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"Systemic stress, interbank market and real economy: a Panel VAR analysis"

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Abstract

This thesis wants to investigate the impact of systemic risk, measured through an innovative financial stress indicator, on the interbank markets and real economies of some Euro Area countries in a Panel VAR framework.

Key words: Panel VAR, interbank market, GMM estimation, CISS, Industrial Production.

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Introduction

The consequences of the global financial and economic crisis have prompted in-depth researches on how to identify, measure and mitigate systemic risk which is defined as "the risk that the financial system, or part of it, may become so impaired that severe negative consequences on the overall economic activity would be inevitable" (Di Cesare & Rogantini Picco, 2018). This kind of risk is by nature multi-pronged and, so, it is complex to catch in a unique and concise framework (Hansen, 2013). The European Central Bank, in order to develop tools which are able to monitor the financial stress levels, has introduced the Composite Indicator of Systemic Stress (CISS) which has been successively developed by Hollo et al. (2012). Taking into consideration other financial stress indices, the major novelty of the CISS is that the aggregation procedure of the sub-indices, which shape the final index, is obtained following the standard portfolio theory that uses time-varying cross-correlations to weigh the assets constituting a portfolio. By doing so, more weight is given to situations in which the financial strains are materialized across different segments in the financial markets.

We are going to use this financial stress index in order to empirically analyze the impact of a shock in systemic stress to the interbank markets of some Euro Area countries (Italy, Spain, Germany and France). We do so since the interbank market is of fundamental importance for the proper functioning of the financial system. Moreover, the interbank market has an important impact on the real economy through the bank lending channel. To analyze that impact, we are going to use a Risk Assessment Indicator provided by the European Central Bank as a proxy for the interbank market activity. In addition to that, we are going to measure the impact of the CISS to the real economies using as a proxy of that variable the Industrial Production Indices of the different countries taken into consideration in our model.

In order to perform the analysis we have constructed a Panel VAR model using the Generalized Method of Moments (GMM) estimator. The model is estimated recursively since this estimation strategy allows us to identify the marginal effects of the additional data included in each time window.

Our results suggest that an increase in systemic stress has, as expected, a negative impact on the interbank market activity and that there is a short-term contraction effect on the real activities of the Euro Area countries taken into consideration in our analysis.

The remainder of the paper is organised as follows. In Chapter 1, we describe the functioning of the interbanks market taking into account the potential intervention of the central banks in substituting the important activity carried out by those markets; we also present an overview of the financial stress indicator used in our analysis. In Chapter 2, we overview the characteristics of the Panel VAR models and present the estimator used in order to perform our analysis. In Chapter 3, we describe the key features of our data set, the econometric strategy and the main results of our study.

Chapter 1

Interbank Market and Systemic Stress

In this Chapter, we are going to talk about the functioning of the interbank markets and of the intervention of the European Central Bank on the functioning of the overnight unsecured interbank market; after that, we are going to introduce and explain the Composite Indicator of Systemic Stress used as financial stress indicator in our analysis.

1.1 The Interbank Market

Interbank markets are among the most important in the financial system. They allow liquidity to be readily transferred from banks with a surplus to banks with a deficit. They are the focus of central banks' implementation of monetary policy and have a significant effect on the whole economy (Allen, Carletti, & Gale, 2009). Under normal circumstances the interbank markets, especially the short term ones, work rather well. On occasion, however, such as in the crisis that started in the summer of 2007, interbank markets stop functioning well inducing central banks to intervene massively in order to try to restore normal conditions (Allen et al., 2009).

The European interbank market dried up on August 9 2007 when BNP-Paribas decided to renege capital redemptions by investors from two of its investment vehicles that were exposed to the U.S. sub-prime mortgage market (Ippolito, Peydró, Polo, & Sette, 2016). The events of August 2007 represented an unexpected shock to wholesale markets for liquidity, as discussed by several authors ((Brunnermeier, 2009); (Gorton, 2012); (Rajan, 2011); among others). As the financial crisis deepened in September 2008, liquidity in the interbank market has further dried up as banks preferred hoarding cash instead of lending it out even at short maturities (Heider, Hoerova, & Holthausen, 2009). The failure of the interbank market to redistribute liquidity has become a key feature of the 2007-09 crisis (Brunnermeier, 2009). Moreover, the tensions in the interbank market in August 2007 implied consequences in terms of lending to the real sectors:

banks that were more exposed to the interbank market reduced their supply of credit to new applicants (Ippolito et al., 2016).

Figure 1.1 illustrates the unprecedented extent of the turbulence.

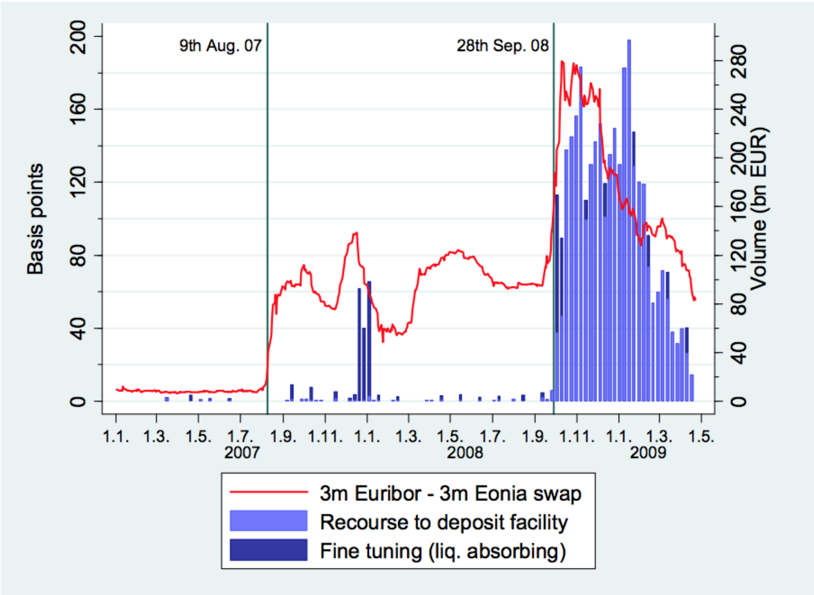

Figure 1.1: Interbank spread and excess reserves[1], 2007m1-2009m4.

It plots:

- the red line which is the spread between the three-month unsecured rate and the overnight index swap in three months' time[2]; it is a standard measure of interbank market tension;
- the light and dark blue bars which are the amounts of excess reserves banks hold with the European Central Bank[3].

A notable feature is the build up of tensions in the interbank market.
Until August 9, 2007, the unsecured euro interbank market is characterized by a very low spread (around five basis points) and negligible amount of excess reserves with the European Central Bank. In "normal" times, banks prefer to lend out excess cash due to the fact that the interest

[1]Source: (Heider et al., 2009). In addition to the interbank spread, the figure shows the recourses to the ECB deposits and liquidity-absorbing fine tuning operations.

[2]The overnight index swap is a measure of what the market expects the overnight unsecured rate to be over a three-months period and, so, controls for interest rate expectations (Heider et al., 2009).

[3]Banks can hold excess reserves with the European Central Bank in two ways. First, they can access the deposit facility, which is a standing facility available for banks on a continuous basis for overnight deposits (these are remunerated at a negative rate). Second, the European Central Bank occasionally offers banks to deposit funds for a short period of time at the policy rate (liquidity-absorbing fine tuning operations) (Heider et al., 2009).

rate on excess reserves is punitive relative to rates available in interbank markets (Heider et al., 2009).
The "turmoil" phase between August 9, 2007 and the last week of September 2008 is characterized by a significantly higher spread, yet excess reserves remain virtually zero (Heider et al., 2009).
From September 28, 2008, the spread increases even more to the peak of 186 basis points. But, the distinctive feature of this "crisis" phase is a dramatic increase in excess reserves: banks are hoarding liquidity. At the same time, the average daily volume in the overnight unsecured interbank market cut by half (Heider et al., 2009).

After the failure of Lehman Brothers in 2008, the increase in the interbank spread was followed by the drying up of the wholesale funding markets: the behaviour of those kind of markets was severely undermined by increased counterparty risk and a shortage of high-quality collateral (De Haan, van den End, & Vermeulen, 2017). From 2011 onward, when the sovereign debt crisis followed the financial one, banks in peripheral euro area countries even faced an accelerating outflow of retail funding[4]. Those funding strains forced banks to adjust their balance sheet in several ways: by reducing maturity mismatches, switching to alternative sources of funding and by deleveraging (De Haan et al., 2017). This activated the so-called liquidity channel of financial transmission through which funding liquidity shocks are propagated to bank lending and the real economy (Foglia et al., 2011).
The Eurosystem has responded to banks' funding strains by various measures: refinancing operations have been extended in terms of maturity, size and conditions; this allowed banks to obtain liquidity from the central bank at fixed rate at full allotment[5] (De Haan et al., 2017). By doing this, the Eurosystem took over part of banks' intermediation function through the money market.

Garcia-de-Andoain et al. (2016) had investigated the "impact of ample liquidity provision by the European Central Bank on the functioning of the overnight unsecured interbank market from 2008 to 2014". They argued that the "European Central Bank acted as a de-facto lender-of-last-resort to the euro area banking system" (Garcia-de Andoain et al., 2016). The task of a lender-of-last-resort is to provide liquidity to the banking system in case of a systemic liquidity crisis. The operational framework of the ECB and the European System of Central Banks does not contain any official reference to the lender-of-last-resort function (Garcia-de Andoain et al., 2016). However, Garcia-de-Andoain et al. (2016) assert that "by providing unlimited liquidity

[4]Usually, it is one of the most stable funding sources.
[5]In particular, the two very long-term refinancing operations (VLTROs) of the end-2011 and early 2012 have alleviated the funding stress.

against a good collateral, and arguably at a penalty rate, since October 2008, the European Central Bank acted as a de-facto lender-of-last-resort[6] for the whole banking system of the euro area".

The authors (Garcia-de Andoain et al., 2016) identified three main effects of central bank liquidity provision on the interbank markets. According to them, the central bank liquidity:

- replaced the demand for reserves in the overnight unsecured interbank market, especially during the financial crisis (2008-2010); the ECB assumed the liquidity provision role of the interbank market; given that the interbank markets came under severe stress due to the repercussion of the Lehman bankruptcy, the ECB indeed acted as a lender-of-last-resort to the euro area banking system;

- not only replaced the interbank market, it also stimulated the supply of liquidity, especially to banks located in stressed countries (Greece, Spain and Italy) during the European sovereign debt crisis (2011-2013); reinsuring the banking system, therefore, can have important extra benefits as it can stimulate bank lending (at least in interbank markets);

- have been able to counteract the capital flow reversal which took place during the sovereign debt crisis when interbank markets became fragmented along national lines.

The results achieved by the authors conclude that when there is more central bank liquidity, there is less trading in the interbank market (Garcia-de Andoain et al., 2016). Also, they found that the impact of an increase in central bank liquidity provision on the functioning of the German interbank market is similar to the interbank market of the entire euro area[7].
Italy presented an interesting case of a normally non-stressed interbank market that became stressed during the sovereign debt crisis: more central bank liquidity led to a lower volume of interbank loans (Garcia-de Andoain et al., 2016).
Finally, they found that the Spanish interbank market was stressed already during the financial crisis stage and before the intensification of the sovereign debt crisis.

Several studies have also analyzed the possible malfunctioning of the interbank markets during periods of stress. Freixas and Holthausen (2004) have theoretically studied interbank markets in an international context finding that cross-border interbank trade can break down due to imperfect information that lenders have about borrowers from abroad. Heider et al. (2009) studied (from a theoretical point of view) the effect of asymmetric information and counterparty credit

[6]Such de-facto "lender-of-last-resort" to the banking system impacts the unsecured overnight interbank market which is the place where banks trade central bank liquidity (reserves).
[7]This is due to the fact that the large fraction of interbank activity in the euro area occurs in Germany.

risk on the functioning of the interbank market showing that, when information asymmetry about counterparty risk is large, interbank market trade can brake down due to a withdrawal of supply and banks hoard liquidity to self-insure against liquidity shocks.

Other authors have conducted empirical studies to analyze the impact of recent financial crisis on certain domestic interbank markets. For instance, Afonso et al. (2011) have studied the unsecured overnight market in the U.S. and have showed that market activity shrinks[8] considerably after the bankruptcy of Lehman Brothers but it does not collapse completely. Brunetti et al. (2010) examined whether central bank interventions improved liquidity in the interbank market. They concluded that public injections of liquidity increases overall uncertainty as measured by higher market volatility and higher spreads[9].

1.2 The Composite Indicator of Systemic Stress - CISS

The consequences of the global financial and economic crisis have prompted in-depth researches on how to identify, quantify and mitigate systemic risk: the risk that the financial system, or part of it, may become so impaired that severe negative consequences on the overall economic activity would be inevitable (Di Cesare & Rogantini Picco, 2018). This kind of risk is by nature multi-pronged and, so, it is complex to catch in a unique and concise framework (Hansen, 2013). Due to the multifaceted nature of systemic risk, an heterogeneous literature has been proposed in the past years which includes different systemic risk indicators.

An indicator of systemic stress (or systemic risk) should measure level of stress in the financial system as a whole. However, in the real world, the financial system is very complex since it is present an intricate system of financial markets, financial intermediaries and financial infrastructures that have an essential role for the solidity of the whole financial system (Hollo et al., 2012).
So, since it is quite impossible to measure the level of stress in the all parts of the financial system, it seem appropriate to focus on the ingredients of the financial system which have a systemic importance. In order to select the individual indicators for financial stress, we start from the basic structure for the construction of financial stress indices proposed by Hollo et al. (2012) represented in figure 1.2.

[8] The shrinking appears to be caused mostly by a withdrawal of supply (Afonso et al., 2011).
[9] According to the authors, asymmetric information is not mitigated by ECB interventions (Brunetti et al., 2010).

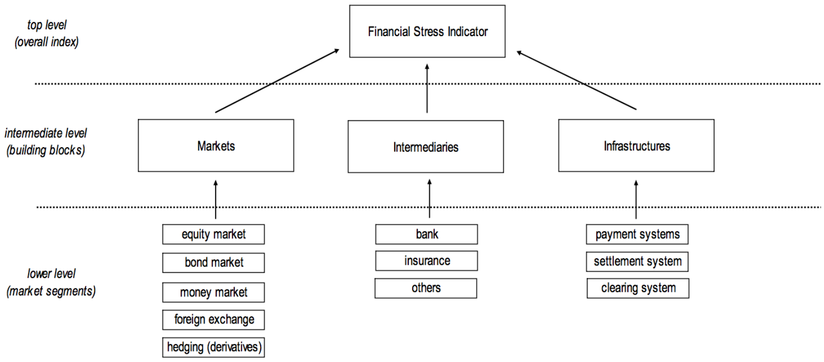

Figure 1.2: Structure for the construction of financial stress indices[10].

As shown in figure 1.2, the financial system can be divided into three main building blocks: markets, intermediaries and infrastructures. Each of these building blocks can be divide into precise segments[11] which, successively, can be in addition disaggregated into individual financial instrument, subsectors or subinfrastructures, according to the building block to which they belong (Hollo et al., 2012).
According to figure 1.2, there are three principal levels at which composite financial stress indexes can be estimated taking into account a particular group of specific stress indicators:

- the lower level[12] (market segments) which can be calculated by aggregating a representative set of constituent individual stress indicators;
- the intermediate level[13] (building blocks) which can be calculated by aggregating the lower-level stress indices;
- the top level[14] (overall index) which includes all the elements present in the lower level building blocks and market segments.

Even so, all the existing financial stress indexes do not have a structure that is as extensive as the structure represented in figure 1.2; this is due to data limitations, in particular, in the building block infrastructures.

In the next subsections, we are going to introduce the financial stress index that we have used

[10]Source: (Hollo et al., 2012).
[11]For example, the intermediaries building block can be divided into different market sectors such as banks, insurance companies, hedge funds and so on.
[12]It comprises segment-specific stress indices.
[13]It comprises stress indices for each of the three building blocks.
[14]It represents the composite financial stress indicator for the whole financial system.

for our analysis. It is a new indicator of contemporaneous stress in the financial system named Composite Indicator of Systemic Stress (CISS) proposed by Hollo et al. (2012).
The main distinctive characteristic of the CISS, in comparison to alternative Financial Stress Indexes, is its focus on the systemic dimension of financial stress. This is obtained by a specif design which is shaped according to standard definitions of systemic risk (Hollo et al., 2012).
We will present the main features of this indicator and we will focus on the analytical aspects.

