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Modelling inflation: different goals call for different solutions

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to my mother

Abstract

Analysing prices behavior is not a unambiguous matter, it requires different methodologies depending on the aim of the study, on the period of time considered and on the available data. In what follows, we explore three different ways to model prices dynamics responding to alternative aims. We start from considering sector-level inflation indexes identifying the method still used in the Banca d'Italia to conduct the NIPE exercise; secondly, we consider individual prices in order to assess the degree of price stickiness in France, Germany and Italy using a factor model able to identify the effects of different kinds of shocks on prices at different level of aggregation; finally, we test the ability of the factor model in forecasting the overall inflation index of the same three Euro countries finding a significant forecasting power in the unobservable factors. Our results confirm that the data and the period of time considered can lead to quite different outcomes; moreover, different models can alternatively be the most precise in foreseeing inflation depending on the horizon of prediction or the country considered. In conclusion, the best way to analyse prices behavior is peculiar to the aim of the study: different methodologies, in fact, can be the most appropriate for different exercises.

Contents

Introduction

The controversial results obtained when trying to model price changes make forecasting inflation one of the most widely investigated issues in econometrics.

Analyses on inflation behaviour can be conducted in different ways depending on the aim of the study, on the frequency at which predictions have to be updated, on the country analysed and on the period of time considered. In what follows we are going to explore different ways to analyse prices behaviour: a sector-level indirect approach used at the Banca d'Italia to frequently update national inflation predictions, a more disaggregate approach starting from individual series (not only prices) summarised in a factor model in order to assess the persistence degree of inflation in the three largest Euro countries, a direct approach comparing alternative models accuracy in forecasting the same national inflation indexes.

The results clearly confirm that the best way to model inflation dynamics is peculiar to the country and to the period of data considered; moreover, different econometric specifications can give more accurate results in catching the influence of macroeconomic shocks hitting the economic system at different horizons.

The interest on price dynamics has increased since 1999, when the euro has been adopted as single currency and the European Central Bank (ECB) has been charged with maintaining the euro's purchasing power and thus price stability in the euro area. This objective is accurately specified in the following statement that defines the so-called 'inflation target': 'an annual Harmonized Index of Consumer Prices (HICP) inflation rate of below, but close to, 2% over the medium term' (ECB [1]). In order to successfully achieve this goal, the European Central Bank calls for a continuous monitoring of inflation developments in the euro area. To this aim the Eurosystem runs every quarter an exercise in which each National Central Bank (NCB) produces a national inflation forecast for a relatively short forecast horizon, varying from 12 to 15 months. The forecast target is the year-on-year growth rate of the Harmonized Index of Consumer Prices. This exercise, named Narrow Inflation Projection Exercise (NIPE), runs parallel to a more articulated one (the (Broad) Macro Projection Exercise) which goes well beyond the NIPE horizon (up to three years ahead) and covers a large number of macro variables.

In fact, although the inflation target refers to the medium term and is related to structural economic conditions, it is useful to consider a short term intermediate objective because it gives a faster indication of the economic situation thus permitting a prompt intervention in case of relevant deviations from the final target.

There are alternative methods to obtain a valid forecast for the overall HICP index:

- modelling the aggregate index in order to obtain a direct projection, getting a rapid estimate of the expected price growth;
- conducting a forecasting exercise on each sub-index, computing the overall inflation as a weighted sum of the sectors' prices growth rates;
- considering all the available information about the economy summarised in a small number of common factors driving macro aggregates as inflation.

The indirect approach has the advantage of taking into account the different variables that influence the price change in each main sector: typically, sectors as clothing and unprocessed food are strongly influenced by seasonality, because of periodic events as sales and climatic changes respectively. Moreover, this strategy has an econometric advantage, as Clements and Hendry [29] show: aggregating forecasts can lead to more accurate results, because the erratic component present in each single price series tends to cancel out. It is still not clear whether the direct or the indirect method would be the most accurate, as different papers have been published supporting one strategy or the other (see the Section 1.1). Alternatively, a factor model avoids any *a-priori* choice about the economic variables to include in the models. Integrated markets and common monetary policies have made economies much more interdependent, so that shocks influence is mutually pervasive across countries; in order to consider all the available information, a factor model identifies a small set of macroeconomic shocks driving economic indicators out of a large number of observable series regarding every aspect of the economic system.

In Chapter 1 we follow an indirect approach to conduct the NIPE exercise, identifying the most accurate forecasting models for the main HICP sub-indexes: Services, Goods, Energy, Processed and Unprocessed Food. For each of these sectors, different linear models have been compared, alternatively testing the forecasting power of various economic variables that could significantly influence price changes. In order to choose the best model in predicting inflation, we consider the specification with the minimum Root Mean Squared Forecast Error (RMSFE) at different horizons. Additionally, the chosen model has been compared with a *naïf* model: for particularly erratic HICP sectors as the Energy component this specification is still hard to overcome in terms of forecasting accuracy. In Chapter 1 we report the final model selected for each sub-index and the relative forecast errors from 1 to 15 steps ahead. In order to obtain the overall expected inflation, the contribution of each component to the predicted price growth will be added up according to the weights of each sector in the HICP composition.

The good performance of the indirect approach in terms of predictions accuracy can be further exploited analysing individual-level economic series regarding every aspect of the economy, not only prices. Important information about unexpected shocks influencing macro aggregates as inflation can be provided by labour, financial and house market indicators; moreover, analysing prices at different levels of aggregation can provide different results in terms of inflation dynamics.

As pointed out in previous works such as Boivin, Giannoni and Mihov[21] and Altissimo and Zaffaroni[5] [1], price responses are quite heterogeneous across different sectors: energy and unprocessed food prices are quite volatile, while goods and services prices change quite infrequently; moreover, price dynamics result to be quite different depending on the level of aggregation of the series. In Chapter 2 we analyse the price series behaviour in the three largest EU countries considering both aggregate and sectoral inflation: the former results less volatile, supporting the sticky price traditional evidence in the short run, while disaggregated series, considering both consumer and producer prices, result more flexible in responding to economic shocks.

The reason of the different price behaviour is in the different kinds of shocks hitting the economy. Recent empirical investigations have shown in fact that disaggregated price series in US appear to be sticky in response to macroeconomic shocks, but they come back to the equilibrium level quite rapidly after a sector-specific shock. Given that these sector-specific shocks are responsible for most of monthly price fluctuations, the series result quite volatile, in contrast to the theoretic hypothesis of most of economic models.

We follow Boivin, Giannoni and Mihov[21] using a factor-augmented vector autoregression model consisting in estimating a small number of factors summarising the economic dynamics out of a large data set of monthly and quarterly series. This model allows us to disentangle the impact of a shock on the common and idiosyncratic component of inflation. Moreover, we investigate the impact of monetary policy on disaggregated inflation identifying a monetary shock by using information from the entire data set.

We conduct the analysis comparing inflation dynamics in the three largest Euro countries, namely France, Germany and Italy, that represent more that 65% of Euro Area's GDP. Moreover, they joined the Euro Monetary Union from the beginning, so statistics are available and complete in the main European databases. Unfortunately, some kind of data is not available in any European database in an homogeneous form and has to be gathered from each national institute of statistics. Each institute considers different categories of products and with a different level of

[1] See also Lünnemann and Mathä[44] and Carvalho[24].

disaggregation, hence in order to obtain a uniform database, series have to be made comparable by product type. Time availability is another shortcoming of European data: while US price series are available for more than thirty years' time, unfortunately European series start only from early 90s.

The results are quite similar for the three countries, both for CPI and for PPI series, apart from French PPI indices that deserve particular attention. Aggregate inflation shows low persistence and volatility mostly due to the macroeconomic component. The idiosyncratic component, instead, is responsible for most of the disaggregated prices fluctuations. On one hand, our findings about inflation volatility are similar to those from previous works; on the other, the degree of price persistence, considering both aggregate and disaggregate series, results much lower. In contrast to Boivin, Giannoni and Mihov[21], we don't find that macroeconomic shocks have a significant impact in the long run: individual prices in fact result to be quite flexible in absorbing a monetary shock. The explanation of this apparent contradiction is in the positive correlation between inflation and persistence: estimating the same model on a period of low inflation (as the one we have experienced since the creation on the Eurosystem) or on a longer span of data including periods of high inflation (as Boivin, Giannoni and Mihov[21] do using US data) can produce very different results in the shock persistence degree.

Given that the FAVAR model provides useful information about prices dynamics, a further step is to test its forecasting ability in correctly estimating future changes in price levels. In Chapter 3 we illustrate the forecasting accuracy of the factor model compared to several alternatives when applied to the same data used in Chapter 2. Though different models result to best predict inflation in the three countries, a factor model that summarises all the available information in a few artificial variables imposing very few restrictions on agents' behaviour results to be significantly useful in correctly foreseeing the future price trend. Moreover, we test the forecasting performance of different models from 2008 to 2009, that is when the economic crisis started hitting the EU countries causing quite serious drawbacks. The predictive accuracy of the factor model in a period characterised by high uncertainty enforces the belief that it is a very useful tool for modelling price behaviour.

The results confirm that combining forecasts from different models can significantly improve the forecasting performance, given the relative accuracy each specification has over different subperiods. Moreover, a forecast combination substantially reduces the uncertainty associated with monetary policy decisions, in line with the literature that encourages for the most complete use of information available in the economy. Therefore, a factor model including artificial variables that summarise all the shocks affecting the economy can provide quite accurate predictions.

Moreover, the idea of combining forecasts from a wide variety of models is already accepted by many Central Banks, like the Banca d'Italia (as described in Chapter 1) and the Bank of England. Kapetanios et al.[41] illustrate the different models composing the so-called 'Suite of Statistical Forecasting Models', ranging from pure statistical to data-free theoretical models. The different forecasts are then summarised using a system of weights based on the AIC information criterion, because different models can be differently affected by the shocks hitting the economy.

The exercise confirms the peculiar nature of forecasting inflation: different models result to be the most accurate at different horizons or for alternative measures of inflation. Unobservable factors taking into account different shocks hitting the economy have predictive power especially at medium and long horizons, while univariate models are more accurate at short horizons. Moreover, different models can result more useful depending on the national inflation index identified as the variable to forecast: we find that Italian HICP is precisely predicted with a factor model, while for the German corresponding series can be more useful a moving average of the first largest factor only.

The forecasting exercises described in Chapters 1 and 3 are not completely alike. Even if they are both driven by the comparison between alternative models in terms of Root Mean Square Forecast Errors, in the former only sector-level prices are considered and the best model for each sub-index is chosen on both statistical and economic basis. The aggregation level and the model selection procedure are chosen in order to respond to the ECB request and to make more explicit the variables driving each component. Abrupt exogenous shocks can influence some sectors only; therefore, the indirect approach provides an easier understanding of the effects of unpredictable disturbances occurring in the economy. On the other hand, setting up and frequently updating a wide data set composed by individual series regarding every aspect of the economy (as the one used in Chapter 3) can result quite time-consuming; moreover, changes in the loadings of unobservable factors could be quite difficult to identify in changes of underlying variables in order to provide an economic explanation of wrong predictions. Considering hundreds of disaggregate series can be useful if otherwise the aim of the exercise is computing proxies of common macroeconomic shocks hitting economies having a common monetary policy as the Euro area. The same ECB decision of intervention can have quite variable effects on the EU countries depending on the transmission mechanism of monetary policy differently affecting national economies and in particular price levels. Besides, considering all the available data allows to avoid *a priori* choices of the variables to include in the model implying the exclusion of a relevant set of information about the country.

In conclusion, analyses on inflation dynamics can be conducted in different ways depending on the goal of the study: different needs require appropriate solutions that can differ in methodology, data and obviously results. In what follows we explore three different ways to analyse price dynamics: starting from the indirect approach implemented at the Banca d'Italia focused on the HICP main sub-indexes, we deepen the analysis considering individual series in order to investigate the stickiness degree of prices at different levels of aggregation and we conclude assessing the predictive power of unobservable macroeconomic shocks directly forecasting three EU countries HICP index.

Chapter 1

Inflation in Italy: models for the NIPE

1.1 The NIPE

As anticipated in the Introduction, the Narrow Inflation Projection Exercise required by the ECB consists in producing inflation forecasts for a relatively short predictive horizon.

The approach behind the NIPE is bottom-up: each country is required to produce a forecast for five sub-indexes: non-energy industrial goods (henceforth NEI-goods), services, processed food, unprocessed food and energy goods, which are subsequently aggregated into a headline inflation projection. A distinctive feature of the exercise is its conditional nature. Inflation forecasts are linked to the development of some important international variables whose path over the forecast horizon is assumed as given: the oil price, the nominal effective exchange rate, the US dollar/euro exchange rate and the prices of internationally traded commodities.

As we previously pointed out, whether the bottom-up approach leads to more accurate forecasts than a direct projection is still a controversial matter. According to Benalal et al. [12], modeling each component can be convenient at short horizons as it allows to follow the peculiar patterns that characterise each sub-index, but its effectiveness is not assured. Using monthly series from 1990 to 2002 for both the HICP components and for the overall index, they estimate a forecast model minimizing the RMSFE of recursive dynamic out-of-sample forecasts. This statistic has been calculated for different horizons, namely 1, 3, 6, 12 and 18 months ahead. Different models can result as the most accurate depending on the time horizon considered, so they average the 5 RMSFE in order to obtain a unique selection criteria. They compare both univariate and multivariate (VAR and BVAR) linear models, finding that the indirect approach is slightly more precise for 1 and 3 months ahead forecasts; the longer the horizon, the better the direct approach results. Considering instead the overall index excluding energy and unprocessed food, the indirect approach outperforms the direct forecasting at all the horizons. In conclusion, considering each component separately seems to be meaningful if applied to short horizons or if used to predict the core inflation index.

Moreover, theoretical reasons in favour of aggregating the forecasts of the subindexes argue that in the aggregation process the forecast errors can cancel between components (Clements and Hendry [29]). Pooling of forecasts may pay dividends by averaging offsetting biases: different models, in fact, are differently affected by unanticipated shifts. Even if it is not easy to prove that a forecasting combination can improve over the best model selected for the overall index, the authors show that averaging does reduce variance, as long as different sources of information are used. It can be interpreted as an intercept change over a baseline model: each component gives a contribution in terms of forecast accuracy to improve the model that best fits the overall price series in case of structural breaks and deterministic mis-specifications.

Empirical applications, however, suggest that this is not always the case. Hubrich [39] uses a wide range of models and selection procedures and finds that aggregating inflation forecasts by components does not always improve the model's forecast accuracy twelve months ahead. The author argues that direct forecasting is a superior method to obtain precise predictions: disaggregated models can be mis-specified, so that they do not improve the forecasting accuracy of the aggregate, especially if some exogenous shocks occur. The author tests different model selection procedures over different forecast horizons using different inflation measures, analysing both the overall HICP index and its core component. Evaluating each model forecasting performance using Monte Carlo simulations for one to twelve steps ahead, Hubrich [39] obtains mixed results: for a short time horizon, aggregating sub-component forecasts outperforms the direct prediction, while for six to twelve months ahead modeling the aggregate inflation index produces more accurate projections. It seems that, as the forecast horizon gets longer, the prediction errors of the sub-components do not cancel out: the different models tend to react to exogenous shocks in the same way so that the forecast bias is not reduced aggregating the sub-indexes. A different result is obtained excluding the most volatile components of HICP, namely energy and unprocessed food, and considering as overall index the so-called 'core' inflation. In this case the indirect approach performs better even at long forecast horizons: aggregating sub components forecasts is not recommended when some components are strongly volatile and so hardly predictable.

Hubrich and Hendry [40] also find mixed results when using disaggregated information to forecast directly headline inflation. They suggest to include information from disaggregated variables in the aggregate model instead of first forecasting each sub-index separately and then aggregating those predictions. Model selection plays an important role in determining the effectiveness of disaggregated variables; moreover, the more the aggregate and the components are variable in the estimation sample, the more the combined estimation improves the forecast accuracy. The authors forecast euro area and US inflation using data from 1992 to 2001 comparing the predictive power of different models: using only the aggregate, indirectly aggregating subcomponents forecasts and finally including the components into the model for the aggregate as explaining variables. Simulated out-of-sample forecasts show that including disaggregated variables in the aggregate model does improve predictability especially at long forecasting horizons. Moreover, practitioners might find forecasting directly aggregate inflation more convenient for other reasons. First, model specification search can quickly become daunting when one considers a high level of disaggregation. Second, since forecast models need to be continuously fine tuned having a single tool is an obvious advantage. Third, breaks and seasonality are less of a problem in aggregate than in disaggregate data.

In practice, although monetary policy in the euro area ultimately targets headline year-on-year inflation over the medium term, the bottom-up approach allows a clearer reading of the underlying inflation signal. Temporary abrupt exogenous shocks can lead to strong base effects with consequent hump-shaped behavior of inflation over the forecast horizon which can be easily reconducted to some underlying components. Recent developments in food and energy prices provide a good example of the added value of considering separately some of the items in the consumption basket. In this respect the disaggregate approach makes the story behind the aggregate figures more explicit. Moreover the transmission mechanism of monetary policy or exogenous shocks to sub-components may differ substantially, as tradable goods are likely, for example, to be influenced by the exchange rate more than services (Aron and Muellbauer [8]). Moreover, the indirect approach allows to use a wider information set specific for each subcomponent, given that the level of competition, the taxation burden and the technological improvements can be different in each sector. While the real exchange rate, labour costs and producer prices are significant for both durable and non durable goods, the union density affects only the second; on the other hand, the service sector equation is the only one where the lagged overall HICP index results significant, evidence that this sub-component is particularly affected by the past aggregate inflation level.

In conclusion, as different HICP sub-indexes have different inflation histories, the indirect approach can substantially improve the forecasting accuracy of the aggregate series. Significant gains can derive from sectoral information, as the effects of exogenous shocks can be different on each component and the forecasting errors can cancel out in the aggregation process.

This Chapter illustrates the models that currently form the basis of the Italian NIPE projections and is structured as follows. In Section 1.2 we have a preliminary look at inflation developments in the past twenty years in Italy and justify our modeling strategy which consists of focusing on the period following the disinflation of the mid-Nineties. In Section 1.3 we clarify the further refinement on the sub-indexes we use with the intent of separating market-based prices from administered ones. In Section 1.4 we describe the model selection criteria. In Section 1.5 we evaluate the models forecasting performance. In Section 1.6 we look at the implied inflation elasticities to a shock to three exogenous variables, namely the nominal effective exchange rate, the oil price and the price of internationally traded food commodities. Section 1.7 concludes.

1.2 Data description and some conceptual issues

The full breakdown of HICP official data is available since 1995. The main sub-indexes, however, have been back-linked for most countries on the basis of national CPIs and are available for Italy since 1987. The year-on-year percentage changes of the overall index and of the five sub-components used in the NIPE are shown in Figure B.1. It is clear that over the past twenty years the inflation process in Italy underwent a strong structural change dropping from an average of around 5% in the first decade to about half this value in the following one. A formal test (Andrews [6]) detects a break in the unconditional mean of the year-on-year inflation rate in June 1996. Visual inspection of the sub-components and a formal analysis confirm that the break is common to NEI-goods, services and processed food.[1] Also notice that NEI-goods inflation presents two low spikes in 2001. These are due to a methodological change introduced by Eurostat which started recording prices inclusive of seasonal discounts. The effect of the introduction of sales price recording on the volatility of inflation rates is quantified in Table 1.1 in which we report the standard deviation of month-on-month rates of growth of NEI-goods, Clothing and Footwear and NEI-goods net of Clothing and Footwear indexes before and after 2001. Clothing and Footwear and NEI-goods inflation rates are twenty and ten times more volatile in the second sub-sample. If one excludes Clothing and Footwear, however, NEI-goods inflation results half as volatile after 2001, consistently with a reduction in volatility of price dynamics observed in the euro area countries since the inception of the monetary union. Figure B.3 shows that the rate of inflation of NEI-goods net of Clothing and Footwear displays indeed a much more regular behavior over the whole sample. We model Clothing and Footwear separately from other NEI-goods in our forecasting system.

[1] The Andrews sup-wald break test detects a change in the constant in November 1996 for NEI-goods, in August 1996 for services and September 1996 for processed food.

	1995-2000	2001-2008
NEI-goods	0.19	1.63
Clothing and Footwear	0.22	4.30
NEI-goods net of Clothing and Footwear	0.26	0.13

Table 1.1: The effect of sales prices recording on inflation volatility

Three main factors contributed to the observed change in aggregate price dynamics in Italy (Gaiotti [37]). First, wage indexation was abolished in 1992 and wage growth in collective bargaining was linked to the Government's inflation target. Second, the attitude of monetary policy towards inflation turned more aggressive in 1995, with the announcement by the Governor of the Banca d'Italia in his annual statement between 1995 and 1997 of a level above which inflation would be intolerable. Third, financial market innovations strengthened the impact of monetary policy credibility on both long-term interest rates and the exchange rate. In summary, in the mid-Nineties a shift in the monetary policy regime towards inflation stabilisation, favoured by decisive changes in the structure of financial and labour markets, effectively anchored actual inflation to expectations. The occurrence of a structural break in the three main sub-items for which labour costs represent a large share of input costs confirms that the activation of an *expectation channel* is behind the moderation of inflation since the second half of the Nineties. Subsequently, the adoption by the ECB of an explicit objective of price stability reinforced the role of inflation expectations in price setting and contributed to keep price growth in Italy at historically low levels.

How to treat such a structural change when setting up a forecasting model is an open issue. Mixing observations across different policy regimes requires allowing for breaks in the parameters, which would complicate the models. Using samples across policy regime shifts also risks to overstate transmission lags and, consequently, inflation persistence. In the case of the euro area, for example, using a long sample and not allowing for breaks O'Reilly and Whelan [48] find that inflation is close to a random walk. However, using the same estimation strategy Benati [13] finds that inflation persistence *since the start of the European Monetary Union* has been close to zero. Our modeling choice was to model inflation under the current low persistence regime and therefore disregard data prior to 1997.

A further complication is given by the fact that the NIPE models need to be flexible enough to give a good forecasting performance on the very short-run (one to three months ahead), and also to be informative on the medium-run (twelve/fifteen months ahead). We illustrate this point with an example. Consider a model specified in year-on-year terms (like, for example, the ones in Aron and Muellbauer [8]) in which year-on-year inflation twelve steps ahead is a function of current exogenous variables. The estimation equation of such a model is:

$$\Delta_{12} log(P_t) = \alpha' X_{t-12} + \epsilon_t \tag{1.1}$$

where the X vector can include variables like unit labour costs, import costs, capacity utilisation and the exchange rate and $\Delta_{12} = (1 - L^{12})$. The one month ahead forecast of this model is given by:

$$\Delta_{12} log(P_{t+1}) = \hat{\alpha}' X_{t-11} \tag{1.2}$$

Equation (1.2) shows that in forecasting one step ahead we are disregarding all the information accumulated in the past eleven months.[2] The most important information we are missing is current year-on-year inflation $\Delta_{12} log(P_t)$ and the month-on-month inflation rate eleven months before: $\Delta_1 log(P_{t-11})$.

Using the following definition:

$$\begin{aligned} (1 - L^{12}) log(P_{t+1}) &= (1 - L^{12}) log(P_t) + (1 - L)(1 - L^{12}) log(P_{t+1}) \\ &= (1 - L^{12}) log(P_t) + (1 - L) log(P_{t+1}) + (1 - L) log(P_{t-11}) \end{aligned} \tag{1.3}$$

it can be seen that, conditional on the current information set (which includes current year-on-year inflation $\Delta_{12} log(P_t)$ and past month-on-month inflation $\Delta_1 log(P_{t-11})$) the accuracy of the one step ahead prediction depends on the term $(1 - L) log(P_{t+1})$ which is the month-on-month inflation rate one month ahead. Since the $(1 - L)$ filter cuts off all the long-run information while retaining seasonal and very high frequencies, a model such as the one in (1.1) which is specifically designed to capture medium-term inflation and is motivated by economic theory is going to be outperformed by simple alternatives geared to high frequency fluctuations. Even a constant plus seasonal dummies is going to be a very hard competitor.

When modeling inflation for the NIPE one therefore lacks a clear loss function (whether to favour short-term or medium-term performance) and needs models that are a hybrid between purely statistical and economics-motivated ones. A viable alternative is to use different models for short and long horizons. Models specified in month-on-month terms could provide the initial condition to which forecasts derived from medium-term models could be linked. As we explain below we explore this possibility in modeling services inflation.

[2] Current information could enter the equation via the parameter α which could be re-estimated every time. If parameters are stable, however the change in α induced by new information is likely to be negligible.

1.3 The sub-indexes used at the Banca d'Italia

When trying to relate price developments to economic determinants a further problem is posed by the existence of prices which are not set on the basis of market conditions but are determined by Public Authorities. This is the case of some public services (like transportation) or of regulated monopolies. For these items (which fall in the category of administered prices) inflation follows Government decisions which are hard to predict.

Some other indexes are more suited to be forecast by purely seasonal models or simply by expert judgement. This is the case of Clothing and Footwear, whose volatility since 2001 is strongly affected by the timing of seasonal sales, or of telephone equipment prices, which are corrected for technological improvements and have therefore been constantly falling in the past ten years.

Considering these issues we further disaggregate the main HICP sub-indexes as shown in Table 1.2. There are two groups of sub-indexes that are explicitly modelled. In the first group there are items for which a forecasting model is developed and tested in a pseudo out-of-sample simulation exercise. In the second group there are items for which we develop a model that provides a reasonable fit but we do not explore forecasting accuracy, either because of recent changes in the tariffs schemes (as is the case of energy tariffs and air transportation), or of recent breaks (as for clothing and footwear). These indexes, however, either have a substantial weight in the basket (energy and clothing and footwear) or have a very volatile profile so that a basic model helps in tracing back some large occasional forecast errors (as is the case for air transport). The items that are excluded altogether (which represent around 7% of the overall index) are forecast either on the basis of information from the relevant price setting Authorities or on the basis of simple seasonal models.

1.4 Model selection criteria

As explained above, NIPE forecasts are conditional on a set of exogenous variables (interest rates, nominal bilateral and effective exchange rates, oil and other commodities prices) whose future path is determined at the beginning of each NIPE. Since the projections produced within the NIPE are conditional on these assumptions, in the out of sample forecast exercise below we use their actual value over the forecast horizon (for example, when projecting energy inflation we assume to know future oil price). Other exogenous variables used in the analysis either enter the equations with sufficient lags so that they do not need to be forecast or are forecast with an autoregressive model. Quarterly variables, when used, are linearly interpolated at the monthly frequency. An important issue is the timing of release of producer prices, which have a strong

FIRST GROUP

	Sub-indexes modelled	Excluded items	Weight in the HICP
1	**NEI-goods**	Telephone and fax equipments, water and medical products, clothing and footwear	18
2	**Services**	Transport Refuse and sewerage collection postal, telephone and education	34
3	**Energy goods**	Energy tariffs	4
4	**Processed food prices**	Tobacco prices	10
5	**Unprocessed food prices**		8.4
			74,4

SECOND GROUP

6	**Air transport**		0.9
7	**Energy tariffs**		3.7
8	**Clothing and footwear**		12

Table 1.2: HICP disaggregation scheme used in the Italian NIPE system

predictive content for consumer prices but are released with one month delay. Whenever we specify a model that uses producer prices the latter are *lagged by one month*. We impose a similar constraint on quarterly variables which are intended as *lagged by three months*, given the delay with which they are published.

For each subcomponent we search across *linear* models based on *observed variables*. These two requirements rule out unobserved components models, time varying coefficients models (including Markov switching models). This allows us to attribute forecast revisions between two successive NIPE either to a change in the assumptions or to forecast errors, rather than to changes in unobserved components which would be hard to explain and would make the communication of inflation forecasts problematic. We therefore work with vector autoregressions (including long-term cointegrating restrictions when not rejected by the data), linear equations or systems of linear equations.

The variables chosen for each model are determined by economic criteria. All the models reflect an assumption of mark-up pricing and therefore relate consumer prices to their relevant costs or to cyclical variables which capture mark-up adjustments over the cycle. The specification search for energy and food inflation models is much less costly as energy and food price developments can be easily linked to oil and food commodity prices. Forecasting models for core components (NEI-goods and Services) could instead contain domestic supply and demand side variables, as well as international prices: they therefore require a more careful model selection process, which we borrow from Aron and Muellbauer ([8]).

The analysis is conducted on data from 1997 to 2008: observations up to December 2004 are used for the model estimation, while the following sub-sample is used for recursive out of sample forecasts. Recursive forecasts are computed for a maximum of fifteen steps ahead and prediction errors are computed for both month-on-month and year-on-year inflation rates. The performance of our models on year-on-year inflation is checked against that of a random walk, which is known to be a tough competitor at low frequencies (Atkeson and Ohanian [9]). The performance on month-on-month inflation for one and two steps ahead is compared to that of a constant plus seasonal dummies. The reason for considering different benchmarks at different horizons relates to the issues highlighted in Section 1.2. On one hand we want our models to have more information than that contained in the seasonal pattern at very short horizons. On the other hand we want them to be able to track medium-term inflation developments.

In order to select the best specification for each model we use the three classical Schwarz (SC), Hannan-Quinn (HQ) and Akaike (AIC) information criteria and the root mean squared forecast error (RMSFE) both in sample and out of sample. In addition, following Den Reijer et al. [32], we also consider 'mixed' criteria, that is we compute the above penalties on a weighted average of in and out of sample errors (with weights equal to 0.6 for the in-sample and 0.4 for the out of sample). When these information criteria give conflicting results the best performing model in terms of 'mixed' AIC is chosen.

1.5 Modelling core items: NEI-goods and Services

1.5.1 Services

The best model at medium-term horizon is a single equation in year-on-year inflation rates. The main determinants of services inflation are found to be unprocessed food prices (relevant for the restaurants and bars component), the oil price (which impacts both through electricity costs and through fuel prices for transportation services), unit labour costs and real value added growth rate. Transmission lags of over a year from costs and cyclical variables to consumer prices are consistent with the evidence provided by Veronese et al. [54] which report a frequency of consumer price changes of about 14/15 months for services in Italy. In the short-run, on the other hand, the predictive accuracy of a VECM in services prices and unit labour costs is superior to that of a purely seasonal model. We therefore run the out of sample exercise combining forecasts from these models. To ensure a smooth link between the two we perform a two months linear interpolation between the VECM and the equation forecasts (see Table 1.3).

The results of the out of sample forecast exercise are shown in the first column of Tables A.1 and A.2. For year-on-year inflation rates our model outperforms the benchmark from the third step ahead onwards; moreover its predictive accuracy does not deteriorate for longer horizons. On monthly inflation rates our model also improves, albeit slightly, upon the naive seasonal model one and two steps ahead.

