WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

Forecasting Inflation in France: an Update of MAPI

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Abstract

In this paper, we present an updated version of the reference model used at Banque de France to forecast inflation: MAPI (*Model for Analysis and Projection of Inflation*). While the conceptual framework of the model remains very close to its initial version, our update takes stock of three different factors. First, since the previous version of the model, the underlying nomenclature used at the European level (ECOICOP) to define some of the main aggregates was changed, therefore requiring a careful review of the relevance of initial equations. Second, in the context of the modification in 2019 of the main semi-structural macroeconomic model used for the macroeconomic projections at Banque de France (FR-BDF), it aims at harmonizing the iterations between MAPI and FR-BDF. Finally, large variations in the wage variables in the midst of the sanitary measures related to the Covid-19 pandemics pushed us to use different concepts of wage and compensation variables. At the crossroads of these considerations, we update the model extending the estimation window, correcting specifications and input variables whenever relevant. The resulting model is an up-to-date, simplified and more parsimonious version of the initial model, entailing a stronger harmonization with the central macroeconomic model FR-BDF. It still involves significant pass-through of wages, oil and exchange rate to HICP. [3]

Keywords: Forecasting, Inflation, Time Series

JEL classification: E37, C32, E31, C53

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NON-TECHNICAL SUMMARY

This paper presents a renovated version of the main model used at Banque de France to forecast inflation: MAPI (*Model for Analysis and Projection of Inflation*). This model was first developed and described in 2017 (De Charsonville & al., 2017), but was gradually modified due to several factors: (i) a change in the European classification used to define HICP aggregates, operated in 2019; (ii) the necessity to strengthen the links between MAPI and the new semi-structural macroeconomic model used at Banque de France (FR-BDF), developed in 2019; (iii) important variations in input data, especially regarding wage and compensation dat, in the midst of the Covid-19 pandemic.

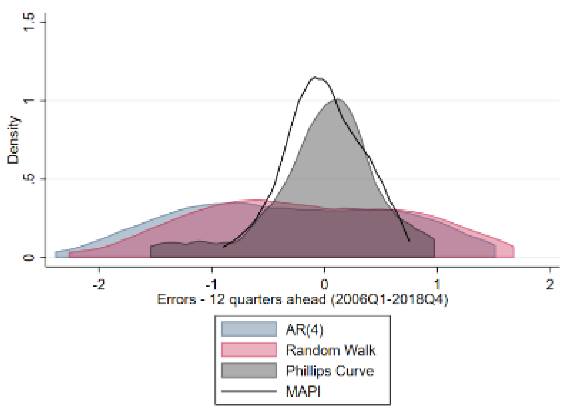
Inflation forecasts at Banque de France are produced within the Eurosystem framework, which requires both monthly and quarterly projections at the disaggregated level. MAPI meets these requirements by gathering a set of disaggregated equations for 12 components, mostly relying on Error Correction Models. More specifically, out of the 12 components we forecast, 7 of them (representing 87% of the HICP basket) are forecasted using Error Correction Models or Autoregressive equations.

Compared to the initial version of MAPI, the updated version relies on the same theoretical framework (i.e. consumer prices are expected to depend in the long run on domestic factors – wages and compensations – and import prices), and the same technical features (regarding the treatment of seasonality or the aggregates considered), but proposes improvements along three dimensions. First, we update the estimating samples up to 2019. Second, we simplify the estimation process by including only input variables that are forecasted within FR-BDF or that are part of Eurosystem assumptions. Finally, we develop equations that are more parsimonious, relying on milder assumptions.

This updated version of MAPI still entails a significant pass-through of the input variables to consumer prices as (i) a 1% permanent shock on wages leads to an increase of 0.3 percentage point (p. p.) of HICP in the long run; (ii) a 10 euros increase in the price of the *Brent* barrel increases HICP by about 0.2 p. p. for an initial *Brent* barrel price of 55 euros: (iii) a 10% appreciation of the euro against all other currencies decreases total HICP by 0.3 pp.

The paper also compares the in-sample predictive performance of the updated version of MAPI to three benchmark models: an AR(4), a Random Walk and a Phillips Curve using the unemployment rate, import prices of energy and an autoregressive term for inflation. We find that MAPI systematically outperforms these models for headline HICP (Figure 1). For HICP excluding food and energy, it outperforms AR(4) and the Random Walk, and has a predictive performance similar to that of the Phillips Curve.

Figure 1: Distribution of forecast errors on y-o-y variations of headline HICP (2006-2018) – 12 quarters ahead



Note: This figure represents forecast errors for y-o-y variations of quarterly headline HICP for 4 types of models between 2006Q1 and 2018Q4: an AR(4), a Random Walk, a Phillips Curve (using import prices of energy, the unemployment rate and a autoregressive term of two quarters for inflation), and the renovated version of MAPI.

Prévoir l'inflation en France : une actualisation du modèle MAPI

RÉSUMÉ

Dans ce papier, nous présentons une version actualisée du modèle de référence utilisé à la Banque de France pour prévoir l'inflation: MAPI (*Model for Analysis and Projection of Inflation*). Bien que le cadre conceptuel du modèle demeure très proche de celui de la version initiale, notre actualisation est motivée par trois facteurs. D'une part, depuis la première version du modèle, la nomenclature sous-jacente utilisée au niveau européen (ECOICOP) pour définir les principaux agrégats a été modifiée, ce qui a nécessité une revue détaillée de la pertinence des équations initiales. D'autre part, dans le cadre de la modification en 2019 du principal modèle semi-structurel utilisé pour les projections macroéconomiques à la Banque de France (FR-BDF), nous avons cherché à harmoniser les interactions entre MAPI et FR-BDF. Enfin, de fortes variations ont été observées sur les variables de salaires suite aux mesures sanitaires mises en œuvre dans le cadre de la pandémie de Covid-19, ce qui nous a conduit à mobiliser des concepts de salaires et de rémunérations différents. À la croisée de ces considérations, nous avons actualisé le modèle en étendant les fenêtres d'estimation et en corrigeant les spécifications et les variables explicatives. Le modèle qui en résulte est une version actualisée, simplifiée et plus parcimonieuse du modèle initial, mieux harmonisée avec le modèle macroéconomique FR-BDF. La transmission à l'IPCH des salaires, du prix du pétrole et du taux de change y reste significative.

Mots-clés : prévisions, inflation, séries temporelles.

1. Introduction

This paper describes an updated version of the reference model of inflation forecasting at Banque de France, *MAPI* (Model for the Analysis and Projection of Inflation). This model was first developed and described in 2017 (De Charsonville & al., 2017), and was designed as a set of disaggregated equations for the main components of Harmonized Consumer Price Index (HICP)[2].

The conceptual framework of the model remains broadly unchanged. However, several factors affecting both input and output variables in the model, led to gradual modifications since its first version. On the input side, the central model of macroeconomic projections at Banque de France was updated in June 2019, switching from Mascotte to FR-BDF (Lemoine & al, 2019)[3]. The transition from Mascotte to FR-BDF induced an effort to strengthen the links between this central model and MAPI, in order to harmonize the forecasting models between the real and the nominal sides of the economy. Furthermore, some important variations observed in the input data during the first sanitary restrictions following the outbreak of Covid-19, especially in the wage and compensation variables, led us to carefully analyse the properties of alternative definitions of variables related to the labor market. On the output side, in 2019, the definition of some of the main aggregates used in the MAPI forecast was changed, following the transition to the ECOICOP5 classification at the Euro Area level. This led us to review the relevance of the initial equations, as such changes, even though they did not affect headline HICP, entailed some substantial changes in the past values of our main aggregates. At the crossroads of these considerations, we updated most of the equations, changing either specifications, input variables or estimation window.

Our changes are the following. First, we extend the estimation windows (either to 2018Q4 or to 2019Q4). Second, and related to our willingness to harmonize FR-BDF and MAPI, we only resort to inputs that are already projected, either through Eurosystem assumptions or through FR-BDF forecasts. Therefore, the model does not resort to *ad hoc* equations projecting necessary inputs. Finally, whenever relevant, we update the specifications (either by changing the way of modelling the long run and short relationships, or by adding or substituting explanatory variables).

The remainder of this paper is structured as follows. In section 2, we describe the data used for our forecasting exercise, as well as the institutional setting. In section 3, we describe the updated equations of MAPI (presenting only the equations that were changed). In section 4, we describe some of the main global properties of the updated model. Section 5 concludes.