1.2.1 General description

The Composite Indicator of Systemic Stress (CISS) is introduced by the European Central Bank ((ECB, 2010); (ECB, 2011)) and then carefully explained by Hollo et al. (2012). The Euro Area CISS is present in the set of analytical instruments used by the European Central Bank to support its macroprudential functions (Di Cesare & Rogantini Picco, 2018).

The CISS aims to "measure the current state of instability in the financial system as a whole or, equivalently, the level of systemic stress" (Hollo et al., 2012). The systemic stress has to interpreted as the amount of systemic risk already materialised. The systemic risk is the risk that the financial instability is so pervasive that undermine the functioning of the financial system with several consequences on the real economy ((De Bandt & Hartmann, 2000); (De Bandt, Hartmann, & Peydró, 2009))[15].
As explained by ECB (2011), the systemic risk has two different perspectives:

- the "horizontal perspective" where the attention is confined to the financial system;
- the "vertical perspective" in which the interactions between the financial system and the real economy are taken into account.

Basically, "the severity of systemic risk and systemic events would be assessed by means of the effect that they have on consumption, investment and growth or economic welfare broadly speaking" (ECB, 2009).

In this context, the CISS is developed in order to satisfy both perspective: to implement the idea of widespread financial instability (horizontal perspective) and to grasp the relevance of financial stress for the real sector (vertical perspective). Both conditions can be related to the notion of systemic importance (Hollo et al., 2012).

[15] Systemic risk is defined as "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy" (IMF, BIS, & FSB, 2009).

The CISS is a coincident indicator that is built up through a process of aggregation (Di Cesare & Rogantini Picco, 2018).

That index takes into account five categories within the financial system which are supposed to represent the core of the financial system:

- the money market;
- the bond market;
- the equity market;
- the financial intermediaries' sector;
- the foreign exchange market.

After that those five segment-specific subindices are computed, they are aggregated in order to have the final composite stress index (Hollo et al., 2012).

1.2.2 Technical description

As just said in the previous subsection, the CISS results from the aggregation of five sub-indices. Each sub-index (Market Segment), in the same way, comes from the aggregation of three raw indicators (Stress Factors) of different market segment as reported in table 1.1[16].

In order to obtain a sub-index which is unit-free and measured on an ordinal scale, an empirical cumulative distribution function is calculated by using order statistics (Hollo et al., 2012). Given the vector of n observations of the raw indicator $x_t = (x_{1,t},...,x_{n,t})$, the respective ordered sample is $(x_{[1],t},...,x_{[n],t})$, where $x_{[n],t}$ is the sample maximum. The empirical cumulative distribution is then calculated as:

$$z_t = F_n(x_t) = \begin{cases} r/n\ , & \text{for} \quad x_{[r]} \leq x_t < x_{[r+1]}, \qquad r = 1,2,...,n-1 \\ 1, & \text{for} \quad x_t \geq x_{[n]} \end{cases} \tag{1.1}$$

In the case of two or more equal observations, the average of the rankings of the equal observations is taken.

[16]For further information on the Stress Factors presented in table 1.1 please refer to (Hollo et al., 2012).
[17]CMAX measures the maximum cumulated loss over a moving two-year window.

Market Segments	Stress Factors
1. Money market	- Realised volatility of the 3-month Euribor rate; - Interest rate spread between 3-month Euribor and 3-month French T-bills; - Monetary Financial Institution's (MFI) emergency lending at Eurosystem central bank.
2. Bond market	- Realised volatility of the German 10-year benchmark government bond index; - Yield spread between A-rated non-financial corporations and government bonds (7-year maturity bracket); - 10-year interest rate swap spread.
3. Equity market	- Realised volatility of the Datastram non-financial sector stock market index; - CMAX[17]for the Datastream non-financial sector stock market index. - Stock-bond correlation ;
4. Financial intermediaries	- Realised volatility of the idiosyncratic equity return of the Datastream bank sector stock market index over the total market index; - Yield spread between A-rated financial and non-financial corporations (7-year maturity); - CMAX as defined above interacted with the inverse price-book ratio (book-price ratio) for the financial sector equity market index.
5. Foreign exchange market	- Realised volatility of the euro exchange rate vis-a-vis the US dollar; - Realised volatility of the euro exchange rate vis-a-vis the Japanese Yen; - Realised volatility of the euro exchange rate vis-a-vis the British Pound.

Table 1.1: Individual financial stress indicators included in the CISS. Source: (Hollo et al., 2012).

The empirical cumulative distribution provides a transformation that projects raw stress indicators into variables which are unit-free and measured on an ordinal scale in the half-open interval $(0,1]$ (Hollo et al., 2012). In addition, the empirical cumulative distribution can be calculated for a bigger sample of $n+T$ observations by simply substituting n with $n+T$ in equation 1.1.

So, now, we have 15 stress factors systematically grouped into 5 market segments as shown in table 1.1. The 3 stress factors $(j=1,2,3)$ of each market segment $(i=1,2,3,4,5)$ are finally aggregated by taking their arithmetic mean into their respective market subindex:

$$s_{i,t} = \frac{1}{3}\sum_{j=1}^{3} z_{i,j,t} \tag{1.2}$$

Hence, from 15 raw indicators, five sub-indices are obtained.

The most innovative part of the CISS, which is where systemic risk comes into play, lies into the aggregation of the five sub-indices in order to obtain the final index (Di Cesare & Rogantini Picco, 2018). For this last step, a standard portfolio approach is applied by weighting the five components with the time-varying cross correlations (Hollo et al., 2012). The CISS is now computed according to equation 1.3 reporting the formula of Hollo et al. (2012). That formula implies that the CISS is continuous, unit-free and bounded by the half-open interval $(0,1]$ which are all the properties inherited from its individual stress factors:

$$CISS_t = (w \circ s_t) C_t (w \circ s_t)' \tag{1.3}$$

$w = (w_1, w_2, w_3, w_4, w_5)$ is the vector of (constant) sub-index weights[18], $s_t = (s_{1,t}, s_{2,t}, s_{3,t}, s_{4,t}, s_{5,t})$ is the vector of sub-indices, $w \circ s_t$ is the Hadamart-product[19] and C_t is the time-varying cross-correlation matrix[20].

In case of perfect correlation across the five sub-indices, matrix C_t is an identity matrix and, within the proposed portfolio-theoretic aggregation framework, the CISS coincides with the square of the the simple arithmetic average of the five sub-indices (namely, the vector $y_t = w \circ s_t$)

[18] The vector w has been calculated "on the basis of the average relative impact of each sub-index on the industrial production growth measured by the cumulative impulse responses from a variety of standard linear VAR models" (Hollo et al., 2012).

[19] It is an element by element multiplication of the vector of sub-index weights and the vector of sub-index values in time t (Hollo et al., 2012).

[20] The time-varying cross correlations are calculated recursively by estimating the respective variances and co-variances with an exponentially weighted moving average ((Di Cesare & Rogantini Picco, 2018); (Hollo et al., 2012).

(Hollo et al., 2012).

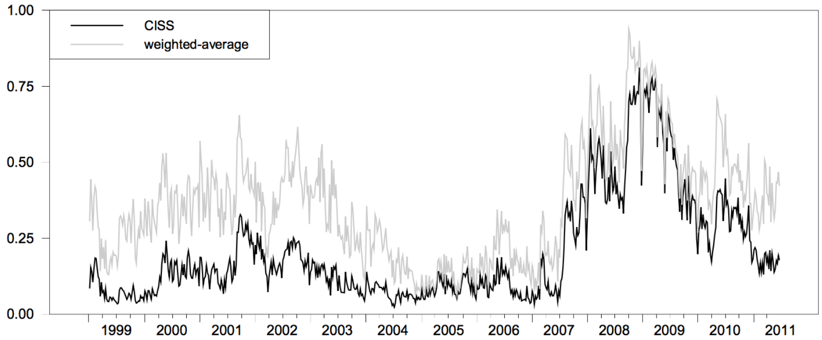

Figure 1.3: CISS versus the squared simple weighted-average of subindices ("perfect correlation")[21].

The case in which there is perfect correlation across the sub-indexes should apply when all of them stand at historically low levels or at historically high level. These are two kinds of situations that are exceptions: it is difficult to have extreme market tranquillity or extreme market stress for a long time of period. In fact, figures 1.3 and 1.4 show us that the CISS and its perfect-correlation counterpart stand relative close to each other when correlations are very high (Hollo et al., 2012).

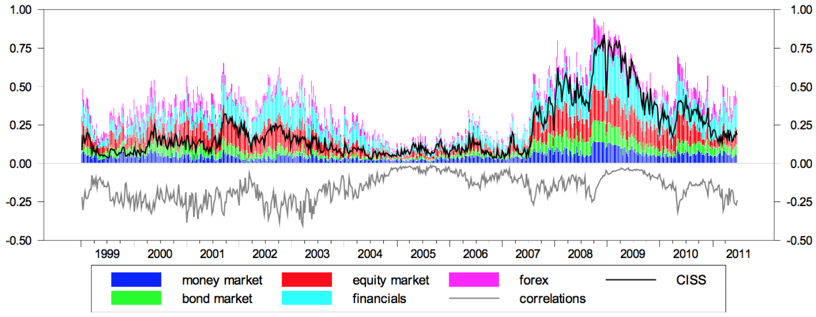

Figure 1.4: Decomposition of the CISS[22].

In figure 1.4 we can appreciate the contribution of each of the five sub-indices which constitute the CISS. In the area below zero is represented the difference between the CISS and its perfect correlation counterpart[23]; that difference represents the impact of cross correlation

[21] Source: (Hollo et al., 2012).

[22] This figure shows the decomposition of the CISS into contributions from each sub-index and from all cross correlations jointly. Source: (Hollo et al., 2012).

[23] We can see both from figure 1.3 and from figure 1.4 that the weighted average acts as an upper boundary for the CISS.

across the sub-indices (Di Cesare & Rogantini Picco, 2018). As said before, when the markets are extremely calm or extremely distressed, the difference between the CISS and its perfect-correlation counterpart is very small: this means that the five sub-indices are highly correlated (Di Cesare & Rogantini Picco, 2018). Instead, when we are in presence of an intermediate situation, the CISS is able to evaluate an increase in cross-correlation among the sub-indices, which is a signal of increased systemic risk (Hollo et al., 2012).
The decomposition represented in figure 1.4 is very helpful for macroprudential authorities in order to perform financial stability surveillance exercises. In fact, as said at the beginning of subsection 1.2.1, the Euro Area CISS is present in the set of analytical instruments used by the European Central Bank to support its macroprodential functions ((ECB, 2010); (ECB, 2011)).

1.2.3 Identification of stress events

What Hollo et al. (2012) said is that "one of the main strengths of the CISS as a financial stress indicator is its explicit foundation on the notion of systemic risk which the CISS aims to measure by compiling appropriately transformed individual stress indicators into a single index through application of portfolio-theoretical economic principles rather than based on purely statistical grounds".
However, it is difficult to assess if a particular financial stress index is a good indicator or not and if an indicator is better than an other one. The CISS' authors have provided different statistical robustness check in order to evaluate the performance of their financial stress index[24].

Usually, in order to evaluate a financial stress index it is adopted the rule to look at the identification of renowned past events of financial stress: if in the past an event has caused a serious disruption in the functioning of the financial system, the indicator of financial stress should be expected to increase drastically (Hollo et al., 2012).
There are different approaches in order to decide which financial stress index performs better among the others. For example, Illing and Liu (2006) apply an event-based criterion into a probabilistic evaluation framework. According to them, the preferred financial stress indicator is the one which matches best the survey results balancing Type I errors (failure to report a high-stress event) against Type II errors (falsely reporting a high-stress event). However, the event-based criterion suffers from substantial conceptual and measurement problems[25].

Hollo et al. (2012) preferred to follow the approach taken by Hakkio et Keeton (2009): assess whether peaks in the CISS are generally associated with well-known historical stress events

[24]For further information on the robustness checks please refer to (Hollo et al., 2012).
[25]For further information about the event-based criterion and its critical issues please refer to (Illing & Liu, 2006) and (Hollo et al., 2012).

(Hollo et al., 2012). Figure 1.5 shows that the sharpest spikes in the CISS tend to occur around very famous which have caused intense stress in the global financial markets. That events highlighted in figure 1.5 are:

- stock market crash in October 1987;
- collapse of the European Exchange Rate Mechanism (ERM) in September 1992;
- collapse of the hedge fund Long-Term Capital Management (LTCM) in September 1998;
- terrorist attacks in the US on September 11, 2001;
- WorldCom bankruptcy in July 2002;
- BNP Paribas suspended three investment funds linked to subprime mortgage debt in August 2007;
- Lehman Brothers filed for bankruptcy protection in September 2008;
- serious concerns about sovereign credit risk in the Euro Area emerged in mid-April 2010.

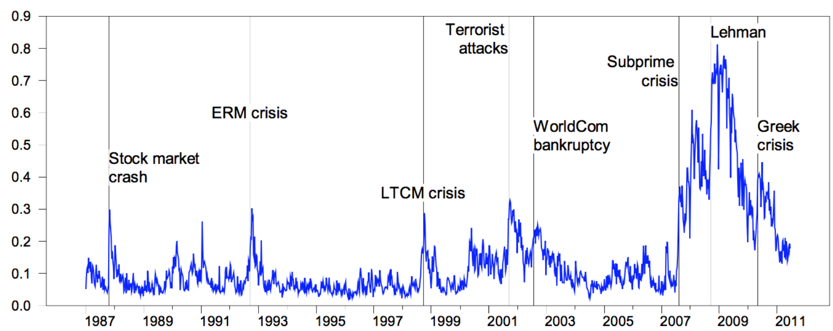

Figure 1.5: CISS and major financial stress events[26].

So, to conclude, from figure 1.5 we can see how all extreme peaks in CISS can be associated with specific financial stress events: this indicate that CISS does not suffer from Type II error (falsely reporting a high-stress event). However, it is more difficult to say if CISS do not fail to report a high-stress event (Type I error).

[26]Source: (Hollo et al., 2012).

Chapter 2

The Panel VAR model and its estimation

In this chapter we are going to overview the characteristics of the Panel VAR model and we will present the estimator used in order to perform the analysis.

2.1 The Panel VAR model

In order to examine economic issues which are present in interdependent economies it is possible to build Panel VAR models. This kind of models has the same starting structure of the well-known Vector Auto Regressive models (VAR) introduced by Sims in 1980[1], with the difference that a cross sectional dimension is added.

VAR models are convenient tools to analyze the economic dynamics of economic entities such as countries, financial markets, trade areas or monetary unions (Dieppe, Legrand, & Van Roye, 2016). However, it may sometimes be desirable to push the analysis further and study the dynamic interactions of several entities at a time, rather than limit the analysis to a single entity. For instance, one may want to study the interactions existing between several countries (for example, as our case, several Euro Area countries as they are characterized by the same monetary policy). In this case, the specific class of VAR models constituted by the Panel VAR models, which considers the dynamics of several entities considered in parallel, are appropriate.
These models are typically richer than simple VAR models because they do not only consider naively the interaction between variables as would a normal VAR model do, but they also add a cross-subsectional structure to the model (Dieppe et al., 2016).
This allows us to separate components which are common from components which are specific, be it in terms of countries, variables, time periods and so on, and then use this structural infor-

[1]For further explanations about VAR model please refer to (Sims, 1980).

mation to improve the quality of the estimation.

