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The Effects of Financial Stress on the Economic Activity of the Euro Area

A Bayesian Approach

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“My passionate sense of social justice and social responsibility has always contrasted oddly with my pronounced freedom from the need for direct contact with other human beings and human communities. I gang my own gait and have never belonged to my country, my home, my friends, or even my immediate family, with my whole heart; in face of all these ties I have never lost an obstinate sense of detachment, of the need for solitude—a feeling which increases with the years. One is sharply conscious, yet without regret, of the limits to the possibility of mutual understanding and sympathy with one’s fellow-creatures. Such a person no doubt loses something in the way of geniality and light-heartedness; on the other hand, he is largely independent of the opinions, habits, and judgements of his fellows and avoids the temptation to take his stand on such insecure foundations.“

Albert Einstein (1959), The World as I See it.

INTRODUCTION

The recent financial crisis, which took place during the 2008-2009 and culminated with the default of the Lehman Brothers, affected both the securities markets and the banking system, causing the greatest fall in the economic activity from the great depression of the 1929.

These events allowed for considerations about the economic effects of strong shocks in the financial markets, pushing to redefine the influence of finance on the real economy.

More specifically, the concept of financial stress emerged as a dangerous condition of the financial markets able to undermine the economic activity, and consequently a new stream of literature rose about different attempts to measure effectively such phenomenon with real-time indexes.

Such indicators were then differently employed in order to improve modelling and to evaluate the actual weight of financial stress on the real economy of different countries.

This thesis is placed in this context, in particular on the light of the present European Sovereign Debt Crisis the aim was to analyse the outlook of the European Monetary Union (EMU) after a financial shock.

Therefore we took advantage of the previous literature for the developing of a financial market stress indicator (FMSI) for the Euro Area through a principal component analysis on a group of banking, securities and foreign exchange variables.

The original contribution of the thesis is twofold. First we study the effects of the proposed FMSI variable on the real economy for a set of key variables of the real economy. Specifically were taken into consideration the annual rate of growth of the industrial production index, the annual inflation rate and the short-term interest rate Euribor. Secondly, we suggests a Bayesian VAR modelling approach to the joint analysis on a group of EMU countries, such as France, Germany, Greece, Italy and Spain. Finally the Bayesian approach also allowed us to study the impact of the International Monetary Fund’s medium and long-run projections on the conclusions of our analysis.

1. FINANCIAL STRESS and ECONOMIC ACTIVITY

1.1 Defining and measuring Financial Stress

Even if financial turmoil lead first the US and then the entire developed world into the greatest recession since the Great Depression of the 1929, the relationship between financial stress and the real economy is far from being completely clear and understood.

The same idea of "financial stress" is something that until the 2006 did not present a clear definition in literature, so that authors used rather to refer to uncertainty or volatility.

But the recent events highlighted that financial stress is a wide phenomenon, which implies uncertainty, and is connected, but not coincident with volatility.

For example new unexpected information could generate volatility, but this not necessary implies stress in the market. On the opposite high financial spreads could determine a lot of stress without significant effects on the volatility.

A clear definition is given by Illing and Liu (2006), who defined financial stress as a phenomenon generally identifiable as the combination of a condition of fragility in the financial markets and an exogenous shock.

Of course as much the financial markets are vulnerable and as much the size of the shocks increases, greater would be the level of stress.

Financial stress is then identifiable as a continuous variable, which peaks are generated in correspondence of stressful events; in particular if high levels of stress become systemic, they can produce negative effects on the real economy, and in the worst cases, crisis.

As a consequence to measure effectively such variable become one of the main objectives of the recent literature. Specifically the general aim is to take advantage from indicators able to capture warning signals from the current scenario, in order to prevent economic downturns.

For this purpose different ways were explored according to the idea that financial stress is reflected in many banking and securities variables, and so capturable using a weighted-sum approach or principal component analysis on a selected group of financial series.

The composite index provided by Illing and Liu (2006) was specifically one of the first and the most influent index, becoming the reference point for the later authors.

Within the weighted-sums, examples are given by the indicators of IMF (2008), Guichard et al. (2009), Grimaldi (2010), or Cardarelli et al. (2011); the majority of last literature instead focused on the principal component analysis as Illing and Liu (2006), the KCFSI of Hakkio and Keeton (2009), the STLFSI of the St. Louis FED, or the FMSI of Van Roye (2011).

Such indexes proposed different solutions also for the variables taken in considerations.

Specifically even if the majority proposed variants of the Illing and Liu FSI, some authors as Grimaldi tried to develop a real-time index that takes into considerations also qualitative information as the ECB assessments.

At this point could be useful to make a further distinction.

The construction of a financial stress indicator would change on the basis of its purpose: a trader or an investor would probably take advantage from a real-time indicator built with very high frequency data, while a researcher interested in a descriptive analysis would be better satisfied with a more comprehensive index.

In this paper would be exploited this last option, according to the purpose of a scenario analysis of the 2003-2012 period.

1.2 Literature on the effects of financial stress

As the literature about these measures was developing, were also rising theories and applications about the effects of financial turmoil on the real economy.

A complete understanding about the relationship between the two dimensions is however still far, particularly due to the absence of an exhaustive theory able to explain the behaviour and the transition period between states of low stress and prosperous activity and states of high stress and low activity.

In order to fill this theoretical gap, many econometrics applications have occurred in short time.

For example Bloom (2009) estimated a VAR model joining the volatility index (VIX) of the S&P 500, with measures of the real economy. Results highlighted that the uncertainty related to episodes of stress has significant effects on the employment and industrial production.

These effects were imputable to the fact that uncertainty causes a break in the investments and in the hiring, causing a fall in the productivity.

One of the main exhaustive theory comes with Davig and Hakkio (2010).

According to the authors, the experience of the 2008-2009 crisis has shown that financial stress carries tighter credit conditions and uncertainty, so that households and firms restrain new investments and purchases.

In particular they explored two theoretical frameworks: the “real options” model, which evaluates uncertainty as a factor related to the time in which to take economic decisions, and the “financial accelerator” model, which examines how the tightening of the borrowing conditions in high stress periods affects investments and leads to further worst consequences on financial activity.

The real options theory focuses on the value of postponing decisions in high stress times in order to wait for lower uncertainty periods. In this sense “option” refers to the possibility for an investor to wait or not to make an investment.

The results of this theory highlighted that in high financial stress times is better to postpone decisions in order to allow uncertainty to dissipate and so to make a correct evaluation of the investment. Therefore high levels of stress would lead to a reduction of the investments in the present, and to an increase in the future.

The financial accelerator model instead considers that when financial stress comes to an increase, to raise funds becomes more difficult and costly; so that if consumers and firms cannot longer get funds for their purchases or investments, these last would fall down as recently happened. Such movements are explained with a model that connects the capability of an actor to obtain funds to its financial position.

The term “financial accelerator” refers to the fact that when the economy is in expansion, firms receive higher profits and seems to be less risky to obtain lower interests on financing; so that new investments are incentivized and further growth is then stimulated.

This process is also true in reverse, and takes the name “adverse feedback loop”, and indicates how fast economic condition would deteriorate in periods of stress.

Davig and Hakkio try also to verify the effects of financial stress on the real economy through the empirical application of their KCFSI to the US economy.

The applied methodology was the estimation of a “regime-switching” model, in which regularly the US economy works in a normal regime with low financial stress and high economic activity, and sometimes passes to a distressed regime with high financial stress and low economic activity.

The data confirmed the theory of the financial accelerator model, showing that in distress regime, so in presence of high uncertainty, financial shocks have larger influence on the production, both in terms of decline peak and in terms of time length. Moreover rises in financial stress seem to increase the probability of switching from the normal to the distress regime; therefore policymakers should always monitor and maintain low the level of stress in order to avoid effects on the real economy.

Another contribution comes from Cardarelli et al. (2011), which analysed the effects of financial stress on 17 advanced economies between the 1980 and the 2007, through the use of an indicator called FSI obtained from the combination of banking, securities, and foreign exchange markets variables.

Results highlighted a connection between financial stress and economic recession, in particular often, but not always, a financial stress peak anticipates a slowdown or a recession in the economic activity.

Specifically major findings regarded:

- Between the three groups of variables, the banking-related seems to be the more influent, with deeper and longer effects on the real economy. Moreover recessions anticipated by banking shocks have double length in comparison to recession not preceded by financial stress.
- The rise of houses price and aggregate credit has a positive correlation with the probability that financial stress could be followed by a slowdown in the economy.
- Arm's-length financial systems demonstrated to be more sensible to banking stress.
- Core financial intermediaries play a key role in transmitting stress in the financial markets to the real economy, therefore policies aimed to the recovery of their capital base can reduce the slowdowns of the economy.

Mallick and Sousa (2011) examined the effects of financial stress in the Eurozone joining the FSI from Cardarelli et al. together with six macroeconomic variables (interest rate, real GDP, inflation rate, commodity price, growth rate of the monetary aggregate) in a Bayesian Structural VAR (BVAR) and a Sign-Restriction VAR.

In the specific the focus of the analysis was the macroeconomic impact of 1) a monetary policy shock and of 2) a financial stress shock.

Results highlighted that contractions in the monetary policy have an important role in raising the level of stress in the financial markets. Moreover shocks in the FSI have consistent effects on the level of the output, and require strong responses by the monetary authorities in order to stabilize the production.

Finally Van Roye (2011) estimated a financial market stress index (FMSI) using a principal component analysis with a dynamic approximate factor on many variables coming from the banking sector, securities, and foreign exchange markets. Then he estimated a BVAR model with Minnesota prior for Germany and the Euro Area joining the FMSI with the GDP growth, the annual inflation rate and a measure of the short-term interest rates.

According to the results, there is evidence of a strong connection between financial stress and real economy, in particular a one-standard deviation shock on the FMSI has shown to account the 30% of Euro GDP variations, 18% of inflation rate and 50% of short-term interest rates.

In the next chapters an application of the Van Roye approach would be implemented to a small Euro Area in order to evaluate the cross effects of a FMSI shock on the real economy of the single countries.

2. A FINANCIAL STRESS INDICATOR

2.1 Introduction

As already stated from the 2009 crisis different solutions to measure the financial stress has been proved. In particular these attempts can be divided in two different groups on the basis of their approach: weighted-sum indexes and principal components indexes.

In this analysis was followed the principal component approach, applied to 18 variables coming from the banking sector, the securities markets and on the foreign exchange markets.

The construction of the index follows mainly the methodology adopted by Hakkio and Keeton for the KCFSI and by Van Roye for the FMSI; nevertheless the estimated indicator is adapted on the basis of data availability, and simplified from the dynamic factor by the reduction of the estimation range and of the number of variables taken into consideration.

2.2 Methodology

The idea behind the construction of this index is that stress in the financial markets is difficult to identify in itself, but it’s something reflected in various financial market variables. So that in order to analyse the phenomenon there’s the need to first identify a proper set of financial variables, and then find a way to extrapolate the useful information.

Following this reasoning, the methodology used in this paper consists in applying a principal component analysis (PCA) to a group of financial variables selected on the basis of previous literature in order to capture most of their variation in just few series.

This technique in fact allows to reduce the number of analysed variables, discarding the linear combinations which absorb small variance, and so allowing to study just the few which absorb the majority of the variation and the correlation.

The final aim is to unify the few relevant combinations through a variance-weighted sum, so that to obtain a single index expression of the phenomenon.

A complete treatment of the principal components analysis is delayed to Anderson (1984) and Jolliffe (1986); here are given just some basic notions on the methodology, in order to justify the adoption of the PCA in itself and to give to the unskilled reader the possibility to understand how the index works.

In the specific let’s consider *n* series, which in this case represent the *n* variables used to extract the financial stress, with known covariance matrix Σ.

The calculus of the real eigenvalues on Σ returns a set *n* of values with the same numerousness of the original series.

The corresponding eigenvectors, named *principal components* (PCs), represent a set of linear uncorrelated combinations of the original series, each absorbing the proportion of total variance expressed by the corresponding eigenvalue.

Therefore a selection of just the eigenvectors which contains a sufficient amount of total variance, allows to reduce the number of series, and so the complexity of the analysis.

Moreover the components taken into consideration can be interpreted as specific parts of the phenomenon, and classifiable as real self-standing indices.

Of course if the original variables have consistent correlations between them, then the first few PCs would retain most of the variation, while the last ones would have very low eigenvalues.

The approach adopted in this paper exploits a variant of this methodology, which implies the use of the correlation matrix instead of ∑[1].

The advantage of this approach consists in using the standardized version of the original variables, making the results more directly comparable: the PCs calculated on covariance matrix are indeed subjected to the units of measurement proper of each variable, while the standardization leads them to the same dimension.

Series with larger variance tend to dominate the others in the PCA, and this is correct until the series are expression of the same dimension (i.e. weight or temperature); but comparing different objects as in this case (i.e. rate of interests, indexes, prices, spreads), it’s inappropriate to overrate a variance just for the different units used in the measure.

Moreover thanks to the transformation the coefficients of the eigenvectors become directly expression of the relevance of the variables in the specific component, thanks to the fact that the series are now directly comparable.

At this point is pretty clear the superiority of a principal component approach rather than a simple weighted-sum: not only the PCA allows for the division in sub-indices for

[1] Jolliffe (1986).

deeper analysis, but, more important, a correct application take into consideration just the useful information, discarding what could be considered just as noise.

Furthermore the coefficients related to each PC jointly to the correlation matrix, allows for an evaluation of the relevance the variables: the ones with near-zero coefficients in the valuable PCs, could be considered as non-relevant and so discarded from the analysis; a precious tools for researchers that aim to estimate an index from the scratch.

By the way the use of the PCA requires the series to have the same length, so that it's needed to have the same publishing data and frequency for each variable, otherwise series are cut to the shortest and less frequent one.

Van Roye (2011) and previous literature[2] found a way to overcome the publication lag problem using a dynamic latent factor passing through the Kalman filter.

In this treatment was instead preferred to discard variables with too short range, and to reduce the estimation period to 2003:1 – 2012:1. This way of proceeding not only simplifies the computation of the index, but also avoids the noisy-effects and consistency controversy deriving from the use of estimated data to produce other estimations.

Finally all the computations and estimations in this section are made using EViews 7.

2.3 Data

The estimation dataset has monthly frequency, so that data with quarterly frequency have been interpolated[3].

As already noted, the estimation period is comprised from 2003:1 to 2012:1 (109 observations) in order to have all the time series available and to avoid situations in which some variables were not yet published.

Moreover the series have been standardized subtracting their mean and dividing them by their standard deviation, so that to have results directly comparable.

Following the methodology used by Cardarelli et al (2011) and by Van Roye (2011), the estimated data are expression of three different financial sectors: banking-related variables, securities market-related variables and foreign exchange-related variables.

In particular:

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[2] For example Hakkio and Keeton (2009).

[3] See Appendix A for details.

- Banking-related variables: TED spread, Money market spread, Bank stock market prices, Bank equity risk index, Expected Lending, Excess Liquidity, Marginal Lending Facility.
- Securities market-related variables: Corporate Credit Spread, Housing Spread, Government Bond Spread, Consumer Credit Spread, Vstoxx, Inverse prices of Eurostoxx 50, Slope of Yield Curve.
- Foreign exchange-related variables: Real Effective Exchange Rate (GARCH(1,1)).

Further detailed information on the variables is given in the Appendix A.

2.4 FMSI

The appliance of the PCA on the 18 variables using the correlation matrix returned the following output:

Principal Components Analysis

Sample: 2003:01 2012:01
Included observations: 109
Computed using: Ordinary correlations
Extracting 18 of 18 possible components

Eigenvalues: (Sum = 18, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	9.846199	6.545331	0.5470	9.846199	0.5470
2	3.300868	0.976051	0.1834	13.14707	0.7304
3	2.324817	1.634020	0.1292	15.47188	0.8595
4	0.690797	0.177175	0.0384	16.16268	0.8979
5	0.513622	0.064849	0.0285	16.67630	0.9265
6	0.448773	0.200610	0.0249	17.12507	0.9514
7	0.248162	0.039636	0.0138	17.37324	0.9652
8	0.208526	0.062623	0.0116	17.58176	0.9768
9	0.145904	0.074526	0.0081	17.72767	0.9849
10	0.071377	0.010176	0.0040	17.79904	0.9888
11	0.061201	0.016639	0.0034	17.86024	0.9922
12	0.044562	0.013622	0.0025	17.90481	0.9947
13	0.030941	0.007575	0.0017	17.93575	0.9964
14	0.023365	0.005849	0.0013	17.95911	0.9977
15	0.017516	0.007398	0.0010	17.97663	0.9987
16	0.010119	0.001634	0.0006	17.98675	0.9993
17	0.008484	0.003717	0.0005	17.99523	0.9997
18	0.004767	---	0.0003	18.00000	1.0000

Table 1: Principal Component Analysis of the 18 financial variables.

The construction of the index is made following the criteria defined by Jolliffe[4] thanks to his long experience in the PCA[5].

The first criterion in choosing a subset of PCs is the cumulative proportion of variance absorbed by the first components.

An optimal value should be located between the 80% and 90%, so that the correct amount of PCs is the smallest that the reaches such range.

To take into consideration the *m* PCs with largest absorbed variance allows to reach the optimal percentage with the smallest number of PCs; therefore in this specific case the choice should be to consider between the first 3 or 4 components (Table).

Of course this way of proceeding implicitly assumes that in the first *m* PCs is localized most of the useful information because they carry the highest correlation between the original variables; so that the criterion tends to ignore PCs with relative independent information.

In this specific case such approach should be correct, in fact the objective of the analysis is to look for a phenomenon which affects all the variable simultaneously.

The second criterion is the so-called Kaiser's rule, which retains significant only those PCs with eigenvalue equal or greater than one.

This rule follows directly from the idea that if all the original variables are independent, than the PCs coincide with the original variables, and have unit variances/eigenvalues (it demands the use of the correlation matrix). As a consequence any PC with λ smaller than one is to be considered as containing less information than one of the original variable alone, and so it could be discarded.

Following this criterion, in this analysis the correct number of PCs should be fixed to the first 3.

Even if it contains a high degree of subjectivity, Jolliffe points out also the "scree graph" as a good help in choosing the number of PCs.

The scree graph was first introduced by Cattell as the plot of the eigenvalues λ against the corresponding number of the components *k*.

[4] Jolliffe (1972), (1986).
[5] In his 1986 text he claims to experience PCA from nearly 20 years.

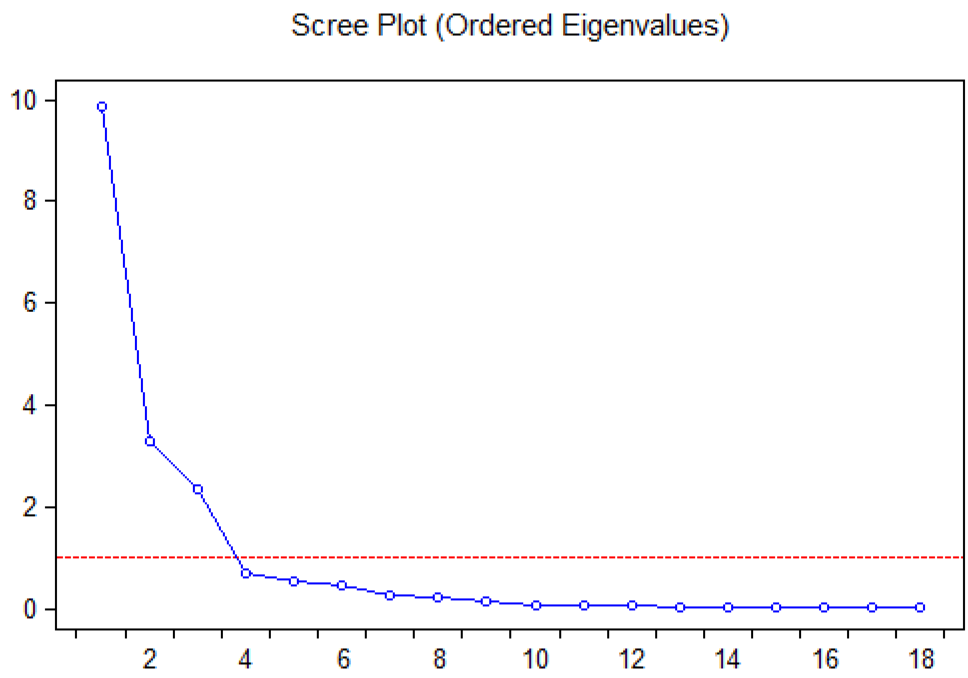

Figure 1: Scree Graph (Ordered Eigenvalues).

At this point the selection should be done choosing a number of PCs *k**, such that the scree graph is "steep" on the left of *k** and "not steep" on its right, or, as formulated by Cattell, *k** should be fixed at the beginning of the more or less straight line defined by the scree graph.

In this analysis the degree of subjectivity is reduced to the minimum, in fact is quite easy to identify the value *k** at 4, which is contrast to the suggestion given by previous criterion.

The above figure gives a graphical representation of this discrepancy: the red line is plotted in correspondence of λ=1 and represents the cutting level according to the Kaiser's rule, while the Cattell's criterion indicates the level corresponding to *k**=4.

With this information a clear decision is not straightforward: even if the size of λ is a statistically founded method, it's also true that scree graph is very clear.

The solution to the impasse is given by Jolliffe (1972), who argued that a cutting level at λ=1 could retain to few variables. In fact variables that carry more or less independent information would have low coefficients in the first PCs, but will emerge in the PCs with λ close to one (remember that uncorrelated variables would have λ=1).

So that Jolliffe on the basis of simulation studies suggested a cut-level at about λ*=0.7.

For sure is questionable discussing about to add or not the 3.84% of the total variance, but according to analytical criteria the selection of 4 PCs seems the best in order to not loose relevant information.

The next step to obtain the PCs is the computation of the eigenvectors[6].

Variable	PC 1	PC 2	PC 3	PC 4
ST_BANKSTOXX	-0.291372	0.055987	-0.181158	0.215044
ST_CONS_CRED_SPR	0.274709	-0.213556	0.117307	0.215627
ST_CORP_CRED_SPR	0.285549	-0.007728	-0.183838	0.075541
ST_EQUITYRISK	-0.257232	0.305443	-0.000321	-0.167046
ST_EXPLENDAV	0.088020	0.364820	0.379616	-0.284826
ST_GARCH	0.199260	-0.070377	0.347264	-0.104339
ST_HOUSING_SPR	0.300106	-0.133762	0.077183	0.137083
ST_LIQUIDITY	0.257467	0.113022	-0.121597	0.361936
ST_MARGINALFACILITY	0.157257	0.274599	0.064357	0.603172
ST_MONEYSPREAD	0.179611	0.433139	-0.012741	0.068232
ST_SLOPE	0.254041	-0.262954	0.188138	0.115050
ST_SPRFRGER	0.277464	0.150045	-0.227682	-0.123707
ST_SPRGRGER	0.239822	0.047104	-0.376211	-0.210479
ST_SPRITGER	0.266342	0.087720	-0.318094	-0.180972
ST_SPRSPGER	0.262052	0.027942	-0.298412	-0.279199
ST_STOXX	0.223543	-0.135975	0.354059	-0.199304
ST_TED	-0.018353	0.495089	0.101300	0.119515
ST_VSTOXX	0.205379	0.245403	0.274323	-0.160705

Table 2: Principal Components' coefficients

A preliminary analysis of the coefficients returns a confirmation about the 4thPC nature: it's pretty clear that the Marginal Lending Facility is the variable that carries the almost independent information, in fact it doesn't exhibit particularly high coefficients in the first three components, while dominates the fourth. Moreover the correlation matrix highlights the relative-independent information carried by this variable in comparison to the others.

The complete analysis of the PCs comes with the graphical representation of the corresponding indices.

Using the above results (table), the coefficients β of the PCs are multiplied for the corresponding standardized variables x^* and then summed in such a way:

[6] The correlation matrix is given in Appendix A.

$$Index_1 = \beta_{PC1,1} * X_1 + \beta_{PC1,2} * X_2 + \cdots + \beta_{PC1,n} * X_n$$
$$Index_2 = \beta_{PC2,1} * X_1 + \beta_{PC2,2} * X_2 + \cdots + \beta_{PC2,n} * X_n$$
$$Index_3 = \beta_{PC3,1} * X_1 + \beta_{PC3,2} * X_2 + \cdots + \beta_{PC3,n} * X_n$$
$$Index_4 = \beta_{PC4,1} * X_1 + \beta_{PC4,2} * X_2 + \cdots + \beta_{PC4,n} * X_n$$

The results are functions that could be considered expression of specific area of the financial stress; in particular the plot of the obtained indexes suggests different interpretations.