Horizon	**Model**	**Endogenous**	**Lags Endogenous**	**Exogenous**
1-2	VECM	$\Delta log(p^{ser}),\ \Delta log(ulc)$	1,12	$\Delta log(p^{uf}_{t-14})$ $\Delta log(va^{ser}_{t-16})$ $\Delta log(p^{oil}_{t-23})$
3-4	Linear Interpolation			
5-12	Single equation	$\Delta_{12} log(p^{ser})$		$\Delta_{12} log(p^{ser}_{t-12})$ $\Delta_{12} log(p^{uf}_{t-12})$ $\Delta_{12} log(p^{oil}_{t-18})$ $\Delta_{12} log(va^{ser}_{t-13})$ $\Delta_{12} log(ulc_{t-16})$

Table 1.3: Models for services inflation

1.5.2 NEI-Goods and Clothing and Footwear

This component is particularly hard to model, given the increasing effect of foreign competition from emerging markets on domestic mark-ups (see Bugamelli et al. [23]). Since it was not possible to establish a significant cointegration relationship between consumer goods prices and unit labour costs we resorted to a VEC model in goods and producer prices (net of food and energy) with capacity utilisation rate and a smooth transformation of the nominal effective exchange rate as exogenous variables (see Table 1.4). We also include two intervention dummies for February 1998 and January 2002. The model is in monthly rates and includes seasonal dummies. The second column of Tables A.2 shows that in terms of month-on-month rates the model and the naive benchmark deliver the same performance. The very low RMSFE (0.11) reflects the low volatility of the series. Despite being tailored to capture high frequency movements the VECM manages to outperform the naive benchmark also on year-on-year growth rates from the first step onwards (see the second column of Table A.1). Given their strong seasonal pattern clothing and footwear are modelled using TRAMO/SEATS. The resulting forecasts are more accurate than the naive benchmarks both at monthly and yearly frequencies at almost all horizons (see the third column of Tables A.1 and A.2).

Horizon	Model	Endogenous	Lags Endogenous	Exogenous
1-12	VECM	$\Delta log(p^{goods})$, $\Delta log(ppi^{nfe})$	1,5,10,12	$\Delta log(cap_{t-12})$ $mave(\Delta log(neer_{t-6}), 7)$ *D1998m2* *D2002m1* *Seas.Dummies*

Table 1.4: Model for non-energy industrial goods inflation

1.5.3 Food

Food prices have been particularly relevant for inflation dynamics in the euro area since the second half of 2007, when they accelerated in the wake of a strong growth of commodity (especially wheat) and milk prices. Since detailed food commodity prices are part of the international assumptions used in the NIPE we use them to construct a food commodity index (FCI) that reflects as closely as possible their weight in the Italian consumer basket. In particular the index is a weighted average of international prices of cocoa, coffee, wheat, sugar, soybeans and milk. The matching of commodities with HICP sub-components and their respective weights is summarised in Table 1.5.

HICP sub-component	Weight in the HICP basket	Corresponding commodity
Bread and cereals	30.83	*Wheat*
Milk, cheese and eggs	23.63	*Milk*
Oils and fats	8.48	*Soya beans*
Sugar et al.	11.46	*Sugar*
Coffee, tea and cocoa	2.54	*Coffee, cocoa*

Table 1.5: Weights used to compute the Food Commodity Index

The FCI is used to model both processed and unprocessed consumer food prices, together with food producer prices. The best model specification, however, is different for the two sub-components: unprocessed food inflation is best forecast with a system of two equations. A long moving average of the FCI monthly growth is used to predict food producer prices, which, in turn, enter the HICP equation (see Table 1.6). Processed food prices, on the other hand, are found to be cointegrated with producer prices with a unitary long-run elasticity. For this sub-component we therefore specify a VEC model in consumer and producer prices that uses a moving average of the FCI as exogenous variable (see Table 1.7).

Results from the out of sample exercises, reported in Tables A.1 and A.2, show that both models outperform the benchmarks for year-on-year inflation (unprocessed food model from the second step onwards) and for monthly inflation one and two steps ahead.

An interesting issue is to what extent the use of commodity prices helps in tracking future food inflation. To gauge the marginal contribution of the FCI we run our models excluding this variable and compare the RMSFE with those obtained using our preferred specifications. In Figures B.4 and B.5 we report the ratios between the RMSFE obtained with and without the FCI and the naive benchmark (values lower than 1 therefore indicate an improvement with respect to the benchmark). Figure B.4 shows that in the case of unprocessed food the contribution of the FCI is modest and confined at long horizons. Figure B.5, on the other hand, shows that in the case of processed food the use of commodity prices induces a significant improvement in forecast accuracy along the whole forecast horizon.

Horizon	**Model**	**Endogenous**	**Lags endogenous**	**Exogenous**
1-12	System-equation 1	$\Delta log(ppi^{food})$	1	$mave(\Delta log(fci), 12)$
				$Seas.Dummies$
1-12	System-equation 2	$\Delta log(p^{uf})$	2,3	$mave(\Delta log(ppi^{food}_{t-3}), 3)$
				$Seas.Dummies$

Table 1.6: Model for unprocessed food inflation

Horizon	**Model**	**Endogenous**	**Lags endogenous**	**Exogenous**
1-12	VECM	$\Delta log(p^{pf})$, $\Delta log(ppi^{food})$	1,2	$mave(\Delta log(fci), 12)$
				$Seas.Dummies$

Table 1.7: Model for processed food inflation

1.5.4 Energy

To model energy prices we exploit the availability of weekly petrol, diesel and gas prices through the Weekly Oil Bulletin (WOB) published by the European Commission every Monday.[3] We use monthly averages of the available fuel prices (including taxes) from the WOB and set up a two steps error correction model (ECM) for each component.[4] The first step in these models takes the form:

$$p_t^{en} = \alpha + \phi p_t^{oil} + \epsilon_t \tag{1.4}$$

where p_t^{en} is the price of petrol, diesel or gas, and the hypothesis of cointegration can be tested for by verifying the stationarity of the estimated residuals $p_t^{en} - \hat{\alpha} - \hat{\phi} p_t^{oil}$. This hypothesis is not rejected in any of the three models considered. The equilibrium relationship in equation (1.4) $ecm_t = p_t^{en} - \hat{\alpha} - \hat{\phi} p_t^{oil}$ is then embedded in an ECM of the form:

$$\Delta p_t^{en} \quad = \quad \theta ecm_{t-1} + \sum_{i=1}^{q} \gamma_i \Delta p_{t-i}^{en} + \beta_0 \Delta p_t^{oil} + \sum_{j=1}^{p} \beta_i \Delta p_{t-j}^{oil} + u_t \tag{1.5}$$

Individual forecasts are then aggregated using HICP weights and this aggregate is used to forecast the HICP fuel and lubricants index. The lag length of the endogenous variables p in equation (1.5) is set to 1 for all three components. The parameter q is set to 5 for petrol, to 1 for diesel and gas on the basis of the AIC criterion.

The out of sample performance of this forecast system is summarised in the last columns of Table A.1 and A.2 which show that the naive benchmarks are dramatically outperformed at every horizon.

1.6 Projection elasticities

The models described in the previous Section can be used to infer the monthly elasticity of the main HICP sub-indexes with respect to the exogenous assumptions used in the NIPE. We consider the effects of a 10% shock to three different exogenous variables, namely the oil price in euros, the nominal effective exchange rate and the food commodity index. We do not consider the effect of a shock to the euro-USD exchange rate as the variables originally denominated in USD (oil and food prices) enter our systems already converted in euros so that an increase of the price in USD of oil or food commodities has the same effect of a depreciation of the euro with respect to the USD. The effects are computed as the differences between two out of

[3] Weekly data are particularly useful to *nowcast* energy inflation since HICP official data are only released in the middle of the following month. Actual forecasts (one step ahead onwards) are based on monthly averages of petrol, diesel and gas prices.

[4] Notice that these models are specified in price *levels* rather than in logarithms of price indexes.

sample conditional forecasts, where the paths of the exogenous variables differ over the forecast horizon by 10 percentage points. We also compare these elasticities with the Projection Updated Elasticities (PUE) computed within the Eurosystem on the basis of the quarterly models used for the Broad Macro Projections Exercises (BMPE).

The results of this exercise are shown in Table A.3 and can be summarised as follows:

- The nominal effective exchange rate (NEER) slightly impacts with a lag of six months on non-energy industrial goods inflation. The effect of a 10% shock builds up progressively reaching one decimal point after a year. Its impact on headline inflation is negligible. According to the PUEs, on the other hand, the effect of a 10% appreciation of the nominal effective exchange rate on domestic inflation is quite substantial (-0.40 in the first year). These numbers, however, are not immediately comparable since the nominal effective exchange rate is an endogenous variable in the Italian model and a large part of its effect on headline HICP seems to come from the energy component. The NEER shock in the PUEs seems, therefore, to incorporate a shock to the euro exchange rate with respect to the USD which in our NIPE system has a direct effect on energy and food components but not on NEI-goods. Also at the euro area level there seems to be some heterogeneity in how the PUE on the NEER is computed. A large part of this elasticity, in fact, comes from HICP energy in some countries (like Germany, France and Austria) while the NEER has no effect on energy inflation in others (like the Netherlands).

- A 10% increase in the FCI has a strong effect on processed food inflation which rises by half a percentage point on average in the first twelve months. The effect on unprocessed food inflation is less pronounced, averaging one decimal point in the first year. The total impact on headline inflation in the first twelve months is estimated to be around 0.05 percentage points. No PUE is available for this variable since the adoption of detailed food commodity prices as a technical assumption is very recent.

- In the first twelve months, one fifth of the original oil shock is passed through to fuels and lubricants inflation, with a decimal point effect on headline HICP. This figure matches quite closely the PUE with respect to an oil shock.

Recently the ECB invited euro area NCBs to answer a questionnaire aimed at extracting monthly inflation projection elasticities from their respective NIPE systems and to compare them with quarterly PUEs. The results reached by that exercise are quite similar to the ones hereby presented. NCBs did not provide any elasticity of HICP inflation with respect to the nominal effective exchange rate claiming that this variable plays a very small role in their models. The effect of an oil price shock on HICP inflation was found to be higher according to the PUEs than to the NIPE elasticities. Part of this difference could be attributed to the fact that in the short-term inflation models the effect of oil on the non-energy component is close to zero. Finally, the effect of a USD shock in the NIPE models was quantitatively comparable to that of an oil shock, indicating that the oil price enters most of these models already converted in euros.

1.7 Conclusion

The NIPE is an important block of quarterly projections run within the Eurosystem. This Chapter has discussed the out of sample forecasting performance of a set of linear models linking the main technical assumptions and some relevant macro variables to the main sub-components of the HICP in Italy, namely services, non-energy industrial goods, processed and unprocessed food and energy goods.

Following the indirect approach, in this Chapter we propose models for each HICP main sub-index that outperform naive conventional benchmarks over the horizons of interest and produce projection elasticities which are to some extent in line with the quarterly Projection Update Elasticities. In order to choose the *best* specification, we minimise the Root Mean Squared Forecast Error from one to twelve steps ahead, selecting different models for each sector. Service inflation can be predicted more accurately in the short run with a VECM in services prices and unit labour costs; in the medium run, however, the forecasting accuracy of the bivariate model deteriorates, so that a single equation in year-on-year inflation rates results to predict more accurately the future price trend. Non-energy industrial goods are harder to model given the increasing effect of foreign competition on the domestic market, nonetheless a VECM model in goods and producer prices provides accurate predictions. For both processed and unprocessed food components a Food Commodity Index, capturing the international market prices' influence on the domestic economy, results highly significant even if in different specifications: unprocessed food inflation is modelled with a system of two equations in producer and unprocessed food prices respectively, while processed food prices are best predicted with a VECM in producer and processed food prices. Finally, for energy inflation we select a two steps error correction model finding a strong cointegration between energy and oil prices.

In order to test the robustness of our models, we calculate the monthly elasticity to the main HICP sub-indexes with respect to the exogenous assumptions used in the NIPE, finding results similar to the Projections Updated Elasticities computed within the Eurosystem.

A further step to take is to deepen the analysis considering individual series regarding every aspect of the economy, in order to analyse price dynamics at different level of aggregation.

Chapter 2

Inflation persistence in the EU area

2.1 Price stickiness

Price stickiness in industrialised countries is one of the key assumptions of the keynesian approach in order to provide a satisfactory explanation of the comovements of real wages, employment and output and of the effects of aggregate demand changes on employment and output. Individual wages and prices respond slowly to an increase in aggregate demand, that on the contrary affects output and employment. Given that wages and prices adjust slowly and not necessarily in the same way, the ratio of the two (the real wage) can change as well. Therefore, if prices are sticky, there is no reason to expect any regular covariation between wages and employment after a demand shock. The reason of these rigidities can be found in the so-called 'coordination problem'. Firms can be reluctant to change prices because of different reasons: they can have already stipulated long-run contracts or they can find more convenient to not adjust prices if the other competitors are not going to do the same. The implication of the sticky prices assumption is that in the short run monetary policy is effective in changing relative prices and quantities, because some prices are more flexible than others, while in the long run real variables do not change, i.e. money is neutral.

Price stickiness can be empirically measured analysing both price volatility and price persistence: how much does a price fluctuate around its mean value and, when it fluctuates, how long does it take for it to return to the equilibrium level? Each of these questions catches an aspect of price stickiness: if prices are sticky, they will be characterised by low volatility and high persistence; on the other hand, if they are flexible, there would be evidence of high dispersion around the mean value and quick convergence toward the long-run level. In fact, when there is a shock in the economy, if prices are flexible they will respond rapidly moving away from the equilibrium and returning to the long-run path just as quickly: in this case there are no market imperfections that prevent prices from following the economic dynamics.

Much of the previous literature has focused only on macro aggregates to asses price responses after a shock, but in a few exceptions sectoral price series have been used. The results are not univocal: the impact of a shock results to be quite transient on individual series, while the effects of the same shock are more lasting on the corresponding aggregate.

Klenow and Kryvstov[42] analyse size and timing of individual price changes; both Bils, Klenow and Kryvtsov[17] and Balke and Wynne[11] use a Vector Autoregression model to investigate the effects of a monetary shock on disaggregated prices, getting however to an inconvenient 'price puzzle': after a negative monetary shock, prices result to increase in contradiction with the economic theory. Sims[51] evidences a specification error in the VAR formulation that can be avoided with a factor model using a larger data set, like in Boivin, Giannoni and Mihov[21]. Therefore, we follow Boivin et al.Boi1 using a factor-augmented vector autoregression model that estimating a small number of factors summarising the economic dynamics allows us to disentangle the impact of a shock on the common and idiosyncratic component of inflation.

Moreover, economic research based on a wide variety of information is usually conducted on US data: prices are observed in a narrower level of disaggregation and they are available for a longer span of time respect to the corresponding Euro data. Therefore, collecting data has been one of the difficulties of this exercise: some kind of data, such as producer price indices, is not available in any European database and has to be gathered from each national institute of statistics; therefore, data has to be made homogeneous in respect to starting and ending date, measure unit and moreover in respect to sector category. Time availability is another shortcoming of European data: while US price series are available for more than thirty years' time, unfortunately series regarding Euro countries start only from early 90s. Examples of studies conducted on European data are Altissimo, Mojon and Zaffaroni[4] and Altissimo, Ehrmann and Smets[3] who investigate the degree of inflation persistence in the EU area. We choose to conduct our analysis on price stickiness considering the three major EU countries: France, Germany and Italy, that represent more that 65% of Euro Area's GDP. Moreover, they joined the Euro Monetary Union from the beginning, so statistics are available and complete in the main European databases.

In contrast to Boivin, Giannoni and Mihov[21], we don't find that macroeconomic shocks have a significant impact in the long run: individual prices in fact result to be quite flexible in absorbing a monetary shock. The low persistence degree we obtain confirms the positive correlation between inflation and persistence found by other authors like Taylor[53] and Benati[12]. Given that we estimate a FAVAR model on a period of inflation targeting, economic agents incorporate in their expectations the Central Bank commitment to controlling the price growth and quickly react to any macroeconomic shock that hits the economy. Therefore, a monetary shock seems not to particularly affect disaggregated prices: it has almost no effects on CPI series of all the three countries, while PPI prices change only of a small amount and in a quite transient way in Germany and in Italy and significantly only in France. The same monetary shock, on the other hand, has significant but temporary effects on overall French and German CPI series; Italian HICP index, instead, remains quite stable after the shock. This conclusion solves the apparent contradiction of different price responses at different aggregation levels: aggregated indices result more influenced given that their volatility depends on the common component driven by macroeconomic shocks; on the other hand, disaggregated inflation is more flexible being affected mainly by short-living sector-specific shocks; most importantly, these results are conditional on the particular time span considered.

The rest of the Chapter proceeds as follows: in Section 2.2 we describe the previous literature results about price stickiness and monetary policy, both for US and European data; in Section 2.3 we illustrate the econometric framework used to disentangle the effects of a shock on the inflation common and idiosyncratic components; in Section 2.4 we describe in detail the database constructed to conduct the exercise; in Section 2.5 we illustrate the main results and finally Section 2.6 concludes.

2.2 Previous Literature

The economic literature has widely investigated price stickiness since it is one of the hypothesis of most economic models: many papers confirm the sluggishness of the overall inflation using aggregate series; only recently, however, disaggregated series have been employed for this scope.

One of the first examples is the paper of Bils, Klenow and Kryvtsov[17], where 350 categories of CPI have been analysed in order to asses sign and magnitude of price responses after a monetary shock. They find monetary policy to have persistent effects on relative prices, but of the wrong sign: after an increase in money supply, prices decrease contradicting what expected from the economic theory. In order to conduct the analysis, they first classify goods depending on the frequency of price changes in two categories: flexible and sticky price goods, that result to have large and persistent differences in their reaction to monetary policy. Using a General Equilibrium Model with monopolistic competitive firms and prices fixed for different duration depending on the group of goods (2 periods for the flexible price sector and 15 periods for the sticky price one), they reject both the sticky prices hypothesis and the exogeneity of monetary shocks. They estimate the following system:

$$\begin{aligned} p_{it} &= \lambda_i + \sum_{j=0}^{n} \beta' x_{t-j} + \phi_{it} \\ \phi_{it} &= \alpha_i + \gamma_i t + \mu_t + \epsilon_{it} \end{aligned} \tag{2.1}$$

where λ_i represents the frequency of price change, x_t the monetary shock, such as a federal fund rate change, μ_t are monthly seasonal dummies, α_i and $\gamma_i t$ respectively the specific level and trend of good i; finally, ϵ_{it} follows an AR(2) model. The authors check for different variables that can be responsible for monetary shocks, not only the federal fund rate level, but also changes in reserves. At the end, they solve an identification problem, finding that monetary shocks are *not* orthogonal to persistent shocks to the ratio between flexible and sticky prices: this evidences mixed effects of monetary and real shocks on price responses. However, the authors find a 'price puzzle' problem to solve: in response to a 1% decrease in the federal fund rate, the ratio between flexible and sticky prices decreases.

Balke and Wynne[11] follow the same way of research, but using individual PPI series instead of CPI ones. Like Bils, Klenow and Kryvtsov[17], they find monetary shocks to have large price effects, but of the wrong sign: when the federal funds rate increases, in the short run a large set of prices moves in the same direction; in the long run, on the other hand, almost all prices decrease as expected from the economic theory. In their opinion, this apparent non-neutrality of money is reflected in price changes in two ways: first, relative prices change because some prices increase after the shock, while others decrease; second, the *real* preferences of economic agents change in response to modifications in relative prices. They model 616 disaggregated PPI series with a 12-lags VAR specification using the following variables: the industrial production index, the personal consumption expenditure index, a commodity price index, the federal funds rate, the money aggregate M2 and dummy variables. Then, they analyse prices impulse response functions after a contracting monetary policy shock: while commodity prices and the M2 aggregate decrease as expected, as well as industrial production that decreases after a short delay, the personal commodity expenditure index *increases* rising a 'price puzzle' dilemma. They investigated this problem with a VAR where for each good i:

$$p_{it} = \Delta_t x_t + A_i(L) p_{i,t-1} + C_i(L) Y_t + \epsilon_{it} \tag{2.2}$$

In equation (2.2) x_t represents the exogenous variables, such as the constant and dummy variables, while in Y_t there are macro variables to identify the shock. They observe an increase in price dispersion; moreover, in the short run the distribution of price changes is shifted to the right, so that more price changes are above their sample mean than below. After 12 months, the number of goods whose price increase equals the number of those whose price decrease. To go in depth about this price puzzle, the authors classify goods in finite, intermediate and crude goods, comparing the time needed for price decreases to overcome price increases, in other words how much time has to pass after a shock to solve the price puzzle and to observe the result predicted by the economic theory. Crude goods prices show the traditional effect from the beginning, intermediate goods need 12 months and finite goods even 20 months to behave as expected: because commodity prices are among finite goods, this explains why the price commodity expenditure index moves in the wrong direction in the VAR model. Finally, they test this result for different specifications of the model, considering oil price and different measures of a monetary policy shock, finding no change in their estimation. The substantial non-neutrality on money at high level of disaggregation can be explained in different ways: first, considering a possible nominal wrong perception of economic agents in distinguishing between a change in relative prices or in the aggregate price level; second, because of sticky prices or sticky information: if prices are not flexible, a monetary shock can produce not proportional changes, and even if prices are fully free to move, information can not be available to every agent and at the same time. They test this hypothesis using a Calvo-type sticky price model in which Ψ firms leave prices unchanged, so that the price average duration results (Ψ/1-Ψ); if each firm optimises its price strategy, this model predicts that monetary policy changes relative prices, but all in the same direction, in contrast to the empirical results of the paper. In conclusion, none of the theoretical models can explain the price puzzle observed in the data: disaggregated prices increase after a contracting monetary shock.

Bernanke et al.[14] propose a new model to investigate the problem, avoiding the principal shortcoming of the VAR approach, that is the inclusion of only a limited information set, that does not reflect the whole information actually available about the economic system. Given that a large number of parameters has to be estimated for each variable included, the choice has to be parsimonious, otherwise the degrees of freedom can result too few to assure the robustness of the results. As a consequence, impulse response functions can be computed only for the included variables, that do not always correspond to all the variables of interest. So, the authors propose to use the classical VAR model augmented by unobservable factors estimated from a large data set, the so-called Factor Augmented Vector Autoregressive (FAVAR) model:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \epsilon_t \tag{2.3}$$

where Y_t are M observed economic variables, F_t are a small number (k) of unobserved factors that summarise additional economic information and $\Phi(L)$ is a lag polynomial of finite order d. If the Data Generating Process is a FAVAR but we estimate it with a VAR in Y_t, we omit relevant variables producing biased and inconsistent estimates. Now, the problem is how to estimate the unobserved factors F_t from a large number N of informative variables X_t. Assuming that $k + M << N$ and

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + \epsilon_t \tag{2.4}$$

where Λ^f and Λ^y are Nxk and NxM matrices of loadings of factors and of observed variables respectively, both Y_t and F_t result to drive the common dynamics of X_t. If F_t includes lags of fundamental factors, the model is called *Dynamic Factor Model*.

The estimation can be conducted in two ways: with a two-steps procedure using the Principal Component approach, that is a non parametric way to compute the common component $C_t = (F_t', Y_t')$, or with a single-step computation of the Bayesian likelihood. In the former case, we first estimate C_t with the first $k + M$ principal components of X_t, obtaining a consistent estimate of the space spanned by the common component, and then we calculate $\hat{F}_t$ as residuals of the space covered by Y_t. The second step consists in the standard estimation of

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} \tag{2.5}$$

but because of estimated $\hat{F}_t$, a problem of 'generated regressors' arises; thus, in order to obtain accurate impulse response functions, a bootstrap procedure, that accounts for the uncertainty in the factors estimation, has to be used. Alternatively, the joint maximum likelihood can be maximised, using an empirical approximation of marginal posterior densities.

The parameters identification deserves particular attention. Using the principal component approach, in the second step we need to set one of the following restrictions:

$$\begin{aligned} \Lambda^{f'} \Lambda^f / N &= I \\ F'F/T &= I \end{aligned} \tag{2.6}$$

for the loadings or for the factors respectively, that give the same results for the common component $\Lambda^f F$ and for the factor space. In the Maximum Likelihood approach, F_t has to be identified against rotation: $F_t^* = AF_t - BY_t$, so that:

$$X_t = \Lambda^f A^{-1} F_t^* + (\Lambda^y + \Lambda^f A^{-1} B) Y_t + \epsilon_t \tag{2.7}$$

where $\Lambda^f A^{-1}$ corresponds to Λ^f and $(\Lambda^y + \Lambda^f A^{-1} B)$ to Λ^y in (2.4), identifying the factors uniquely. The authors apply the FAVAR model to 120 series, considering the federal funds rate as the only observed factor Y_t and as the monetary policy instrument. They compute latent factors as indicators of real activity and price movements, assuming that they do not respond to monetary policy within the first month. In order to identify the parameters, they first consider 'slow moving' factors F_t^s as the principal components of slow moving variables and compute:

$$\begin{aligned} \hat{C}_t &= b_{F^s}\hat{F}_t^s + b_y Y_t + \epsilon_t \\ \hat{F}_t &= \hat{C}_t - \hat{b}_y Y_t \end{aligned} \tag{2.8}$$

Then, they consider the first k 'slow moving' factors and recursively update the structure in the transition equation (2.3). Finally, they find the principal component approach getting more plausible responses than a VAR model without imposing explicit measures of economic activity.

Using the same model specification, Boivin, Giannoni and Mihov[21] give a possible response to the price puzzle enlightened by Bils, Klenow and Kryvtsov[17] and Balke and Wynne[11]. Disaggregated series, in fact, appear to be sticky in response to macro fluctuations such as monetary shocks, but flexible after sector-specific shocks that are responsible for 85% of the prices variability. They solve the apparent empirical contradiction for which prices are sticky if considered as aggregates but much more volatile if analysed at a disaggregated level, changing in US on average each 4.3 months with a magnitude of more than 13%. To explain this different behaviour, we need to distinguish between sector-specific and aggregate source of fluctuations, using a FAVAR model that conveys the information contained in a large panel of economic indicators and individual price series in a small number of common factors representing the macro forces driving the economy. The result is that disaggregated prices are sticky in response to monetary policy, but flexible to sector-specific shocks that account for most of their overall variability. Moreover, there is a high heterogeneity in magnitude and persistence across price categories, related to the degree of market power in the industry. They reach these results estimating a FAVAR model as in equation (2.3), considering the federal funds rate R_t as the only observable factor and estimating other k unobservable factors representing the economic activity and the general level of price productivity. Using the observation equation (2.4), they extract the first k principal components from X_t, obtaining consistent estimates of $\hat{F}_t$; in the second step, they add R_t to $\hat{F}_t$ estimating the structural VAR, as reported in (2.3). They consider a balanced panel of 653 series transformed to be stationary, consisting in economic variables such as exchange rates and monetary aggregates, disaggregated data on personal consumption expenditure and aggregate price indices, producer prices and industry characteristics like the concentration ratio or profit margins. To assess the extent of persistency due to different shocks, they estimate the following equation:

$$\pi_{it} = \lambda_i^{'} C_t + \epsilon_{it} \tag{2.9}$$

where π_{it} is the monthly log change of the respective price series i, $\lambda_i^{'} C_t$ are the macro factors representing the diffuse effects of the shock and finally ϵ_{it} is the residual corresponding to the sector-specific component. Estimating the FAVAR (2.3) model with $k = 5$ and 13 lags, they observe different dynamics for each sector after a macro shock. While overall indices result to have a volatility of 0.24% mostly due to the common component, disaggregated series are much more variable (1.15%) especially in the sector-specific component; moreover, the strong positive correlation between the volatility of the common and the sector-specific component may reflect a possible price setting behaviour: firms that find convenient to regularly change their price in response to sector-specific shocks, probably change their price after a macro shock equally frequently. In order to measure the degree of inflation persistence, they estimate $\forall \pi_{it}, \lambda_i^{'} C_t, \epsilon_{it}$

$$w_t = \rho(L) w_{t-1} + e_t \tag{2.10}$$

with $\rho(L)$ as a 13-lags polynomial: the sum of the $\rho(L)$ coefficients is a measure of the inflation duration. This is equal to 0.93% for the overall indices, while sectoral inflation results much less persistent (0.49%) and mostly in the common component part, even if it presents a high heterogeneity of values across sectors. Besides, they observe a relatively weak correlation (-0.19) between volatility and persistence of the sector-specific component, while the same correlation is much stronger (-0.49) for the common component. Once observed different price dynamics after a macroeconomic shock, a second aim of the paper is to analyse the effects of different shocks on prices at different levels of aggregation. After sector-specific shocks, inflation and consumption show no persistence; moreover, a negative correlation between the sector-specific component of PCE prices and quantities, measured in growth rates, shows that the disturbances are of the supply-type (i.e. shocks in productivity). After macroeconomic shocks, instead, prices and quantities fall by a moderate amount in a sluggish and persistent way; in this case the correlation between prices and quantities is evenly distributed in the interval [-1,1] so that both supply and demand-type shocks are present. Particular attention must be payed to the effect of monetary policy on disaggregated series: in order to identify it, the authors suppose that R_t can respond to contemporaneous fluctuations in the estimated factors, while the latent factors F_t cannot respond within a month to changes in monetary policy. They compute prices impulse response functions after a 25 basis points increase of R_t: while the VAR specification leads to a price puzzle, suggesting an increase in prices and a strong persistence on the industrial production index, confirming the rejection of the long run money neutrality, the FAVAR model gives different results. Although there is a high heterogeneity in disaggregated series, most indices are almost stable in the short run and they start falling only later; moreover, sectoral responses are quite persistent after a macroeconomic shock and there is a negative correlation between price and quantity changes: prices fall the most in sectors where quantities fall the least. Relative prices change in a substantial number of sectors in the first year after the shock, while after 5 or 6 years money results to be neutral. Analysing the cross sectional variation, the authors observe a strong negative correlation between disaggregated prices impulse response functions and both idiosyncratic volatility and persistence: firms in sectors where prices are highly volatile adjust their prices faster even after a macroeconomic shock, while in sectors with higher inflation persistence, firms adjust their price immediately after both common and sectoral shocks, because they are both permanent. Augmenting the impulse response functions with variables about industry characteristics (like the gross product), these result strongly positively correlated, so that more competitive firms have higher price flexibility, while in sectors where market power is stronger, prices are stickier.

Up to now, we have described analysis on US data, while hardly any research has been conducted on EU data, given the difficulties in gathering comparably large data sets requested for factor models estimation. Disaggregated PPI series, for example, are not collected by any European institution, so they have to be downloaded from each national institute and then made comparable in terms of time span and most of all in terms of categories of goods; PCE quantities, instead, are not available at all; finally, data is generally available for a shorter length of time and with a higher delay respect to the correspondent US data.

Among the studies on inflation persistence based on EU data, Altissimo, Mojon and Zaffaroni[4] confirm the results obtained by Boivin, Giannoni and Mihov[21] for US data: disaggregated prices adjust quite fast, while aggregate inflation indices are quite persistent. They estimate a dynamic factor model using 404 inflation sub-indices of European CPI, obtaining quite heterogeneous responses across sectors, in particular they observe a slower propagation for services. The aggregation process therefore can be responsible for the different degree of persistence observed passing from individual series to overall indices: sectors with a higher weight in the aggregate index are those with a more persistent response. They model each sector price as an AR(1) with a composite error given by the sum of a common and an idiosyncratic component: the impulse response function of the common component decays much slower towards zero with this specification than in the homogeneous coefficient case. The estimation of the two error components is conducted with a recursive ARMA(p_i, q_i) model for each good i that alternatively estimates lag operator coefficients and residuals. They find one common factor to account for 30% of overall variability and confirm the high volatility and low persistence of disaggregated series, in contrast with the sluggishness and smoothness of aggregate inflation.