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[2] De Charsonville et al. (2017) built upon previous work of Célérier (2009) and Jondeau, Le Bihan and Sedillot (1999). These papers detailed the previous models used in order to forecast inflation at Banque de France.
[3] This note describes the forecasting process at Banque de France, using a suite of models : Méthodologie des prévisions macroéconomiques réalisées par la Banque de France

2. Framework of the inflation forecast

2.1. Harmonized Index of Consumer Prices (HICP)

The inflation projection exercises within the Eurosystem consists in projecting the Harmonized Index of Consumer Prices (HICP). This index is a chained Laspeyres index, relying on the E-COICOP5 classification of about 250 components, and using annually updated constant weights representative of the past year. This index is published in a two-step fashion. A flash estimate for month M is typically released at the end of month M. Data available include HICP Headline, Excluding food and energy, Food, Non-Energy Industrial Goods, Energy and Services. A final estimate for month M is typically released in mid-month M+1. Available data include all 250 components at the finest level of the E-COICOP classification.

2.2. Forecasting HICP within the Eurosystem

The inflation forecasts at Banque de France take place along two types of exercises within the Eurosystem[4]. First, the Narrow Inflation Projection Exercises (NIPE), with monthly 11-months ahead inflation forecasts produced every quarter by National Central Banks. Secondly, the Broad Macroeconomic Projection Exercises (BMPE), carried out by National Central Banks in the second and fourth term of each year, which are quarterly macroeconomic forecasts at a two or three years ahead horizon (and which take on board the NIPE for the first four quarters). Regarding the quarterly forecast produced by the ECB in the first and third quarter of each year (the Macroeconomic Projection Exercises, or MPE), they also embed the relevant NIPE produced by the National Central Banks. Every quarter, the Banque de France publishes its quarterly macroeconomic forecasts for France.

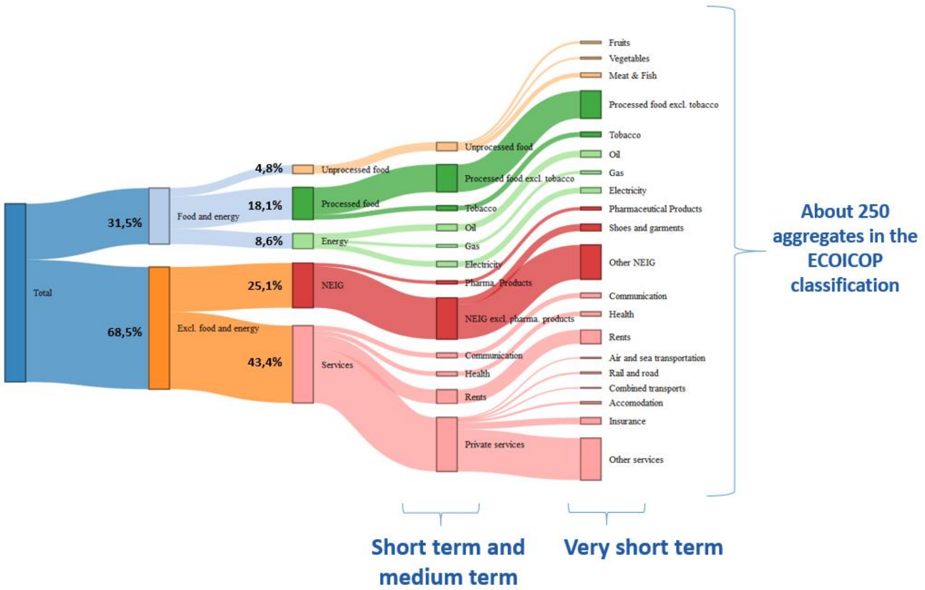
This framework is at the core of the motivation behind the structure of MAPI. The model aims at producing forecasts for different frequencies, disaggregation levels and horizons in an integrated fashion. MAPI is therefore based on a disaggregated approach, with distinct equations and processes for each relevant component.

First, the levels of aggregation used in MAPI differ on the forecasting horizon (**Figure 1**). A very short-term monthly forecast for the current quarter based on 20 components: this forecast is made using univariate time-series methodologies, augmented with expert judgment.

The short-term monthly projections (11 months NIPE) and the medium-term quarterly forecast (2 to 3 years ahead) are then produced using a set of equations for 12 components, mostly relying on Error-Correction Models. This paper focuses specifically on this block of equations.

[4] See *A guide to the Eurosystem/ECB staff macroeconomic projection exercises* (here)

Figure 1: Main HICP aggregates used in the forecast



2.3. A disaggregated model of inflation

In the updated version of MAPI, the theoretical framework and technical features remain unchanged compared to the initial version of the model.

As regards the theoretical framework, de Charsonville et al. (2017) emphasized that, in the long run, log consumer prices were a weighted average of log import prices and log domestic prices. Domestic prices were themselves assumed to be set under monopolistic competition, with a Cobb-Douglas production function using labor and capital, so that eventually log consumer prices are a weighted sum of capital cost and wages. This simple theoretical framework was used a reference for long run relationships estimated for each component. In the updated model, this theoretical framework remains unchanged, and we still aim at capturing, in the long run relationships, determinants of consumer prices stemming both from domestic factors (through wages and compensation) and imported factors (through import prices).

As regards the technical features, much of the updated version of the model is unchanged compared to the initial version. First, the aggregates that we use in the different steps of the forecasting process are the same than those of the initial version MAPI. **Figure 1** describes them with weights as of 2021 (representative of 2020)[5]. Out of the twelve components used in the short-run and medium-run projections, seven of them (representing 87% of the HICP basket) are forecasted using ECM or AR equations, and five of them are forecasted using random walks augmented with expert judgment. In **Table C** in Appendix C, we summarize, for

[5] Note that, while generally speaking, the annually weights of HICP move slowly from a year to the other, they varied sharply in 2021, due to the change in consumption structure observed in 2020, as a consequence of the Covid-19 pandemics. The weights presented in this paper are therefore markedly different from those presented in de Charsonville et al. (2017), with higher weights of food, lower weights of services (and notably of air transportations), and lower weights of energy. See the Macroeconomic Projections of March 2021 for a description of the effect of such change of weights in the projection exercises, and Castelletti-Font et al. (2021) for a description of the effects of such movements on the measure of inflation in France.

each of the 12 components, the approach and variables used in the initial version of MAPI and in the updated version. One should only note that, since the first version of MAPI, while the main aggregates under consideration in the process are the same, their scope was revised following the transition to the ECOICOP5 classification. The main changes entailed a transfer of some items from unprocessed food to processed food (notably frozen products), from processed food to unprocessed food (eggs), from manufactured products to services (mainly repair services), and from services to manufactured products (telephones). Second, as in the initial version of the model, the equations for petroleum products and gas components are based on monthly non-seasonally adjusted data, while for other components, the equations are based on seasonally adjusted data (at quarterly frequency, except for unprocessed food, which entails a monthly equation). MAPI thus entails a transformation of non-seasonally adjusted monthly data into seasonally adjusted quarterly data as the start of the process and from quarterly seasonally adjusted to monthly non-seasonally adjusted data at its end. The way to handle this seasonal adjustment is similar to that of the initial version of MAPI (through a Kalman filter with a break in 2011 taking into account a structural change in the way of collecting seasonal indices). The interested reader is invited to report to de Charsonville et al. (2017).

2.4 MAPI and interaction with FR-BDF and the Eurosystem assumptions

Two types of inputs are crucial to insert MAPI in the forecasting process. First, the Eurosystem, forecasting exercises are based on a set of common technical assumptions regarding notably oil and commodity prices, as well as exchange rates. Second, the forecasting process at Banque de France is based on a suite of models and iteration between the forecast for the nominal side produced with MAPI and the global forecast for France prepared with FR-BDF. When MAPI was first built, this model was Mascotte, which was subsequently changed to FR-BDF in 2019 (Lemoine & al, 2019). In this context, as described in **Table 1**, the updated MAPI uses as inputs technical assumptions from the Eurosystem as well as projections stemming from the core model of the macroeconomic projections.

