A SUITE OF INFLATION FORECASTING MODELS

2017

Luis J. Álvarez and Isabel Sánchez

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BANCO DE ESPAÑA

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Abstract

This paper describes the econometric models used by the Banco de España to monitor consumer price inflation and forecast its future trends. The strategy followed heavily relies on the results from a set of econometric models, supplemented by expert judgment. We consider three different types of approaches and highlight the relevance of heterogeneity in price-setting behaviour and the importance of using models that allow for a slowly evolving local mean when forecasting inflation.

Keywords: inflation, forecasting, Phillips curves, transfer functions, judgemental forecasts.

JEL Classification: C53, E31, E37.

Resumen

En este trabajo se describen los modelos econométricos utilizados por el Banco de España para hacer el seguimiento de la inflación y prever sus tendencias futuras. La estrategia empleada se fundamenta en gran medida en los resultados de un conjunto de modelos econométricos, que se complementa con el juicio de expertos. Se consideran tres tipos diferentes de enfoques y se destaca la relevancia de la heterogeneidad en la determinación de precios y la importancia de utilizar modelos que permitan una evolución lenta de la media local cuando se prevé la inflación.

Palabras clave: inflación, predicción, curvas de Phillips, funciones de transferencia, predicción de experto.

Códigos JEL: C53, E31, E37.

INDEX

1 Introduction

> Essentially, all models are wrong, but some are useful.
> Box and Draper (1987)

The aim of this paper is to describe the econometric models used by Banco de España to monitor[1] consumer price inflation and forecast its future trends[2]. For central banks, the availability of accurate inflation forecasts is extremely important given that price stability is typically their main objective, as for the Eurosystem, or a prominent one, as is the case of the Federal Reserve System. This general interest has been renewed recently, following the abrupt changes in the economy, including in price setting behavior, during the Great Recession and its aftermath[3].

The strategy followed to try to achieve accurate inflation forecasts heavily relies on the results from a set of econometric models, described below and each with their advantages and drawbacks, which are supplemented by expert judgment. There are several reasons to justify the subjective approach we follow. First, experts process a lot of information that is hard to be included endogenously in a formal econometric model. For instance, a future indirect tax change may be announced prior to its coming into force and experts may use available information to quantify its impact and improve model-based forecasts. Indeed, available evidence suggests that subjective inflation forecasts improve on a variety of model-based ones (e.g. Faust and Wright (2013)). Second, any model is just an imperfect stylized representation of the true world and some transmission channels may be modelled imperfectly or not at all, so it cannot be expected to produce perfectly accurate projections. Third, different models[4] may be useful to a different extent for forecasting and storytelling and their relative merits may also depend on the nature of the shocks (e.g. changes in trend inflation), so that an approach considering a suite of models is to be preferred to just using a single model[5]. In particular, structural models, such as DSGE models, provide a theoretically sound explanation of relationships among variables, but generally are not very accurate for short term forecasting. On the other hand, atheoretical models, such as time series models, are much more reliable for short term projections, but do not necessarily provide good economic explanations

Among possible inflation measures, our focus here is on consumer price indices (CPIs). On the one hand, CPIs are the main tool used by central banks to set inflation targets, this function being fulfilled in the case of the Eurosystem by the Harmonised Index of Consumer Prices (HICP)[6]. On the other hand, CPIs are frequently used as a benchmark in

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1 To assess fresh data, models are reestimated once a year, so that changes in forecasts do not reflect changes in model parameters, except in the case of large or systematic errors where intervention analysis is considered within the year.

2 We do not consider here results from the Banco de España Quarterly Macroeconomic model (MTBE).

3 See e.g. Ciccarelli and Osbat (2017).

4 Alternative time series models could also be used to forecast inflation. See e.g. Faust and Wright (2013) or Öğünç et al. (2013) for a comparison of a wide variety of methods.

5 There is a vast literature on forecast combination methods starting from Bates and Granger (1969). These methods have been shown to be useful when dealing with structural breaks, noise and different information sets (Timmermann (2006)). However, in practice, complex combination procedures generally fail to consistently outperform the simple mean over forecasts of competing models. In order to address this issue, time varying machine learning combinations approaches have recently been proposed (e.g. Mandel and Sami (2016)).

6 The main purpose of the HICP, which is very similar to the CPI, is to provide an aggregate indicator comparable with the HICPs of the other EU countries. Conceptual differences between both indicators are very small, the main one being that weights in the CPI refer to national consumption, whereas those of the HICP refer to domestic consumption. The HICP is a key indicator for the Eurosystem, since it provides the basis for the definition of price stability in the euro area, which is the primary aim of the single monetary policy. Within the Eurosystem, the HICP is the preferred inflation measure.

wage bargaining, pension reviews and various types of nominal contractual agreements. Moreover, the CPI is the main indicator used to estimate the private consumption deflator, one of the most important deflators of the National Accounts.

The structure of this paper is the following. In Section 2 we present a brief overview of the CPI and justify a breakdown that has been commonly used to analyse and forecast it. In Sections 3, 4 and 5 we present the 3 different groups of models used. Specifically, in the third Section, to deal with heterogeneity in price setting behavior we present the aggregation of disaggregated univariate time series models. The use of these monthly models is in line with results in Stock and Watson (2010), that have pointed out that it is exceedingly difficult to improve systematically upon simple non-stationary univariate forecasting models. The good performance of this type of models may be explained on the basis that they are able to account for a slowly evolving local mean[7] for inflation, and this ability has been stressed by Faust and Wright (2013) as a key principle of successful inflation forecasting models[8]. Indeed, during recent years, stationary models of inflation -whose forecasts converge to its unconditional mean as the horizon gets large- have tended to generate unreasonably high forecasts at longer horizons because inflation has been persistently above its full sample average. In Section 4, we present monthly transfer function models that include indicators, such as oil prices, producer prices or unit labour costs and that also allow for a slowly evolving local mean and which are found to improve on univariate models. In Section 5, we present quarterly macro-based models, including hybrid New Keynesian Phillips curves. These models have a theoretical foundation and include forward looking elements. In Section 6, we describe the procedure we use to arrive at final forecasts. The final section presents the conclusions.

7 Sánchez and Peña (2001) show that when forecasting highly persistent series using overdifferenced models may lead to gains in forecast accuracy.

8 Other approaches that allow for a slowly varying local mean include Kozicki and Tinsley (2012) and Wright (2013).

2 Overview of the CPI

As it is well known, the purpose of the CPI is to track changes in the cost to consumers of purchasing a representative basket of goods and services. To compile the CPI, a price sample representative of the full set of goods and services available to consumers that takes account of the relative weight of each item in overall household expenditure is needed. This sample is defined and weights are determined on the basis of information drawn from the Household Budget Survey, as well as additional sources. The current CPI, which has 2011 as its base year, is designed as a dynamic consumption basket that can be adjusted to changes in the structure of consumption and in the type of items consumed[9]. In technical terms, the CPI is a chained Laspeyres index and geometric averages are used to aggregate elementary price quotes. The sample includes around 220.000 price quotes every month corresponding to 489 products. Prices indices are released for 126 subindices, following the COICOP (Classification of Individual Consumption according to Purpose) at the five digit level. Prices are mostly collected in brick and mortar stores in 177 cities and towns, although prices of some items are computed on the basis of information provided by the main companies (e.g. telephone prices).

Retail prices of products tend to display a high degree of heterogeneity. On the one hand, there is a large heterogeneity in product markets in terms of demand and supply elasticities. On the other hand, price stickiness (Álvarez et al. (2006)) and inflation persistence (Lünnemann and Mathä (2004)) are found to vary across goods and services. For analysis purposes, overall CPI data are generally broken down into smaller groups of relatively homogeneous items. A breakdown that is often employed considers processed and unprocessed foods, non-energy industrial goods, services and energy. The properties of the different groups differ for a variety of reasons. First, the level of foreign competition facing price setters varies across groups. Indeed, most services, for example, are less exposed to external competition than manufactured goods. Second, excise duties just apply to some products; specifically, certain processed foods and to some energy products. Third, some prices are subject to government regulation (e.g. gas prices or public universities' fees). Fourth, temporary supply shocks particularly affect prices of unprocessed foods and energy products. Last, discounts and special offers are particularly significant in some non-energy industrial goods and processed foods.

Chart 1 presents the contribution of the main components of the CPI to its growth rate[10]. The moderation of inflation following the Great Recession is particularly clear. Moreover, in 2014, 2015 and 2016 CPI growth moved into negative territory, mainly reflecting the contribution of energy prices. Chart 2 plots average growth rates of the CPI and its main components in the period 2002 to 2008 and the period 2009-2016. The marked reduction in the average growth of prices presents some challenges to stationary models of inflation. Heterogeneity in inflation subcomponents is also observed in terms of the variability of growth rates, as can be seen in Chart 3, where the standard deviation of year-on-year growth rates is plotted. The variability of energy and unprocessed food prices stands out, in contrast with the relatively stable developments for core CPI components (services, non-energy industrial goods ºand processed food).

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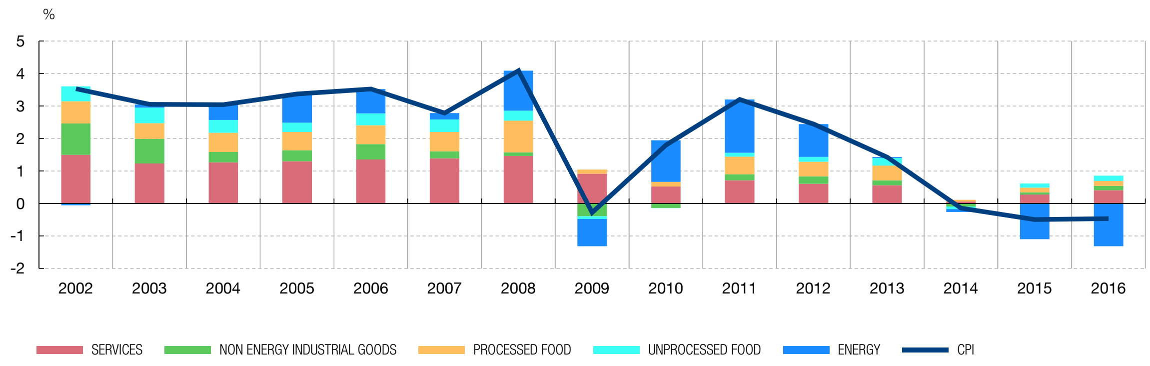
9 As from 2017, the new CPI base 2016 will come into force.

10 Our sample period, starts in 2001 when there was a major change in the methodology of the CPI. Annual growth rates, therefore, start in 2002.

CONTRIBUTIONS TO THE CPI GROWTH RATE

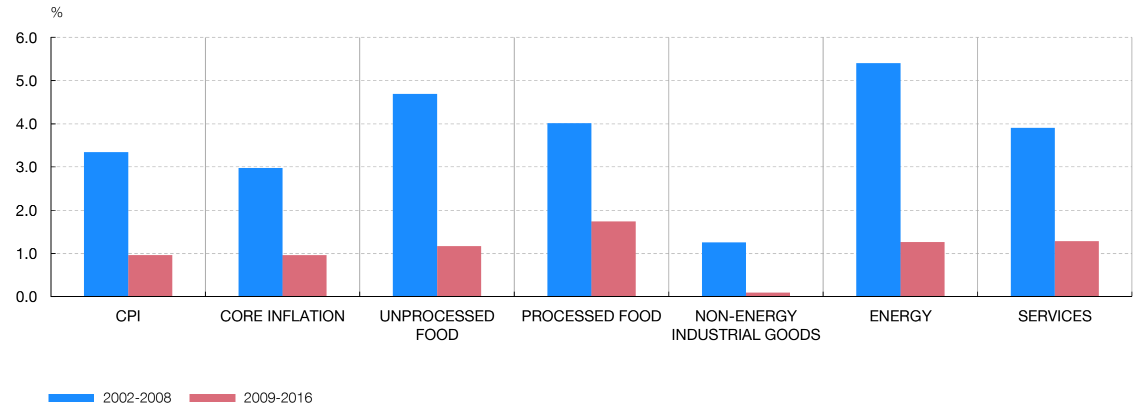
CHART 1



Source: INE.

CPI GROWTH RATE

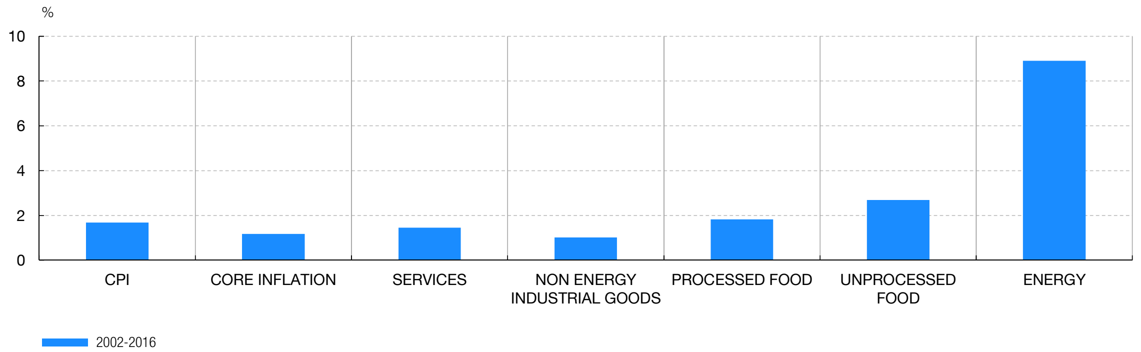
CHART 2



Source: INE.

VARIABILITY OF CPI COMPONENTS (a)

CHART 3



SOURCE: INE.

a Standard deviation of year-on-year rate.

Box 1: An inflation heat map

Headline CPI can be broken down into smaller component indexes, each representing a different subset of goods and services. Hence, changes in the aggregate price level can be traced back to changes in the price levels of different subcomponents. Indeed, there are published indices for 12 groups (COICOP-2), 37 subgroups (COICOP-3), 79 classes (COICOP-4) and 126 subclasses (COICOP-5).

Monitoring and interpreting changes in these component indexes is time consuming and not particularly easy to communicate, since there are many indices and their underlying characteristics vary widely both in terms of mean and standard deviation of growth rates. To simplify the analysis of these series, we follow McGillicuddy and Ricketts (2015) and use a heat map that visually represents the relative inflation levels of various CPI components since 2008.

Each colored box of the heat map represents the relative level of inflation for a given CPI component index for a particular month. For each component index, we define inflation as the year-over-year percent change in the index, which we normalize to take into account differences in long-term trends and volatility across series by subtracting the component-specific mean and dividing by its standard deviation. Blue represents an inflation value below the long-term trend of the index and red represents an inflation value above the long-term trend. The darker the color, the greater the difference between that particular inflation value and the long-run average for the component index (in terms of standard deviations). The choice of colors reflects the fact that inflation, like water temperature, is undesirable both if it is too high or too low.

The fact that series are normalized involves that comparison across series is in terms of standard deviations relative to the long-term mean, so that two series may have the same normalized value but very different year-on-year growth rates or they may have different colours, but have the same growth rate.