Altissimo, Ehrmann and Smets[3] assess the degree of price persistence in the EU area using the Inflation Persistence Network (IPN), a large data set on European basis. They find that prices increase at a moderate rate in Europe, even if retail prices are stickier in EU than in US. They confirm the sectoral heterogeneity in the degree of stickiness already observed by other authors mentioned above. Finally, they observe quite often price decreases, except in the services sector. To conduct their analysis, first of all they restrict the time span of the data to the current monetary regime starting in 1995, in order to avoid possible structural breaks in the series, corresponding to monetary regime changes that would determine a shift in the value of the coefficients. The result is a moderate degree of price persistence due to the fact that agents anchor inflation to future expectations, so that prices result less past dependent and less persistent. They observe price changes in the consumer sector every 4 or 5 quarters and in the producer sector every 4 quarters, while in US they are more flexible, changing every 2 quarters, because of a more stable economic environment. Structural inefficiencies make prices in EU less volatile: first of all, long-term commercial relationships, that prevent prices to change in response to changes in the economic conditions because of already stipulated contracts; secondly, explicit contracts that are costly to renegotiate; finally, the so-called 'coordination problem': firms do not change prices unless they are sure their competitors will do the same. Another point to underline is that prices change differently in different sectors: energy and unprocessed food change quite frequently, while non energy industrial goods and services are quite sticky; this heterogeneity is mainly due to two factors: the variability in input costs, in fact prices are stickier in sectors with a larger labour input, and the degree of competition that negatively affects price persistence. They estimate the following reduced-form equation, where aggregate inflation depends on its own past values:

$$\pi_t = \mu + \sum_{j=1}^{k} a_j \pi_{t-j} + \epsilon_t \tag{2.11}$$

and compute the degree of inflation persistence as $\rho = \sum_{j=1}^{k} a_j$: the higher ρ, the higher the sluggishness degree. They observe that in empirical research ρ results lower for shorter periods and changes in the mean when the policy regime changes: the evidence of this causality effect is in the time correspondence of the events, in the fact that this happens for most sectoral series and that changes in the inflation rate are often related to changes in nominal variables that depend on monetary policy decisions. The structural model is

$$\pi_t = \gamma \pi_{t-1} + (1-\gamma) E_t \pi_{t-1} - \lambda \hat{\mu}_t + \xi_t \tag{2.12}$$

where $\hat{\mu}_t$ is the deviation of the actual from the desired mark-up. As we can see, overall inflation depends on expectations, this is the reason why among the ECB explicit criteria there is the credibility of the Institution in controlling the inflation target: successfully anchoring inflation to expectations reduces its persistence; moreover, transparent information makes the agents able to disentangle permanent and transitory effects. Another important point is that the authors confirm the higher persistence of aggregate inflation respect to the average persistence of its sub-components: on one hand, idiosyncratic shocks tend to cancel out in the aggregation process, on the other higher weights are assigned to more persistent series. Individual prices, instead, are characterised by a high level of heterogeneity due to structural differences across and within product categories: consumer habits, methodological differences in computing the index, like the inclusion of sales and promotions that regards only selected categories of goods, and prices regulated by Authorities such as energy tariffs. Frequent changes regard unprocessed food and energy where raw materials are more important. Moreover, prices decreases are not uncommon (except in the service sector) and represent 40% of the observed changes. The authors observe that prices change in two steps: first, there is a price review, from one to three times a year, then there is the actual price change, once a year; moreover, prices change more frequently, the higher the degree of competition. In US consumer prices are less persistent than in Europe, even if data sets are not entirely comparable and shocks can have a different influence in different time samples, while producer prices are quite similar in the persistence degree across the two countries. The price setting rule can be time dependent if there is an exogenous periodic revision, or state dependent when prices change after a shock occurs: according to the latter rule, prices should change more frequently; moreover, the authors find empirical evidence of seasonal patterns observing prices changing more often in January and in September. Finally, they conclude with some considerations about monetary policy: in order to reduce prices stickiness, reforms are necessary both to encourage market competition and to induce higher flexibility in wages. They estimate a DSGE model to analyse the response of a medium term oriented monetary policy to cost-push shocks under different intrinsic inflation persistence and stickiness degree. They calibrate a Central Bank's loss function that depends on the Bank's own credibility in determining the future state-dependent interest rate path. The results are that a lower intrinsic inflation implies a lower monetary policy instrument (i.e. the interest rate); as a consequence, inflation expectations and negative output responses are lower and the real interest rate is less persistent. On the other side, a high degree of price stickiness induces persistent output responses, a high inflation persistence level, a high sacrifice ratio to reduce inflation and a more aggressive monetary policy that has to consistently affect the real interest rate and output. These findings are subject to some limitations: first, there is always a certain degree of uncertainty about monetary policy; second, if agents learn from expectations, there is a problem of endogeneity between monetary policy regime and ex-post inflation persistence: policy effectiveness depends on how well inflation and inflation expectations are anchored; third, wage stickiness can induce price stickiness and finally the heterogeneity in the volatility degree of the HICP sub-components can lead to misleading results, so that considering the core component of the overall index is recommended.

In conclusion, most of the previous literature has been conducted on US data, first with a

VAR model and then with a FAVAR model, trying to explain the apparent contradiction between sticky aggregate prices - the empirical evidence that confirms the economic theory - and flexible and more variable individual prices. The different behaviour depends on the different nature of the shock: while macroeconomic shocks have a permanent effect on the aggregates, idiosyncratic shocks are responsible for the higher variability of the disaggregated series. Further studies on EU data confirm the high level of heterogeneity in the price behaviour across sectors and the overall price stickiness.

2.3 Econometric Framework

In the previous Section it has been seen that, in order to analyse price dynamics, two are the models mainly used: a VAR approach, that in some cases leads to a 'price puzzle', or a FAVAR method, simple in the implementation and easy in the interpretation of the results. Therefore, we choose to follow Bernanke et al.[14] and Boivin, Giannoni and Mihov[21] approach enriching the FAVAR model with the use of both monthly and quarterly series.

The idea of summarising the information from many variables in a pool of artificial factors is not new in literature and has been used for different purposes: Stock and Watson[52] use diffusion indices to forecast macroeconomic time series; moreover, the dynamic factor model approach is used in business cycle economics, as modern dynamic general equilibrium models often suppose that a small number of variables are responsible for macroeconomic changes, like in Forni and Reichlin[35] among others. Here, we use this approach in order to asses the degree of price persistence and volatility in the three largest EU countries: France, Germany and Italy.

The FAVAR system[1] is the same as in Equation (2.3) that we report here for convenience:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \epsilon_t \tag{2.13}$$

where we consider the EONIA interest rate R_t as the only observed factor Y_t. In order to consistently estimate the k unobserved factors F_t, we extract the principal components from a large set of X_t variables, that can be disentangled in a common component summarising the macro shocks occurring in the economy, and a residual sector specific component:

$$X_t = \Lambda C_t + \epsilon_t \tag{2.14}$$

[1] See Forni et al.[34] for a punctual explanation of the model identification and estimation.

where

$$C_t = \begin{bmatrix} F_t \\ R_t \end{bmatrix} \tag{2.15}$$

An important contribution of this work is the implementation of the classical FAVAR model with a mixed frequency data set. The vector X_t used to extract principal components can include both monthly and quarterly series, given that important information is sometimes provided by aggregates available only each three months, such as the employment rate or the unit labour cost. We propose two alternative ways to deal with this problem that give back the same results.

The first one refers to Schumacher and Breitung[50] that propose an Estimation-Maximisation (EM) algorithm that recursively estimates both factors and loadings up to convergence. This procedure consists in three steps:

1. First, they transform the observed quarterly series X_i^{obs} in monthly observations using the unconditional mean of each series, obtaining a unique monthly data-set. Then they compute a first estimate of both factors and loadings.

2. *E-Step*: For each iteration j, they compute an estimate of the correspondent series in monthly frequency $X_i^{(j)}$ as:

$$\hat{X}_i^{(j)} = E(X_i|X_i^{obs}, \hat{F}^{(j-1)}, \hat{\Lambda}^{(j-1)}) = \hat{F}^{(j-1)}\hat{\Lambda}_i^{(j-1)} + A_i'(A_iA_i')^{-1}(X_i^{obs} - A_i\hat{F}_i^{(j-1)}\hat{\Lambda}^{(j-1)}) \tag{2.16}$$

3. *M-Step*: They re-estimate both factors $\hat{F}^{(j)}$ and loadings $\hat{\Lambda}^{(j)}$ using principal components of the covariance matrix until reaching a fixed criterion of convergence expressed as a maximum percentage change in the variables estimation.

The matrix A_i is called *selection* or *aggregator* matrix, as it permits to transform data in different frequencies: in our case of interest,

$$A_i = 1/3 \begin{pmatrix} \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \cdots & 3 & 2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \cdots & 0 & 1 & 2 & 3 & 2 & 1 & 0 & 0 & 0 \\ \cdots & 0 & 0 & 0 & 0 & 1 & 2 & 3 & 2 & 1 \end{pmatrix} \tag{2.17}$$

with as many rows as the quarterly observations (T^{obs}) and as many columns as the monthly observations. If quarterly observations are not available for the last n correspondent months, because usually monthly indicators are more rapidly available, the correspondent n rows of A_i (2.17) has to be removed. An important remark regards the nature of the quarterly series to be transformed, if they are stock or flow variables respectively. As Stock and Watson[52] report in the Appendix, stock variables are point-in-time levels, so they can be treated as monthly variables with missing values every three months: in this case

$$\hat{X}_{it} = X_{it} \tag{2.18}$$

if X_{it} is observed or

$$\hat{X}_{it} = \hat{\lambda}_i' \hat{F}_t \tag{2.19}$$

for the other values. A quarterly flow variable, instead, is the average or the sum of unobserved monthly variable, so it can be considered as

$$X_{it}^q = 1/3(X_{it-2} + X_{it-1} + X_{it}) \tag{2.20}$$

for $t = 3, 6, 9, 12$ and missing for the other values of t. A further complication arises if the monthly underlying series are not stationary, as often occurs. In the case of stock variables, if X_t represents the monthly first difference of the variable,

$$X_{it}^q = (X_{it-2} + X_{it-1} + X_{it}) \tag{2.21}$$

for $t = 3, 6, 9, 12$ and missing for the other values of t. So the A_i matrix has in each row values equal to 1 in correspondence of $t-2, t-1, t$ and equal to 0 otherwise. For I(1) flow variables,

$$X_{it}^q = (1/3)(X_{it-4} + 2X_{it-3} + 3X_{it-2} + 2X_{it-1} + X_{it}) \tag{2.22}$$

for $t = 3, 6, 9, 12$ and missing for the other values of t. This is the most common case even in our model and A_i results as (2.17).

This method is quite computer-consuming, because factors and loadings have to be iteratively computed for the whole data set each time, so it can require many computations especially if there are a large number of series to be transformed. Alternatively, a different procedure can be followed:

1. First, factors $\hat{F}$ are computed on monthly series alone.

2. Then, they are transformed in quarterly frequency using the aggregator matrix A:

$$\hat{F}^q = A\hat{F} \tag{2.23}$$

   Loadings are computed simply as OLS coefficients regressing each quarterly series X_i^{obs} on the factors:

$$\hat{\Lambda} = (\hat{F}^{q\prime} \hat{F}^q)^{-1} \hat{F}^{q\prime} X^{obs} \tag{2.24}$$

3. At the j^{th} iteration the correspondent monthly series is estimated as:

$$\hat{X}_i^{(j)} = \hat{\Lambda}_i^{(j-1)} \hat{F}^{(j-1)} + A_i^{'}(A_i^{'} A_i)^{-1}(X_i^{obs} - A_i \hat{F}_i^{(j-1)} \hat{\Lambda}^{(j-1)'}) \tag{2.25}$$

4. Finally, from the monthly data set obtained using all the series, factors are re-estimated until a fixed criterion of convergence is reached.

The good performance of this estimation method is confirmed by Boivin and Ng[22] who compare the FAVAR approach to other econometric models; moreover, the uncertainty about the factors estimation becomes negligible whenever the number of series N is large in comparison to the number of observations in the time period T, as Bai[10] documents.

Once we have obtained consistent estimates of the unobserved factors, we are able to analyse volatility and persistence of both disaggregated and overall inflation series. The volatility degree is simply computed as the series standard deviation (in %); moreover, in order to assess if it is mostly due to common factors or to sector-specific shocks, it is disentangled thanks to equation (2.14) in a common and an idiosyncratic component. Another aspect of price stickiness is the time length needed to come back to the long run equilibrium level after a system disturbance, the so-called inflation persistence degree: it can be due to a sequence of adverse shocks, to inertial responses following a single shock or to other reasons (i.e. nominal rigidities). Persistence can be determined by different factors: if it is in the determinants of inflation, like marginal costs or the output gap, it is said to be a case of 'extrinsic persistence'; alternatively if it is caused by its dependence from its own past values, we identify it as a case of 'intrinsic persistence'; finally, it can be 'expectations-based' if it depends on the agents' economic perspectives. In our analysis we test only for the intrinsic component, modelling each inflation rate and its common and idiosyncratic component as an AR(13):

$$\pi_t = \rho(L)\pi_{t-1} + \epsilon_t \tag{2.26}$$

where $\rho(L)$ is a 13 lags polynomial whose coefficients sum up in a measure of the persistence degree. We choose to discard the other two components because of the lack of information about agents' expectations on one hand and about the normal income level on the other.

For each observed series X_t and its components we then compute impulse response functions (IRFs) after a negative unidentified shock equal to the standard deviation of the series. Recursively computing the impact of this disturbance on a series following an AR(13) model, we obtain the following vector

$$\begin{bmatrix} -\sigma_\pi & -\beta_1\sigma_\pi & -(\beta_1^2 + \beta_2)\sigma_\pi & -(\beta_1^3 + 2\beta_1\beta_2 + \beta_3)\sigma_\pi & ... \end{bmatrix}' \tag{2.27}$$

with as many rows as the number of periods in the IRFs including period 0.

After having estimated the FAVAR system, we compute IRFs for common components as well, identifying a monetary shock with an unexpected EONIA increase of 25 basis points. Using the Cholesky factorisation of the covariance matrix of the residuals multiplied by the shock vector, we obtain a measure of the impulse; iteratively multiplying this impulse by the loadings of the FAVAR, we estimate the IRFs of the common component of each series. Finally, multiplying these values by the coefficients estimates of the observation equation (2.14), we obtain the IRF of each X_t series after a macroeconomic shock. We then compute bootstrapped simulations for the IRFs of both the common component and the observed variables in order to obtain valid confidence intervals and verify that, as more months pass after the shock, more inflation series converge towards the cross-section average price response.

Finally, we check the robustness of our results testing for long run restrictions. More precisely, we set disaggregated inflation responses equal to the main price index response (a) after h periods. Starting from equation (2.14), the response of X_{it} after h periods results:

$$\hat{X}_{ih} = \lambda_i' \hat{C}_h \tag{2.28}$$

where $\hat{C}_h$ is the estimated common component h steps ahead. Because inflation series are measured in first differences, we cumulate the responses in order to obtain the price log level response:

$$\lambda_i' \sum_{h=0}^{H} \hat{C}_h = a \tag{2.29}$$

Estimating equation (2.14) subject to such restrictions leads to the following formula for restricted loadings λ_i^r:

$$\lambda_i^r = \lambda_i^u - (C_t' C_t)^{-1} \left(\sum_{h=0}^{H} \hat{C}_h \right) \left[\left(\sum_{h=0}^{H} \hat{C}_h \right)' (C_t' C_t)^{-1} \left(\sum_{h=0}^{H} \hat{C}_h \right) \right]^{-1} \left(\lambda_i^{u\prime} \sum_{h=0}^{H} \hat{C}_h - a \right) \tag{2.30}$$

where λ_i^u are the unrestricted OLS estimates of the loadings of X_i. We test these restrictions for horizons of 4 and 10 years, in order to exclude any effect of monetary shocks on relative prices given that all the disaggregated prices responses have to converge to the same value of the overall index.

In conclusion, we follow Bernanke et al.[14] and Boivin, Giannoni and Mihov[21] using a FAVAR approach for the estimation of the effects of common and idiosyncratic shocks on disaggregated and overall inflation series, enriching the model with information coming from a mixed frequency data set of both monthly and quarterly series. We then compute the variability and the persistence degree of each common and idiosyncratic component, checking their IRFs convergence in the long run. Finally, we test the robustness of our results imposing long-run restrictions on the values of such responses.

2.4 Data

As said above, most of the literature about price stickiness is based on US data given its prompt availability at a disaggregated level: US databases, in fact, timely provide a wide range of data about prices, output, labour and financial markets.

Unfortunately for EU data this is not the case, as there are only a few examples of papers using large amounts of data based on EU countries. Moreover, only some data, like the disaggregated HICP series, is already available in a comparable form in terms of time period and product categories; other series, such as sector PPI data, have to be downloaded from each national statistics institute and made uniform for both start date and reference good. One of the contributions of this work is the creation of a database with a wide range of series referring to the three largest EU countries, France, Germany and Italy, regarding different aspects of the countries economy. 828 monthly series and 45 quarterly series spanning from 1995 to 2009 are collected from different European databases, mainly ECB, EuroStat and OECD and from national statistics institutes; the following Tables 2.1 and 2.2 list the series composing the data set whose complete description can be found in the Appendix C.[2]

Monthly Series		
	No. Series	Trasformation
HICP	450	5
PPI	306	5
Consumption volumes	9	5
Housing Starts	5	5
Unemployment Rate	3	1
Real Output and Income	24	5
Stock Prices	2	5
Exchange Rates	5	5
Interest Rates	15	1
Money Aggregates	4	5
Expectation	5	2
TOTAL	828	

Table 2.1: Monthly series

[2]Note to Table 2.1 and 2.2: The transformation codes are: 1 - no transformation; 2 - first difference; 5 - first difference of logarithm. In the last column of Table 2.2, 1 correspond to flow series and 2 to stock series.

Quarterly Series			
	No. Series	Trasformation	Flow/Stock
Value Added	1	5	1
Employment Rate	12	5	2
ULC	6	5	1
Consumption Volumes	20	5	1
Gross Income	6	5	1
TOTAL	45		

Table 2.2: Quarterly Series

Many authors such as Altissimo, Ehrmann and Smets[3] show that the degree of inflation persistence changes depending on the length of time considered: on long periods, monetary policy changes can cause structural breaks in the series and, as a consequence, shifts in the values of the parameters, so that inflation results to be more persistent than how it really is. For this reason, we consider data since 1995 that is when harmonised Euro data started to be collected.

As previously anticipated, the data has been collected from different sources which in some cases do not release it at the same frequency: consumption volumes, for instance, are released each month by the French national statistic institute (INSEE), but they are accessible only in quarterly frequency for Germany and Italy; moreover, this data is not released into comparable categories and it is not available at a very disaggregated level, so we use consumption volumes only to estimate the factors, without proceeding in any further investigation.

Producer Price Indices deserve a further explanation: as they are not available in any European database at a disaggregated level, they have to be attained from each national institute database and made comparable in terms of time span and good categories. The type of sampled goods and the disaggregation level are not the same across the EU countries: while France releases price indices only for the main industrial sectors, Germany on the other hand publishes quite a detailed list of producer prices, even if not all of them are available for a long period of time. In order to obtain a homogeneous database, only goods available for all the three countries and for the whole period spanning from 1995 to 2009 are considered.

Moreover, we checked series seasonality, as this is a problem affecting all the price indices and in particular producer prices. If a series presents a high degree of seasonality, the real effect of a shock can be confused with the periodic fluctuation of the data, so that the degree of price persistence and the level of price volatility result higher than how they really are. Besides, impulse response functions of highly seasonal data show an erratic behaviour erroneously predicting that prices need quite a long time after a shock to go back to their long-run level. All these reasons make seasonality an important problem to account for. From a preliminary graphical analysis, French producer prices result to be highly seasonal, so that their response functions after a monetary shock come out to be quite unstable and highly persistent in strong contrast with the other two countries PPI responses. Although in what follows we report the results using seasonally adjusted producer prices, French PPI series still deserve further investigations on their computation and aggregation method because their behaviour remains quite different from German and Italian correspondent series.

As said above, data has to be stationary in order to correctly compute the factors, therefore we conduct unit root tests to detect the order of integration of each series and operate the relative transformation: for example,we consider the first difference of the logarithmic transformation of all the price series. Moreover, before calculating the factors, each series has been standardised in order to better evaluate the correlation between the series removing the differences in variability deriving from different units of measure. We have to precise that after having estimated factors and impulse responses coefficients with the standardized series, all the results reported below refer to the price series in the original level, therefore they are influenced by the sector variability and mean level.

A final important issue regards the transformation to apply to the EONIA rate that we consider as the only observable factor responsible for the monetary shock. It is clearly non-stationary, so its logarithmic transformation should be differentiated like the other series of the same type, but by doing so an increase of 25 basis points would produce a shock of 3 times the standard deviation of the series, a quite high value if compared with Boivin, Giannoni, Mihov[21]'s work, where they use the Federal Funds Rate's 25 basis points increase as a monetary shock, obtaining a value of 0.068 times the standard deviation. For this reason, in order to obtain a more realistic shock magnitude, the EONIA rate has *not* been differentiated, so the monetary shock results 0.20 times the EONIA standard deviation. As the following Figure 2.1 shows, both the FFR and the EONIA rates are quite erratic, but given the longer time span considered for US data (from 1976 to 2005), along the whole period the FFR rate results stationary. As already emphasised, the time span considered in this work has been adapted on the HICP series that are available only since 1995.

In conclusion, collecting EU data regarding a wide range of disaggregated series for a long time interval can be a quite challenging task, given the difficulties in retrieving data that is not comparable neither in terms of product categories nor in terms of starting date; moreover, some series are not available in the same time frequency or in the same sector disaggregation.

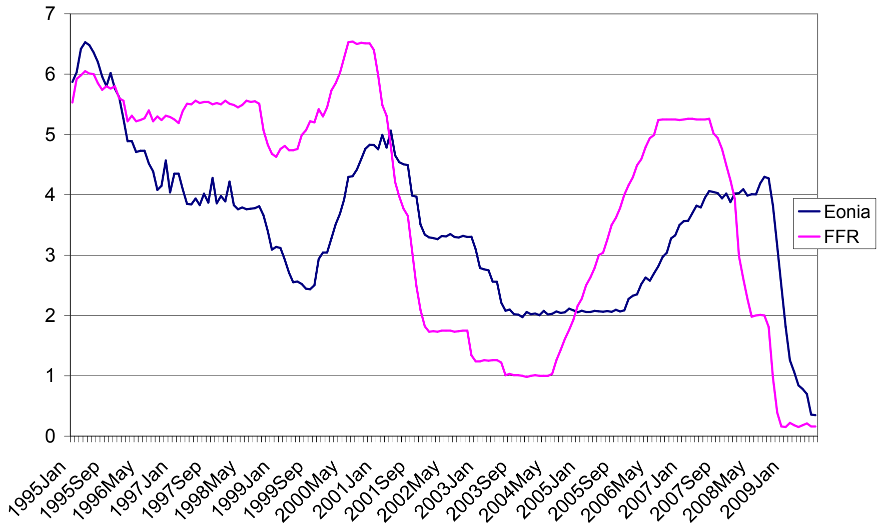

Figure 2.1: EONIA and FFR interest rate in the period 1995-2009

Therefore, the setting up of this database represents one of the important contributions of this work.

2.5 Results

The estimation of the system formed by Equation (2.13) with 5 unobserved factors and 13 lags and Equation (2.14) for all the observed series Xs, determines the results showed in the following paragraph. In the first subsection we analyse the degree of inflation volatility and inflation persistence for both overall and disaggregated price series; in the second one, we observe the effects of macroeconomic and sector specific shocks on prices.

2.5.1 Inflation volatility and persistence

From Tables A.4, A.5 and A.6, that report some summary statistics regarding both aggregate and sector price series, some general results valid for all the three countries can be derived: aggregated series are generally less volatile than sector prices and in most cases their volatility is mostly due to the common component; on the other hand, disaggregated series result much more variable especially given their sector specific component that accounts for almost 80% of the prices variance. Among the three countries analysed, Italian overall HICP index results the most volatile (0.44%), on the opposite French overall inflation results the least variable (0.27%); among aggregated components, 'Clothing and Footwear' is the most volatile (its standard deviation is 4.16% in Italy), closely followed by 'Energy' and 'Unprocessed Food': not surprisingly, these are the subcomponents characterised by the highest volatility given their dependence on periodic sales, oil price and weather conditions respectively. Disaggregated series are much more volatile, especially in France (2.73%) which is the only country where PPI indices are more volatile than CPI ones, but this is due to the different behaviour of French producer prices explained above; in particular, the most volatile PPI series (with a standard deviation of 16.84%) corresponds to 'Pharmaceutical products' that presents a high variability at the end of the sample maybe due to the market liberalisation. A final important remark to point out about price volatility is the high heterogeneity across products already observed in previous works: as single prices are aggregated, volatility tends to cancel out, so that the aggregated indices result less variable. Like in Boivin, Giannoni and Mihov[21], the standard deviation of the common and of the sector specific component are highly positively correlated considering both CPI and PPI series, as Figure B.6 shows. Tables A.7, A.8 and A.9 report the values of these correlations, ranging from 0.58 for French PPI to 0.89 for German CPI: this means that sectors with a highly volatile prices due to sector specific shocks respond equally quickly to macroeconomic shocks. This can be due to the price-setting behaviour in the market: if firms are used to frequently adjust their price in response to sector specific changes, they can profit from adjusting it after macroeconomic changes as well.

If the results found for price volatility are quite similar in size and magnitude to the values obtained by other studies both on US and EU data, the observed degree of price persistence is quite different from what reported in previous analysis. Boivin, Giannoni and Mihov[21] calculate a US overall inflation persistence degree of 0.93, the same index ranging from 0.74 to 0.94 for the main aggregates; moreover, they find disaggregated prices less persistent with a value of ρ in Equation (2.26) of 0.49 on average even if extremely heterogeneous across products and mainly due to the common component of each series. The corresponding values resulting from our analysis range from 0.09 for the overall French HICP to -0.07 for the Italian overall inflation, becoming even highly negative for some main aggregates, as Tables A.4, A.5 and A.6 show. Disaggregated prices persistence varies from 0.12 in Germany to -0.54 in France on average and as expected it is especially driven by the series common component. The low persistence observed for both aggregated and sectoral prices means that inflation is not affected by its own previous values, therefore a shock has only negligible effects and prices come back to their normal level after only a short time. The striking difference between our results and what found by previous researches can be justified both on economic and statistical basis. First of all, given the data availability, we consider data since 1995, avoiding structural breaks caused by changes in monetary policy regimes. Secondly, as Taylor[53] and Benati[12] evidence, inflation is positively correlated with inflation persistence: in periods of low inflation, like the one we consider, inflation persistence is low because agents adapt their expectations on the Central Bank's commitment to inflation targeting and as a consequence, monetary policy becomes more effective in the short run. We test these hypotheses running the FAVAR model on the U.S. data covering the same period we consider in this Chapter: the results, available on request, confirm a much lower value of inflation persistence, equal to 0.06 for the overall index. Therefore, the results found by Boivin, Giannoni and Mihov[21] are peculiar to the period of time considered and substantially change when considering different monetary regimes separately. In fact, different authors confirm that allowing for inflation to change in the mean over time when monetary policy changes leads to lower inflation persistence: among others Cogley and Sargent[30] and [31], Levin and Piger[43] and Clark[27].

We can further analyse the correlation between volatility and persistence of the sector-specific component: from Tables A.7, A.8 and A.9, it results almost null for Germany, quite negative for Italy (-0.29) and highly negative for France (-0.54). As expected, volatile prices need less time to return to the equilibrium level after a shock; on the other hand, the effects of a shock result more persistent on sticky prices. The same result concerns the common component, whose volatility and persistence result even more negatively correlated with values varying from -0.35 for Germany to -0.46 for Italy.

2.5.2 The effects of macroeconomic and sector-specific shocks

As shown in the previous subsection, price dynamics change depending on their level of aggregation; this result can be explained analysing the various types of shocks that can hit the economy. As described in Section 2.3, we compute for all the observed price series and their common and idiosyncratic components Impulse Response Functions after an unidentified shock of one standard deviation; secondly, we identify a macroeconomic shock, as an unexpected 25 basis points increase in the EONIA rate, evaluating its effects on both CPI and PPI series as well.

The identification of a macroeconomic shock helps to solve the 'price puzzle' described in Section 2.2 resulting from the VAR approach: this method is quite common in econometrics given its easy implementation and its unrestricted form free from heavy theoretical hypothesis, however the large number of parameters to be estimated makes it possible to include only selected information to avoid the consequent degrees of freedom problem. On the opposite, the FAVAR model is based on artificial variables, the factors, that summarise a large set of information about the economic environment, so that it achieves better results than the simple VAR, as shown in Figures B.8, B.9 and B.10. In these Figures, we show the response of the EONIA rate, of the Industrial Production Index and of the CPI overall index after an identified monetary shock using different models: our FAVAR model, a VAR model with the three variables and the same VAR model augmented with the first factor. As Figures B.8, B.9 and B.10 show, the VAR model leads to some inconsistencies with the economic theory: first of all, CPI indices increase in the first periods, in contrast to the traditional effect expected after a negative monetary shock; using the FAVAR model, instead, French and German overall consumer prices decrease from the beginning, while Italian correspondent series remains quite stable. The second result from a VAR approach that is in contrast to the economic theory is the permanent effect of the monetary shock on the Industrial Production Index considered a proxy of economic activity, especially in Germany and Italy: if monetary policy can influence real variables in the long run, it is clearly non neutral. As we can see from these Figures, the FAVAR model is the only one that gives reasonable results when computing the effects of a macroeconomic shock on the economic system. Tables A.10, A.11 and A.12 report in the first rows aggregated price responses after a monetary shock, as predicted using a FAVAR model: the overall HICP indices result to be almost stabilised after one year, given that the deviation from the previous level decreases analysing the impact after 6 and 12 months, ending up to be even positive in the case of the Italian index.

We then analyse the effects of a shock on disaggregated prices. The left and the central panels of Figure B.7 show the results of an unidentified shock on the observed price series common and idiosyncratic components for the three countries: apart from French PPI series, they all seem quite stable and affected very little by the disturbance. In particular, a shock to the sector-specific component has quite a transient effect, so that prices come back to their normal level after only a short time; a shock to the common component results slightly more persistent, affecting prices behaviour only to a small extent. French producer prices are the only ones on which a disturbance has quite a significant effect: a shock to the sector specific component has a strong negative contemporaneous impact on prices, in the months following the shock the effects become slightly less negative but are not wiped out even after 2 years; a shock on the common component, instead, has a more gradual but equally permanent impact on prices. This different effects on French PPI data can be due to the series intrinsic behaviour which remains highly variable even after removing the seasonal component.