Table 1 – Input variables used in the updated version of MAPI

Label	**Source over the forecasting horizon**
Crude oil prices in dollars	Eurosystem assumptions
Euro dollar exchange rate	Eurosystem assumptions
Nominal effective exchange rate	Eurosystem assumptions
Farm gate prices	Eurosystem assumptions
Farm gate prices - Fats	Eurosystem assumptions
Compensation per hours worked in the market sector	FR-BDF
Wages per hours worked in the market sector	FR-BDF
Minimum wage	FR-BDF
Unemployment rate	FR-BDF
Import prices of goods and services excluding energy	FR-BDF
Import prices of goods and services including energy	FR-BDF
Real GDP	FR-BDF
Wholesale price of gas in euros per MWh	Refinitiv (TTF market)

3. Equations in the updated MAPI model

3.1 Services

3.1.1 Private services

Private services is the main aggregate of services (**Figure 1**), and represents 30.3% of total HICP. It is modelled as an error-correction equation. In the long run, as in the initial version of MAPI, the HICP of private services is assumed to closely follow compensations in the private sector, as it is mainly labour intensive. However, contrarily to the initial version of the model, the measure of labour cost we use is wages per hours worked. The choice to use wages per hours worked rather than wages per employee is commanded by the strong divergence between hours worked and number of employees due to the sanitary restrictions induced by the Covid-19 pandemic (with the former decreasing much more than the latter). Therefore, wages per employee fell sizably in 2020, while wages per hours worked increased. While wages per employee and wages per hours worked evolved in very similar ways historically (thus leading to close estimates when used in our equations), wages per hours worked lead to an easier interpretation when used in a forecast setting. The long run equation is simply defined as a relation between the log seasonally adjusted private services and the log compensation per hour (contrarily to the initial version of MAPI where it was assumed that the log-ratio of prices and wages followed a trend):

$$p_t^{ser} = c_{lt} + \alpha \; comphour_t + \varepsilon_t$$

where p_t^{ser} is the log of seasonally adjusted HICP of private services and $comphour_t$ is the log of compensation per employee.

In the short run, the HICP of private services is assumed to be affected by variations in minimum wage and unemployment. We also include a dummy equal to 1 before 2006Q4 and 0 after, which captures a break in the ratio of private services HICP to compensations (which was decreasing before 2006Q4, and increasing after) which could reflect a break in the evolution of productivity or possibly measurement issues. The short run therefore writes:

$$\Delta p_t^{ser} = c_{st} - \gamma \varepsilon_{t-1} + \phi \Delta p_{t-1}^{ser} + \alpha u_{t-2} + \beta \Delta SMIC_t + \rho \; \delta_{20006Q4} + \nu_t$$

where u_{t-2} is the unemployment rate in *t-2*, $\Delta SMIC_t$ is the log variation of minimum wage (SMIC) between *t-1* and *t*, $\delta_{20006Q4}$ is a dummy variable equal to 1 before the fourth quarter of 2006 and zero after[6]. Both long run and short run equations are estimated on 2005Q3-2018Q4. The estimated coefficients are displayed in **Table 2**:

[6] We also tested the hypothesis that the price of crude oil affects the HICP of private services, as it can notably affect the prices of transportation services. However, on this sample, we did not find any significant effect of crude oil prices, whether contemporaneous or delayed, and this variable is therefore not included as an exogenous variable for the HICP of private services.

Table 2 – Estimated coefficients in the updated equation of private services

Long run – Sample 2005Q3-2018Q4						
c_{lt}	α	R^2				
8.95***	1.24***	0.99				
Short run – Sample 2005Q3-2018Q4						
c_{st}	γ	ϕ	α	β	$\delta_{20006Q4}$	R^2
0.02***	0.09***	-0.12	-0.0013***	0.05**	0.002**	0.46

Figure 2 – Dynamic simulation and observed data of seasonally adjusted HICP of private services (y-o-y, %)

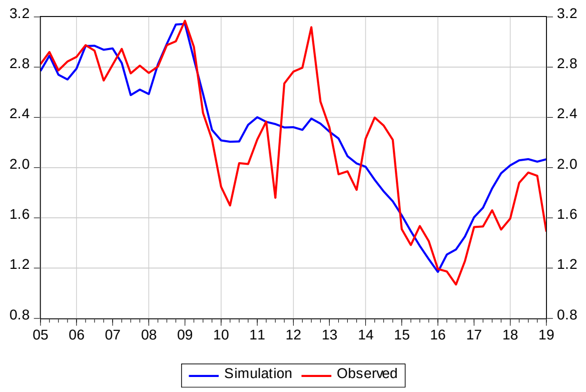


Figure 3 – Econometric contributions – HICP Private Services

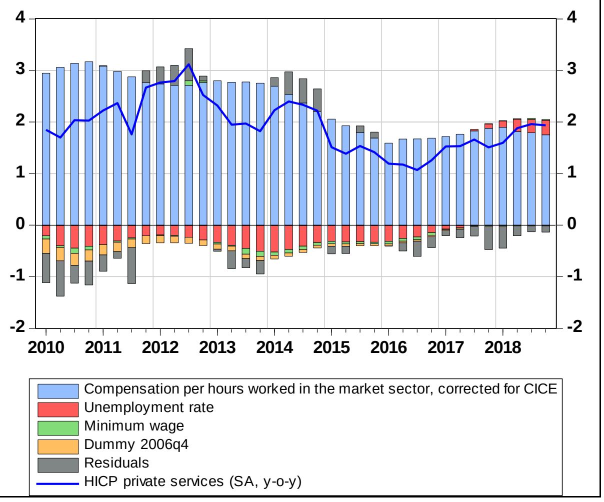


Table 3 reports the impulse response functions for the HICP of private services. In the long run, and contrarily to the initial version of the model where the pass-through of compensation per hour worked into services prices was equal to 1, the latter is now greater than 1 (see section 4.1 for a discussion on this topic). Besides, a permanent shock on the unemployment rate has a permanent but small effect on the level of the private services index as it enters in level in the short run equation. Finally, a 1% shock on the minimal wage (SMIC) has a very limited impact on HICP services in the long run. The effects of both unemployment and minimum wage are very close to those estimated in the first version of MAPI. Note however, that those IRF are partial equilibrium in the specific equation. In reality, and in the interaction between MAPI and FR-BDF, a shock on the minimum wage would also affect compensation and would thus be amplified.

Table 3 – Impulse response functions of the level of prices of private services to permanent shocks (in index points)

	Updated version of MAPI							
	Q1	Q2	Q3	Q4	1A	2A	3A	LT
+1% permanent on compensation per hour worked	0.00	0.12	0.23	0.32	0.17	0.53	0.80	1.24
+1pp permanent on unemployment rate	0.00	0.00	-0.15	-0.26	-0.10	-0. 52	-0.85	-1.30
+1% on minimum wage	0.06	0.05	0.04	0.04	0.05	0.03	0.02	0.00

3.1.2 Rents

Rents account for 7.8% of the total HICP. While they are set freely in France, they are partly controlled. First, the annual increase cannot be above the year-on-year change of the Housing Rent Reference Index (*Indice de Référence des Loyers*, IRL), which is equal to CPI inflation excluding rents and tobacco. Moreover, a significant part of rents corresponds to subsidized housing, whose rents depend on the IRL, but also on the tenant's income. In the long run, we expect rents to reflect changes in economic activity, which we proxy by the quarterly change of GDP. We specify the equation using the y-o-y change of the IRL (Δ^{yoy}):

$$\Delta p_t^{rents} = c + \alpha \Delta^{yoy} IRL_t + \beta \Delta GDP_t + \lambda_1 dummy_{2000} + \lambda_2 dummy_{2001} + \varepsilon_t$$

where p_t^{rents} is the log of the rent component of HICP, GDP_t the log of the real GDP, and $dummy_{2000}$ and $dummy_{2001}$ two dummies accounting for spurious change in the HICP rent index.

Table 4 – Estimated parameters of the equation

Sample 1997Q4 – 2015Q4					
c	α	β	λ_1	λ_2	R^2
1.30^{-3}***	1.7^{-3}***	0.07*	-0.01***	-0.01***	0.80

3.2 Manufactured products excluding pharmaceutical products

Manufactured products excluding pharmaceutical products represent 23.3% of total HICP. This item is highly volatile due to seasonal sales. However, once the usual sales seasonality is stripped away, the variability and dynamics of HICP of manufactured products excluding pharmaceutical products are low, which makes it hard to reconcile with traditional macroeconomic determinants. In particular, contrarily to evidence on the Euro Area (Chatelais

& Schmidt, 2017), the long-run pass-through of producer prices and import prices to NEIG HICP is unlikely to sum to 1, and the estimated pass-through is largely dependent on the choice of sample[7].

Following the theoretical framework, the HICP of this item is modelled as depending on the prices of imported goods and services (both including and excluding energy), on the domestic price of value-added in the whole economy and on the nominal effective exchange rate, over the period 2005Q2-2018Q4. However, contrarily to the initial model, we relax the assumption that the sum of the coefficients of import prices and domestic prices are equal to one. More specifically, we include import price of energy in the long-run relationship, in order to take into account indirect effects of oil prices on non-energy components, which have been found to be sizable in France (Kalantzis & Ouvrard, 2018). An ideal measure of import prices would have excluded services, but since FR-BDF does not produce separate forecasts for import prices excluding services, this would have required a satellite equation. Furthermore, domestic value-added in the whole economy (which is forecasted in FR-BDF) is very close to the deflator of market services that was used (which was used in the initial version of MAPI but which required a satellite equation).