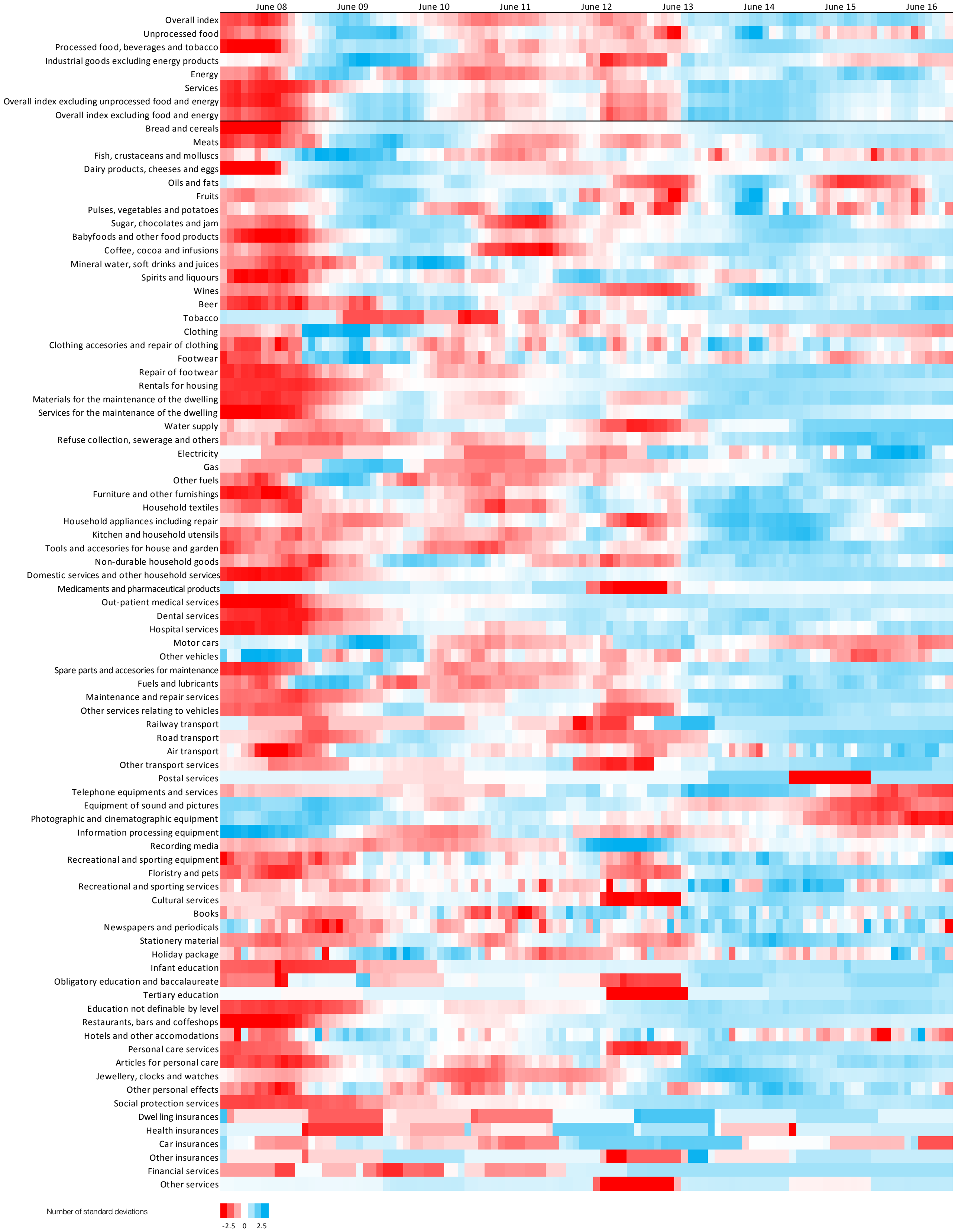
This heat map offers a fast and convenient way to keep track of specific inflation pressures considering in the top part special aggregates and in the bottom one the COICOP-4 disaggregation, so that it fits in one page.

Some elements are worth highlighting in this map. First, following the Great Recession, Spanish inflation has tended to be below its long-run mean. Second, VAT rises in 2010 and 2012 resulted in increases in y-o-y rates for many components. Third, there are important changes in relative prices, so that the growth rate of the overall price level isn't necessarily indicative of how the price levels of specific goods and services are changing.

INFLATION HEAT MAP

CHART B.1.1

NORMALIZED YEAR ON YEAR RATES OF THE CPI AND ITS COMPONENTS (a)



Sources: INE and Banco de España.

a Interannual rates typified by subtracting the average and dividing by the standard deviation of the 2008-2016 period.

3 Highly disaggregated univariate models

Stock and Watson (2010) stressed tremendous changes in recent decades in inflation dynamics in the United States, which led to considerable instability in inflation forecasting models. These authors point out that it is exceedingly difficult to improve systematically upon simple univariate forecasting models, such as the Atkeson and Ohanian (2001) model or the time-varying unobserved components model in Stock and Watson (2007), so it is natural to consider simple univariate models in a suite of models.

Moreover, a case can be made to consider highly disaggregated models for a number of reasons. As mentioned above, there is wide heterogeneity in factors such as demand and supply elasticities, price stickiness or inflation persistence. In principle, enlarging the information set leads to improvements in the precision of forecasts when the data generating process is known. However, in practice, DGPs are not known and bottom up approaches need not necessarily improve direct forecasts. At the end of the day, this is simply an empirical matter[11].

Among the class of univariate models, we note that the favoured univariate unobserved component model of Stock and Watson (2007) has a IMA (1,1) representation. In our approach, we consider more general ARIMA(p,d,q)x(ps,ds,qs) models augmented with intervention analysis. Specifically, for each of the COICOP-5 items (over 120 series) denoted by the superscript *i*, we estimate by maximum likelihood models for a sample period starting in 2001:

$$\Delta^{d^i} {\Delta_{12}}^{{d_s}^i} \varphi^i(L)[p_t^i - \sum {\alpha_j}^i D_{jt}] = \theta^i(L)\epsilon_t$$

where d^i and ${d_s}^i$ are the order of the product specific regular and seasonal difference operators, $\varphi^i(L)$ and $\theta^i(L)$ are product specific polynomial lag operators, D_{jt} are time dummies and t refers to the month.

To specify models, we follow the Gómez and Maravall (2001) algorithm. This algorithm first determines the number of unit roots for each of the models by estimating general mixed (regular and seasonal) models. Roots are considered to be unit roots if their modulus is greater than a pre-specificed value[12]. Second, the order of autoregressive and moving average polynomials is determined using a penalty function method à la Hannan-Rissanen[13]. The underlying idea is that parsimonious models are to be preferred to models with many parameters. The algorithm allows for deterministic variables, such as those corresponding to Easter or to outliers. Finally, the chosen model is estimated by maximum likelihood.

11 Hubrich (2005) and Hendry and Hubrich (2011) present interesting applications of aggregate versus disaggregate inflation forecasting.

12 These estimators are consistent. Moreover, standard unit root tests have low power when moving average components are present.

13 The Hannan and Rissanen is based on a Bayesian Information Criterion (BIC), where the estimates of ARMA model parameters are computed by means of linear regressions.

Models are found in Appendix 1 and model characteristics are summarized in Table 1, and as expected, a high degree of heterogeneity is observed. We find that 77% of models present a slowly varying local mean and most models have 1 regular and 1 seasonal unit root. Given the model selection criterion, estimated models also tend to be quite parsimonious. Indeed, the average number of AR and MA parameters is 2.4. We find that there is no clear pattern for regular polynomials, whereas seasonal polynomials are predominantly of the moving average type. As expected, the modal model is the so called airline model [ARIMA(0,1,1)x(0,1,1), which is identified in 19% of cases.

MODEL CHARACTERISTICS TABLE 1

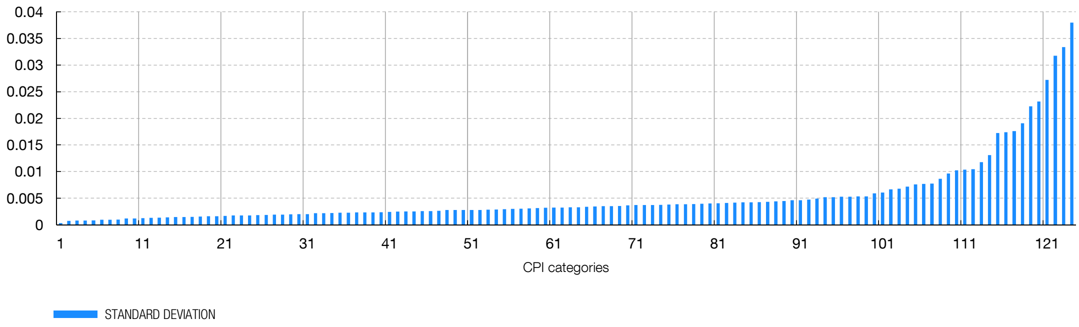
	NUMBER OF MODELS WITH UNIT ROOTS (%)			
	0	1	2	TOTAL
REGULAR UNIT ROOTS	2.4	84.7	12.9	100.0
SEASONAL UNIT ROOTS	33.1	66.9	0.0	100.0
	ORDER OF REGULAR POLYNOMIALS			
	1	2	3	TOTAL
PURE AUTOREGRESSIVE	17.7	7.3	4.8	29.8
PURE MOVING AVERAGE	29.8	1.6	2.4	33.9
MIXED MODEL	9.7	2.4	6.5	18.5
NO POLYNOMIAL				17.7
	ORDER OF SEASONAL POLYNOMIALS			
	1	2	3	TOTAL
PURE AUTOREGRESSIVE	13.7	0.0	0.0	13.7
PURE MOVING AVERAGE	58.9	0.0	0.0	58.9
MIXED MODEL	13.7	0.0	0.0	13.7
NO POLYNOMIAL				13.7
AVERAGE NUMBER OF MODEL PARAMETERS				2.4

Source: Own elaboration.

We also find a high heterogeneity in predictability in terms of the residual standard deviation of estimated models (Chart 4). As expected, harder to forecast prices correspond to energy (e.g. electricity, gas, fuels) and unprocessed food (e.g. beef, poultry and potatoes) items, but also some services, such as hotels and travel packages. Most other services prices are typically easy to forecast (e.g. university education, rents and health insurance), in the sense of having low residual standard deviations.

RESIDUAL STANDARD DEVIATION OF CPI COMPONENTS

CHART 4



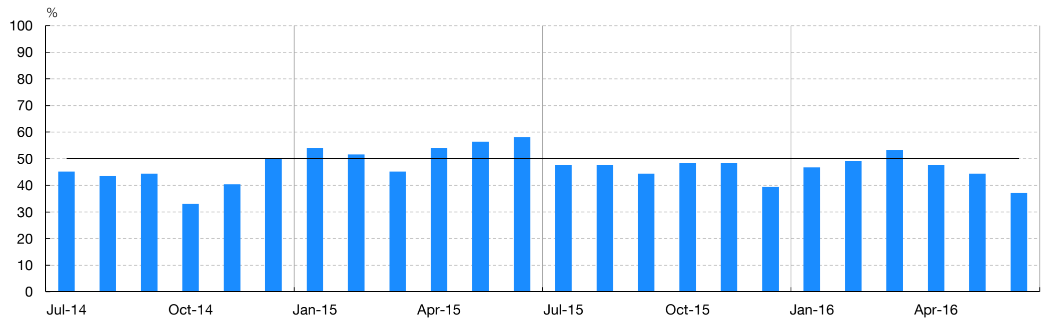
Source: Banco de España.

The availability of disaggregated forecasts also allows us to compute diffusion indices of forecast errors. In our case, diffusion indexes measure the proportion of the components that have a positive forecast error. If a greater number of the series do present positive forecast errors, the index will be above 50. Typically, the higher (lower) is the distance from the value 50 of such a measure the higher (lower) the more likely that it will be a common shock, which tends to be more persistent. As an example, we plot the diffusion index over the most recent period (Chart 5). Considering both unweighted and weighted[14] measures, we can see that in some periods there are forecast errors that are not widespread (i.e. the diffusion index is close to 50), but rather correspond to some specific items with a relatively high weight (i.e. the weighted diffusion index is not close to 50).

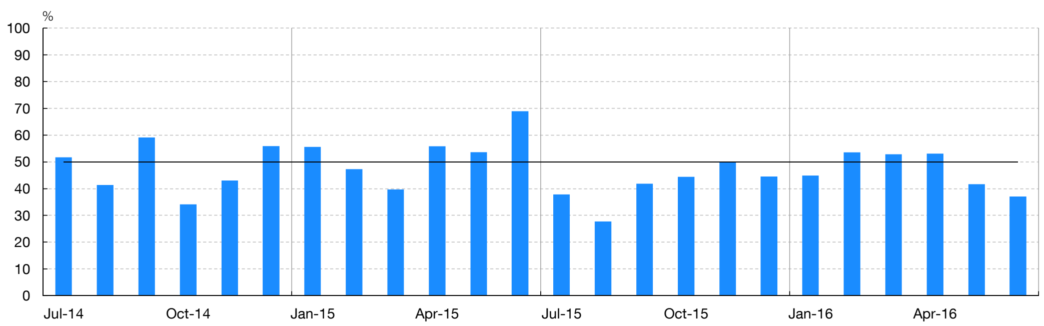
DIFFUSION INDICES

CHART 5

DIFFUSION INDICES OF ONE STEP AHEAD FORECAST ERRRORS



DIFFUSION INDICES OF WEIGHTED ONE STEP AHEAD FORECAST ERRRORS



Source: Own elaboration.

14 Weighted indexes use CPI weights.

4 Transfer function models

Univariate models, such as those presented in the previous section, do not consider the role of explanatory variables. In contrast, transfer function models [Box et al. (2015)] are single equation models that describe the relationship between a variable Y and one or more explanatory variables X. Responses of explanatory factors are modelled parsimoniously through rational polynomials in the lag operator. These models are able to account for a slowly evolving local mean for inflation, which is typically a desirable feature of forecasting models and they are more general than regression or autoregressive distributed lag models. Formally, the monthly transfer function model is specified as follows:

$$\Delta^{d^i}\Delta_{12}{}^{d_s{}^i}\varphi^i(L)[p_t^i-\sum\alpha_j{}^i D_{jt}-\sum\frac{\omega_j^i(L)}{\delta_j^i(L)}x_{jt}^i]=\theta^i(L)\epsilon_t$$

where d^i and $d_s{}^i$ are the order of the product specific regular and seasonal difference operators, $\varphi^i(L)$ and $\theta^i(L)$ are component specific polynomial lag operators, D_{jt} are time dummies and $\omega_j^i(L)$ and $\delta_j^i(L)$ are component specific polynomial lag operators associated with the explanatory variable x_{jt}^i

Indicators used are summarized in Table 2, Charts 6 to 10 and Table 3 present the transfer functions, which are estimated by maximum likelihood, that are used to produce forecasts for the main CPI components[15]. Deterministic variables starting with an S represent step functions and those starting with D dummy variables. The Easter variable captures the number of days in a given month that correspond to Easter. Among model diagnostics, average values and standard deviations of the residuals are presented, along with Q statistics that represent portmanteau residual autocorrelation statistics up to a given order, simple and partial autocorrelation functions and Bera-Jarque normality tests. We find that residuals generally have an autoregressive moving average structure.

TRANSFER FUNCTION MODELS FOR THE MAIN CPI COMPONENTS

TABLE 2

	INDICATORS	FREQUENCY	SOURCES
UNPROCESSED FOOD			
FRUITS AND VEGETABLES	FRUITS AND VEGETABLES AGRICULTURAL PRICES	WEEKLY	MINISTRY OF AGRICULTURE AND FISHERIES, FOOD AND ENVIRONMENT AND BANCO DE ESPAÑA
	MEAT AND EGGS AGRICULTURAL PRICES	WEEKLY	
PROCESSED FOOD	INDUSTRIAL AND IMPORT PRICES	MONTHLY	INSTITUTO NACIONAL DE ESTADÍSTICA AND BANCO DE ESPAÑA
NON ENERGY INDUSTRIAL GOODS	INDUSTRIAL PRICES	MONTHLY	INSTITUTO NACIONAL DE ESTADÍSTICA AND BANCO DE ESPAÑA
ENERGY	FUELS PRICES	WEEKLY	MINISTRY OF ENERGY, TOURISM AND THE DIGITAL AGEND
	OIL PRICES	DAILY	REUTERS
SERVICES	UNIT LABOUR COSTS MARKET SERVICES	QUARTERLY	INSTITUTO NACIONAL DE ESTADÍSTICA

Source: Own elaboration.

15 Models for the main HICP components are presented in Appendix 2.

To forecast unprocessed food items, we consider the CPI for fruit and vegetables, considering as indicators producer prices of fruits and vegetables and the rest of unprocessed food items, which consider agricultural prices as indicators. Forecasting processed food prices takes into account industrial and import prices of those goods. There are no official indexes corresponding to these indicators, so we build CPI-weighted indicators that just consider those producer prices which are directly related to each of these CPI components. Other factors include changes in indirect taxation, particularly corresponding to changes in excise duties on tobacco. To forecast the non-energy industrial goods component, a transfer function is used considering an indicator based on the producer price index. Similarly to the indicator for processed food items, we have built a CPI-weighted indicator of those producer prices which are directly related to non-energy industrial goods (e.g. producer prices of clothing and those for footwear). Although imported goods account for a substantial proportion of expenditure in these products close, stable relationships between changes in consumer prices of these items and import prices are not easily identifiable. Forecasts for the services' component are obtained by a transfer function model that includes unit labour costs per unit of value added for market services.

Forecasts for the energy component have to bear in mind that there is substantial heterogeneity by product type, that the relationship between consumer prices and oil prices is a non-linear one [Álvarez et al. (2011)] and that nowcasts can be made on the basis of weekly information on fuel prices.

The index of energy prices, is composed of two subsets of clearly differentiated items. The first subset corresponds to fuel products, where nowcasts are produced on the basis of petrol and diesel retail prices. The CPI is released with a, roughly, biweekly delay with respect to the calendar month. Given the high volatility of fuel prices, considering this information for the current calendar month significantly improves the precision of forecasts. For horizons different from the current month, forecasts are made conditional on weekly information and the price of crude oil futures, assumed future trends in the euro exchange rate and expected changes in indirect taxation. The second subset includes electricity, whose prices are highly variable, as well as butane gas and natural gas, whose prices are regulated.