Hitherto we have described the effects an unidentified shock, that can result from a mixture of macroeconomic disturbances affecting the economic system: therefore, we cannot exclude that among these there could be one that changes prices permanently. For this reason, we identify a monetary shock as an unexpected increase of 25 basis points of the EONIA interest rate and we analyse its effects on both CPI and PPI series. The right panel of Figure B.7 shows the effects of the identified monetary shock on both CPI and PPI disaggregated series. The effects on the CPI indices of all the three countries appear quite transient and not significant, while Italian and German PPI show a small but wavering decline. As before, the shock has a significant impact only on French PPI series: after a first positive effect, prices strongly decrease in the following 12 months, then they increase again up to almost the original level and continue fluctuating, proving that the shock still has permanent effects. These results about the effects of a monetary shock on prices can be quantified observing the last two columns of Tables A.10, A.11 and A.12: Germany and Italy present a similar situation with the average disaggregated prices response decreasing very little (-0.03%) after 6 months and only by -0.04% after a year; moreover, CPI series are almost stable, while PPI indices show on average a weak but stable decline with a value of price persistence going from -0.06% after 6 months to -0.10% after one year. The low persistence is also confirmed by the inflation autocorrelation coefficients reported up to the 12th order, which decay faster as more months pass after the shock. The same monetary shock results to have more persistent effects on French disaggregated prices: after 6 months they decrease on average by -0.13% and after one year by more than the double (-0.27%); the effects, however, are not the same on CPI and PPI indices: while the first decrease by -0.05% after 6 months but they stabilise soon after (after one year they decrease only by -0.03%), the latter are much more affected, decreasing by -0.23% after only 6 months and by more than the double (-0.57%) after one year. In conclusion, a monetary shock has sensible effects only on disaggregated PPI series: while in Italy and in Germany its effects are limited, it results quite persistent and relevant in France. As already observed in previous studies, there is a high degree of heterogeneity across sectors in the size and the magnitude of the impact of a monetary shock: as we can see from the right panel of Figure B.7, the single sectors impulse response functions are widely distributed around the mean, especially for French PPI indices. On the contrary, in the other two panels the individual series are quite similar to the mean, indicating that the aggregation weights do not play any role in influencing price responses after an unidentified shock. A particular feature to notice is that PPI indices are more influenced by a shock than CPI ones: this is especially true for France, but is valid in general for all the three countries and it is confirmed even in studies on US data such as Boivin, Giannoni and Mihov[21].

To analyse more in depth the disaggregated price responses, we study the extent of relative price changes, calculating the percentage of sectors whose response function exceeds the cross-sectional average response. With a bootstrap procedure involving 1000 iterations, we compute the 10% confidence interval of the impulse responses' distribution; then, for each period i following the shock, we compute the fraction of sectors h whose response is $f_i^h < 0.05$ or $f_i^h > 0.95$. The results are reported in Figure B.11: half of the sectors relative prices show a substantial change in France and Germany only in the first 6 months; in Italy 30% of relative prices change soon after the shock but generally any effect dies out after less that 2 years, confirming the long-run neutrality of money.

Next, we analyse how price responses vary across sectors: from Tables A.7, A.8 and A.9 we can observe the value of the correlation of IRFs after 6 and 12 periods with both idiosyncratic persistence and volatility. As we identify a contractionary monetary policy shock, a more negative value of the impulse responses correlation means a stronger price decrease and therefore a quicker adjustment. Considering Italian and French prices, idiosyncratic volatility is strongly negatively correlated with IRFs: the more prices are flexible, the sooner they adjust after a monetary shock; on the other hand, analysing German prices this correlation results only slightly negative: from the second and third panel of Table A.8 we can see that CPI indices are responsible for this result given that the idiosyncratic component of the PPI indices is negatively correlated with IRFs as expected. As we can see from Figure B.12, while for France and Italy the higher the idiosyncratic volatility, the lower the price responses are after a year, German CPI and PPI series compensate their price responses so that the regression line results almost flat. This apparent contradiction is explainable considering again Table A.11: 12 months after the shock, CPI responses are already positive (0.02%), meaning that the negative effect of the monetary shock has already been absorbed. So, the contractionary effect on the IRFs is not observable after a year because it has already been incorporated in the new price level: the series with a high idiosyncratic variability showing positive price responses are 'Liquid Fuels', 'Air passengers', 'Holidays' and 'Holidays Accommodations', all sectors characterised by a high volatility that allows prices to quickly revert towards their normal level. The correlation between IRFs and the idiosyncratic persistence degree is slightly positive or null for all the countries as expected: if prices are sluggish, the effects of a shock last for many periods. Therefore, these findings confirm what already observed in Figure B.6: firms that respond quickly to idiosyncratic shocks, tend to change their price equally rapidly even in response to macroeconomic shocks.

Finally, as described in Section 2.3, we impose long-run restrictions on the values of the price responses estimating the loadings of the FAVAR model with Equation (2.30). Figure B.13 reports the results of a monetary shock on both disaggregated CPI and PPI series imposing IRFs equal to the overall corresponding series response after both 4 and 10 years. As appears evident, the result is similar to Figure B.7, meaning that the cross-sectional distribution does not significantly change in the long-run.

In conclusion, while aggregated prices result less volatile especially in response to changes in the common component, sectoral inflation is highly flexible mainly due to its specific component. A monetary shock appears not to affect in a significant way disaggregated CPI series; it has a small impact on German and Italian PPI indices and on the other hand a strong and lasting influence on French PPI series. An important finding, different from previous studies, is the very low value of inflation persistence that can be reasonably explained considering the limited time period of analysis characterised by inflation targeting regime. Inflation persistence in fact results to be strongly influenced by the time period considered: a long span of data easily includes changes in the monetary policy, so that a macroeconomic shock results to have a much more significant and persistent effect on both overall and disaggregated prices. This is in line with Cecchetti and Debelle[25] who conclude that 'the conventional wisdom that inflation has a high level of persistence is not robust. Once one controls for a break in the mean of inflation, measured persistence is considerably lower'[3]. Several papers confirm that Boivin, Giannoni and Mihov[21] analyse data over a period characterized by changes in monetary policy: among others Bernanke and Mihov[15], Clarida, Gal and Gertler[26], Boivin[18], Boivin and Giannoni[19] and [20]. On the opposite, limiting the analysis to a period of time corresponding to the same monetary policy allows to observe how agents adapt their expectations on the Central Bank's target limiting the influence of a shock on the normal level of inflation. Moreover, a cross-sectional analysis of price responses confirms two important hypotheses: first, more volatile prices have more rapid adjustments; second, firms that respond promptly to sector specific disturbances, change their price equally quickly after a macroeconomic shock. Finally, we checked the robustness of our findings imposing long-run restrictions on the value of price responses observing no significant change in the results.

2.6 Conclusion

In conclusion, the results regarding prices variability are in line with other researches, while the observed price stickiness degree is quite surprising: inflation seems to adjust almost immediately after a shock, both at sector and aggregate level. This can be explained considering the particular time period of the data: given the limited HICP availability, the series start only in 1995, therefore the period analysed corresponds to a monetary policy of inflation targeting; as previous works evidence, inflation is positively correlated with persistence: given that the last decade has

[3]Bilke[16] analyses the impact of breaks in the mean on the level of inflation persistence in France.

been characterised by low and stable inflation, both variability and persistence have small and stationary values.

In order to disentangle the effects of different kinds of shocks, we identify a monetary shock as an unexpected increase of 25 basis points of the EONIA interest rate and we analyse its effects both on aggregate and on sectoral inflation. Using a FAVAR model we are able to exploit a wide set of useful information from many observed variables, so that overall inflation results decreasing as predicted by the economic theory after a contractionary monetary shock, avoiding the 'price puzzle' coming out using a VAR model. The same monetary shock has different effects on sectoral series: it has quite transient consequences on CPI indices of all the three countries considered; on the opposite, it has a small impact on Italian and German PPI indices and a significant one on French PPI series. These latter deserve further analysis, given the highly variable behaviour they maintain even after having eliminated the seasonal component: probably there are differences from the other countries in the way they are computed or aggregated even at a sectoral level.

Given that the FAVAR model provides useful information about price dynamics, a further step is to test its forecasting ability in precisely predicting overall inflation index.

Chapter 3

Forecasting inflation with disaggregated data

3.1 Forecasting inflation

The Central Bank controls the interest rate affecting the economic system depending on the alternative operating rules of monetary policy it chooses to use. The monetary authority has to deal with the trade-off between output and inflation stabilisation: it dislikes deviations of inflation from the target value, but at the same time its optimal level of output has to remain constant. Moreover, in case of nominal rigidities depending on agents' expectations, monetary policy can be more or less effective. In fact, under adaptive expectations, the monetary authority can achieve a level of output higher then the natural one, albeit at the cost of accelerating inflation (the *accelerationist* result derived by Friedman[36] and Phelps[49]); under rational expectations, monetary policy cannot affect the average level of output in any case. In both cases the future inflation path is not determined and the only action the Central Bank can take is to set a nominal anchor at a base level for the interest rate, from which deviations will take place.

Therefore, predicting inflation dynamics is quite a challenging task given that prices are significantly influenced by many variables regarding the economic, social and financial features of a country. Economic models traditionally link the inflation level to alternative economic indicators such as output gap or industrial production. In any case, only a small number of observable series is considered, ignoring all the remaining available information about the country.

Given that the factor model described in the previous Chapter provides such useful information about prices dynamics, a further step is to test its forecasting ability in correctly estimating future changes in price levels. The results we obtain are very interesting, considering that the estimated factors, using all the information available in the economy and imposing very few restrictions on agents' behaviour, result to be significantly useful in correctly foreseeing the future price trend.

Altavilla and Ciccarelli[2] analyse a wide set of competing models in order to assess the best specification to forecast inflation, considering both linear and non-linear alternatives. The authors formulate a typical Taylor rule assuming that the Central Bank reacts to changes in inflation forecasts computed with alternative models. The most important result they obtain is that combining forecasts from different models can significantly increase predictive accuracy, given the relative accuracy each specification has over different sub-periods. Moreover, a forecast combination substantially reduces the uncertainty associated with monetary policy decisions, in line with the literature that encourages for the most complete use of information available in the economy. Even if the authors do not test the factor model in their work, their conclusions enforce the hypothesis that considering artificial variables that summarise all the shocks affecting the economy can provide significantly accurate predictions.

Gavin and Kliesen[38] use a dynamic factor model to forecast different measures of inflation, finding a significant improvement in predictive accuracy compared to alternative models. In particular, they augment a simple auto-regressive model with artificial factors computed using all the information available in the economy and they then compare the two nested models using the Mc Cracken[28] test. Adding the first principal components to a standard AR model results to significantly improve the predictive accuracy of the model. They test the model on US data spanning from 1987 to 2007, computing recursive forecasts on the sub-sample starting in 1997.

We decide to test the forecasting accuracy of artificial factors on Euro price data spanning from 1995 to 2009, starting to compute the recursive forecasts from January 2008. In this way we test the predictive accuracy of the factor model during the first period of the economic crisis that has hit the Euro countries. Moreover, we find that different models result to be the most accurate depending on the horizon of prediction.

The rest of the Chapter proceeds as follows: in Section 3.2 we describe the previous literature about forecasting inflation and the main results found about the predictive accuracy of the factor model; in Section 3.3 we illustrate the compared models and the forecasting tests, both for nested and non-nested models, used to assess the significance of differences in the competing models predictive power; in Section 3.4 we describe the database constructed to conduct the exercise; in Section 3.5 we illustrate the main results and finally Section 3.6 concludes.

3.2 Previous Literature

Recent technological development has made millions of data regarding almost all the countries in the world available in real time and at a negligible cost: this huge amount of information can be easily used to identify the co-movements driving important macro variables such as economic activity or price inflation.

One of the first works proposing to forecast macroeconomic variables using a large panel of series summarised in a few artificial variables is the one by Stock and Watson[52]. Their aim is to exploit all the available information about the economy using *diffusion indexes*, a small set of artificial variables driving macro time series. They carry out the exercise in two steps: first, they estimate the factors using principal components analysis on a large set of observable data; then, they forecast the dependent macro variable with the estimated factors. They test the model on US data spanning from 1970 to 1998, forecasting alternative measures of economic activity and inflation. Comparing the predictive accuracy of the diffusion indexes with benchmark models, they find a significant reduction in the forecast errors. They start from the following representation of the dynamic factor model:

$$\begin{cases} y_{t+1} = \beta(L) f_t + \alpha(L) y_t + \epsilon_{t+1} \\ x_{it} = \lambda_i(L) f_t + e_{it} \end{cases}$$

where f_t are r common dynamic factors, y_t is the dependent variable to forecast and x_{it} is the *i-th* variable observed at time t. In order to estimate the factors with principal components, the authors reduce the infinite lag polynomials $\beta(L)$ and $\lambda(L)$ to finite orders of at most q, doing so the dynamic factor model can be rewritten in a static form:

$$\begin{cases} y_{t+1} = \beta' F_t + \alpha(L) y_t + \epsilon_{t+1} \\ x_{it} = \Lambda F_t + e_{it} \end{cases}$$

where $F_t = (f_t', ..., f_{t-q}')'$ is a *rx1* array and the *i-th* row of Λ is $(\lambda_{i0}', ..., \lambda_{iq}')'$. The h steps-ahead forecast value of y_t result to be:

$$y_{t+h}^h = \mu_h + \beta_h(L) F_t + \alpha_h(L) y_t + \epsilon_{t+h}^h \tag{3.1}$$

As said before, the estimation process follows two steps:

- First, principal components are extracted from the whole panel of observable variables X_t with $t = 1, \dots, T_{end}$: these estimated factors $\hat{F}_t$ represent the *diffusion indexes* summarising all the shocks in the economy.
- Second, from Equation (3.1) $\hat{\mu}_h$, $\hat{\beta}_h(L)$ and $\hat{\alpha}_h(L)$ are estimated regressing y_{t+1} on a constant, $\hat{F}_t$ and lags of y_t.

Under a few moment conditions on the error terms and on the estimated factors and an asymptotic rank condition on Λ, the forecasts are first-order efficient: their mean square errors tend to the mean square errors of the optimal infeasible forecasts as the number of observed variables and the time span tend to infinite. The authors apply the model on a data set of 215 economic monthly series, extracting three sets of empirical principal components: one from 149 variables constituting the balanced sample of series available for the full period; a second set from all the 215 available variables and a third one augmenting the 149 complete variables each with its own first lag, obtaining 298 variables. As benchmark models, they consider the auto-regressive model with p lags selected by the BIC information criterion, a VAR model with the monthly real activity growth, the change in monthly inflation and the change in US treasury bill rate as variables. In order to assess the predictive accuracy of the leading indicators, they compute recursive forecasts, using data from 1959 to 1969 to estimate parameters and the consecutive sub-sample from 1970 to 1998 to compute forecasts. The model for real activity variables shows a substantial reduction in the MSE using leading indicators, especially those extracted from the whole set of data, at a predictive horizon of 12 months ahead. The same model applied to price series outperforms the benchmark alternatives less often; moreover, the inclusion of lagged inflation significantly improves the model performance to such an extent that without these variables the diffusion indexes model would have forecast worse than the auto-regressive one. In conclusion, the best model to forecast price dynamics results the one including lags of inflation and a single factor; an important finding is that only six factors account for nearly the whole variability of the data set, suggesting that there are only a few important sources of macroeconomic shocks. Among the open issues the authors leave for future research there are the possibility of using a mixed-frequency data-set, because important information can be contained in economic series released on quarterly basis, and the opportunity to test the leading indicator model on data from other countries. In what follows, we try to improve the model in both the directions suggested.

The encouraging results found by Bernanke et al.[14] and Boivin, Giannoni and Mihov[21] using a FAVAR model to assess the inflation persistence degree lead authors such as Gavin and Kliesen[38] to test the model's predictive accuracy. The idea underlying the Dynamic Factor Model is that economy is hit by a few fundamental shocks, depending on changes in technology, agents' preferences or economic policy, and many idiosyncratic ones coming from the individual behaviour of firms and households. Each economic indicator can be decomposed into a small number of fundamental factors and a residual idiosyncratic component, as already seen in Equation (3.1). They apply this model on 157 economic series x_t spanning from 1983 to

2007, decomposing each of them as:

$$x_{i,t} = \lambda_{1,t}(L)f_{1,t} + \lambda_{2,t}(L)f_{2,t} + ... + \lambda_{q,t}(L)f_{q,t} + \epsilon_{i,t} \tag{3.2}$$

where f_t are q fundamental factors and $\epsilon_{i,t}$ is the idiosyncratic component uncorrelated with the factors. If only contemporaneous factors are included, they can be consistently estimated with the first q principal components of X. Forni et al.[34] extended the static factor model to the dynamic case in which lags of the factors are included, showing that the q dynamic principal components converge to the factor space as the number of X variables goes to infinity. So, the authors use lags of the largest principal components of X in order to estimate the factors in the forecasting exercise. The Dynamic Factor Model is compared with two benchmark alternatives: a random walk and a simple autoregressive model with 12 lags using data up to December 1996 and recursively testing the predictive accuracy of the models from January 1997 onwards. The DFM is constructed augmenting the AR specification with lags of the estimated factors:

$$\pi_t = \mu + \sum_{i=1}^{12} \alpha_i \pi_{t-i} + \sum_{j=1}^{q} \sum_{k=1}^{m} PC_{j,t-k} + \epsilon_t \tag{3.3}$$

where π_t is the generic inflation index at time t. The model is tested with different values of q and m: quite surprisingly, they find a better performance of the model using 6 or 7 factors and a large number of lags. Comparing the simple AR model and the DFM in terms of forecasting accuracy using the MC Cracken test for nested models described in detail in Section 3.3, they confirm that the computed factors have a significant predictive power at horizons of 3, 12 and 24 months ahead.

A possible implementation of this approach is to combine forecasts from different models, given that different specifications can be optimal in response to different shocks, as Altavilla and Ciccarelli[2] propose. They compare the predictive accuracy of a number of linear and non-linear models in forecasting inflation, proposing as an alternative the weighted average of all the models analysed, finding that the forecasts combination outperforms all the others according to the theory that different models can be more accurate in different sub-samples. Moreover, combining different forecasts enlarges the set of information taken into account, as well as the FAVAR specification is more accurate that the simple VAR model, including artificial variables summing all the available information about the economy. They analyse eight competing models: a driftless random walk process (RW); a univariate autoregressive moving-average model (ARMA); a spectral model (SP); a four-variable vector autoregressive model (VAR); an exponential smooth transition autoregressive model (ESTAR), a univariate markov-switching autoregressive model (MS-AR); a markov-switching VAR (MS-VAR); and a combination of all the previous methods (COM(1-7)). Each of these models is the best in capturing a particular kind of shock occurring in the economy, so that combining the different forecasting abilities of each specification allows to compensate the weaknesses and beat the naive benchmark. They use quarterly data on US and Euro inflation from 1970 to 2005, starting to compute recursive forecasts from 1990 onwards. Comparing the models forecast accuracy in terms of Root Mean Square Errors (RMSE), each model results to beat the RW at different horizons, clearly indicating that a forecast combination can perform even better, as confirmed especially at longer horizons. Moreover, the combination model is significantly more accurate than the benchmark alternative, as the Diebold and Mariano test of equal forecast accuracy, reported in the next Section, shows. A second aim of their work is to investigate the degree of uncertainty surrounding monetary policy decisions. Therefore, they analyse the impact of a monetary shock replacing in the VAR specification the actual value of inflation with the one forecast by each competing model. They find that the transmission of a shock depends on the set of information available to the Central Bank and normally the longer the forecast horizon is, the more uncertainty increases; the highest levels of uncertainty are observed using inflation prediction from non-linear models, while the lowest is associated with the forecast combination. In conclusion, the Central Bank faces a certain degree of uncertainty when trying to forecast inflation, for this reason in case of deviation from the target level it does not have to strongly react, but instead it should undertake a cautious monetary policy. Finally, the authors confirm that using the largest information set available significantly improves the predictive accuracy of the model, that is exactly what we are going to verify in what follows.

Altavilla and Ciccarelli[2] conduct their analysis on US and Euro countries data, but this is one of a few examples. In fact, while there are quite a few works conducted on US data, there is little investigation on Euro countries, given the scarcity of data released in a homogeneous format respect to starting and ending date, measure unit and moreover respect to the sector category observed.

An example of analysis conducted on Euro countries is Marcellino et al.[45], who compare different models performance in predicting economic indicators. Using mixed-frequency data spanning from 1982 to 1997, they compare forecasts at one, two and four quarter horizons. The models analysed are autoregressions, VARs, a model in which the Euro-aggregate is used as a predictor at the country-specific level, a model in which the corresponding variables in the United States are used as explicative variables and a dynamic factor model. The last specification derives from the hypothesis that there are a small number of co-movements common to all the European countries useful to predict macroeconomic indicators. They find only little evidence of this, given that the best way to predict the aggregate Euro area indicator results pooling the country-level univariate models; significant predictive accuracy of the factor model is observed only in comparison to the other multivariate alternatives: this can be explained given the time period considered, limited by the data availability and characterised by the relevant economic changes that occurred in Europe in that period. The authors conduct the analysis on a mixed-frequency data set of both monthly and quarterly economic series for each Euro country, testing the best level of aggregation in order to forecast the overall Euro economic indicators. A first aim of the paper is in fact to assess if the Euro area macrovariables are better predicted using a direct approach or alternatively aggregating the corresponding forecasts at country-level. For each economic indicator, different forecasting models are compared, estimating the h months ahead predicted value of the dependent variable as a linear projection on its own lags and alternative predictors:

$$y_{t+h} = \mu + \alpha(L)y_t + \gamma(L)'Z_t + \epsilon_{t+h} \tag{3.4}$$

The various models considered differ in the choice of Z_t. Inflation is predicted as monthly percentage change and the autoregressive polynomial has two lags in each model. The models compared are a simple autoregressive without Z_t variables; a three-variable VAR in the industrial production index, the consumer price index and the unemployment rate; an AR model with the correspondent Euro aggregate of the specific series being forecast as Z_t; an AR model including the US aggregate of the corresponding series; a factor model with Z_t as the first principal component of a set of alternative predictors consistently estimating the common co-movements underlying the economy. The authors compute two sets of factors: a first set is computed at country level considering only the series pertaining the specific country whose economic indicator is to be forecast; an alternative set is computed considering economic series from all the Euro countries. These two sets of factors are alternatively used in three forecasting models: one including only country-specific factors, one considering Euro-wide factors and a third one with both of them. All the models are computed both directly considering economic series at Euro area and at single country-level, and indirectly computing a weighted average of single country's prediction in order to obtain a comparable overall forecast. In order to assess the best method to accurately predict Euro economic indicators, models are compared both on the overall sample and computing out-of-sample recursive forecasts compared in terms of RMSE. They find that none of the multivariate models significantly outperforms the univariate alternative both for the Euro area and at country-specific level; second, the indirect method results to be more accurate, given that different models can be more appropriate for different countries, moreover the residuals from different specifications can compensate each other in the aggregation process; third, there is no evidence that US indicators help forecasting Euro aggregates; finally, factor models outperform the other multivariate specifications, once again confirming that enlarging the information set used in the estimation can significantly improve the forecasting accuracy of the model.

Another example of analysis conducted on Euro data is Angelini et al.[7] who, following the approach of Stock and Watson[52], explore the ability of artificial factors in forecasting economic indicators. Using a set of quarterly data spanning from 1977 regarding all the country members of the Euro Area from 1999 to 2000, they compute factors from two alternative sets of variables: one comprehensive of all the information available about the economies, measuring cycling factors, the other using only price series potentially measuring inflation trend. A first step consists in comparing the two sets of factors on the whole sample analysing the statistical correlation between the artificial factors extracted and the original series; secondly, different forecasting models are compared using out-of-sample recursive predictions. The factors extraction proceeds as in Stock and Watson[52]: each observable variable x_t can be decomposed in a common component, the factors, and an error process uncorrelated with the factors as in Equation (3.2). Under regularity conditions, the unobservable factors can be consistently estimated with the largest principal components of X. The authors use a mixed-frequency data set with both monthly and quarterly series including even incomplete series, computing factors with the EM algorithm described in detail in Chapter 2 that consists in a two-steps iterative procedure starting from factors derived on the balanced panel and projecting the estimated factors on the original data-set until convergence. Analysing the loadings of the factors, re-scaled to lie between -1 and 1, gives a direct and easily-read measure of goodness of fit of the factors on each variable. A first result is that the largest factor computed on the whole data set is similar to the first price factor; moreover, it results strongly correlated with most price variables. Other variables with a significant relationship with this factor result to be earnings, employment and unemployment series, most notably the unemployment rate. Survey variables related to manufacturing also show a visible degree of correlation with this factor: capacity utilisation, order-book commands, new orders and stocks in manufacturing firms. Other variables, instead, are clearly less related to this factor, most notably GDP and monetary aggregates. An important point to be stressed is that factors are not linked to any specific country variables, but they seem to represent Euro area-wide features. The second aim of the paper is to assess the forecasting accuracy of the factors compared to alternative measures of inflation, modelling the prediction of the dependent variable h months ahead as follows:

$$\frac{y_{t+h} - y_t}{h} = A(L)\Delta y_t + \Gamma(L)' z_t + \epsilon_t \tag{3.5}$$

where z_t is the forecasting indicator under test. The indicators considered include the overall, price and non-price factors for a maximum of five factors; alternative indicators employed to forecast the euro area inflation are the euro area unemployment rate, the output gap and the growth of nominal M3. After computing recursive forecasts on the sub-sample spanning from 1990 to 1995, each model is compared in terms of RMSE against a benchmark RW model that assumes no change from its last observed value. The combination of the first two factors, especially from the overall data set, results to outperform the naive model at short horizons of one or two quarters ahead; on the other hand, at longer horizons factors perform relatively poorly and the best model results the one using the M3 growth rate. The HICP index results to be best forecast by the unemployment rate and the first two factors. An important conclusion that can be drawn is that there is no indicator that performs well at every horizon, supporting the opportunity of using a forecasting combination. Moreover, inflation seems to be influenced by pure nominal determinants, given that these latter are strongly correlated with all the factors extracted from price series, and by additional information coming from a wider set of information comprehensive of real-activity variables, given the significant relationship found with the second overall factor.

In conclusion, many previous works have compared different models trying to assess the best model in forecasting inflation, both using US and Euro data. One of the overall conclusions that can be derived is that the best specification varies depending on the sub-sample of data and the country analysed: each indicator, in fact, is the best in capturing specific shocks occurring in the economy in different periods. Forecasting combination represents a possible answer, combining the forecasting accuracy of different indicators at different horizons. A second important conclusion regards the predictive power of artificial factors summarising all the information available in the economy. Augmenting simple univariate or VAR models with artificial factors has a positive and significant impact on the models forecasting accuracy, supporting the hypothesis that there are a small number of common co-movements driving macro indicators.

In what follows, we are going to test the forecasting accuracy of the factor model on Euro data in the period 2008-2009, when the crisis started to hit the Euro countries. Unobservable factors prove to be significantly useful in correctly predicting price changes even on a period characterised by high uncertainty.

3.3 Forecasting models and tests

This forecasting exercise is conducted at country level comparing the predictive accuracy of alternative models in terms of RMSE. The same models are tested for each national inflation series selecting the order of the polynomial lag that gives the best predictive performance.

The benchmark model is the Random Walk specification, where only casual shocks are supposed to occur in the economy otherwise leaving the forecast value h steps ahead equal to the last-observed one:

$$\pi_{i,t+h} = \pi_{i,t} + \epsilon_{i,t+h} \tag{3.6}$$

where $\pi_{i,t}$ represents the inflation index observed in country i at time t.

The first alternative is a simple autoregressive model, where the inflation index is supposed to be influenced only by its own past values:

$$\pi_{i,t} = \mu + \alpha_1 \pi_{i,t-1} + \alpha_2 \pi_{i,t-2} + \ldots + \alpha_p \pi_{i,t-p} + \epsilon_{i,t} \tag{3.7}$$

The best value of p results to be 12 for all the countries considered.

A second alternative is a single-equation model with a moving-average polynomial of the largest factor as predictor. As previous works confirm, there are common co-movements in the economy leading macro indicators such as inflation: summarising all the observable variables in a small number of artificial factors can significantly help the predictive accuracy of a model. The largest unobservable factor is consistently estimated by the largest principal component of X, a mixed-frequency data set of both monthly and quarterly series. Once the largest factor is computed as explained in Chapter 2, each national inflation index is regressed as follows:

$$\pi_{i,t} = \mu + \frac{1}{p} \sum_{k=0}^{p-1} f_{t-k} + \epsilon_{i,t} \tag{3.8}$$

Like in the previous model, in this case the best value for p results 12 too. For German inflation, we find significant improvements in the forecasting accuracy of the model adding the lagged month-on-month oil inflation and the euro-dollar exchange rate, Δp^{oil}_{t-6} and $\Delta p^{\$}_{t-1}$ respectively: therefore, for German HICP index only, the model (3.8) labelled 'MA' includes these extra variables.

A third competing model is a three-variables VAR specification including the industrial production index, the inflation rate and the EONIA interest rate. This is a sort of second benchmark model for multivariate alternatives, as in order to predict future price trends it uses only information from a limited number of variables that does not reflect the whole information actually available about the economic system. Given that a large number of parameters has to be estimated for each variable included in the model, the choice has to be parsimonious, otherwise the degrees of freedom can result too few to assure the robustness of the results. We choose to include the industrial production index and the EONIA interest rate as proxies of real activity and financial markets respectively:

$$\begin{bmatrix} ip_{i,t} \\ cpi_{i,t} \\ EONIA_t \end{bmatrix} = A(L) \begin{bmatrix} ip_{t-1} \\ cpi_{t-1} \\ EONIA_{t-1} \end{bmatrix} + \epsilon_t \tag{3.9}$$

In order to enlarge the information set considered by the VAR, we augment the previous model with the first largest factor, obtaining a four-variable specification:

$$\begin{bmatrix} factor_t \\ ip_{i,t} \\ cpi_{i,t} \\ EONIA_t \end{bmatrix} = A(L) \begin{bmatrix} factor_{t-1} \\ ip_{t-1} \\ cpi_{t-1} \\ EONIA_{t-1} \end{bmatrix} + \epsilon_t \tag{3.10}$$

Doing so, all the information available in the economy is summarised in the artificial variable added as proxy of the common co-movements driving macroeconomic series.

As a last alternative, we regress the national inflation index on the five largest factors and the EONIA rate considered the only observable variable Y_t in the observation equation (2.4). For this model as well we consider the number of lags p that gives the most accurate predictions in terms of RMSE for each national inflation index.

$$\pi_{i,t} = \mu + \sum_{j=1}^{q} \sum_{k=1}^{p} \beta_q f_{q,t-k} + \epsilon_{i,t} \tag{3.11}$$

where q is equal 6, including the five largest estimated factors and the EONIA interest rate. This model results to be significantly more precise in computing Italian inflation forecasts if the lagged oil price growth Δp_{t-3}^{oil} is included, hence from now on where this model (3.11) labelled 'Factor' is mentioned referring to Italian HICP it is augmented by this extra variable.

Each of these models is tested on each national inflation index, estimating the values of the parameters up to observation T and recursively computing out-of-sample forecasts of the dependent variable from time $T+1$ to $T+h$. In what follows we are going to explain the method in detail.