There is a wide literature in which Panel VAR have been used in order to address several issues of interest to, among others, policymakers and macro-economists. Authors conducting researches related to the business cycle literature have employed Panel VAR to investigate the similarities and convergences among G-7 cycles (Canova, Ciccarelli, & Ortega, 2007) and the similarities and convergences of macroeconomic fluctuations in the Mediterranean basin cycles (Canova & Ciccarelli, 2012).
Panel VAR models are also used to analyze the transmission of idiosyncratic shocks across unit and time (Canova & Ciccarelli, 2013). For instance, Canova et al. (2012) have studied the effects that the Maastricht Treaty, the creation of the ECB, and the Euro changeover had on the dynamics of European business cycles[2]. Some other authors have investigated heterogeneity and spillovers in macro-financial linkages across developed economies, with a particular emphasis on the most recent recession (Ciccarelli, Ortega, & Valderrama, 2012).
It is also possible to apply Panel VAR analysis to conduct researches on the importance of interdependencies and in checking whether feedbacks are generalized or only involve certain pairs of units (Canova & Ciccarelli, 2013). In this context, it is possible to use a Panel VAR to test the small economy assumption or to evaluate same exogeneity assumptions that are generally constructed in the international economics literature (Canova & Ciccarelli, 2013). For example, De Grauwe and Karas (2010) have conducted a Panel VAR analysis in order to show that the dynamics of deposits and interest rates of "good" and "bad" banks differs in response to bank run shocks demonstrating that the differences in the safety of their balance sheet are of second order importance and what really matters is whether banks are insured or not by regulators (Canova & Ciccarelli, 2013).

The terminology of Panel VAR models is now introduced. The approach followed in this section refers, principally, to Canova and Ciccarelli (2013) and to Dieppe (2016).
Specifically, a Panel VAR model comprises N entities or "units", which can be firms, industries, countries and so forth. The structure has the shape as a simple VAR: each unit includes n endogenous variables and p lags defined over T periods of time. Usually, panels that are taken into consideration are the ones that the n variables are the same for each units and are defined over the same T periods of time; these are the so called *balanced* panels.

We are not going to take into consideration, in the Panel VAR, exogenous variables for the sake of simplicity and since we are not going to use them in our Panel VAR analysis.

[2]They have also studied the propagation of US interest rates' shocks to ten European economies and how German shocks are transmitted to the remaining nine economies.

We can write the general form of the Panel VAR model for unit i (with i = 1,2,...,N) as:

$$\begin{aligned} y_{i,t} &= \sum_{j=1}^{N}\sum_{k=1}^{p} A^k_{ij,t} y_{i,t-k} + \varepsilon_{i,t} \\ &= A^1_{i1,t} y_{1,t-1} + ... + A^p_{i1,t} y_{1,t-p} \\ &+ A^1_{i2,t} y_{2,t-1} + ... + A^p_{i2,t} y_{2,t-p} \\ &+ ... \\ &+ A^1_{iN,t} y_{N,t-1} + ... + A^p_{iN,t} y_{N,t-p} \\ &+ \varepsilon_{i,t} \end{aligned} \tag{2.1}$$

with:

$$y_{i,t} = \underbrace{\begin{pmatrix} y_{i1,t} \\ y_{i2,t} \\ \vdots \\ y_{in,t} \end{pmatrix}}_{nx1} \qquad A^k_{ij,t} = \underbrace{\begin{pmatrix} a^k_{ij,11,t} & a^k_{ij,12,t} & \cdots & a^k_{ij,1n,t} \\ a^k_{ij,21,t} & a^k_{ij,22,t} & \cdots & a^k_{ij,2n,t} \\ \vdots & \vdots & \ddots & \vdots \\ a^k_{ij,n1,t} & a^k_{ij,n2,t} & \cdots & a^k_{ij,nn,t} \end{pmatrix}}_{nxn} \qquad \varepsilon_{i,t} = \underbrace{\begin{pmatrix} \varepsilon_{i1,t} \\ \varepsilon_{i2,t} \\ \vdots \\ \varepsilon_{in,t} \end{pmatrix}}_{nx1} \tag{2.2}$$

$y_{i,t}$ denotes a n x 1 vector which includes the n endogenous variables of unit i at time t, while $y_{ij,t}$ is the j^{th} endogenous variables of unit i. $A^k_{ij,t}$ is a n x n matrix of coefficients providing the response of unit i to the k^{th} lag of unit j at period t. For matrix $A^k_{ij,t}$, the coefficient $a^k_{ij,lm,t}$ provides the response of variable l of unit i to the k^{th} lag of variable m of unit j. In conclusion, $\varepsilon_{i,t}$ denotes a n x 1 vector of residuals for the variables of unit i, with the given features:

$$\varepsilon_{i,t} \sim N(0, \Sigma_{ii,t}) \tag{2.3}$$

with:

$$\Sigma_{ii,t} = \mathbb{E}(\varepsilon_{i,t}\varepsilon^{'}_{i,t}) = \begin{pmatrix} \varepsilon_{i1,t} \\ \varepsilon_{i2,t} \\ \vdots \\ \varepsilon_{in,t} \end{pmatrix} \begin{pmatrix} \varepsilon^{'}_{i1,t} & \varepsilon^{'}_{i2,t} & \dots & \varepsilon^{'}_{in,t} \end{pmatrix} = \underbrace{\begin{pmatrix} \sigma_{ii,11,t} & \sigma_{ii,12,t} & \cdots & \sigma_{ii,1n,t} \\ \sigma_{ii,21,t} & \sigma_{ii,22,t} & \cdots & \sigma_{ii,2n,t} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{ii,n1,t} & \sigma_{ii,n2,t} & \cdots & \sigma_{ii,nn,t} \end{pmatrix}}_{nxn} \tag{2.4}$$

$\varepsilon_{i,t}$ is assumed to be non-autocorrelated, so that $\mathbb{E}(\varepsilon_{i,t}\varepsilon^{'}_{i,t}) = \Sigma_{ii,t}$, while $\mathbb{E}(\varepsilon_{i,t}\varepsilon^{'}_{i,s}) = 0$ when $t \neq$s.

We have to take into consideration that in this generic frame the variance-covariance matrix

for the VAR residuals is enabled to be period-specific, which implies a generic form of heteroskedasticity.
For each variable in unit i, the dynamic equation at period t contains a total of $k = Nnp$ coefficients to be estimated; that implies $q = n(Nnp)$ coefficients to be estimated for the whole unit. Stacking over the N units, the model is reformulated as:

$$\begin{aligned} y_t &= \sum_{k=1}^{p} A_t^k y_{t-k} + \varepsilon_t \\ &= A_t^1 y_{t-1} + ... + A_t^p y_{t-p} + \varepsilon_t \end{aligned} \tag{2.5}$$

or:

$$\begin{aligned} \begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{N,t} \end{pmatrix} &= \begin{pmatrix} A_{11,t}^1 & A_{12,t}^1 & \cdots & A_{1N,t}^1 \\ A_{21,t}^1 & A_{22,t}^1 & \cdots & A_{2N,t}^1 \\ \vdots & \vdots & \ddots & \vdots \\ A_{N1,t}^1 & A_{N2,t}^1 & \cdots & A_{NN,t}^1 \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{N,t-1} \end{pmatrix} + ... \\ &+ \begin{pmatrix} A_{11,t}^p & A_{12,t}^p & \cdots & A_{1N,t}^p \\ A_{21,t}^p & A_{22,t}^p & \cdots & A_{2N,t}^p \\ \vdots & \vdots & \ddots & \vdots \\ A_{N1,t}^p & A_{N2,t}^p & \cdots & A_{NN,t}^p \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{N,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{N,t} \end{pmatrix} \end{aligned} \tag{2.6}$$

with:

$$y_t = \underbrace{\begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{N,t-p} \end{pmatrix}}_{Nnx1} \qquad A_t^k = \underbrace{\begin{pmatrix} A_{11,t}^k & A_{12,t}^k & \cdots & A_{1N,t}^k \\ A_{21,t}^k & A_{22,t}^k & \cdots & A_{2N,t}^k \\ \vdots & \vdots & \ddots & \vdots \\ A_{N1,t}^k & A_{N2,t}^k & \cdots & A_{NN,t}^k \end{pmatrix}}_{NnxNn} \qquad \varepsilon_t = \underbrace{\begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{N,t} \end{pmatrix}}_{Nnx1} \tag{2.7}$$

The vector of residuals ε_t has the following properties:

$$\varepsilon_t \sim N(0, \Sigma_t) \tag{2.8}$$

with:

$$\Sigma_t = \mathbb{E}(\varepsilon_t \varepsilon_t^{'}) = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{N,t} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t}^{'} & \varepsilon_{2,t}^{'} & \dots & \varepsilon_{N,t}^{'} \end{pmatrix} = \underbrace{\begin{pmatrix} \Sigma_{11,t} & \Sigma_{12,t} & \dots & \Sigma_{1N,t} \\ \Sigma_{21,t} & \Sigma_{22,t} & \dots & \Sigma_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{N1,t} & \Sigma_{N2,t} & \dots & \Sigma_{NN,t} \end{pmatrix}}_{NnxNn} \tag{2.9}$$

The assumption of absence of autocorrelation is then enlarged to the entire model: $\mathbb{E}(\varepsilon_t \varepsilon_t^{'}) = \Sigma_t$, while $\mathbb{E}(\varepsilon_t \varepsilon_s^{'}) = 0$ when $t \neq$s.

Formulation 2.6 of the model implies that there are $h = Nq = Nn(Nnp)$ coefficients to estimate.

So, in this section, we have illustrated the most generic form of Panel VAR model without taking into account exogenous variables[3]. Under this form, the Panel VAR model is characterized by four properties (Dieppe et al., 2016):

1. Dynamic interdependencies: the dynamic behaviour of each unit is determined by lagged values of its-self, but also by lagged values of all the other endogenous variables of all other units. In other words, $A^k_{ij,t} \neq 0$ with $i \neq$ j;
2. Static interdependencies: the $\varepsilon_{i,t}$ are allowed to be correlated across units. That is, in general $\Sigma_{ij,t} \neq 0$ with $i \neq$ j;
3. Cross-subsectional heterogeneity: the VAR coefficients and the residual variances are allowed to be unit-specific. In other words, $A^l_{ik,t} \neq A^l_{jk,t}$ and $\Sigma_{ii,t} \neq \Sigma_{jj,t}$ with $i \neq$ j;
4. Dynamic heterogeneity: the VAR coefficients and the residual variance-covariance matrix are allowed to be period-specific. In other words, $A^k_{ij,t} \neq A^k_{ij,s}$ and $\Sigma_{ij,t} \neq \Sigma_{ij,s}$ with $t \neq$ s.

In practice, this general structure may be too complex in order to obtain precise estimates. As it consumes many degrees of freedom, if one has legitimate reason to assume that some of the properties will not hold, better estimates can be obtained by relaxing them and opt for less degrees-of-freedom consuming procedures (Dieppe et al., 2016). For example, if one takes into account a group of countries that are very homogeneous and tend to react in a similar way to structural economic shocks, it may reasonable to relax property 3.
So, according to the features of the panel that one wants to take into account, there are different estimators with different way to proceed that can be used. In the next section, we are going to introduce the estimator that we have used for our analysis.

[3]For further explanations please refer to (Canova & Ciccarelli, 2013) and (Dieppe et al., 2016).

2.2 The GMM estimator

In this section, we are going to provide a concise overview of the estimation of a Panel VAR model through the *Generalized Method of Moments* (GMM) estimator following the work made by Abrigo and Love (2016). This framework of estimation has been used to conduct the empirical analysis in this paper.

2.2.1 GMM estimation of a Panel VAR

Let's consider a k-variate homogeneous panel VAR of order p with panel-specific fixed effects represented by the following system of linear equations:

$$\begin{gathered} Y_{it} = Y_{it-1}A_1 + Y_{it-2}A_2 + ... + Y_{it-p}A_p + \upsilon_i + \varepsilon_{it} \\ i \in (1,2,...,N), \quad t \in (1,2,...,T) \end{gathered} \tag{2.10}$$

where Y_{it} a $(1xk)$ vector of dependent variables; υ_i and ε_{it} are $(1xk)$ vectors of dependent variable-specific panel fixed-effects and idiosyncratic errors, respectively. The (kxk) matrices A_1, A_2,..., A_{p-1}, A_p are parameters to be estimated. We assume that the innovations[4] have the following characteristics:

$$\begin{gathered} E[\varepsilon_{it}] = 0 \\ E[\varepsilon_{it}^{'}\varepsilon_{it}] = \Sigma \\ E[\varepsilon_{it}^{'}\varepsilon_{is}] = 0 \quad \text{for all} \quad t > s. \end{gathered} \tag{2.11}$$

The parameters may be consistently estimated using a Generalized Method of Moments (GMM) framework[56]. Since we have assumed that the errors are serially uncorrelated, the forward orthogonal deviation (Arellano & Bover, 1995) is a transformation that may be consistently estimated equation-by-equation by instrumenting lagged differences; this transformation subtracts the average of all available future observation thereby minimizing data loss. Since past realizations are not included in this transformation, they remain valid instruments (Abrigo & Love, 2016).

While equation-by-equation GMM estimation yields consistent estimates of panel VAR, estimating the model as a system of equations may result in efficiency gains (Holtz-Eakin, Newey,

[4]The *innovations* are used in the time series the same way as errors in cross-sectional analysis. They are called *innovations* because in time series context the errors bring new information to the system. In cross-sectional context it doesn't make a sense to call them new as the observations come not in time-ordered sequence.

[5]See Canova and Ciccarelli (2013) for a survey of random coefficient panel VAR models.

[6]Various estimators based on Generalized Method of Moments have been proposed to calculate consistent estimates of equation 2.10, (Abrigo & Love, 2016).

& Rosen, 1988). Let's consider the Panel VAR model based on equation 2.10 with some variables transformation and in a more compact form:

$$
\begin{aligned}
Y_{it}^{*} &= \overline{Y_{it}^{*}}A + \varepsilon_{it} \\
Y_{it}^{*} &= \begin{bmatrix} y_{it}^{1*} & y_{it}^{2*} & \dots & y_{it}^{k-1*} & y_{it}^{k*} \end{bmatrix} \\
\overline{Y_{it}^{*}} &= \begin{bmatrix} Y_{it-1}^{*} & Y_{it-2}^{*} & \dots & Y_{it-p+1}^{*} & Y_{it-p}^{*} \end{bmatrix} \\
\varepsilon_{it}^{*} &= \begin{bmatrix} \varepsilon_{it}^{1*} & \varepsilon_{it}^{2*} & \dots & \varepsilon_{it}^{k-1*} & \varepsilon_{it}^{k*} \end{bmatrix} \\
A^{'} &= \begin{bmatrix} A_{1}^{'} & A_{2}^{'} & \dots & A_{p-1}^{'} & A_{p}^{'} \end{bmatrix}
\end{aligned} \tag{2.12}
$$

where the asterisk denotes some transformation of the original variable.
If we denote the original variable as m_{it}, then the first difference transformation imply that $m_{it}^{*} = m_{it} - m_{it-1}$, while for the forward orthogonal deviation $m_{it}^{*} = (m_{it} - \overline{m_{it}})\sqrt{T_{it}/(T_{it}+1)}$, where T_{it} is the number of available future observations for panel i at time t, and $\overline{m_{it}}$ is its average.

As proposed by Abrigo and Love (2016), let's suppose to stack observations over panel then over time. The GMM estimator is given by:

$$
Y_{it}^{*} = (\overline{Y^{*\prime}}Z\hat{W}Z^{'}\overline{Y^{*}})^{-1}(\overline{Y^{*\prime}}Z\hat{W}Z^{'}Y^{*}) \tag{2.13}
$$

where $\hat{W}$ is a (LxL) weighted matrix assumed to be non-singular, symmetric and positive semidefinite. Assuming that $E[Z'\varepsilon] = 0$ and rank $E[\overline{Y^{*\prime}}Z] = kp$, the GMM estimator is consistent. The choice of the weighting matrix $\hat{W}$ has to be done accordingly to the maximization of the efficiency (Hansen, 1982).

Once that we have looked at the GMM estimator, we are going to look at the model selection.

2.2.2 Model Selection

Panel VAR analysis is predicated upon choosing the optimal lag order in both panel VAR specification and moment condition (Abrigo & Love, 2016). Consistent moment condition and model selection criteria (MMSC) for Generalized Method of Moment models have been proposed by Andrew and Lu (2001) based on Hansen's (1982) J statistic of over-identifying restrictions. These criteria of moment and model selection are similar to generally used maximum likelihood-based model selection criteria; these are:

- the Bayesian information criteria (BIC) (Schwarz et al., 1978);
- the Akaike information criteria (AIC) (Akaike, 1969);
- the Hannan-Quinn information criteria (HQIC) (Hannan & Quinn, 1979).