The relationship between the log change in the price of oil and the log change in the corresponding price index can be expected to be nonlinear, partly due to the existence of excise duties, which are not proportional to the final price. To account for this feature, we estimate monthly non-linear models, which allow for an interaction between the change in the oil price and its level.

$$\Delta P_t^C = \alpha \Delta P_t^O + \beta \Delta P_{t-1}^O + \gamma P_t^O \Delta P_t^O$$

where ΔP_t^C refers to the log change in the CPI index of a refined oil product, ΔP_t^O to the log change of the euro denominated price of Brent crude oil and P_t^O to its level.

Estimates show that there are significantly positive non-linear effects for transport fuels and heating oil. With this specification, higher (lower) elasticities are obtained with higher (lower) oil prices.

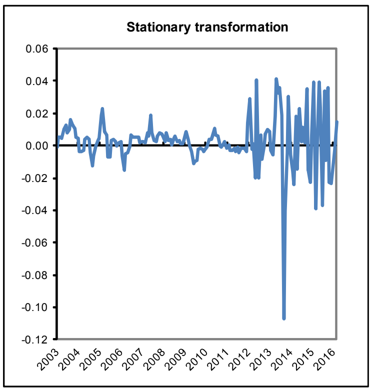
We also present the nowcasting equations that relate CPI fuel components to retail prices of gasoline, diesel and heating oil and which are standard regressions. This way we take into account consumer price data available prior to the release of the CPI data.

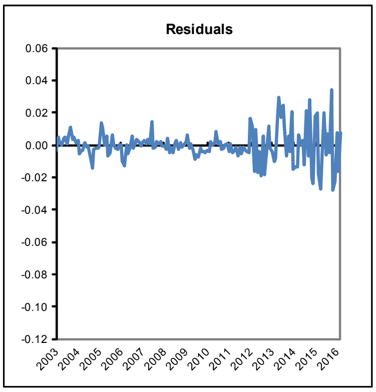
CHART 6

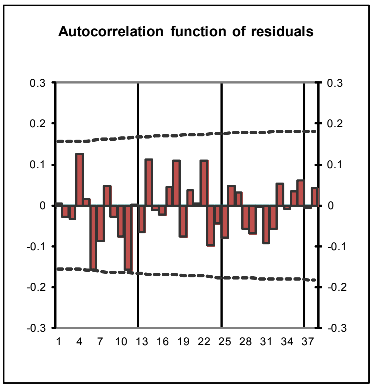
Unprocessed food CPI: fruits and vegetables
Transfer function

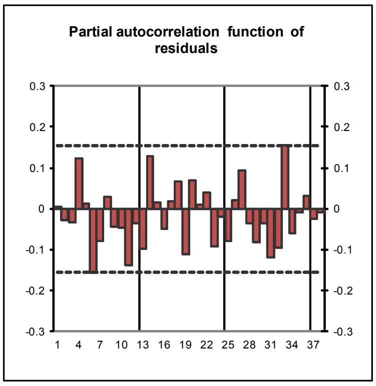
Sample period: January 2002- March 2016

Model	Coefficient	T statistic
Δ ln CPI =		
Dummies		
Constant	0.0029	2.6
SJun2012	0.0472	5.4
SSep2013 (0)	-0.0943	-9.5
SSep2013 (1)	-0.0315	-3.2
DApr2014	0.0165	3.1
DFeb2015	0.0149	5.0
DMay2016	0.0447	6.6
Indicators		
Fruits (0)	0.0643	3.3
Vegetables (0)	0.0191	2.6
Stochastic structure		
AR(2)	0.1550	1.9
AR(3)	-0.2434	-3.0
MA(1)	-0.4289	-5.1
MA(12)	-0.1745	-1.9
Residuals		
Average	0.0000	0.0
Standard deviation (%)	0.96	
Q (14)	17.9	
Q (26)	28.2	
Q (38)	34.5	
Bera-Jarque normality test	27.9	
	RMSE	**Average error**
1 Forecast period (Jul. 2014-Jun. 2016)	0.0276	0.0003
2 Forecast period (Aug. 2014-Jul. 2016)	0.0420	0.0012
3 Forecast period (Sep. 2014-Aug. 2016)	0.0455	0.0015









Source: Own elaboration.

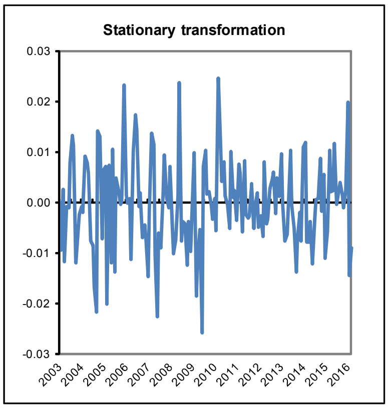
Unprocessed food CPI: meat, fish and eggs
Transfer function

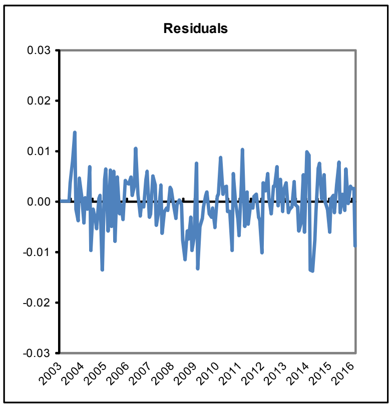
Sample period: January 2002- March 2016

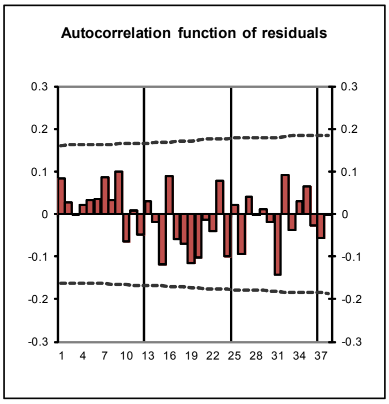
Model

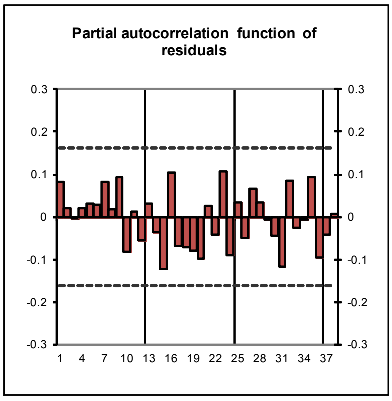
	Coefficient	T statistic
$\Delta\,\Delta_{12}$ ln CPI =		
Dummies		
SJun2008	0.0229	4.7
DJan2016	0.0145	3.9
Indicators		
Agricultural prices (0)	0.8194	8.3
Agricultural prices (1)	0.4523	4.6
Agricultural prices (2)	0.1868	1.9
Stochastic structure		
AR(3)	0.1451	1.8
MA(12)	0.7789	14.6
Residuals		
Average	-0.0003	-0.7
Standard deviation (%)	0.52	
Q (14)	6.0	
Q (26)	20.5	
Q (38)	28.7	
Bera-Jarque normality test	1.5	

	RMSE	**Average error**
1 Forecast period (Jul. 2014-Jun. 2016)	0.0045	0.0012
2 Forecast period (Aug. 2014-Jul. 2016)	0.0065	0.0023
3 Forecast period (Sep. 2014-Aug. 2016)	0.0078	0.0030







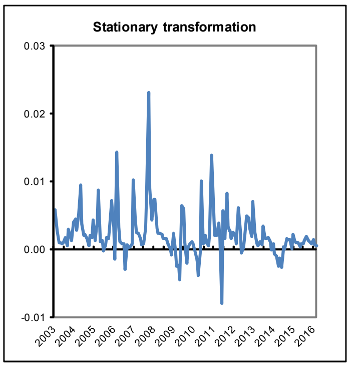


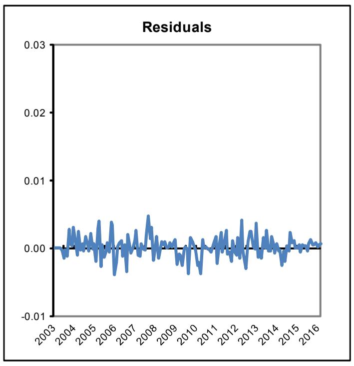
Source: Own elaboration.

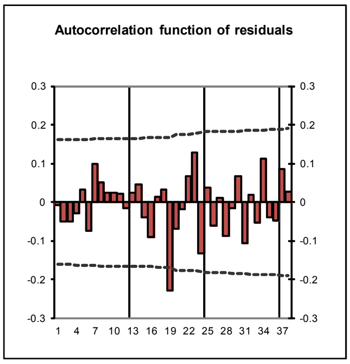
CHART 8

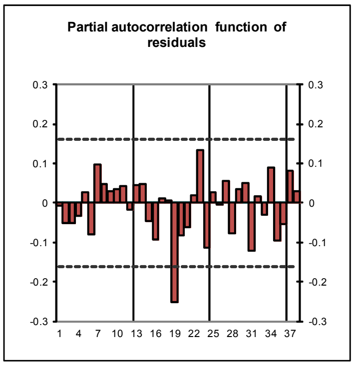
Processed food CPI:
Transfer function model with producer and import prices

Sample period: January 2002- March 2016		
Model	Coefficient	T statistic
Δ ln CPI =		
Dummies		
SMay2004	0.0058	4.0
SMar2006	0.0122	8.1
SJan2007	0.0010	4.1
SOct2007	0.0137	9.1
SJun2009	0.015	5.9
SJun2010	0.0088	5.7
SDec2010	0.0100	6.9
SJun2011	-0.0053	-3.2
SSep2011	0.0088	5.0
Indicators		
Industrial prices (0)	0.2650	6.5
Industrial prices (1)	0.1215	3.7
Industrial prices (2)	0.0681	1.9
Industrial prices (3)	0.1076	3.1
Import prices (0)	0.0211	1.2
Stochastic structure		
AR(1)	0.4478	5.8
AR(12)	0.2131	2.6
Residuals		
Average	0.0002	1.8
Standard deviation (%)	0.16	
Q (14)	4.8	
Q (26)	25.0	
Q (38)	35.2	
Bera-Jarque normality test	1.2	
	RMSE	**Average error**
1 Forecast period (Jul. 2014-Jun. 2016)	0.0009	0.0004
2 Forecast period (Aug. 2014-Jul. 2016)	0.0017	0.0008
3 Forecast period (Sep. 2014-Aug. 2016)	0.0026	0.0014









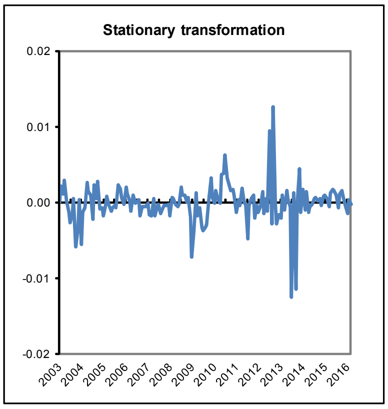
Source: Own elaboration.

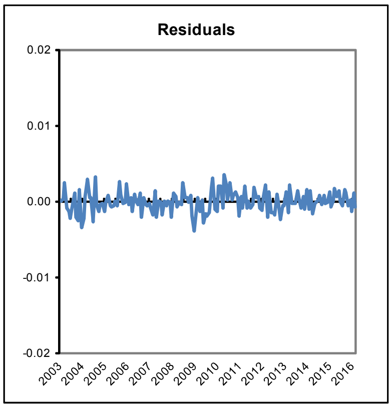
CHART 9

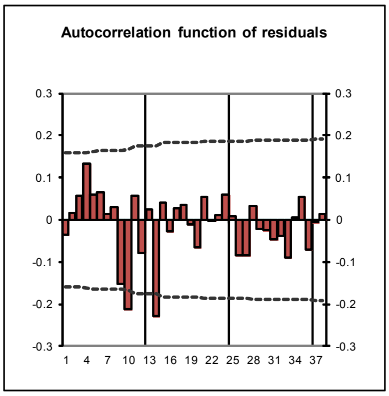
Non energy industrial goods CPI:
Transfer function model with prices of domestic production

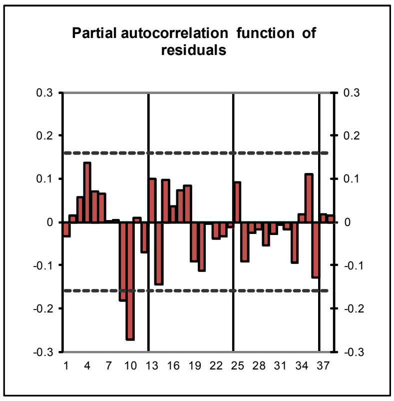
Sample period: January 2002- March 2016

Model	Coefficient	T statistic
$\Delta\,\Delta_{12}$ ln CPI =		
Dummies		
DJan2002-Jan2003	0.0022	2.8
SOct2003	-0.0039	-4.3
DJan-Feb2009	-0.0023	-3.5
SVATJul2010	0.0044	4.8
SJul2012	0.0113	12.3
SVATSep2012	0.0123	13.4
SNov2011-Nov2012	-0.0037	-4.1
Indicator		
Industrial prices (0)	0.2566	3.4
Stochastic structure		
AR(1)	0.3816	5.0
Residuals		
Average	-0.0001	-0.5
Standard deviation (%)	0.14	
Q (14)	27.6	
Q (26)	31.8	
Q (38)	37.6	
Bera-Jarque normality test	0.4	
	RMSE	**Average error**
1 Forecast period (Jul. 2014-Jun. 2016)	0.0009	0.0002
2 Forecast period (Aug. 2014-Jul. 2016)	0.0013	0.0004
3 Forecast period (Sep. 2014-Aug. 2016)	0.0019	0.0009









Source: Own elaboration.

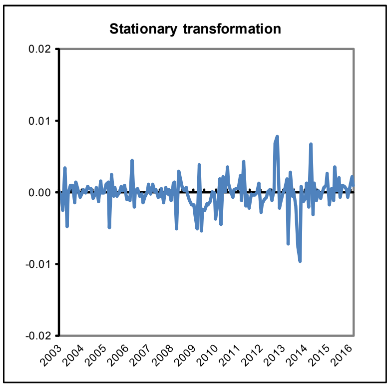
CHART 10

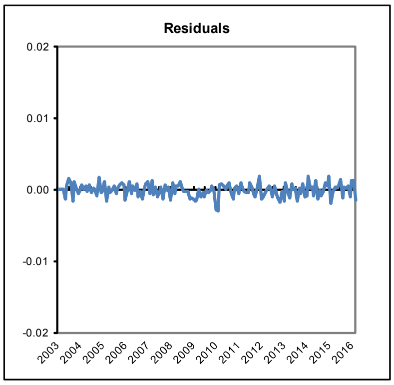
Services CPI:
Transfer function model with unit labour costs

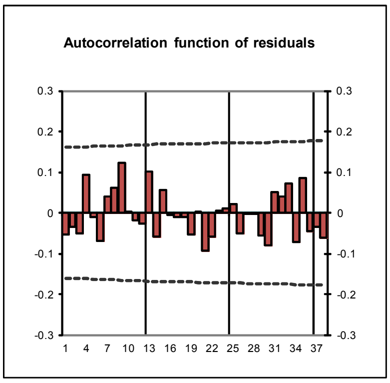
Sample period: January 2002- March 2016

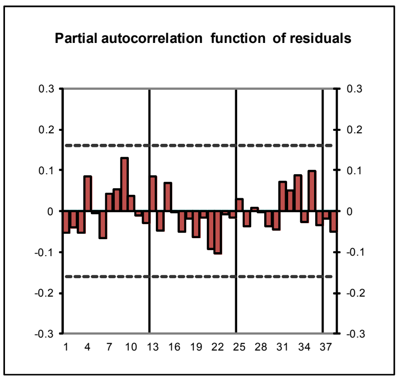
Model

	Coefficient	T statistic
$\Delta\ \Delta_{12}$ ln CPI =		
Dummies		
DJan2002-2009	0.0013	2.2
SVATJul2010	0.0027	3.7
SJan2012	-0.0016	-2.1
SVATSep2012	0.0075	10.1
SOct2012	0.0090	12.1
SMay2015	0.0028	3.2
Easter	0.0027	16.9
Indicators		
ULC market services (0)	0.0290	1.9
Stochastic structure		
AR(1)	0.1893	2.2
AR(2)	0.2105	2.6
AR(3)	0.2015	2.5
MA(12)	0.3541	4.8
Residuals		
Average	-0.0001	-1.4
Standard deviation (%)	0.09	
Q (14)	9.1	
Q (26)	13.0	
Q (38)	20.7	
Bera-Jarque normality test	2.0	
	RMSE	**Average error**
1 Forecast period (Jul. 2014-Jun. 2016)	0.0011	0.0000
2 Forecast period (Aug. 2014-Jul. 2016)	0.0016	0.0002
3 Forecast period (Sep. 2014-Aug. 2016)	0.0021	0.0004









Source: Own elaboration.