Secondly, we include, both in the long term and short term equation, the nominal effective exchange rate, in order to take into account potential indirect effects of change that would not be completely captured by import prices. Finally, all the input variables of the long run equation are included as a moving average over two quarters. Beyond the fact that such moving averages are more significant than contemporaneous levels, this echoes several studies finding significant delay in the transmission of import prices to consumer prices of manufactured products[8]. Such moving averages over two quarters therefore reflect this lagged transmission, without adding too much inertia to our forecast.

Our long term equation is defined as such:

$$p_t^{NEIG} = c_{lt} + \alpha\, \overline{imp_t} + \beta\, \overline{VAdeflator_t} + \gamma\, \overline{neer_t} + \varepsilon_t$$

where $\overline{imp_t}$ is the log of moving average over quarters *t-1* and *t* of import prices of goods and services including energy, $\overline{VAdeflator_t}$ the log of moving average over quarters *t-1* and *t* of the deflator of value added in the whole economy, $\overline{neer_t}$ the log of moving average over quarters *t-1* and *t* of the nominal effective exchange rate within the Euro Area.

The short term equation is then defined as:

$$\Delta p_t^{NEIG} = c_{st} - \gamma \varepsilon_{t-1} + \beta_1 \Delta p_{t-1}^{NEIG} + \beta_2 \Delta p_{t-2}^{NEIG} + \beta_3 \Delta imp_{xnrj,t-3} + \beta_4 \Delta neer_{t-1} + \nu_t$$

where $\Delta imp_{xnrj,t-3}$ is the variation of log prices of import of goods and services excluding energy between *t-4* and *t-3*, and $\Delta neer_{t-1}$ is the variation of log nominal effective exchange

[7] One of the main issues in that respect is that, between 1996 and 2004, import prices of goods exhibited a downward trend while the prices of manufactured products were overall increasing. This trend reverted after 2004. Furthermore, the deflator of production of market services, which exhibited a positive trend throughout the estimation sample, grew markedly slower after 2009. Therefore, the coefficients of unconstrained relationships between these two variables and the HICP of manufactured products excluding pharmaceutical products are generally small and highly dependent on the choice of samples.

[8] See for example Insee's *Note de conjoncture* of July 2021, where it is argued that input prices are passed through to consumer prices of manufactured products within 3 quarters. A study published in the ECB Bulletin N°5 (2021) argues that complete pass-through of import prices to NEIG prices could take up to 2 years.

rate between *t-2* and *t-1*. Both long run and short run equations are estimated on the sample 2005Q2-2018Q2. The estimated coefficients are summarized in **Table 5:**

Table 5 – Estimated coefficients in the updated equation

Long run – Sample 2005Q2-2018Q4						
c_{lt}	α	β	γ	R^2		
4.77***	0.08***	0.07***	-0.03**	0.64		
Short run – Sample 2005Q2 – 2018Q4						
c_{st}	γ	β_1	β_2	β_3	β_4	R^2
7.84e-5	0.19***	0.02	0.38***	0.07	-0.01	0.45

The sum of α and β is far below 1, reflecting the muted estimated response of manufactured products HICP to variations in import and domestic prices.

Table 6 summarizes the impulse response functions to permanent shocks in the model and in the initial one. As expected from the use of moving averages, the reaction of HICP to shocks on inputs is quite progressive: it takes between 1.5 years and 2 years for a shock on import prices including energy and on value-added prices to fully affect the HICP of manufactured products. Compared to the initial version of MAPI, the reaction to import prices is much more muted (as the estimated coefficient for import prices was equal to 0.6).

Figure 4 – Dynamic simulation and observed data of seasonally adjusted HICP of manufactured products excluding pharmaceutical products (y-o-y, %)

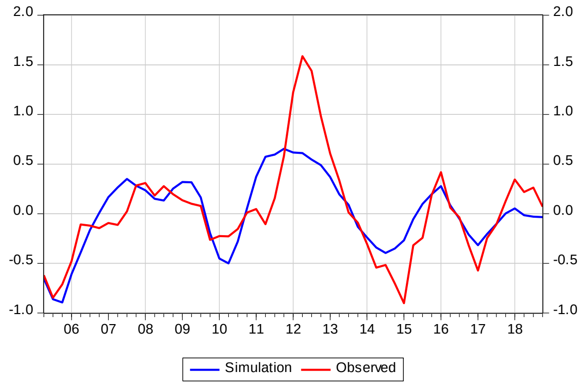


Figure 5 – Econometric contributions

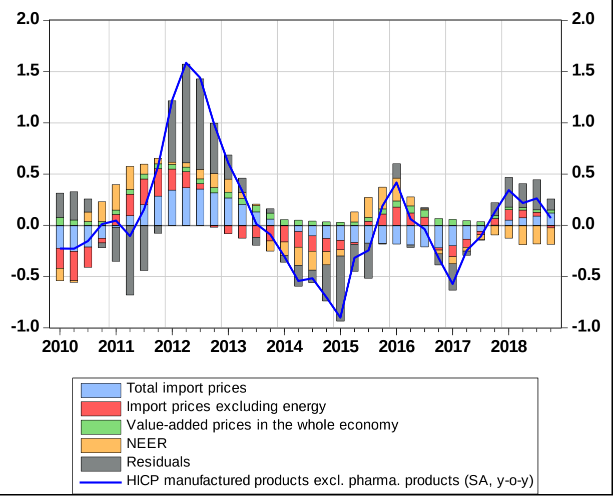


Table 6 – Impulse response functions of the price of manufactured products excluding pharmaceutical products to permanent shocks (in levels)

	Updated version of MAPI							
	Q1	Q2	Q3	Q4	1A	2A	3A	LT
+1% on import prices of goods and services incl. energy*	0.00	0.007	0.02	0.03	0.01	0.06	0.08	0.08
+1% on import prices excl. energy and +0.9% on import prices incl. energy**	0.00	0.006	0.02	0.10	0.03	0.11	0.09	0.07
+1% on deflator of value-added in the whole economy	0.00	0.006	0.02	0.03	0.01	0.05	0.07	0.07
+1% on the NEER	0.00	-0.02	-0.02	-0.03	-0.02	-0.03	-0.03	-0.03

*This shock corresponds to a 10% shock on import prices of energy
**This shock corresponds to a 1% shock on import prices excluding energy

3.3 Food

3.3.1 Processed food excluding tobacco

Processed food excluding tobacco is a component that represents 15.4% of total HICP. The prices of processed food depend on prices of raw material, on labor costs and on regulation affecting retailing margins.

Following the theoretical framework, in the long run, we model processed food prices as depending both on domestic and import prices. However, contrarily to the initial version of MAPI, we directly integrate Eurosystem assumptions on farm-gate prices in the equation, rather than through its effect on the production prices in the agri-food sector: this stems from the observation that the two variables are strongly correlated, and that using directly the former avoids resorting to a satellite equation[9].

The long run equation is therefore defined as such:

$$p_t^{bht} = c_{lt} + \alpha food_{DGAGRI,t} + \beta wageperhour_t + \varepsilon_t$$

[9] Retailing margins, which are likely to be affected by regulation, also play in principle an important role. However, in our specification we do not find a strong effect of retail margins in the equations.

with p_t^{bht} the log of quarterly seasonally adjusted index of processed food excluding tobacco, $food_{DGAGRI,t}$ the log of Eurosystem assumptions on international farm-gate prices and $wageperhour_t$ is the log of wage per hours worked.

The short run equation is defined as:

$$\Delta p_t^{bht} = c_{st} - \gamma \varepsilon_{t-1} + \chi \Delta p_{t-1}^{bht} + \alpha \Delta wageperhour_{t-1} + \nu dchatel_t + \nu_t$$

with $dchatel_t$ a dummy in 2007Q1, corresponding to the implementation of the Chatel law on retail prices, that led to a large drop in the prices of processed food. The equations are estimated from 2000Q1 to 2019Q4[10]. The coefficients are summarized in **Table 7**.