Applying Andrews and Lu's moment and model selection criteria to the Generalized Method of Moments estimator in 2.13, their proposed criteria select the pair of vectors (p,q) that minimizes:

$$MMSC_{BIC,n}(k,p,q) = J_n(k^2p, k^2q) - (|q| - |p|)k^2 \ln n \tag{2.14}$$

$$MMSC_{AIC,n}(k,p,q) = J_n(k^2p, k^2q) - 2k^2(|q| - |p|) \tag{2.15}$$

$$MMSC_{HQIC,n}(p,q) = J_n(k^2p, k^2q) - Rk^2(|q| - |p|) \ln \ln n \tag{2.16}$$

where $J_n(k,p,q)$ is the J statistic of over-identifying restriction for a k-variate panel VAR of order p and moment conditions based on q lags of the dependent variables with sample size n (Abrigo & Love, 2016).

By construction, the Above moment and model selection criteria are available only when $q > p$. As an alternative criterion, the overall coefficient of determination (CD) may be calculated even with just-identified GMM models. As proposed by Abrigo and love (2016), suppose we denote the (kxk) unconstrained covariance matrix of the dependent variables by Ψ. The coefficient of determination captures the proportion of variation explained by the Panel VAR model and can be calculated as:

$$CD = 1 - \frac{det(\Sigma)}{det(\Psi)} \tag{2.17}$$

Finally, we are going to look at the calculation of the Impulse Response Functions using the Generalized Method of Moments estimator.

2.2.3 Impulse Response Functions

A VAR model is stable if and only if all moduli of the companion matrix $\overline{A}$ are stricty less than one ((Hamilton, 1994);(Lütkepohl, 2005)). The companion matrix $\overline{A}$ is given by:

$$\overline{A} = \begin{bmatrix} A_1 & A_{2,} & \dots & A_p & A_{p-1} \\ I_k & 0_k & \dots & 0_k & 0_k \\ 0_k & I_k & \dots & 0_k & 0_k \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0_k & 0_k & \dots & I_k & 0_k \end{bmatrix} \tag{2.18}$$

Stability implies that the Panel VAR is invertible and has an infinite-order vector moving-average (VMA) representation, providing known interpretation to estimated impulse-response functions and forecast-error variance decompositions (Abrigo & Love, 2016).
The simple impulse-response function ϕ_i may be computed by rewriting the model as an infinite vector moving-average, where ϕ_i are the vector moving-average parameters.

$$\phi_i = \begin{cases} I_k \, , & \text{i} = 0 \\ \sum_{j=1}^{i} \phi_{t-j} A_j, & \text{i} = 1,2,.. \end{cases} \tag{2.19}$$

However, the simple impulse response functions do not have causal interpretation. Since the innovations ε_{it} are correlated contemporaneously, a shock on one variable is likely to be accompanied by shocks in other variables, as well (Abrigo & Love, 2016). Suppose we have a matrix P, such that $P'P = \Sigma$. Then P may be used to *orthogonalize* the innovations as $\varepsilon_{it} P^{-1}$ and to transform the vector moving-average parameters into the orthogonalized impulse-responses $P\phi_i$. The matrix P effectively imposes identification restrictions on the system of dynamic equations (Abrigo & Love, 2016). In order to impose a recursive structure on a VAR, Sims (1980) proposed the *Cholesky* decomposition of Σ. However, the decomposition is not unique but depends on the ordering of variables in Σ.

Impulse-response function confidence intervals may be derived analytically based on the panel VAR parameters and the cross-equation error variance-covariance matrix (Abrigo & Love, 2016). Alternatively, the confidence interval may likewise be estimated using Monte Carlo simulation and bootstrap resampling methods (Lütkepohl, 2005).

Chapter 3

Empirical Analysis

In this Chapter we are going to explain the data used for the analysis, the econometrical strategy applied for this specified case and the results that came out from the analysis.

3.1 Data description

In our study, we have used monthly data from January 1999 to June 2019[1] for some Euro Area Countries: Germany, France, Spain and Italy. Data for Composite Indicator of Systemic Stress (*CISS*), Share of interbank loans in total loans (*IBL/TL*) and Euro OverNight Index Average (*EONIA*) were taken from the European Central Bank Statistical Data Warehouse[2] while the data for Industrial Production Index (*IPI*) were received from the Eurostat[3]. The CISS and EONIA variables are common across the Euro Area countries taken into account in this panel. The IBL/TL and IPI are, instead, country specific.

The Industrial Production Index of each country included in the panel is used in order to test the response of the real economic performance to changes in systemic stress. It is used as a GDP proxy since the data are available with a monthly frequency instead of the availability of the GDP data with a quarterly frequency. Such index includes different economic activities: mining and quarrying, manufacturing, electricity, gas, steam and air conditioning supply. The data have been seasonally and calendar adjusted. The index is measured with reference to the 2015 base level of 100 points (Index, 2015=100) [4].

[1]The time period we choose is due to data availability.

[2]Website: https://sdw.ecb.europa.eu

[3]Website: https://ec.europa.eu/eurostat/data/database

[4]For further information about the data included and the methodology used for the construction of the Industrial Production Index please refer to the Eurostat website page http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=sts$_{i}npr_{m}lang = en$

The Euro OverNight Index Average (EONIA) has been taken into account as a variable in this panel to identify the single Euro Area monetary policy shocks following the work made by Ciccarelli et al. (2013).
The Governing Council of the European Central Bank sets three key policy rates (Ciccarelli et al., 2013): the rates for the deposit facility, the main refinancing operations and the marginal lending facility. These rates constitute the corridor in which the overnight rate fluctuates. Prior to the 2008 crisis, the EONIA had the same path of the rate of the main refinancing operations (MRO). When the crisis kicks in, the European Central Bank decided to provide liquidity to the banking sector in an huge amount. As a consequence, the EONIA rate dropped below the MRO rate indicating that the impact of these non-standard monetary policy measures[5] (Ciccarelli et al., 2013).
The EONIA rate is presented on ECB Statistical Data Warehouse[6] as "the closing rate for the overnight maturity calculated by collecting data on unsecured overnight lending in the euro area provided by banks belonging to the EONIA panel". Since the EONIA observations are in percentage but with a daily frequency, we have applied a simple average transformation in order to have a monthly frequency.

In order to study the reaction of the interbank market to a shock in systemic stress, we have used a Risk Assessment Indicator which is measured as the "Share of interbank loans in total loans" for each country of the panel . This ratio is taken from the Risk Assessment Indicators Database of the ECB Statistical Data Warehouse [7]. This indicator is calculated using aggregated bank data at a country level which is the sum of the harmonised balance sheets of all the Monetary Financial Institutions of the euro area Member State[8]. The observations are in percentages with a monthly frequency; so, we do not need to apply none frequency transformation.

Finally, in order to measure the Systemic Stress for the Euro Area we have used the Composite Indicator of Systemic Stress (CISS) of which we have talked about in section 1.2. As said before, this indicator is designed not only to identify systemic risk within the financial system (the

[5]For further explanations please refer to (Soares & Rodrigues, 2013) and (Trichet, 2009).

[6]For more information about the data description please look at the ECB Statistical Data Warehouse website page https://sdw.ecb.europa.eu/browse.do?node=9689692

[7]As expressed by the ECB Statistic department, for confidentiality reasons not all the Risk Assessment Indicator series (like the ratio of the "Share of interbank loans in total loans" that we are interested in) can be reconstructed by data available publicly; those that are publicly available can be found by inserting the code into the search field of ECB Statistical Data Warehouse http://sdw.ecb.europa.eu/, replacing “*” with “?”. It is also possible to use the Macroprudential Database available at the ECB Statistical Data Warehouse website page https://sdw.ecb.europa.eu/browse.do?node=9689335.

[8]For further information on the aggregation of bank data at a country level please refer to the ECB Statistical Data Warehouse website page https://sdw.ecb.europa.eu/browse.do?node=9691115

"horizontal perspective") but also to consider the systemic risk stemming from the interaction between the financial system and the real economy (the "vertical perspective") (Di Cesare & Rogantini Picco, 2018).
The index is measured in a $(0,1]$ interval and has weakly observations; so, we have applied a simple average transformation in order to have a monthly frequency.

3.2 Econometric strategy

In order to perform the analysis which takes into account the relationships among Systemic Stress, EONIA, Interbank loans and the Industrial production, we have used the Stata *pvar* package of programs developed by Abrigo and Love (2016). This package of Stata programs allows us to perform a Panel VAR model and it is an updated version of the package of programs used previously by Love and Zicchino (2006)[9].
It allows for individual heterogeneity in the levels of the variables by including panel specific fixed effects into the model. Starting from equation 2.10, if we take into consideration only one lag and none exogenous variables, the Panel VAR model can be written as:

$$\begin{gathered} Y_{it} = Y_{it-1}A_1 + \upsilon_i + \varepsilon_{it} \\ i \in (1,2,...,N), \quad t \in (1,2,...,T) \end{gathered} \tag{3.1}$$

where Y_{it} is a $(1x4)$ vector of the four endogenous variables[10]; υ_i is the vector of dependent variable-specific panel fixed-effects and ε_{it} is the vector of the idiosyncratic errors.
As the fixed effects are correlated with the regressors, we use forward mean differencing (the Helmert procedure) following Arellano and Bover (1995) to remove panel-fixed effects.

As explained in section 2.2, we estimate the coefficients by using the *Generalized Method of Moments* (GMM). Taking into account the estimation method used by Ciccarelli and al. (2013), the model is estimated recursively[11] and the first estimation is run over the sample January1999-

[9]Prior to the publication of the paper in the (2016), the earlier version of the package of programs (Love & Zicchino, 2006) has been informally distributed by the authors to several researcher who have used it in order to carry out sereval anaysis which have been published in different reviews such as: American Economic Review (Head, Lloyd-Ellis, & Sun, 2014), Applied Economics (Mora & Logan, 2012) and Journal of Macroeconomics (Carpenter & Demiralp, 2012).
[10]The four variables are: Industrial Production Index, EONIA, Interbank loans/Total loans, Composite Indicator of Systemic Stress (CISS). The CISS and EONIA variables are, as said before, common for all countries.
[11]We follow a moving window approach: we start from a sample of monthly observation and, then, we add one year at a time until we cover the all sample.

December2012. In the subsequent estimations we then add one year at a time (12 monthly observations) so that the second estimation covers the sample January1999-December2014, and so on, until the last months of 2019 are included[12]. This estimation strategy allows us to identify the marginal effects of additional monthly data included in the time sample.

Prior to estimate our Panel VAR, we need to take into consideration the nature of our variables. Usually when you work with a model that presents variables in a time-series form, you have to take into account the possibility that such time series are not stationary since may have unit roots. In the econometric literature we can find different approach in order to make a time series stationary when there is a unit root[13]. If it is known that a series has a unit root, the series can be differenced to render it stationary.
So, we have tested for unit roots presence in our time series using the Im-Pesaran-Shin test (Im, Pesaran, & Shin, 2003). We have checked the order of integration of the variables present in our model and we have taken the first difference of the variables that were integrated of order 1.
Once that the time series variables have been transformed in order to have them stationary, we can use transformed variables in our panel model.

As we have seen in section 2.2, the simple *Impulse Response Functions* have causal interpretation only when the innovations ε_{it} are uncorrelated. But, usually, the innovations ε_{it} tend to be correlated contemporaneously: a shock on one variable is likely to be accompanied by shocks in other variables as well (Abrigo & Love, 2016). So, the simple *Impulse Response Functions* have no causal interpretation. Sims (1980) proposed the *Cholesky* decomposition of Σ which gives a structure to the model. However, the structure changes accordingly with the ordering of the variables in Σ.
Taking into account the Cholesky decomposition of Σ, we have:

$$\begin{pmatrix} \lambda_t^{y_1} \\ \lambda_t^{y_2} \\ \lambda_t^{y_3} \\ \lambda_t^{y_4} \end{pmatrix} = \begin{pmatrix} \alpha & 0 & 0 & 0 \\ \beta & \gamma & 0 & 0 \\ \delta & \varepsilon & \zeta & 0 \\ \eta & \theta & \iota & \kappa \end{pmatrix} \begin{pmatrix} \upsilon_t^1 \\ \upsilon_t^2 \\ \upsilon_t^3 \\ \upsilon_t^4 \end{pmatrix} \tag{3.2}$$

where the Greek letters are coefficients different than 0.
The structural innovations are obtained from the triangular Cholesky-factorisation of the variance-

[12]In the last sample, in which should be taken into account the 2019 monthly observations, are only taking into consideration 6 observations regarding data from January to June due to data availability at the time when the analysis has been done.

[13]The presence of unit roots in some time series of the Panel VAR model would give wrong estimates of the Impulse Response Functions. So, it is fundamental to analyze the stationary characteristic of the variables present in the model.

covariance matrix of the residuals ((Abrigo & Love, 2016); (Hollo et al., 2012)).

This procedure allows us to orthogonalize the errors with a covariance diagonal matrix: triangular orthogonalization (Cholesky decomposition) with a specific ordering of the variables.

As just said, the ordering of the variables is critical in VAR specification and, therefore, for Panel VAR ((Türkay, 2018); (Abrigo & Love, 2016); (Hollo et al., 2012)). The position of the variables in the vector of endogenous variables should follow a rational disposal, taking into account the economic sense of the several variables.
So, the variables that are more exogenous come earlier in the system and the ones that are endogenous appear later. It means that the variables that come earlier affect the following variables both simultaneously and with a lag while the variables that come later impact previous variables just with a lag (Türkay, 2018).

In the Cholesky decomposition of Σ represented in 3.2, variable y_1 is present in the first position of the ordering if it does not respond simultaneously to shocks in variables y_2, y_3 and y_4. Then, we insert variables y_2, y_3 and y_4 which react in a contemporaneously way to a shock in variable y_1. However, also the ordering of the variables that follow the first one is crucial; it has to be done accordingly with the possibility that a variable can affect the other contemporaneously. So, a shock in variable y_2 affects contemporaneously both variables y_3 and y_4 since υ_t^2 is multiplied by ε in $\lambda_t^{y_3}$ equation and by θ in $\lambda_t^{y_4}$ equation. Instead, variables y_3 and y_4 do not affect contemporaneously variable y_2 since υ_t^3 and υ_t^4 are multiplied by 0 in $\lambda_t^{y_2}$ equation. The same apply for the variables following y_2 taking into consideration the ordering which is crucial.

Looking to our case and taking into account the economic sense of each variables, the Industrial Production Index should be included in the first position since it does not respond contemporaneously to shocks in Eonia, Interbank loans and Systemic stress. Subsequently, we will include all the other variables that respond in a contemporaneously way to one shock in the real economy[14]. As just said in the previous paragraph, also the ordering of the variables that follow the first one is crucial; it has to be done accordingly with the possibility that a variable can affect the other contemporaneously. In this way, we will include the other variables accordingly to their economic sense and, so, following this order: Eonia, Interbank loans and Systemic stress.

[14]The Industrial Production Index is the variable that is used as a proxy for the real economy.

In this way, we can write the Cholesky decomposition of Σ as:

$$\begin{pmatrix} \lambda_t^{ipi} \\ \lambda_t^{eonia} \\ \lambda_t^{ibl} \\ \lambda_t^{ciss} \end{pmatrix} = \begin{pmatrix} \alpha & 0 & 0 & 0 \\ \beta & \gamma & 0 & 0 \\ \delta & \varepsilon & \zeta & 0 \\ \eta & \theta & \iota & \kappa \end{pmatrix} \begin{pmatrix} \upsilon_t^1 \\ \upsilon_t^2 \\ \upsilon_t^3 \\ \upsilon_t^4 \end{pmatrix} \tag{3.3}$$

However, even if we want to study how the Systemic Stress impact the Interbank lending and the real economy, the structure of the Panel VAR tells us that the shocks start from a change in the real economy since the Industrial Production Index is included in the first position due it its economic sense.