TABLE 3

Energy CPI:
Models of components

Forecasting

CPI transport fuels
Sample period: January 2002- March 2016
Model

	Coefficient	T statistic
Δ ln (CPI fuels)=		
Indicator		
Δ ln Oil prices [t]	0.0934	2.9
Δ ln Oil prices [t-1]	0.1534	13.1
Oil price [t] *Δ ln (Oil price [t])	0.0034	5.0
Residual standard deviation	1.25	
R^2	0.83	

CPI heating oil
Sample period: January 2002- March 2016
Model

	Coefficient	T statistic
Δ ln (CPI other fuels)=		
Indicator		
Δ ln Oil prices [t-1]	0.2812	12.2
Oil price [t] *Δ ln (Oil price [t])	0.0066	14.0
Residual standard deviation	2.47	
R^2	0.72	

Nowcasting

CPI transport fuels
Sample period: January 2002- March 2016
Model

	Coefficient	T statistic
Δ ln (CPI fuels)=		
Indicador		
Δ ln(Gasoline price)	0.5286	23.9
Δ ln (Diesel price)	0.4573	19.8
Residual standard deviation	0.47	
R^2	0.97	

CPI heating oil
Sample period: January 2002- March 2016
Model

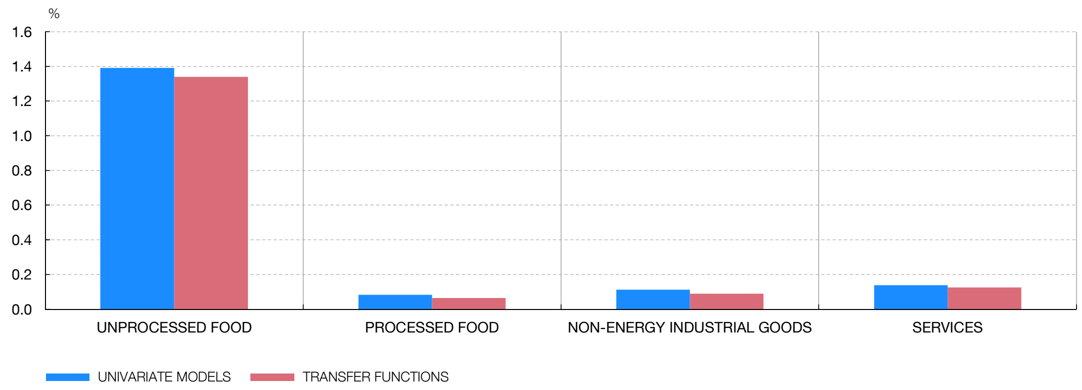
	Coefficient	T statistic
Δ ln (CPI other fuels)=		
Indicator		
Δ ln (Heating oil price)	0.9232	33.0
Residual standard deviation	1.69	
R^2	0.87	

Source: Own elaboration.

To compare the forecasting accuracy of the transfer functions for the non-energy components vis-à-vis the disaggregated univariate models described in the previous section, we carry out a real time out-of-sample forecast accuracy comparison that allows us to deal with data revisions and changes in model specification. In Chart 11, we present root mean squared one month ahead forecast errors for both the aggregation of univariate models and for transfer function for the main CPI non-energy components for an evaluation period of two years (from July 2014 to July 2016). The much higher unpredictability of unprocessed food clearly stands out. In Chart 12 we present relative mean square forecast errors. A value higher (lower) than one for this statistic means the aggregation of univariate forecasts is less (more) precise than the transfer function model. We present result for 1, 2 and 3 months ahead forecasts. We find that transfer function models outperform bottom up univariate forecasts. Relative gains tend to diminish the higher is the forecast horizon, reflecting difficulties in forecasting explanatory variables. Despite the fact that, on average, transfer function models are more precise than univariate models we find the cross check quite useful. This is particularly the case when there is an outlier for a particular subindex (e.g. package holidays), which is not clearly reflected in the aggregate

ROOT MEAN SQUARED FORECAST ERRORS
One month step ahead

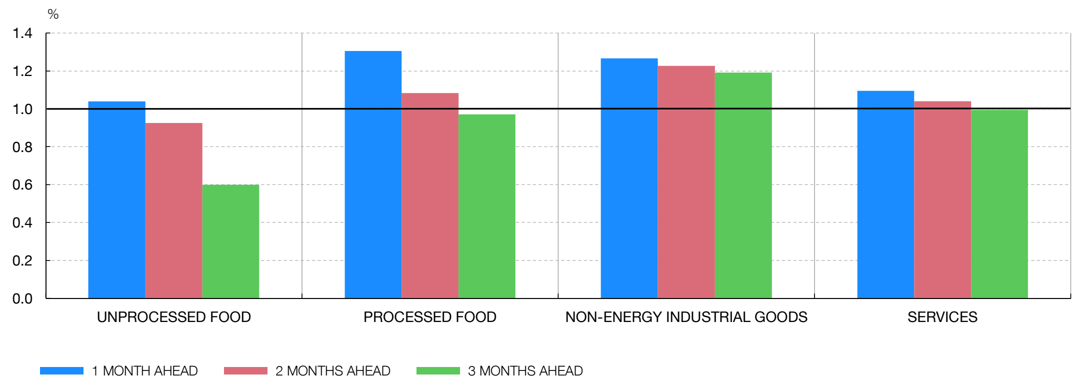
CHART 11



Source: Own elaboration.

RELATIVE ROOT MEAN SQUARED FORECAST ERRORS (a)
H month step ahead

CHART 12



Source: Own elaboration.

a Ratio of mean squared forecast errors of the aggregation of univariate models to those of transfer function

Box 2: Assessing the impact of VAT changes

In 2010 and 2012 there were increases in value added tax rates. This box presents estimates of the effects of this increase in indirect taxation on consumer prices, using a partial equilibrium approach. Obviously, any increase in indirect taxation affects the decisions of the different private and public agents in various ways, which may, in turn, generate second round effects on prices, although these impacts have not been considered here.

From a theoretical viewpoint, the degree of pass-through of changes in indirect taxation to consumer prices depends on many factors, which have different effects in different product markets. These factors include the degree of competition, the elasticity of consumer demand, firms' cost structures and the role of expectations in price formation processes. The difficulty of this quantification also relates to the timing of the pass-through, since firms may decide to change their prices before the entry into force of the rate increase, at the time it takes place or in a later period. In practice, measurement of the impact of changes in indirect taxation and their distribution over time is hampered by the difficulty of separating a change in the actual CPI into that part which genuinely reflects a pass-through of tax from that which is attributable to normal seasonal changes or to changes in the proximate determinants of consumer prices (for example, industrial prices and the price of oil).

In any event, the hypothesis of complete pass-through of the tax change enables us to put an upper limit on the impact of the rise in taxes on prices. This can be obtained from a comparison of the HICP (Harmonised Index of Consumer Prices) and the HICP-CT (Harmonised index of consumer prices at constant taxes) published by the Spanish Statistical Institute (INE).

To estimate the impact of VAT, three different approaches have been used. Each approach has advantages and disadvantages, so that to estimate the impact it is advisable to consider the range of results obtained. The first method is non-parametric, whereas methods 2 and 3 are fully model-based. The first two methods considered are unconditional, in that they only use consumer price data, while the third is conditional, insofar as models are used to remove the effect of the changes in the proximate determinants of consumer prices.

Specifically, the first method is based on the following procedure: the change in consumer prices around the date of each VAT change has been broken down for each of the 126 sub-indices of the CPI (e.g. fresh fish) into a normal seasonal component (corresponding to the month-on-month changes recorded in the same months of the previous year) and a residual term, associated with the increase in VAT. To avoid estimates for any particular sub-index implying a pass-through of the VAT increase of less than zero or of more than one hundred percent estimates we have constrained them.

$$pt_{mt}^{i} = \begin{cases} \Delta p_{mt}^{i} - \Delta p_{mt-1}^{i} & \text{if } 0 < \Delta p_{mt}^{i} - \Delta p_{mt-1}^{i} < \Delta\tau^{i} \\ 0 & \text{if } \quad \Delta p_{mt}^{i} - \Delta p_{mt-1}^{i} < 0 \\ \Delta\tau^{i} & \text{if } \quad \Delta p_{mt}^{i} - \Delta p_{mt-1}^{i} > \Delta\tau^{i} \end{cases}$$

where pt_{mt}^{i} denotes the pass through for product i in month m of year t, Δp_{mt}^{i} the price change for product i in month m of year t and $\Delta\tau^{i}$ the tax rate change for product i

Results have been aggregated subsequently using the CPI weights of each subindex ω^{i}

$$pt_{mt} = \sum \omega^{i} pt_{mt}^{i}$$

The second method uses, for each CPI sub-index, a univariate model with intervention analysis identified and estimated automatically, to try to identify extraordinary changes during these months that may be attributable to the rise in VAT, as in Section 3 of this paper. The degree of pass through is constrained to lie between zero and one and results are CPI-weighted.

The third procedure is a conditional estimate, which strips out that part of the change in the actual CPI that reflects a change in its proximate determinants (e.g. industrial prices) using a transfer function model of the five main components of the CPI, as in Section 4 of this paper.

Table B.2.1 presents the estimates for VAT changes along with their degree of pass though. The estimated degree of pass-through of the 2010 VAT increase lies between 30% and 52% of the total potential impact, whereas that of the VAT increase in 2012 lies between 35% and 48% of the full pass-through estimate. These pass-throughs are smaller than those estimated for other episodes of VAT rises (such as in 1992 and 1995)[16] in which estimated pass-throughs were close to 1, reflecting the weakness of household spending, which would have led firms to absorb part of the tax increase in their margins. We also note that there is an important heterogeneity in terms of pass-through across components.

Chart B.2.1 presents the Core CPI inflation rate, along with the contribution of the estimated impact of VAT increases and rises in regulated prices. It can be seen that the bulk of the impact is observed in the month that the VAT change takes place and that the transmission to retail prices is quite quick.

16 According to internal Banco de España estimates prepared at that time, using a similar methodological approach to the one presented in this Box.

EFFECTS OF VAT INCREASE ABOUT CPI

TABLE B.2.1

VAT INCREASE IN 2010

	ESTIMATED IMPACT				DEGREE OF PASS-THROUGH (%)		
	METHOD 1 (a)	METHOD 2 (b)	METHOD 3 (c)	THEORETICAL UNDER FULL PASS-THROUGH	METHOD 1 (a)	METHOD 2 (b)	METHOD 3 (c)
OVERALL	0.57	0.33	0.42	1.10	52.0%	29.6%	37.8%
CORE INFLATION	0.57	0.29	0.40	1.10	51.5%	26.4%	36.2%
UNPROCESSED FOOD	0.25	0.00	0.00	0.50	50.4%	0.0%	0.0%
PROCESSED FOOD	0.30	0.04	0.00	0.79	37.6%	5.1%	0.0%
NON ENERGY INDUSTRIAL GOODS	0.77	0.61	0.58	1.40	55.2%	43.9%	41.5%
ENERGY	0.83	0.83	0.83	1.51	55.0%	55.0%	55.0%
SERVICES	0.51	0.14	0.41	0.99	51.8%	14.5%	41.4%

VAT INCREASE IN 2012

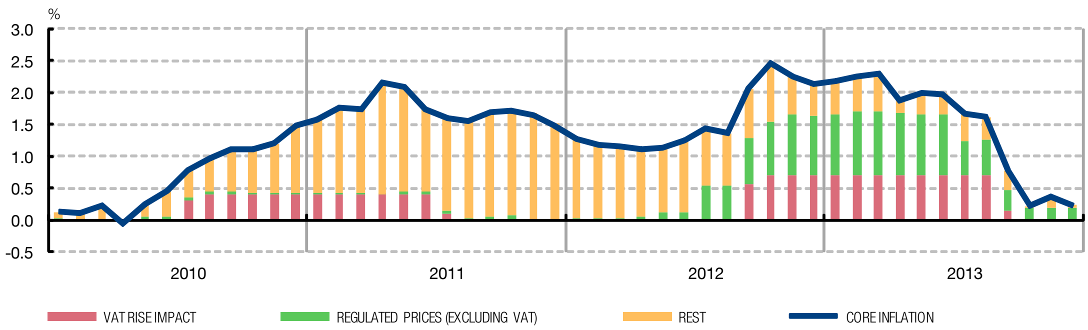
	ESTIMATED IMPACT				DEGREE OF PASS-THROUGH (%)		
	METHOD 1 (a)	METHOD 2 (b)	METHOD 3 (c)	THEORETICAL UNDER COMPLETE TRANSLATION	METHOD 1 (a)	METHOD 2 (b)	METHOD 3 (c)
OVERALL	0.94	0.68	0.84	1.96	47.8%	34.7%	42.9%
CORE INFLATION	0.92	0.70	0.85	1.97	46.8%	35.7%	43.4%
UNPROCESSED FOOD	0.46	0.41	0.00	1.03	44.2%	40.0%	0.0%
PROCESSED FOOD	0.49	0.31	0.00	1.52	32.3%	20.1%	0.0%
NON ENERGY INDUSTRIAL GOODS	1.04	0.85	0.87	2.20	47.3%	38.6%	39.6%
ENERGY	1.31	0.67	1.22	2.43	54.0%	27.7%	50.1%
SERVICES	1.00	0.75	1.16	1.98	50.6%	37.9%	58.7%

Source: Own elaboration.

a Unconditional estimate.
b Estimation from univariate disaggregated models.
c Conditional estimate using transfer function model of main components.

CONTRIBUTIONS TO THE CORE INFLATION GROWTH RATE

CHART B.2.1



Source: INE and own elaboration.

5 Macroeconomic models

Models in Section 3 did not consider explanatory variables, while those in Section 4 considered short-term indicators. The purpose of this section is to present models that consider other macroeconomic variables, such as, e.g. inflation expectations or the output gap.

The macroeconomic literature on price-setting stresses the effect of the cyclical position on prices. Indeed, for instance, price setting in DSGE models is typically modeled using a Phillips curve that can provide some helpful insight when forecasting inflation in the short and medium-term

According to the Phillips curve approach, current inflation (π_t) depends on expected inflation (π_t^e), the degree of cyclical slack in the economy (s_t) and an error term (e_t). Current inflation is greater (lesser) if expected inflation increases (decreases), and lesser (greater) if economic slack increases (decreases). The cyclical sensitivity of inflation is given by the coefficient α. The estimated relationship[17] is as follows:

$$\pi_t = \pi_t^e + \alpha s_{t-1} + \varepsilon_t$$

Expected inflation is a variable which cannot be observed, so assumptions need to be made about its behaviour. In this paper, we take the approach of Ball and Mazumder (2011). These authors consider inflation expectations to be a linear combination of a forward-looking component and a backward-looking component (as in standard hybrid New Keynesian Phillips curves), with weights given, respectively, by γ and $1-\gamma$. The forward looking component can be identified with the central bank's inflation target (π^0) and the backward component with average inflation in the past year. In this setup, $1-\gamma$ can be interpreted as measuring the degree of persistence in the price dynamics. The higher (lower) is this coefficient, the greater (smaller) is the inflation inertia.

With quarterly data, the relationship used to proxy inflation expectations is as follows:

$$\pi_t^e = \gamma\pi^0 + (1-\gamma)\frac{1}{4}(\pi_{t-1} + \pi_{t-2} + \pi_{t-3} + \pi_{t-4})$$

The estimation of the Phillips curve seeks to determine the effect of changes in demand on inflation. Therefore, to minimize the effect of supply-side shocks (which affect inflation and activity in opposite directions), the inflation measure used is a measure of core inflation which excludes from the overall index the energy and unprocessed food components, as well as the effect of tax changes and regulated prices, and which is seasonally adjusted. The degree of cyclical slack in the economy is proxied by the quarter-on-quarter GDP rate[18].

Table 4 shows the results of the estimates of the symmetrical Phillips curve. The cyclical sensitivity coefficient α is statistically significant and shows inflation responding to the position in the cycle in a similar way to that found by Álvarez and Urtasun (2013). Specifically, an increase (decrease) in GDP growth of 1 percentage point (pp) translates into an inflation

17 To avoid simultaneity problems, GDP growth is lagged by one period.
18 Open economy versions of the Phillips curve show similar results. Álvarez and Urtasun (2013) also present results using the year-on-year change in the unemployment rate.

rate 0.1 pp higher (lower). According to this model, inflation expectations are determined both by forward-looking and backward-looking elements, although past inflation is more important than medium-term expectations in determining price fluctuations.

The model above implies that inflation's response to activity remains constant, regardless of its cyclical position. However, there is some evidence suggesting that the response of inflation to output is asymmetric. Indeed, survey data suggest price-setting behavior of firms is more reactive in recessions than in expansions[19]. In this regard, Álvarez, Gómez and Urtasun (2015) find that Spanish inflation behaves differently over the course of the economic cycle[20].