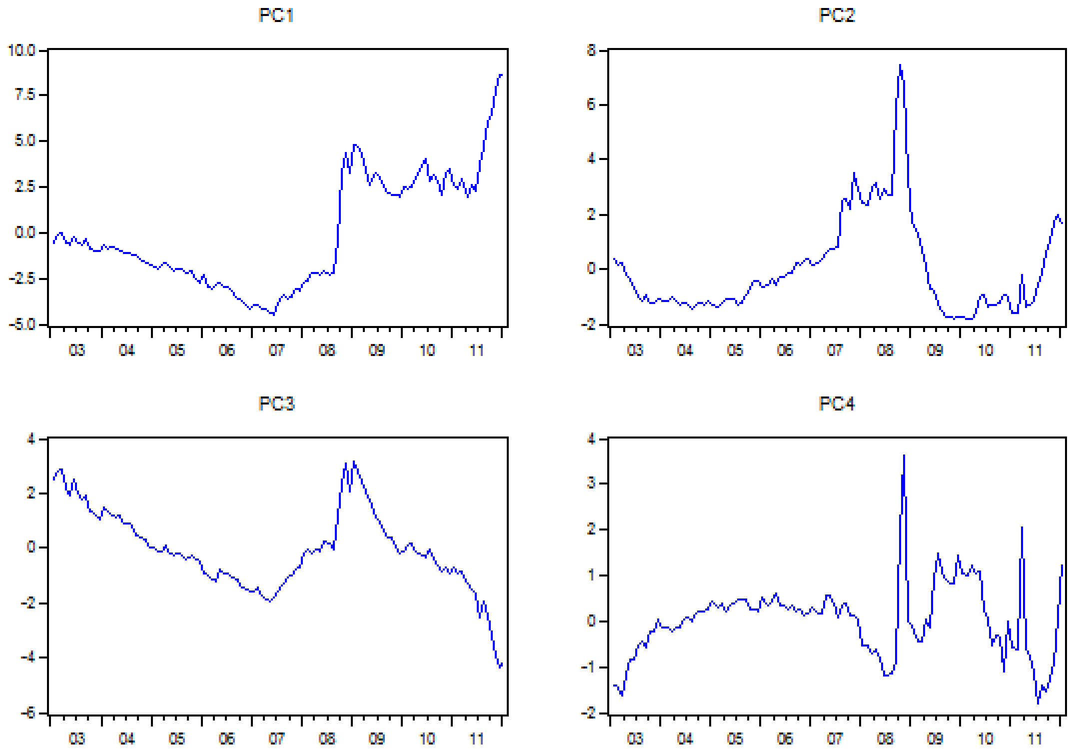

Figure 2: Principal Components plots.

The first one is for sure the most important with over 50% of total variation absorbed. Specifically looking at the coefficients it can be considered as a sort of generalized market stress indicator, with just the Ted Spread and the Expected Lending low comprised in the index. But it's also true that coefficients highlights a little greater sensitivity to the Securities variables in comparison to other financial sectors, probably due to the higher correlation.

The graph confirms this idea: even if there are relevant peaks within the 2009 Great Recession and the 2010 Liquitity Drought, the plot exibits a particular sensitivity for the 2011 Sovereign Debt Crisis with a strong peak in correspondence of the end of the year.

From this considerations it could be approximately named as “Security Market Stress Indicator” (SMSI).

The second index is less debatable: an analysis of the coefficients easly reveals a strong dominance of the Banking-related variables with the exception of the Eurostoxx Banks. In particular the PC seems to be dominated by the TED spread because of its high correlation with the banking variables and very low with the other sectors.

The graph analysis demonstates a particular sensitivity for the 2008 Great Recession and two smaller peaks, one coming from the 2002 Worldcom bankruptcy and Corporate scandals, and one within the 2011 Sovereign Debt Crisis.

Therefore it’s pretty clear that the index absorbs mostly the variations coming from the banking sector, so that it can be named as Banking Sector Stress Indicator (BSSI).

The third PC could be something harder to interpret.

The coefficients reveal strong positive contributions from the Expected Lending, REER (Garch), Eurostoxx inverted prices and VStoxx, while relevant negative influences come expeccially from the Sovereign Bond Spreads and, to a lesser extent, from the Eurostoxx Banks prices and the Corporate Credit Spread.

The graph exibits a decreasing trend from the 2003, followed by a new shock within the 2008 crisis and finally fall down at the minimum with the 2011 crisis.

Such considerations lead to the conclusion that this index reflects the stress in the stock market. On one side in fact the increase in volatility and the fall of the stock prices for sure increase the stress in such sector, while on the other hand the deteriorating considtions on the bonds market would be reflected positively: the increase of risk on the government bonds in fact lead the stock market to be a better investment choice.

Within this arguments, the index could be summarized as Stock Market Stress Indicator (KMSI).

Finally the last index, which absorbed a very strict proportion of the total variance, graphically exibits an increasing trend after the 2002 events, then reaching stability until 2008. After that the representation become quite troubled: first a fast decrease until the 2009, followed by a strong shock within Lehman Brother default, and then alternating peak in correspondence of the beginning of 2010 (the lonmgest in term of time), 2011 and 2012.

At the coefficients level, the most involved variables are positively Marginal Lending Facility, Excess Liqudity, Eurostoxx Bank prices and Consumer Credit Spread, while negatively Expected Lending, Government Bonds Spreads (particularly Spain, Greece and Italy) and the inverted Eurostoxx prices.

So the stress in this specific area seems to be influenced positively by banking financing conditions and negatively by the increase in lending expectations and by positive trends in the bonds and stock markets. In particular this last consideration leads to the idea that the index registers a reduction in the stress level when there's more convenience in maintaining liquidity instead of invest in the financial markets.

Therefore regarding liquidity, lending and more generally banking financing conditions, the index can be identified as Bank Liquidity Stress Indicator (BLSI).

This four indicators represent the different aspects of which the financial stress in composed.

In order to obtain a generalized index of financial stress, these four are grouped with a weighted-sum average, in particular are weighted by the proportion of the total variance absorbed, so that preserving their contribution to the financial stress.

Such computation leads to the final Financial Market Stress Indicator (FMSI).

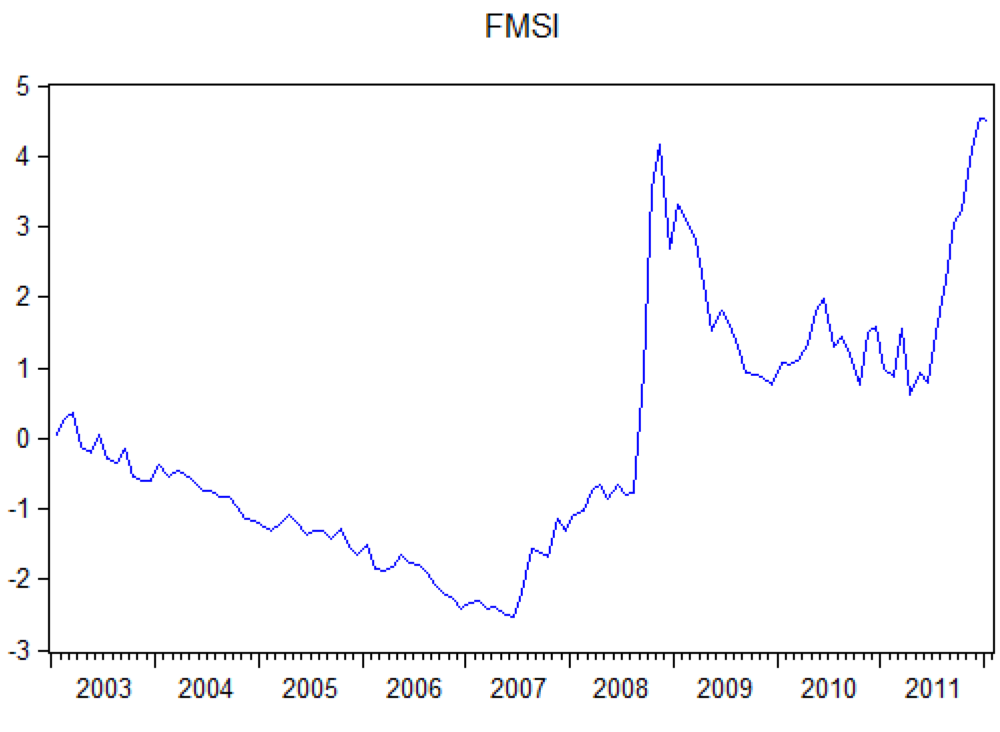

Figure 3: Financial Market Stress Indicator.

In order to identify episodes of stress the Bank of Canada and IMF refer to the standard deviation of the index. Specifically the first considers stressful episodes that exceed the mean by 2 times the standard deviation, while the second imposes a stricter cut at 1 time the standard deviation.

As Hakkio and Keeton (2009) referred, these methods are strongly affected by the sample dimension: adding observations influences both the mean and the s.d., so that some events could change their status from stressful to normal and vice versa by simply expanding or shrinking the sample.

Always Hakkio and Keeton suggested other solutions as a cut level based of the percentile in order to reduce the sampling influence, i.e. to consider stressful events that exceed the 90^{th} percentile, or to refer to a subjective benchmark independent from the sample, such as a specific episode.

But the conclusion is that all such methods could lead to misleading if evaluated outside the context.

For example the mid2009-mid2011 period register a significant reduction on the level of stress in comparison to the 2008 peak, but still remains much higher than the 2003-2007 arc. So that if observed separately, one could consider the mid2009-mid2011 frame as stress-less, but a wider analysis would account it as dangerous.

Moreover also the duration of the stress is important: short, isolated episode of stress could in effect not produce economically relevant consequences.

In conclusion in this paper wasn't followed a rigid approach based on statistics, but the graphical representation was evaluated on the basis of the overall trend and of its behavior in correspondence of specific stressful events, so that to determine the sensitivity of the index.

Going deeply into the analysis of the indicator, the plot starts with a decreasing trend after the 2002 Worldcom default and Corporate scandals, reaching the minimum level at half of the 2007.

The 2008 CDO crisis bursts rapidly the index, reaching the second maximum with the default of Lehman Brothers.

Between 2009-2011 the graph highlights different small peaks in correspondence of highly stress events:

- May 2010: Liquidity Drought and Greece downgrade by the rating agencies.

- December 2010: strong Ireland downgrade by the rating agencies.
- March 2011: strong Portugal downgrade by the rating agencies.

Finally from half of the 2011 the events of the Sovereign Debt Crisis lead the indicator to his maximum in correspondence with the end of the year.

In synthesis the index exhibits a good sensitivity for the financial stress, in particular it seems able to satisfactorily identify the main stress episodes of the considered period.

Moreover it doesn’t exhibit false alarm episodes, namely the graph doesn’t present peaks that do not corresponds to any stressful event or period.

In the next section the FMSI will be used into a Bayesian VAR model in order to evaluate the effects of episodes of financial stress on the real economy.

3. BAYESIAN VAR MODELS

3.1 Introduction

The effects of financial stress on the real economy are evaluated through a Bayesian Vector AutoRegressive (BVAR) model joining the FMSI index with crucial variables of the real economy of five representative EMU states.

In particular for every country were chosen the annual rate on growth of the Industrial Production Index (IPI), the annual rate of change of the Consumer Price Index (i.e. the annual inflation rate), and the short-term interest rate 3-month Euribor.

The countries taken into consideration are between the most discussed upon the 2011 European Sovereign Debt Crisis, i.e. Germany, France, Italy, Spain and Greece.

This way of proceed allows not only for a direct evaluation of the effects of financial stress on the economic activity, but highlights also how such effects are transmitted in a small Euro Area.

The short period taken into consideration leads to a scarcity of data with respect to the number of parameters (overfitting). Therefore in order to improve the estimation was chosen a Bayesian approach with informative prior, in order to include out-of-sample information.

So first the BVAR is estimated, then results are evaluated combining an analysis of the coefficients with an impulse response and variance decomposition analysis. Finally a sensitivity analysis discusses the incidence of the prior on results through the evaluation of a model with non-informative prior.

3.2 Methodology

The most common approach to evaluate a set of simultaneous equations is through the use of a Vector Auto Regressive model (VAR).

Introduced by the Nobel prize Christopher Sims in the 1980[7], the VAR models have become increasingly important in economics thanks to their support in studying the dynamic evolution of a group of variables from their past history.

A complete treatment of the VAR models is given in Verbeek (2006) and Hamilton (1994); here as in chapter 2 are explained just the basic notions of the methodology

[7] Sims (1980).

useful to the reader and for a better understanding of the results presented in the rest of this thesis.

The first step is to consider a basic situation in which a researcher is interested in studying the causality relationship of a group of variables starting from the information of the previous period.

Defining the vector of variables at the current time *t* as $[y_{1t}, y_{2t}, \dots, y_{nt}]$, the formalization of model is given by the following representation:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \dots \\ y_{nt} \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \dots \\ \delta_n \end{bmatrix} + B \cdot \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ \dots \\ y_{nt-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \dots \\ \varepsilon_{nt} \end{bmatrix}$$

Where δ_i, *i=1,…,n*, are the intercepts of the equations, *B* is the *nxn* matrix of the regression coefficients and ε_{it}, *i=1,…,n*, are possibly correlated white noise processes.

In this case the model assumes the name of VAR(1), where the term between the parenthesis refers to the number of lags considered by the explanatory variables.

Of course the *B* coefficients matrix and the $\sum$ variance/covariance matrix are the main sources of interest for the researcher, in fact any b_{ij} element of *B* represents the contribution of one variable in explaining another, and any σ_{ij} element of $\sum$ with $i \neq j$ represents the correlation between them.

The model can be easily extended for any number *p* of lags:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \dots \\ y_{nt} \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \dots \\ \delta_n \end{bmatrix} + B(1) \cdot \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ \dots \\ y_{nt-1} \end{bmatrix} + \dots + B(p) \cdot \begin{bmatrix} y_{1t-p} \\ y_{2t-p} \\ \dots \\ y_{nt-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \dots \\ \varepsilon_{nt} \end{bmatrix}$$

Or

$$Y_t = \Delta + B(1) \cdot Y_{t-1} + \dots + B(p) \cdot Y_{t-p} + E_t$$

Where $Y_t = [y_{1t}, y_{2t} \dots y_{nt}]'$, $\Delta = [\delta_1, \delta_2 \dots \delta_n]'$, $Y_{t-p} = [y_{1t-p}, y_{2t-p} \dots y_{nt-p}]'$ and $E_t = [\varepsilon_{1t}, \varepsilon_{2t} \dots \varepsilon_{nt}]'$.

Usually increasing the number of lags would improve the estimation, but it’s also true that a researcher would probably like to analyse together as much variables as possible, especially in economics. The problem in increasing the number of lags of the model is that the number of parameters to estimate would increase dramatically, and in many cases there are few observations available for the variables in the VAR model (overfitting problem).

For example analysing n variables, a researcher has to estimate n parameters for the δ vector, n^2xp parameters for the *B(p)* matrixes and $\frac{n(n+1)}{2}$ parameters for the variance/covariance matrix. It's easy to see that with just 5 variables and 4 lags the model would contain 120 parameters to estimate and not always a proportional number of data is available.

This is the situation that occurred in this analysis, where with 12 variables and 1 lag (234 parameters) the 12x109 available observations were barely sufficient for a good estimation of a VAR(1) model.

This consideration explains the choice of using one general indicator of financial stress rather than the four specific identified in chapter 2: as long as the observations are limited, estimations would take advantage of the use of one overall index rather than four, even if this means to reduce the generality of the analysis.

The choice of a VAR(1) still implies an overfitting problem in our analysis, so that out-of-sample information was added in order to fill the gap.

The inclusion of such external source was possible through the use of a Bayesian VAR (BVAR) model: following the strand of literature that emphasises the superiority of the BVAR models with valuable prior information[8], the estimation was improved through the use of an informative prior on the steady-state growth from the IMF and OECD projections[9].

There are many sources which explain the Bayesian approach[10] at which the complete treatment is delayed; in this analysis was followed in particular the formulation given by Koop (2006), considering it the most straightforward.

The foundations of the Bayesian approach inference can be found on the well-known *Bayes' rule*, which expresses the probability of an event B given an event A, as the probability of A given B, times the probability of B divided by the probability of A:

$$p(B|A) = \frac{p(A|B)p(B)}{p(A)}$$

Where *A* and *B* are subsets of probability space (Ω, *p)*.

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[8] E.g. Litterman (1985), Goldstein (2006).

[9] IMF (2012), OECD (2012).

[10] Koop (2006), Zellner (1996).

Such rule can be applied to econometrics considering a sample y of data on which a researcher is interested in, and a vector or a matrix of parameters θ, which define a model that seeks to explain y.

With this new notation, the formulation of the *Bayes' rule* become:

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)}$$

Where $p(\theta|y)$ represents the posterior density function of the parameters given the data (i.e. how well the parameters fit the sample), $p(y|\theta)$ the likelihood function (i.e. how the sample fit the parameters), $p(\theta)$ the prior density function of the parameters and $p(y)$ the marginal distribution of y: $\int p(y|\theta)p(\theta)d\theta$.

As long as a researcher is interested in studying the parameters of a model, this last term can be ignored, so that the final formulation becomes:

$$p(\theta|y)\ \alpha\ p(y|\theta)p(\theta)$$

An expression also known as "posterior is proportional to likelihood times prior".

The idea underlying the Bayesian methodology is: to complete the information coming from the data, i.e. from the likelihood function, combining it with the specification of a prior probability density function based on out-of-sample information.

The prior information could come from past studies conducted on other samples of data, usually referred as "data-based" prior, or just from opinions or theoretical considerations, in general called "nondata-based" prior, or finally from a combination of the two (informative prior).

It's to note that the Bayesian approach does not require the prior to carry additional information. In fact a non-informative or so-called objective Bayesian approach (in contrast with the informative or subjective approach) is even possible.

As a matter of fact the objective Bayesian approach still remains a valid alternative to the *frequentist econometrics*, allowing the researcher to enjoy many advantages from the use of this methodology[11], such as the employment of MCMC simulation methods for complex problems, or the possibility to use small data samples.

Deeper considerations about the use of Subjective and Objective Bayesian approach are delayed to Berger (2006) and Goldstein (2006), but it's still noteworthy to underline the validity and complementarity of both the methodologies.

[11] Berger (2006)

It's also to say that as long as informative priors add out-of-sample information, an even higher degree of scientific accuracy is required. In particular a subjective approach cannot leave aside from a detailed discussion about the prior, both in terms of its reliability and of its influence on the results.

Specifically researcher's reliability about the prior is easily reflected by the weight that he decides to give to the parameters. In fact, as long as the prior would be defined by a specific value for each parameter, the related standard deviation reflects the researcher's opinion on its reliability: as much the prior is considered valid as much the standard deviation would be small.

The Bayesian approach returns a posterior density function (p.d.f.), but usually a researcher is interested in measures that summarize such information, like the mean or the variance for a Normal distribution.

But the computation of these parameters usually involves very complex integrals. For example given a parameter θ, the mean conditional to the data would be given by:

$$E(\theta|y) = \int \theta \cdot p(\theta|y) d\theta$$

Since very rarely such integrals could be analytically computed, the predominant approach is to take advantage from the so-called *posterior simulation*.

This methodology provides the approximation of the point of interest by its computation on a random sample derived using an algorithm usually belonging to the Markov Chain Monte Carlo (MCMC)[12] class.

In this thesis we apply a Gibbs sampling algorithm applied to the generalization of the traditional multivariate regression models (VAR models included), which takes the name of Seemingly Unrelated Regressions (SUR) Model introduced by Zellner in the 1962[13].

In order to proceed with the estimation, the previous formulation of the VAR needs some manipulations. Specifically there's the need to include the intercept vector Δ in the *B* coefficients matrix and bring back the model to the common SUR formulation

$$Y = X\beta + E$$

So the initial VAR(1) model has the form illustrated before:

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[12] Further reference on Monte Carlo integration is given by Robert and Casella (1999).
[13] Zellner (1962).

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \cdots \\ y_{nt} \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \cdots \\ \delta_n \end{bmatrix} + B \cdot \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ \cdots \\ y_{nt-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \cdots \\ \varepsilon_{nt} \end{bmatrix}$$

Which can be synthesized into:

$$Y_t = \Delta + BY_{t-1} + E_t$$

Then transposing we obtain:

$$Y_t' = \Delta' + (BY_{t-1)})' + E_t'$$

Or in vector form:

$$Y_t' = (1 \quad Y_{t-1}') \begin{pmatrix} \Delta' \\ B' \end{pmatrix} + E_t'$$

At this point apply the Vec operator[14] to both sides returns:

$$Vec(Y_t') = Vec\left((1 \quad Y_{t-1}') \begin{pmatrix} \Delta' \\ B' \end{pmatrix} \right) + Vec(E_t')$$

and exploiting the property of Vec operator such that $Vec(ABC) = (C' \otimes A)Vec(B)$[15], where C is *nxn* identity matrix and $\otimes$ represents the Kronecker Product[16], the previous becomes:

$$Y_t = \big(I \ \otimes (1 \quad Y_{t-1}')\big) Vec \begin{pmatrix} \Delta' \\ B' \end{pmatrix} + E_t$$

Where $\big(I \ \otimes (1 \quad Y_{t-1}')\big)$ is a *nxn(n+1)* block diagonal matrix composed by *n* vectors on the diagonal of *nx1* dimension, each of which consisting of (1, y_{1t-1},…, y_{nt-1}); overall it takes the name X_t. Instead $Vec \begin{pmatrix} \Delta' \\ B' \end{pmatrix}$ is a *(n+1)nx1* vector composed by stacking *n* vectors of dimension *n+1* with the intercept δ_i on the head followed by the *n* coefficients of the corresponding variable $b_{i1}, b_{i2}, \dots, b_{in}$; overall it takes the name β.

So that as a final result the model assumes the formulation:

$$Y = X\beta + E$$

Where $Y = [Y_1 \dots Y_T], X = [X_1 \dots X_T]$, $E = [E_1 \dots E_T]$ and $\beta = vec \begin{pmatrix} \Delta' \\ B' \end{pmatrix}$.

The structure of the error terms for this model resemble the VAR(1) one, in particular the errors ε_{it} are considered to be independent by time, but potentially correlated across the observations; so that every $\varepsilon_i$would be i.i.d., and distributed as $N(0, \Sigma)$.

[15, 16, 17] Lutkepohl (2005).

Therefore the E term is distributed as $N(0,\Omega)$, where $\Omega = (I_T \otimes \Sigma)$ is a block-diagonal matrix, with each block consisting of a Σ matrix.

3.3 Prior

The prior selected for the SUR model comes from the independent Normal-Wishart distribution, defined as:

$$p(\beta,\Sigma) = p(\beta)p(\Sigma)$$

The attribute *independent* derives from the fact that the distributions of the parameters are independent from each other; in particular $p(\beta)$ is distributed as a Normal, while $p(\Sigma)$ is distributed as an Inverted Wishart, or, using the notation of Koop, is possible to define a matrix $H = \Sigma^{-1}$, so that $p(H)$ would be distributed as a common Wishart:

$$p(\beta) = f_N(\beta|\beta_a, V_a)$$

$$p(H) = f_W(H|v_a, H_a)$$

Where β_a, V_a, v_a, H_a are the so-called *prior hyperparameters*, i.e. the parameters that reflect the prior information and define the prior distributions.

The chosen prior has the characteristics to be: Proper (mathematically “well-defined”), Informative (brings out-of-sample information) and Conjugate (the posterior has the same distribution).

Specifically the prior for the regression coefficients brings data-based information, coming from medium-term projections for the fourth quarter of the 2013; so that the IPI and CPI reflects the IMF outlook projections[17], while the short-term interest rate comes from the OECD outlook[18].

It’s to notice that even if the estimated model analyses the industrial production, the correspondent prior is about the real GDP. The choice was made on the lights of different factors: on one side the IPI is a more precise measure of the real economy, so it’s more appropriate for the objective of the analysis, and, equally important, is monthly published, allowing to avoid the analysis of interpolated series; on the other hand IPI is a leading series for the GDP, so that the IMF projections are still suitable.