So, what we want to do now is to insert in the first position the Systemic stress even if we do not respect the economic sense of the variables present in the model. We do so since we want to estimate the impact of the Systemic stress on a bank risk indicator ratio[15] and on the real economy when the shock start from the indicator of Systemic Stress.

The ordering of the endogenous variables allows that the shocks in the CISS can have a contemporaneous impact on the real economy (but not conversely). This structural shock identification can be justified, for instance, from an informative perspective (Hollo et al., 2012). Due to the lag in the publication of the industrial production index, it is possible to say that the current level of the industrial production can not be directly observed by the actors present in the financial markets and, as a consequence, the contemporaneous asset prices do not incorporate those information (Hollo et al., 2012).
However, it is possible that the actors operating in the financial markets can anticipate future data of the industrial production using business cycle indicators but it is difficult that they can predict in a systemic way industrial production data from information included in past indicators. In addition to what said before, it seems possible to assume that shocks in the Composite Indicator of Systemic Stress tend to originate principally from within the financial sector particularly during crisis times (Hollo et al., 2012); as a consequence of that, producers react quickly to large uncertainty shocks with a rapid drop in aggregate output reflecting a transitory pause in their investment and labour hiring[16] in response to increased uncertainty (Bloom, 2009).
On the other hand, it may also be possible that output news drive simultaneous shocks in financial stress even in crisis time since the actors participating in the financial markets may react instantaneously to clear evidences of adjustments in the output (Hollo et al., 2012).

[15] The share of interbank loans in total loans.
[16] According to the so called "wait-and-see" attitude.

So, due to the reasons just explained, we will perform the analysis taking into account the two different variables ordering in which the shocks can start from the real economy or from the financial markets.

We will see that the path of both Impulse Response Function is the same compared with the previous variables order with the difference that the response of the two variables at the zero lag will be different than zero since the response variables are included after the impulse variables and, so, they respond contemporaneously to a shock in Systemic Stress. Taking into account this new variable order, we can write the Cholesky decomposition of Σ as:

$$\begin{pmatrix} \lambda_t^{ciss} \\ \lambda_t^{ipi} \\ \lambda_t^{eonia} \\ \lambda_t^{ibl} \end{pmatrix} = \begin{pmatrix} \alpha & 0 & 0 & 0 \\ \beta & \gamma & 0 & 0 \\ \delta & \varepsilon & \zeta & 0 \\ \eta & \theta & \iota & \kappa \end{pmatrix} \begin{pmatrix} \upsilon_t^1 \\ \upsilon_t^2 \\ \upsilon_t^3 \\ \upsilon_t^4 \end{pmatrix} \tag{3.4}$$

The two model that are of interest for us in our analysis are the two that present the Cholesky decomposition of Σ as represented in equations 3.3 and 3.4 since:

- in the first one, the order of the variables in the Cholesky decomposition is done taking into account the economic sense of the variables included in the model;
- the second one want to see the response of the two variables of interest (Interbank lending and Industrial Production Index) to an impulse of the systemic stress when the shock start from that variable and not from the real economy.

So, in the following section we will present the results for the two application:

- the first application, with the Cholesky decomposition of equation 3.3;
- the second application, with the Cholesky decomposition of equation 3.4.

We will see the likeness of the two applications; this is a proof of the robustness of our model. Also, in the Appendix C we will show the results of the Panel VAR with different variables orders to provide an additional evidence of robustness.

3.3 Results

In this section we are going to present the Impulse Response Functions where the impulse is given from the indicator of Systemic Stress to the two variables of interest:

- the Share of interbank loans in total loans: this is a Risk Assessment Indicator;
- the Industrial Production Index: this variables is used as a proxy for the real economy.

As said in the previous section, we are going to estimate the model recursively and we will present the results of both Impulse Response Functions with the two different variables order taking into account the Cholesky decomposition of Σ as represented in equations 3.3 and 3.4.

3.3.1 Application 1

In the first application, we are taking into account the Cholesky decomposition of Σ as represented in equation 3.3 in which the variables order has been chosen taking into account the economic sense of the nature of the variables. So, in the first position we find the Industrial Production Index. In this way, when we will estimate the Impulse Response Functions we know that the shocks start from the real economy even if the variable that gives the impulse is an other one.

In the figure 3.1 we have the response of the Share of Interbank loans in total loans (IBL/TL) due to an impulse in Systemic Stress measured by the CISS index.

On the "x" axis of the figure we can find the *Steps* of the Impulse Response Functions which correspond to the months; so, the number represented (3,6,9,...) are the quarters.
On the "y" axis (*Response* axis) are represented the values of the response to the shock in the impulse variable.
On the "z" axis (*Years* axis) are represented the time windows for each sample: 12 means that we take into consideration the data from the 1999 to 2012, 13 means that we take into consideration the data from the 1999 to 2013, and so on up to when we arrive to 19 when all the data are included. So, the "z" axis is used in the cases in which you want to estimate the Impulse Response Functions recursively[17].

[17] If we do not take into account the "z" axis, we have the usual Impulse Response Function of a VAR model with the *Steps* on the "x" axis and the *Response* on the "y" axis.

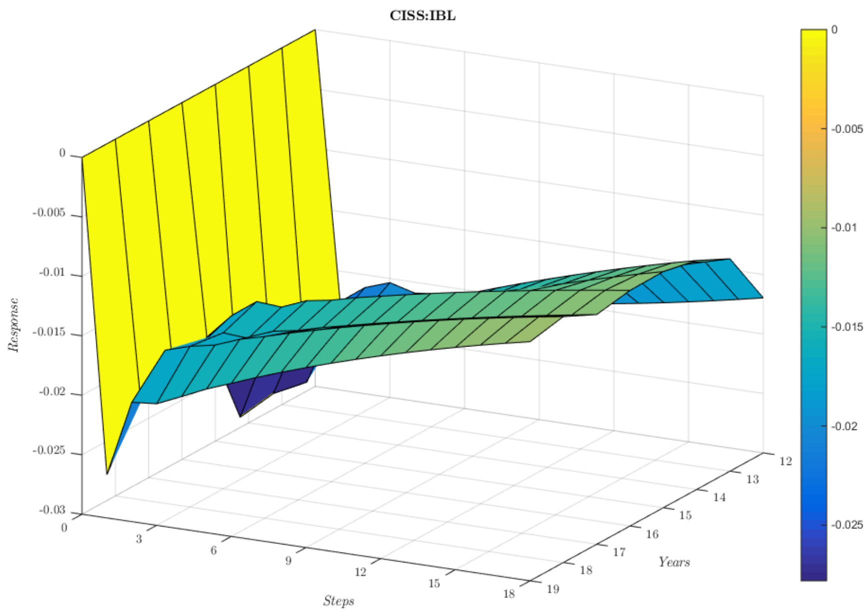

Figure 3.1: Impulse Response Function: Shock CISS on IBL/TL.

The paths of the Impulse Response Functions in figure 3.1 are pretty similar for the all time windows taken into consideration: there is a fast decrease in the ratio Interbank loans over total loans with a negative peak after 1 step (so, after a month) and then there is a graduated recovery. However, there is a main difference in the magnitude of the negative peak and, consequently, of the subsequent recovery for the different time windows.

For the samples of data that go from the one that include data up to 2012 to the sample that include data up to 2015, the negative peak is greater with respect to the same peak when we take into consideration also the data of the years following the 2015.
This difference of magnitude could be addressed to the monetary policies carried out by the European Central Bank with the aim to reduce tensions present in the financial markets and, in particular, in the interbank market which is crucial for the well functioning of the real economy through the credit channel.

Our empirical results are supported by the existing literature since there are evidences that, in time of financial distress, the actors present in the interbank market are unwilling to lend to the other banks and prefer to increase their liquidity position (Iyer & Peydro, 2011).

In the figure 3.2 we have the response of the Industrial Production Index (IPI) due to an impulse in Systemic Stress measured by the CISS index.

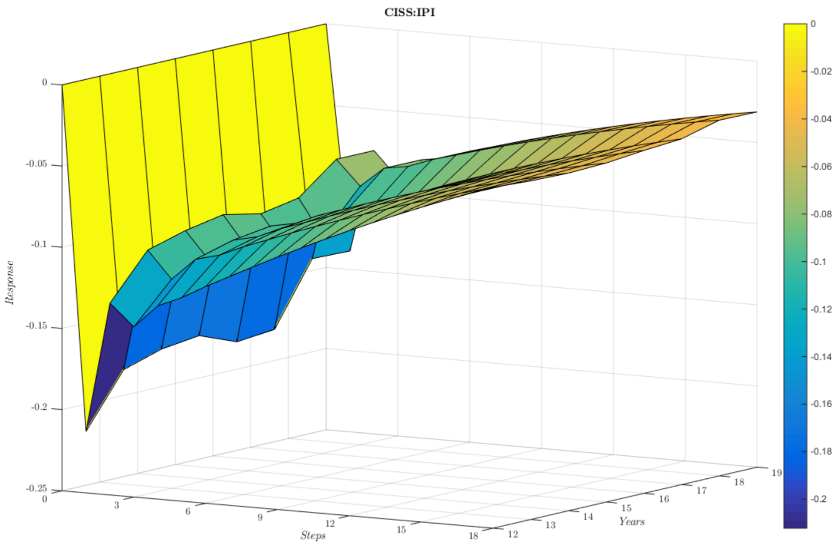

Figure 3.2: Impulse Response Function: Shock CISS on IPI.

Like what we have observed in figure 3.1, the paths of the Impulse Response Functions in figure 3.2 are pretty similar for the all time windows taken into consideration: there is a fast decrease in the Industrial Production Index with a peak after 1 step (so, after a month) and then there is a graduated recovery. However, like for the previous graph, there is a main difference in the magnitude of the negative peak and, consequently, of the subsequent recovery for the different time windows.

So, we can observe that the economies of the four countries of the Euro Area taken into consideration are affected by a contraction of the real activity when there is an increase of stress in the financial markets. However, in the long run there is a gradual recovery and the effects of that increase in the Systemic Stress disappear.

The real economy is dependent by the bank lending and, so, by the interbank market: if there is a reduction in the lending level across banks due to systemic stress, retail actors and firm can not borrow money from the market and there is a subsequent reduction in the levels of consumption and investment.

3.3.2 Application 2

In the second application, we are taking into account the Cholesky decomposition of Σ as represented in equation 3.4 in which the order of the variables has been chosen not taking into account the economic sense of the variables but we start from the indicator of Systemic Stress since we want that the shocks start from the financial system and not from the real economy. So, in the first position we find the Composite Indicator of Systemic Stress and the following variables follow the logical order determined by their economic sense.

In this way, since the indicator of Systemic Stress take the first place in the model, at lag 0 the response of the two variables of interest will be different than zero due to the fact that the two response variables are included after the impulse variables.
We will see from the following figures that this is the main difference with respect to the results of the previous application when we were following the economic sense for all the variables present in the model.

In the figure 3.3 we have the response of the Share of Interbank loans in total loans (IBL/TL) due to an impulse in Systemic Stress measured by the CISS index.

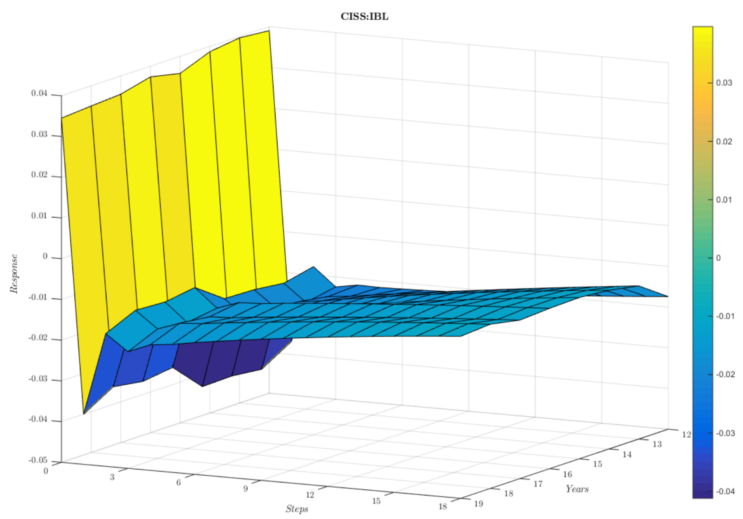

Figure 3.3: Impulse Response Function: Shock CISS on IBL/TL[18].

[18]Impulse response functions for orthogonalised innovations (Cholesky factorisation) with shocks in the CISS allowed to have a contemporaneous impact on the IPI.

As said before, the paths of the Impulse Response Functions in figure 3.3 are similar to those of figure 3.1 where the variable order in the Cholesky decomposition of Σ is different.
The main difference is in the lag zero: the response is different from zero since the Interbank market variable react is a contemporaneously way to a shock in the Systemic Stress due to the variables order. After the negative peak there is a gradual recovery of the response to the shock.

In the figure 3.4 we have the response of the Industrial Production Index (IPI) due to an impulse in Systemic Stress measured by the CISS index.

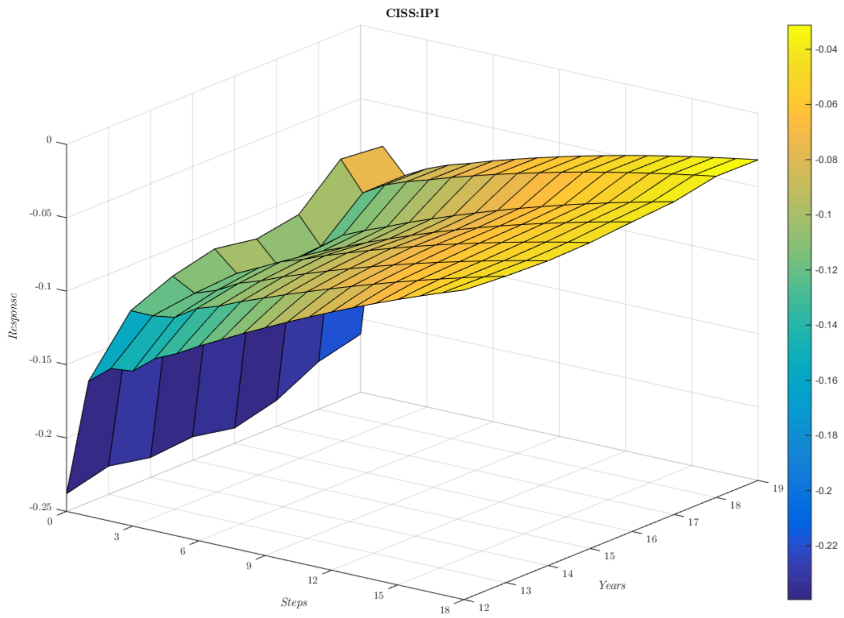

Figure 3.4: Impulse Response Function: Shock CISS on IPI[19].

As we should expect, we can see in figure 3.4 a negative response of the Industrial Production Index to an increase in Systemic Stress. The negative peak starts at the zero lag for all the time windows and, then, a subsequent recovery applies.
Again, the main difference with respect to figure 3.2, in which the variable order respect the economic sense of the variables, is the variable response at lag zero which is different from zero due to the reasons explained above.

Thus, to conclude, we have seen the response of the Interbank market lending over total lending

[19]Impulse response functions for orthogonalised innovations (Cholesky factorisation) with shocks in the CISS allowed to have a contemporaneous impact on the IBL/TL.

and of the Industrial Production Index when the impulse is given by an indicator of Systemic Stress using a recursively approach and taking into consideration two different application:

- the first application where the economic sense of the variables is respected;
- the second application where we wanted to see the Impulse Response Functions when the shock starts from the financial system.

So, we have seen that the qualitative results from the Impulse Response Functions remain robust to a change in the ordering of the variables in the structural shock identification.

In Appendix B, we are going to present the procedure followed in order to implement the Panel VAR analysis in Stata for both applications of which results have been just presented. We will also illustrate the Impulse Response Functions in which all the time sample (from January 1999 to June 2019) is taken into consideration in order to show the 95% Confidence Interval[20] which we have not included in the previous graphs otherwise it would have hidden the results surface.

In Appendix C, we are going to perform some robustness checks for our model taking into account different variables orders.