Table 7 – Estimated coefficients in the updated equation

Long run – Sample 2000Q1 – 2019Q4					
c_{lt}	α	β	R^2		
5.76***	0.07***	0.39***	0.96		
Short run – Sample 2000Q1 – 2019Q4					
c_{st}	γ	χ	α	ν	R^2
$1.0e^{-4}$	0.14***	0.65***	0.02	-0.01***	0.63

The reaction of processed food to a 1% shock on farm-gate price is 0.08pp in the long-run, and its full effect is reached after two years. The reaction of processed food to a 1% on wages per hours worked is 0.4pp and is almost reached in three years. The different pass-through partly reflects different variabilities of the two variables: the standard deviation of q-o-q variations of farm-gate prices is 3.7, while it is only 1.2 for wages per hours worked. Still, the HICP of unprocessed food excluding tobacco reacts slightly more to a 1SD shock on wages per hours worked than to a 1SD shock on farm-gate prices. Finally, the pass-through of wages to processed food prices is lower than in the initial version of MAPI (as it reached 0.8 after 2 years). This is likely to come from the fact that we now model processed food prices in one-step, while the initial model did it in two steps (the first step modelled the production prices in the agri-food sector as depending on compensations per employee).

Table 8 – Impulse response functions of processed food (in index points)

	Updated version of MAPI							
	Q1	Q2	Q3	Q4	1A	2A	3A	LT
+1% on farm-gate prices	0.00	0.01	0.03	0.05	0.02	0.08	0.09	0.07
+1% on wages per hours worked	0.00	0.08	0.19	0.29	0.14	0.44	0.47	0.39

[10] In 2019 Q1 a law regarding retailing margins was implemented, which is likely to have had a positive impact on the prices of processed food. However, we do not find significant effect for a dummy on 2019 Q1, and therefore do not include it in our specification.

Figure 6 – Dynamic simulation and observed data of seasonally adjusted HICP of processed food HICP (y-o-y, %)

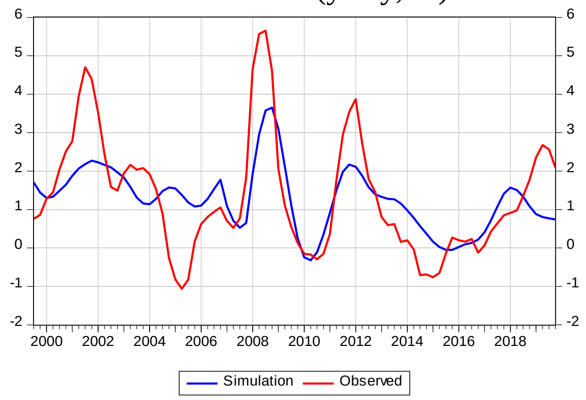
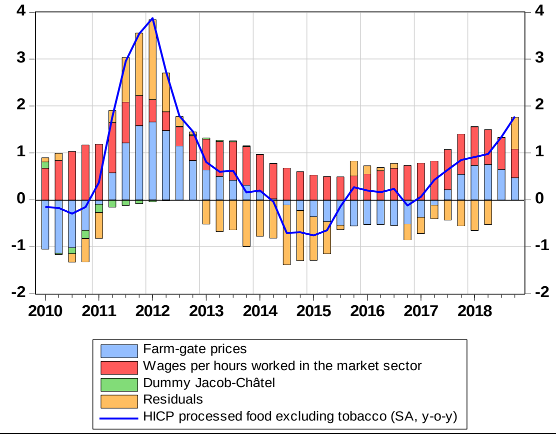


Figure 7 – Econometric contributions



3.3.2 Unprocessed food

Unprocessed food accounts for 4.8%[11] of the total HICP and includes fruits (1.2%), vegetables (1.1%) and meat and fish (2.5%). As already acknowledged in De Charsonville & al. (2017), this component is highly seasonal and is particularly hard to forecast given its strong dependence on external shocks (notably meteorological)[12]. However, this variable exhibits an increasing trend of 0.2% in terms of monthly variations.

The equation therefore uses an autoregressive specification, which guarantees that the forecast spontaneously converges towards its historical mean. Furthermore, in this setting, we find the Eurosystem assumptions on the price of fats to play a significant role in explaining the HICP of unprocessed food. The specification is defined as such:

$$\Delta p_t^a = c_t + \alpha \Delta p_t^{fats} + \chi_1 \Delta p_{t-1}^a + \chi_2 \Delta p_{t-2}^a + \nu_t$$

with p_t^a the log of the monthly seasonally-adjusted unprocessed food HICP, p_t^{fats} the log of prices of fats on international food markets.

Table 9 – Estimated parameters of the updated equation

Sample 2001M01 – 2019M12				
c_t	α	χ_1	χ_2	R^2
1.10^{-3}***	0.01**	0.77***	-0.30***	0.44

As expected from this volatile component, the goodness of fit of the model is modest, and the dynamic simulation hardly captures the peaks and troughs observed in the data (**Figure 8**).

[11] This weight is sizably lower than the one provided in the first version of MAPI: this stems from the change of composition of unprocessed food operated in 2019, when several items of unprocessed food were defined as items of processed food. Therefore, symmetrically, the change of definition of HICP main aggregates increased the weight of processed food.

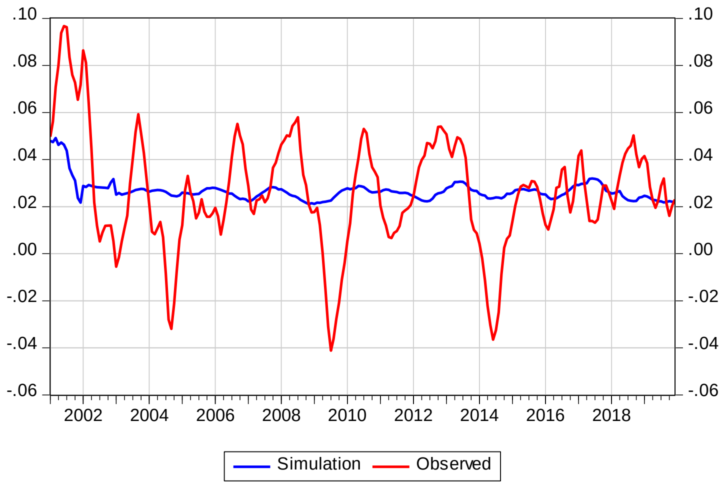
[12] During the first lockdown following the Covid-19 outbreak, the HICP of unprocessed food was one of the component that was the most affected, reaching a historical high of 12.2% in y-o-y variations, due to both an increase in consumption and to disrupted supply chains.

However, the average year-on-year variation is the same in the observed data and in the dynamic simulation.

Table 10 – Impulse response functions of unprocessed food (in index points)

	Updated version of MAPI							
	Q1	Q2	Q3	Q4	1A	2A	3A	LT
+1% on fats	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01

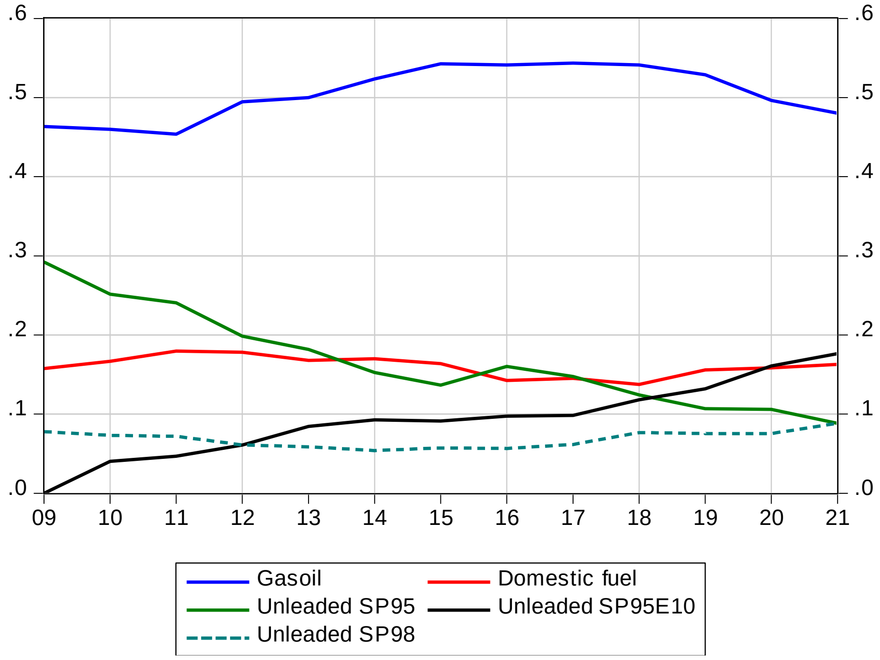
Figure 8 – Dynamic simulation and observed data of seasonally adjusted HICP of unprocessed food (y-o-y, %)



3.4 Petroleum products

As of 2021, petroleum products is the main component of the energy HICP basket, and it accounts for 43% of it. It represents 3.7% of total HICP and is made of five types of retail fuel: gasoil, domestic fuel, unleaded gasoline SP98, unleaded gasoline SP95 and unleaded gasoline SP95E10. In the initial version of the MAPI model, only 4 types of retail fuels were modelled (gasoil, domestic fuel, unleaded gasoline SP98, unleaded gasoline SP95), and the forecast of SP95E10 was based on the estimated coefficients for the equation of SP95. This was warranted by the fact that the weight of SP95E10 was by then negligible, and that this fuel was a close substitute to SP95. However, over time, the weight of SP95E10 grew larger, as it is progressively replacing SP95. It became higher than that of SP95 as of 2019 (**Figure 9**) and in 2021 it even became the second type of fuel with the highest weight (far behind gasoil, though).