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17 IMF (2012).

18 OECD (2012).

Since no prior was available for the FMSI built in chapter 2, for this variable was selected a non-informative prior, defined with zero mean and standard deviation equal to 4 ($\beta_a = 0, V_a = 16$).

The standard deviations for CPI and IPI come from the IMF valuation on projections[19], in particular are set on the mean of the forecast error for one year ahead. For the short-term interest rate was followed Van Roye (2011), but was chosen stricter value in order to increase the relevance of the prior.

It's to notice that the IMF and OECD projections are evaluation on the mean value for the medium term, but the structure of the model doesn't allow to set directly a prior on the mean terms without having priors on all the regression coefficients. In fact under the hypothesis of stationarity[20], the mean of an autoregressive process is defined as:

$$\mu = (I - B)^{-1}\Delta$$

and imposing a zero-mean prior on the B matrix coefficients with wide standard deviation, allows for the use of the projections means as a prior for the intercepts.

The prior for the variance matrix instead requires the parameters for the Wishart distribution, i.e. the number of degree of freedom v_a and a fixed positive definite matrix H_a.

Specifically v_a was set to be equal to the number of variables plus one (being for definition equal or greater to N+1), and the scale matrix H_a to be equal to an identity matrix of order N (each observation is then considered to be independent from the others and to come from a Standard Normal distribution).

3.4 Bayesian Computation

The Bayesian computation for the SUR model is implemented by posterior simulation using a MCMC algorithm, i.e. a Gibbs sampler with 500 retained draws and 150 burn-in replications.

Being prior and posterior conjugate, the parameters would come from the same distributions, in particular[21]:

$$\beta | y, H \sim N(\beta_0, V_0)$$

With:

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19 IMF (2010).

20 Verbeek (2006).

21 Algebric details on the posterior parameters derivation are available in Appendix B.

$$V_0 = (V_a^{-1} + \sum_{i=1}^{N} X_i' H X_i)^{-1}$$

$$\beta_0 = V_0(V_a^{-1}\beta_a + \sum_{i=1}^{N} X_i' H y_i)$$

And

$$H|\mathrm{y}, \beta \sim W(v_0, H_0)$$

Where

$$v_0 = N + v_a$$

$$H_0 = (H_a^{-1} + \sum_{i=1}^{N} (y_i - X_i\beta)(y_i - X_i\beta)')^{-1}$$

As long as β and H depend on each other, the starting point for the Gibbs chain was set to the β matrix, which exploits the OLS estimations on the sample as value for the parameter matrix H (remember that $H = \Sigma^{-1}$).

Bayesian computations are implemented with MATLAB.

3.5 Estimation

3.5.1 Introduction

Our Bayesian VAR model includes the following endogenous variables:

$$Y_t = \begin{pmatrix} \pi(France)_t \\ \pi(Germany)_t \\ \pi(Greece)_t \\ \pi(Italy)_t \\ \pi(Spain)_t \\ \Delta IPI(France)_t \\ \Delta IPI(Germany)_t \\ \Delta IPI(Greece)_t \\ \Delta IPI(Italy)_t \\ \Delta IPI(Spain)_t \\ i_t \\ FMSI_t \end{pmatrix}$$

Where π_t is the annual rate of change of the Consumer Price Index, ΔIPI_t is the annual rate of growth of the Industrial Production Index, i_t is the short term interest rate 3-month Euribor, and $FMSI_t$ represents the financial stress index at time t.

The model produced the following estimation for the dependent variables:

	Prior			Posterior		
Variable	**Mean**	**St. Dev.**	**95% C. l.**	**Mean**	**St. Dev.**	**95% C. I.**
Inflation (France)	1.6	1	[-0.4; 3.6]	1.61	0.31	[0.99; 2.23]
Inflation (Germany)	1.8	1	[-0.2; 3.8]	1.85	0.34	[1.17; 2.53]
Inflation (Greece)	0	1	[-2; 2]	3.07	0.40	[2.27; 3.87]
Inflation (Italy)	0.8	1	[-1.2; 2.8]	1.91	0.29	[1.33; 2.49]
Inflation (Spain)	1.5	1	[-0.5; 2.5]	3.16	0.41	[2.34; 3.98]
ΔIPI (FR)	1.4	0.3	[0.8; 2]	-4.99	1.94	[-8.87; -1.11]
ΔIPI (GER)	1.6	0.3	[1; 2.2]	-3.51	1.81	[-7.13; 0.11]
ΔIPI (GRE)	3.2	0.3	[2.6; 3.8]	3.46	3.26	[-3.06; 9.98]
ΔIPI (IT)	0.7	0.3	[0.1; 1.3]	-4.92	2.30	[-9.52; -0.32]
ΔIPI (SP)	1.3	0.3	[0.7; 1.9]	-2.95	2.16	[-7.27; 1.37]
3-month Euribor	0.2	1.5	[-2.8; 3.2]	5.44	0.17	[5.1; 5.78]
FMSI	0	4	[-8; 8]	-3.41	0.42	[-4.25; -2.57]

Table 3: prior and posterior mean and standard deviation of the estimated variables.

The table highlights the discrepancies between prior and posterior, in particular when the posterior mean exceeds the prior confidence interval is possible to state that the prior adds relevant information to the estimations.

According to this criterion, a first analysis of the inflation rates shows in-line estimations for Germany, France and Italy; so a preliminary consideration on the IMF projections is that there’s a quite strong underestimation for the Greece inflation rate with respect to posterior. To a lesser extent this observation is also true for Spain, which exceeds a little the confidence interval of the prior.

For the industrial productions instead there’s a more ragged scenario. The posterior mean in fact presents high levels of standard deviation, which affect strongly the reliability of the measures. Therefore any interpretation has to be considered on the light of the weakness of the estimations, because hasty conclusions could lead to strong misunderstandings.

Beside this advice, the prior outlook differs much from the posterior, showing also in this case a more optimistic view. In particular the model highlights a contraction of the industrial productions for the medium-term in the majority of the cases, while the prior shows a scenario already in recovery.

This preliminary analysis allows to formulate a first idea on the model and on the prior: the IMF medium-term projections define an overall positive scenario, where the strong injections of liquidity implemented from the 2008 are completely absorbed by the market, in fact the considered countries respect the aim of the ECB of an annual inflation rate lower than the 2%.

So the prior defines a world with a still high thirst of liquidity, but that exhibits at the same time good signals of recovery on the production front.

On the other hand the posterior draws a quite different scenario: while France, Germany and Italy confirm their price stability, Spain and Greece seem to suffer the effects of the great amount of liquidity injected during the crisis.

From the side on the production growth instead results are so uncertain that is not possible to extrapolate reliable conclusions, but according to the mean value the general view is of a Europe more probably still in recession than in recovery.

3.5.2 Lagged Effects

The analysis is deepened through the evaluation of the regression coefficients[22].

The regressors allow to evaluate results both in terms of equations and of explaining variables; in particular a graphical representation of the prior and posterior parameters allows to identify the contribution of the variables in explaining each equation.

In this graph the coefficients are ordered by regressors number, so that the first 12 points represent the intercepts, the second 12 the contributions of the first variable $\beta_{1,n}$, and so on.

The continuous red line shows the prior mean and the dashed are the boundaries of the corresponding 95% credibility region calculated adding and subtracting two times the standard deviation to the mean.

The continuous blue line instead depicts the posterior mean, and consequently the dashed are the corresponding 95% credibility region calculated using the 0.025 and the 0.975 quantiles of the distribution in order to avoid any problem regarding the symmetry of the interval[23].

[22] Appendix B.

[23] The symmetry of the distribution should however be theoretically granted by the use of a conjugate prior.

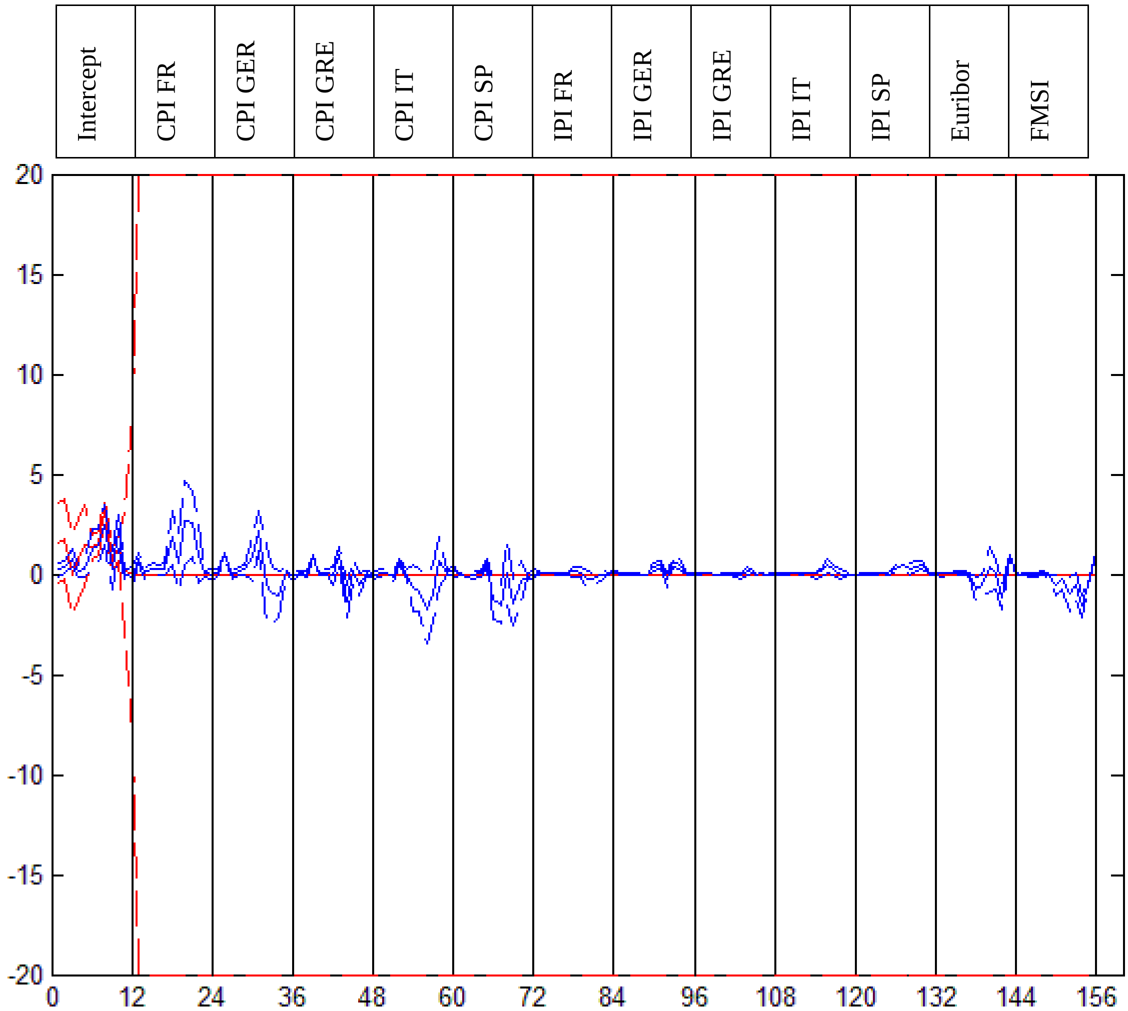


Figure 4: Graphical representation of the prior (red) and posterior (blue) regression coefficients.

Since with the exception of the intercepts the prior mean is set to zero for all the coefficients, it's quite easy to identify which ones of the posterior regressors could be considered non-significant: if the continuous red line passes inside the credibility region defined by the two dashed blue lines, then the corresponding regressor is non-significant.

In the next pages is given a synthesis of the lagged affect from the financial variables (figure) and from the macrovariables (figure).

Figure 5: 95% CR Lagged effects from the financial variables (negative in red and positive in blue).

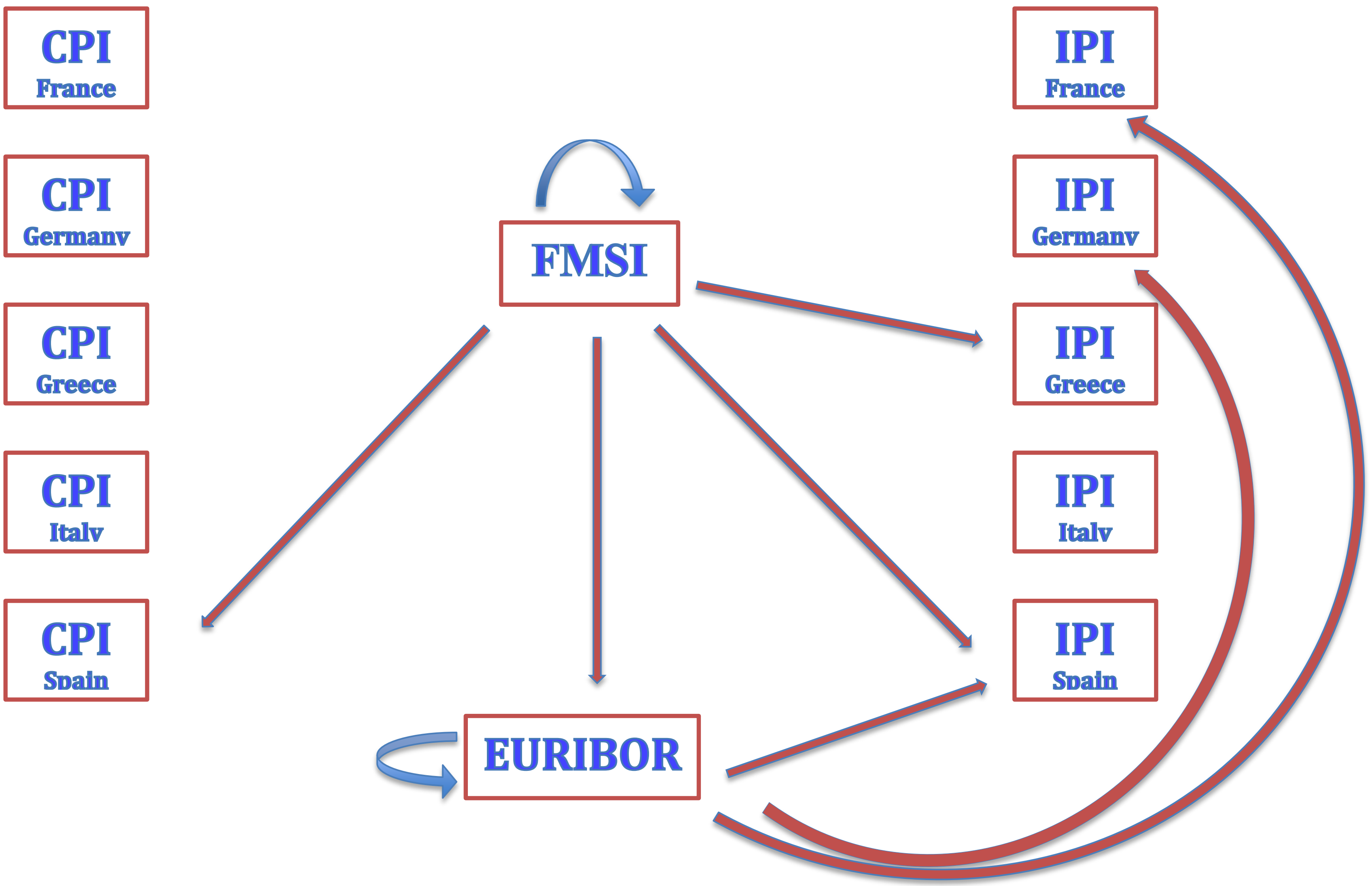
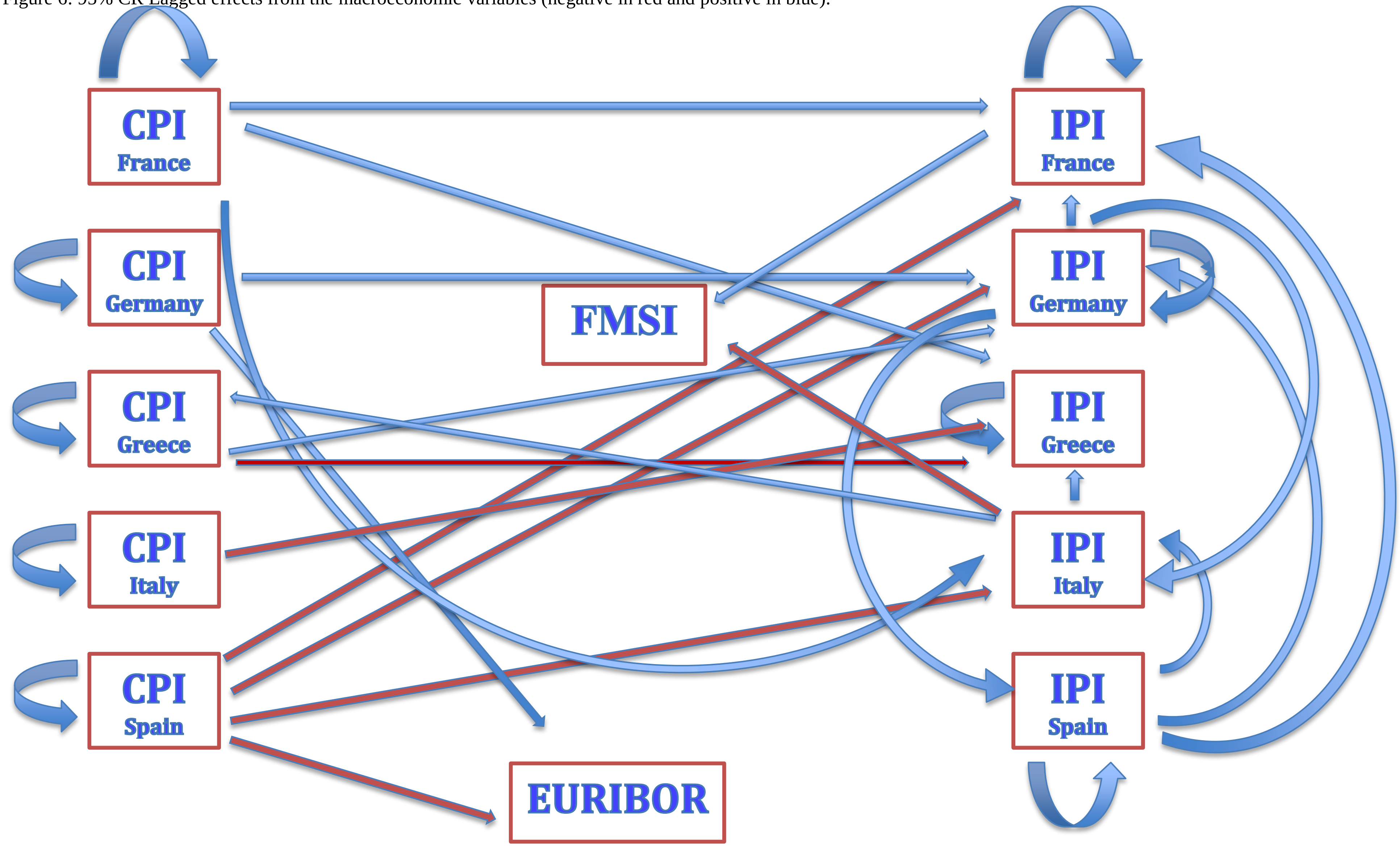


Figure 6: 95% CR Lagged effects from the macroeconomic variables (negative in red and positive in blue).



Being primarily interested in investigating how financial stress affects the economic activity, a detailed look at the last 12 observations allows to clearly analyse the relevance of the FMSI in explaining the real economy variables.

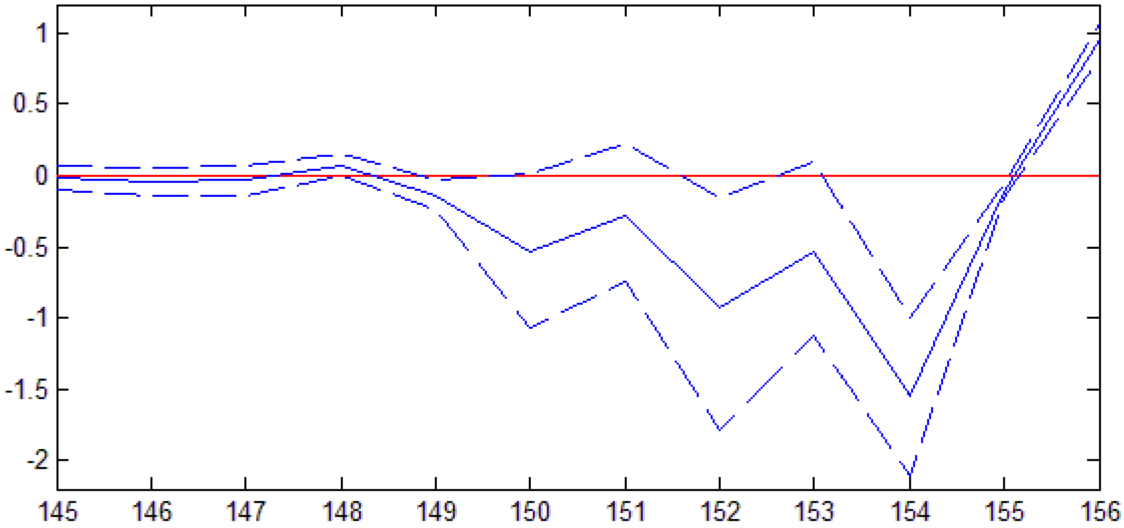


Figure 7: FMSI coefficients in the 12 VAR equations.

The impact of the FMSI seems to be less significant for the inflations, while plays a major role in explaining the industrial productions, in particular of those countries which have a weaker industry.

In the specific at the 95% confidence level the FMSI affects positevly the FMSI itself (point 156), while negatively the short-term interest rate Euribor (155), the industrial production rate of growth of Spain (154) and Greece (152), and the Spain inflation rate (149).

A deeper analysis also reveals that at the 90% of confidence, the FMSI affects also negatively the Italian and France industrial productions (respectively 153 and 150) and positively Italian inflation (148).

An immediate reaction to these results lead to the consideration that Germany is the country less directly affected by financial stress, both at the monetary and production level.

But it’s to underline the concept of “directly affected”: the advantage of estimating such a wide model, is that the analysis allows not only to identify the effects on a “closed” system, but also to look at the trasmission of such effects between variables.

The autoregressive structure of the model, in fact implies that a dependent variable at the time t would become an explanatory at $t + 1$, so that the consequences of a financial shock could pass between countries by means of other variables.

Starting from the Euribor, a focus on its regressors reveals the direct influences of the short-term interest rate to the system.

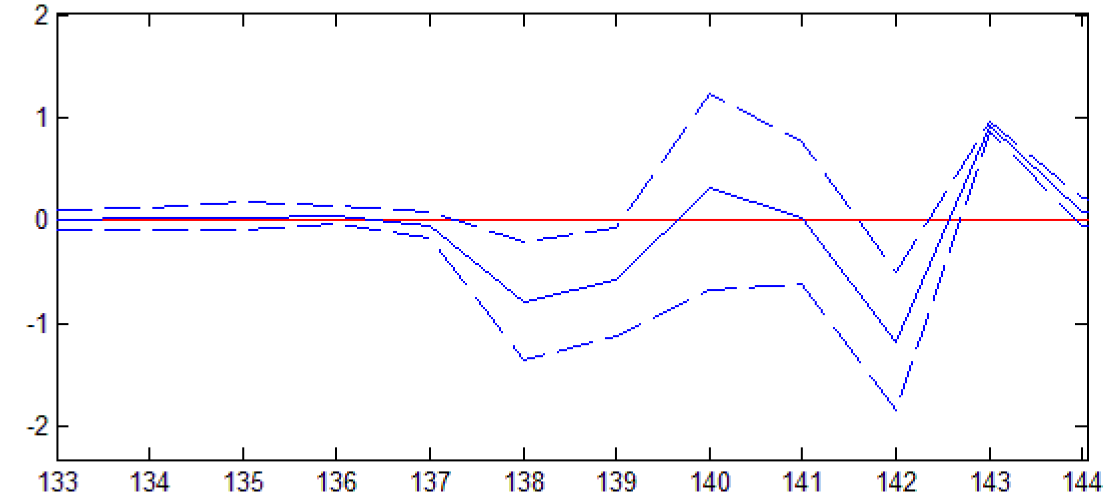


Figure 8: Euribor 3m coefficients in the 12 VAR equations.