[20]Since the impulse-response functions are constructed from the model's estimated coefficients, the latter's standard errors need to be taken into account. We calculate the standard errors and generate confidence intervals of the impulse response functions using Monte Carlo simulations. This is conducted by taking random draws of the model's coefficients, using the estimated coefficients and their variance-covariance matrix. We take 200 draws. The 5th and 95th percentiles of the resulting distribution are used for the 90% confidence intervals of the impulse-responses.

Conclusions and future works

The main objectives of this dissertation were to provide an empirical estimation of the impact of a shock in systemic stress to the interbank markets and real economies of some Euro Area countries. We have described the functioning of the interbank markets, the peculiarities of the Composite Indicator of Systemic Stress and we have presented the Panel VAR framework used for the Impulse Response Functions analysis. After that, we have presented the data, the econometric strategy and the results.

We have found that systemic stress has a negative impact of the interbank market activity and on the real economies. We have also seen that the negative peaks of the IRFs are followed by a gradual recovery. The recursively method, used in order to perform the IRFs, allows us to appreciate the differences in the negative peaks for the various time windows taken into consideration. We have concluded that the reduction in the negative peak for the interbank market IRFs, including additional data in the different time windows, is due to the intervention of the European Central Bank whose monetary policies have reduced the stress present in the financial markets and, in particular, in the interbank market which is of crucial importance for the well functioning of the real economy through the credit channel.

Future works could take into account "smallest" countries of the Euro Area which have been not taken into account in this analysis since they would have had the same weight in terms of interbank markets and real economies of the "biggest" countries included in our panel. To do so, should be appropriate to use the so-called Global VAR model in which it is possible to give different weights to the different economies included in the model. In addition to that, it could be possible to analyze the impact of a shock in systemic stress to others Risk Assessment Indicators proposed by the European Central Bank such as leverage, maturity mismatch and non-deposit funding.

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Appendix A

Data description

- IPI: Industrial Production Index.
- EONIA: Euro OverNight Index Average.
- IBL_TL: Share of interbank loans in total loans.
- CISS: Composite Indicator of Systemic Stress.

Variables	*Sources*	*Observations*	*Transformed Frequency*	*Measurement*	*Data coverage*
IPI	Eurostat	monthly	none	Level (base 2015)	1999m1-2019m6
EONIA	ECB Statistics	daily	monthly through simple average	Percentages	1999m1-2019m6
IBL_TL	ECB Statistics	monthly	none	Percentages	1999m1-2019m6
CISS	ECB Statistics	weakly	monthly through simple average	(0,1] interval	1999m1-2019m6

Table A.1: Data description.

Appendix B

Stata procedure

Now, we are going to show the procedure followed in order to implement the Panel VAR analysis in Stata following the *pvar* package developed by Abrigo and Love (2016) for both applications of which results have been represented in section 3.3. The Impulse Response Functions represented take into account all the time sample from January 1999 to June 2019 (they are the same of the IRF represented in section 3.3 where the time window include all the data).

B.1 Application 1

```
. pvarsoc IPI EONIA IBL_TL CISS, maxlag(3) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
...

 Selection order criteria
 Sample:  472 - 712                          No. of obs      =       964
                                             No. of panels   =         4
                                             Ave. no. of T   =   241.000
```

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9991618	164.0881	1.32e-14	-151.9156	68.08806	-16.82901
2	.9993569	64.75828	.0005343	-145.9108	.7582786	-55.8531
3	.9994386	28.48454	.0276527	-76.85001	-3.515463	-31.82115

```
. pvar IPI EONIA IBL_TL CISS, instl(1/4)

Panel vector autoregresssion


GMM Estimation

Final GMM Criterion Q(b) =      .223
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                             No. of obs      =       964
                                             No. of panels   =         4
                                             Ave. no. of T   =   241.000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
IPI						
IPI L1.	-.3411998	.0409606	-8.33	0.000	-.421481	-.2609186
EONIA L1.	.0233613	.0346102	0.67	0.500	-.0444735	.0911961
IBL_TL L1.	-.2661291	.0822936	-3.23	0.001	-.4274217	-.1048366
CISS L1.	-2.323775	.5304008	-4.38	0.000	-3.363342	-1.284209
EONIA						
IPI L1.	.0127275	.0035584	3.58	0.000	.0057532	.0197019
EONIA L1.	1.003906	.0035962	279.16	0.000	.9968579	1.010955
IBL_TL L1.	-.0098187	.0085971	-1.14	0.253	-.0266687	.0070314
CISS L1.	-.4584575	.0492152	-9.32	0.000	-.5549175	-.3619974
IBL_TL						
IPI L1.	.0100136	.0095663	1.05	0.295	-.0087361	.0287632
EONIA L1.	.0158073	.0118043	1.34	0.181	-.0073286	.0389433
IBL_TL L1.	-.2440318	.0604144	-4.04	0.000	-.362442	-.1256217
CISS L1.	-.4422448	.1192915	-3.71	0.000	-.6760519	-.2084377
CISS						
IPI L1.	-.0009868	.0015275	-0.65	0.518	-.0039806	.002007
EONIA L1.	.0015141	.0011566	1.31	0.190	-.0007527	.0037809
IBL_TL L1.	-.0070997	.0035515	-2.00	0.046	-.0140605	-.000139
CISS L1.	.9319781	.0239351	38.94	0.000	.8850662	.97889

Instruments : **l(1/4).(IPI EONIA IBL_TL CISS)**

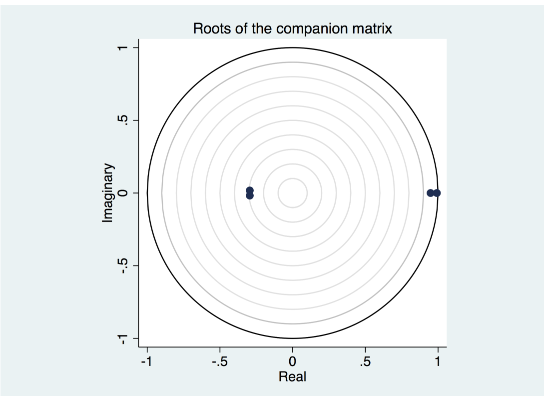
```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

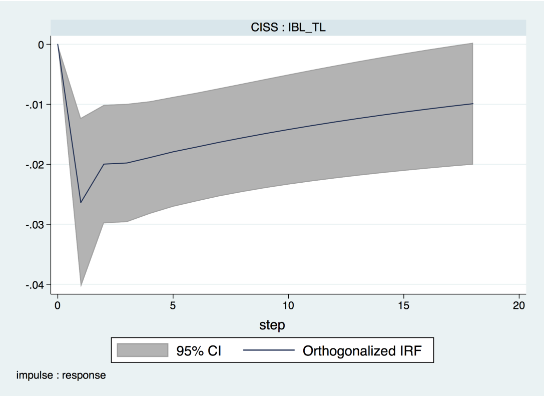
Equation \ Excluded	chi2	df	Prob > chi2
IPI			
EONIA	0.456	1	0.500
IBL_TL	10.458	1	0.001
CISS	19.195	1	0.000
ALL	32.561	3	0.000
EONIA			
IPI	12.793	1	0.000
IBL_TL	1.304	1	0.253
CISS	86.776	1	0.000
ALL	113.220	3	0.000
IBL_TL			
IPI	1.096	1	0.295
EONIA	1.793	1	0.181
CISS	13.744	1	0.000
ALL	17.626	3	0.001
CISS			
IPI	0.417	1	0.518
EONIA	1.714	1	0.190
IBL_TL	3.996	1	0.046
ALL	6.148	3	0.105

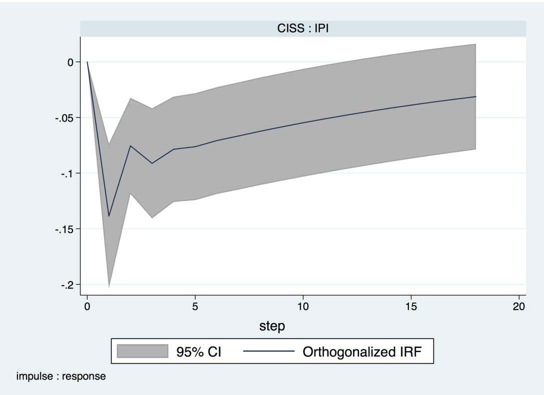
```
. pvarstable, graph

   Eigenvalue stability condition
```

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.9919325	0	.9919325
.9484688	0	.9484688
-.2948743	.0175061	.2953935
-.2948743	-.0175061	.2953935

```
   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```







B.2 Application 2

```
. pvarsoc CISS IPI EONIA IBL_TL, maxlag(3) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
...

 Selection order criteria
 Sample:  472 - 712                                  No. of obs      =       964
                                                     No. of panels   =         4
                                                     Ave. no. of T   =   241.000
```

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9991618	164.0881	1.32e-14	-151.9156	68.08806	-16.82901
2	.9993569	64.75828	.0005343	-145.9108	.7582786	-55.8531
3	.9994386	28.48454	.0276527	-76.85001	-3.515463	-31.82115

```
. pvar CISS IPI EONIA IBL_TL, instl(1/4)

Panel vector autoregresssion



GMM Estimation

Final GMM Criterion Q(b) =      .223
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                No. of obs      =       964
                                                No. of panels   =         4
                                                Ave. no. of T   =   241.000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
CISS						
CISS L1.	.9319781	.0239351	38.94	0.000	.8850662	.97889
IPI L1.	-.0009868	.0015275	-0.65	0.518	-.0039806	.002007
EONIA L1.	.0015141	.0011566	1.31	0.190	-.0007527	.0037809
IBL_TL L1.	-.0070997	.0035515	-2.00	0.046	-.0140605	-.000139
IPI						
CISS L1.	-2.323775	.5304008	-4.38	0.000	-3.363342	-1.284209
IPI L1.	-.3411998	.0409606	-8.33	0.000	-.421481	-.2609186
EONIA L1.	.0233613	.0346102	0.67	0.500	-.0444735	.0911961
IBL_TL L1.	-.2661291	.0822936	-3.23	0.001	-.4274217	-.1048366
EONIA						
CISS L1.	-.4584575	.0492152	-9.32	0.000	-.5549175	-.3619974
IPI L1.	.0127275	.0035584	3.58	0.000	.0057532	.0197019
EONIA L1.	1.003906	.0035962	279.16	0.000	.9968579	1.010955
IBL_TL L1.	-.0098187	.0085971	-1.14	0.253	-.0266687	.0070314
IBL_TL						
CISS L1.	-.4422448	.1192915	-3.71	0.000	-.6760519	-.2084377
IPI L1.	.0100136	.0095663	1.05	0.295	-.0087361	.0287632
EONIA L1.	.0158073	.0118043	1.34	0.181	-.0073286	.0389433
IBL_TL L1.	-.2440318	.0604144	-4.04	0.000	-.362442	-.1256217

Instruments : **l(1/4).(CISS IPI EONIA IBL_TL)**

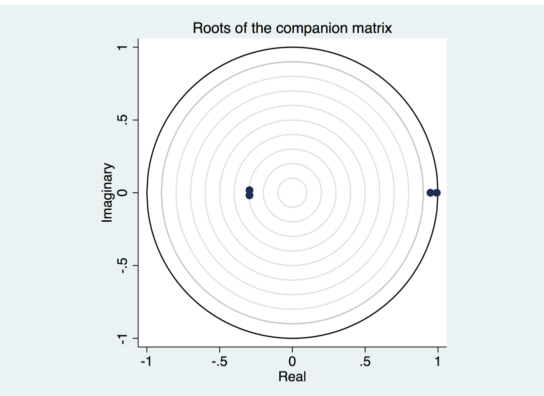
```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

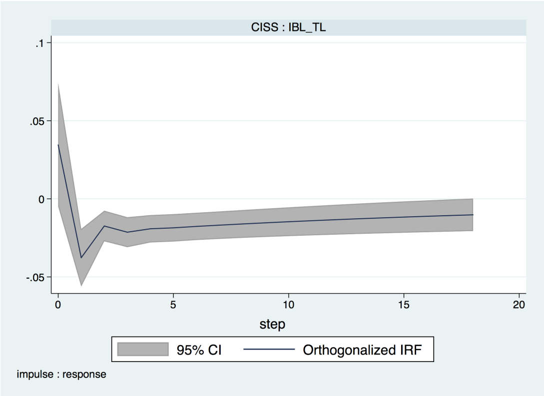
Equation \ Excluded	chi2	df	Prob > chi2
CISS			
IPI	0.417	1	0.518
EONIA	1.714	1	0.190
IBL_TL	3.996	1	0.046
ALL	6.148	3	0.105
IPI			
CISS	19.195	1	0.000
EONIA	0.456	1	0.500
IBL_TL	10.458	1	0.001
ALL	32.561	3	0.000
EONIA			
CISS	86.776	1	0.000
IPI	12.793	1	0.000
IBL_TL	1.304	1	0.253
ALL	113.220	3	0.000
IBL_TL			
CISS	13.744	1	0.000
IPI	1.096	1	0.295
EONIA	1.793	1	0.181
ALL	17.626	3	0.001

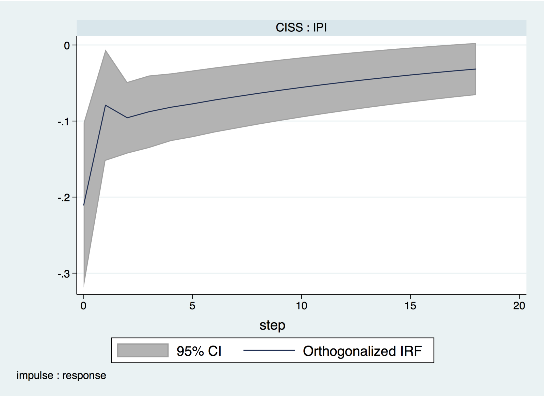
```
. pvarstable, graph

   Eigenvalue stability condition
```

Eigenvalue		
Real	Imaginary	Modulus
.9919325	0	.9919325
.9484688	0	.9484688
-.2948743	.0175061	.2953935
-.2948743	-.0175061	.2953935

```
   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```




CISS : IBL_TL
.1
.05
0
-.05
0
5
10
15
20
step
95% CI
Orthogonalized IRF
impulse : response


CISS : IPI
0
-.1
-.2
-.3
0
5
10
15
20
step
95% CI
Orthogonalized IRF
impulse : response

Appendix C

Robustness checks

Now, we are going to show the results of the Panel VAR analysis using different variables orders as a robustness check. The Impulse Response Functions represented take into account all the time sample from January 1999 to June 2019.

