-Hill Companies.

A stronger regulatory framework is now awaiting the rating agencies, since the U.S. Securities and Exchange Commission recommend stricter regulation in the industry, who has harshly criticized that, sparked the recent financial crisis. The Securities and Exchange Commission proposed new rules, which provide more rigorous internal controls to rating agencies, rein in conflicts of interest and periodic monitoring of working skills in these companies.

4.3. Institutional reforms and proposals

Institutions like the financial stability Board (FSB) and Basel Committee on Banking Supervision are focused on safeguarding financial stability and propose the necessary reforms. 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. It brings together national authorities responsible for financial stability in significant international financial centres, international financial institutions, sector-specific international groupings of regulators and supervisors, and committees of central bank experts. The FSB was established in April 2009 as the successor to the Financial Stability Forum (FSF). 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.

The FSB moves towards to bolstering the resilience of the international financial system is a broad project encompassing a considerable number of related measures. This crisis has highlighted the moral hazard risks posed by institutions that have become too big to fail or that, by their interconnected nature, are too complex to resolve. Notwithstanding the actions above to strengthen capital and liquidity, additional steps are needed to reduce the moral hazard risks and economic damage associated with institutions that are “too big to fail”.

1. Strengthening the global capital framework
2. Making global liquidity more robust
3. Reducing the moral hazard posed by systemically important institutions
4. Strengthening accounting standards
5. Improving compensation practices
6. Expanding oversight of the financial system
7. Strengthening the robustness of the OTC derivatives market
8. Re-launching securitisation on a sound basis
9. Adherence to international standards

Therefore, a new regulatory structure for the financial system is starting to take shape, with a number of legislative proposals already tabled. Credit-rating agencies should be stripped of their public franchise. Hedge funds contributed to the financial crisis in any manner, the idea that they should be subject to regulation, and even prudential supervision like banks. Create a regulatory structure for large banks and other financial institutions that is based on misleading concepts of systemic risk and systemic instability and is likely to augment moral hazard and the potential liabilities for taxpayers in countries hosting large financial centres. Some policy-makers and commentators consider that the only feasible solution to tackle moral hazard and the 'too-big-to-fail' problem is to cut down by decree all large financial organisations to a size that no longer threatens systemic stability, or legally separate commercial and investment banking, or make illegal proprietary trading by deposit banks. A financial system in which all the big financial institutions are guaranteed by the government entails massive moral hazard and is inherently unstable, since the fundamental check on reckless behaviour by bankers and financiers, the danger of going bankrupt, would be eliminated. An effective system to manage banking crises must possess two features: it must be able to keep depositors safe, as well as reassure counterparties in the normal running of business on the continuity of basic functions – of systemic relevance – of the failing financial institution.

The recent financial crisis made evident the absence or inadequate scope of resolution tools to deal with failing financial institutions across the globe. Authorities were often confined to two alternatives:

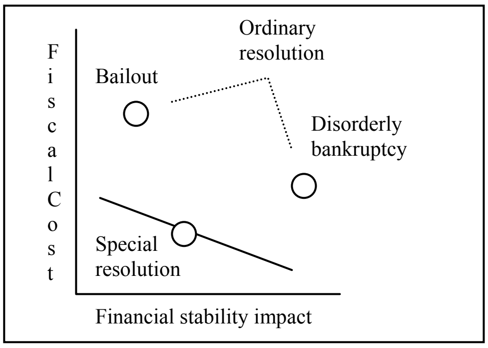
1. corporate bankruptcy
2. an injection of public funds

Events have shown that both these options can be very costly. A disorderly bankruptcy can magnify the systemic impacts of the failure of a financial institution. When the authorities aim to avoid these impacts by injecting capital to support the institution, an open-ended commitment has been shown to require large fiscal outlays. A special resolution regime would allow authorities to avoid the choice between "disorderly bankruptcy" and "injection of public funds", thus improving efficiency by containing both fiscal costs and systemic impact.

A consensus is beginning to emerge about the features that a special resolution framework should comprise. In particular, sound practice is for the framework to

1. allow the banking authorities to take control of the financial institution at an early stage of its financial difficulties through “official administration”,
2. empower the authorities to use a wide range of tools to deal with a failing financial institution, without the consent of shareholders or creditors,
3. establish an effective and specialised framework for liquidation of the institution that assigns a central role to the authorities and effectively protects depositors,
4. ensure clarity as to the objectives of the regime, including preserving financial stability, and the scope of judicial review,
5. promote information sharing and coordination among all authorities involved in supervision and resolution.

Figure 4.1. Fiscal cost and systemic impact in resolution regimes, Source: Čihák & Nier (2009).



5. Conclusions

Over the past decade, safeguarding financial stability has become an increasingly dominant objective in economic policymaking. This is illustrated by the periodic Financial Stability Reports that have been launched by more than a dozen central banks and several international financial institutions (including the IMF, the Bank for International Settlements (BIS), and the World Bank), as well as by the more prominent place given to financial stability in many of these institutions, organizational structures and mandates.

The first part of the present Thesis is consisted by the literature review on financial stability while the second part encloses the empirical analysis. The last part is consisted with the appropriate policy measures on financial stability. 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. In our empirical analysis we used a VAR model with three proxies variables that allows the investigation of the financial stability effects to economic activity, to price levels and vice versa. Our principal objective was to search for evidence of the relation of financial stability with the key macroeconomic variables. As a financial stability measure we tested two different financial stress indexes. We used quarterly time series over a 20 year period for a single country.

Our analysis has important policy implications, and sheds some additional light on the existence or not of a trade-off between growth, monetary stability and financial stability. In overall, the results imply that in both cases financial stability seems to be positive affected after an improvement in financial conditions while is negative affected by an increase in the price level. Additionally, 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. Both models suggest the importance of the financial stability and its effect on the real economy. The VAR analysis performed in this study reveals some interesting findings regarding the dynamic interaction between financial stability, growth and monetary stability. In terms of causality, IRFs and VDCs show that in most cases financial stability leads to higher growth and inflation. The reverse causal relationship is not refuted, notably in the case of growth, but evidence is weaker. Most IRFs show that causality runs from financial stability to growth and inflation, which share a positive relationship, though the reverse causality can not be excluded. Assuming FSIs as measure of financial stability, we find evidence that a trade-off between efficiency and financial stability may exist even if it is weak. This finding has significant implications for regulators and supervisors, whose task is to establish a secure as well as an efficient financial system. A prudent policy advice would request from banks, in particular those with a low distance to default, to intensify efforts to lower exposure to risky activities. Even though this thesis provides important information on financial stability, a number of issues are still open and require further research. The low intensity of the impulse responses and the low contributions of the two key variables 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.

The last part of the thesis is consisting by the necessary policy measures that need to be taken in order the financial stability to be safeguarded and secured. The deregulation of the financial system brought to surface moral hazard problems and banks that are too big to fail. In the present financial crisis the policy maker had to decide between two alternative options that were either highly costly, corporate bankruptcy or an injection of public funds. Furthermore, is necessary an assessment of the rating agencies at the present crisis and their inability for accurate ratings. The discussion for a global transaction or a bank tax in order to moderate financial fluctuations and speculation is still open. Finally, institutions like the financial stability Board (FSB) and Basel Committee on Banking Supervision, are focused on safeguarding financial stability and propose the necessary reforms moving toward establishing a new more restrict framework without localize financials system efficiency.

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