At the 95% confidence, Euribor affects positively itself (143), while negatively the industrial productions of Spain (142), Germany (139) and France (138).

So passing through the short term interest rate, the financial stress affects also Germany at the production level.

Other indirect effects at $t+1$ pass through the Spain IPI.

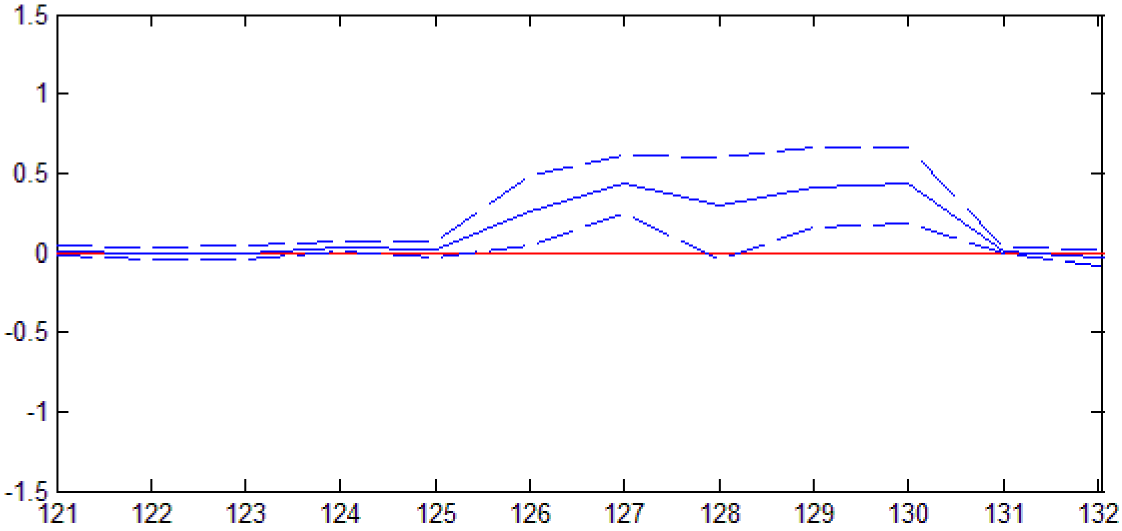


Figure 9: Spain IPI coefficients in the 12 VAR equations.

The Spain industrial production at the 95% positively influences itself, the Italian, German, France IPI and the Italian inflation.

Moreover at the 90% also Greece IPI is to be considered affected.

This last exihibits a quite interesting graph:

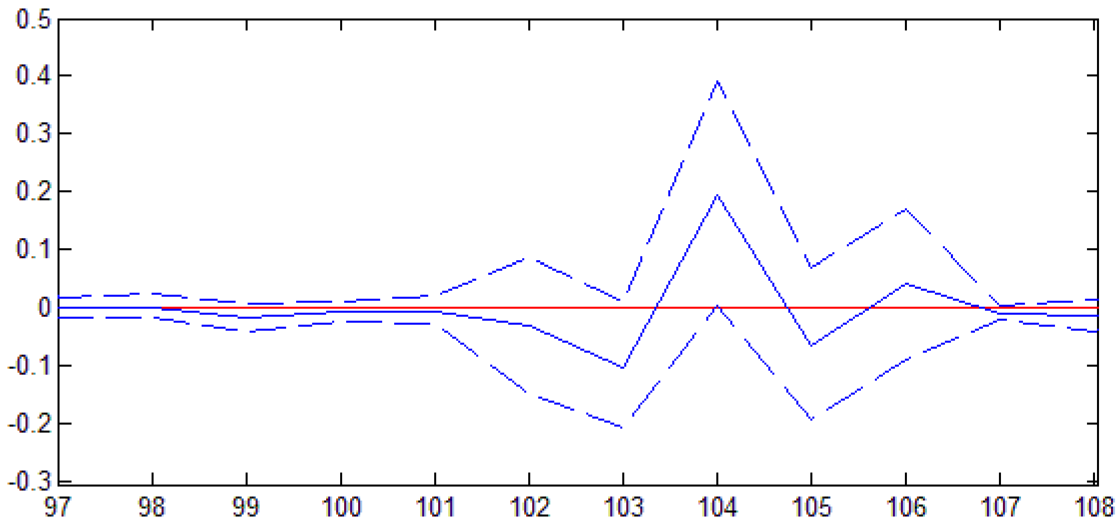


Figure 10: Greece IPI coefficients in the 12 VAR equations.

The Greece production in fact seems to affect positively just itself at the 95%, and at the 90% also the German production negatively.

Such result leads to a quite important consideration: an interpretation of the regressors in fact could retain that the Greece is in some manner still outside from a theoretical "European production". In particular its contribution doesn't have any positive effects on the other european economies. On the contrary the only shy connection is even negative, so that a burst in Greece IPI would affect negatively the German production.

Of course such result, as previous for the FMSI, is to be intended as "direct effects", in fact an analysis of the variance/covariance matrix could highlight other important results.

The last variable directly influenced by FMSI (at the 95%) is the Spain inflation.

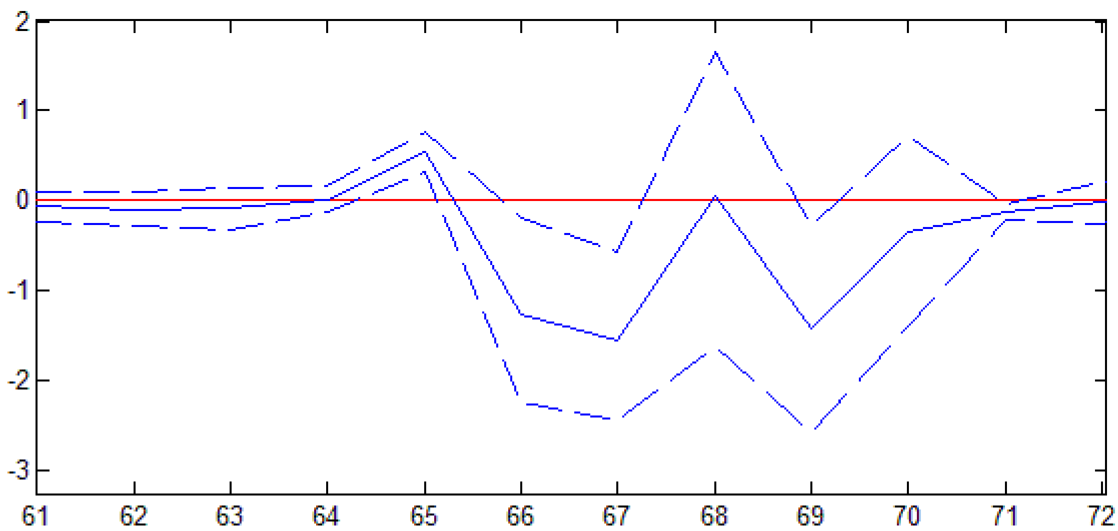


Figure 11: Spain CPI coefficients in the 12 VAR equations.

The Spain CPI affects positively (at 95% C.I.) itself, while has negative effects on the short-term interest rate and on the Italian, German and France productions.

Clearly the transmission of financial stress doesn't end here, but the contagion would continue also at $t+2, t+3, \ldots, t+n,$ so that even if the stress affects directly only some dimensions, the connections between them ensure that the consequences would indirectly transmitted also to the other variables.

Of course an analysis of the coefficients in itself does not allow a completely understanding of the contagion phenomenon; in the next section an impulse response and variance decomposition analysis would be implemented to combine the regressors with the covariances.

What is possible to conclude at this point, is that the France and German inflations seems to be the more independent measures from the a financial stress shock, at least in the first two periods. This consideration is however confirmed by the stability of the time series with respect to those of the other countries, and, moreover, both the prior and the posterior projections had anticipated such consideration, highlighting values nearly perfectly aligned with the ECB objective.

On the other hand Spain seems to be the more influenced country, recording the strongest negative direct effects on both the industrial production and the inflation rate.

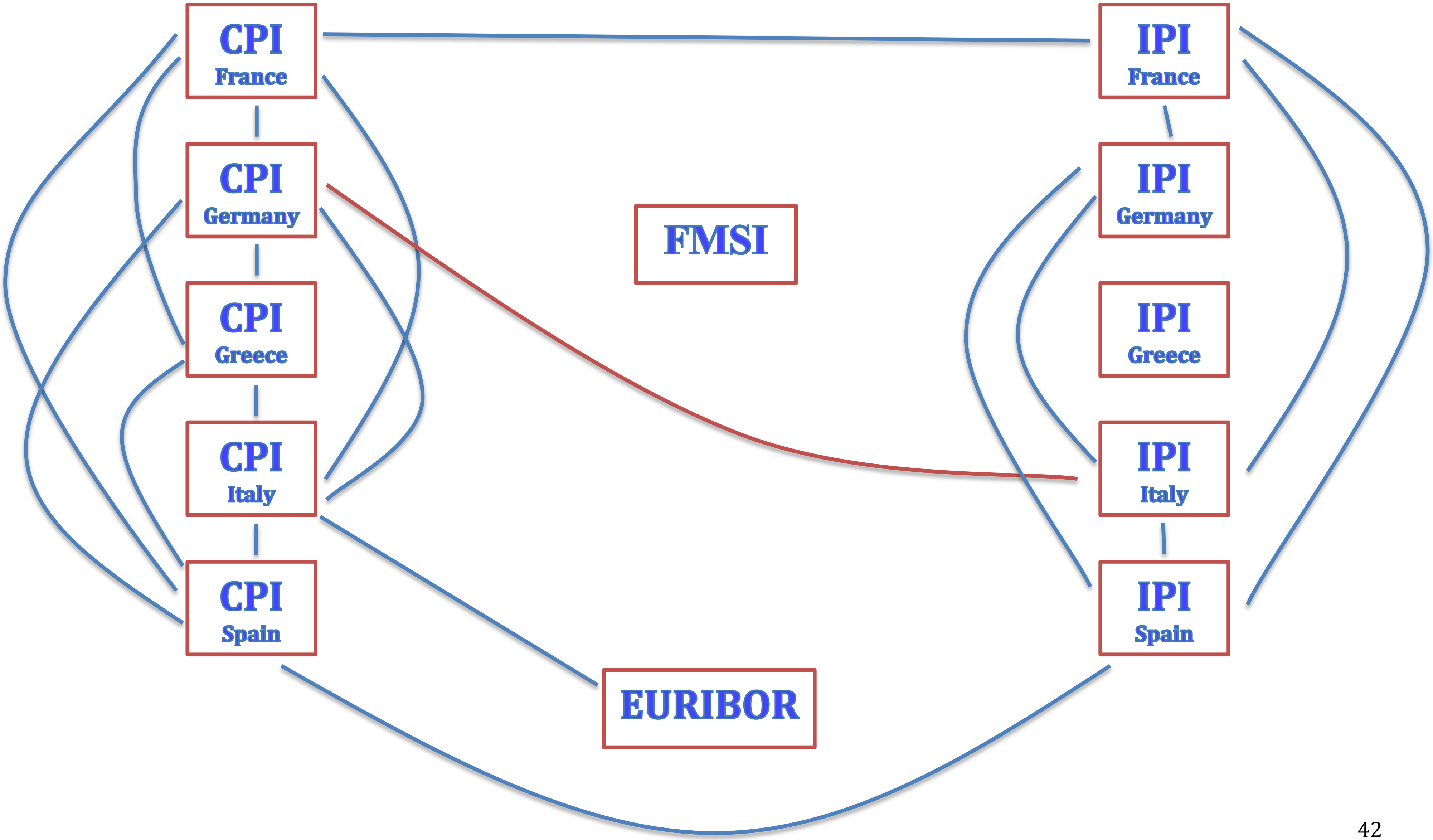
Such considerations could be developed by an analysis of the covariances; in fact even if variables are not connected at the regressors level, this does not exclude a correlation between them, i.e. how they vary together.

3.5.3 Simultaneous Effects

The complete estimations of the covariance matrix is released in Appendix B.

As for the regression coefficients, a graphical synthesis of the overall effects would allow an easier understanding of the interpendences.

Figure 12: 95% CR Simultaneous effects (blue positive, red negative).



The variances/covariances are ordered by variable[24] and plotted with a continuos blue line, while as before the blue dashed ones represent the 0.025 and 0.975 quantiles of the distribution. Finally a dashed red line is plotted in correspondence of the zero in order to evaluate the significance of the parameters.

The first figure present a focus on the first 12 values, which allows to evaluate the correlations with the France inflation.

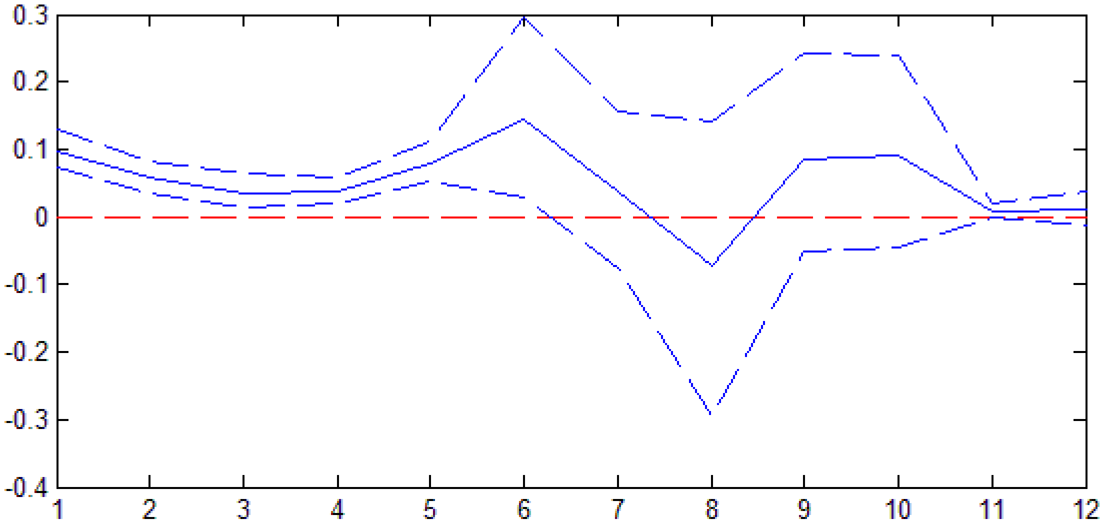


Figure 13: France CPI variance/covariances.

Within a 95% C.I. the graph exihibits relevant connessions with the variations of all the other inflations and with the France IPI. In particular this last factor indicates a strong sensitivity of the economic activity to shocks in the inflation rate.

A similar behaviour is performed also by German inflation.

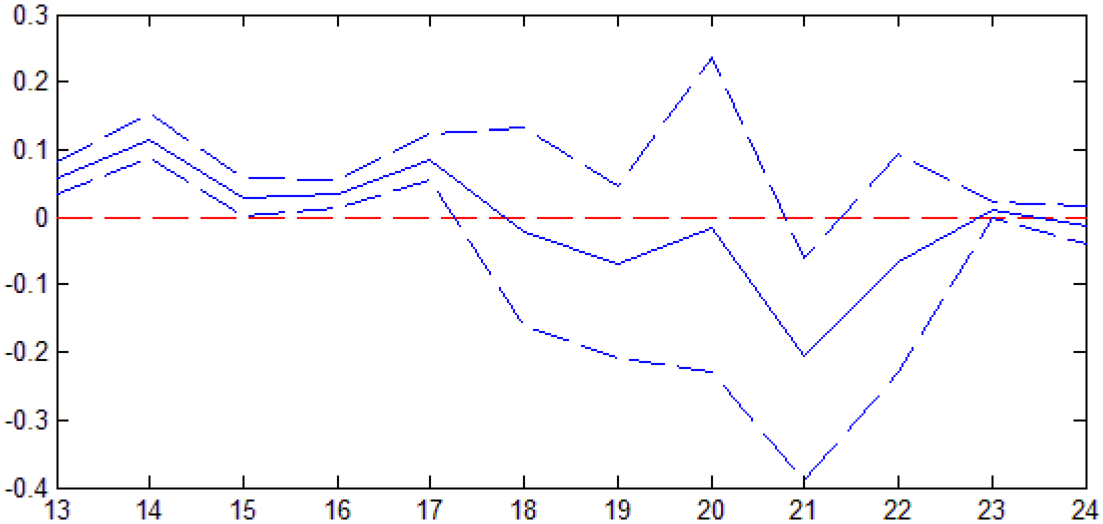


Figure 14: German CPI variance/covariances.

[24] The order follows the vector released at the beginning of the section.

German CPI in fact is linked to the variations of the other inflation rates, but curiosly is also connected to the Italian IPI. An interpretation of this linkage probably goes beyond this model.

However the graph highlights once again the good independence of German economy from inflationary shocks.

At the 90% of confidence there exists also a relationship with the Euribor variations; such connection could be explained by the fact that probably the short-term interest rates are lowered more for the needs of other EMU countries than for Germany, which as a consequence has to manage more money than what required by the maket.

A similar situation characterizes also Greece and Italian inflations.

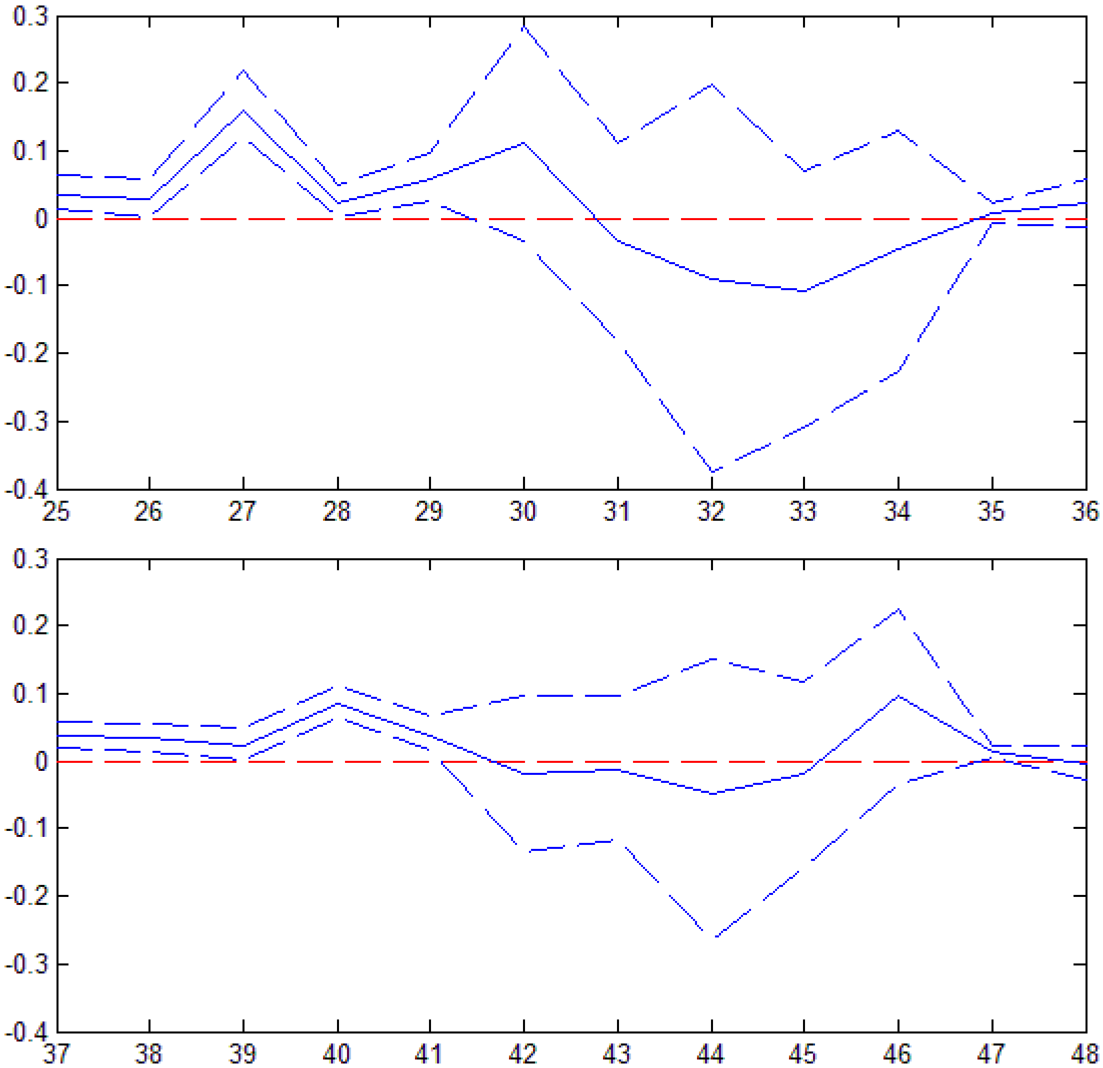


Figure 15: Greece (above) and Italian (below) CPI variance/covariances.

Both these countries' CPI present the already seen connection with the other inflations. It's only noteworthy the linkage of the Italian inflation with the Euribor: as for Germany this relationship could be interpreted as another symptom of the inefficiency of a unified monetary policy.

Finally the interdependences with the Spain CPI give the last piece of the inflation rates scenario.

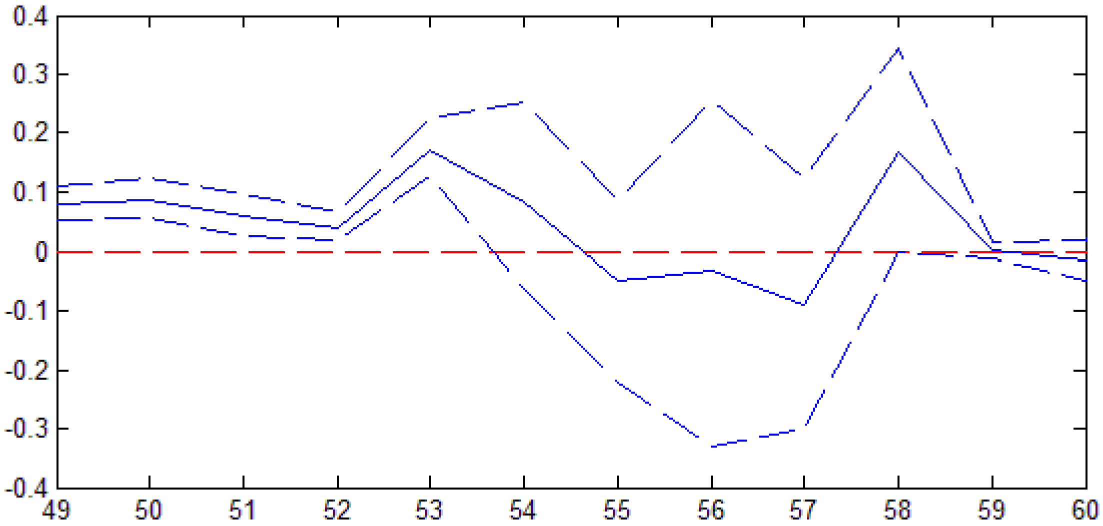


Figure 16: Spain CPI variance/covariances.

The Spain shows the same scenario of the France highlighting linkages also with its own economic activity, so delineating a sensitivity of its production in correspondence of monetary shocks.

To track some general considerations about the inflation rates, it's possible to conclude that as expected there's great connection upon the analysed countries, specifically due to the implementation of the same monetary policy.

This reflection easily leads to understand that every phenomenon affecting one country's prices, immediatly affects also the inflations of the other EMU members.

So even if the analysis of the regressors demonstrated some resistance of the France and Germany CPI to financial stress shocks, the strong linkages between inflation rates make so that the affected countries quickly infect the others.

Of course the stability of the prices demonstrated by some countries rather than by others suggests that the common monetary policy better suits the needs of just some of the EMU members.

Such conclusion opens the door to old but particularly actual questions: was the admison to the EMU of some countries appropriated or too hasty? Could some better convergence policies be done with respect to these countries? Are the interests of all the EMU economies evaluated with the same weight by the ECB?

As a final consideration is to notice that France and Spain industrial productions are affected by changes in the level of prices. So inflationary shocks could pass also to the productions of at least these two countries, but the analysis of the industrial productions covariances could reveal further details.