A simple way of capturing the possible asymmetry of the response of inflation to output is by introducing a dummy variable (d_r) that takes a value of 1 during a recession and 0 during an expansion[21]. The asymmetrical response of inflation to output in recessions would be given by the coefficient α_r

$$\pi_t = \pi_t^e + \alpha s_{t-1} + \alpha_r d_r s_{t-1} + \varepsilon_t$$

PHILLIPS CURVE ESTIMATIONS TABLE 4

	Estimated coefficients	*p-value*
Equation [1]. Model with symmetrical response to GDP and forward- and backward-looking inflation expectations		
Inflation expectations (γ)	0.22	0.015
GDP growth (α)	0.10	0.002
Adjusted R^2	0.64	
Equation [2]. Model with asymmetrical response to GDP and forward- and backward-looking inflation expectations		
Inflation expectations (γ)	0.24	0.005
GDP growth (α)	0.06	0.063
Recession dummy (α_r)	0.27	0.001
Adjusted R^2	0.70	

Source: Own elaboration.

Table 4 presents the estimates for the asymmetric model. According to these estimates, the sensitivity of inflation depends on the position in the cycle, and the response is statistically greater in recessions than expansions. Specifically, in a recession, a 1 pp reduction in GDP reduces inflation by 0.3 pp, while in an expansion, the rise in inflation associated with a 1 pp increase in GDP is less than 0.1 pp. This result is consistent with the analysis by Álvarez and Hernando (2007), who found the prices set by Spanish businesses to be more flexible on the downside than the upside in the face of demand shocks. Similarly, Izquierdo and Jimeno (2015) describe more frequent prices changes in response to negative than to positive demand shocks, which is in line with an increase in cyclical sensitivity during these periods.

19 Álvarez and Hernando (2007) and Izquierdo and Jimeno (2015).

20 This result is similar to that found for other European economies [Oinonen and Paloviita (2014) and Riggi and Venditti (2015)] but contrary to findings for other advanced economies like the United States [Matheson and Stavrev (2013) and IMF (2013)], which show how inflation is less sensitive to changes in output.

21 The corresponding periods of recession and expansion are determined by the business cycle dating information published by the Asociación Española de Economía.

An alternative transfer model is presented in Chart 13, where the change in the year-on-year rate of the CPI excluding unprocessed food and energy depends on the output gap, unit labour costs in the market economy, the import deflator and changes in VAT rates, which are accounted for by using dummy variables. All variables have a positive and significant effect, as are ARMA terms. In contrast with the models above, this one allows for a locally varying mean and implicitly assumes that inflation expectations are completely backward looking.

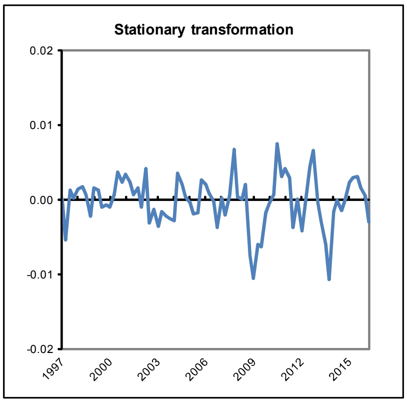
An additional transfer function model is presented in chart 14, linking changes in the year-on-year rate of the CPI excluding unprocessed food and energy on those in GDP and unit labour costs. This model also allows for a locally evolving mean of inflation. As in models above, the cyclical sensitivity coefficient is statistically significant. Specifically, an increase (decrease) in GDP growth of 1 pp translates into an inflation rate 0.1 pp higher (lower), as in the symmetric Philips curve model above. As the previous model, allowing for a locally varying mean implies that inflation expectations are assumed to be completely backward looking.

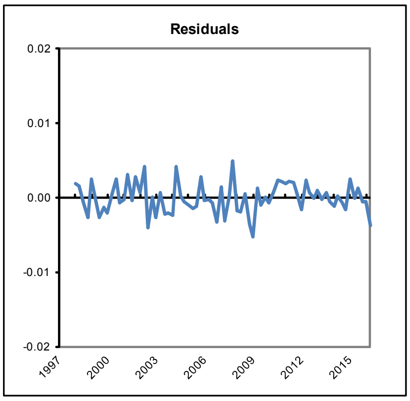
CPI excluding energy and unprocessed food:
Transfer function model with Output Gap, unit labour costs and imports deflator

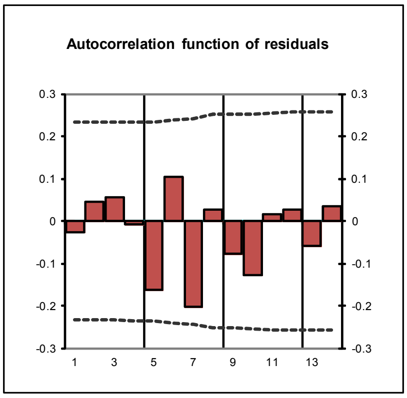
Sample period: 1996 Q1-2016 Q2

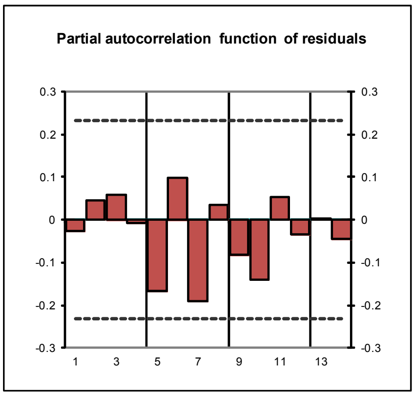
Model

	Coefficient	T statistic
$\Delta \Delta_4$ ln CPI =		
Dummies		
S2001q1	0.0035	2.3
SVAT2010q3	0.0057	3.8
SVAT2012q3	0.0059	3.7
SVAT2012q4	0.0095	6.0
Indicators		
Output Gap (1)	0.0006	3.3
ULC market economy (2)	0.0508	1.8
Imports deflator (0)	0.0266	2.5
Stochastic structure		
AR(1)	0.3736	3.3
MA(4)	0.2270	2.0
Residuals		
Average	-0.0001	-0.4
Standard deviation (%)	0.20	
Q (6)	3.5	
Q (10)	8.9	
Q (14)	9.4	
Bera-Jarque normality test	0.1	
	RMSE	**Average error**
1 Forecast period (2013 Q2-2016 Q1)	0.0010	-0.0001
2 Forecast period (2013 Q3-2016 Q2)	0.0021	-0.0005
3 Forecast period (2013 Q4-2016 Q3)	0.0029	-0.0010









Source: Own elaboration.

CHART 14

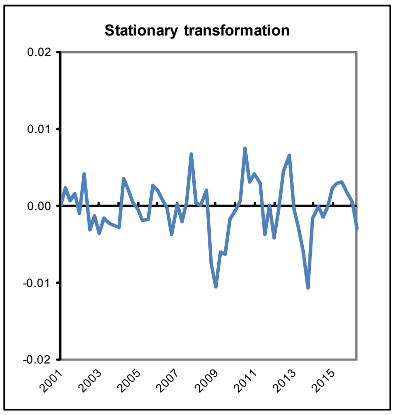
CPI excluding energy and unprocessed food:
Transfer function model with GDP and unit labour costs

Sample period: 2000 Q1-2016 Q2

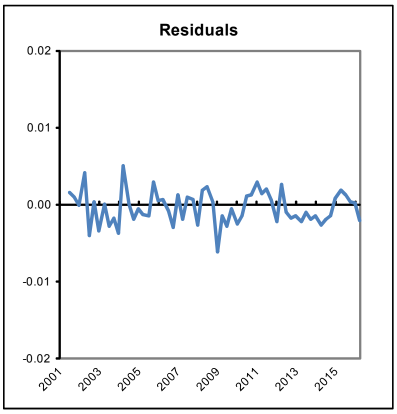
Model

	Coefficient	T statistic
$\Delta \Delta_4$ ln CPI =		
Dummies		
S2007q4	0.0055	3.2
SVAT2010q3	0.0046	2.7
SVAT2012q3	0.0054	3.0
SVAT2012q4	0.0094	5.3
Indicators		
GDP (1)	0.1094	2.0
ULC market economy (0)	0.0914	2.7
Stochastic structure		
MA(1)	-0.2769	-2.1
MA(4)	0.3096	2.6
Residuals		
Average	-0.0004	-1.6
Standard deviation (%)	0.22	
Q (6)	3.3	
Q (10)	10.8	
Q (14)	13.4	
Bera-Jarque normality test	0.1	

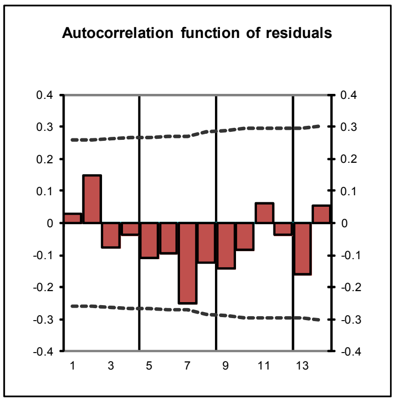
	RMSE	**Average error**
1 Forecast period (2013 Q2-2016 Q1)	0.0022	-0.0013
2 Forecast period (2013 Q3-2016 Q2)	0.0044	-0.0027
3 Forecast period (2013 Q4-2016 Q3)	0.0064	-0.0038



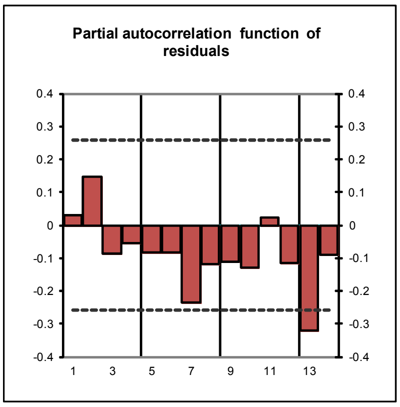
Stationary transformation



Residuals



Autocorrelation function of residuals



Partial autocorrelation function of residuals

Source: Own elaboration.

To illustrate the forecasting performance of the different models, we present in Chart 15 conditional forecasts from them for 4 different forecast horizons. Forecasts from 2008Q4 show that macroeconomic models were quite useful in anticipating the decline in Spanish inflation that took place in 2008 and 2009, in contrast with the transfer function model. Obviously, forecasts from that origin from both models did not anticipate the VAT related pick up in Spanish inflation that took place in 2010. Forecasts from 2010Q4 show that the transfer function model accurately anticipated inflation developments, whereas macroeconomic models substantially underpredicted inflation. Again, both types of models were not able to anticipate the 2012 VAT-related pick up in Spanish inflation. Forecasts from 2014Q4 show a substantial overprediction of the Phillips curve model, whereas the rest of models led to some undeprediction. Forecasts from 2015Q4 show a very satisfactory performance of the transfer function and the model with GDP and unit labour costs, whereas the other models clearly overpredicted inflation.

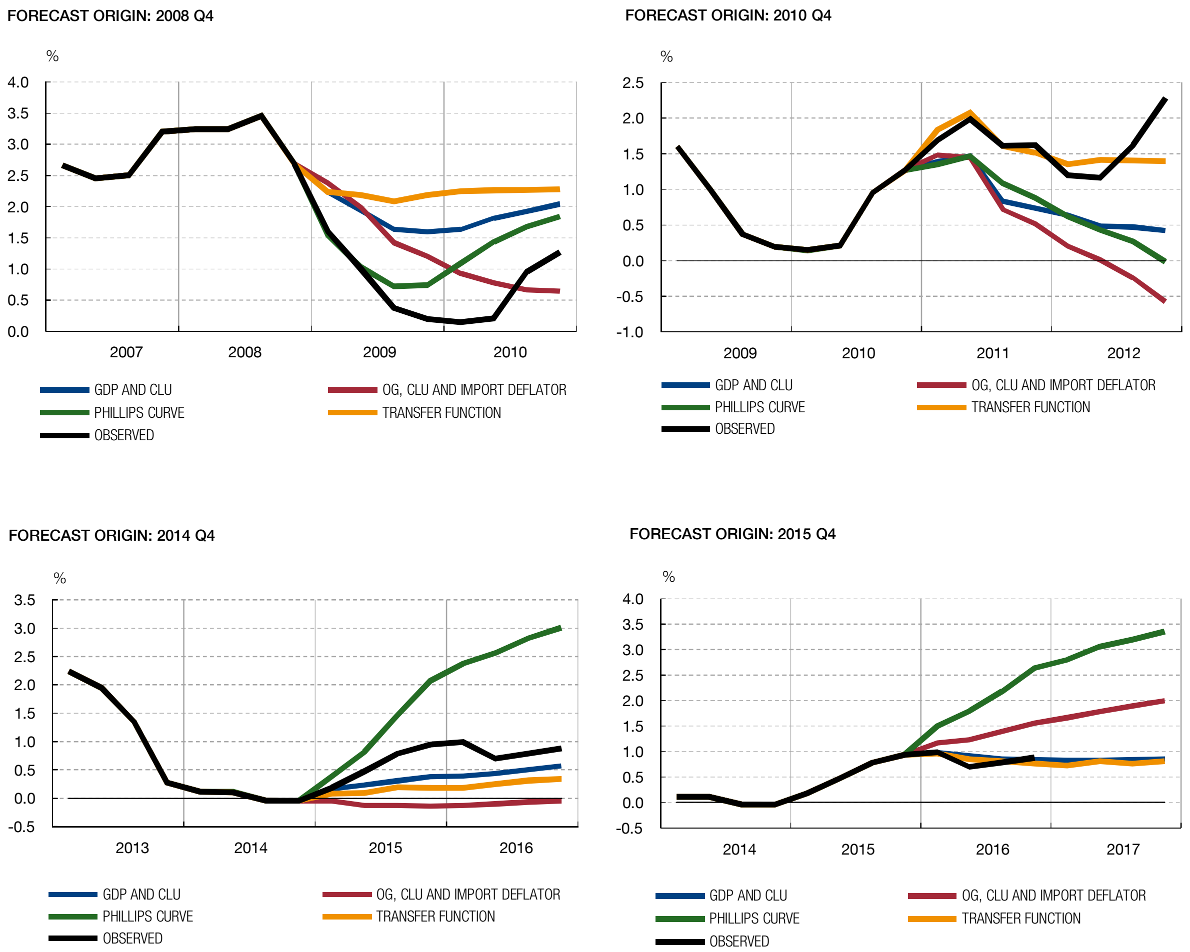
To have a more precise idea of the forecasting performance of the different models in table 5 we present the root mean square forecast error. In Chart 16 we present relative mean square standard errors. A value higher (lower) than one for this statistic means that the forecasts from a given macro model is less (more) precise than the transfer function model. The evaluation sample starts in 2012 and ends in 2016Q3. We consider one, two and three quarter ahead forecasts. For one quarter ahead forecasts, the transfer function model is by far the most precise one. Specifically, its RMSE is close to the half of the RMSE of the second best performing model and close to a third of the worst one. As expected, forecast performance deteriorates along with the horizon for the different models. The transfer function model is in all cases the most precise one, but its relative advantage is smaller for two and three quarter ahead forecasts than for one quarter ahead one. The finding that Phillips curve models tend to show a forecasting performance inferior to other models is a typical result in the literature (e.g. Stock and Watson (2007), Faust and Wright (2013), Dotsey et al. (2015)).

Regarding biases in terms of mean forecast error, we observe that the Phillips curve model has tended to systematically overpredict inflation by a substantial amount. The other models do not show large mean forecasts errors. The transfer function model has tended to under predict somewhat inflation, whereas the one with ULCs and GDP show a slight overprediction. For the model considering ULCs, the output gap and the import deflator the sign of the mean error depends on the forecast horizon.

Even though the transfer function model outperforms the rest of models, we feel that they are useful as a cross-check, particularly at times in which there are major changes in macroeconomic conditions, which the transfer function model is unable to consider.

FORECAST CORE INFLATION

CHART 15



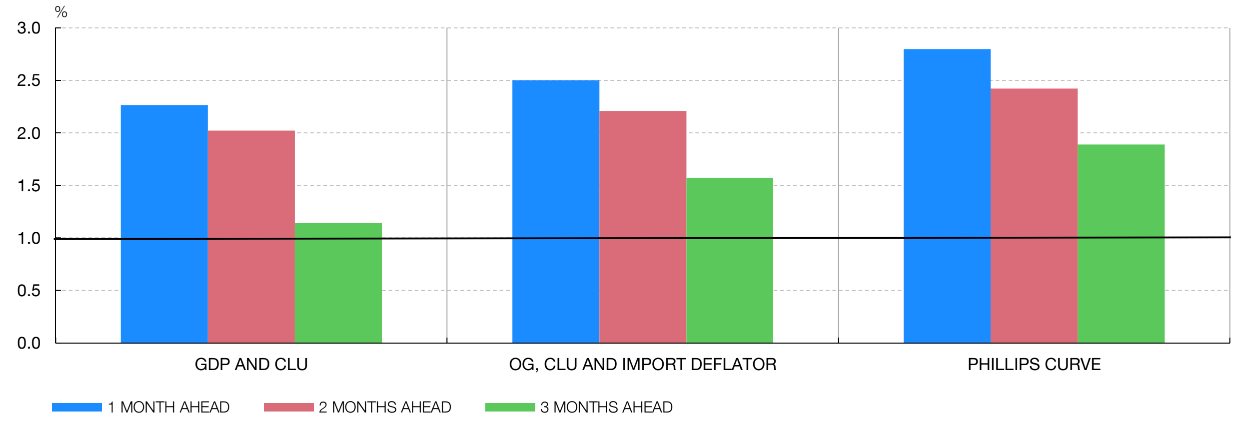
Source: Own elaboration.