The overall sample of data is divided in two non-overlapping sub-samples: one, going from $t = 1$ to $t = T$, is used for estimation and the subsequent, from $t = T + 1$ to the end of the sample $t = T_{end}$, is used for forecasting. Each model is estimated using data up to T, obtaining estimates of the parameters $\hat{\mu}$, $\hat{\alpha}_i$ or $\hat{\beta}_i$. The dependent variable is then iteratively estimated h times one month ahead:

$$\hat{\pi}_{i,T+s} = \hat{\mu} + \sum_{k=1}^{p} \hat{\gamma}_k \hat{z}_{i,T+s-k} \tag{3.12}$$

where s=1,...,h, $\hat{\gamma}_k$ is the generic coefficient already estimated and z_t is the generic explicative variable. At each iteration the lagged values of the predictors are updated with the values estimated in the previous iteration, while the values of the parameters $\hat{\gamma}_k$ remain the ones estimated on the sample up to T. At each iteration s, the value of the forecast error $e_{i,t+s}^{m}$ of model m is computed as the difference between the estimated and the actual value of the national inflation index:

$$e^m_{i,T+s} = \hat{\pi}_{i,T+s} - \pi_{i,T+s} \tag{3.13}$$

The whole procedure is iteratively repeated estimating all the models up to $T+1$ and computing forecasts h steps ahead and so on up to using all the observations up to $T_{end} - h$ for estimation.

For each model m, each national inflation index i and each step s=*1,...,h*, Root Mean Square Errors are computed as:

$$RMSE_{i,m,s} = \sqrt{\frac{\sum_{j=1}^{n} (e^m_{i,s})^2}{n}} \tag{3.14}$$

where $n = T_{end} - T - h$ is the number of iterative estimations conducted.

Finally, in order to assess the significance of RMSE differences between competing models indicating actual predictive accuracy of one alternative as opposed to the other, we employ different forecasting tests depending on if the two models are nested or not.

If the competing models are non-nested we use the test proposed by Diebold and Mariano[33] to compare their predictive accuracy: suppose that $e^1_{i,t+s}$ and $e^2_{i,t+s}$ are the forecast errors from model *1* and *2* respectively s steps ahead for $s = 1, \ldots, h$. In order to determine if a model predicts better than another we test the null hypothesis

$$H_0 : E[L(e^1_{i,t+s})] = E[L(e^2_{i,t+s})]$$

against the alternative

$$H_1 : E[L(e^1_{i,t+s})] \neq E[L(e^2_{i,t+s})]$$

The Diebold-Mariano test is based on the loss differential

$$d_t = L(e^1_{i,t+s}) - L(e^2_{i,t+s})$$

where L($\cdot$) is the loss function used to measure the predictive accuracy of each model. Diebold and Mariano[33] propose this test assuming that parameters are known in advance; West[55] accounts for parameters estimation error but limits his analysis to continuously differentiable loss functions. McCracken[46] and [47] extends these results to a wider range of loss functions L($\cdot$) in the linear regression framework providing the following t-statistic:

$$DM = n^{1/2} \frac{n^{-1} \sum_{t=T}^{T_{end}} [d_t]}{\hat{\Omega}^{1/2}_{T_{end}}} \tag{3.15}$$

where $n = T_{end} - T - h$ is the number of iterative estimations conducted. The null of equal predictive accuracy is then

$$H_0 : E[d_t] = 0$$

Computation of Equation (3.15) is not always simple because $\hat{\Omega}_{T_{end}}$, representing a consistent estimate of the numerator variance, has to take into account not only sample forecast errors' variability, but also parameters estimation errors, otherwise the statistic can be biased. In a small number of cases, however, parameters errors are negligible, and $\hat{\Omega}_{T_{end}}$ reduces to $Var[L(e^1_{i,t+s}) - L(e^2_{i,t+s})]$, so that Equation (3.15) results the same proposed by Diebold and Mariano[33]. Fortunately, this is the case for the models considered in this analysis, because the loss function L(·) - mean square forecast error - is the same used to consistently estimate regression parameters by OLS. In this case the derivative of the expected loss differential $[EL(e^1_{i,t+s}) - EL(e^2_{i,t+s})]$ evaluated on the population parameters values is zero. Diebold and Mariano[33] show that under the null of equal predictive accuracy it is asymptotically true the following:

$$DM \sim N(0,1)$$

Since we test different non-nested models against the benchmark RW model *1*, we specify the alternative hypothesis as:

$$H_1 : E[L(e^1_{i,t+s})] > E[L(e^2_{i,t+s})]$$

If the loss function of the benchmark model is significantly greater than the one of the alternative model, the latter is more precise in forecasting inflation. Therefore, the competing model beats the naive alternative if

$$DM > 1,64$$

at 5% confidence interval.

Alternatively, if the linear models to be compared are nested, Clark and McCracken[28] propose three different encompassing tests, with asymptotic distribution depending on the value of $\pi = \frac{n}{T}$. These statistics have a standard asymptotic distribution only if the ratio π is negligible, i.e. if, as long as more observations become available, the estimation sample remains significantly larger than the forecast period. Fortunately this is the case, otherwise the encompassing tests would have had a non-standard asymptotic distribution. For the same reason, Mc Cracken[46] focuses on 1-step ahead forecasts: in case of multi-step predictions, in fact, the asymptotic distributions of the tests generally appear to depend on the parameters of the data-generating process.

The three tests are based on the forecast errors covariance $c_{t+1} = e^R_{t+1}(e^R_{t+1} - e^U_{t+1})$ where the superscripts R and U denote the restricted and unrestricted models, respectively. The statistics are:

$$ENC - T = (n-1)^{1/2} \frac{\bar{c}}{\sqrt{n^{-1} \sum_{t=T}^{T_{end}} (c_{t+1} - \bar{c})^2}} \tag{3.16}$$

$$ENC-REG = (n-1)^{1/2}\frac{\bar{c}}{\sqrt{n^{-1}\sum_{t=T}^{T_{end}}(e_{t+1}^{R}-e_{t+1}^{U})^2(n^{-1}\sum_{t=T}^{T_{end}}(e_{t+1}^{R})^2)-\bar{c}^2}} \tag{3.17}$$

$$ENC-NEW = n\frac{\bar{c}}{n^{-1}\sum_{t=T}^{T_{end}}(e_{t+1}^{U})^2} \tag{3.18}$$

where $\bar{c}$ is the errors covariance mean. All these tests are one-sided: if the errors covariance is negative the restricted model encompasses the extended one and the null hypothesis cannot be rejected. The first two tests are asymptotically equivalent under the null, so that critical values are the same. The last test replaces the variance of $\bar{c}$ with the variance of a forecast errors series in the denominator, to take into account the fact that, under the null, residuals from the two models are asymptotically the same, making $\bar{c}$ equal to zero, and so possibly affecting the results in small samples; for these statistics critical values are computed by Clark and McCracken[28] for each value of π.

In conclusion, we compare a number of models in order to identify the most accurate one in predicting Euro countries inflation index from 1 to 12 months ahead. The alternatives reflect different hypotheses underlying price movements: from a naive RW model supposing that no useful information is embedded in the observable variables, to factor models where artificial variables summarising all the available information in the economy are used as predictors. Forecast errors of each competing model are then compared conducting a set of tests of equal forecasting accuracy.

3.4 Data

The data used in this forecasting exercise is the same used to assess the inflation persistence degree in the previous Chapter.

The dependent variable in each model is the national overall inflation index observed from 1995 to 2009 in the three main Euro countries, namely France, Germany and Italy alternatively.

As explained above, 828 monthly series and 45 quarterly series spanning from 1995 to 2009 are collected from different European databases; we report the same Tables 2.1 and 2.2 here again for convenience.[1]

[1]Note to Table 3.1 and 3.2: The transformation codes are: 1 - no transformation; 2 - first difference; 5 - first difference of logarithm. In the last column of Table 3.2, 1 correspond to flow series and 2 to stock series.

Monthly Series		
	No. Series	Trasformation
HICP	450	5
PPI	306	5
Consumption volumes	9	5
Housing Starts	5	5
Unemployment Rate	3	1
Real Output and Income	24	5
Stock Prices	2	5
Exchange Rates	5	5
Interest Rates	15	1
Money Aggregates	4	5
Expectation	5	2
TOTAL	828	

Table 3.1: Monthly series

The considered time period, as said before, is the maximum available for HICP: our interest is in fact in modelling Euro inflation since the constitution of the EU area, given that the common monetary policy of inflation targeting has certainly reduced prices erratic behaviour; moreover, before the adoption of a single currency, common co-movements were less evident and significant in driving key economic indicators. We checked for series seasonality as well: in order to avoid seasonality, we augment the above-described alternative models with monthly dummies taking into account the periodic fluctuations observed in the national inflation indexes.

Having collected data spanning from January 1995 to August 2009, we fix $T = 155$ corresponding to 2007:12 and compute recursive forecasts from 2008:1 to the end of the sample, in this way obtaining a value of $\pi = \frac{9}{155} \approxeq 0$. We choose to split the data in this way for both a statistical and an economic reason.

First, having a negligible value of π, the first two McCracken statistics described in Equations (3.16) and (3.17) are normally distributed, not being affected by small samples bias. Secondly, assessing the models forecasting accuracy after 2007 allows to evaluate how the models would have performed in predicting the effects of the economic crisis that hit the world economy in the same period. Economies worldwide started slowing during this period, as credit tightened and international trade declined. Governments and Central Banks responded with unprecedented fiscal stimulus, monetary policy expansion and institutional bailouts. So it is interesting to test

Quarterly Series			
	No. Series	Trasformation	Flow/Stock
Value Added	1	5	1
Employment Rate	12	5	2
ULC	6	5	1
Consumption Volumes	20	5	1
Gross Income	6	5	1
TOTAL	45		

Table 3.2: Quarterly Series

the models on this unpredictable period of instability.

In conclusion, collecting a wide range of data regarding the three largest Euro countries allows to obtain artificial variables, the factors, signalling common macroeconomic shocks driving inflation indexes. The forecasting exercise, conducted on a period during which Euro area indicators experienced significant and lasting fluctuations, evaluates the predictive power of these factors.

3.5 Results

In what follows we are going to describe the forecasting performance of the competing models described above, both in terms of RMSE and of their relative predicting accuracy.

In particular, two important considerations emerge: first of all, factors have significant forecasting power especially at medium and long horizons, encompassing the predictive accuracy of simple univariate models. These artificial indicators summarise a wide range of economic variables containing important information influencing inflation rates in all the Euro countries analysed.

Secondly, different models result to be the most accurate depending on the forecasting horizon. For German and Italian inflation, in fact, more than one model forecasts are combined in order to obtain more accurate predictions: as previous works confirm, alternative specifications can better model different kinds of shocks hitting the economy; moreover, different variables have significant predictive power depending on the interval of prediction from the last-observed value.

Finally, different models result to be more accurate depending on the national inflation index to be predicted. Factors are generally significant, but German prices are more accurately forecast by a polynomial of the largest factor only, while for predicting Italian prices an auto-regressive model of the five largest factors augmented with the EONIA interest rate is more useful. This explicitly indicates how the forecasting exercise is peculiar to the economy examined, strongly supporting the indirect approach proposed among others by Marcellino et al.[45], who suggest aggregating each country's predictions in order to obtain the Euro area correspondent series.

In Figure B.14 the HICP month-on-month changes of the three largest EU countries, namely Italy, France and Germany, are illustrated. These are the dependent variables to be forecast: as we can see, they have some common features but they not completely alike. All the national indexes show the most negative changes in January from December of the previous year, probably due to the annual review of the weighting system of the panel of products composing the index; the highest peaks, on the opposite, are not observed in the same months because of different price review timing in the three countries.

Seasonality is present in all the three series, but its influence is stronger on Italian inflation, especially from 2000 when sales prices started to be recorded. Italian inflation is in fact the most volatile, so that it results difficult to predict the future price trend in this case; therefore artificial variables collecting all the information available about the economy significantly help predicting price changes.

Figure B.15 illustrates alternative models performance in terms of RMSE when predicting the French inflation index. Compared to the RW benchmark model, the Factor specification gives less accurate predictions, while the other models result to outperform the naive alternative, namely the simple univariate autoregression model, the three-variable VAR model and the same VAR augmented with the first factor, respectively described in Equations (3.7), (3.9) and (3.10). At longer horizons, the MA model (3.8) gives accurate predictions too.

The values of the Root Mean Square Error are reported in Table A.16: the RW gives the lowest errors only 12 months ahead, while at the other forecasting horizons different alternatives result the most accurate. The MA model results the best in predicting French inflation one month ahead, while the simple univariate alternative is the most accurate 2 and 3 steps ahead. At medium horizons multivariate models produce the most precise forecasts: from 4 to 6 months ahead the best model results the VAR augmented with the largest factor, while from 7 to 9 months ahead the three-variable VAR is preferred. Finally, at longer horizons up to 11 months ahead, the most accurate model is the MA again.

In order to assess the significance of the different performances, in Table A.19 we report the value of the Diebold and Mariano[33] statistic for non-nested alternatives calculated as Equation (3.15) illustrates. The univariate AR and the VAR models significantly outperform the benchmark alternative 7 and 8 moths ahead, while the MA model gives significantly more accurate predictions at longer horizons of 10 and 11 months. Finally, the low value of RMSE provided by the naive model at 12 months horizon is not significantly different from the alternatives.

The McCracken statistics are used to test the predictive power of nested alternatives, as the VAR against the same model augmented with the first factor. Applying the models to the French inflation index, the tests are not significant, therefore the null hypothesis is not rejected and the simpler alternative model is valid.

In conclusion, the best models in predicting French inflation result to be the simple univariate autoregression model, the three-variable VAR model and the same VAR augmented with the first factor; at long horizons the MA model results to significantly outperform the benchmark as well.

The same models perform differently when forecasting German inflation.

As Figure B.16 illustrates, the Factor model and the three-variable VAR even if augmented with the first factor result to poorly predict price changes in this case; on the other hand, the univariate AR model illustrated in Equation (3.7) and the moving average of the largest factor reported in Equation (3.8) perform better than the benchmark alternative.

As Table A.17 confirms, the AR model gives more accurate predictions at short horizons up to 3 months ahead, while at medium and long horizons the moving average alternative is more precise. Therefore, in order to take advantage of the models different abilities in correctly predicting price changes, we choose to combine the two alternatives as Table 3.3 illustrates.

h	**Model**	*lags*	*Extra exogenous variables*
1-3	AR	12	
4-12	$MA(f_1)$	1,6,12	$\Delta log(p^{oil}_{t-6})$, $\Delta log(p^{\$}_{t-1})$

Table 3.3: Model for German Inflation

The benchmark RW model results to give the most precise predictions only at 7 months-forecast horizon, but, as Table A.20 reports, this difference is not significant. On the contrary, the combined model results to significantly outperform the naive alternative at short, medium and long horizons, in particular 1, 4, 6, 8, 10 and 11 months ahead.

Even if the two nested multivariate alternatives, namely the VAR and the same model augmented with the first factor, are not better than the RW in forecasting German inflation, nonetheless the McCracken test ENC-T (3.16) results to be significant (equal to 2.39 against a critical value of 1.64 at 5% confidence interval), indicating that the actual forecasting power of the added artificial variable does not depend on the particular sample of data considered.

In conclusion, German inflation results to be accurately predicted by single-equation models, conside-
ring just one or two exogenous variables and drawing all the current and past information available about the economy from the first principal component extracted from a wide set of observable economic series.

Moreover, this country represents a valid example confirming two above-mentioned important issues about inflation forecasting. First of all, it proves that inflation forecasting is significantly improved by artificial factors containing information about macroeconomic shocks driving leading economic indicators; secondly, it confirms that combining forecasts from alternative models can result the best method to accurately take into account the different shocks influencing price series.

Finally, we illustrate the forecasting performance of the alternative models on the Italian inflation index.

As Figure B.17 illustrates, in this case as observed for German prices the VAR model does not outperform the Random Walk, even if augmented by the first factor. The other alternatives, namely the AR, the MA and the Factor models, forecast more accurately than the benchmark model, even if this latter provides lowest errors 6 and 12 months ahead, probably due to the high seasonal fluctuations that characterise this index.

As shown in Table A.18, the RW provides the lowest errors only at a forecasting horizon of 12 months, while other models are more precise at short, medium and long horizons respectively. The MA alternative is the best 1 and 2 steps ahead; the simple univariate AR model is the most accurate in forecasting inflation 3 and 4 months after the last-observed value; the Factor model gives the best predictions from 5 to 11 months ahead. Therefore, we choose to combine the before-mentioned three models as the following Table 3.4 illustrates.

h	**Model**	*lags*	*Extra exogenous variables*
1-2	$MA(f_1)$	12	
3-4	AR	12	
5-12	$Factor(f_1, f_2, f_3, f_4, f_5, EONIA)$	7	$\Delta log(p^{oil}_{t-3})$

Table 3.4: Model for Italian Inflation

Table A.21 reports the Diebold and Mariano[33] test values: the alternative models result to significantly out-perform the RW 1 and 2 months ahead; at medium and long horizons, the

Factor model is significantly more accurate 7 and 9 months ahead considering a 10% confidence interval.

The poor forecasting performance of the competing models at horizons of 6 and 12 months depends on the data seasonality, that strongly influences month-on-month price changes. Considering the annual inflation rate for long horizons improves the forecasting performance of the models, in particular of the factor alternatives. Therefore, as the following Table 3.5 illustrates, MA monthly forecasts for short and medium horizons are combined with Factor yearly predictions for long horizons. As Figure B.18 shows, this combined model significantly outperforms the RW benchmark.

h	*Endogenuos*	**Model**	*lags*	*Extra exogenous variables*
1-5	$\Delta log(p^I)$	$MA(f_1)$	12	
6-8		*Linear interpolation*		
9-12	$\Delta_{12} log(p^I)$	$Factor(f_1, f_2, f_3, f_4, f_5, EONIA)$	5	$\Delta log(p^{oil}_{t-1})$

Table 3.5: Combined model for Italian Inflation

Italy is the only country among those examined whose inflation is accurately predicted by the Factor model considering as exogenous variables both observable and unobservable factors as in Equation (2.4) extracted from a wide set of economic series regarding the Euro area. At medium and long horizons of predictions, these diffusion indexes prove to predict more accurately than both univariate and single-factor models, signalling that there are macroeconomic shocks influencing prices especially in the long-run.

As previously said for German inflation, the analysis on Italian HICP confirms the same important results: first of all, combining different models depending on the forecast horizon is a useful method to take into account different kinds of shocks hitting the economy; secondly, summarising all the available information in a small set of factors is determinant for accurately forecasting price changes.

In conclusion, the forecasting exercise has highlighted some interesting features to take into account when predicting inflation.

First of all, the same models forecast quite differently depending on the country analysed: therefore, we recommend to use an indirect approach when forecasting aggregate series both because of the different predicting ability of alternative models in catching the influence of shocks on different countries prices and because of the possible offsetting of the error series in the aggregation process.

Secondly, even when forecasting the same inflation index, alternative models can result more or less accurate depending on the horizon of prediction. For this reason combining different models predictions can significantly improve the result.

Third, artificial variables, estimated extracting all the information available in the economy, provide significantly more precise forecasts, isolating the macro co-movements driving leading indicators like inflation. These variables are important especially at medium and long horizons capturing economy-wide shocks that can have greater impact in the long-run.

3.6 Conclusion

The results of the forecasting exercise show that diffusion indexes summarising all the information available in the economy have significant forecasting power in predicting national inflation; moreover, the forecasting simulation has been conducted on a period of high and widespread instability following the economic crisis that started in the United States at the end of 2007. Forecasting economic indicators in a period of high uncertainty requires every possible information about the country, given that economic agents decisions can be differently influenced in the short, medium and long run; moreover, the agents' expectations can change quite rapidly as more information about the effects of the economic crisis becomes available. Even if tested on a period of such instability and uncertainty in the economy, factor models prove to be significantly useful in predicting inflation.

Factors result to have forecasting power especially at medium and long horizons of prediction, while simple univariate models are more accurate in predicting 1 or 2 months ahead. Moreover, factors can be used in different econometric frameworks to build an accurate forecasting model: while for German inflation the best specification results a moving average polynomial of the first largest factor only, Italian HICP is accurately predicted by the first five unobservable factors plus the EONIA interest rate considered the observable indicator for monetary shocks.

In conclusion, this forecasting exercise presents innovative features both in the econometric method used and in the data set considered, finding interesting results for predictions of the French, German and Italian inflation index. As more Euro data becomes available, forecasting accuracy can be tested on a longer span of data possibly considering a larger number of countries and computing overall Euro area inflation forecasts by aggregating national predictions.

Conclusions

Modelling inflation dynamics requires different data and methodologies depending on the aim of the study: we described above three different ways to analyse prices behaviour responding to alternative objectives and needs.

In Chapter 1 we shed some light on the level of aggregation used at the Banca d'Italia and on the difficulty in setting up a tool that provides both accurate short-term (one/two steps ahead) forecasts and credible inflation projections over the medium-term. The best level of aggregation to choose is still a controversial matter: on one hand, in fact, predicting the aggregate index directly allows for a simpler implementation and a more rapid calculation; alternatively, each sub-index can be forecast separately, obtaining the overall inflation as a weighted sum of the sectors' prices growth rates. This indirect approach has several advantages: first of all, different variables result to have a significant effect on the main sub-indices; moreover, the influence of seasonality and climatic changes is better identified analysing each sector separately, as they are mainly determinant on sectors as clothing and unprocessed food respectively; finally, other researches confirm that forecasting errors from different sectors cancel out in the aggregation process providing more accurate predictions.

Alternatively, prices behaviour can be analysed in terms of inflation stickiness, computing prices variability and sluggishness after a shock. Previous studies on price stickiness have pointed out a different behaviour of aggregated and sectoral inflation after a monetary shock: while overall and main components indices are quite sluggish in response to macroeconomic disturbances, sector prices are more volatile and rapidly return to their long-run equilibrium; moreover, while aggregated indices respond more to common component variations, disaggregated inflation variability is mostly due to the sector-specific component that accounts for almost 80% of their total volatility. In addition, most of the literature is based on US data, given their availability in a detailed form and for a long time period; EU data, instead, is not always published in a comparable form for all the countries, in some cases it has to be collected from national sources and made homogeneous in the time period and in the product category. We build up a large data set regarding the three main EU countries, namely France, Germany and Italy, gathering series from both European databases and national statistics institutes.

In Chapter 2, we use a large set of information to compute artificial variables able to predict inflation dynamics in the main EU countries after shocks from different sources; the FAVAR model permits to identify a monetary shock and to analyse its effects on prices at different levels of aggregation. In order to compute the factors, we implement the FAVAR model considering both monthly and quarterly series, as some important information is embedded in economic variables released only every three months. Our findings about the low price persistence degree and the consequent transient effects of a monetary shock on sectoral inflation are quite surprising: monetary policy results to have a weak impact on prices in the medium and long-run.

In Chapter 3 we explored the issue of forecasting inflation considering some innovative features respect to the previous literature regarding both the collected data and the compared econometric methods. Standard models allow only a limited number of exogenous variables to avoid the degrees of freedom problem; therefore, the series to include have to be selected in a parsimonious perspective inevitably omitting important information. Estimating factors summarising all the information available in the economy solves this problem: every observable series is included in the information set from which the common components are extracted, therefore the macroeconomic co-movements driving leading indicators like inflation sum up all the different kinds of shocks hitting the economy. Moreover, the increasing importance of common policies and integrated markets makes factor models more and more useful summarising shocks coming from other countries but influencing the economic system observed. The recent financial crisis has shown how the world economies are closely connected in a global system where every shock has to taken into account given its influence on all the countries involved. Therefore, considering all the information available can be very useful when analysing prices dynamics both in terms of persistence degree and of forecasting.

Given the above-mentioned peculiarity of inflation forecasting, the best model to predict price changes differs depending on the aim of the study. One of the main conclusions of this work is in fact that prediction is peculiar to the specific series taken into account, so that the most accurate model depends on the economic indicator, the country and the period of data considered. Enlarging the number of countries considered and confirming the validity of the factor models proposed as more data becomes available are in our view important steps for future research.

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Appendix A

Tables

	Services		**NEI-Goods**		**Cloth-Footwear**		**Proc. Food**		**Unp. Food**		**Energy**	
Horizon	Naive	Model	Naive	Model	Naive	Model	Naive	Model	Naive	Model	Naive	Model
1	0.19	0.19	0.11	**0.10**	1.81	**0.87**	0.19	**0.16**	**0.52**	0.54	2.87	**1.50**
2	**0.22**	0.27	0.15	**0.13**	2.48	**0.94**	0.32	**0.22**	0.96	**0.79**	4.20	**1.61**
3	0.26	**0.25**	0.18	**0.14**	2.68	**0.86**	0.46	**0.31**	1.35	**1.04**	4.46	**1.65**
4	0.32	**0.24**	0.19	**0.16**	2.53	**0.84**	0.63	**0.44**	1.72	**1.25**	4.98	**1.90**
5	0.36	**0.25**	0.19	**0.16**	1.95	**0.91**	0.82	**0.61**	2.04	**1.43**	5.81	**1.89**
6	0.40	**0.25**	0.20	**0.17**	**0.75**	1.00	1.01	**0.76**	2.33	**1.61**	6.77	**1.76**
7	0.45	**0.26**	0.21	**0.17**	1.94	**0.90**	1.20	**0.92**	2.58	**1.77**	7.84	**1.67**
8	0.47	**0.25**	0.21	**0.16**	2.64	**0.83**	1.40	**1.10**	2.78	**1.89**	8.94	**1.70**
9	0.51	**0.26**	0.22	**0.16**	2.73	**0.93**	1.62	**1.30**	2.96	**2.02**	9.65	**1.79**
10	0.55	**0.25**	0.22	**0.17**	2.53	**0.90**	1.83	**1.51**	3.06	**2.12**	10.01	**1.85**
11	0.57	**0.25**	0.22	**0.17**	1.90	**1.08**	2.02	**1.70**	3.10	**2.17**	10.92	**2.08**
12	0.61	**0.25**	0.23	**0.18**	**0.78**	1.19	2.20	**1.87**	3.11	**2.10**	12.05	**2.31**
13	0.62	**0.25**	0.21	**0.17**	**0.94**	0.98	2.38	**2.05**	3.10	**2.03**	12.76	**1.56**
14	0.66	**0.25**	0.20	**0.18**	1.00	**0.94**	2.53	**2.21**	3.06	**1.90**	13.10	**1.51**
15	0.68	**0.25**	0.19	0.19	**0.98**	0.99	2.65	**2.34**	3.04	**1.79**	13.29	**1.50**

Table A.1: Recursive root mean squared forecast error 2004-2008, 1 to 15 months ahead

Note to Table A.1: the forecast errors are computed over year-on-year inflation rates. The naive forecast for year-on-year inflation h steps ahead ($\Delta_{12}log(P_{t+h})$) is current inflation ($\Delta_{12}log(P_t)$). The lowest RMSFE for each index is printed in bold face.

	Services		**NEI-Goods**		**Cloth-Footwear**		**Proc. Food**		**Unp. Food**		**Energy**	
Horizon	Naive	Model	Naive	Model	Naive	Model	Naive	Model	Naive	Model	Naive	Model
1	0.19	**0.18**	0.11	0.11	1.72	**0.83**	0.20	**0.17**	0.36	**0.32**	2.48	**1.77**
2	0.19	**0.17**	0.11	0.11	1.73	**0.87**	0.23	**0.20**	0.36	**0.34**	3.27	**1.03**

Table A.2: Recursive root mean squared forecast error 2004-2008, 1 to 2 months ahead

Note to Table A.2: the forecast errors are computed over month-on-month inflation rates. The naive model is a constant plus seasonal dummies. The lowest RMSFE for each index is printed in bold face.

Effects of a 10% NEER shock		Effects of a 10% FCI shock			Effects of a 10% OIL shock	
Months ahead	**NEI Goods**	Months ahead	**Proc. Food**	**Unproc. Food**	Months ahead	**Fuels and lubricants**
1	0,0	1	0,0	0,0	1	1,3
2	0,0	2	0,1	0,0	2	2,2
3	0,0	3	0,1	0,0	3	2,3
4	0,0	4	0,2	0,0	4	2,4
5	0,0	5	0,2	0,0	5	2,3
6	0,0	6	0,3	0,1	6	2,0
7	0,0	7	0,3	0,1	7	2,0
8	0,0	8	0,4	0,1	8	2,2
9	0,0	9	0,5	0,1	9	2,4
10	0,0	10	0,6	0,2	10	2,6
11	-0,1	11	0,6	0,2	11	2,9
12	-0,1	12	0,7	0,2	12	3,1
13	-0,1	13	0,8	0,3	13	1,6
14	-0,1	14	0,8	0,3	14	0,6
15	-0,1	15	0,8	0,3	15	0,5
Average first year	0,0	**Average first year**	0,4	0,1	**Average first year**	2,0
On Overall HICP	0,0	**On Overall HICP**	0,1		**On Overall HICP**	0,1
PUE	-0,4	**PUE**	NA		**PUE**	0,1

Table A.3: Impact of a 10% shock to an exogenous variable on HICP (%)

Note to Table A.3: the effect of the shocks on headline inflation is simply obtained by multiplying the effects on the sub-components by their weight in the HICP basket. The effect of an FCI shock on services inflation (via unprocessed food inflation) is negligible in the first twelve months and therefore it is not shown. The effect of an oil shock on energy tariffs is excluded from this exercise for comparability with the quarterly PUEs which consider only the effect on fuels inflation. Also for comparability the PUE reported for the oil shock is only the elasticity with respect to the HICP energy component (the effect on total inflation through non-energy HICP is an additional 0.03%).

FRANCE		Std dev (in%)				Persistence		
		Infl	**CommComp**	**Sector Spec**	R^2	**Infl**	**CommComp**	**Sector Spec**
Aggreg P	**HICP**	0,27	0,24	0,13	0,78	0,09	0,42	0,28
	Food	0,62	0,40	0,47	0,42	0,27	0,72	0,38
	Proc FoodNAT	0,25	0,10	0,22	0,16	0,63	0,77	0,58
	Proc FoodAT	0,38	0,18	0,33	0,23	0,49	0,78	0,49
	Unproc F	1,06	0,66	0,83	0,39	-0,13	0,74	0,40
	Goods	0,49	0,45	0,20	0,83	-0,15	0,27	0,23
	Cloth	3,45	3,07	1,58	0,79	-6,30	-0,08	-0,39
	Energy	1,55	1,40	0,67	0,81	-0,02	0,22	-0,04
	Serv	0,28	0,25	0,14	0,75	0,71	0,83	0,27
All	**Average**	2,73	1,00	2,45	0,22	-0,54	0,62	-0,42
	Median	1,88	0,75	1,46	0,14	-0,28	0,65	-0,32
	Min	0,14	0,04	0,13	0,01	-6,65	-0,10	-3,05
	Max	16,84	5,63	16,45	0,86	0,92	1,11	0,89
	Std	2,81	1,00	2,71	0,21	1,26	0,23	0,86
CPI	**Average**	1,05	0,65	0,76	0,29	-0,32	0,67	0,06
	Average (weighted)	2,05	1,39	1,37	0,86	-0,47	1,47	0,17
	Median	0,47	0,20	0,42	0,18	0,26	0,74	0,20
	Min	0,14	0,04	0,13	0,01	-6,65	-0,10	-1,59
	Max	7,81	5,63	5,41	0,86	0,92	1,11	0,84
	Std	1,37	1,06	0,93	0,24	1,47	0,27	0,56
PPI	**Average**	4,72	1,40	4,45	0,14	-0,81	0,56	-0,97
	Median	4,31	1,33	4,09	0,09	-0,58	0,58	-0,89
	Min	0,65	0,19	0,62	0,01	-3,58	0,17	-3,05
	Max	16,84	4,21	16,45	0,69	0,82	1,00	0,89
	Std	2,78	0,75	2,77	0,13	0,88	0,16	0,82

Table A.4: Summary Statistics for France

Note to Table A.4: Sample is 1995:1 2009:8. Inflation is measured as $\pi_{it} = p_{it} - p_{it-1}$ where p_{it} is the log of the price series i. Common components are $\lambda_i C_t$. Sector-specific components are ϵ_{it}. R^2 statistics measure the fraction of the variance of π_{it} explained by $\lambda_i C_t$. Persistence is based on estimated AR processes with 13 lags. Weighted average of statistics for disaggregated CPI series is obtained using expenditure shares in year 2005 as weights.