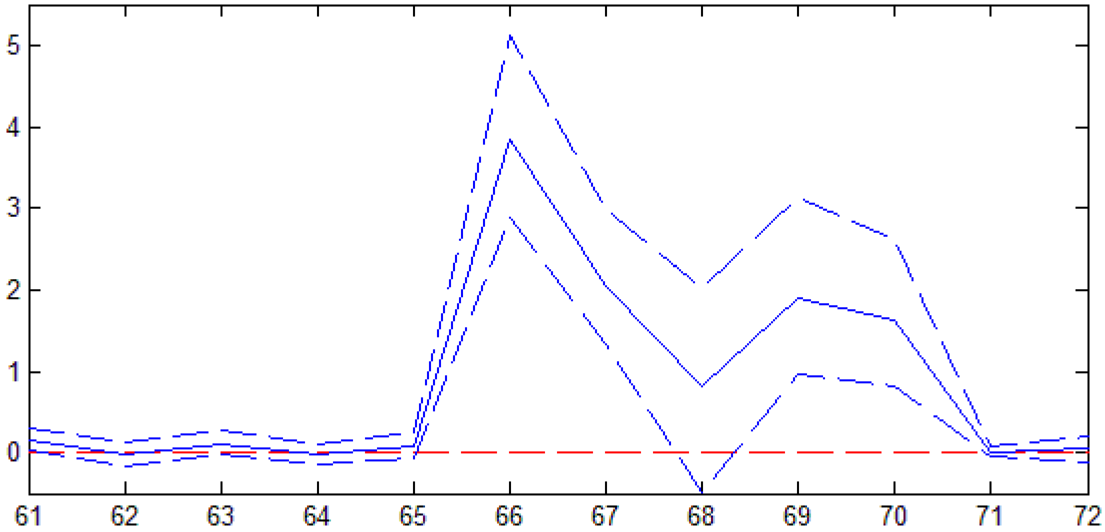


Figure 17: France IPI variance/covariances.

The France industrial production exibits a strong connession with the variations of German, Italian and Spain IPI; correlations confirmed also by the analysis of these countries[25] covariances, which present reciprocal linkages.

On the other hand Greece IPI seems to be out of this circle:

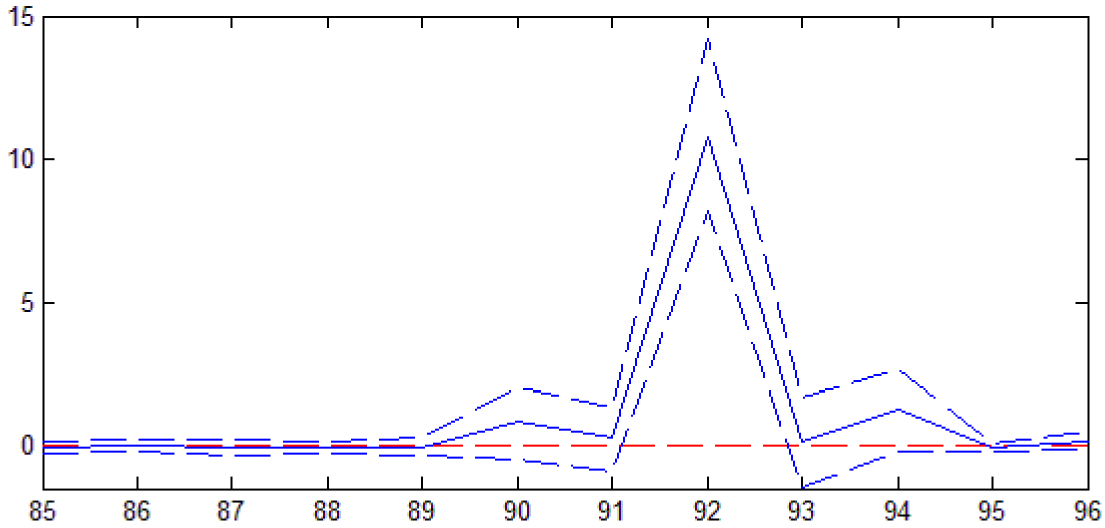


Figure 18: Greece IPI variance/covariances.

[25] Zoom on the German, Italian and Spain IPI variance/covariances are available in Appendix B.

In fact while France, Germany, Italy and Spain shape a sort of unified area also for the industrial productions, Greece economy's variations instead results to be independent from changes in any other variable other than the Spain IPI at the 90%.

So the analysis of the IPIs confirms results optained with the analysis of the regressors: while France, Germany, Italy and Spain are almost integrated countries both at the monetary and at the production level, Greece seems to be still outside from European trends. Not only in fact the regressors coefficients have just a weak connection with the German IPI, but also the variations are independent from this small EMU system.

This passage allows also to complete the previous formulation about the relationship between monetary and production shocks: variations in the first field easily lead to changes in the second thanks to the strong linkages between EMU economies; just Greece seems to be partially immune from this process.

But this interdependence could be pushed even further looking at the variations of the short-term interest rate.

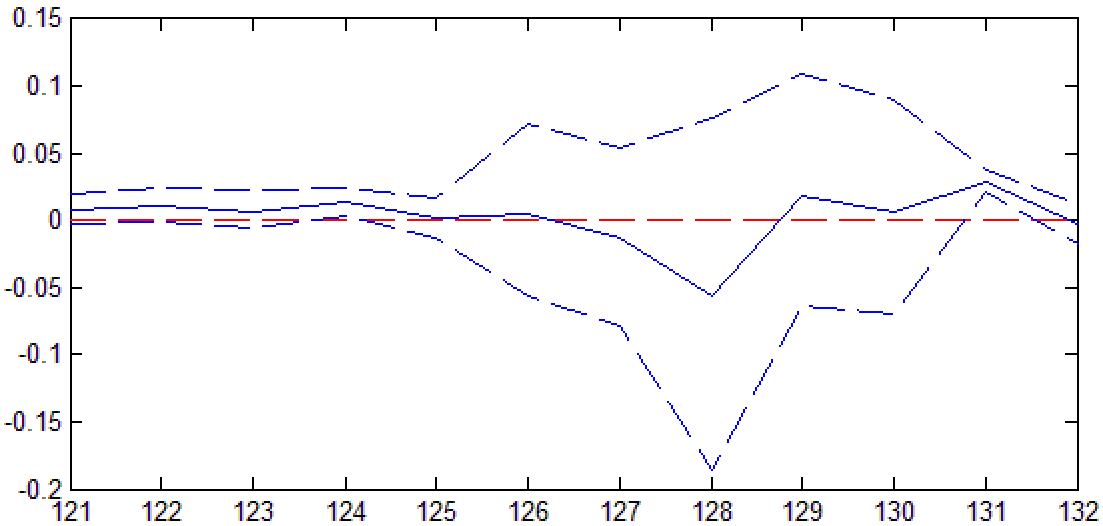


Figure 19: Euribor 3m variance/covariances.

The graph highlights at the 95% confidence interval a connection with the Italian CPI, while at the 90% there's also significance with the German CPI.

But such result unified with the previous considerations, easily leads to the idea that Euribor is correlated to the inflation rate of all the considered countries: variations on the Euribor leads to variations on Italian and German CPI, which in turn leads to variations on all the inflations.

Such connection was widely expected being directly connected with the liquidity of the system.

Moreover linkages between inflations and productions on one hand expand the range of the contagion, on the other highlight the weak influence of the short-term interest rate on Greece IPI.

The last graph summarizes all the previous information about the covariances with the financial stress index.

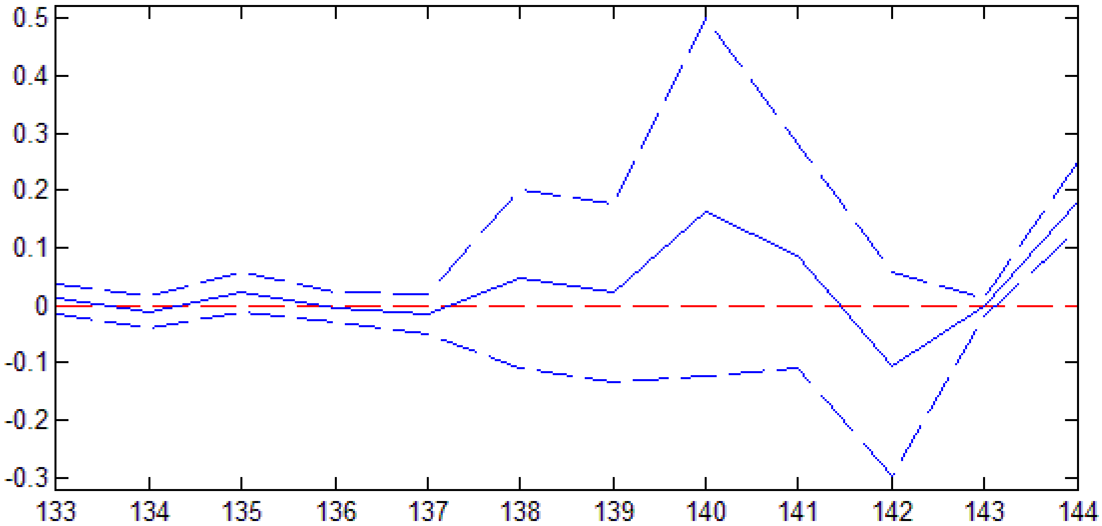


Figure 20: FMSI variance/covariances.

As already seen there’s no evidence of significant linkages between variations in the financial stress and the other considered variables.

The interpretation of this phenomen comes from the idea that variations in the financial markets happen nearly in real time, and very often are just part some cyclical trend.

The real economy is instead subjected to much a longer reaction time: changes in the level of demand are translated in changes in the production level at least in the medium period, which in turn needs time to be translated in changes on the salaries and so in the level of prices and in the short-term interest rates.

So in order to translate variations in the financial markets into variations in the real economy, financial shocks must be not only relevant in the sense of stress-peak, but they should also be protracted for a certain amount of time.

On the light of these considerations, variations in the FMSI are obviously not directly connected to variations in the real economy variables, which are much more stable.

In the following section an impulse response analysis and a variance decomposition allow to analyse the combined effect of the regressor and the covariances.

3.6 Impulse responses and variance decomposition

An impulse response analysis allows to analyze the persistency of the effects caused by a shock in the financial stress index, combining all the previous considerations about the coefficients and the covariances.

Following Lutkepohl[26], the analysis was conducted using responses to orthogonal impulse in order to capture the interdependences between variables; in particular a Choleski decomposition of the variance/covariance matrix allows for uncorrelated, one-standard deviation shocks.

Defining a VAR(1) system as in (1), the responses of the system to a shock in one variable are defined as:

$$\Theta_0 = P$$
$$\Theta_1 = \Phi_1 P$$
$$\Theta_2 = \Phi_2 P$$
$$\dots$$
$$\Theta_n = \Phi_n P$$

Where P is the lower triangular matrix of the Choleski decomposition of the variance matrix $\sum$, and Φ_i are defined as $\Phi_i = B_k^i$, where k is an indicator of the variable in which occurs the shock.

The shocks are instead defined as $\omega_t = P^{-1}u_t$, where P^{-1} is the upper triangular matrix of the Choleski decomposition and u_t is a *n*-length vector of the innovations, which assumes value 1 in correspondence of the variable in which the shock occurs.

Together with the response functions, is conducted also a variance decomposition analysis in order to determine the amount of variation in the variables that is imputable to the financial stress after a shock in the FMSI.

Specifically in correspondence of each forecast period h the amount of variance accountable by the variable *j* after a ω_t shock in the variable *k* is given by:

$$\varpi_{jk,h} = \sum_{i=0}^{h-1} \left(e_j' \Theta_i e_k\right)^2 / MSE[y_{j,t}(h)]$$

Where e_k is the *k-th* column of a I_n matrix, and $MSE[y_{j,t}(h)]$ is the h-step Mean Squared Error of the variable *j* given by $MSE[y_t(h)] = \sum_{i=0}^{h-1} \Theta_i \, \Theta_i'$.

[26] Lutkepohl (2005).

The results of the analysis are plotted within a horizon of 24 periods, corresponding to 2 years ahead the shock, considering it the boundary for the medium-term projections. Estimations are evaluated with a confidence interval of the 70% defined the 0.15 and the 0.85 quantiles.

France

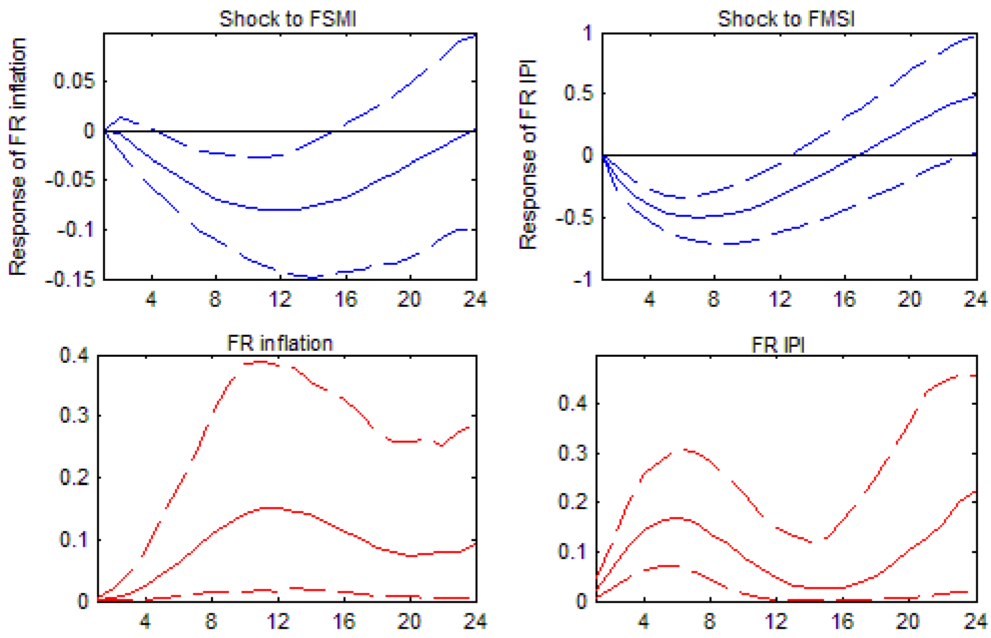


Figure 21: Impulse responses and variance decomposition of France inflation and IPI growth.

In the France economy one standard deviation shock in the FMSI leads to a restrained reduction in the inflation rate of less than 10% percentage points after 1 year, with a complete recovery in about 2 years.

This result confirms the good independence of the inflation rates emerged with the analysis of the coefficients. The variance decomposition in fact highlights that just the 15% of the variation is imputable to the FMSI, while the remaining comes mainly from endogenous factors.

More significant are the effects on the industrial production growth: within 2 quarters the rate of growth is reduced up to 50% and a complete recovery comes just after 16 months from the shock.

The variance decomposition assigns to the financial stress about the 15% of the changes in the industrial production growth, so on the basis of previous considerations other causes should be found on the France inflation and on the changes of Spanish, Italian and German productions.

Germany

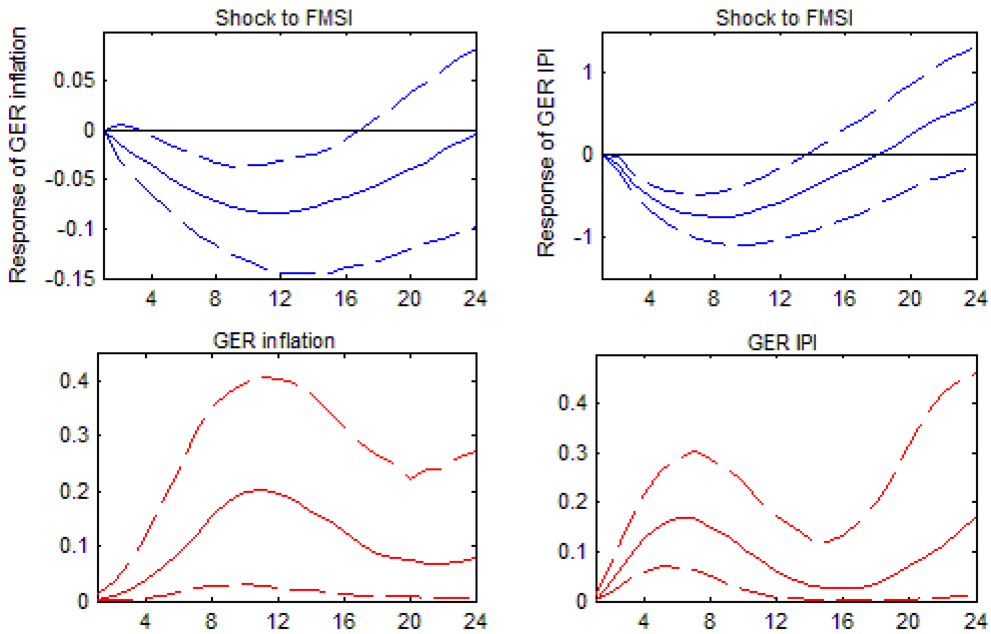


Figure 22: Impulse responses and variance decomposition of Germany inflation and IPI growth.

German inflation rate as anticipated exhibits a trend very similar to France: also in this case a FMSI shock causes a reduction of the 10% of the CPI within a year, with a completely recovery in two. According to the variance decomposition the financial stress explains up to the 20% of the level of prices, so a bit higher than France.

The effects on the industrial production are instead stronger: the reduction on the IPI growth in fact surpasses the 70%.

The major impact of the output is also confirmed also by the data, in fact in concomitance with the 2009 crisis, the German real GDP annual rate of growth suffered a reduction of -5.1%, in comparison with the -2.6% of France[27].

Anyway the reduction seems again only partially imputable to the financial stress, which absorbs about the 15% of the industrial production changes; so even if the reduction of production is greater in Germany than in France, this difference is not imputable to a greater sensitivity to the financial stress.

[27] IMF (2012)

Greece

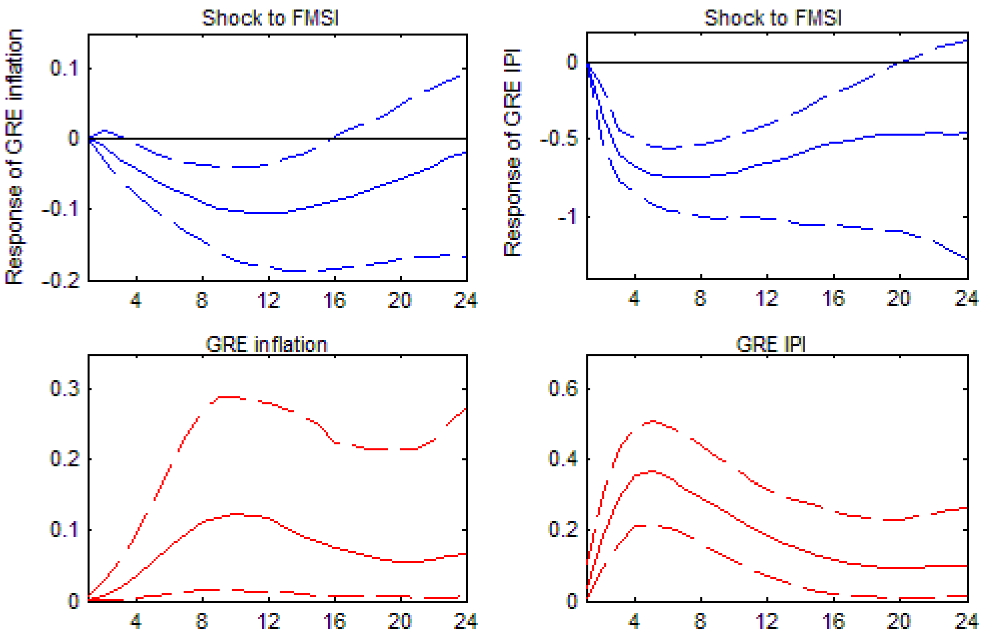


Figure 23: Impulse responses and variance decomposition of Greece inflation and IPI growth.

On the side of the inflation rate, Greece is in line with the preceding countries.

The level of prices in fact suffers a reduction of the 10% in one year and restore within two. Just the 10% of the variations are imputable to the FMSI, so also in this case changes are probably caused mostly by shocks on the inflations of the other countries.

The impulse responses instead highlight a much more alarming scenario with respect to the productivity: the reaction to a financial stress shock leads the industrial production growth to a reduction of the 70% just after one quarter demonstrating an extremely high sensibility of the Greece economy. Moreover the rate of growth has strong difficulties in restoring the initial level: after one year the level is still below the 50% and after that the standard deviation increases exponentially opening the door for any scenario, from the recovery to a greater fall.

The Greece industrial production was seen to be strongly independent from the system, a finding confirmed by the variance decomposition: the economic activity is highly affected by the financial stress, almost reaching the 40% of the total variation.

Italy

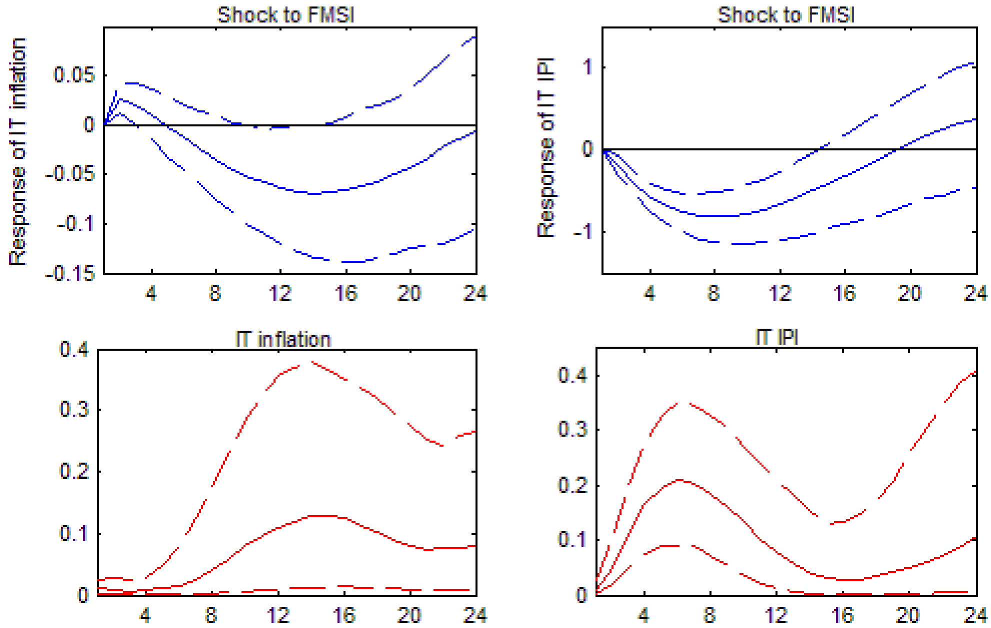


Figure 24: Impulse responses and variance decomposition of Italy inflation and IPI growth.

Italian situation lies a small step worse than France and Germany, but still distant from Greece.

Inflation rate after a little increase in the first quarter, fall of less than the 10% within 14 month and reaches a complete recovery within 2 years.

So the level of prices after a financial shock still remains a bit higher with respect to the other considered countries as confirmed by IMF data for the 2003-2012 period[28].

On the other hand even if industrial production suffer a fall that reaches the 80% in the second quarter (-5.5% of real GDP growth in 2009), within about 20 months the situation reaches a complete recovery.

So even if the peak of IPI loss is even stronger than the Greece one, Italy demonstrates a recovery in line with France and Germany, probably thanks to a more integrated economy that could benefits of the pulling of the other EMU countries.

Variance decomposition confirms that the sensitivity to financial stress is in line with France and Germany, with the 10% of the inflation accountable to the FMSI and the 20% of the industrial production variations.