C.1 Check 1

```
. pvarsoc IPI CISS EONIA IBL_TL, maxlag(3) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
...

 Selection order criteria
 Sample:  472 - 712                              No. of obs      =       964
                                                 No. of panels   =         4
                                                 Ave. no. of T   =   241.000
```

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9991618	164.0881	1.32e-14	-151.9156	68.08806	-16.82901
2	.9993569	64.75828	.0005343	-145.9108	.7582786	-55.8531
3	.9994386	28.48454	.0276527	-76.85001	-3.515463	-31.82115

```
. pvar IPI CISS EONIA IBL_TL, instl(1/4)

Panel vector autoregresssion


GMM Estimation

Final GMM Criterion Q(b) =      .223
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                 No. of obs      =       964
                                                 No. of panels   =         4
                                                 Ave. no. of T   =   241.000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
IPI						
IPI L1.	-.3411998	.0409606	-8.33	0.000	-.421481	-.2609186
CISS L1.	-2.323775	.5304008	-4.38	0.000	-3.363342	-1.284209
EONIA L1.	.0233613	.0346102	0.67	0.500	-.0444735	.0911961
IBL_TL L1.	-.2661291	.0822936	-3.23	0.001	-.4274217	-.1048366
CISS						
IPI L1.	-.0009868	.0015275	-0.65	0.518	-.0039806	.002007
CISS L1.	.9319781	.0239351	38.94	0.000	.8850662	.97889
EONIA L1.	.0015141	.0011566	1.31	0.190	-.0007527	.0037809
IBL_TL L1.	-.0070997	.0035515	-2.00	0.046	-.0140605	-.000139
EONIA						
IPI L1.	.0127275	.0035584	3.58	0.000	.0057532	.0197019
CISS L1.	-.4584575	.0492152	-9.32	0.000	-.5549175	-.3619974
EONIA L1.	1.003906	.0035962	279.16	0.000	.9968579	1.010955
IBL_TL L1.	-.0098187	.0085971	-1.14	0.253	-.0266687	.0070314
IBL_TL						
IPI L1.	.0100136	.0095663	1.05	0.295	-.0087361	.0287632
CISS L1.	-.4422448	.1192915	-3.71	0.000	-.6760519	-.2084377
EONIA L1.	.0158073	.0118043	1.34	0.181	-.0073286	.0389433
IBL_TL L1.	-.2440318	.0604144	-4.04	0.000	-.362442	-.1256217

Instruments : **l(1/4).(IPI CISS EONIA IBL_TL)**

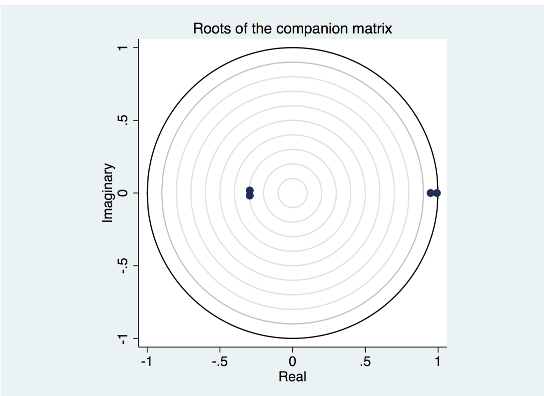
```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

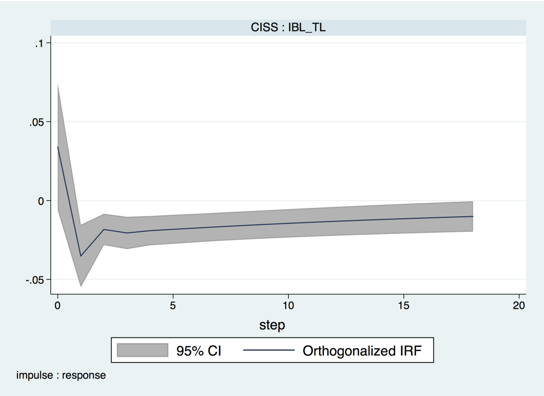
Equation \ Excluded	chi2	df	Prob > chi2
IPI			
CISS	19.195	1	0.000
EONIA	0.456	1	0.500
IBL_TL	10.458	1	0.001
ALL	32.561	3	0.000
CISS			
IPI	0.417	1	0.518
EONIA	1.714	1	0.190
IBL_TL	3.996	1	0.046
ALL	6.148	3	0.105
EONIA			
IPI	12.793	1	0.000
CISS	86.776	1	0.000
IBL_TL	1.304	1	0.253
ALL	113.220	3	0.000
IBL_TL			
IPI	1.096	1	0.295
CISS	13.744	1	0.000
EONIA	1.793	1	0.181
ALL	17.626	3	0.001

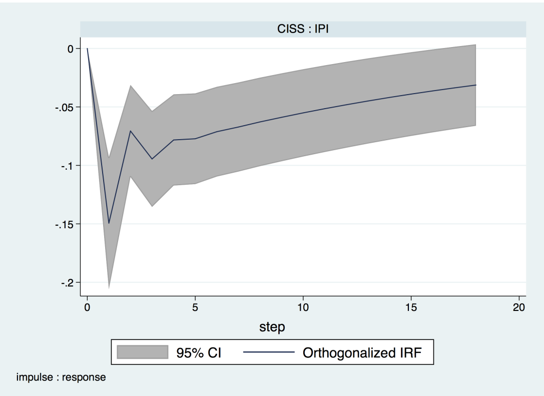
```
. pvarstable, graph

   Eigenvalue stability condition
```

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.9919325	0	.9919325
.9484688	0	.9484688
-.2948743	.0175061	.2953935
-.2948743	-.0175061	.2953935

```
   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```







C.2 Check 2

```
. pvarsoc CISS EONIA IBL_TL IPI , maxlag(3) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
...

 Selection order criteria
 Sample:  472 - 712                                No. of obs      =       964
                                                   No. of panels   =         4
                                                   Ave. no. of T   =   241.000
```

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9991618	164.0881	1.32e-14	-151.9156	68.08806	-16.82901
2	.9993569	64.75828	.0005343	-145.9108	.7582786	-55.8531
3	.9994386	28.48454	.0276527	-76.85001	-3.515463	-31.82115

```
. pvar CISS EONIA IBL_TL IPI, instl(1/4)

Panel vector autoregresssion


GMM Estimation

Final GMM Criterion Q(b) =      .223
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                   No. of obs      =       964
                                                   No. of panels   =         4
                                                   Ave. no. of T   =   241.000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
CISS						
CISS L1.	.9319781	.0239351	38.94	0.000	.8850662	.97889
EONIA L1.	.0015141	.0011566	1.31	0.190	-.0007527	.0037809
IBL_TL L1.	-.0070997	.0035515	-2.00	0.046	-.0140605	-.000139
IPI L1.	-.0009868	.0015275	-0.65	0.518	-.0039806	.002007
EONIA						
CISS L1.	-.4584575	.0492152	-9.32	0.000	-.5549175	-.3619974
EONIA L1.	1.003906	.0035962	279.16	0.000	.9968579	1.010955
IBL_TL L1.	-.0098187	.0085971	-1.14	0.253	-.0266687	.0070314
IPI L1.	.0127275	.0035584	3.58	0.000	.0057532	.0197019
IBL_TL						
CISS L1.	-.4422448	.1192915	-3.71	0.000	-.6760519	-.2084377
EONIA L1.	.0158073	.0118043	1.34	0.181	-.0073286	.0389433
IBL_TL L1.	-.2440318	.0604144	-4.04	0.000	-.362442	-.1256217
IPI L1.	.0100136	.0095663	1.05	0.295	-.0087361	.0287632
IPI						
CISS L1.	-2.323775	.5304008	-4.38	0.000	-3.363342	-1.284209
EONIA L1.	.0233613	.0346102	0.67	0.500	-.0444735	.0911961
IBL_TL L1.	-.2661291	.0822936	-3.23	0.001	-.4274217	-.1048366
IPI L1.	-.3411998	.0409606	-8.33	0.000	-.421481	-.2609186

Instruments : **l(1/4).(CISS EONIA IBL_TL IPI)**

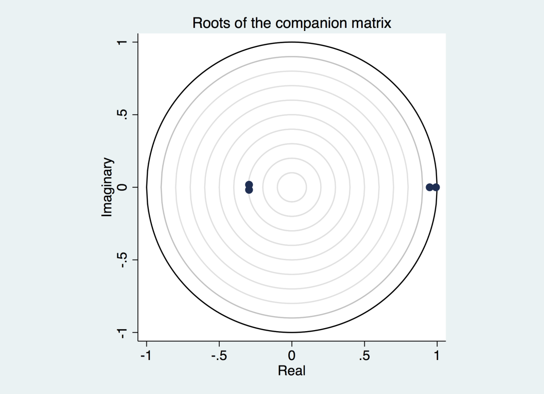
```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

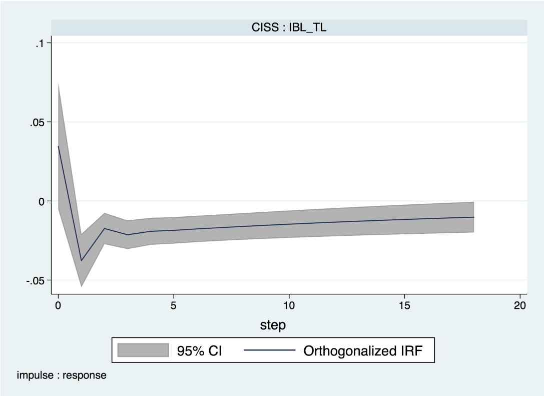
Equation \ Excluded	chi2	df	Prob > chi2
CISS			
EONIA	1.714	1	0.190
IBL_TL	3.996	1	0.046
IPI	0.417	1	0.518
ALL	6.148	3	0.105
EONIA			
CISS	86.776	1	0.000
IBL_TL	1.304	1	0.253
IPI	12.793	1	0.000
ALL	113.220	3	0.000
IBL_TL			
CISS	13.744	1	0.000
EONIA	1.793	1	0.181
IPI	1.096	1	0.295
ALL	17.626	3	0.001
IPI			
CISS	19.195	1	0.000
EONIA	0.456	1	0.500
IBL_TL	10.458	1	0.001
ALL	32.561	3	0.000

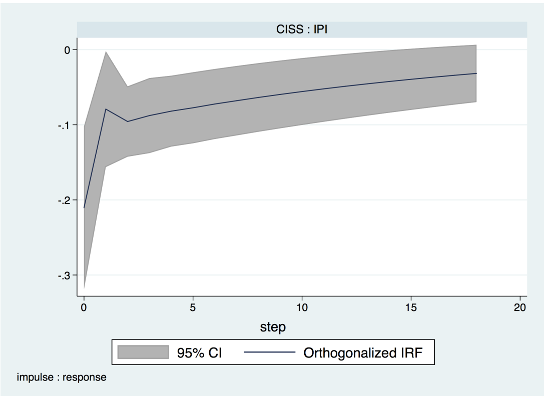
```
. pvarstable, graph

   Eigenvalue stability condition
```

Eigenvalue		
Real	Imaginary	Modulus
.9919325	0	.9919325
.9484688	0	.9484688
-.2948743	-.0175061	.2953935
-.2948743	.0175061	.2953935

```
   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```







C.3 Check 3

```
. pvarsoc IBL_TL EONIA CISS IPI, maxlag(3) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
...

 Selection order criteria
 Sample:  472 - 712                          No. of obs      =       964
                                             No. of panels   =         4
                                             Ave. no. of T   =   241.000
```

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9991618	164.0881	1.32e-14	-151.9156	68.08806	-16.82901
2	.9993569	64.75828	.0005343	-145.9108	.7582786	-55.8531
3	.9994386	28.48454	.0276527	-76.85001	-3.515463	-31.82115

```
. pvar IBL_TL EONIA CISS IPI, instl(1/4)

Panel vector autoregresssion



GMM Estimation

Final GMM Criterion Q(b) =      .223
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                             No. of obs      =       964
                                             No. of panels   =         4
                                             Ave. no. of T   =   241.000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
IBL_TL						
IBL_TL						
L1.	-.2440318	.0604144	-4.04	0.000	-.362442	-.1256217
EONIA						
L1.	.0158073	.0118043	1.34	0.181	-.0073286	.0389433
CISS						
L1.	-.4422448	.1192915	-3.71	0.000	-.6760519	-.2084377
IPI						
L1.	.0100136	.0095663	1.05	0.295	-.0087361	.0287632
EONIA						
IBL_TL						
L1.	-.0098187	.0085971	-1.14	0.253	-.0266687	.0070314
EONIA						
L1.	1.003906	.0035962	279.16	0.000	.9968579	1.010955
CISS						
L1.	-.4584575	.0492152	-9.32	0.000	-.5549175	-.3619974
IPI						
L1.	.0127275	.0035584	3.58	0.000	.0057532	.0197019
CISS						
IBL_TL						
L1.	-.0070997	.0035515	-2.00	0.046	-.0140605	-.000139
EONIA						
L1.	.0015141	.0011566	1.31	0.190	-.0007527	.0037809
CISS						
L1.	.9319781	.0239351	38.94	0.000	.8850662	.97889
IPI						
L1.	-.0009868	.0015275	-0.65	0.518	-.0039806	.002007
IPI						
IBL_TL						
L1.	-.2661291	.0822936	-3.23	0.001	-.4274217	-.1048366
EONIA						
L1.	.0233613	.0346102	0.67	0.500	-.0444735	.0911961
CISS						
L1.	-2.323775	.5304008	-4.38	0.000	-3.363342	-1.284209
IPI						
L1.	-.3411998	.0409606	-8.33	0.000	-.421481	-.2609186

Instruments : **l(1/4).(IBL_TL EONIA CISS IPI)**

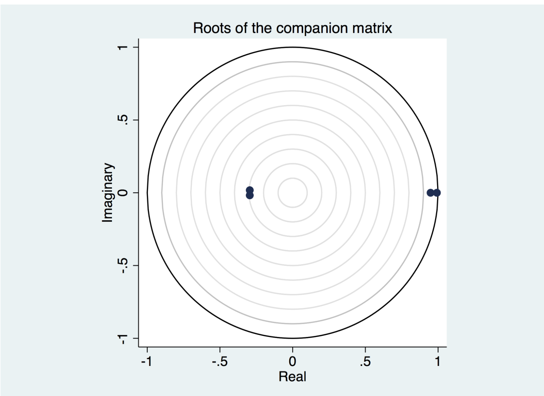
```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

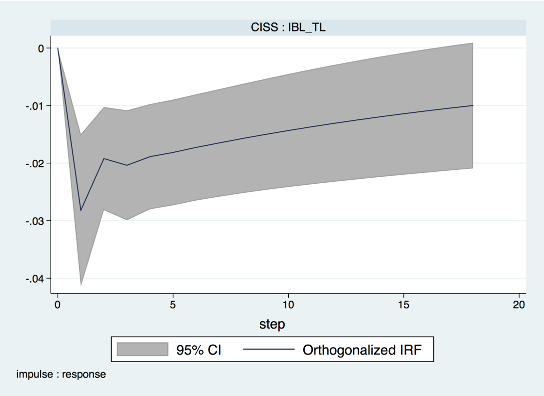
Equation \ Excluded	chi2	df	Prob > chi2
IBL_TL			
EONIA	1.793	1	0.181
CISS	13.744	1	0.000
IPI	1.096	1	0.295
ALL	17.626	3	0.001
EONIA			
IBL_TL	1.304	1	0.253
CISS	86.776	1	0.000
IPI	12.793	1	0.000
ALL	113.220	3	0.000
CISS			
IBL_TL	3.996	1	0.046
EONIA	1.714	1	0.190
IPI	0.417	1	0.518
ALL	6.148	3	0.105
IPI			
IBL_TL	10.458	1	0.001
EONIA	0.456	1	0.500
CISS	19.195	1	0.000
ALL	32.561	3	0.000

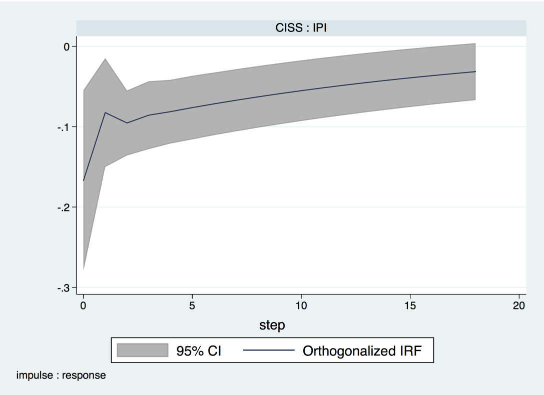
```
. pvarstable, graph

   Eigenvalue stability condition
```

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.9919325	0	.9919325
.9484688	0	.9484688
-.2948743	.0175061	.2953935
-.2948743	-.0175061	.2953935

```
   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```







C.4 Check 4

```
. pvarsoc CISS IBL_TL EONIA IPI, maxlag(3) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
...