GERMANY		Std dev (in%)				Persistence		
		Infl	**CommComp**	**Sector Spec**	R^2	**Infl**	**CommComp**	**Sector Spec**
Aggreg P	**HICP**	0,34	0,26	0,22	0,59	0,01	0,45	0,09
	Food	0,73	0,51	0,52	0,49	0,45	0,77	0,51
	Proc FoodNAT	0,32	0,12	0,30	0,13	0,63	0,74	0,62
	Proc FoodAT	0,42	0,15	0,39	0,13	0,25	0,76	-0,13
	Unproc F	1,39	0,95	1,02	0,46	-0,02	0,81	0,73
	Goods	0,39	0,35	0,19	0,78	0,04	0,41	0,17
	Cloth	0,96	0,81	0,52	0,70	0,33	0,48	-0,21
	Energy	1,65	1,47	0,75	0,79	0,04	0,10	-0,50
	Serv	0,79	0,69	0,40	0,75	-0,64	0,41	0,28
All	**Average**	0,97	0,51	0,77	0,20	0,12	0,69	0,15
	Median	0,43	0,15	0,39	0,15	0,34	0,72	0,19
	Min	0,14	0,03	0,10	0,01	-7,68	0,01	-1,49
	Max	11,09	9,51	5,70	0,83	1,17	1,03	0,95
	Std	1,52	1,21	0,96	0,18	0,89	0,19	0,41
CPI	**Average**	1,02	0,60	0,76	0,22	0,04	0,70	0,19
	Average (weighted)	2,24	1,54	1,49	0,86	-0,71	1,48	0,14
	Median	0,38	0,15	0,34	0,16	0,33	0,74	0,27
	Min	0,14	0,03	0,13	0,01	-7,68	0,01	-1,00
	Max	11,09	9,51	5,70	0,78	1,17	1,00	0,95
	Std	1,79	1,50	1,04	0,20	1,13	0,20	0,40
PPI	**Average**	0,90	0,41	0,78	0,18	0,22	0,68	0,09
	Median	0,49	0,16	0,44	0,13	0,35	0,70	0,15
	Min	0,14	0,03	0,10	0,01	-1,84	0,08	-1,49
	Max	7,64	5,79	4,98	0,83	0,99	1,03	0,71
	Std	1,12	0,75	0,86	0,15	0,47	0,19	0,41

Table A.5: Summary Statistics for Germany

Note to Table A.5: See Table A.4.

ITALY		**Std dev (in%)**				**Persistence**		
		Infl	**CommComp**	**Sector Spec**	R^2	**Infl**	**CommComp**	**Sector Spec**
Aggreg P	**HICP**	0,44	0,38	0,23	0,73	-0,07	0,33	-0,27
	Food	0,29	0,20	0,21	0,47	0,69	0,75	0,33
	Proc FoodNAT	0,23	0,15	0,17	0,45	0,70	0,79	0,68
	Proc FoodAT	0,30	0,15	0,26	0,25	0,38	0,74	0,22
	Unproc F	0,44	0,27	0,35	0,36	0,61	0,75	0,43
	Goods	0,44	0,27	0,35	0,36	0,61	0,75	0,43
	Cloth	4,16	3,61	2,06	0,75	-3,44	0,31	0,04
	Energy	1,21	0,97	0,73	0,64	0,25	0,31	0,13
	Serv	0,23	0,15	0,18	0,43	0,00	0,70	0,67
All	**Average**	0,91	0,48	0,73	0,23	0,06	0,67	0,07
	Median	0,53	0,21	0,49	0,19	0,18	0,71	0,11
	Min	0,13	0,05	0,11	0,02	-3,69	-0,17	-1,66
	Max	6,12	3,85	4,91	0,78	0,86	0,98	0,79
	Std	0,97	0,76	0,67	0,18	0,68	0,18	0,44
CPI	**Average**	0,96	0,53	0,74	0,24	-0,05	0,66	0,11
	Average (weighted)	2,53	1,82	1,60	1,00	-1,14	1,44	0,04
	Median	0,52	0,19	0,50	0,19	0,17	0,71	0,14
	Min	0,13	0,05	0,11	0,02	-3,69	-0,17	-1,66
	Max	6,12	3,85	4,91	0,78	0,86	0,94	0,79
	Std	1,13	0,89	0,76	0,20	0,87	0,20	0,48
PPI	**Average**	0,86	0,41	0,73	0,22	0,18	0,67	0,02
	Median	0,54	0,22	0,48	0,18	0,19	0,71	0,08
	Min	0,22	0,09	0,20	0,02	-0,68	0,15	-0,92
	Max	3,44	2,94	2,60	0,78	0,76	0,98	0,64
	Std	0,74	0,55	0,54	0,17	0,31	0,15	0,37

Table A.6: Summary Statistics for Italy

Note to Table A.6: See Table A.4.

FRANCE

All P	**Sd(π)**	**Sd($\lambda'C$)**	**Sd(ϵ)**	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,73	0,99	-0,20	-0,43	-0,15	-0,51	-0,13	-0,24	-0,17	-0,40
Sd($\lambda'C$)		1,00	0,62	0,34	-0,53	-0,41	-0,19	-0,28	-0,24	-0,36	-0,48
Sd(ϵ)			1,00	-0,32	-0,36	-0,08	-0,54	-0,07	-0,23	-0,13	-0,38
R^2				1,00	-0,18	-0,44	0,34	-0,33	0,03	-0,08	0,06
$\rho(\pi)$					1,00	0,40	0,44	0,30	-0,01	0,26	0,16
$\rho(\lambda'C)$						1,00	0,26	0,38	0,16	0,26	0,23
$\rho(\epsilon)$							1,00	0,15	0,19	0,03	0,13
AC1								1,00	0,51	-0,13	-0,13
AC12									1,00	-0,07	0,16
IRF6										1,00	0,88
IRF12											1,00

CPI	**Sd(π)**	**Sd($\lambda'C$)**	**Sd(ϵ)**	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,96	0,95	0,50	-0,71	-0,41	-0,14	-0,32	-0,07	-0,48	-0,35
Sd($\lambda'C$)		1,00	0,82	0,66	-0,71	-0,53	-0,13	-0,41	-0,11	-0,37	-0,23
Sd(ϵ)			1,00	0,28	-0,62	-0,23	-0,12	-0,17	-0,01	-0,53	-0,44
R^2				1,00	-0,46	-0,68	-0,09	-0,49	-0,12	-0,14	-0,01
$\rho(\pi)$					1,00	0,46	0,35	0,36	0,02	0,48	0,28
$\rho(\lambda'C)$						1,00	0,30	0,59	0,34	-0,04	-0,22
$\rho(\epsilon)$							1,00	0,18	0,09	0,00	-0,09
AC1								1,00	0,53	0,01	-0,16
AC12									1,00	-0,18	-0,20
IRF6										1,00	0,94
IRF12											1,00

PPI	**Sd(π)**	**Sd($\lambda'C$)**	**Sd(ϵ)**	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,64	1,00	-0,42	-0,29	0,38	-0,22	-0,14	-0,01	0,17	0,00
Sd($\lambda'C$)		1,00	0,58	0,20	0,05	0,12	0,26	-0,02	-0,15	-0,27	-0,56
Sd(ϵ)			1,00	-0,48	-0,31	0,38	-0,26	-0,15	0,00	0,20	0,06
R^2				1,00	0,39	-0,19	0,59	0,18	-0,09	-0,34	-0,42
$\rho(\pi)$					1,00	0,08	0,61	0,13	-0,24	0,05	-0,05
$\rho(\lambda'C)$						1,00	0,02	-0,25	-0,28	0,53	0,43
$\rho(\epsilon)$							1,00	0,28	-0,08	-0,26	-0,37
AC1								1,00	0,70	-0,34	-0,23
AC12									1,00	-0,20	0,01
IRF6										1,00	0,92
IRF12											1,00

Table A.7: French Inflation Cross-Sectional Correlations

Notes to Table A.7: Sample is 1995:1-2009:8. Sd(π_i) = standard deviation of sectoral inflation π_{it} over time; Sd($\lambda'C$) = st. dev. of the component of π_{it} driven by common factors; Sd(ϵ_i) = st. dev. of sector-specific component; $\rho()$ represents the persistence measure mentioned in Table A.4. AC1 and AC12 are the first- and twelfth-order autocorrelations of the inflation response of π_{it} to a monetary policy shock. IRF6 and IRF12 are price level responses to a monetary shock,at horizons of 6 and 12 months, expressed in percent deviations from price level prior to shock.

GERMANY

All P	**Sd**(π)	**Sd**($\lambda'C$)	**Sd**(ϵ)	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,97	0,96	0,48	-0,66	-0,37	0,02	-0,48	-0,08	-0,01	0,09
Sd($\lambda'C$)		1,00	0,85	0,59	-0,70	-0,35	0,03	-0,55	-0,08	0,05	0,18
Sd(ϵ)			1,00	0,34	-0,55	-0,36	0,00	-0,34	-0,07	-0,08	-0,03
R^2				1,00	-0,31	-0,37	-0,01	-0,49	-0,21	0,01	0,08
$\rho(\pi)$					1,00	0,24	0,27	0,66	-0,06	-0,05	-0,25
$\rho(\lambda'C)$						1,00	0,18	0,35	0,40	-0,18	-0,14
$\rho(\epsilon)$							1,00	0,02	-0,04	-0,08	-0,06
AC1								1,00	0,42	-0,19	-0,32
AC12									1,00	-0,13	-0,07
IRF6										1,00	0,95
IRF12											1,00

CPI	**Sd**(π)	**Sd**($\lambda'C$)	**Sd**(ϵ)	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,98	0,96	0,54	-0,83	-0,38	-0,03	-0,58	0,06	0,21	0,49
Sd($\lambda'C$)		1,00	0,89	0,63	-0,84	-0,37	0,00	-0,63	0,03	0,24	0,53
Sd(ϵ)			1,00	0,42	-0,77	-0,38	-0,08	-0,47	0,09	0,16	0,41
R^2				1,00	-0,49	-0,43	-0,15	-0,58	-0,18	0,16	0,34
$\rho(\pi)$					1,00	0,30	0,10	0,74	-0,09	-0,03	-0,31
$\rho(\lambda'C)$						1,00	0,20	0,46	0,47	-0,38	-0,41
$\rho(\epsilon)$							1,00	0,04	0,02	-0,17	-0,13
AC1								1,00	0,34	-0,15	-0,34
AC12									1,00	-0,12	-0,08
IRF6										1,00	0,93
IRF12											1,00

PPI	**Sd**(π)	**Sd**($\lambda'C$)	**Sd**(ϵ)	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,94	0,98	0,34	0,05	-0,36	0,09	-0,04	-0,34	-0,49	-0,61
Sd($\lambda'C$)		1,00	0,85	0,51	0,07	-0,36	0,08	-0,08	-0,34	-0,48	-0,59
Sd(ϵ)			1,00	0,21	0,06	-0,33	0,10	0,01	-0,30	-0,48	-0,61
R^2				1,00	0,33	-0,30	0,16	-0,19	-0,27	-0,30	-0,34
$\rho(\pi)$					1,00	0,13	0,88	0,09	-0,03	-0,10	-0,12
$\rho(\lambda'C)$						1,00	0,16	0,18	0,32	0,08	0,14
$\rho(\epsilon)$							1,00	0,07	-0,09	-0,01	-0,05
AC1								1,00	0,80	-0,29	-0,26
AC12									1,00	-0,14	-0,06
IRF6										1,00	0,98
IRF12											1,00

Table A.8: German Inflation Cross-Sectional Correlations

Notes to Table A.8: See Table A.7.

ITALY

All P	**Sd(π)**	**Sd($\lambda'C$)**	**Sd(ϵ)**	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,93	0,94	0,49	-0,63	-0,39	-0,26	-0,27	-0,06	-0,27	-0,16
Sd($\lambda'C$)		1,00	0,75	0,72	-0,67	-0,46	-0,19	-0,32	-0,06	-0,26	-0,08
Sd(ϵ)			1,00	0,22	-0,50	-0,26	-0,29	-0,18	-0,03	-0,30	-0,25
R^2				1,00	-0,34	-0,42	0,04	-0,24	-0,03	-0,27	-0,10
$\rho(\pi)$					1,00	0,36	0,51	0,32	-0,08	0,04	-0,17
$\rho(\lambda'C)$						1,00	0,20	0,34	0,10	0,20	0,11
$\rho(\epsilon)$							1,00	0,12	-0,01	0,17	0,14
AC1								1,00	0,52	-0,07	-0,16
AC12									1,00	-0,14	-0,08
IRF6										1,00	0,94
IRF12											1,00

CPI	**Sd(π)**	**Sd($\lambda'C$)**	**Sd(ϵ)**	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,94	0,94	0,56	-0,78	-0,33	-0,35	-0,32	0,05	-0,26	-0,01
Sd($\lambda'C$)		1,00	0,77	0,76	-0,81	-0,41	-0,25	-0,41	0,04	-0,22	0,11
Sd(ϵ)			1,00	0,30	-0,65	-0,19	-0,41	-0,19	0,06	-0,32	-0,18
R^2				1,00	-0,51	-0,42	0,04	-0,45	-0,03	-0,18	0,14
$\rho(\pi)$					1,00	0,47	0,53	0,38	-0,14	0,19	-0,11
$\rho(\lambda'C)$						1,00	0,30	0,44	0,14	0,22	0,03
$\rho(\epsilon)$							1,00	0,19	-0,10	0,27	0,21
AC1								1,00	0,39	0,09	-0,10
AC12									1,00	-0,05	0,03
IRF6										1,00	0,89
IRF12											1,00

PPI	**Sd(π)**	**Sd($\lambda'C$)**	**Sd(ϵ)**	R^2	$\rho(\pi)$	$\rho(\lambda'C)$	$\rho(\epsilon)$	**AC1**	**AC12**	**IRF6**	**IRF12**
Sd(π)	1	0,90	0,94	0,34	0,01	-0,54	-0,07	-0,16	-0,25	-0,36	-0,44
Sd($\lambda'C$)		1,00	0,68	0,65	0,03	-0,60	-0,08	-0,10	-0,25	-0,40	-0,46
Sd(ϵ)			1,00	0,07	0,02	-0,42	-0,04	-0,16	-0,19	-0,31	-0,40
R^2				1,00	0,26	-0,42	0,04	0,11	-0,03	-0,41	-0,42
$\rho(\pi)$					1,00	-0,07	0,72	0,09	0,08	-0,22	-0,26
$\rho(\lambda'C)$						1,00	0,00	0,15	0,04	0,21	0,26
$\rho(\epsilon)$							1,00	0,01	0,12	0,04	0,01
AC1								1,00	0,71	-0,24	-0,21
AC12									1,00	-0,23	-0,20
IRF6										1,00	0,98
IRF12											1,00

Table A.9: Italian Inflation Cross-Sectional Correlations

Notes to Table A.9: See Table A.7.

FRANCE		Autocorr of P condit on a shock				P responses (%)	
		1st order	3rd order	6th order	12th order	6 mo.	12 mo.
Aggreg P	**HICP**	0,97	0,91	0,81	0,64	-0,06	-0,04
	Food	0,97	0,90	0,81	0,64	-0,09	-0,05
	Proc FoodNAT	0,97	0,89	0,74	0,47	0,01	0,01
	Proc FoodAT	0,97	0,92	0,84	0,69	-0,05	-0,05
	Unproc F	0,97	0,91	0,82	0,66	-0,19	-0,14
	Goods	0,97	0,90	0,79	0,61	-0,07	-0,04
	Cloth	0,68	0,52	0,32	0,14	-0,25	0,01
	Energy	0,91	0,64	0,18	-0,18	0,03	0,00
	Serv	0,97	0,92	0,82	0,67	-0,05	-0,06
All	**Average**	0,95	0,86	0,71	0,45	-0,13	-0,27
	Median	0,96	0,89	0,77	0,56	-0,08	-0,09
	Min	0,69	0,44	-0,12	-0,21	-1,34	-2,30
	Max	0,99	0,94	0,87	0,72	1,26	1,11
	Std	0,05	0,09	0,16	0,25	0,32	0,48
CPI	**Average**	0,95	0,86	0,73	0,53	-0,05	-0,03
	Average (weighted)	2,24	2,04	1,72	1,27	-0,15	-0,09
	Median	0,97	0,90	0,79	0,62	-0,03	0,00
	Min	0,69	0,44	-0,12	-0,10	-1,26	-1,17
	Max	0,99	0,94	0,87	0,72	0,53	0,60
	Std	0,06	0,09	0,16	0,21	0,20	0,20
PPI	**Average**	0,95	0,85	0,68	0,36	-0,23	-0,57
	Median	0,96	0,88	0,73	0,42	-0,19	-0,53
	Min	0,86	0,69	0,35	-0,21	-1,34	-2,30
	Max	0,99	0,94	0,87	0,71	1,26	1,11
	Std	0,03	0,08	0,15	0,26	0,39	0,55

Table A.10: Response of French Price Series to a Monetary Shock

Note to Table A.10: Sample is 1995:1 2009:8. Autocorrelations are computed on responses to monetary policy shock. Price responses at horizons of 6 and 12 months are expressed in percent deviations from price level prior to shock. Weighted average of statistics for disaggregated PCE series is obtained using expenditure shares in year 2005 as weights.

GERMANY		Autocorr of P condit on a shock				P responses (%)	
		1st order	3rd order	6th order	12th order	6 mo.	12 mo.
Aggreg P	**HICP**	0,96	0,89	0,76	0,60	-0,05	-0,02
	Food	0,97	0,92	0,83	0,67	-0,20	-0,18
	Proc FoodNAT	0,98	0,91	0,77	0,53	0,00	0,00
	Proc FoodAT	0,98	0,94	0,86	0,70	-0,12	-0,14
	Unproc F	0,97	0,91	0,83	0,67	-0,43	-0,37
	Goods	0,97	0,91	0,81	0,64	-0,07	-0,06
	Cloth	0,84	0,76	0,59	0,30	-0,02	0,06
	Energy	0,87	0,61	0,13	-0,24	0,09	0,09
	Serv	0,56	0,43	0,08	0,29	-0,01	0,04
All	**Average**	0,95	0,88	0,74	0,54	-0,03	-0,04
	Median	0,97	0,91	0,82	0,65	-0,02	-0,01
	Min	0,50	0,41	0,00	-0,42	-1,42	-1,20
	Max	0,99	0,95	0,88	0,73	1,12	1,18
	Std	0,05	0,09	0,17	0,24	0,22	0,28
CPI	**Average**	0,95	0,87	0,73	0,54	-0,01	0,02
	Average (weighted)	2,24	2,05	1,73	1,29	-0,18	-0,13
	Median	0,97	0,91	0,82	0,65	-0,01	0,00
	Min	0,50	0,41	0,06	-0,37	-1,42	-1,18
	Max	0,99	0,94	0,88	0,73	1,12	1,18
	Std	0,07	0,10	0,17	0,24	0,23	0,26
PPI	**Average**	0,96	0,89	0,76	0,55	-0,06	-0,10
	Median	0,97	0,92	0,82	0,65	-0,02	-0,03
	Min	0,84	0,54	0,00	-0,42	-0,89	-1,20
	Max	0,99	0,95	0,87	0,71	0,51	0,56
	Std	0,03	0,08	0,16	0,24	0,20	0,28

Table A.11: Response of German Price Series to a Monetary Shock

Note to Table A.11: See Table A.10.

ITALY		**Autocorr of P condit on a shock**				**P responses (%)**	
		1st order	**3rd order**	**6th order**	**12th order**	**6 mo.**	**12 mo.**
Aggreg P	**HICP**	0,95	0,86	0,73	0,53	-0,03	0,01
	Food	0,97	0,91	0,82	0,64	-0,05	-0,03
	Proc FoodNAT	0,97	0,90	0,74	0,46	0,01	0,02
	Proc FoodAT	0,98	0,92	0,83	0,65	-0,03	-0,02
	Unproc F	0,97	0,91	0,82	0,65	-0,09	-0,07
	Goods	0,97	0,91	0,82	0,65	-0,09	-0,07
	Cloth	0,94	0,90	0,85	0,72	0,04	0,40
	Energy	0,97	0,83	0,58	0,30	-0,06	-0,13
	Serv	0,98	0,93	0,84	0,67	-0,03	-0,03
All	**Average**	0,97	0,90	0,77	0,56	-0,03	-0,04
	Median	0,98	0,92	0,83	0,65	-0,02	-0,02
	Min	0,71	0,59	0,09	-0,36	-0,73	-0,96
	Max	0,99	0,95	0,88	0,73	0,45	0,57
	Std	0,03	0,06	0,13	0,21	0,16	0,22
CPI	**Average**	0,96	0,90	0,77	0,56	-0,01	0,01
	Average (weighted)	2,30	2,10	1,77	1,31	-0,19	-0,10
	Median	0,97	0,92	0,82	0,65	0,00	0,01
	Min	0,71	0,60	0,09	-0,36	-0,69	-0,77
	Max	0,99	0,94	0,87	0,73	0,45	0,57
	Std	0,03	0,06	0,13	0,21	0,15	0,19
PPI	**Average**	0,97	0,90	0,78	0,56	-0,06	-0,10
	Median	0,98	0,93	0,84	0,65	-0,03	-0,05
	Min	0,80	0,59	0,29	-0,12	-0,73	-0,96
	Max	0,99	0,95	0,88	0,72	0,43	0,40
	Std	0,03	0,07	0,14	0,21	0,18	0,24

Table A.12: Response of Italian Price Series to a Monetary Shock

Note to Table A.12: See Table A.10.

FRANCE		Autocorr of P condit on a shock				P responses (%)	
		1st order	3rd order	6th order	12th order	6 mo.	12 mo.
Aggreg P	**HICP**	0,97	0,90	0,78	0,60	-0,06	-0,03
	Food	0,92	0,80	0,59	0,29	0,01	0,08
	Proc FoodNAT	0,97	0,92	0,83	0,67	-0,06	-0,06
	Proc FoodAT	0,97	0,91	0,82	0,66	-0,05	-0,04
	Unproc F	0,90	0,76	0,50	0,15	0,06	0,16
	Goods	0,96	0,88	0,74	0,54	-0,05	0,00
	Cloth	0,86	0,76	0,64	0,46	-0,26	-0,04
	Energy	0,94	0,74	0,37	0,01	0,05	0,07
	Serv	0,97	0,92	0,83	0,68	-0,07	-0,07
All	**Average**	0,95	0,87	0,72	0,48	-0,12	-0,26
	Median	0,96	0,89	0,76	0,50	-0,08	-0,09
	Min	0,71	0,54	0,11	-0,28	-0,73	-2,10
	Max	0,98	0,94	0,87	0,75	0,42	0,84
	Std	0,04	0,08	0,15	0,21	0,15	0,39
CPI	**Average**	0,95	0,88	0,76	0,59	-0,07	-0,04
	Average (weighted)	2,28	2,10	1,81	1,40	-0,17	-0,11
	Median	0,97	0,91	0,82	0,66	-0,07	-0,06
	Min	0,71	0,54	0,12	-0,22	-0,28	-0,18
	Max	0,98	0,94	0,87	0,75	0,42	0,84
	Std	0,05	0,08	0,15	0,17	0,08	0,12
PPI	**Average**	0,94	0,86	0,68	0,35	-0,18	-0,52
	Median	0,96	0,88	0,73	0,42	-0,17	-0,48
	Min	0,74	0,60	0,11	-0,28	-0,73	-2,10
	Max	0,98	0,91	0,79	0,56	0,24	0,43
	Std	0,04	0,07	0,14	0,18	0,18	0,44

Table A.13: Response of French Price Series to a Monetary Shock with Long-Run Restrictions imposed at horizon of 4 years

Note to Table A.13: Sample is 1995:1 2009:8. Autocorrelations are computed on responses to monetary policy shock. Price responses at horizons of 6 and 12 months are expressed in percent deviations from price level prior to shock. Weighted average of statistics for disaggregated PCE series is obtained using expenditure shares in year 2005 as weights.

GERMANY		**Autocorr of P condit on a shock**				**P responses (%)**	
		1st order	**3rd order**	**6th order**	**12th order**	**6 mo.**	**12 mo.**
Aggreg P	**HICP**	0,96	0,88	0,74	0,57	-0,04	-0,01
	Food	0,93	0,79	0,52	0,13	0,06	0,14
	Proc FoodNAT	0,98	0,92	0,83	0,66	-0,05	-0,04
	Proc FoodAT	0,98	0,93	0,84	0,68	-0,05	-0,07
	Unproc F	0,95	0,84	0,62	0,25	0,16	0,33
	Goods	0,94	0,84	0,65	0,40	0,00	0,03
	Cloth	0,93	0,85	0,72	0,51	-0,09	-0,02
	Energy	0,89	0,65	0,19	-0,23	0,14	0,20
	Serv	0,93	0,85	0,71	0,59	-0,10	-0,06
All	**Average**	0,95	0,88	0,75	0,57	-0,05	-0,05
	Median	0,97	0,91	0,81	0,65	-0,05	-0,05
	Min	0,61	0,48	0,10	-0,35	-0,80	-0,72
	Max	0,98	0,95	0,88	0,74	0,63	1,22
	Std	0,05	0,09	0,16	0,20	0,11	0,14
CPI	**Average**	0,94	0,86	0,73	0,56	-0,05	-0,02
	Average (weighted)	2,26	2,08	1,79	1,40	-0,18	-0,12
	Median	0,97	0,90	0,81	0,65	-0,05	-0,05
	Min	0,61	0,48	0,10	-0,35	-0,80	-0,34
	Max	0,98	0,94	0,88	0,74	0,63	1,22
	Std	0,07	0,10	0,19	0,21	0,14	0,15
PPI	**Average**	0,97	0,90	0,77	0,57	-0,04	-0,07
	Median	0,97	0,91	0,82	0,65	-0,05	-0,05
	Min	0,89	0,64	0,15	-0,29	-0,26	-0,72
	Max	0,98	0,95	0,88	0,73	0,23	0,30
	Std	0,02	0,05	0,13	0,19	0,06	0,11

Table A.14: Response of German Price Series to a Monetary Shock with Long-Run Restrictions imposed at horizon of 4 years

Note to Table A.14: See Table A.13.

ITALY		**Autocorr of P condit on a shock**				**P responses (%)**	
		1st order	**3rd order**	**6th order**	**12th order**	**6 mo.**	**12 mo.**
Aggreg P	**HICP**	0,91	0,75	0,52	0,24	-0,01	0,03
	Food	0,96	0,84	0,58	0,15	0,03	0,07
	Proc FoodNAT	0,96	0,82	0,53	0,11	0,02	0,05
	Proc FoodAT	0,96	0,82	0,54	0,15	0,01	0,04
	Unproc F	0,96	0,86	0,63	0,24	0,04	0,10
	Goods	0,96	0,86	0,63	0,24	0,04	0,10
	Cloth	0,55	0,36	0,40	0,16	-0,16	0,14
	Energy	0,94	0,71	0,26	-0,18	0,07	0,07
	Serv	0,96	0,87	0,70	0,50	0,00	0,00
All	**Average**	0,93	0,83	0,65	0,40	-0,02	-0,02
	Median	0,96	0,86	0,70	0,46	-0,02	-0,01
	Min	0,52	0,32	0,09	-0,38	-0,27	-0,48
	Max	0,98	0,94	0,87	0,74	0,18	0,24
	Std	0,08	0,12	0,19	0,26	0,05	0,09
CPI	**Average**	0,90	0,77	0,56	0,28	-0,01	0,02
	Average (weighted)	2,35	2,17	1,87	1,46	-0,20	-0,11
	Median	0,94	0,81	0,60	0,30	0,00	0,01
	Min	0,52	0,32	0,09	-0,38	-0,27	-0,48
	Max	0,97	0,93	0,84	0,73	0,13	0,24
	Std	0,10	0,13	0,17	0,24	0,05	0,08
PPI	**Average**	0,97	0,89	0,76	0,55	-0,04	-0,06
	Median	0,97	0,91	0,81	0,63	-0,04	-0,05
	Min	0,68	0,52	0,21	-0,19	-0,21	-0,40
	Max	0,98	0,94	0,87	0,74	0,18	0,23
	Std	0,03	0,07	0,14	0,20	0,05	0,09

Table A.15: Response of Italian Price Series to a Monetary Shock with Long-Run Restrictions imposed at horizon of 4 years

Note to Table A.15: See Table A.13.

France

h	RW	AR(12)	MA	VAR	VARF	Factor
1	0,0041	0,0034	**0,0031**	0,0034	0,0032	0,0038
2	0,0047	**0,0037**	0,0052	0,0040	0,0041	0,0077
3	0,0048	**0,0041**	0,0070	0,0042	0,0042	0,0114
4	0,0055	0,0044	0,0044	0,0042	**0,0037**	0,0117
5	0,0059	0,0052	0,0063	0,0052	**0,0047**	0,0181
6	0,0060	0,0055	0,0071	0,0054	**0,0053**	0,0094
7	0,0071	0,0050	0,0065	**0,0049**	0,0051	0,0066
8	0,0068	0,0047	0,0058	**0,0046**	0,0049	0,0055
9	0,0059	0,0046	0,0051	**0,0045**	0,0047	0,0085
10	0,0057	0,0045	**0,0039**	0,0044	0,0044	0,0131
11	0,0052	0,0052	**0,0030**	0,0050	0,0052	0,0114
12	**0,0047**	0,0050	0,0049	0,0048	0,0054	0,0075

Table A.16: Recursive Root Mean Squared Forecast Errors 2008-2009, 1 to 12 months ahead - French Inflation Index

Note to Table A.16: Inflation is measured as $\pi_t = p_t - p_{t-1}$ where p_t is the log of the HICP series. The values in bold indicate the minimum RMSE at each forecast horizon corresponding to the most accurate model.