[28] IMF (2012)

Spain

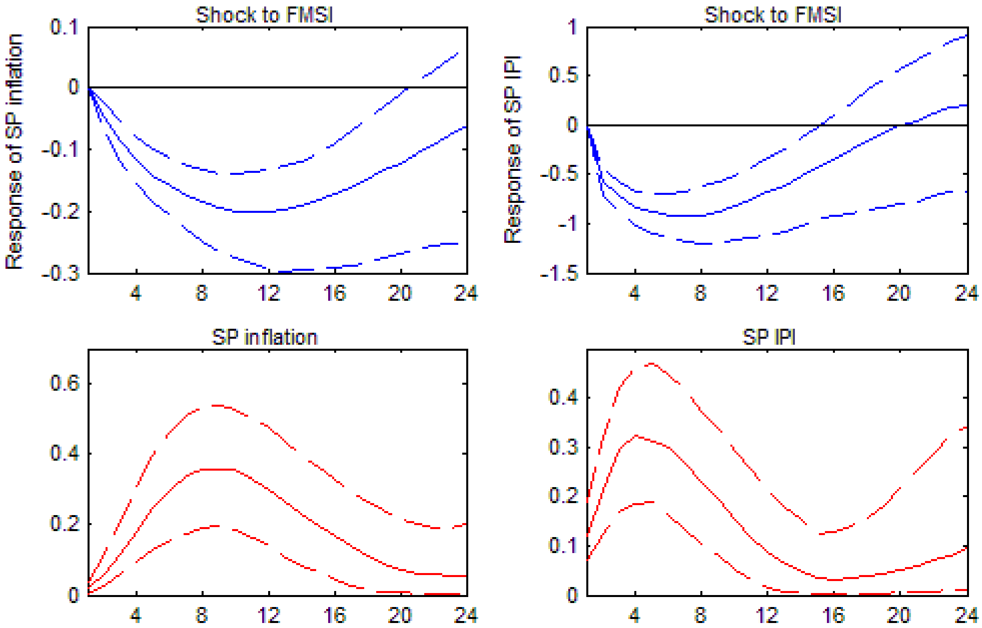


Figure 25: Impulse responses and variance decomposition of Spain inflation and IPI growth.

As anticipated by the analysis of the coefficients, Spain inflation confirms its major sensibility to financial stress shocks, recording a reduction that reaches the 20%. Such fall is indeed caused by the financial stress for at least the 30%, the highest data registered.

Also the industrial production records the highest peak of the system with a decrease over than the 90%.

However the recovery comes quite fast in comparison with Greece, in fact after 20 months the index returns to the initial level as for the other countries. As for Italy is reasonable to think that differently from Greece the major integration of the industry plays as knock-on effect.

Again the variance decomposition records that more than the 30% of the variations are accountable to the financial stress, so it’s possible to conclude that Spain presents the most vulnerable economy to financial shocks.

Euribor 3m and FMSI

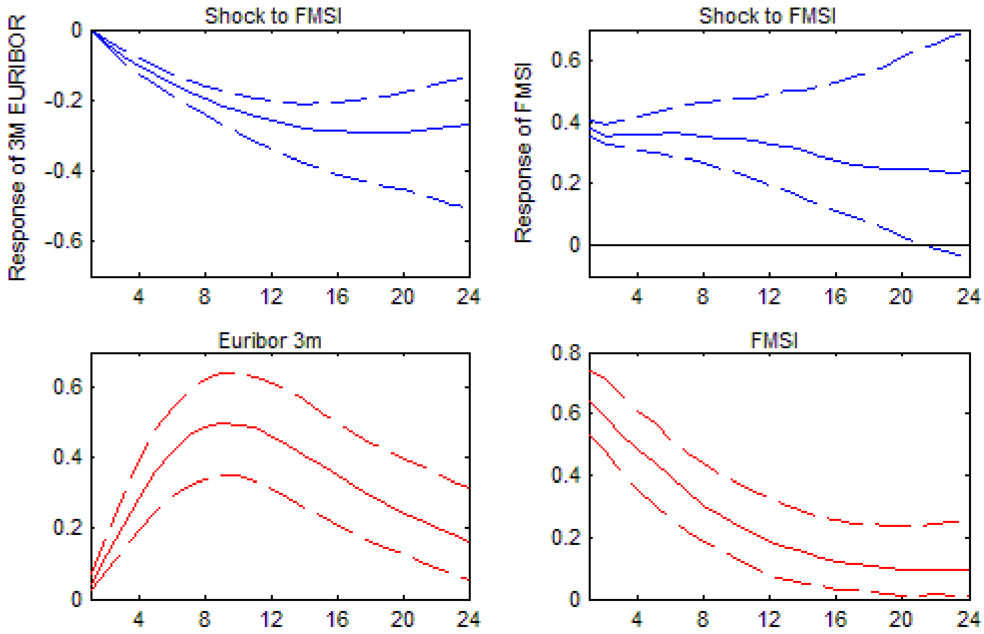


Figure 26: Impulse responses and variance decomposition of Euribor 3m and FMSI.

Finally a financial shock produces a fall in the short-term interest rates of about the 30% in two years, with a convergence that shyly starts only after 4 quarters with a very slow trend.

Of course as one of the main ECB weapon for fight the liquidity thirst, the short-term interest rate is highly determined by the financial markets' behaviours, with almost 50% of the variation caused by FMSI.

The financial stress instead remains quite stable for one year and then decreases slowly, even if after one year the standard deviation become much widespread so that any consideration after that has very low consistency.

What is certain is that financial stress has mostly endogenous causes has demonstrated by the previous analysis and by the variance decomposition.

3.7 Prior sensitivity analysis

A correct application of the subjective Bayesian approach cannot leave aside from an evaluation of the prior weight on the results.

Hence the sensitivity of the model to the prior information is discussed through a comparison between the already specified model, or informative, and a new model specified so that the prior doesn't bring relevant information for all the parameters, or so called non-informative.

The non-informativeness is therefore achieved by setting the regressor coefficients matrix β equal to 0 and the corresponding standard deviations to a significantly wide value as 10. Moreover the prior upon the Inverted-Wishart is set to have degrees of freedom $v_a = 0$ and scale matrix $H_a = 0_{nxn}$.

The new specified model returned the following results:

	Prior			Posterior		
Variable	**Mean**	**St. Dev.**	**95% C. l.**	**Mean**	**St. Dev.**	**95% C. I.**
Inflation (France)	0	10	[-20; 20]	1.60	0.32	[0.96; 2.24]
Inflation (Germany)	0	10	[-20; 20]	1.91	0.35	[1.21; 2.61]
Inflation (Greece)	0	10	[-20; 20]	3.16	0.42	[2.32; 4.00]
Inflation (Italy)	0	10	[-20; 20]	1.83	0.29	[1.25; 2.41]
Inflation (Spain)	0	10	[-20; 20]	3.28	0.43	[2.42; 4.14]
ΔIPI (FR)	0	10	[-20; 20]	-5.22	2.10	[-9.42; -1.02]
ΔIPI (GER)	0	10	[-20; 20]	-3.73	1.93	[-7.59; 0.13]
ΔIPI (GRE)	0	10	[-20; 20]	4.89	3.31	[-1.73; 11.51]
ΔIPI (IT)	0	10	[-20; 20]	-4.76	2.46	[-9.68; 0.16]
ΔIPI (SP)	0	10	[-20; 20]	-3.10	2.32	[-7.74; 1.54]
3-month Euribor	0	10	[-20; 20]	5.95	0.14	[5.67; 6.23]
FMSI	0	10	[-20; 20]	-3.94	0.44	[-4.82; -3.06]

Table 4: Mean and standard deviation for the non-informative model.

Comparing this output with the previous model, the posterior distribution differs just for the industrial productions, even if without any strong differences.

This refines the previous observations upon the relevance of the prior; from the output of the informative model in fact also other variables had a good probability to be influenced, such the Greek and Spanish inflations.

For sure such result was at least largely predictable from the prior specification itself, specifically because industrial productions' standard deviations on the parameters were the strictest.

At a more general level instead the overall poor informativeness of the prior was determined by the structure of the prior: the means of medium-term projections were used just as priors on the intercepts while the other parameters were already set to be non-informative.

The coefficients' estimations allow some deeper considerations[29].

[29] Appendix B.

First the inference confirms the greater sensibility of the IPI, which coefficients demonstrate the most notable changes. Of course the major differences regard the intercepts, which presents more than the double of the standard deviation with respect to the informative model.

The other variables are instead less influenced; it’s only to notice that the standard deviations record a little decrease with non-informative prior, in particular with respect to the short-term interest rate.

The percentage variations of the coefficients also reveal some underlying economic considerations of the prior.

The table highlights how the most important changes regard the Greece.

Specifically the non-informative model reduces consistently the contribution of the Greece CPI in explaining the corresponding IPI; moreover notable are also the reductions in the France and Italian CPI regressors, and of the Greece IPI itself, while there’s an increase in the Spain CPI relevance.

Important differences in the Greece IPI are also present at the regressor level: strong reductions in fact affect the contribution of Greece IPI in explaining the France and German CPI.

	CPI FR	CPI GER	CPI GRE	CPI IT	CPI SP	IPI FR	IPI GER	IPI GRE	IPI IT	IPI SP	Euribor	FMSI
δ_n	-22,20	-12,19	5,74	19,58	18,31	-231,88	-461,91	185,94	123,06	38,72	-81,18	56,02
$\beta_{1,n}$	-1,22	0,72	7,35	0,38	1,80	-7,33	-25,92	-17,71	-7,43	3,48	5,08	42,00
$\beta_{2,n}$	0,89	0,14	19,22	-6,14	-8,16	-2,01	0,78	-234,56	-1,78	7,73	-3,53	-18,01
$\beta_{3,n}$	18,61	177,64	-1,86	189,91	-20,08	243,07	20,50	-1060,15	66,85	37,21	-9,09	-81,53
$\beta_{4,n}$	4,59	4,67	11,19	-1,10	24,43	-30,14	-34,49	-89,64	-29,00	-45,89	-13,02	12,20
$\beta_{5,n}$	0,70	3,51	-8,61	23,93	1,54	0,93	3,13	91,96	4,58	-83,39	-3,88	61,40
$\beta_{6,n}$	-5,48	-4,60	-7,68	11,54	-5,62	-24,94	-34,44	14,09	4,94	-44,23	-53,23	-4,79
$\beta_{7,n}$	-6,42	-4,47	-5,47	-8,95	-37,63	1,52	-1,50	6,75	-0,29	2,10	0,45	-3,79
$\beta_{8,n}$	-241,74	-313,45	-0,84	-10,10	-0,90	40,08	19,21	-149,06	27,70	39,22	-5,41	20,07
$\beta_{9,n}$	-0,23	4,71	1,40	-15,59	29,45	92,84	-36,16	-66,07	-47,53	173,34	-39,26	10,36
$\beta_{10,n}$	8,70	-29,25	7,35	-6,18	-15,77	10,23	8,86	39,24	8,58	-13,80	-7,50	-31,86
$\beta_{11,n}$	92,30	9,25	9,72	-3,82	-8,19	-6,87	-8,27	48,14	93,61	5,85	0,00	8,23
$\beta_{12,n}$	-12,24	4,77	-27,32	-0,25	0,15	1,73	4,76	10,63	5,24	-1,30	-0,42	-0,28

Table 5: Percentage of change of the β coefficients from the informative to the non-informative model. (In yellow changes greater than the 90%)

Changes in the Greece inflation instead are mostly focused the regressor level: the informative model underestimates its contribution of in the German and Italian CPI, and in the France IPI.

Relevant changes for the other countries are more scattered.

It's to notice the increase in relevance of the Italian IPI in the France and Spain IPI passing to the non-informative prior.

Finally also the short-term interest rate increases its relevance in the France CPI and Italian IPI.

Even if this kind of analysis does not express any consideration about changes in the significance of the parameter, it allows to focus on the main changes of the regressors and to summarize the main differences between the models.

In particular it's quite evident that the prior carries information mostly relevant for Greece, being its variable the most affected by changes.

Specifically the non-informative model depicts an overview of a less self-dependent Greece, so that the Hellenistic economy suffers much less the consequence of a fall in the previous period.

On the other hand the inflation seems to be much more integrated in the system with respect to what comes from the informative prior.

So the IMF projections highlight a worse scenario for Greece, in particular the country with the informative model presents a more difficult recovery after a financial shock.

The estimation of the variance/covariance matrix[30] released less stable parameters, in fact more or less all the equations register a higher variance and corresponding standard deviation with the non-informative model.

Changes in the variances of course affect also the covariances, so in order to determine the effects on the relationship between the variables, better suits a comparison with the correlation matrixes.

The following table highlights the percentage variations in the correlation matrixes from the informative prior model to the non-informative one.

[30] Appendix B.

	CPI FR	CPI GER	CPI GRE	CPI IT	CPI SP	IPI FR	IPI GER	IPI GRE	IPI IT	IPI SP	Euribor	FMSI
CPI FR	0,00	10,62	7,69	14,19	9,33	9,20	11,49	-4,58	16,75	20,61	29,41	17,98
CPI GER	10,62	0,00	15,47	10,65	9,54	10,40	6,84	-32,58	7,33	3,35	29,20	11,12
CPI GRE	7,69	15,47	0,00	-1,14	7,72	4,74	5,07	6,66	4,30	35,54	19,76	5,24
CPI IT	14,19	10,65	-1,14	0,00	8,93	-16,32	-50,13	-43,30	-31,22	13,63	31,27	-16,75
CPI SP	9,33	9,54	7,72	8,93	0,00	18,03	-11,20	-53,51	-4,06	2,22	-3,94	-0,85
IPI FR	9,20	10,40	4,74	-16,32	18,03	0,00	-0,20	-9,35	-0,42	7,04	-77,21	8,24
IPI GER	11,49	6,84	5,07	-50,13	-11,20	-0,20	0,00	-103,13	-3,13	10,04	59,25	-48,93
IPI GRE	-4,58	-32,58	6,66	-43,30	-53,51	-9,35	-103,13	0,00	-752,32	39,74	15,76	-13,83
IPI IT	16,75	7,33	4,30	-31,22	-4,06	-0,42	-3,13	-752,32	0,00	10,13	20,58	7,49
IPI SP	20,61	3,35	35,54	13,63	2,22	7,04	10,04	39,74	10,13	0,00	-39,75	-11,23
Euribor	29,41	29,20	19,76	31,27	-3,94	-77,21	59,25	15,76	20,58	-39,75	0,00	-10,76
FMSI	17,98	11,12	5,24	-16,75	-0,85	8,24	-48,93	-13,83	7,49	-11,23	-10,76	0,00

Table 6: Percentage of change of the correlation matrix from the informative to the non-informative model. (In yellow changes greater than the 50%)

Once again the main differences regard the Greece.

The non-informative prior reduces significantly the majority of the interdependences with the industrial production, in particular the ones with the Italian and German IPI, and to a lesser extent, with the Spain CPI.

So inside the IMF projections there's a stronger belief in the correlation between these dimensions with respect to what comes just from the data, depicting the image of a country a bit more integrated in the system.

Also German IPI presents some notable differences, such as the reductions in the correlation with the Italian CPI, the above mentioned with Greece IPI and with the FMSI. Therefore prior adds some more connections of German economy with the financial stress indicator.

The other interdependences with financial stress don't exhibit strong modifications, as expected from the fact that a non-informative prior was used in both models.

As a final summary, results confirm the low informativeness of the prior, but in any case an analysis of the coefficients revealed that the low information added increases the interdependences of the system from the Greece economy. Moreover the projections highlight a worse outlook for the Greece itself, which seems to be more influenced by its past trend.

3.8 Long-term projections

As seen in the prior specification, under the hypothesis of stationarity[31] the mean of the VAR model is defined as:

$$\mu = (I - B)^{-1}\Delta$$

Such a formulation primarily requires the mean to be the same for all the time *t*, so that allows to consider μ as a long-term projection for the steady-state.

The data sample considered by the model is particularly short and focused on a troubled period, so that long-term estimations are of course very low reliable. But for the sake of completeness is released a comparison between different scenarios.

Specifically are estimated three kind of model, which differ for the underlying prior: long-term IMF projection[32], medium-term IMF projection, and non-informative prior.

[31] Verbeek (2006).
[32] IMF (2012).

	Long-term		Medium-term		Non-informative	
Variable	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
Inflation (France)	1.59	0.32	1.61	0.31	1.60	0.32
Inflation (Germany)	1.81	0.34	1.85	0.34	1.91	0.35
Inflation (Greece)	3.03	0.40	3.07	0.40	3.16	0.42
Inflation (Italy)	1.90	0.29	1.91	0.29	1.83	0.29
Inflation (Spain)	3.03	0.41	3.16	0.41	3.28	0.43
ΔIPI (FR)	-4.48	1.96	-4.99	1.94	-5.22	2.10
ΔIPI (GER)	-2.80	1.82	-3.51	1.81	-3.73	1.93
ΔIPI (GRE)	2.46	3.29	3.46	3.26	4.89	3.31
ΔIPI (IT)	-4.58	2.34	-4.92	2.30	-4.76	2.46
ΔIPI (SP)	-2.95	2.14	-2.95	2.16	-3.10	2.32
3-month Euribor	4.97	0.17	5.44	0.17	5.95	0.14
FMSI	-2.91	0.42	-3.41	0.42	-3.94	0.44

Table 7: estimation results for the long-term projections.

Results highlight important differences, in particular with the narrowing of the projections horizon, worst become the scenario depicted by the model.

Going into details of some economic considerations, the outlook depicted by the non-informative model, i.e. just from the data sample, is an economy with a diffused strong recession, with the only exception of Greece.

Moreover the level of financial stress is extremely low, so that the industrial crisis seems to be independent by a protracted state of financial tension.

The level of prices is instead much more in-line with a positive trend, at least for France, Germany and Italy, in fact Spain and Greece instead suffer of a pretty high inflation rate.

Finally the short-term interest rate returns to high level after the period of low rates started after the 2009 crisis.

Adding the IMF projections improves the scenario: the long-term IMF outlook provides an extended recovery, with a return to a stable rate of growth and inflation.

	CPI FR	CPI GER	CPI GRE	CPI IT	CPI SP	IPI FR	IPI GER	IPI GRE	IPI IT	IPI SP	Euribor	FMSI
Mean	2.0	2.0	1.4	1.5	1.5	2.0	1.3	2.9	1.2	1.8	0.6	0
St. D.	0.3	0.3	0.3	0.3	0.3	1.0	1.0	1.0	1.0	1.0	1.5	4

Table 8: IMF long-term projection prior.

Of course the influence of such information on the model can only be positive.

The long-term prior model in fact exhibits less extreme values, but the scenario is still in recession and distant from the IMF projections. In particular the inflation rates do not register relevant changes, while the negative growth rate of the IPI are sensibly reduced. For the Greece, the only economy with a positive trend, the recovery is also pushed to a lower value, while also the Euribor assumes a more stable rate.
The medium-term prior is placed between the two scenarios, being influenced by the IMF projections for the end of the 2013.
As already expressed at the beginning of the section, such long-term outlooks present very low consistency in consideration of the fact that are based on a strict and economically (and statistically) difficult period; but this analysis allows to evaluate the projections of the small EMU economy if the present conditions would be protracted for an indefinite amount of time.
In particular this leaves us with an interesting food for thought: we have seen that the model considers the Greece production mostly independent from the system; so why in the long run it’s the only economy with a positive rate of growth while the rest of the EMU area is falling? Is the EMU system the actual source of the European crisis?

CONCLUSIONS

This thesis has analysed the impact of financial stress on the real economy of a representative Euro Area through the use of a Bayesian VAR model with informative prior.

The combination of the lagged effects (i.e. the regression coefficients) together with the simultaneous (i.e. the covariances) highlighted a strong influence of a financial shock in the economic activity, not only directly but also triggering a chain reaction in the system's variables which leads to strong dampening in the EMU economies.

Between the 15% and the 40% of the variations in the IPI growth are directly accountable to the financial stress, with also an influence of the 10-30% on the annual inflation rate and a 50% on the short-term interest rates.

The analysis allowed also to derive a general evaluation on the resistance of the single countries to the financial stress, demonstrating that Germany and France suffer much less troubles with respect both to the strength of the crisis peak and to the recovery rate.

On the other hand Spain and Greece are the most influenced states, in particular the first exhibits the highest sensitivity to the direct effects, while the second suffers the longest recession.

A specific analysis of the coefficients also revealed that while on the front of the inflation rate the system has reached a high level of integration, on the side of the IPI the Greece is still outside from an integrated European trend.

Finally the comparison with a non-informative model allowed for an evaluation of the IMF projections. The most relevant considerations regard the Greece, which is much more influenced by its past history in the informative model, and so exhibits a much worse outlook in the recession periods.

As a last consideration the long-term projections, even if based on a strict data sample, leaves open important questions about the European integration, in particular showing how the crisis in the long-run quickly involve the most integrated countries.

As future developments, the analysis could be replied for the dollar-area and the yen-area, and subsequently extended putting in relation results in order to evaluate the transmission of the effects to a global scale.

APPENDIX A

In this appendix are given detailed information on the data definition[33], data computations and data sources about the Financial Market Stress Indicator.

- **Banking-related variables**

TED spread: The TED spread is the difference between the 3-month euro Libor and the 3-month euro Generic Governments Bonds. Being the Generic Governments Bonds considered as risk-free, and Libor the credit risk of lending to commercial banks, the spread is an important money market indicator, especially of the confidence in the banking sector. An increase in the TED spread leads to an increase in the FMSI. Source: Bloomberg.

Money Market Spread: The money market spread is the difference between the 3-month Euribor (the average interest rate at which European banks lend unsecured funds to other market participants) and Eurepo (the benchmark for secured money market operations). An increase in the spread reflects an increase in uncertainty in the money market and can be interpreted as a risk premium. Source: Bloomberg

Bank stock market prices: This index is a capitalization-weighted index, which includes countries participating to the EMU (Eurostoxx Banks index). A decrease in the bank stock market prices leads to an increase in the financial market stress indicator. Source: Bloomberg.

Banking equity risk index: The difference between the bank stock market returns (calculated as the log-differences of the Eurostoxx Banks prices index) and a risk-free interest rate (the one-month secured money market rate 1m Eurepo). Source: Bloomberg, Author's calculations.

Excess Liquidity: Value of bank deposits at the ECB that exceed the minimum reserve requirements. A high usage of the ECB deposit facility reflects uncertainty in the interbank market. Banks prefer to hold their excess reserves with the ECB rather than lending it to the non-financial sector or to other banks in the interbank market. Source: Bloomberg.

Marginal Lending Facility: Value of bank lending at the ECB that is demanded outside the main refinancing operations at a higher interest rate. Source: ECB.

[33] Sources: Van Roye (2011), Bloomberg, ECB.

Expected Lending: ECB's bank lending survey. It contains the assessments of 90 banks of all the euro area countries about how credit markets and lending policies would evolve in the next three months. The data is reported on a quarterly basis, so it was adapted through a quadratic-match average interpolation. Increasing values indicate an expected tightening in credit and lending standards contributing positively to the FMSI. Source: Bloomberg, Author's calculations.

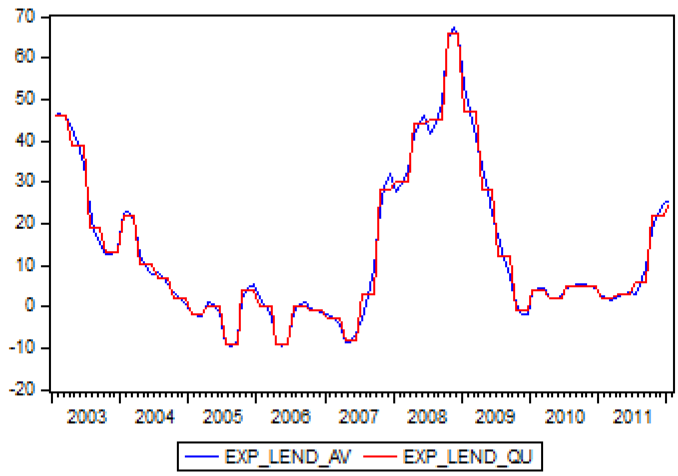


Figure 27: comparison between quarterly Expected Lending and quadratic-match average.

- **Securities market-related variables**

Corporate credit spread: The corporate credit spread measures the difference between the yield on one to two year loans to non-financial corporations and the secured money market rate (Eurepo). Source: ECB, Author's calculations.

Housing spread: The housing spread measures the difference between the interest rates of all housing loans to private households and the secured money market rate (Eurepo). Source: ECB, Author's calculations.

Government Bond Spreads: The Government Bond Spread is calculated as the difference between the 10Y government bonds of Italy, Spain, France and Greece over the 10Y government bonds of Germany (the less risky EMU government bonds).

Source: Bloomberg, Author's calculations.

Consumer credit spread: The consumer credit spread measures the difference between the interest rates of all consumption loans to private households and secured money market rate (Eurepo). Source: ECB, Author's calculations.