STATISTICS OF FORECAST ERRORS IN CORE INFLATION MODELS (2012-2016) TABLE 5

		GDP AND CLU	OG, CLU AND IMPORT DEFLATOR	PHILLIPS CURVE	TRANSFER FUNCTION
RMSE	1 FORECAST PERIOD	0.2940	0.3248	0.3630	0.1299
	2 FORECAST PERIOD	0.3445	0.3766	0.4128	0.1705
	3 FORECAST PERIOD	0.2804	0.3864	0.4636	0.2456
		GDP AND CLU	**OG, CLU AND IMPORT DEFLATOR**	**PHILLIPS CURVE**	**TRANSFER FUNCTION**
AVERAGE ERROR	1 FORECAST PERIOD	-0.0882	-0.0051	-0.2665	0.0039
	2 FORECAST PERIOD	-0.0529	0.0382	-0.3093	0.0247
	3 FORECAST PERIOD	-0.0352	0.0246	-0.3788	0.0706

Source: Own elaboration.

RELATIVE ROOT MEAN SQUARED FORECAST ERRORS (a)
H month step ahead CHART 16



Source: Own elaboration.

a Ratio of mean squared forecast errors of macroeconomic models to those of transfer function.

6 The elaboration of forecasts: different tools and informed judgment

As stressed in the introduction, the forecasting approach that we favour combines the results from different types of models, which are supplemented by expert judgment. The forecasting performance of the transfer function models presented in Section 4 has been found to be better than those from alternative models, so it is only natural that they are the starting point from which to base our final forecasts. Other types or models are used as a cross-check to force us to examine in more detail the baseline provided by transfer functions. Bottom up univariate approaches are particularly useful in the case of idiosyncratic shocks which affect some particular subindices (e.g. package holidays). In the case of these shocks, a model for the aggregate of services is less useful, since it treats all shocks for its different subcomponents equally, regardless of the subindex they come from. This is particularly relevant in the case of subindices whose dynamics differs substantially from the aggregate. In turn, macroeconomic models are particularly useful when there are changes in the macroeconomic environment (*e.g.* at the start of the Great Recession), given that indicators considered in the transfer function models in Section 4 are more sector-specific.

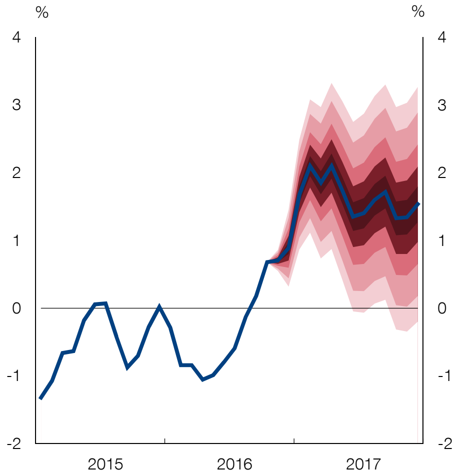
The role of judgment in the forecasts reflects different considerations. First, judgment affects the relative weights that are used in aggregating the results of the different models, which depend on their forecasting performance in the recent past. More (less) weight is given is a particular model has had a high (low) precision in the recent past. Second, judgment is applied in order to determine whether idiosyncratic shocks are of a permanent or a transitory nature, and to this end we carefully examine inflation developments at the COICOP-5 level to inform our judgment and consider heat maps. Third, other sources of off-model information (e.g. fiscal or regulated price changes) are also taken into account. This is also the case for some item specific shocks (e.g. anticipated supply changes in agricultural markets or anticipated changes in the demand for tourism services).

On the basis of the above considerations, each month a set of final forecasts and forecast errors are computed for different monthly horizons. These forecast errors allow the computation of predictive densities, which are represented as fan charts in Figure 16 both for headline CPI and CPI ex unprocessed food and energy. As can be seen, uncertainty around point forecasts is not negligible and forecast intervals are much wider for headline inflation than for core inflation, reflecting the uncertainty in projecting the most volatile CPI components. Presentation of fan figures is typically made along with a qualitative assessment of possible asymmetries in the direction of some possible shocks to some variables, which are not necessarily included in any of the considered econometric models.

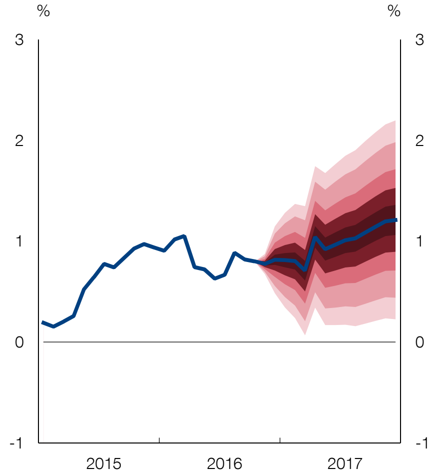
INFLATION PROSPECTS FOR SPAIN

CHART 17

CPI
Year-on-year rates of change



CPI EXCL. ENERGY AND UNPROCESSED FOOD PRICES
Year-on-year rates of change



Probability of CPI or the CPI excluding energy and unprocessed food prices being within the interval (a)

20% 40% 60% 80% 90%

SOURCES: INE and own elaboration.

a The right- and left-hand charts show the uncertainty around the central projection. Intervals with probabilities of 20%, 40%, 60%, 80% and 90%, respectively, based on historical projection errors.

7 Conclusions

In this paper, we have presented the suite of models that is currently used by Banco de España to monitor and forecast consumer price inflation. We heavily rely on the results from the set of econometric models that are described in Sections 3 to 5 of this paper, which are supplemented by expert judgment, as discussed in Section 6.

Three points that have been stressed in the paper are that inflation forecasting models have to account for a slowly evolving local mean, in order to be able to cope with changes in trend inflation that stationary forecasting models are unable to deal with, as in the period after the Great Recession. Furthermore, differences in the features of product markets suggest that it is relevant to employ some sort of disaggregation to deal with heterogeneity in price setting. Finally, transfer function models tend to show a better forecasting performance than alternative tools, which are used as cross-checks.

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Annex 1

Highly disaggregated univariate models

TABLE A.1

	Standard Deviation	Constant Coefficient	Constant T statistic	AR(1) Coefficient	AR(1) T statistic	AR(2) Coefficient	AR(2) T statistic	AR(3) Coefficient	AR(3) T statistic	MA(1) Coefficient	MA(1) T statistic	MA(2) Coefficient	MA(2) T statistic	MA(3) Coefficient	MA(3) T statistic	AR(12) Coefficient	AR(12) T statistic	MA(12) Coefficient	MA(12) T statistic
Overall index	0.0024	0.0000	0.0	-0.4032	-7.1													-0.5699	-11.2
Overall index exc. unprocessed food and energy	0.0013	0.0000	0.0	-0.2113	-3.6	-0.2540	-4.3											-0.2724	-4.6
Overall index excluding energy products	0.0015	0.0000	0.0	-0.3028	-5.0	-0.1894	-3.2									0.3694	6.5		
Goods	0.0035	0.0000	0.0	-0.4073	-7.2													-0.6855	-15.1
Food, beverages and tobacco	0.0037	0.0000	0.0	-0.3030	-5.2													-0.6866	-15.3
Industrial goods	0.0049	0.0000	0.0							0.3653	6.3							-0.7233	-16.9
Food and non-alcoholic beverages	0.0038	0.0000	0.0							0.3629	6.3							-0.6860	-15.2
Alcoholic beverages and tobacco	0.0020	0.0014	4.9	-0.3489		-6.1913										-0.3620	-6.5		
Clothing and footwear	0.0023	0.0000	0.0	-0.3152	-2.9	0.0757	1.2	0.3398	5.8	-0.4557	-4.1							0.7239	16.6
Housing	0.0043	0.0000	0.0							0.1827	3.0							-0.6198	-12.9
Furnishings, household equipment and routine maintenance of the house	0.0013	0.0000	0.0	-0.8022	-10.3					-0.5330	-4.9							-0.2076	-3.5
Health	0.0019	0.0014	4.0													-0.7123	-17.0		
Transport	0.0090	0.0000	0.0							0.4042	7.2							-0.9400	-44.8
Communications	0.0023	-0.0010	-2.3	-0.0171	-0.3	0.1415	2.7	-0.4893	-8.5							-0.3691	-3.8	0.3272	3.3
Recreation and culture	0.0046	0.0000	0.0							-0.1589	-2.7	-0.2095	-3.5					-0.2492	-4.2
Education	0.0012	-0.0003	-2.5															0.5337	10.3
Restaurants, cafés and hotels	0.0017	0.0000	0.0	-0.2574	-4.2	-0.0644	-1.0	-0.1085	-1.8										
Miscellaneous goods and services	0.0015	0.0000	0.0															-0.2514	-4.3
Unprocessed food	0.0079	0.0000	0.0							0.1274	2.1							-0.7162	-16.8
Bovine meat	0.0037	0.0000	0.0	-0.4395	-7.9													-0.7198	-16.6
Swine meat	0.0096	0.0000	0.0	-0.5576	-10.7													-0.7042	-15.8
Sheep meat	0.0191	0.0289	14.5	-0.5886	-10.0					0.7696	11.8	0.2414	4.0					-0.8103	-20.1
Poultry meat	0.0318	0.0000	0.0							0.2007	3.3							-0.7528	-18.6
Other meat and offal	0.0174	0.0000	0.0							0.2305	3.9							-0.7856	-20.7
Fresh and frozen fish	0.0167	0.0000	0.0							-0.4580	-8.3							-0.5335	-10.2
Fresh fish	0.0104	0.0000	0.0															-0.5062	-7.4
Crustaceans and molluscs	0.0077	0.0000	0.0															-0.7322	-17.6
Eggs	0.0076	0.0000	0.0	-0.6247	-13.0											-0.8265	-12.0	-0.5649	-5.6
Fresh fruits	0.0118	0.0000	0.0							0.4538	8.3	0.4779	8.8					-0.4418	-7.9
Fresh pulses and vegetables	0.0103	0.0000	0.0	-0.9324	-12.6	0.3568	4.4	0.1328	2.2	-0.1741	-1.8							-0.6103	-11.9
Dried pulses and vegetables	0.0087	0.0000	0.0	-0.6792	-6.0					-0.3862	-2.8					-0.9	-17.5	-0.4847	-5.9
Potatoes and their preparations	0.0334	0.0000	0.0							0.6153	12.4							-0.8250	-23.3
Processed food	0.0028	0.0022	3.2	-0.4102	-7.4											-0.6022	-12.4		
Bread and cereals	0.0020	0.0000	0.0							-0.6306	-13.0							-0.4272	-7.6
Bread	0.0023	0.0000	0.0	-0.4002	-7.1													-0.3817	-6.7
Cereals and by-products	0.0031	0.0000	0.0	-0.1749	-2.9	-0.2205	-3.7	-0.2192	-3.7									-0.6250	-12.9
Rice	0.0054	0.0000	0.0							-0.6630	-14.8								
Pasta products	0.0068	0.0000	0.0	-0.8084	-8.3					-0.6258	-4.9							-0.6984	-15.5
Bakery and coocked pastries	0.0035	0.0000	0.0	-0.1245	-2.1													-0.6119	-12.6
Flours and cereals	0.0049	0.0000	0.0							-0.8154	-23.1					-0.4022	-7.2		
Cold meat	0.0025	0.0000	0.0	-0.6009	-6.7	-0.1846	-3.1			-0.4	-4.1					-0.8788	-21.5	-0.4644	-6.1
Meat preparations	0.0037	0.0000	0.0													-0.8717	-20.7	-0.4458	-5.8
Canned fish and fish preparations	0.0031	0.0000	0.0							-0.6418	-13.4							-0.5093	-9.4
Frozen fish																			
Milk	0.0037	0.0000	0.0	-0.7073	-16.2											-0.8782	-16.5	-0.6447	-7.5
Dairy products	0.0038	0.0000	0.0							-0.8471	-25.9					-0.5844	-11.7		
Other dairy products	0.0060	0.0000	0.0													-0.6066	-12.8		
Cheeses	0.0028	0.0000	0.0	-0.8410	-13.9					-0.5550	-6.0					-0.9	-14.4	-0.5886	-6.4
Oils and fats	0.0106	0.0000	0.0	-1.0778	-18.2	0.2833	4.8											-0.8683	-27.8
Butter and margarine	0.0040	0.0000	0.0	-0.4750	-8.9											-0.5137	-9.8		

Highly disaggregated univariate models

TABLE A.1 Cont.

	Standard Deviation	Constant		AR(1)		AR(2)		AR(3)		MA(1)		MA(2)		MA(3)		AR(12)		MA(12)	
		Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic
Oils	0.0104	0.0000	0.0	-1.1425	-19.7	0.3324	5.8											-0.8614	-26.9
Canned and dried fruits	0.0041	0.0000	0.0	-0.8843	-21.9					-0.4604	-6.1							-0.8169	-22.5
Frozen and canned pulses and vegetables	0.0037	0.0000	0.0							-0.8807	-30.5					-0.4443	-8.1		
Sugar	0.0042	0.0000	0.0	-0.6954	-11.3	-0.1045	-1.7											-0.7312	-17.1
Other food products	0.0021	0.0000	0.0	-0.8544	-16.8					-0.5020	-6.0					-0.9	-16.3	-0.5389	-6.3
Chocolates and jams	0.0024	0.0019	2.1	-0.7979	-9.8					-0.5482	-4.9					-0.9	-16.9	-0.4936	-5.9
Other food products	0.0028	0.0000	0.0	-0.8816	-18.1					-0.6048	-7.4							-0.6989	-15.5
Babyfoods	0.0042	0.0000	0.0	-0.3031	-3.4														
Non-alcoholic beverages	0.0041	0.0000	0.0	-0.5249	-10.1											-0.8698	-14.6	-0.6575	-7.2
Coffee, cocoa and infusions	0.0059	0.0000	0.0	-0.7474	-18.2											-0.8964	-14.4	-0.7602	-8.3
Mineral waters, soft drinks and juices	0.0046	0.0000	0.0															-0.6175	-12.9
Alcoholic beverages	0.0026	0.0000	0.0	-0.7805	-12.2					-0.3248	-3.4							-0.7798	-19.7
Spirits and liqueurs	0.0032	0.0000	0.0							0.2205	3.7							-0.6945	-15.7
Wines	0.0041	0.0000	0.0	-0.8983	-25.5					-0.4089	-5.7							-0.7785	-19.7
Beer	0.0046	0.0000	0.0							0.1585	2.6							-0.6051	-12.4
Tobacco	0.0022	0.0009	4.8							0.3969	7.2								
Industrial goods excluding energy	0.0017	0.0000	0.0	-0.7664	-6.6					-0.5801	-3.9							-0.0704	-1.2
Clothing	0.0022	0.0000	0.0	-0.3062	-3.3	-0.0573	-1.0	0.5042	9.4	-0.3297	-3.1							0.8032	21.4
Clothing for men	0.0025	0.0000	0.0	-0.2156	-3.6	-0.0374	-0.6	0.2586	4.4							-0.5072	-9.5		
Men outwear	0.0023	0.0000	0.0	-0.2688	-4.5	-0.0087	-0.1	0.1953	3.2							-0.5997	-12.1		
Men underwear	0.0034	0.0000	0.0	-0.2391	-1.4	0.0781	1.3	0.2315	3.9	-0.3534	-2.2							0.1029	1.7
Clothing for women	0.0036	0.0000	0.0													-0.5095	-9.7		
Women outwear	0.0039	0.0000	0.0	-0.0222	-0.4	0.0091	0.2	0.1762	2.9									0.5406	10.5
Women underwear	0.0033	0.0000	0.0							-0.0777	-1.3	-0.2171	-3.8	-0.2645	-4.5				
Clothing for children and babies	0.0042	0.0000	0.0	-0.0073	-0.1	0.0906	1.6	0.3604	6.2	-0.9147	-34.9							0.4011	7.1
Clothing accessories	0.0053	0.0000	0.0	-0.9400	-10.0	0.3279	3.5											0.1487	1.5
Footwear	0.0026	0.0000	0.0	0.0673	1.2	0.0850	1.5	0.3053	5.2							-0.4184	-7.5		
Footwear for men	0.0029	0.0000	0.0	-0.0769	-1.4	-0.0548	-1.0	0.4979	9.3	-0.9063	-33.0							0.1829	3.0
Footwear for women	0.0039	0.0000	0.0													-0.4048	-7.2		
Footwear for children and babies	0.0033	0.0000	0.0	0.0345	0.6	-0.0180	-0.3	0.3033	5.2									0.4497	8.2
Materials for the maintenance of the dwelling	0.0018	0.0000	0.0	-0.3022	-5.1	-0.0953	-1.5	-0.2396	-4.0									-0.6336	-13.2
Water supply	0.0035	0.0000	0.0															-0.1351	-2.2
Furniture and floor covering	0.0020	0.0000	0.0	-0.2213	-3.7													-0.5091	-9.6
Furniture and other furnishings	0.0020	0.0000	0.0	-0.2245	-3.8													-0.5078	-9.6
Furniture	0.0020	0.0000	0.0							0.3101	4.1							-0.4690	-6.7
Other household equipment	0.0024	0.0000	0.0															-0.6093	-9.7
Household textiles	0.0027	0.0000	0.0							0.1726	2.9							-0.1831	-3.0
Refrigerators, washing-machines and dishwashers	0.0016	-0.0002	-2.1	-0.2727	-4.6													-0.5002	-9.4
Cookers and ovens	0.0022	0.0000	0.0							-0.7628	-19.1					-0.8177	-13.3	-0.4716	-5.0
Air conditioners and heating appliances	0.0044	0.0000	0.0							0.2334	4.0					-0.8945	-33.3		
Other household appliances	0.0020	0.0000	0.0							0.1265	2.1							-0.2909	-5.0
Household utensils and tools	0.0019	0.0000	0.0							-0.8367	-24.6					0.4207	7.5		
Glassware, tableware and cutlery	0.0038	0.0000	0.0													0.5321	10.3		
Other kitchen and household utensils	0.0026	0.0000	0.0							0.1776	3.0	0.1353	2.2	-0.2091	-3.5			-0.5616	-11.0
Tools and accesories for house and garden	0.0020	0.0000	0.0	-0.8856	-15.4					-0.6968	-7.8							-0.6970	-15.4
Non-durable household goods	0.0027	0.0000	0.0	-0.6604	-7.5					-0.1977	-1.8					-0.6	-12.7		
Cleanig products for household	0.0032	0.0000	0.0	-0.6598	-7.3					-0.2115	-1.8					-0.6	-11.3		
Other non-durable household goods	0.0032	0.0000	0.0							-0.7155	-16.2							-0.6610	-13.9
Medicaments and therapeutic equipment	0.0022	0.0006	3.8	-0.1784	-3.0														
Medicaments and other pharmaceutical products	0.0022	0.0008	6.0																