Germany

h	RW	AR(12)	MA	VAR	VARF	Factor
1	0,0077	0,0063	**0,0047**	0,0065	0,0063	0,0075
2	0,0062	**0,0050**	0,0064	0,0078	0,0066	0,0115
3	0,0062	**0,0046**	0,0048	0,0255	0,0065	0,0107
4	0,0079	0,0049	**0,0048**	0,0165	0,0088	0,0165
5	0,0063	0,0067	**0,0046**	0,0201	0,0117	0,0186
6	0,0089	0,0071	**0,0052**	0,0212	0,0127	0,0102
7	**0,0051**	0,0067	0,0052	0,0236	0,0157	0,0106
8	0,0085	0,0063	**0,0049**	0,0279	0,0159	0,0104
9	0,0057	0,0062	**0,0046**	0,0278	0,0145	0,0143
10	0,0077	0,0063	**0,0046**	0,0271	0,0131	0,0181
11	0,0071	0,0061	**0,0044**	0,0251	0,0097	0,0151
12	0,0053	0,0043	**0,0037**	0,0220	0,0114	0,0120

Table A.17: Recursive Root Mean Squared Forecast Errors 2008-2009, 1 to 12 months ahead - German Inflation Index

Note to Table A.17: Inflation is measured as $\pi_t = p_t - p_{t-1}$ where p_t is the log of the HICP series. The values in bold indicate the minimum RMSE at each forecast horizon corresponding to the most accurate model.

Italy

h	RW	AR(12)	MA	VAR	VARF	Factor
1	0,0092	0,0088	**0,0075**	0,0089	0,0091	0,0096
2	0,0109	0,0084	**0,0078**	0,0102	0,0102	0,0084
3	0,0098	**0,0080**	0,0087	0,0181	0,0195	0,0094
4	0,0093	**0,0056**	0,0063	0,0216	0,0215	0,0069
5	0,0102	0,0085	0,0089	0,0226	0,0169	**0,0083**
6	0,0071	0,0092	0,0083	0,0207	0,0236	**0,0069**
7	0,0116	0,0099	0,0097	0,0183	0,0283	**0,0072**
8	0,0136	**0,0099**	0,0105	0,0189	0,0213	0,0104
9	0,0121	0,0094	0,0108	0,0203	0,0189	**0,0069**
10	0,0123	**0,0092**	0,0101	0,0205	0,0225	0,0105
11	0,0103	0,0102	0,0100	0,0215	0,0218	**0,0078**
12	**0,0048**	0,0100	0,0092	0,0184	0,0268	0,0121

Table A.18: Recursive Root Mean Squared Forecast Errors 2008-2009, 1 to 12 months ahead - Italian Inflation Index

Note to Table A.18: Inflation is measured as $\pi_t = p_t - p_{t-1}$ where p_t is the log of the HICP series. The values in bold indicate the minimum RMSE at each forecast horizon corresponding to the most accurate model.

DM

h	RW / AR(12)	RW / MA	RW / VAR	RW / VARF	RW / Factor
1	1,2881	1,6111	1,1955	**1,6437**	0,6071
2	0,8609	-0,4809	0,6161	0,5654	-1,9527
3	0,7804	-1,3803	0,7195	0,7085	-1,7730
4	0,6751	0,7140	0,8875	1,3762	-1,6526
5	0,5081	-0,2317	0,4752	0,8882	-2,3106
6	0,4833	-1,7591	0,5081	0,5764	-1,3879
7	**3,2475**	0,7774	**3,0572**	**2,7991**	0,3310
8	**1,6716**	1,1289	**1,7421**	1,3024	0,6427
9	1,4435	0,7603	1,3499	1,1629	-1,0702
10	0,8658	**1,6703**	0,9348	1,0435	-7,6603
11	0,0055	**2,1625**	0,1898	-0,0213	-1,4479
12	-0,3171	-0,1900	-0,0990	-0,6488	-0,9212

Table A.19: Diebold and Mariano statistics - French Inflation Index

Note to Table A.19: The test statistic is asymptotically distributed as a standard normal under the null hypothesis of equal forecasting accuracy. Results are showed from 1 to 12 steps ahead comparing non-nested alternatives. The values in bold indicate the rejection of the null alternative and therefore the predictive significance of the alternative model.

DM

h	RW / AR(12)	RW / MA	RW / VAR	RW / VARF	RW / Factor
1	**2,1238**	**2,5351**	**1,6417**	1,5472	0,3753
2	0,8539	-0,1607	-1,2808	-0,3355	-1,7933
3	1,2362	0,8898	-5,4049	-0,1088	-1,4472
4	**1,8798**	**2,4857**	-4,5367	-0,4063	-3,0969
5	-0,1987	1,0584	-5,5330	-4,2318	-3,1113
6	**1,7731**	**3,0765**	-4,9101	-1,6798	-0,5773
7	-1,2113	-0,1286	-6,3974	-3,0725	-2,0531
8	**1,9806**	**3,5513**	-8,3048	-2,6720	-0,6906
9	-0,1752	0,8138	-9,7710	-2,5764	-1,6089
10	1,2122	**2,6425**	-6,2854	-1,4181	-2,5677
11	0,6919	**2,0020**	-9,7570	-1,1518	-2,0489
12	0,6005	1,1096	-6,0265	-1,3939	-2,0512

Table A.20: Diebold and Mariano statistics - German Inflation Index

Note to Table A.20: The test statistic is asymptotically distributed as a standard normal under the null hypothesis of equal forecasting accuracy. Results are showed from 1 to 12 steps ahead comparing non-nested alternatives. The values in bold indicate the rejection of the null alternative and therefore the predictive significance of the alternative model.

DM

h	RW / AR(12)	RW / MA	RW / VAR	RW / VARF	RW / Factor
1	0,3819	**1,8867**	0,2295	0,1178	-0,8967
2	1,3224	**2,5741**	0,2344	0,2449	0,7710
3	0,9384	0,5389	-2,8957	-2,6584	0,2443
4	0,9201	0,8376	-4,8447	-2,0166	0,7757
5	0,9680	0,7229	-3,6056	-1,2075	0,9641
6	-1,1354	-0,5946	-3,5241	-1,1488	0,0853
7	1,4419	1,5632	-2,7316	-1,3945	1,5730
8	**1,8722**	**1,6642**	-1,9217	-1,0092	1,1501
9	1,1947	0,6185	-3,4105	-1,1028	1,6296
10	0,6580	0,4859	-2,8612	-1,1700	0,3134
11	0,1461	0,2056	-3,2606	-1,6781	1,5991
12	-2,7409	-2,4158	-3,0055	-1,2705	-3,3728

Table A.21: Diebold and Mariano statistics - Italian Inflation Index

Note to Table A.21: The test statistic is asymptotically distributed as a standard normal under the null hypothesis of equal forecasting accuracy. Results are showed from 1 to 12 steps ahead comparing non-nested alternatives. The values in bold indicate the rejection of the null alternative and therefore the predictive significance of the alternative model.

Appendix B

Figures

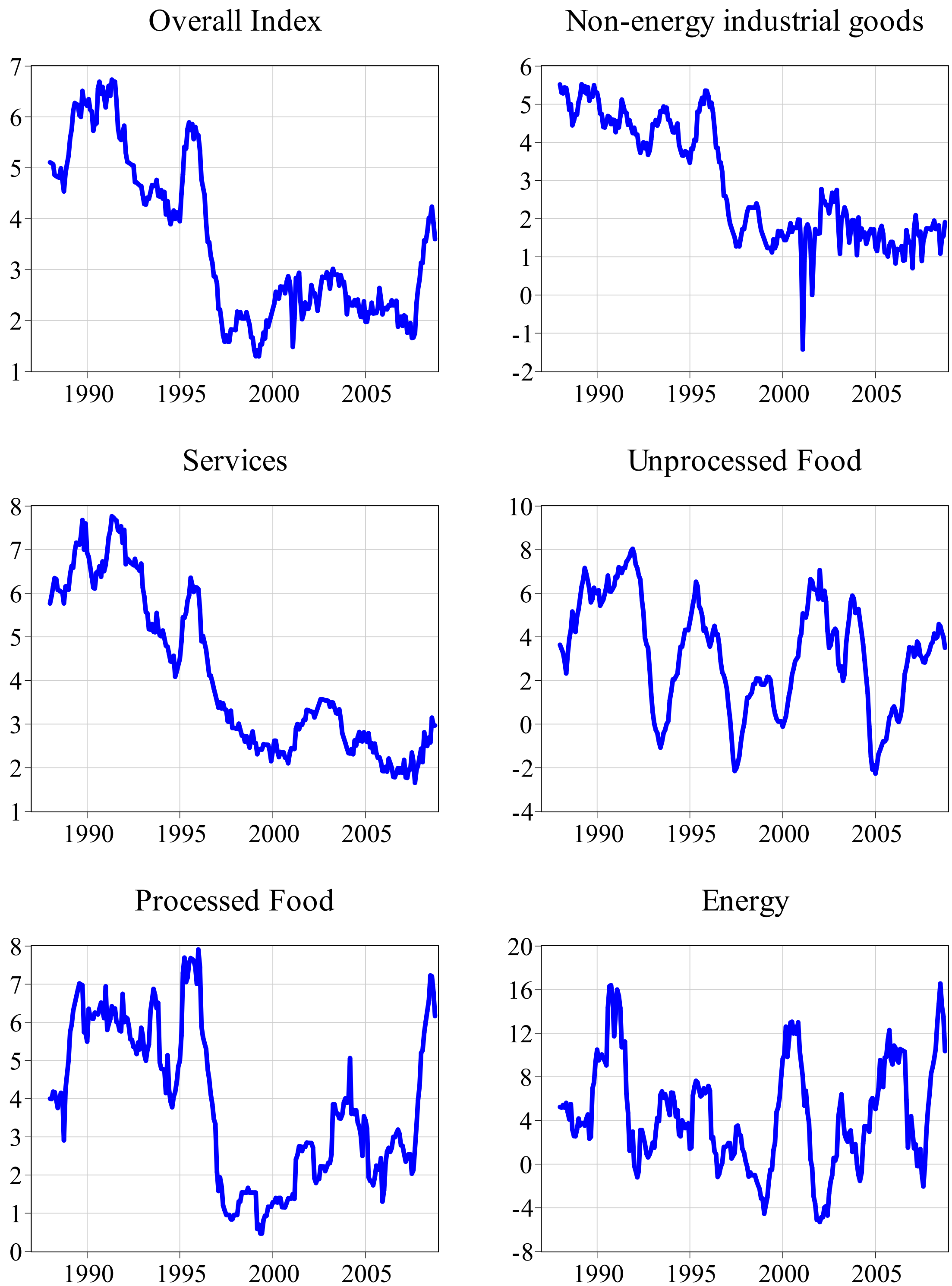

Figure B.1: Year on year HICP growth rates (%)

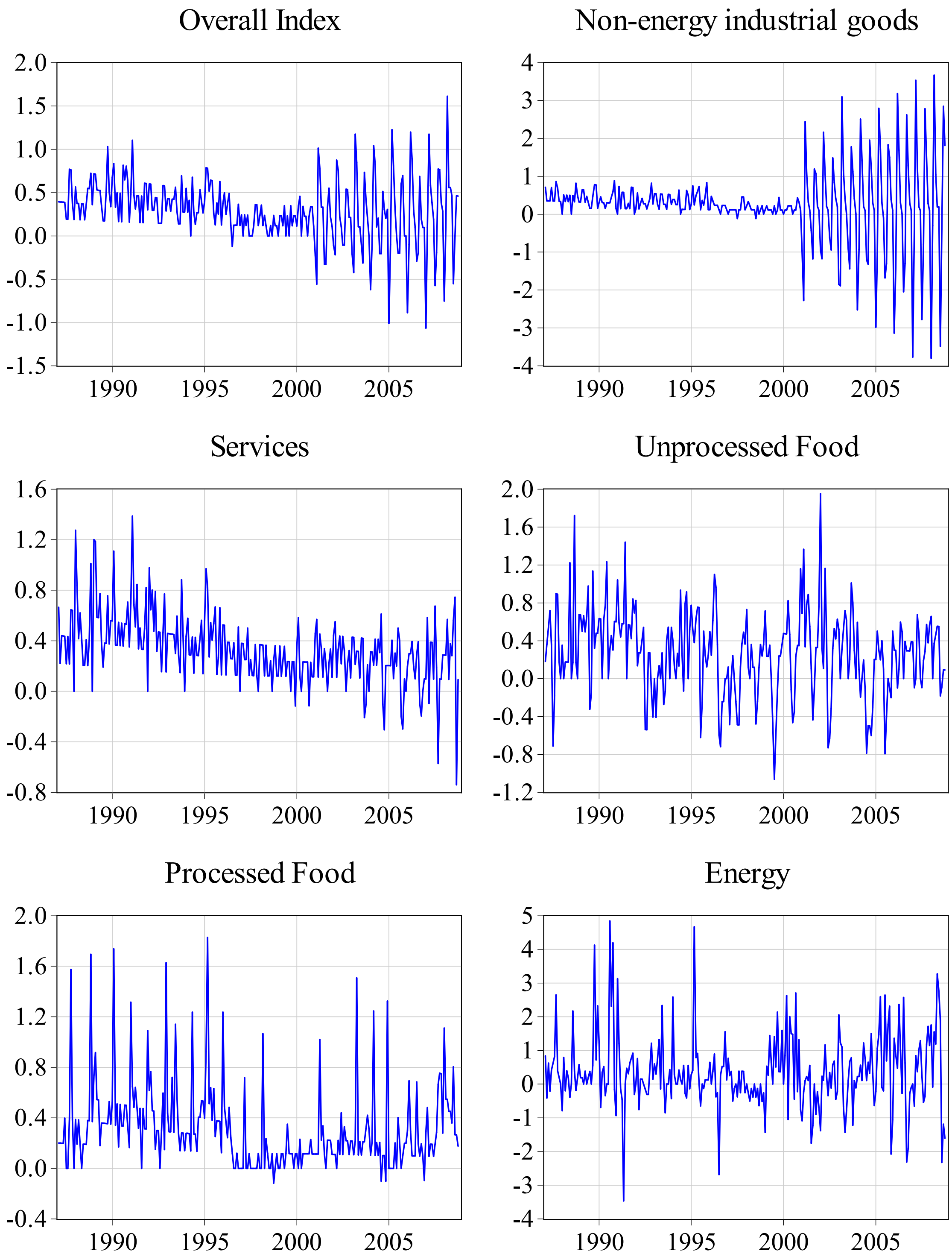

Figure B.2: Month on month HICP growth rates (%)

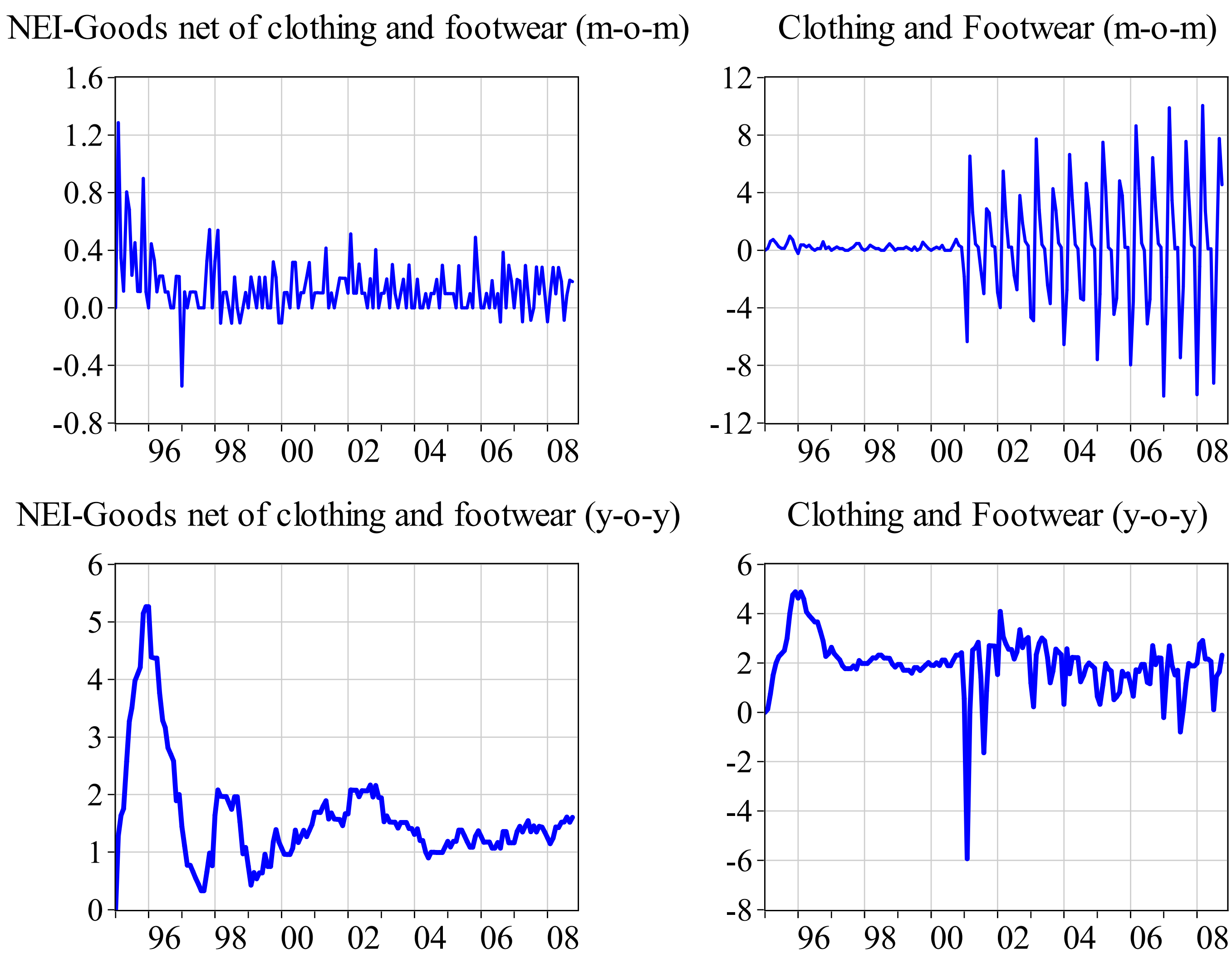

Figure B.3: NEI-goods and Clothing and Footwear inflation rates (%)

Note to Figure B.3: data for the sub-components have not been back-linked. They are therefore available only since 1995.

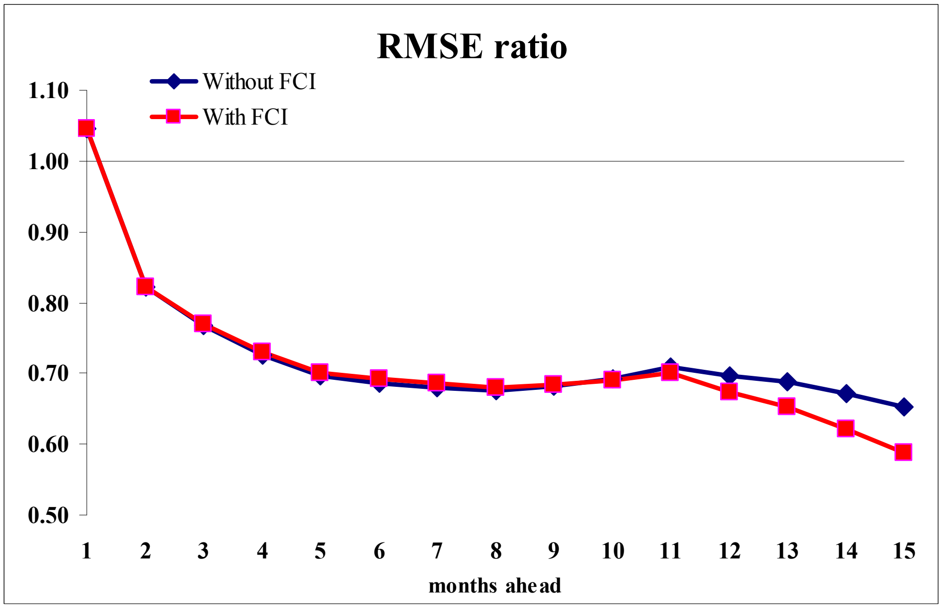

Figure B.4: Unprocessed food forecast accuracy with and without FCI

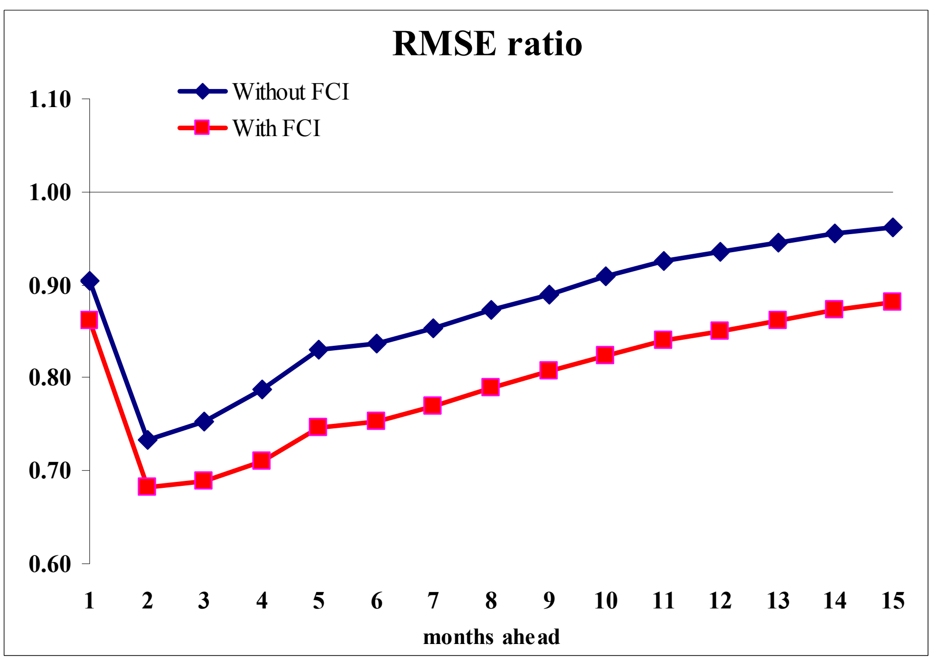

Figure B.5: Processed food forecast accuracy with and without FCI

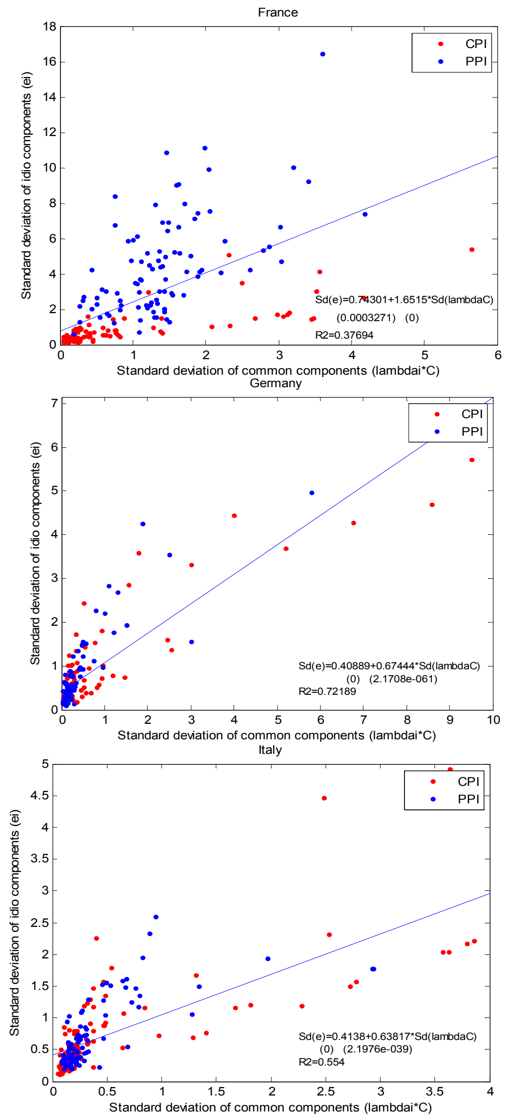

Figure B.6: Volatility of Common and Sector Specific Components of Sectoral Inflation Rates

Note to Figure B.6: Standard deviations (expressed in %) refer to sector-specific and common components of sectoral inflation rates (CPI and PPI prices). Solid line represents cross-sectional regression line.

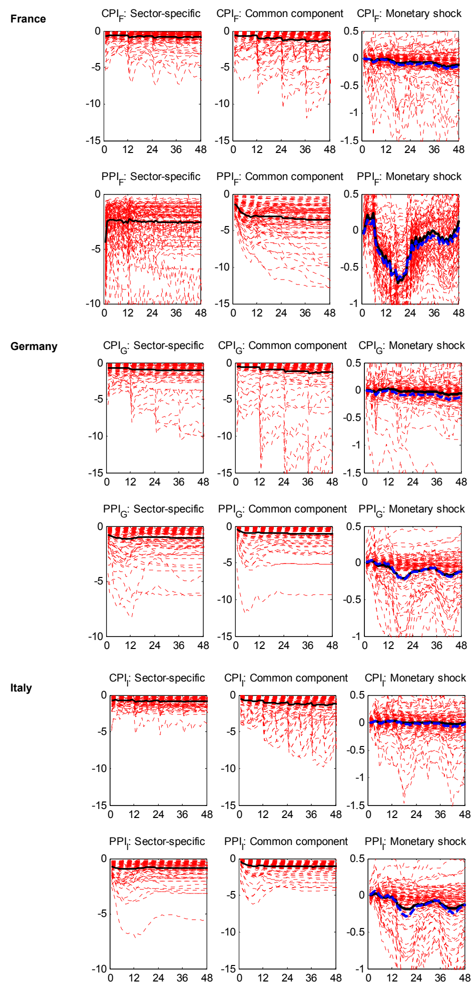

Figure B.7: Sectoral Price Responses

Note to Figure B.7: Estimated impulse responses of sectoral prices (in %) to a sector-specific shock ϵ_{it} of one standard deviation (left panels), to a shock to the common component $\lambda_i' C_t$ of one standard deviation (middle panels), and to an identified monetary policy shock (right panels). The monetary shock is a surprise increase of 25 basis points in the EONIA rate. Thick solid lines represent unweighted average responses. Thick dashed lines represent the response of the aggregate CPI and PPI(finished) price indices to a monetary policy shock.

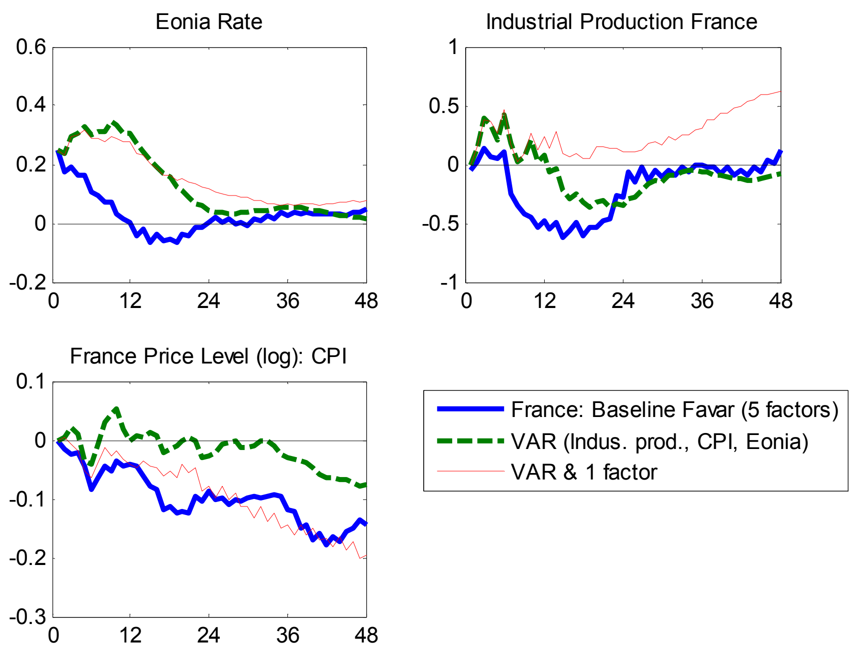

Figure B.8: Estimated Impulse Responses of French indicators to an Identified Monetary Shock

Note to Figure B.8: Sample is 1995:1-2009:8. Monetary shock is an unexpected increase of 25 basis points in the EONIA rate. Responses reported are estimated using a baseline FAVAR (thick solid line), a 3-variable VAR (thick dashed line) and the same VAR augmented with the first principal component of a large data set.

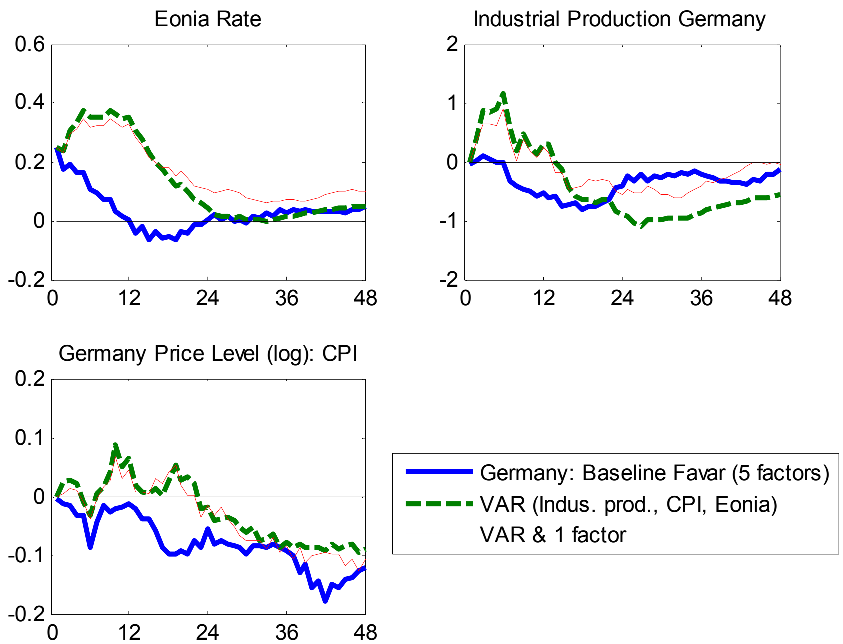

Figure B.9: Estimated Impulse Responses of German indicators to an Identified Monetary Shock

Note to Figure B.9: See Figure B.8.

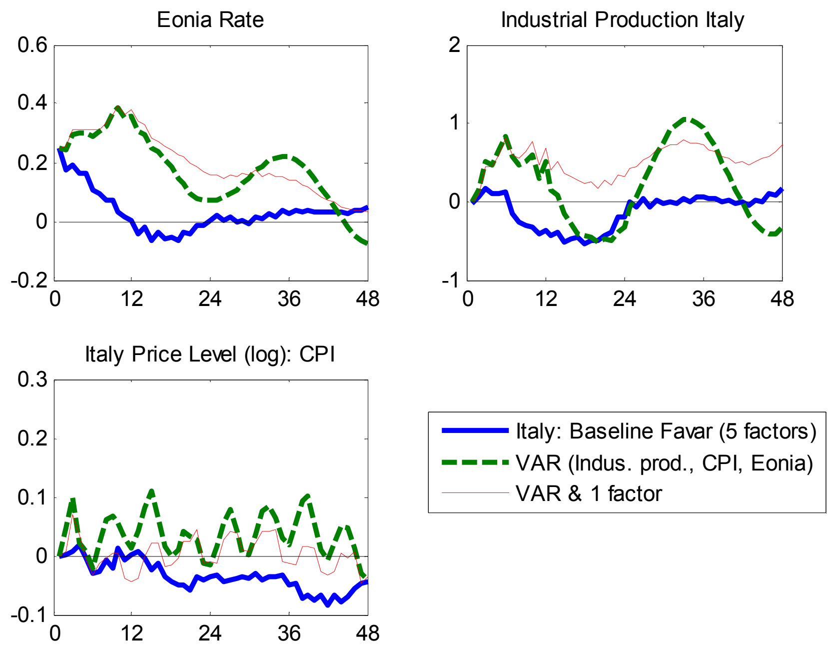

Figure B.10: Estimated Impulse Responses of Italian indicators to an Identified Monetary Shock

Note to Figure B.10: See Figure B.8.