VStoxx: Measures stock return volatility. An increase in stock market volatility is usually translated in a higher degree of uncertainty, and so in an increase of risk perception by investors. Source: Bloomberg.

Inverted Eurostoxx 50 prices: This variable measures the inverted monthly prices of the Eurostoxx 50, a stock index representing the major societies of the EMU. Increasing values leads to an increase in the FMSI. Source: Bloomberg.

Slope of the yield curve: The slope of the yield curve is determined taking the differences between the 1Y (short-term) and 10Y (long-term) yields on government issued securities. Usually banks generate profits by intermediating short-term liabilities (deposits) to long-term assets (loans), so that a negative slope of the yield curve stands for a loss of bank profitability. Source: Eurostat.

- **Foreign exchange-related variables:**

Real effective exchange rate: This variable measures the volatility of the real effective exchange rate (REER). The REER is deflated on the CPI-basis with respect to 20 trading partners. An ARCH-test confirmed the presence of GARCH effects on a significance level of 95%. Therefore in order to determine real exchange rate volatility, has been used a GARCH(1,1) model upon the 1999:1 – 2012:1 period. The results are displayed below. Source: Deutsche Bundesbank, Author's calculations.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	9.78E-06	8.73E-06	1.119847	0.2628
ARCH(-1)	0.169810	0.081601	2.080976	0.0374
GARCH(-1)	0.792970	0.093784	8.455282	0.0000

Table 9: Arch-test for the Real Effective Exchange Rate

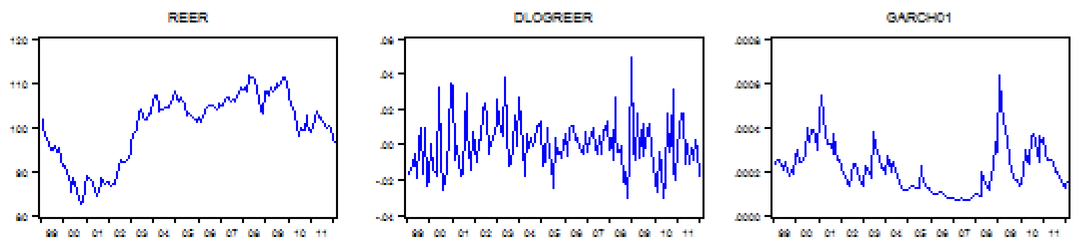


Figure 28: REER transformation from the original series (upper figure), to variation rate (mid), to finally Garch(1,1) volatility (lower).

Correlation matrix of the Principal Component Analysis for the FMSI

	ST_BANKSTOXX	ST_CONS_CRED_SPR	ST_CORP_CRED_SPR	ST_EQUITYRISK	ST_EXPLENDAV	ST_GARCH	ST_HOUSING_SPR	ST_LIQUIDITY
ST_BANKSTOXX	1.000000							
ST_CONS_CRED_SPR	-0.835008	1.000000						
ST_CORP_CRED_SPR	-0.718530	0.764703	1.000000					
ST_EQUITYRISK	0.763756	-0.946123	-0.751469	1.000000				
ST_EXPLENDAV	-0.387290	0.041604	0.051034	0.181005	1.000000			
ST_GARCH	-0.700875	0.643016	0.431733	-0.567592	0.367510	1.000000		
ST_HOUSING_SPR	-0.884793	0.962383	0.843050	-0.915699	0.145202	0.665312	1.000000	
ST_LIQUIDITY	-0.597648	0.638581	0.757538	-0.571076	0.208343	0.301105	0.714680	1.000000
ST_MARGINALFACILITY	-0.377710	0.271802	0.366420	-0.163115	0.421256	0.276734	0.372650	0.530307
ST_MONEYSPREAD	-0.412966	0.218024	0.527920	-0.041743	0.641454	0.241125	0.360194	0.624164
ST_SLOPE	-0.843119	0.945613	0.647362	-0.921642	0.056045	0.668089	0.923587	0.522688
ST_SPRFRGER	-0.677215	0.571198	0.855567	-0.535822	0.262854	0.340034	0.702552	0.794412
ST_SPRGRGER	-0.568491	0.457078	0.767267	-0.526418	-0.002379	0.153575	0.580856	0.681281
ST_SPRITGER	-0.639134	0.538460	0.848281	-0.563664	0.087822	0.262751	0.666659	0.744579
ST_SPRSPGER	-0.672503	0.548191	0.856488	-0.600388	0.022303	0.356821	0.679949	0.638798
ST_STOXX	-0.888417	0.753252	0.403975	-0.675051	0.388034	0.653652	0.732230	0.388264
ST_TED	0.114157	-0.316553	-0.052584	0.500572	0.591043	-0.040999	-0.227227	0.120712
ST_VSTOXX	-0.653469	0.431344	0.461499	-0.242202	0.694896	0.510881	0.541567	0.533800

ST_MARGINALFACILITY	ST_MONEYSPREAD	ST_SLOPE	ST_SPRFRGER	ST_SPRGRGER	ST_SPRITGER	ST_SPRSPGER	ST_STOXX	ST_TED	ST_VSTOXX
1.000000									
0.628084	1.000000								
0.197633	0.086268	1.000000							
0.476805	0.704021	0.459775	1.000000						
0.345624	0.463613	0.375074	0.895478	1.000000					
0.400518	0.590895	0.426561	0.959552	0.953988	1.000000				
0.316041	0.492888	0.471724	0.890260	0.910958	0.950293	1.000000			
0.258233	0.159867	0.803919	0.370524	0.276897	0.330242	0.326062	1.000000		
0.368508	0.723298	-0.395289	0.123298	-0.110747	-0.011803	-0.085804	-0.224807	1.000000	
0.489674	0.670216	0.398520	0.532886	0.280367	0.425136	0.389072	0.576085	0.368572	1.000000

Table 10: Correlation matrix of the FMSI.

APPENDIX B

In this appendix are given detailed information about the model computation and estimation.

- Algebraic details upon Bayesian computation

The probability density functions of the prior model distributed as

$$p(\beta) = f_N(\beta|\beta_a, V_a)$$
$$p(H) = f_W(H|v_a, H_a)$$

Are defined by

$$p(\beta) = \frac{1}{|V_a|}(2\pi)^{-\frac{m}{2}} exp\left\{-\frac{1}{2}(\beta - \beta_a)' V_a^{-1}(\beta - \beta_a)\right\}$$

$$p(H) = exp\left\{-\frac{1}{2}tr(H_a^{-1}H)\right\}\frac{|H|^{\frac{v_a - n - 1}{2}}}{|H_a|^{\frac{v_a}{2}}} \cdot \frac{1}{2^{\frac{1}{2}v_a n}\Gamma_n\left(\frac{v_a}{2}\right)}$$

Where

$$\Gamma_n\left(\frac{v_a}{2}\right) = \pi^{\frac{1}{4}n(n-1)} \prod_{j=1}^{n} \Gamma\left(\frac{v_a}{2} - \frac{1}{2}(j-1)\right)$$

The likelihood function is defined as

$$\mathcal{L}(Y|\beta, \Sigma) = \frac{1}{(2\pi)^{\frac{T_n}{2}}} \frac{1}{|\Sigma \otimes I_T|^{\frac{1}{2}}} exp\left\{-\frac{1}{2}(Y - X\beta)'(\Sigma \otimes I_T)(Y - X\beta)\right\}$$

So the posterior density functions for the β are given by

$$p(\beta|\Sigma, Y) \propto exp\left\{-\frac{1}{2}(-2Y'(\Sigma \otimes I_T)^{-1}X\beta + \beta' X'(\Sigma \otimes I_T)^{-1}X\beta)\right\}$$
$$\cdot\, exp\left\{-\frac{1}{2}(\beta' V_a^{-1}\beta - 2\beta' V_a^{-1}\beta_a)\right\}$$

$$p(\beta|\Sigma, Y) \propto exp\left\{-\frac{1}{2}[\beta'(V_a^{-1} + X'(\Sigma \otimes I_T)^{-1}X)\beta - 2\beta'(V_a^{-1}\beta_a + X'(\Sigma \otimes I_T)^{-1}Y)]\right\}$$

$$p(\beta|\Sigma, Y) \propto N_m(V_0(V_a^{-1}\beta_a + X'(\Sigma \otimes I_T)^{-1}Y), V_0 = \left(V_a^{-1}\beta + X'^{(\Sigma \otimes I_T)^{-1}}X\right)^{-1})$$

While the posterior density functions for the H matrix is given by

$$p(H|\beta,Y) \propto exp\left\{-\frac{1}{2}tr(H_a^{-1}H)\right\}|H|^{\frac{v_a-n-1}{2}}$$

$$\cdot\, exp\left\{-\frac{1}{2}tr(Y-X\beta)'(\Sigma\otimes I_T)(Y-X\beta)\right\}\frac{1}{|\Sigma\otimes I_T|^{\frac{1}{2}}}$$

$$p(H|\beta,Y) \propto exp\left\{-\frac{1}{2}tr\left(H_a^{-1}+\sum_{t=1}^{T}(Y_t-X_t\beta)\,(Y_t-X_t\beta)'H\right)\right\}|H|^{\frac{T+v_a-n-1}{2}}$$

$$p(H|\beta,Y) \propto W_n\left(v_a+T,\left(H_a^{-1}+\sum_{t=1}^{T}(Y_t-X_t\beta)\,(Y_t-X_t\beta)'\right)^{-1}\right)$$

- Posterior density functions

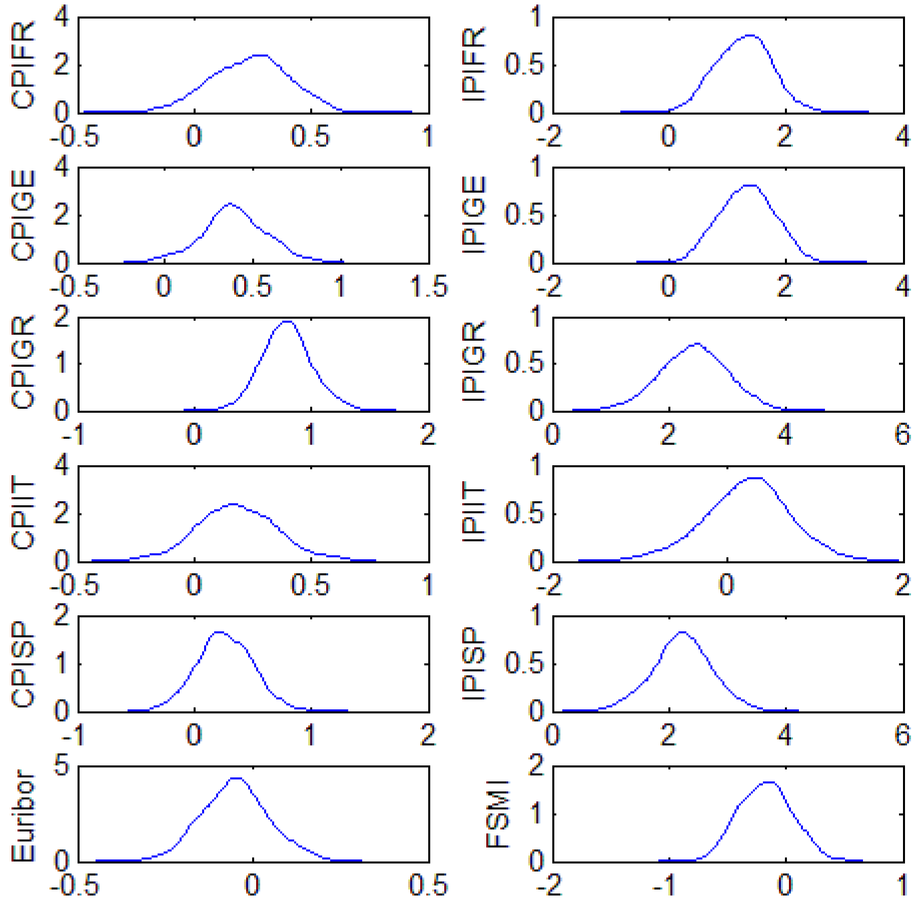


Figure 29: Intercepts posterior density functions.

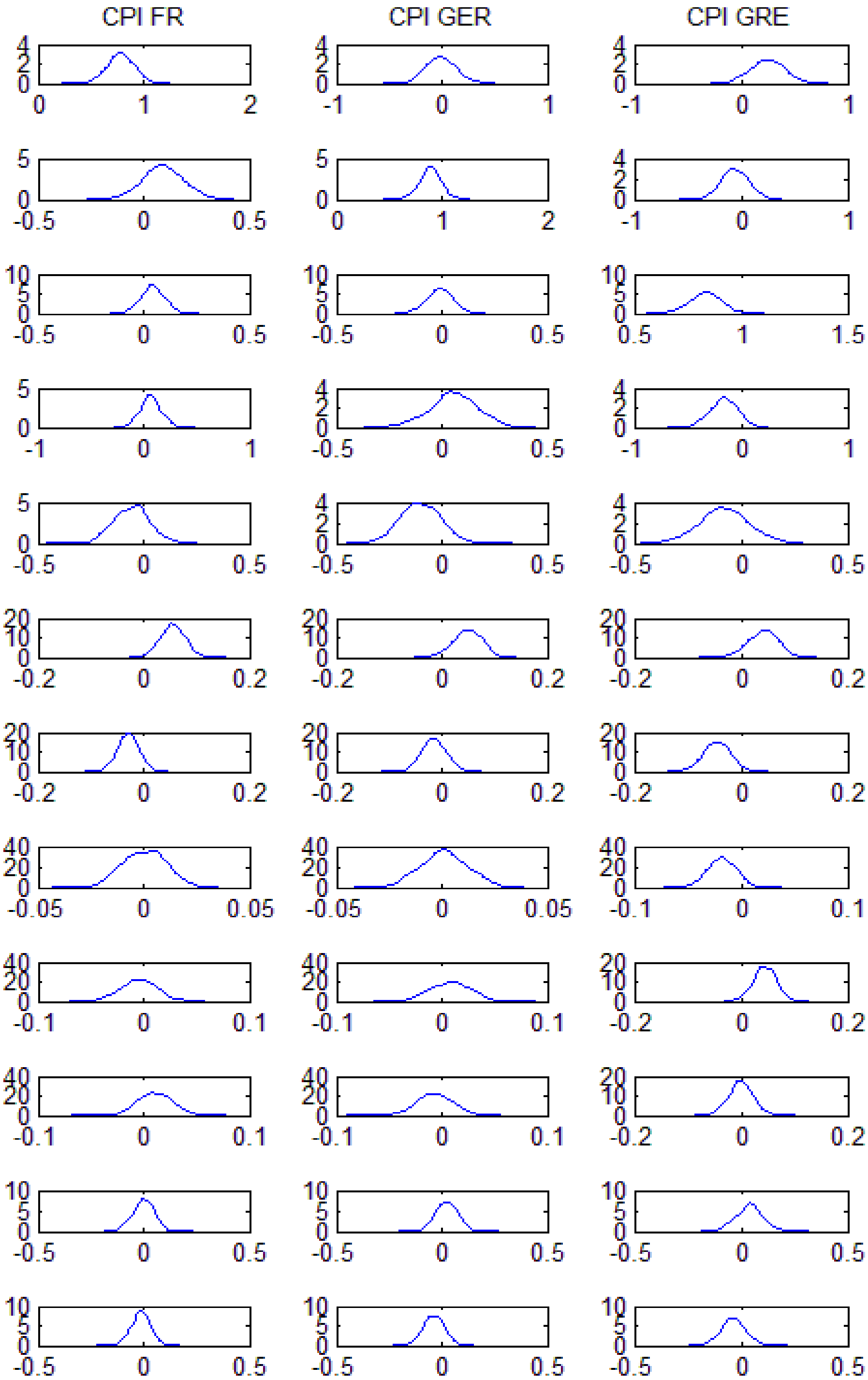


Figure 30: CPI FR, CPI GER, CPI GRE regressors posterior density functions.

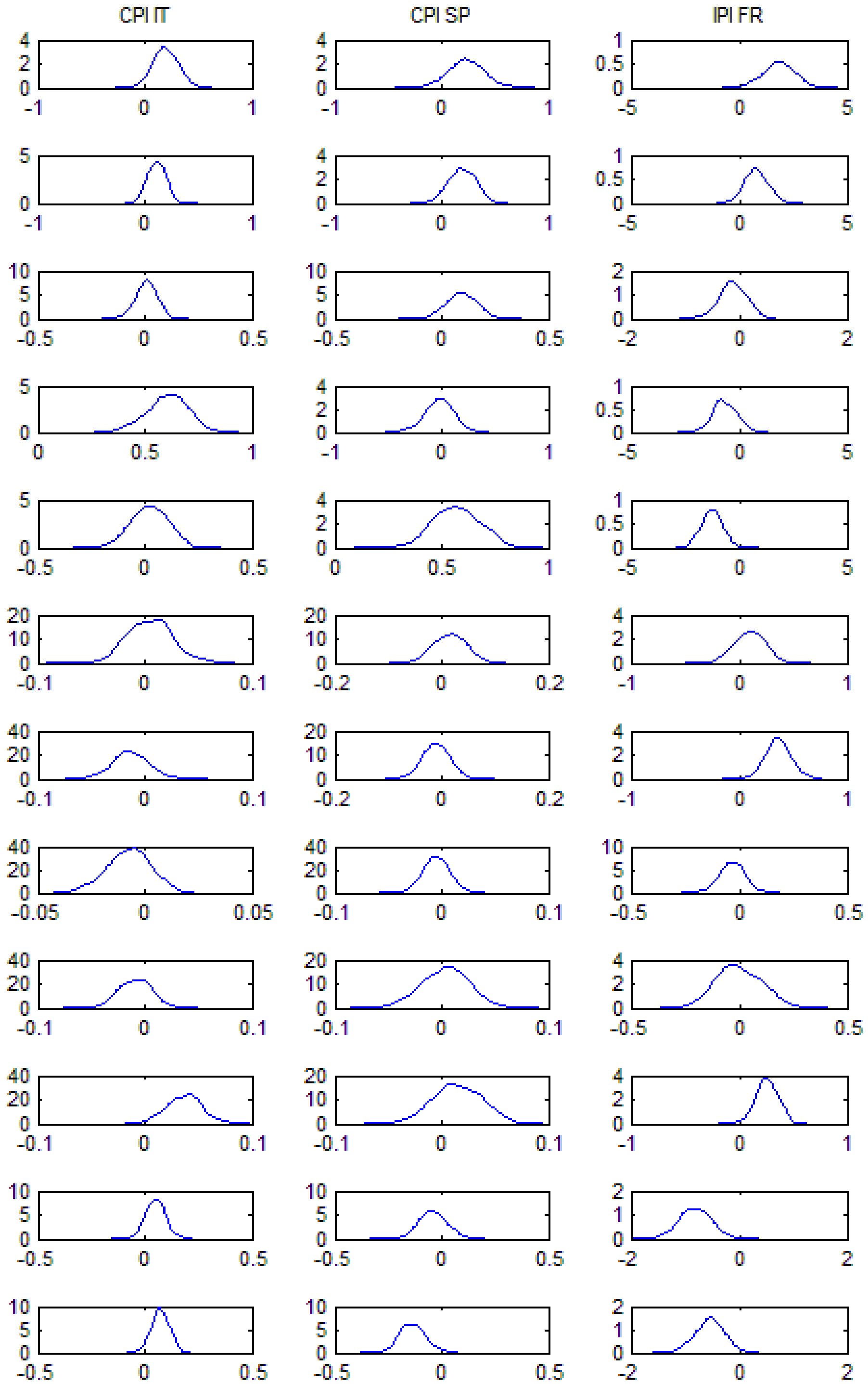


Figure 31: CPI IT, CPI SP, IPI FR regressors posterior density functions.

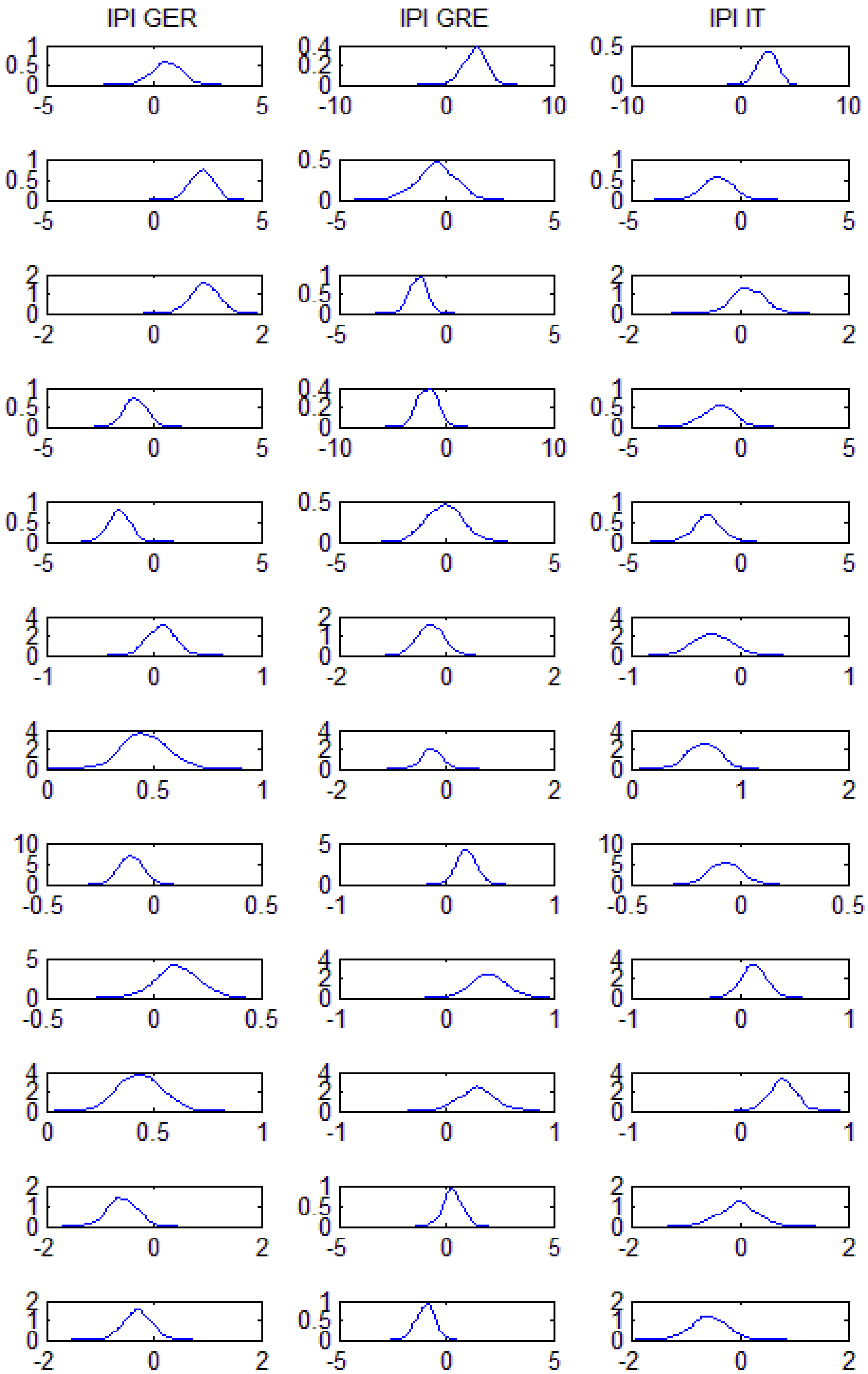


Figure 32: IPI GER, IPI GRE, IPI IT regressors posterior density functions.