Figure 9 – Weights of the 5 types of fuels considered in petroleum products HICP



The logic of the initial version of the model is kept intact in the updated model, but we extend the estimation window in order to update the coefficients[13]. First, we implement an equation for refined products, which is defined as:

$$\Delta P_t^{ref\,j} = c_{st,j} - \gamma_j \left(P_{t-1}^{ref\,j} - P_{t-1}^{brent} \right) + \alpha_1 \Delta P_t^{brent} + \varepsilon_{t,j}$$

With $P_t^{ref\,j}$ the refined product's price (which can be of two types j, diesel or gasoline) and P_t^{brent} the price of crude oil, both in euros. We only consider contemporaneous effects of variations of brent prices on variations of wholesale gasoline and diesel prices, which is coherent with the idea that the pass-through of crude oil prices to refined products prices is very fast and faster than a month (Gautier, Marx & Vertier, 2021).

We then estimate the four equations specified in the initial version of the paper, and we add a specific equation for unleaded SP95e10[14]. The specifications are the following:

$$\Delta P_t^{retail_i,HT} = c_{st,i} - \gamma_i \left(P_{t-1}^{retail_i,HT} - P_{t-1}^{ref\,j_i} - \beta t_{t-1} \right) + \sum_{k_{i=1}}^{K_i} \alpha_{k_i} \Delta P_{t-k_i-1}^{ref\,j_i} + \varepsilon_{t,i}$$

With $P_t^{retail_i,HT}$ the before-tax price of fuel of type i, and t_{t-1} a trend capturing the evolution of retailing margins. Importantly, the refined product considered in each equation depends on the type of fuel. The price of diesel is an input for the equations regarding the price of gasoil and domestic fuel, while the price of gasoline is an input for the equations regarding the price of unleaded SP95, unleaded SP95e10 and unleaded SP98. Also, the exact the maximum number

[13] In particular, all equations are estimated in levels of prices rather than in log, as we assume that the price of output is linear in the price of input, and because of excise taxes, whose effect would not be accurately captured by a specification in log.
[14] Since the price series for this type of fuel are only available since 2013, and in order to we retropolate past data of SP95e10 with those of SP95.

of lags of the price variations of refined products (K_i) depend on the type of fuel under consideration. Diesel plays only contemporaneously for the equation of domestic fuel ($K_{fuel} = 1$), while it plays with up to 3 lags in the equation of gasoil ($K_{gasoil} = 4$). For the equation of unleaded SP98, gasoline plays with up to 2 lags ($K_{sp98} = 3$), while it plays with up to 3 lags in the equations of unleaded SP95 and SP95e10 $K_{sp95} = K_{sp95e10} = 4$)[15]. The equations are estimated on monthly data, over the period 1999M01 to 2018M12 (**Table 11**).

The forecast of tax-included fuel prices are then obtained by adding the VAT and the excise tax on petroleum products (TICPE), using the following equation:

$$P_t^{retail_i,TTC} = (1 + \tau_t^{VAT})(P_t^{retail_i,HT} + TICPE_t)$$

Finally, the month-on-month variations of these tax-included fuel prices are aggregated using the weights of each type fuel, yielding the following month-on-month variations of petroleum products HICP:

$$\Delta I_t^{pet} = \sum_{i=1}^{5} \frac{w_i \Delta P_t^{retail_i,TTC}}{P_t^{retail_i,TTC}}$$

Table 11 – Estimates of the equations in the initial and updated versions of the model

Updated version of the model – Sample 1995M02 – 2018M12 (Gasoline and Diesel) Sample 1999M01 – 2018M12 (Gasoil, Fuel, SP95, SP95e10, SP98)								
	c_{st}	γ_j	α_1	α_2	α_3	α_4	$\gamma\ \beta$	R^2
Gasoline	0.73	0.21	1.05	n.a.	n.a	n.a	n.a.	0.73
Diesel	0.38	0.07	1.02	n.a.	n.a	n.a	n.a.	0.85
Gasoil	1.33	0.25	0.90	0.10	0.01	n.a	0.005	0.93
Fuel	0.69	0.23	0.89	n.a.	n.a	n.a	0.008	0.92
SP95	0.59	0.15	0.83	0.10	-0.03	-0.06	0.004	0.92
SP95e10	0.66	0.15	0.83	0.10	-0.02	-0.06	0.004	0.92
SP98	0.34	0.14	0.82	0.12	-0.03	n.a	0.007	0.93

The response of petroleum products to a shock on crude oil prices in the updated model are displayed in **Table 12**. Since the equation is defined in levels, the response of HICP of petroleum products to a shock on crude oil is not linear, and depends on the initial level of the price of crude oil. Given the weight of petroleum products in total HICP, the effect of a 10 euros shock on crude oil ranges between 0.16pp (115 euros per barrel) and 0.26pp (30 euros per barrel).

[15] Evidence from micro daily data point to a total pass-through of refined products to retail fuel that is typically faster than a month (Gautier et Le Saout, 2017) , and we do find that coefficients on contemporaneous months (α_1) are much larger than coefficients for previous months ($\alpha_k, k > 1$). However, lags of the refined products appears to have a significant impact on the estimation.

Table 12 – Impulse-response function on HICP of petroleum products, for different 10 euros shocks on the price of the barrel of crude oil

Updated version of the model								
Crude oil price	Q1	Q2	Q3	Q4	1A	2A	3A	LT
Impact in index points								
30€	6.90	7.05	7.11	7.14	7.05	7.16	7.16	7.15
55€	6.85	6.99	7.04	7.07	6.99	7.09	7.09	7.09
85€	6.81	6.95	7.00	7.03	6.95	7.05	7.06	7.05
115€	6.89	7.00	7.02	7.03	6.98	7.03	7.04	7.03
Impact in %								
30€	6.72	6.87	6.93	6.96	6.87	6.97	6.95	6.93
55€	5.68	5.80	5.85	5.87	5.80	5.89	5.88	5.85
85€	4.80	4.90	4.94	4.96	4.90	4.97	4.97	4.95
115€	4.20	4.27	4.28	4.28	4.26	4.28	4.27	4.26

3.5 Gas

Gas accounts for 1.3% of the total HICP. For the gas market, 99% of the gas consumed in France is imported. While there are also regulated tariffs for gas (even if they are to disappear definitively on July 1, 2023), these are adjusted monthly since 2013, and not annually as for electricity. Therefore, the final price of gas reflects the evolution of wholesale prices on the world markets, and in particular on the TTF market, considered as the reference at the European level. We build a simple model in which the final gas price is determined by the wholesale gas price (through *futures* on the TTF market) observed two months before (lag giving the strongest correlation). We add two dummies to capture for the first one the bearish effect of the generalization of shale gas on the world markets in 2009 and for the second the effect of an increased national tax on gas consumption.

$$gas_t = c + \alpha\ wholesaleprice_{t-2} + \lambda_1 dummy_{2009Q3} + \lambda_2 dummy_{2018Q1} + \varepsilon_t$$

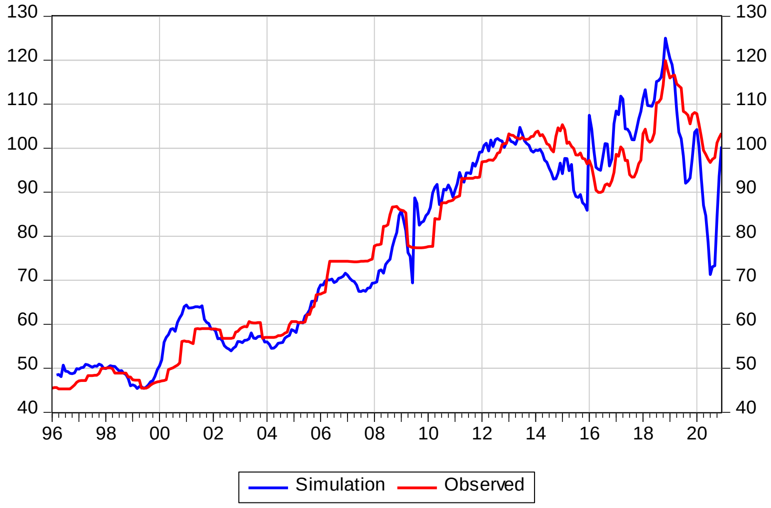
where gas_t is the log of the final price of gas, $wholesaleprice_{t-2}$ the log of the two months lagged wholesale price, $dummy_{2009Q3}$ and $dummy_{2018Q1}$ are two dummies accounting respectively for the massive generalization of shale gas which had a downward effect on international gas prices and for an increase in a specific national tax (known as “TICGN”).