Highly disaggregated univariate models

TABLE A.1 Cont.

	Standard Deviation	Constant Coefficient	Constant T statistic	AR(1) Coefficient	AR(1) T statistic	AR(2) Coefficient	AR(2) T statistic	AR(3) Coefficient	AR(3) T statistic	MA(1) Coefficient	MA(1) T statistic	MA(2) Coefficient	MA(2) T statistic	MA(3) Coefficient	MA(3) T statistic	AR(12) Coefficient	AR(12) T statistic	MA(12) Coefficient	MA(12) T statistic
Therapeutic equipment	0.0031	0.0000	0.0							-0.9212	-37.7							-0.6032	-12.0
Vehicles	0.0034	0.0000	0.0							-0.8354	-25.4								
Motor cars	0.0035	0.0000	0.0							-0.8235	-24.2								
Other vehicles	0.0043	0.0000	0.0							0.0897	1.5								
Spares parts and accessories for maintenance	0.0033	0.0000	0.0							0.2236	3.7							-0.4911	-9.2
Telephone equipments	0.0272	-0.0121	-3.6							0.3107	3.5								
Image and sound equipments	0.0028	0.0000	0.0	-0.7843	-10.9					-0.4377	-4.2								
Photographic and cinematographic equipment	0.0072	0.0000	0.0	0.0970	1.5					-0.9084	-32.1					-0.8	-14.9	-0.3904	-4.5
Computer equipment	0.0077	0.0000	0.0							-0.7682	-19.0							-0.7418	-17.5
Support for recording image and sound	0.0038	0.0000	0.0	-0.0003	0.0	-0.2222	-3.8									-0.9	-26.1	-0.5598	-8.0
Games and toys	0.0047	0.0000	0.0							-0.1114	-1.8							-0.4916	-9.2
Other recreational and sporting items	0.0036	0.0000	0.0															-0.2270	-3.8
Major sports teams	0.0053	0.0000	0.0	-0.3138	-3.3													-0.9500	-30.3
Floristry and pets	0.0054	0.0000	0.0															-0.4322	-7.8
Floristry	0.0052	0.0000	0.0							-0.3627	-3.8							-0.6669	-8.8
Pets	0.0040	0.0000	0.0							-0.9141	-23.7								
Books	0.0040	0.0000	0.0	0.1506	2.5													-0.6618	-14.4
Entertainment books	0.0067	0.0000	0.0	0.1789	1.9														
Text books	0.0003	0.0000	0.0													-0.8677	-17.5		
Newspapers and periodicals	0.0043	0.0000	0.0							-0.1686	-2.8							-0.5719	-11.4
Stationery materials	0.0026	0.0000	0.0	-0.3256	-5.6	-0.2046	-3.4	-0.2894	-4.9									-0.6710	-14.5
Articles for personal care	0.0023	0.0000	0.0															-0.4977	-9.4
Jewellery, costume jewellery, clocks and watches	0.0039	0.0000	0.0	-0.6210	-10.2	-0.0114	-0.2	-0.2073	-3.5									-0.7430	-17.6
Other personal effects	0.0028	0.0000	0.0															-0.3253	-5.6
Energy products	0.0162	0.0000	0.0							0.4352	8.1								
Electricity	0.0030	0.0000	0.0							0.1993	3.4								
Gas	0.0176	0.0000	0.0	-0.2112	-3.6														
Other fuels	0.0380	0.0000	0.0							0.4394	8.2								
Fuels	0.0232	0.0000	0.0	-0.4399	-8.2														
Services	0.0013	0.0000	0.0	-0.1592	-2.6	-0.1151	-1.9											-0.1641	-2.7
Cleaning and repair of clothing	0.0019	0.0000	0.0	-0.6514	-8.8											-0.9094	-15.7	-0.6011	-5.4
Repair of footwear	0.0019	0.0000	0.0	-0.3576	-6.2													-0.5020	-9.4
Rentals for housing	0.0008	0.0000	0.0	-0.5351	-9.2	-0.2997	-5.1											-0.5886	-11.7
Services for the maintenance of the dwelling	0.0016	0.0000	0.0	-0.8516	-16.8					-0.4872	-5.8					-0.9	-24.9	-0.3346	-4.7
Refuse collection, sewerage and other services	0.0021	0.0000	0.0							-0.8686	-27.8							-0.6153	-12.4
Refuse collection	0.0019	0.0015	2.6	0.0431	0.2	-0.1189	-1.3	-0.2748	-3.0	0.2785	1.0							0.6466	8.5
Sewerage	0.0026	0.0019	4.2													-0.5108	-6.3		
Other services relating to the dwelling	0.0014	0.0000	0.0							-0.5559	-6.5	0.1337	1.3	-0.4607	-5.4	-0.6267	-8.2		
Repair of household appliances	0.0018	0.0000	0.0							0.1618	2.8	0.2936	5.0					-0.4763	-8.8
Domestic services and other household services	0.0014	0.0028	5.0	-0.2846	-4.7	-0.0670	-1.1									-0.9	-25.9	-0.4214	-5.9
Out-patient medical and paramedical services	0.0018	-0.0002	-2.7	-0.1161	-2.0	-0.2569	-4.3											-0.5791	-11.5
Dental services	0.0016	0.0019	3.5	-0.1249	-2.1											-0.9074	-29.1	-0.3751	-5.5
Hospital services	0.0025	0.0000	0.0	-0.4296	-7.7													-0.5113	-9.6
Maintenance and repair services	0.0017	0.0000	0.0	-0.5540	-10.8													-0.3256	-5.6
Other services related to vehicles	0.0028	0.0000	0.0							0.0870	1.4							-0.0925	-1.5
Transport services	0.0036	0.0000	0.0	-0.2468	-4.1	0.0565	0.9	-0.2181	-3.6									-0.6707	-14.6
Public urban transport	0.0024	0.0000	0.0	-0.2316	-3.8	-0.1472	-2.4												
Road transport	0.0029	-0.0003	-1.5	-0.6085	-4.2	-0.0651	-1.1			-0.4	-2.6							-0.4435	-7.9
Public intercity transport	0.0064	0.0000	0.0															-0.7002	-16.1
Rail transport	0.0018	0.0000	0.0	-0.3145	-5.4													0.7348	17.5

Highly disaggregated univariate models

TABLE A.1 Cont.

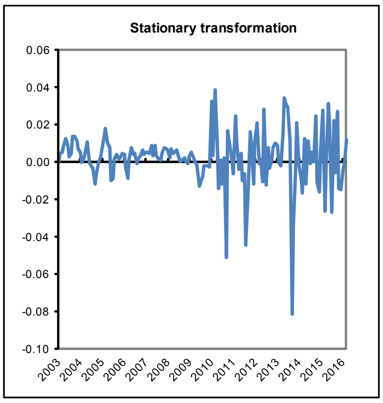
		Constant		AR(1)		AR(2)		AR(3)		MA(1)		MA(2)		MA(3)		AR(12)		MA(12)	
	Standard Deviation	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic	Coefficient	T statistic
Air transport	0.0131	0.0000	0.0															-0.4708	-8.7
Other transport services	0.0052	0.0000	0.0	0.1860	3.2	-0.3256	-5.6												
Communications	0.0023	-0.0010	-2.3	-0.0171	-0.3	0.1416	2.7	-0.4893	-8.5							-0.3691	-3.8	0.3272	3.3
Postal services	0.0030	0.0000	0.0													0.8375	3.9	0.7848	3.2
Telephone equipments and services	0.0023	-0.0011	-2.3	-0.0235	-0.4	0.1519	2.9	-0.4837	-8.5							-0.4847	-5.5	0.2452	2.6
Telephone services	0.0012	0.0000	0.0	0.9574	25.9	0.9216	25.0											0.2871	3.1
Recreational, sporting and cultural services	0.0037	0.0020	3.0													-0.8407	-16.8	-0.4228	-5.1
Recreational and sporting services	0.0054	0.0000	0.0							-0.3970	-7.0							-0.5051	-9.5
Cultural services	0.0045	0.0024	2.5													-0.7483	-18.9		
Education	0.0011	-0.0003	-2.2							0.1043	1.7							0.6265	13.1
Telephone equipments and services	0.0023	-0.0011	-2.3	-0.0235	-0.4	0.1519	2.9	-0.4837	-8.5							-0.4847	-5.5	0.2452	2.6
Infant education	0.0015	0.0000	0.0							0.2496	4.2							0.2533	4.3
Primary and lower-secondary education	0.0015	0.0000	0.0							0.1261	2.1							0.2064	3.5
Upper-secondary education	0.0008	-0.0003	-1.7							0.4968	5.7					-0.1820	-1.8		
Tertiary education	0.0008	0.0000	0.0	-0.0944	-1.6													0.9500	49.8
Education not definable by level	0.0014	-0.0001	-2.9							0.2279	3.8							-0.5711	-11.3
Tourism and catering	0.0029	0.0000	0.0	-0.1141	-1.9	0.1062	1.7											-0.2519	-4.3
Package travel	0.0223	0.0301	4.7	-0.2519	-3.1	-0.6130	-9.9	0.1398	2.3	0.6901	9.6							-0.2886	-4.8
Restaurants, cafés and hotels	0.0017	0.0000	0.0	-0.2574	-4.2	-0.0644	-1.0	-0.1085	-1.8										
Restaurants, cafés and the like and canteens	0.0011	0.0000	0.0	-0.8385	-14.9					-0.4917	-5.5							-0.0924	-1.5
Restaurants, bars and coffeshops	0.0007	0.0000	0.0	-0.7968	-13.1													-0.2571	-2.6
Canteens	0.0010	0.0000	0.0							0.2638	2.9					-0.8723	-18.8		
Hotels and other accomodations	0.0173	0.0000	0.0	-0.8852	-12.2	0.1224	2.0			-0.9	-34.7					-0.2311	-3.9		
Services for personal care	0.0012	0.0000	0.0	0.0913	1.0	0.1711	2.8	0.1884	3.1	-0.5437	-6.8							-0.4769	-8.4
Social protection services	0.0013	0.0000	0.0							0.2436	4.1							0.0808	1.3
Insurance for housing	0.0024	0.0000	0.0							-0.1457	-2.4							0.3482	6.1
Medical insurances	0.0013	0.0000	0.0																
Automobile insurance	0.0025	0.0019	4.4													-0.8013	-13.8	-0.3639	-4.0
Other insurances	0.0010	0.0000	0.0															0.7031	16.2
Financial services																			
Other services	0.0010	-0.0001	-3.1													0.2318	3.9		
Other headings																			
Other meats	0.0028	0.0000	0.0	-0.3429	-5.8	-0.1728	-2.9									-0.9	-20.0	-0.4383	-5.6
Crustaceans, molluscs and processed fish	0.0045	0.0000	0.0															-0.6796	-15.2
Processed pulses and vegetables	0.0042	0.0000	0.0	-0.8158	-11.2					-0.5558	-5.3					-0.6	-11.7		
Clothing accesories and repair of clothing	0.0037	0.0000	0.0	-0.9499	-8.9	0.3645	6.4			-0.7	-7.5					-0.2817	-4.7		
Heating, lighting and water supply	0.0090	0.0021	3.1							0.2590	4.5								
Maintenance of the dwelling	0.0015	0.0000	0.0	-0.3298	-5.7													-0.4694	-8.6
Household textiles and decorations	0.0026	0.0000	0.0							0.1803	3.0							-0.1885	-3.1
Household appliances including repair	0.0018	0.0000	0.0	0.0691	0.3	-0.1009	-1.7	-0.1119	-1.9	0.2753	1.0					-0.8817	-24.5	-0.1982	-2.8
Non-durable household goods	0.0027	0.0000	0.0	-0.6833	-7.9					-0.2430	-2.2					-0.6	-12.4		
Household services	0.0016	0.0031	4.5													-0.8945	-33.5		
Medical and a like services	0.0010	0.0000	0.0	-0.1222	-2.0														
Personal transport	0.0087	0.0000	0.0							0.4101	7.3							-0.9377	-43.8
Recreational items	0.0025	0.0000	0.0															-0.2939	-5.0
Publications	0.0041	0.0019	5.7													-0.2841	-5.0		
Infant and primary education	0.0012	0.0000	0.0	-0.2861	-4.9														
Secondary education	0.0017	-0.0002	-2.9	0.1986	3.3														
Tertiary education	0.0009	0.0000	0.0															0.9500	49.8
Other educational costs	0.0012	0.0000	0.0	-0.3378	-5.8													-0.5214	-9.9
Personal effects	0.0015	0.0000	0.0	-0.1766	-2.9	-0.1158	-1.9	-0.2018	-3.4									-0.4719	-8.7
Other goods and services	0.0014	0.0000	0.0	-0.8244	-13.5					-0.4806	-5.1							-0.3837	-6.7

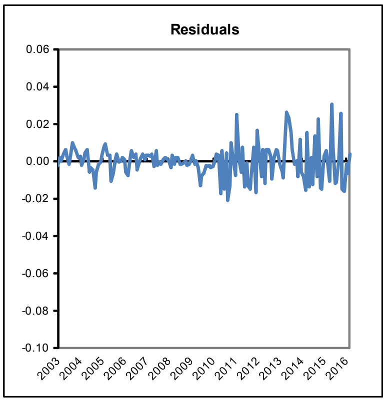
Unprocessed food HICP: fruits and vegetables
Transfer function