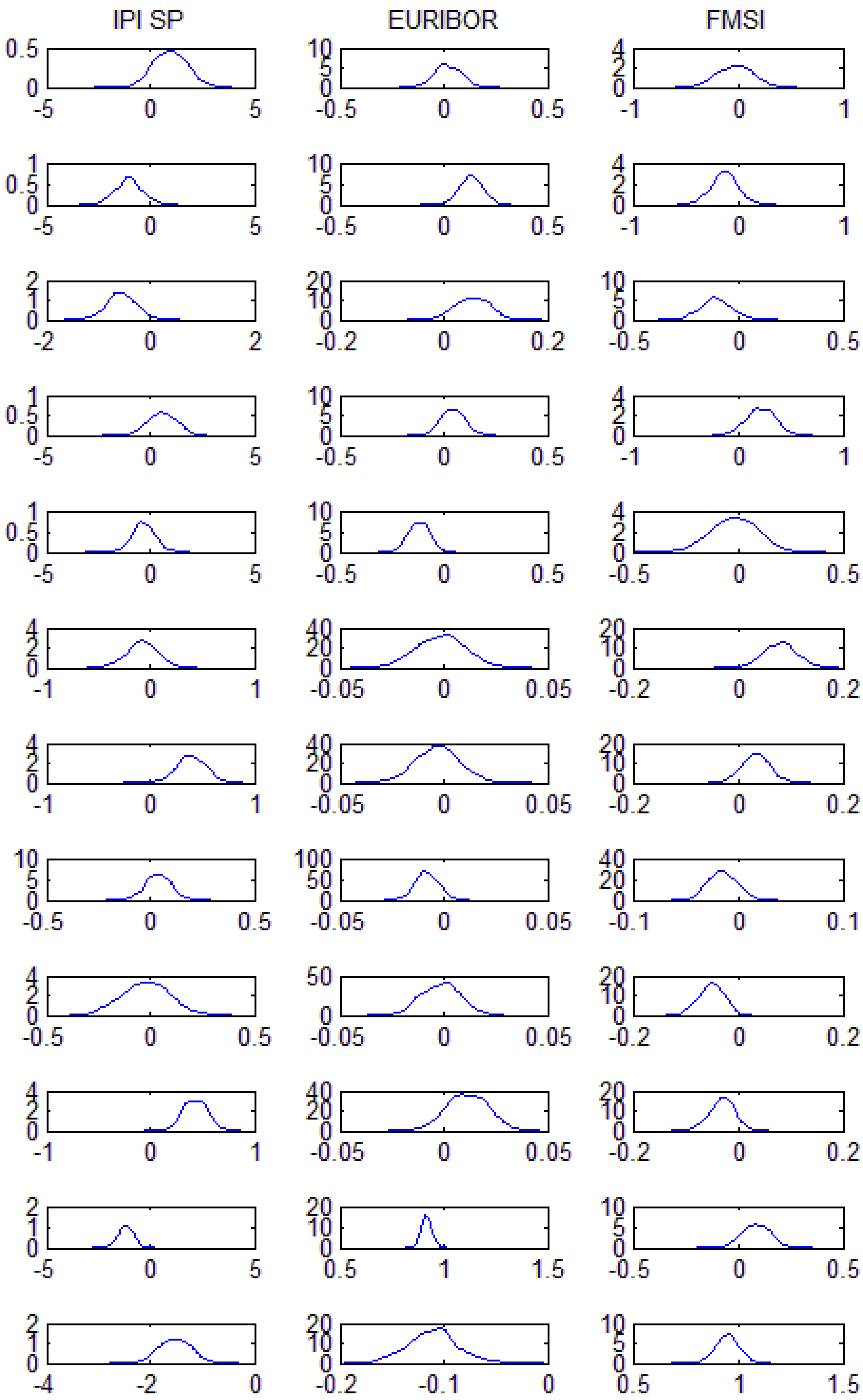


Figure 33: IPI SP, Euribor, FMSI regressors posterior density functions.

- Coefficients estimations

The estimation gave the following results for the β coefficients matrix (informative prior):

	CPI FR	CPI GER	CPI GRE	CPI IT	CPI SP	IPI FR	IPI GER	IPI GRE	IPI IT	IPI SP	Euribor	FMSI
δ_n	0,24 (0,16)	0,39 (0,18)	0,79 (0,21)	0,18 (0,17)	0,26 (0,23)	1,27 (0,47)	1,34 (0,46)	2,43 (0,56)	0,23 (0,47)	2,23 (0,50)	-0,05 (0,09)	-0,17 (0,22)
$\beta_{1,n}$	0,79 (0,12)	0,00 (0,12)	0,26 (0,15)	0,21 (0,11)	0,25 (0,15)	1,80 (0,71)	0,60 (1,64)	2,68 (1,10)	2,56 (0,80)	1,01 (0,73)	0,02 (0,06)	-0,02 (0,18)
$\beta_{2,n}$	0,10 (0,09)	0,90 (0,10)	-0,05 (0,12)	0,12 (0,09)	0,21 (0,12)	0,84 (0,58)	2,24 (0,50)	-0,46 (0,88)	-0,94 (0,64)	-0,99 (0,59)	0,13 (0,05)	-0,14 (0,13)
$\beta_{3,n}$	0,04 (0,05)	-0,01 (0,05)	0,83 (0,07)	0,00 (0,05)	0,10 (0,07)	-0,10 (0,25)	0,97 (0,23)	-1,31 (0,37)	0,16 (0,29)	-0,53 (0,29)	0,06 (0,03)	-0,11 (0,08)
$\beta_{4,n}$	0,06 (0,10)	0,06 (0,11)	-0,17 (0,13)	0,60 (0,09)	-0,02 (0,14)	-0,72 (0,57)	-0,85 (0,55)	-1,84 (0,95)	-1,06 (0,67)	0,53 (0,64)	0,04 (0,05)	0,21 (0,13)
$\beta_{5,n}$	-0,06 (0,09)	-0,11 (0,09)	-0,08 (0,11)	0,02 (0,08)	0,56 (0,11)	-1,22 (0,49)	-1,58 (0,45)	0,01 (0,82)	-1,45 (0,58)	-0,35 (0,53)	-0,12 (0,05)	0,00 (0,12)
$\beta_{6,n}$	0,05 (0,02)	0,05 (0,02)	0,04 (0,03)	0,00 (0,02)	0,01 (0,03)	0,09 (0,13)	0,07 (0,12)	-0,29 (0,22)	-0,26 (0,16)	-0,08 (0,15)	0,00 (0,01)	0,08 (0,03)
$\beta_{7,n}$	-0,03 (0,02)	-0,01 (0,02)	-0,05 (0,03)	-0,01 (0,02)	-0,01 (0,03)	0,35 (0,12)	0,46 (0,11)	-0,27 (0,19)	0,67 (0,14)	0,40 (0,12)	0,00 (0,01)	0,04 (0,03)
$\beta_{8,n}$	0,00 (0,01)	0,00 (0,01)	-0,02 (0,01)	-0,01 (0,01)	0,00 (0,01)	-0,03 (0,06)	-0,10 (0,05)	0,18 (0,10)	-0,06 (0,07)	0,04 (0,06)	-0,01 (0,01)	-0,01 (0,01)
$\beta_{9,n}$	0,00 (0,02)	0,01 (0,02)	0,05 (0,02)	-0,01 (0,02)	0,00 (0,02)	0,01 (0,10)	0,11 (0,10)	0,40 (0,16)	0,14 (0,12)	-0,02 (0,11)	0,00 (0,01)	-0,05 (0,02)
$\beta_{10,n}$	0,01 (0,02)	-0,01 (0,02)	0,00 (0,02)	0,04 (0,02)	0,02 (0,02)	0,26 (0,10)	0,43 (0,09)	0,31 (0,17)	0,41 (0,11)	0,43 (0,12)	0,01 (0,01)	-0,03 (0,02)
$\beta_{11,n}$	0,00 (0,05)	0,02 (0,05)	0,04 (0,06)	0,05 (0,04)	-0,04 (0,07)	-0,79 (0,30)	-0,58 (0,28)	0,31 (0,49)	-0,01 (0,35)	-1,19 (0,33)	0,92 (0,03)	0,09 (0,07)
$\beta_{12,n}$	-0,01 (0,04)	-0,04 (0,05)	-0,03 (0,06)	0,07 (0,04)	-0,13 (0,06)	-0,51 (0,26)	-0,29 (0,25)	-0,93 (0,43)	-0,53 (0,30)	-1,53 (0,29)	-0,11 (0,02)	0,95 (0,06)

Table 11: Coefficients matrix for the informative model.

Results for the variance ∑ matrix (informative prior):

	CPI FR	CPI GER	CPI GRE	CPI IT	CPI SP	IPI FR	IPI GER	IPI GRE	IPI IT	IPI SP	Euribor	FMSI
CPI FR	0,10 (0,01)	0,06 (0,01)	0,04 (0,01)	0,04 (0,01)	0,08 (0,02)	0,14 (0,07)	0,04 (0,06)	-0,08 (0,11)	0,08 (0,07)	0,09 (0,07)	0,01 (0,01)	0,01 (0,01)
CPI GER	0,06 (0,01)	0,12 (0,02)	0,03 (0,01)	0,03 (0,01)	0,09 (0,02)	-0,02 (0,07)	-0,07 (0,06)	-0,02 (0,12)	-0,21 (0,08)	-0,06 (0,08)	0,01 (0,01)	-0,01 (0,01)
CPI GRE	0,04 (0,01)	0,03 (0,01)	0,16 (0,02)	0,02 (0,01)	0,06 (0,02)	0,11 (0,08)	-0,03 (0,07)	-0,09 (0,16)	-0,11 (0,10)	-0,05 (0,09)	0,01 (0,01)	0,02 (0,02)
CPI IT	0,04 (0,01)	0,03 (0,01)	0,02 (0,01)	0,08 (0,01)	0,04 (0,01)	-0,02 (0,06)	-0,01 (0,05)	-0,05 (0,10)	-0,02 (0,07)	0,10 (0,07)	0,01 (0,01)	0,00 (0,01)
CPI SP	0,08 (0,02)	0,09 (0,02)	0,06 (0,02)	0,04 (0,01)	0,17 (0,03)	0,08 (0,08)	-0,05 (0,08)	-0,05 (0,14)	-0,09 (0,10)	0,18 (0,10)	0,00 (0,01)	-0,02 (0,02)
IPI FR	0,14 (0,07)	-0,02 (0,07)	0,11 (0,08)	-0,02 (0,06)	0,08 (0,08)	3,81 (0,59)	2,04 (0,42)	0,81 (0,67)	1,88 (0,54)	1,61 (0,48)	0,00 (0,03)	0,05 (0,09)
IPI GER	0,04 (0,06)	-0,07 (0,06)	-0,03 (0,07)	-0,01 (0,05)	-0,05 (0,08)	2,04 (0,42)	3,28 (0,49)	0,23 (0,62)	2,13 (0,52)	0,90 (0,43)	-0,02 (0,03)	0,02 (0,08)
IPI GRE	-0,08 (0,11)	-0,02 (0,12)	-0,09 (0,16)	-0,05 (0,10)	-0,05 (0,14)	0,81 (0,67)	0,23 (0,62)	10,84 (1,55)	0,15 (0,80)	1,22 (0,76)	-0,06 (0,06)	0,15 (0,16)
IPI IT	0,08 (0,07)	-0,21 (0,08)	-0,11 (0,10)	-0,02 (0,07)	-0,09 (0,10)	1,88 (0,54)	2,13 (0,52)	0,15 (0,80)	5,38 (0,81)	1,81 (0,60)	0,02 (0,04)	0,08 (0,10)
IPI SP	0,09 (0,07)	-0,06 (0,08)	-0,05 (0,09)	0,10 (0,07)	0,18 (0,10)	1,61 (0,48)	0,90 (0,43)	1,22 (0,76)	1,81 (0,60)	4,72 (0,71)	0,00 (0,04)	-0,11 (0,10)
Euribor	0,01 (0,01)	0,01 (0,01)	0,01 (0,01)	0,01 (0,01)	0,00 (0,01)	0,00 (0,03)	-0,02 (0,03)	-0,06 (0,06)	0,02 (0,04)	0,00 (0,04)	0,03 (0,00)	0,00 (0,01)
FMSI	0,01 (0,01)	-0,01 (0,01)	0,02 (0,02)	0,00 (0,01)	-0,02 (0,02)	0,05 (0,09)	0,02 (0,08)	0,15 (0,16)	0,08 (0,10)	-0,11 (0,10)	0,00 (0,01)	0,18 (0,03)

Table 12: Variance/covariances matrix for the informative mode

Results for the β coefficients matrix (non-informative prior):

	CPI FR	CPI GER	CPI GRE	CPI IT	CPI SP	IPI FR	IPI GER	IPI GRE	IPI IT	IPI SP	Euribor	FMSI
δ_n	0,20	0,36	0,84	0,24	0,32	0,37	0,21	-2,79	-1,20	3,58	-0,02	-0,37
	(0,16)	(0,17)	(0,21)	(0,15)	(0,21)	(0,98)	(0,93)	(1,45)	(1,20)	(1,02)	(0,07)	(0,23)
$\beta_{1,n}$	0,80	0,01	0,27	0,22	0,25	1,64	0,48	2,26	2,28	1,00	0,02	-0,05
	(0,13)	(0,14)	(0,16)	(0,11)	(0,17)	(0,76)	(0,67)	(1,11)	(0,91)	(0,81)	(0,05)	(0,17)
$\beta_{2,n}$	0,10	0,91	-0,06	0,11	0,21	0,88	2,25	-0,16	-0,90	-1,11	0,13	-0,12
	(0,10)	(0,11)	(0,13)	(0,09)	(0,13)	(0,61)	(0,58)	(0,94)	(0,73)	(0,66)	(0,04)	(0,13)
$\beta_{3,n}$	0,05	0,00	0,82	-0,01	0,08	0,12	1,24	-0,11	0,51	-0,85	0,05	-0,06
	(0,05)	(0,06)	(0,07)	(0,05)	(0,07)	(0,33)	(0,32)	(0,48)	(0,40)	(0,36)	(0,02)	(0,08)
$\beta_{4,n}$	0,06	0,05	-0,18	0,59	-0,03	-0,51	-0,66	-0,97	-0,75	0,39	0,04	0,25
	(0,10)	(0,11)	(0,13)	(0,09)	(0,14)	(0,60)	(0,55)	(0,96)	(0,72)	(0,65)	(0,05)	(0,13)
$\beta_{5,n}$	-0,06	-0,12	-0,07	0,02	0,56	-1,30	-1,67	-0,53	-1,54	-0,18	-0,12	-0,03
	(0,09)	(0,09)	(0,11)	(0,08)	(0,12)	(0,56)	(0,51)	(0,81)	(0,65)	(0,58)	(0,04)	(0,12)
$\beta_{6,n}$	0,05	0,04	0,04	0,00	0,01	0,10	0,07	-0,35	-0,25	-0,05	0,00	0,08
	(0,02)	(0,02)	(0,03)	(0,02)	(0,03)	(0,14)	(0,13)	(0,23)	(0,17)	(0,15)	(0,01)	(0,03)
$\beta_{7,n}$	-0,03	-0,01	-0,04	-0,01	-0,01	0,34	0,45	-0,29	0,66	0,40	0,00	0,03
	(0,02)	(0,02)	(0,03)	(0,02)	(0,03)	(0,13)	(0,12)	(0,21)	(0,15)	(0,13)	(0,01)	(0,03)
$\beta_{8,n}$	0,00	0,00	-0,02	-0,01	0,00	-0,05	-0,13	0,07	-0,09	0,07	-0,01	-0,02
	(0,01)	(0,01)	(0,01)	(0,01)	(0,01)	(0,06)	(0,06)	(0,11)	(0,08)	(0,07)	(0,00)	(0,01)
$\beta_{9,n}$	0,00	0,01	0,05	-0,01	0,01	-0,02	0,07	0,26	0,09	0,02	0,00	-0,05
	(0,02)	(0,02)	(0,02)	(0,02)	(0,02)	(0,12)	(0,10)	(0,18)	(0,13)	(0,12)	(0,01)	(0,02)
$\beta_{10,n}$	0,01	-0,01	0,00	0,03	0,01	0,28	0,47	0,47	0,44	0,37	0,01	-0,02
	(0,02)	(0,02)	(0,02)	(0,02)	(0,02)	(0,12)	(0,10)	(0,18)	(0,13)	(0,12)	(0,01)	(0,02)
$\beta_{11,n}$	0,00	0,02	0,04	0,04	-0,05	-0,75	-0,50	0,60	0,08	-1,24	0,91	0,10
	(0,05)	(0,06)	(0,06)	(0,04)	(0,07)	(0,30)	(0,29)	(0,51)	(0,38)	(0,36)	(0,02)	(0,07)
$\beta_{12,n}$	-0,01	-0,04	-0,03	0,07	-0,13	-0,55	-0,31	-1,06	-0,56	-1,49	-0,11	0,95
	(0,04)	(0,05)	(0,05)	(0,04)	(0,06)	(0,27)	(0,26)	(0,43)	(0,31)	(0,32)	(0,02)	(0,06)

Table 13: Coefficients matrix for the non-informative model.

Results for the variance ∑ matrix (non-informative prior):

	CPI	CPI	CPI	CPI	CPI	IPI	IPI	IPI	IPI	IPI	Euribor	FMSI
CPI FR	0,10 (0,02)	0,07 (0,01)	0,04 (0,01)	0,04 (0,01)	0,09 (0,02)	0,17 (0,08)	0,04 (0,07)	-0,09 (0,12)	0,11 (0,09)	0,11 (0,08)	0,01 (0,01)	0,01 (0,02)
CPI GER	0,07 (0,01)	0,12 (0,02)	0,03 (0,02)	0,04 (0,01)	0,10 (0,02)	-0,03 (0,08)	-0,09 (0,08)	-0,03 (0,12)	-0,24 (0,10)	-0,07 (0,09)	0,01 (0,01)	-0,01 (0,02)
CPI GRE	0,04 (0,01)	0,03 (0,02)	0,17 (0,03)	0,03 (0,01)	0,07 (0,02)	0,12 (0,10)	-0,04 (0,09)	-0,10 (0,14)	-0,13 (0,12)	-0,06 (0,11)	0,01 (0,01)	0,03 (0,02)
CPI IT	0,04 (0,01)	0,04 (0,01)	0,03 (0,01)	0,09 (0,01)	0,04 (0,02)	-0,02 (0,07)	-0,01 (0,06)	-0,02 (0,10)	0,00 (0,08)	0,11 (0,07)	0,02 (0,00)	0,00 (0,01)
CPI SP	0,09 (0,02)	0,10 (0,02)	0,07 (0,02)	0,04 (0,02)	0,19 (0,03)	0,09 (0,10)	-0,06 (0,09)	-0,03 (0,15)	-0,09 (0,12)	0,19 (0,11)	0,00 (0,01)	-0,02 (0,02)
IPI FR	0,17 (0,08)	-0,03 (0,08)	0,12 (0,10)	-0,02 (0,07)	0,09 (0,10)	4,40 (0,75)	2,31 (0,55)	0,71 (0,78)	2,17 (0,63)	1,96 (0,58)	0,00 (0,03)	0,05 (0,10)
IPI GER	0,04 (0,07)	-0,09 (0,08)	-0,04 (0,09)	-0,01 (0,06)	-0,06 (0,09)	2,31 (0,55)	3,78 (0,59)	0,01 (0,73)	2,45 (0,59)	1,15 (0,48)	-0,02 (0,03)	0,01 (0,10)
IPI GRE	-0,09 (0,12)	-0,03 (0,12)	-0,10 (0,14)	-0,02 (0,10)	-0,03 (0,15)	0,71 (0,78)	0,01 (0,73)	11,07 (1,75)	-0,19 (0,91)	1,88 (0,91)	-0,05 (0,05)	0,13 (0,16)
IPI IT	0,11 (0,09)	-0,24 (0,10)	-0,13 (0,12)	0,00 (0,08)	-0,09 (0,12)	2,17 (0,63)	2,45 (0,59)	-0,19 (0,91)	6,22 (1,02)	2,22 (0,68)	0,02 (0,04)	0,08 (0,12)
IPI SP	0,11 (0,08)	-0,07 (0,09)	-0,06 (0,11)	0,11 (0,07)	0,19 (0,11)	1,96 (0,58)	1,15 (0,48)	1,88 (0,91)	2,22 (0,68)	5,24 (0,81)	0,00 (0,04)	-0,10 (0,11)
Euribor	0,01 (0,01)	0,01 (0,01)	0,01 (0,01)	0,02 (0,00)	0,00 (0,01)	0,00 (0,03)	-0,02 (0,03)	-0,05 (0,05)	0,02 (0,04)	0,00 (0,04)	0,02 (0,00)	0,00 (0,01)
FMSI	0,01 (0,02)	-0,01 (0,02)	0,03 (0,02)	0,00 (0,01)	-0,02 (0,02)	0,05 (0,10)	0,01 (0,10)	0,13 (0,16)	0,08 (0,12)	-0,10 (0,11)	0,00 (0,01)	0,20 (0,03)

Table 14: Variance/covariances matrix for the non-informative model.

- **Further details**

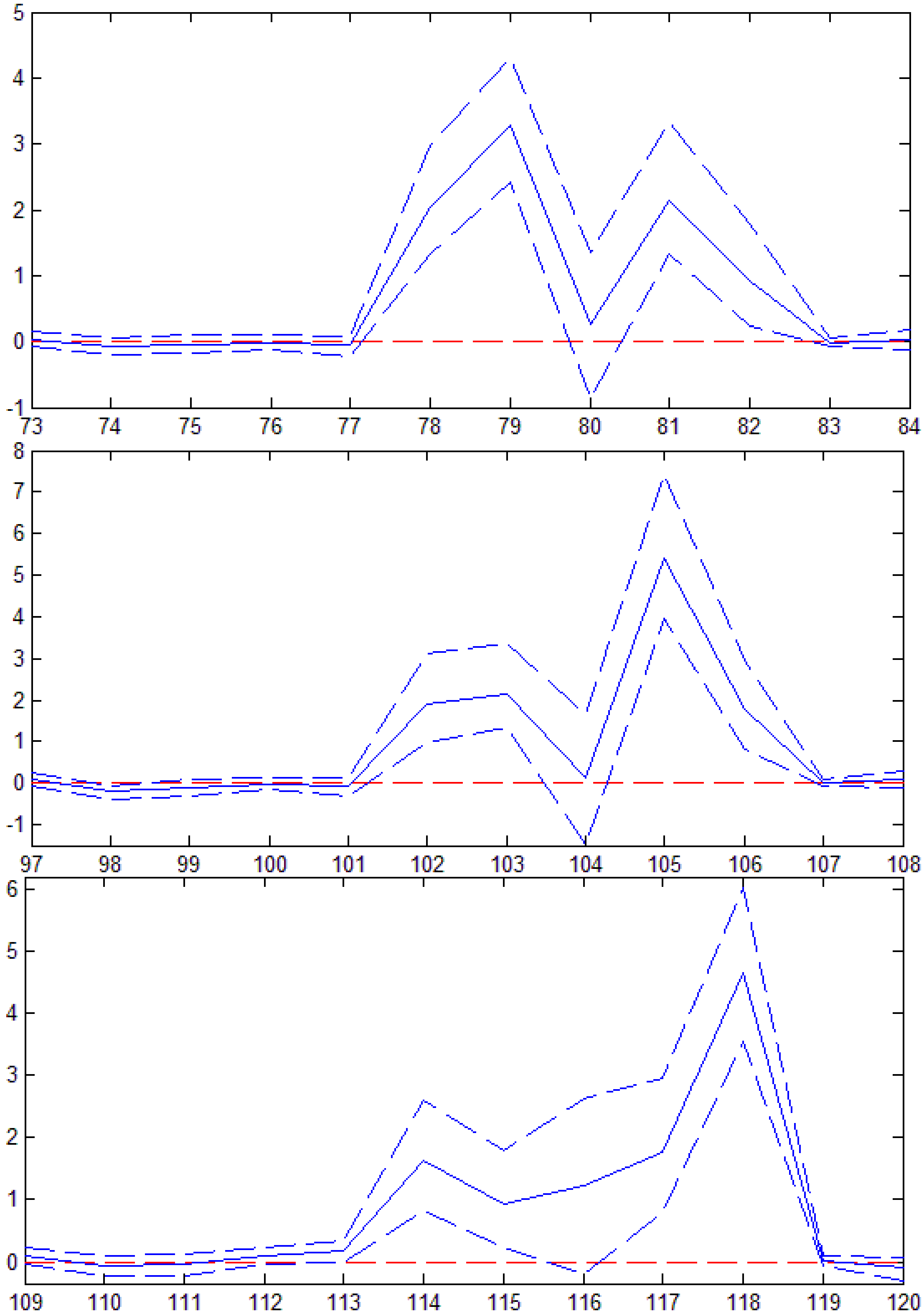


Figure 34: Zoom on the German (up), Italian (mid) and Spain IPI (low) variance/covariances.

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