Table 13 – Estimated parameters of the gas equation

Sample 1996M03 – 2021M08				
c	α	λ_1	λ_2	R^2
3.24***	0.32***	0.27***	0.24***	0.93

The model gives a pass-through of 0.32 for the link between the wholesale price and the final price. This pass-through corresponds relatively well to the share of the raw material in the final price over the long term. However, in a period where the wholesale price would rise significantly, its share in the final price would be much larger[16].

Figure 10 - Dynamic simulations and observed data for the gas HICP (level)



3.6 Other components

Five components are forecasted with more simple approaches: communication services (2.8%), tobacco (2.7%), pharmaceutical products (1.9%), health services (2.5%) and electricity (3.2%). Communication services and tobacco follow a random walk (incorporating information on future regulations of their prices whenever relevant[17]). Pharmaceutical products follow a downward trend, reflecting the long-run decrease in prices observed since 2010. Health services follow the average seasonal pattern of the previous 4 years.

As regards electricity, the French electricity market is highly regulated, and regulated tariffs (known as *"tarifs réglementés de vente"*) are proposed at the beginning of each year by an independent institution (*"Commission de régulation de l'énergie"* - CRE) based on the evolution of suppliers' costs, and then validated by the public authorities. In addition, a significant part (around 30%) of the final price of electricity is composed of various taxes and levies. In order to encourage the opening of the market to competition, which began in 2003, a mechanism for access to nuclear energy (known as *"ARENH"*) was introduced in 2010 by the public authorities. The underlying idea is to give access to new suppliers to a part of the nuclear electricity, which is cheaper to produce than renewable electricity. Thus, alternative suppliers have access to 100 TWh of electricity from nuclear origin at a price of 42 euros per MWh (applicable price in 2021). Suppliers must then purchase the remainder directly on the wholesale electricity market. Therefore, it is not possible to find a statistically significant relationship between the wholesale price and the final price due to this ARENH mechanism. However, by applying the calculation formula of the independent institution, we can estimate in December of a given year the increase

[16] Therefore, we also use an accounting approach to estimate the variation in the final price resulting from the change in the cost of the raw material, with the other costs fixed. This approach is used to benchmark the forecast obtained with the econometrical model.

[17] For example, the price of the pack of cigarettes was substantially increased by the French government between 2017 and 2020, with announcements made well ahead of their implementation, which enabled us to include them in our forecasts.

that could affect the regulated tariffs at the beginning of the following year. Overall, our forecast of electricity prices follow legal announcements in the short run, and a seasonal pattern based on observed price hikes announced by the CRE in the past (typically in February and August).

4. General properties of the updated model

4.1 Main changes compared to the initial model

This section summarizes the main changes compared to the initial version of MAPI (see also **Table C** in Appendix C for a summary table). Overall, the updated model we propose improves on the first version of MAPI in several ways.

First, it is more parsimonious: all inputs are already projected in FR-BDF before being integrated into MAPI. We thus do not need to resort to satellite equations (as was previously the case in the equations of manufactured products excluding pharmaceutical products and processed food excluding tobacco) and this reinforces the consistency with projections in FR-BDF which entails the main macroeconomic mechanisms, notably through the wage Phillips curve entailed in the macroeconomic model.

Second, the estimation samples are extended in most equations. However, as in the initial version of MAPI, estimation samples are not fully harmonized across equations, as our aim is to strike a balance between actualization and forecasting performance[18]. Furthermore, they do not go beyond 2019. including observations following the outbreak of the Covid-19 would

Second, the updated model is less constrained than the initial version. This is notably the case for the equations of the two main components of HICP excluding energy and food, i.e. manufactured products and private services. In the case of manufactured products, the initial specification assumed that the sum of pass-through of import prices and domestic prices was equal to one. However this theoretical assumption implied long run simulations of manufactured products which were way more dynamic than the historical regularities would have predicted. The updated equation entails a reaction of manufactured products to the inputs considered which is in line with past observations. In the case of private services, the initial version of the model assumed that, in the long run, the ratio of private services inflation to wages follows a trend. While this hypothesis was overall warranted, the movements in compensations due to the implementation of the *CICE* between 2014 and 2019 made this assumption more fragile.

Third, the new model takes on board structural changes within the components we forecast, notably within petroleum products, whose mix increasingly rely on unleaded SP95E10.

Finally, generally speaking, while in the first version of MAPI wages and compensation were expressed per employee, they are now expressed per hours worked, which presumably better reflects the movements of wages observed during the Covid-19 crisis.

[18] In the case of rents, for example, we did not update the sample as in recent years, reforms of social housing rents made the index move strongly.

Such changes make the mode morel easily interpretable and easier to handle in a forecasting framework. However, they also comes at a cost. First, the new model exhibits smoother dynamic simulations compared to the initial version: overall, while the model is successful at capturing the trends of price indices, it captures less accurately peaks and troughs. The second cost is specific to private services: maintaining significant error correction coefficient and cointegration relationship while relaxing the trend assumption entails a long run elasticity between wages and private services HICP greater than 1 (while it was equal to 1 in the initial version of MAPI). However, the model still entails significant pass-through of domestic and imported factors to consumer prices, as we emphasize in the next section.

4.2 Global responses to shocks on wage, change and import prices

In **Table 14**, we report the effect of a permanent 1% increase in compensation per hours worked, wage per hours worked and minimum wage. This simulation does not take into account backwash-effects of wages on prices, which, in the context of projections or scenario analysis would come through the interaction of MAPI with FR-BDF. The effect on headline HICP is of about 0.1pp after 1 year, 0.2pp after 2 years and 0.3pp after 3 years, and stems both from the effect on the HICP of processed food excluding tobacco (0.5 pp after three years), and private services (0.9pp after three years). The effect on HICP excluding food and energy is of 0.1pp within 1 year, 0.2pp within 2 years and 0.4pp within 3 years. The pass-through of wages to total HICP after three years appears very close to the initial version of MAPI (0.3), but slightly more muted after one year (0.2 against 0.3 in the initial version of MAPI). The more muted reaction after one year comes from the lower response of processed food excluding tobacco, and it is compensated in the longer run by the stronger reaction of private services. Note however that in this exercise, we do not take into account the indirect effect of wage through the deflator of value-added (which enters the equation of manufactured products excluding pharmaceutical products). In this version of the model, this indirect effect has a modest effect on total HICP: indeed, while in FR-BDF the pass-through of wages to value-added prices is equal to 1 in the long run, the transmission is slow (0.5 after 2 years). In our equation of manufactured products excluding tobacco (which represent 23.3% of HICP), the pass-through of value-added prices is only of 0.07: after two years the indirect effect to manufactured products would therefore not be higher than 0.01pp.

Table 14 - 1% shock on wages (in index points)

Updated version of MAPI							
	Q1	Q2	Q3	Q4	1A	2A	3A
Processed food excl. tobacco (15.4%)	0.00	0.08	0.19	0.29	0.14	0.44	0.47
Private services (30.4%)	0.00	0.12	0.23	0.32	0.17	0.53	0.80
HICP excl. food and energy (68.5%)	0.00	0.05	0.10	0.14	0.08	0.24	0.36
Total HICP	0.00	0.05	0.10	0.14	0.07	0.23	0.32

In **Table 15**, we report the effect of an appreciation of the euro against the nominal effective exchange rate and the dollar. We calibrate the shocks as such: we assume that the euro increases by 10% against the dollar and by 10% against the nominal effective exchange rate. In MAPI, the shock on the euro-dollar exchange rate affects the price of the Brent barrel: in this exercise, we assume an initial value of the barrel of 70 euros (i.e. the value of the barrel as of October 2021). Therefore, the shock corresponds to a drop of 7 euros in the price of the barrel. In MAPI, the shock on the nominal effective exchange rate has a direct effect on the prices of manufactured products excluding pharmaceutical products. However, in this exercise, we take on board the effect that this shock has on import prices, through FR-BDF. The latter in turn affect the prices of manufactured products through the MAPI equation. Here again, effects coming through the impact of activity that would eventually induce effects on wages, modelled in FR-BDF, are ignored.