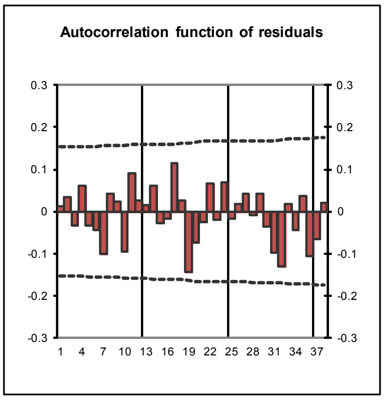
Sample period: January 2002- March 2016

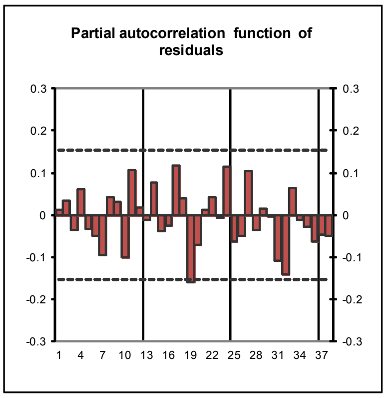
Model

	Coefficient	T statistic
Δ ln HICP =		
Dummies		
Constant	0.0028	2.7
SJan2010	0.0337	4.1
SMar2010	0.0314	3.9
DSep2010	-0.0343	-6.6
DAug2011 (0)	-0.0325	-4.8
DAug2011 (1)	-0.0283	-4.2
DJun2012	0.0239	4.7
SSep2013 (0)	-0.0778	-8.6
SSep2013 (1)	-0.0282	-3.2
DFeb2015	0.0225	4.5
DJul2015	-0.0174	-3.0
Indicators		
Fruits (0)	0.0481	2.5
Vegetables (0)	0.0208	3.0
Stochastic structure		
MA(1)	-0.3047	-3.8
MA(12)	-0.1786	-2.1
Residuals		
Average	0.0000	-0.1
Standard deviation (%)	0.86	
Q (14)	7.9	
Q (26)	17.8	
Q (38)	28.7	
Bera-Jarque normality test	23.7	









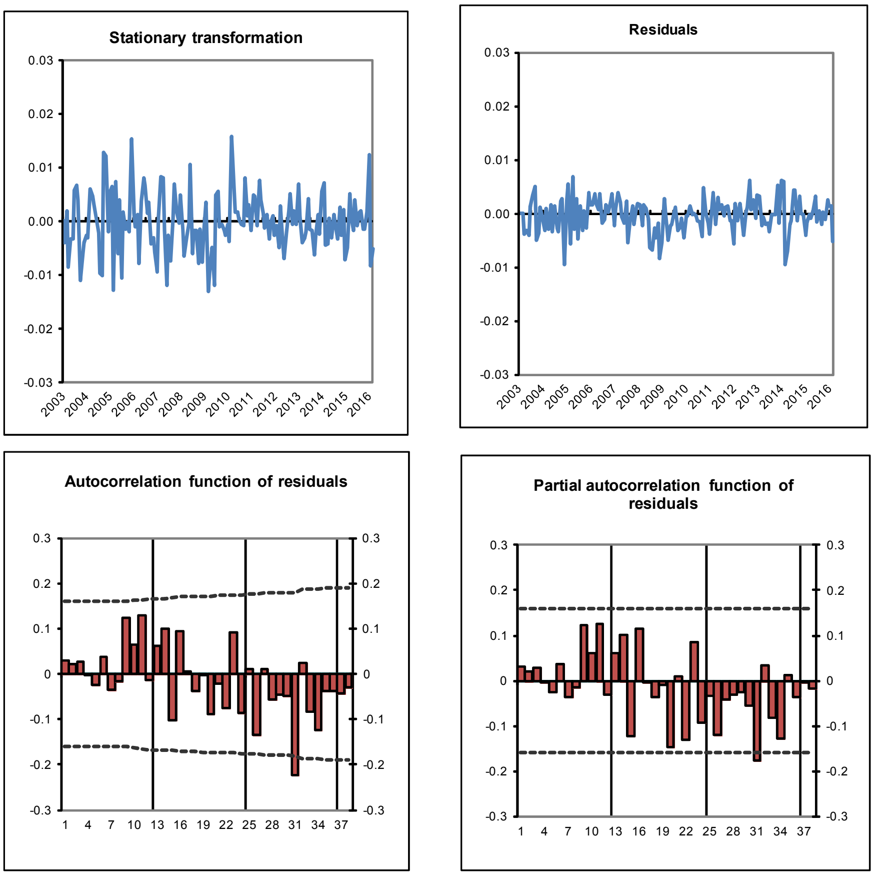
Source: Own elaboration.

Unprocessed food HICP: meat and fish
Transfer function

Sample period: January 2002- March 2016

Model

	Coefficient	T statistic
$\Delta\,\Delta_{12}$ ln HICP =		
Dummies		
SJun2008	0.0103	3.6
SMar2009	-0.0113	-3.9
DJan2016	0.0096	4.3
Indicators		
Agricultural prices (0)	0.4752	7.5
Agricultural prices (1)	0.3227	5.1
Agricultural prices (2)	0.1653	2.6
Stochastic structure		
MA(12)	0.6750	11.5
Residuals		
Average	-0.0004	-1.4
Standard deviation (%)	0.31	
Q (14)	9.4	
Q (26)	22.1	
Q (38)	39.1	
Bera-Jarque normality test	2.4	



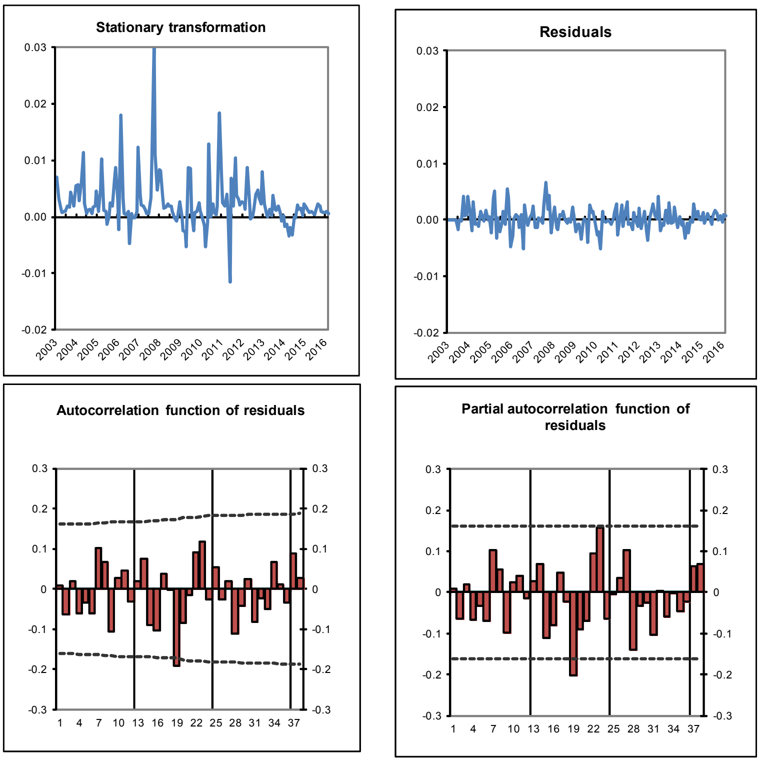
Source: Own elaboration.

CHART A.3

Processed food HICP
Transfer function model with producer and import prices

Sample period: January 2002- March 2016

Model	Coefficient	T statistic
Δ ln HICP =		
Dummies		
SMay2004	0.0079	4.4
SMar2006	0.0159	8.5
SJan2007	0.0078	4.2
SOct2007	0.0188	10.1
SJun2009	0.0205	6.4
SJun2010	0.0118	6.3
SDec2010	0.0136	7.5
SJun2011	-0.0087	-4.2
SSep2011	0.0106	4.9
SApr2012	0.0062	3.4
Indicators		
Industrial prices (0)	0.2909	5.8
Industrial prices (1)	0.1237	3.1
Industrial prices (2)	0.0742	1.7
Industrial prices (3)	0.1002	2.3
Import prices (0)	0.0259	1.2
Stochastic structure		
AR(1)	0.4447	5.6
AR(12)	0.1833	2.2
Residuals		
Average	0.0002	1.4
Standard deviation (%)	0.20	
Q (14)	8.2	
Q (26)	24.3	
Q (38)	32.0	
Bera-Jarque normality test	5.6	



Source: Own elaboration.

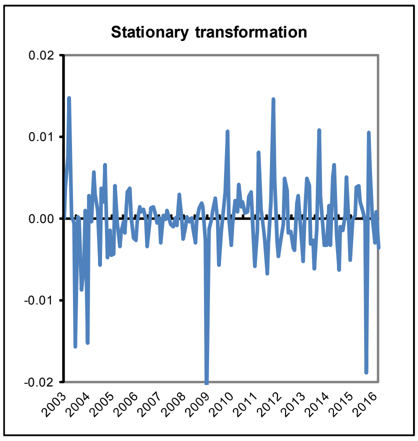
CHART A.4

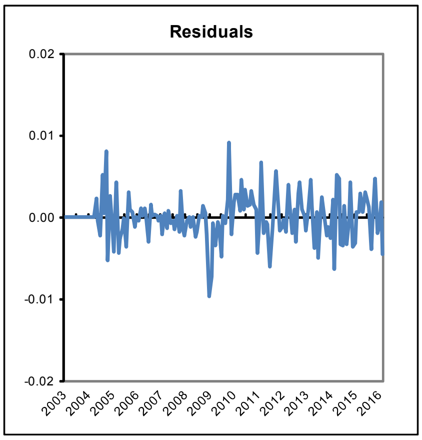
Non energy industrial goods CPI: clothing and footwear
Transfer function model with prices of domestic production

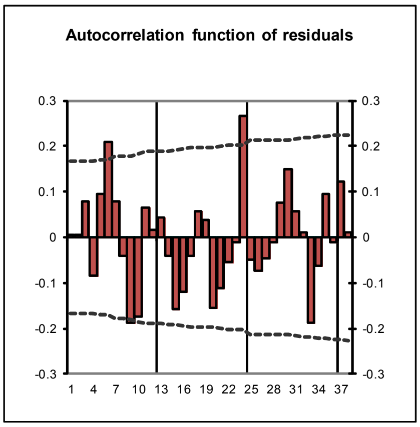
Sample period: January 2002- March 2016

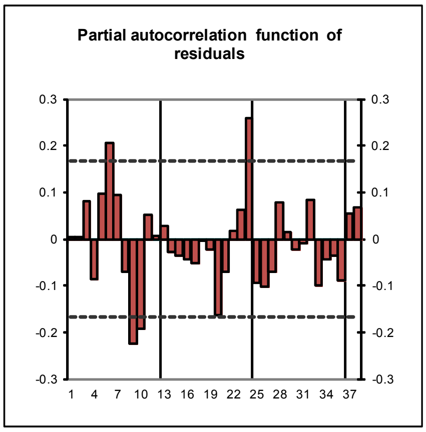
Model

	Coefficient	T statistic
$\Delta\,\Delta_{12}$ ln HiCP =		
Dummies		
DJan2002-2008	0.1000	6.1
SOct2011	0.0056	3.2
SVATSep2012	-0.0058	-3.2
DSep2015	-0.0133	-8.0
Indicator		
Industrial prices (0)	0.1349	1.9
Stochastic structure		
AR(1)	0.2899	3.6
AR(3)	-0.2182	-2.6
MA(2)	0.3065	3.7
AR(12)	0.1433	2.0
Residuals		
Average	0.0000	-0.2
Standard deviation (%)	0.29	
Q (14)	22.9	
Q (26)	50.6	
Q (38)	68.9	
Bera-Jarque normality test	5.0	









Source: Own elaboration.

CHART A.5

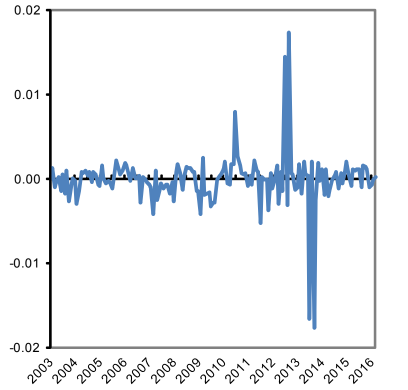
Non energy industrial goods HICP except clothing and footwear
Transfer function model with prices of domestic production

Sample period: January 2002- March 2016

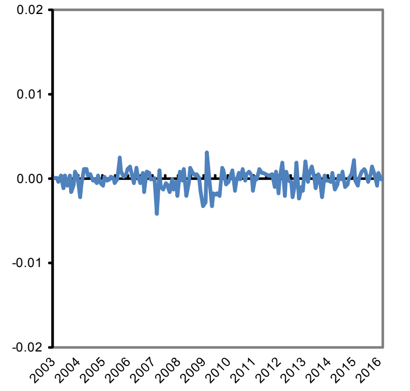
Model

	Coefficient	T statistic
$\Delta\, \Delta_{12}$ ln HiCP =		
Dummies		
SVATJul2010	0.0065	6.3
SNov2011	-0.0026	-2.5
SJul2012	0.0153	14.6
SVATSep2012	0.0178	17.1
Indicator		
Industrial prices (0)	0.1290	1.7
Stochastic structure		
AR(2)	0.1814	2.3
MA(12)	0.6331	10.2
Residuals		
Average	-0.0002	-1.7
Standard deviation (%)	0.11	
Q (14)	16.6	
Q (26)	23.7	
Q (38)	27.8	
Bera-Jarque normality test	12.8	

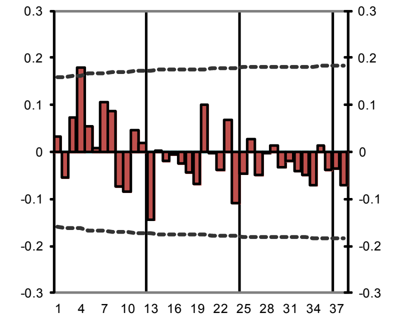
Stationary transformation



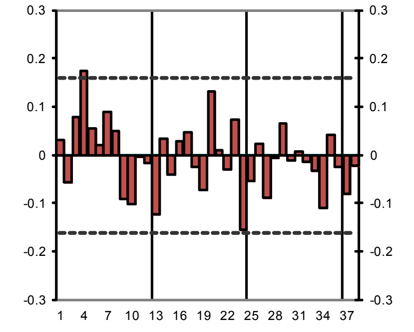
Residuals



Autocorrelation function of residuals



Partial autocorrelation function of residuals



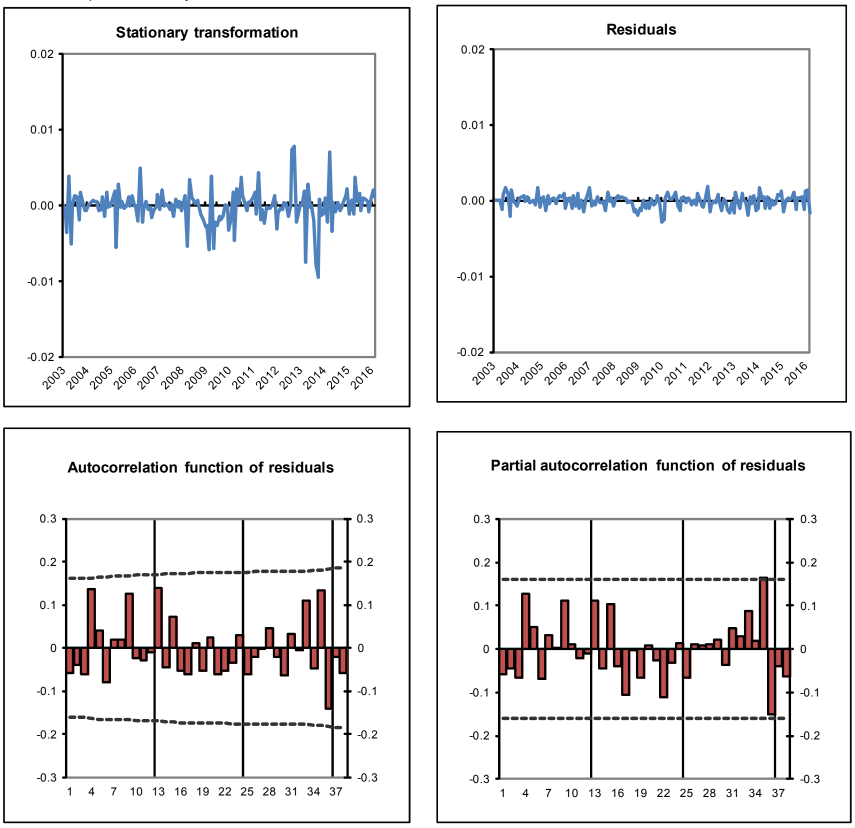
Source: Own elaboration.

Services HICP
Transfer function model with unit labour costs

Sample period: January 2002- March 2016

Model

	Coefficient	T statistic
$\Delta\,\Delta_{12}$ ln HICP =		
Dummies		
SMar2007	0.0021	3.0
DJan2002-2009	0.0010	2.0
SVATJul2010	0.0027	3.8
SJan2012	-0.0018	-2.6
SVATSep2012	0.0078	10.9
SOct2012	0.0092	12.8
SMay2015	0.0028	3.4
Easter	0.0029	20.1
Indicators		
ULC market services (0)	0.0263	1.7
Stochastic structure		
AR(1)	0.2821	3.4
AR(2)	0.1686	2.0
AR(3)	0.1969	2.4
MA(12)	0.3786	5.2
Residuals		
Average	-0.0001	-1.3
Standard deviation (%)	0.09	
Q (14)	12.3	
Q (26)	17.4	
Q (38)	30.1	
Bera-Jarque normality test	3.4	



Source: Own elaboration.

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