 Selection order criteria
 Sample:  472 - 712                              No. of obs      =       964
                                                 No. of panels   =         4
                                                 Ave. no. of T   =   241.000
```

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9991618	164.0881	1.32e-14	-151.9156	68.08806	-16.82901
2	.9993569	64.75828	.0005343	-145.9108	.7582786	-55.8531
3	.9994386	28.48454	.0276527	-76.85001	-3.515463	-31.82115

```
. pvar CISS IBL_TL EONIA IPI, instl(1/4)

Panel vector autoregresssion


GMM Estimation

Final GMM Criterion Q(b) =       .223
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                 No. of obs      =       964
                                                 No. of panels   =         4
                                                 Ave. no. of T   =   241.000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
CISS						
CISS L1.	.9319781	.0239351	38.94	0.000	.8850662	.97889
IBL_TL L1.	-.0070997	.0035515	-2.00	0.046	-.0140605	-.000139
EONIA L1.	.0015141	.0011566	1.31	0.190	-.0007527	.0037809
IPI L1.	-.0009868	.0015275	-0.65	0.518	-.0039806	.002007
IBL_TL						
CISS L1.	-.4422448	.1192915	-3.71	0.000	-.6760519	-.2084377
IBL_TL L1.	-.2440318	.0604144	-4.04	0.000	-.362442	-.1256217
EONIA L1.	.0158073	.0118043	1.34	0.181	-.0073286	.0389433
IPI L1.	.0100136	.0095663	1.05	0.295	-.0087361	.0287632
EONIA						
CISS L1.	-.4584575	.0492152	-9.32	0.000	-.5549175	-.3619974
IBL_TL L1.	-.0098187	.0085971	-1.14	0.253	-.0266687	.0070314
EONIA L1.	1.003906	.0035962	279.16	0.000	.9968579	1.010955
IPI L1.	.0127275	.0035584	3.58	0.000	.0057532	.0197019
IPI						
CISS L1.	-2.323775	.5304008	-4.38	0.000	-3.363342	-1.284209
IBL_TL L1.	-.2661291	.0822936	-3.23	0.001	-.4274217	-.1048366
EONIA L1.	.0233613	.0346102	0.67	0.500	-.0444735	.0911961
IPI L1.	-.3411998	.0409606	-8.33	0.000	-.421481	-.2609186

Instruments : **l(1/4).(CISS IBL_TL EONIA IPI)**

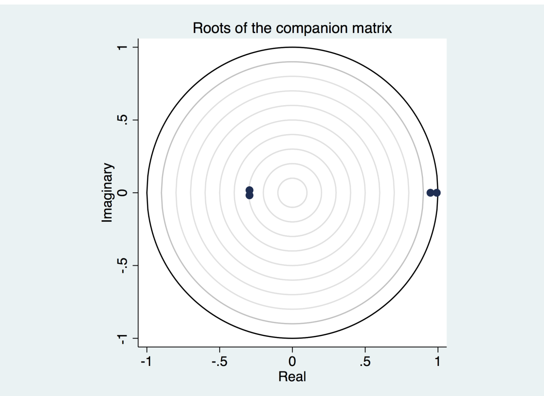
```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

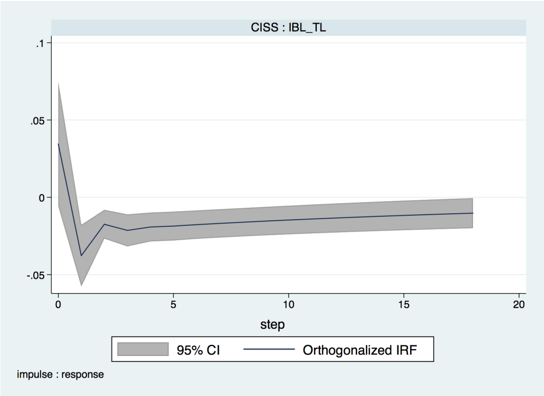
Equation \ Excluded	chi2	df	Prob > chi2
CISS			
IBL_TL	3.996	1	0.046
EONIA	1.714	1	0.190
IPI	0.417	1	0.518
ALL	6.148	3	0.105
IBL_TL			
CISS	13.744	1	0.000
EONIA	1.793	1	0.181
IPI	1.096	1	0.295
ALL	17.626	3	0.001
EONIA			
CISS	86.776	1	0.000
IBL_TL	1.304	1	0.253
IPI	12.793	1	0.000
ALL	113.220	3	0.000
IPI			
CISS	19.195	1	0.000
IBL_TL	10.458	1	0.001
EONIA	0.456	1	0.500
ALL	32.561	3	0.000

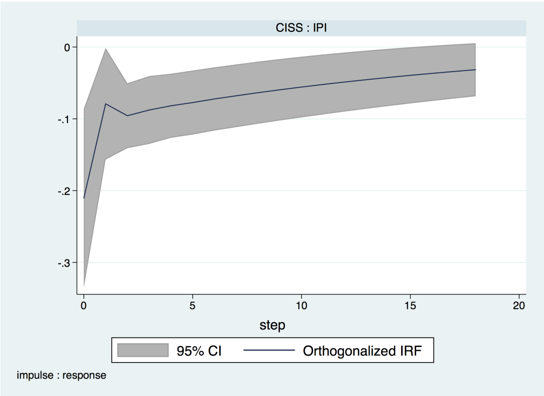
```
. pvarstable, graph

   Eigenvalue stability condition
```

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.9919325	0	.9919325
.9484688	0	.9484688
-.2948743	-.0175061	.2953935
-.2948743	.0175061	.2953935

```
   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```







C.5 Check 5

```
. pvarsoc EONIA IPI IBL_TL CISS, maxlag(3) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
...

 Selection order criteria
 Sample:  472 - 712                              No. of obs      =        964
                                                 No. of panels   =          4
                                                 Ave. no. of T   =    241.000
```

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9991618	164.0881	1.32e-14	-151.9156	68.08806	-16.82901
2	.9993569	64.75828	.0005343	-145.9108	.7582786	-55.8531
3	.9994386	28.48454	.0276527	-76.85001	-3.515463	-31.82115

```
. pvar EONIA IPI IBL_TL CISS, instl(1/4)

Panel vector autoregresssion



GMM Estimation

Final GMM Criterion Q(b) =      .223
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                 No. of obs      =        964
                                                 No. of panels   =          4
                                                 Ave. no. of T   =    241.000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
EONIA						
EONIA L1.	1.003906	.0035962	279.16	0.000	.9968579	1.010955
IPI L1.	.0127275	.0035584	3.58	0.000	.0057532	.0197019
IBL_TL L1.	-.0098187	.0085971	-1.14	0.253	-.0266687	.0070314
CISS L1.	-.4584575	.0492152	-9.32	0.000	-.5549175	-.3619974
IPI						
EONIA L1.	.0233613	.0346102	0.67	0.500	-.0444735	.0911961
IPI L1.	-.3411998	.0409606	-8.33	0.000	-.421481	-.2609186
IBL_TL L1.	-.2661291	.0822936	-3.23	0.001	-.4274217	-.1048366
CISS L1.	-2.323775	.5304008	-4.38	0.000	-3.363342	-1.284209
IBL_TL						
EONIA L1.	.0158073	.0118043	1.34	0.181	-.0073286	.0389433
IPI L1.	.0100136	.0095663	1.05	0.295	-.0087361	.0287632
IBL_TL L1.	-.2440318	.0604144	-4.04	0.000	-.362442	-.1256217
CISS L1.	-.4422448	.1192915	-3.71	0.000	-.6760519	-.2084377
CISS						
EONIA L1.	.0015141	.0011566	1.31	0.190	-.0007527	.0037809
IPI L1.	-.0009868	.0015275	-0.65	0.518	-.0039806	.002007
IBL_TL L1.	-.0070997	.0035515	-2.00	0.046	-.0140605	-.000139
CISS L1.	.9319781	.0239351	38.94	0.000	.8850662	.97889

Instruments : **l(1/4).(EONIA IPI IBL_TL CISS)**

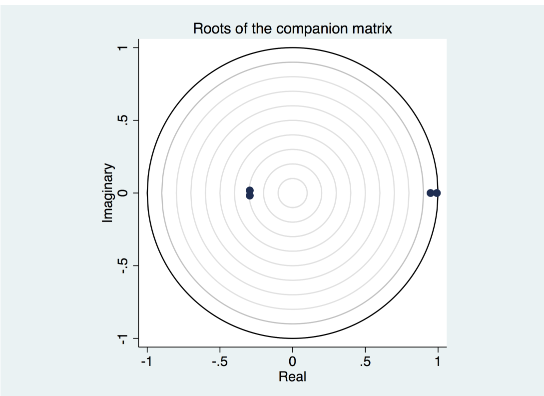
```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

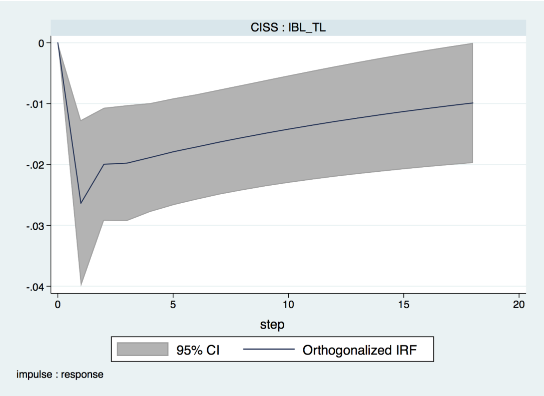
Equation \ Excluded	chi2	df	Prob > chi2
EONIA			
IPI	12.793	1	0.000
IBL_TL	1.304	1	0.253
CISS	86.776	1	0.000
ALL	113.220	3	0.000
IPI			
EONIA	0.456	1	0.500
IBL_TL	10.458	1	0.001
CISS	19.195	1	0.000
ALL	32.561	3	0.000
IBL_TL			
EONIA	1.793	1	0.181
IPI	1.096	1	0.295
CISS	13.744	1	0.000
ALL	17.626	3	0.001
CISS			
EONIA	1.714	1	0.190
IPI	0.417	1	0.518
IBL_TL	3.996	1	0.046
ALL	6.148	3	0.105

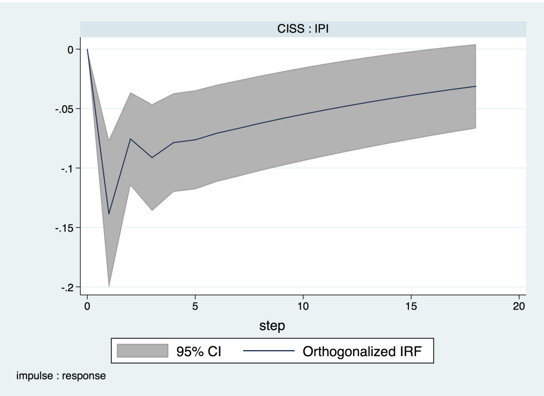
```
. pvarstable, graph

   Eigenvalue stability condition
```

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.9919325	0	.9919325
.9484688	0	.9484688
-.2948743	.0175061	.2953935
-.2948743	-.0175061	.2953935

```
   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```







C.6 Check 6

```
. pvarsoc IPI IBL_TL CISS EONIA, maxlag(3) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
...

 Selection order criteria
 Sample:  472 - 712                                 No. of obs      =       964
                                                    No. of panels   =         4
                                                    Ave. no. of T   =   241.000
```

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9991618	164.0881	1.32e-14	-151.9156	68.08806	-16.82901
2	.9993569	64.75828	.0005343	-145.9108	.7582786	-55.8531
3	.9994386	28.48454	.0276527	-76.85001	-3.515463	-31.82115

```
. pvar IPI IBL_TL CISS EONIA, instl(1/4)

Panel vector autoregresssion


GMM Estimation

Final GMM Criterion Q(b) =       .223
Initial weight matrix: Identity
GMM weight matrix:      Robust
                                                     No. of obs      =       964
                                                     No. of panels   =         4
                                                     Ave. no. of T   =   241.000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
IPI						
IPI						
L1.	-.3411998	.0409606	-8.33	0.000	-.421481	-.2609186
IBL_TL						
L1.	-.2661291	.0822936	-3.23	0.001	-.4274217	-.1048366
CISS						
L1.	-2.323775	.5304008	-4.38	0.000	-3.363342	-1.284209
EONIA						
L1.	.0233613	.0346102	0.67	0.500	-.0444735	.0911961
IBL_TL						
IPI						
L1.	.0100136	.0095663	1.05	0.295	-.0087361	.0287632
IBL_TL						
L1.	-.2440318	.0604144	-4.04	0.000	-.362442	-.1256217
CISS						
L1.	-.4422448	.1192915	-3.71	0.000	-.6760519	-.2084377
EONIA						
L1.	.0158073	.0118043	1.34	0.181	-.0073286	.0389433
CISS						
IPI						
L1.	-.0009868	.0015275	-0.65	0.518	-.0039806	.002007
IBL_TL						
L1.	-.0070997	.0035515	-2.00	0.046	-.0140605	-.000139
CISS						
L1.	.9319781	.0239351	38.94	0.000	.8850662	.97889
EONIA						
L1.	.0015141	.0011566	1.31	0.190	-.0007527	.0037809
EONIA						
IPI						
L1.	.0127275	.0035584	3.58	0.000	.0057532	.0197019
IBL_TL						
L1.	-.0098187	.0085971	-1.14	0.253	-.0266687	.0070314
CISS						
L1.	-.4584575	.0492152	-9.32	0.000	-.5549175	-.3619974
EONIA						
L1.	1.003906	.0035962	279.16	0.000	.9968579	1.010955

Instruments : **l(1/4).(IPI IBL_TL CISS EONIA)**

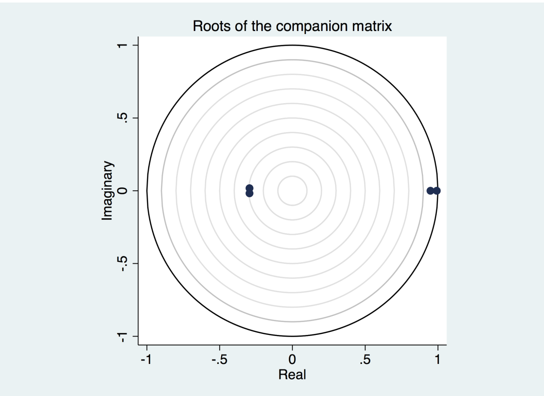
```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

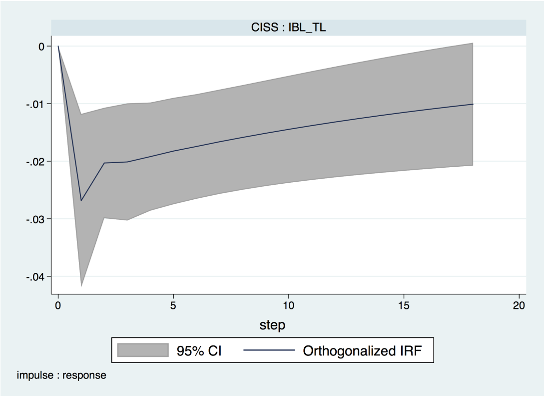
Equation \ Excluded	chi2	df	Prob > chi2
IPI			
IBL_TL	10.458	1	0.001
CISS	19.195	1	0.000
EONIA	0.456	1	0.500
ALL	32.561	3	0.000
IBL_TL			
IPI	1.096	1	0.295
CISS	13.744	1	0.000
EONIA	1.793	1	0.181
ALL	17.626	3	0.001
CISS			
IPI	0.417	1	0.518
IBL_TL	3.996	1	0.046
EONIA	1.714	1	0.190
ALL	6.148	3	0.105
EONIA			
IPI	12.793	1	0.000
IBL_TL	1.304	1	0.253
CISS	86.776	1	0.000
ALL	113.220	3	0.000

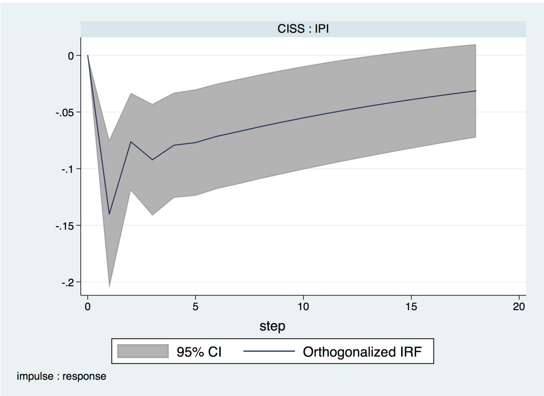
```
. pvarstable, graph

   Eigenvalue stability condition
```

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.9919325	0	.9919325
.9484688	0	.9484688
-.2948743	-.0175061	.2953935
-.2948743	.0175061	.2953935

```
   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```




CISS : IBL_TL
0
-.01
-.02
-.03
-.04
0
5
10
15
20
step
95% CI
Orthogonalized IRF
impulse : response


CISS : IPI
0
-.05
-.1
-.15
-.2
0
5
10
15
20
step
95% CI
Orthogonalized IRF
impulse : response