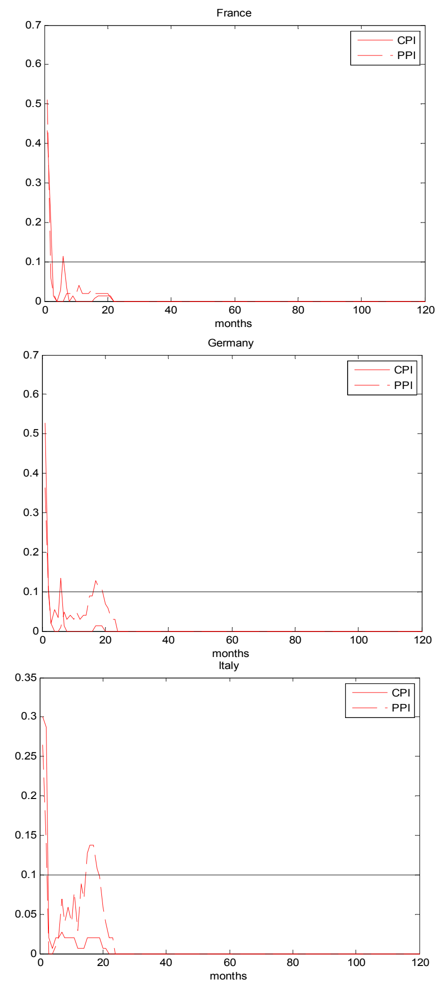

Figure B.11: Fraction of Relative Prices Significantly Different from Average at a 10% Confidence Level after a Monetary Shock

Note to Figure B.11: Fraction of the sectors i for which the bootstrapped price responses to a monetary policy shock are such that $f_i^h > 0.95$ or $f_i^h < 0.05$, as a function of the horizon h. The numbers f_i^h denote for each sector i and horizon h the fraction of the bootstrapped price responses that are larger than the cross-sectional average price response. Bootstrapped impulse responses involve 1,000 iterations.

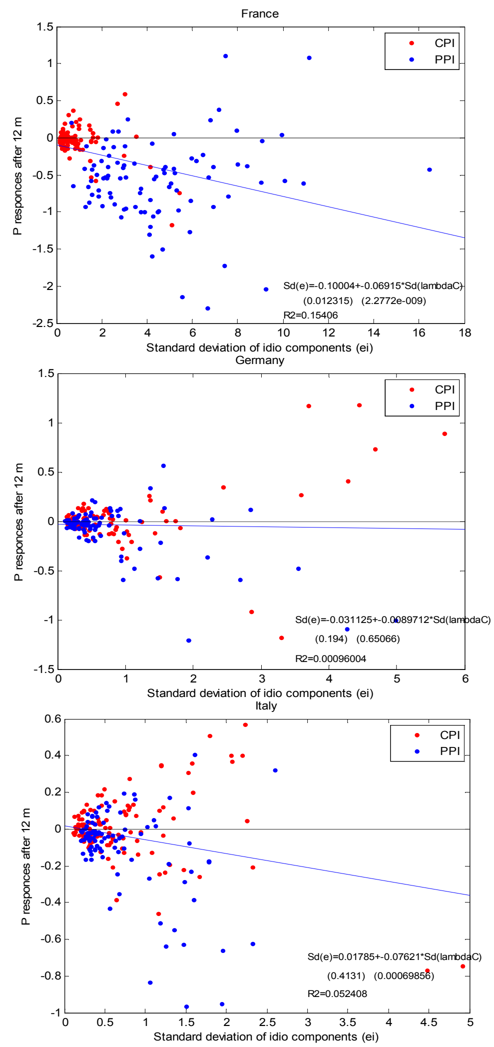

Figure B.12: Price Responses to Monetary Shock after one year and Volatility of Sector Specific Components

Note to Figure B.12: Estimated impulse responses of sectoral prices to identified monetary policy shock are expressed in %. The monetary shock is a surprise increase of 25 basis points in the EONIA rate. Solid line represent cross-sectional regression line.

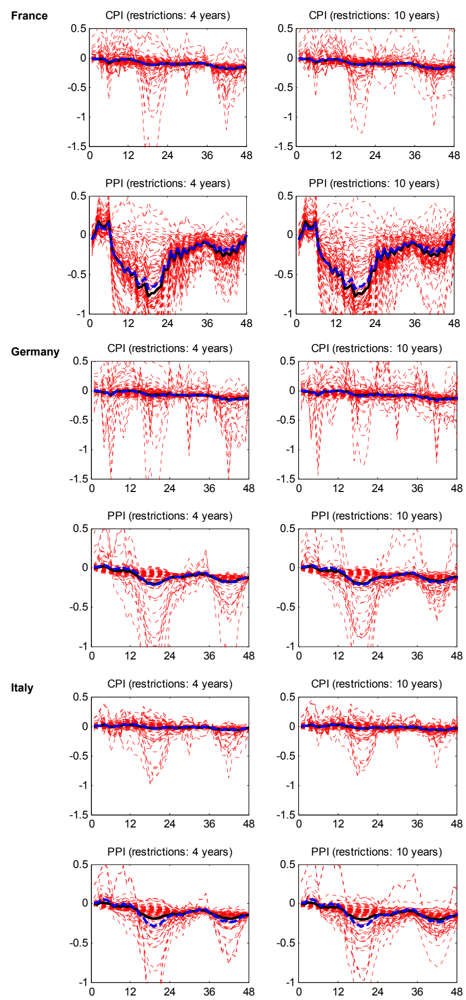

Figure B.13: Sectoral Price Responses to Monetary Shocks with Long-Run Restrictions at Horizon of 4 and 10 years

Note to Figure B.13: Estimated impulse responses of sectoral prices (in %) to an identified monetary policy shock. The monetary shock is a surprise increase of 25 basis points in the EONIA rate. Thick solid lines represent unweighted average responses. Thick dashed lines represent the response of the aggregate CPI and PPI (finished) price indices to a monetary policy shock. In left panels, all price responses are constrained to be equal to the aggregate price response at the horizon of 4 years. In right panels, the constraints apply at the horizon of 10 years.

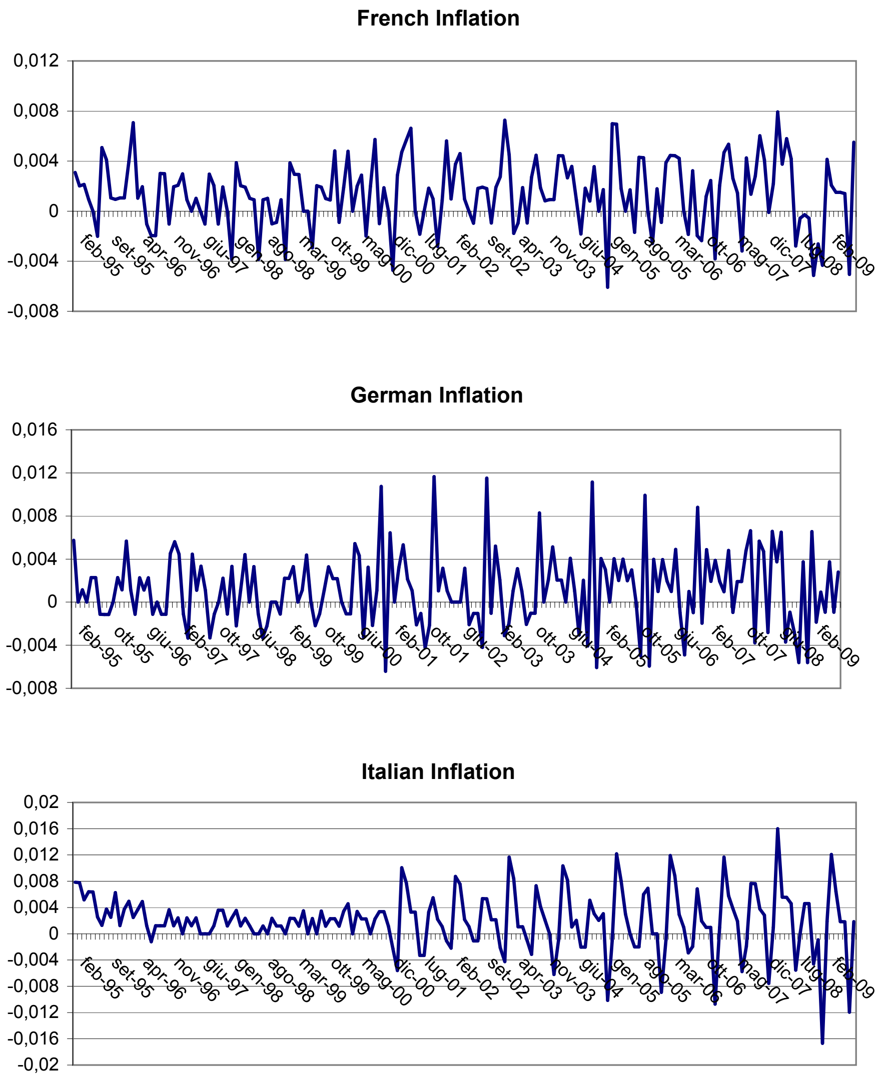

Figure B.14: HICP month-on-month changes

Note to Figure B.14: Inflation indexes of the three main Euro countries, namely France, Germany and Italy, expressed in the first difference of the logarithm: $\pi_t = p_t - p_{t-1}$ where p_t is the log of the HICP series.

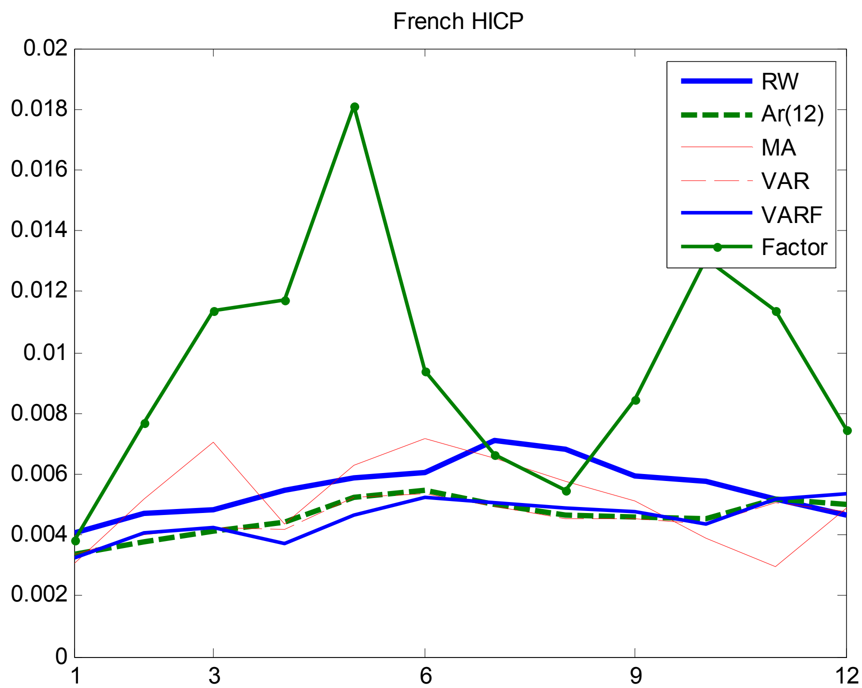

Figure B.15: RMSE of alternative models - French HICP

Note to Figure B.15: Alternative models forecasting accuracy in terms of RMSFE from 1 to 12 months ahead.

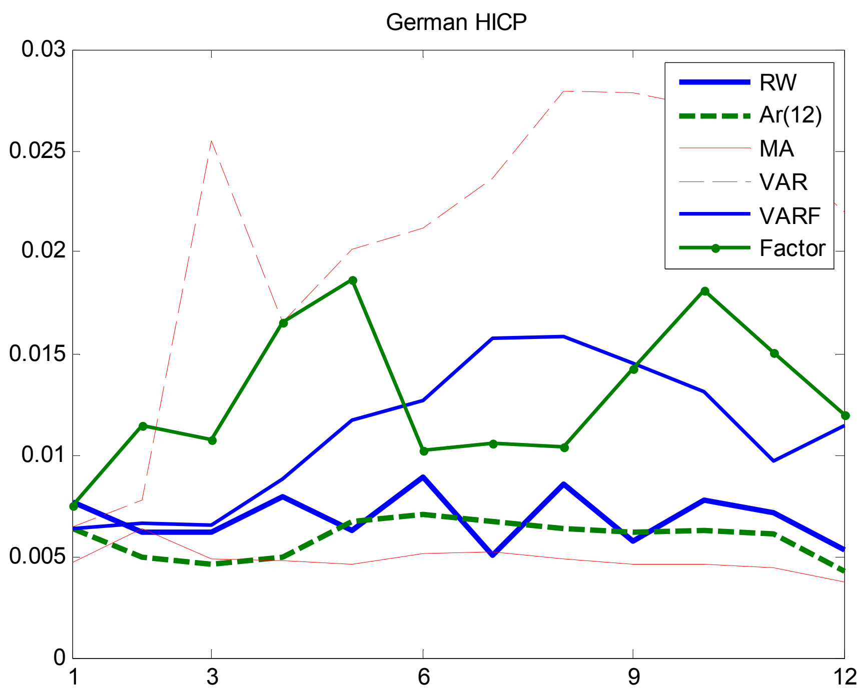

Figure B.16: RMSE of alternative models - German HICP

Note to Figure B.16: Alternative models forecasting accuracy in terms of RMSFE from 1 to 12 months ahead.

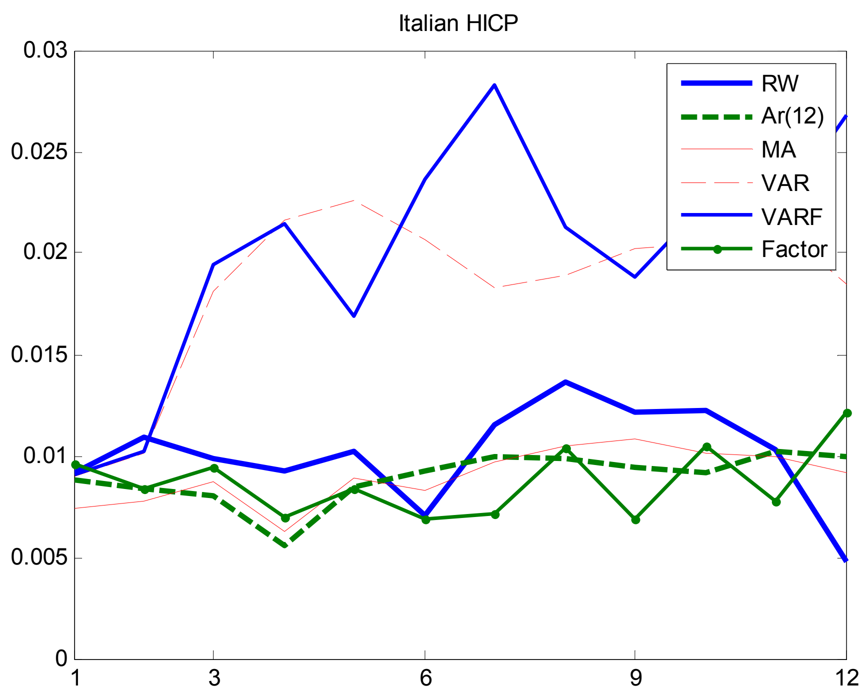

Figure B.17: RMSE of alternative models - Italian HICP

Note to Figure B.17: Alternative models forecasting accuracy in terms of RMSFE from 1 to 12 months ahead.

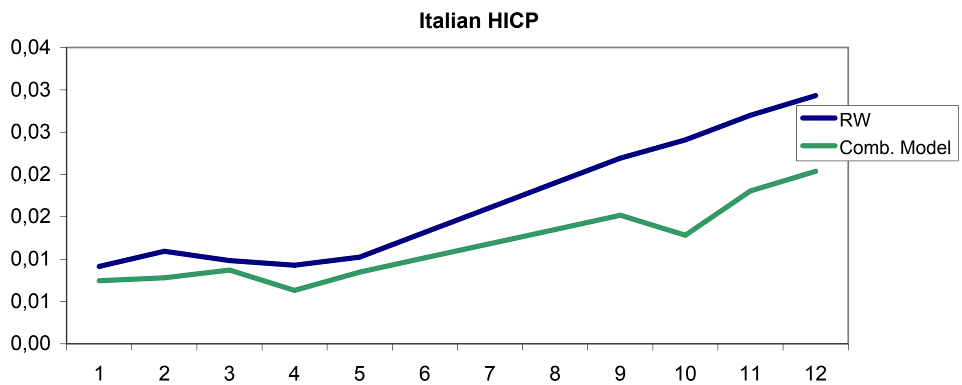

Figure B.18: RMSE of the combined model against the RW benchmark - Italian HICP

Note to Figure B.18: Predicting accuracy in terms of RMSFE of the model combining monthly and annual forecasts.

Appendix C

Data description

	Title	Source	Trans
HICP	OVERALL	BCE	5
	FOOD AND NON-ALCOHOLIC BEVERAGES	BCE	5
	FOOD	BCE	5
	Bread and Cereals	BCE	5
	Meat	BCE	5
	Fish	BCE	5
	Milk, cheese and eggs	BCE	5
	Oils and fats	BCE	5
	Fruit	BCE	5
	Vegetables	BCE	5
	Sugar, jam, honey, chocolate and confectionery	BCE	5
	Food products n.e.c.	BCE	5
	Non-alcoholic beverages	BCE	5
	Coffee, tea and cocoa	BCE	5
	Mineral waters, soft drinks, fruit and vegetable juices	BCE	5
	ALCOHOLIC BEVERAGES, TOBACCO	BCE	5
	Alcoholic beverages	BCE	5
	Spirits	BCE	5
	Wine	BCE	5
	Beer	BCE	5
	Tobacco	BCE	5
	CLOTHING AND FOOTWEAR	BCE	5
	Clothing	BCE	5
	Garments	BCE	5
	Other articles of clothing and clothing accessories	BCE	5
	Cleaning, repair and hire of clothing	BCE	5
	Footwear	BCE	5
	Shoes and other footwear including repair and hire of footwear	BCE	5
	HOUSING, WATER, ELECTRICITY, GAS AND OTHER FUELS	BCE	5

Actual rentals for housing	BCE	5
Actual rentals paid by tenants including other actual rentals	BCE	5
Maintenance and repair of the dwelling	BCE	5
Materials for the maintenance and repair of the dwelling	BCE	5
Services for the maintenance and repair of the dwelling	BCE	5
Water supply and misc. services relating to the dwelling	BCE	5
Water supply	BCE	5
Other services relating to the dwelling n.e.c.	BCE	5
Electricity, gas and other fuels	BCE	5
Electricity	BCE	5
Gas	BCE	5
Liquid fuels	BCE	5
FURNISHINGS, HOUSEHOLD EQUIP. AND ROUTINE HOUSE MAINT.	BCE	5
Furniture and furnishings, carpets and other floor coverings	BCE	5
Furniture and furnishings	BCE	5
Carpets and other floor coverings	BCE	5
Household textiles	BCE	5
Household appliances	BCE	5
Major household appliances, small electric hous. appl.	BCE	5
Repair of household appliances	BCE	5
Glassware, tableware and household utensils	BCE	5
Tools and equipment for house and garden	BCE	5
Major tools and equip. and small tools and misc. accessories	BCE	5
Goods and services for routine household maintenance	BCE	5
Non-durable household goods	BCE	5
Domestic services and household services	BCE	5
HEALTH	BCE	5
TRANSPORT	BCE	5
Purchase of vehicles	BCE	5
Motor cars	BCE	5
Motor cycles, bicycles and animal drawn vehicles	BCE	5
Operation of personal transport equipment	BCE	5
Spare parts and accessories for personal transport equipment	BCE	5
Fuels and lubricants for personal transport equipment	BCE	5
Maintenance and repair of personal transport equipment	BCE	5
Other services in respect of personal transport equipment	BCE	5

Transport services	BCE	5
Passenger transport by railway	BCE	5
Passenger transport by road	BCE	5
Passenger transport by air	BCE	5
Passenger transport by sea and inland waterway	BCE	5
Combined passenger transport	BCE	5
Other purchased transport services	BCE	5
COMMUNICATION	BCE	5
Postal services	BCE	5
Telephone and telefax equipment	BCE	5
Telephone and telefax equipment and tel. and telefax services	BCE	5
Telephone and telefax services	BCE	5
RECREATION AND CULTURE	BCE	5
Audio-visual, photographic and information processing equip.	BCE	5
Equip. for reception, recording and reprod. of sound and pictures	BCE	5
Photographic and cinematographic equip. and optical instruments	BCE	5
Information processing equipment	BCE	5
Repair of audio-visual, photographic, info. processing equip.	BCE	5
Other major durables for recreation and culture	BCE	5
Major durables for in/outdoor recreation incl. musical instr.	BCE	5
Other recreational items and equipment, gardens and pets	BCE	5
Games, toys and hobbies	BCE	5
Equipment for sport, camping and open-air recreation	BCE	5
Gardens, plants and flowers	BCE	5
Pets and related prod. incl. veterinary and other serv. for pets	BCE	5
Recreational and cultural services	BCE	5
Recreational and sporting services	BCE	5
Cultural services	BCE	5
Newspapers, books and stationery	BCE	5
Books	BCE	5
Newspapers and periodicals	BCE	5
Misc. printed matter and stationery and drawing materials	BCE	5
Package holidays	BCE	5
EDUCATION	BCE	5

RESTAURANTS AND HOTELS	BCE	5
Catering services	BCE	5
Restaurants, cafes and the like	BCE	5
Canteens	BCE	5
Accommodation services	BCE	5
MISCELLANEOUS GOODS AND SERVICES	BCE	5
Personal care	BCE	5
Hairdressing salons and personal grooming establishments	BCE	5
Electric appliances and other appliances etc. for pers. Care	BCE	5
Personal effects n.e.c.	BCE	5
Jewellery, clocks and watches	BCE	5
Other personal effects	BCE	5
Insurance	BCE	5
Insurance connected with transport	BCE	5
Financial services n.e.c.	BCE	5
Other services n.e.c.	BCE	5
Communication services	BCE	5
Education, health and social protection	BCE	5
Energy and unprocessed food	BCE	5
Electricity, gas, solid fuels and heat energy	BCE	5
Energy and seasonal food	BCE	5
Processed food excluding alcohol and tobacco	BCE	5
Food incl. alcohol and tobacco	BCE	5
Processed food incl. alcohol and tobacco	BCE	5
Unprocessed food	BCE	5
Liquid fuels and fuels and lubricants for pers. transport equip.	BCE	5
Goods	BCE	5
Housing services	BCE	5
Industrial goods	BCE	5
Industrial goods excluding energy	BCE	5
Industrial goods excluding energy, durables only	BCE	5
Industrial goods excluding energy, non-durables only	BCE	5
Industrial goods excluding energy, semi-durables only	BCE	5
Miscellaneous services	BCE	5

	Energy	BCE	5
	Recreation and personal services	BCE	5
	Package holidays and accommodation services	BCE	5
	Other recreation and personal services	BCE	5
	Seasonal food	BCE	5
	Services	BCE	5
	Transport services	BCE	5
	All-items excluding alcoholic beverages, tobacco	BCE	5
	All-items excluding tobacco	BCE	5
	All-items excluding housing, water, elect., gas and other fuels	BCE	5
	All-items excluding energy	BCE	5
	All-items excl. education, health and social protection	BCE	5
	All-items excluding energy and food	BCE	5
	All-items excluding energy and unprocessed food	BCE	5
	All-items excluding energy and seasonal food	BCE	5
	All-items excl. liquid fuels and fuels and lubricants	BCE	5
	All-items excluding seasonal food	BCE	5
PPI	Intermediate goods	Nat Stat Inst.	5
	Investments goods	Nat Stat Inst.	5
	Durables goods	Nat Stat Inst.	5
	Non durables goods	Nat Stat Inst.	5
	Consumption goods	Nat Stat Inst.	5
	Precious metals	Nat Stat Inst.	5
	Oil and natural gas	Nat Stat Inst.	5
	Extraction industry	Nat Stat Inst.	5
	Stones and soil	Nat Stat Inst.	5
	Other mineral products	Nat Stat Inst.	5
	Manufactures	Nat Stat Inst.	5
	Food and beverages	Nat Stat Inst.	5
	Meat	Nat Stat Inst.	5
	Fruit and vegetables	Nat Stat Inst.	5
	Oils and fats	Nat Stat Inst.	5
	Milk	Nat Stat Inst.	5

Pasta	Nat Stat Inst.	5
Animals food	Nat Stat Inst.	5
Other food products	Nat Stat Inst.	5
Beverages	Nat Stat Inst.	5
Tobacco	Nat Stat Inst.	5
Textile industry	Nat Stat Inst.	5
Fiber	Nat Stat Inst.	5
Textiles	Nat Stat Inst.	5
Knitwear	Nat Stat Inst.	5
Cloths	Nat Stat Inst.	5
Other cloth products	Nat Stat Inst.	5
Tailored textiles	Nat Stat Inst.	5
Bags	Nat Stat Inst.	5
Shoes	Nat Stat Inst.	5
Wood industry	Nat Stat Inst.	5
Paper	Nat Stat Inst.	5
Carton	Nat Stat Inst.	5
Paper and carton manufactures	Nat Stat Inst.	5
Other paper manufactures	Nat Stat Inst.	5
Printing	Nat Stat Inst.	5
Coke and minerals	Nat Stat Inst.	5
Oil	Nat Stat Inst.	5
Chemical products	Nat Stat Inst.	5
Fertilisers	Nat Stat Inst.	5
Pesticides	Nat Stat Inst.	5
Ink and paints	Nat Stat Inst.	5
Pharmaceutical products	Nat Stat Inst.	5
Soaps and perfumes	Nat Stat Inst.	5
Other chemical products	Nat Stat Inst.	5
Synthetic fibres	Nat Stat Inst.	5
Gum and plastic products	Nat Stat Inst.	5
Non metallic materials	Nat Stat Inst.	5
Glass	Nat Stat Inst.	5
Ceramic materials	Nat Stat Inst.	5

Ceramics used in constructions	Nat Stat Inst.	5
Glass, ceramic, stone	Nat Stat Inst.	5
Cement	Nat Stat Inst.	5
Cement products	Nat Stat Inst.	5
Metals	Nat Stat Inst.	5
Steel products for constructions	Nat Stat Inst.	5
Iron and steel products	Nat Stat Inst.	5
Steel tubes	Nat Stat Inst.	5
Semifinished metals	Nat Stat Inst.	5
Foundry productions	Nat Stat Inst.	5
Metal products	Nat Stat Inst.	5
Construction products	Nat Stat Inst.	5
Radioactive metals containers	Nat Stat Inst.	5
Boiler	Nat Stat Inst.	5
Forged metal sheets	Nat Stat Inst.	5
Iron and steel transformation	Nat Stat Inst.	5
Cutlery	Nat Stat Inst.	5
Other metal products	Nat Stat Inst.	5
Machines	Nat Stat Inst.	5
Steel semifinished products	Nat Stat Inst.	5
Other non specialised machines	Nat Stat Inst.	5
Agricultural machines	Nat Stat Inst.	5
Utensils machines	Nat Stat Inst.	5
Other specific machines	Nat Stat Inst.	5
Electrical appliances	Nat Stat Inst.	5
Other electrical appliances	Nat Stat Inst.	5
Computer	Nat Stat Inst.	5
Optical and electric instruments	Nat Stat Inst.	5
Motors	Nat Stat Inst.	5
Electric circuits	Nat Stat Inst.	5
Watches and navigation instruments	Nat Stat Inst.	5
Accumulators and batteries	Nat Stat Inst.	5
Electric lamps	Nat Stat Inst.	5
Installed electric appliances	Nat Stat Inst.	5

	Pc and electric instruments	Nat Stat Inst.	5
	Electric appliances	Nat Stat Inst.	5
	Photographic and optic instruments	Nat Stat Inst.	5
	Electroterapeutical instruments	Nat Stat Inst.	5
	Watches	Nat Stat Inst.	5
	Automobile industry	Nat Stat Inst.	5
	Cars	Nat Stat Inst.	5
	Chassis	Nat Stat Inst.	5
	Car services	Nat Stat Inst.	5
	Other transports	Nat Stat Inst.	5
	Wares	Nat Stat Inst.	5
	Furniture	Nat Stat Inst.	5
	Instruments	Nat Stat Inst.	5
	Energy supply	Nat Stat Inst.	5
	Energy production and distribution	Nat Stat Inst.	5
	Gas production	Nat Stat Inst.	5
	Water services	Nat Stat Inst.	5
	Total	Nat Stat Inst.	5
Housing starts	Permits issued for dwellings	OECD	5
	Orders for consumption goods	EuroStat	5
	Orders for capital goods	EuroStat	5
	Gross VA at basic prices for construction in Italy	Nat Stat Inst.	5
Labour market Data	Unemployment Rate	ECB	1
	Employment Rate	ECB	5
	ULC	OECD	5
Financial market Data	DJ Euro Stoxx 50 Index	ECB	5
	DJ Euro Stoxx 50 Industrial Index	ECB	5
	Canadian Dollar Exchange Rate	ECB	5
	Swiss Franc Exchange Rate	ECB	5
	Pound Sterling Exchange Rate	ECB	5
	Yen	ECB	5

	US Dollar Exchange Rate	ECB	5
	EONIA	ECB	1
	1-month Bond	Bloomberg	1
	3-months Bond	Bloomberg	1
	6-months Bond	Bloomberg	1
	12-months Bond	Bloomberg	1
	5-years Bond	Bloomberg	1
	10-years Bond	Bloomberg	1
	Monetary aggregate M1 (SA)	ECB	5
	Monetary aggregate M2 (SA)	ECB	5
	Monetary aggregate M3 (SA)	ECB	5
	M2 Supply(% change m/m-1 SA)	ECB	1
Income Data	Gross Income	Eurostat	5
	Gross Disposable Income	Eurostat	5
	Total Industrial Production	OECD	5
	IP for Manufactures	OECD	5
	IP for Manufactured Intermediate goods	OECD	5
	IP for Manufactured Investment goods	OECD	5
	IP for Manufactured durable consumption goods	OECD	5
	IP for Manufactured non durable consumption goods	OECD	5
	IP for Energy goods	OECD	5
	IP for Capital goods	OECD	5
Expectations	Orders for constructions	ECB	2
	Orders for Investments	ECB	2
	UE Consumption Expectations 12 months	ECB	2
	Employment Expectations in construction	ECB	2
	Euro Total Industry survey - selling price expectations	ECB	2