The effect on total HICP is of -0.2pp within 1 year and -0.3pp after two to three years. It stems from effects on manufactured products excluding energy (-0.6pp after 3 years) and on energy (-1.5pp after three years). The effect on HICP excluding food and energy is of -0.1pp after 1 year, and -0.2pp after 2 to 3 years.

Table 15 – Appreciation of the euro by 10% against the dollar and the nominal effective exchange rate (in index points)

	Updated version of MAPI						
	Q1	Q2	Q3	Q4	1A	2A	3A
Manufactured goods excl. PP (23.3%)	0.00	-0.18	-0.21	-0.43	-0.20	-0.57	-0.58
Energy (8.6%)	-1.68	-1.70	-1.69	1.65	-1.68	-1.61	-1.52
HICP excl. food and energy (68.5%)	0.00	-0.06	-0.07	-0.15	-0.07	-0.19	-0.20
Total HICP	-0.15	-0.19	-0.20	-0.24	-0.19	-0.27	-0.27

4.3 Predictive performance

In **Tables 16 and 17**, we report the RMSEs of our main equations, simulated using the observed values of the MAPI inputs, against an AR (4) and a random walk, on the period 2006-2018. Regarding the subcomponents, MAPI systematically outperforms an AR (4) and Random Walks at any horizon considered. We also compare our forecasts for HICP and HICP excluding food and energy[19] (also comparing them to a Phillips Curve[20]). The predictive performances of MAPI are similar to those of Phillips curves for HICP excluding food and energy, but MAPI

[19] The forecasts of total HICP and HICP excluding food and energy presented in these tables section are done using the forecasts of the 7 main MAPI equations. For the 5 remaining components, we assumed that their monthly variation is equal to the average over the period 2006-2018. As regards petroleum products, the forecasts are done with observed values of wholesale gasoline and diesel traded at Rotterdam, and assuming flat TICPE and VAT (which is likely to explain the underestimation at the end of the forecasting horizon, as TICPE increased sizably between 2015 and 2018).

[20] A description of the specification used for our Phillips curve equations can be found in Appendix D.

yields substantially more accurate forecasts for total HICP at any considered horizon. Figures 11 and 12 report the distributions of forecast errors for total HICP and HICP excluding food and energy. Regarding total HICP, the distributions of errors for MAPI forecasts are more concentrated peaked around 0 and have smaller tails (the Phillips curves notably have fatter negative tails, indicating that a larger number of strong overestimations of inflation). Regarding HICP excluding food and energy, while the RMSEs for MAPI and the Phillips Curve are similar, the mode of the forecast errors for MAPI is more centered around 0 and the Phillips Curve display fatter positive tails (indicating a larger number of strong underestimations of inflation). The distributions of forecast errors by component are reported in Appendix E.

Table 16 – RMSE of MAPI for total HICP and HICP excluding food and energy (2006-2018)

RMSE – 4 quarters ahead				
	AR(4)	**RW**	**Phillips Curve**	**MAPI**
Total	1.08	0.98	0.49	0.32
Excluding food and energy	0.38	0.40	0.25	0.24
RMSE – 8 quarters ahead				
Total	1.06	1.01	0.51	0.40
Excluding food and energy	0.39	0.38	0.24	0.26
RMSE – 12 quarters ahead				
Total	0.95	0.89	0.48	0.32
Excluding food and energy	0.38	0.34	0.25	0.23

Table 17 – RMSE of the MAPI equations (2006-2018)

RMSE – 4 quarters ahead			
	AR(4)	**RW**	**MAPI**
Private services	0.53	0.54	0.26
Manufactured products excluding pharmaceutical products	0.54	0.52	0.28
Processed food excluding tobacco	1.60	1.57	0.81
Unprocessed food	2.41	2.33	2.18
Rents	0.50	0.89	0.55
Petroleum products	12.26	12.28	2.74
Gas and other combustibles	6.44	6.23	5.72
RMSE – 8 quarters ahead			
Private services	0.58	0.52	0.28
Manufactured products excluding pharmaceutical products	0.56	0.54	0.35
Processed food excluding tobacco	1.67	1.64	0.95
Unprocessed food	2.42	2.44	2.35
Rents	0.61	0.79	0.55
Petroleum products	12.82	12.72	3.04
Gas and other combustibles	6.50	6.40	6.56
RMSE – 12 quarters ahead			
Private services	0.60	0.48	0.29
Manufactured products excluding pharmaceutical products	0.57	0.57	0.35
Processed food excluding tobacco	1.25	1.20	0.69
Unprocessed food	2.42	2.44	2.35
Rents	0.72	0.78	0.57
Petroleum products	12.38	12.29	2.98
Gas and other combustibles	6.36	6.22	6.93

Figure 11: Distribution of forecast errors on y-o-y variations, Total HICP (2006-2018)

Figure 11.a – 4 quarters ahead | **Figure 11.b** – 8 quarters ahead | **Figure 11.c** – 12 quarters ahead

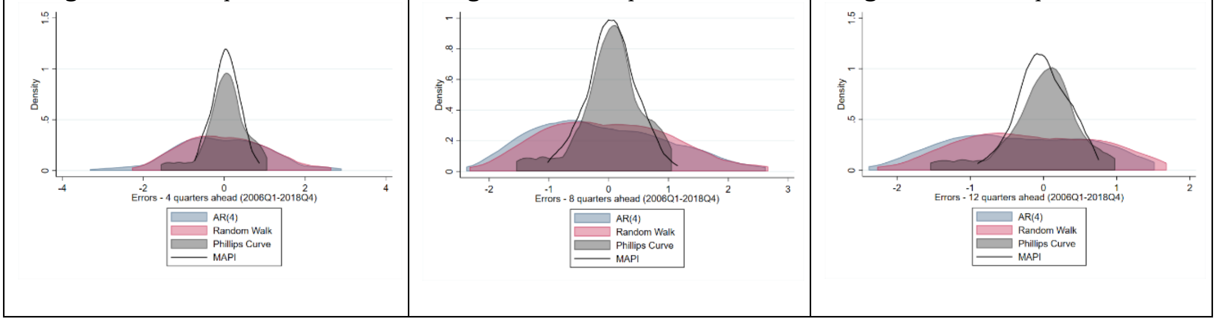
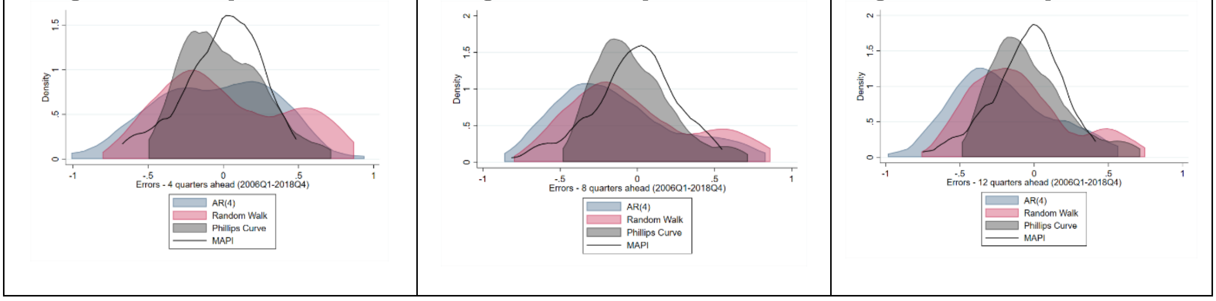


Figure 12: Distribution of forecast errors on y-o-y variations, HICP excluding food and energy (2006-2018)

Figure 12.a – 4 quarters ahead | **Figure 12.b** – 8 quarters ahead | **Figure 12.c** – 12 quarters ahead



5. Conclusion

The updated model we propose simplifies the initial version of MAPI. While the conceptual framework remains broadly unchanged, the specifications we implement are overall more parsimonious and less constrained. In particular, since we resort only to variables projected through FR-BDF or the Eurosystem assumptions, no satellite equation is needed to project inputs (as was previously the case in the equations of processed food and manufactured products excluding pharmaceutical products). Furthermore, previous specifications that relied upon strong assumptions are now modelled in a more flexible way, making them likely to be more resilient out of sample. These changes substantially simplify the usage and the interpretation of the model in a forecasting setting, while exhibiting reaction functions in line with the reaction functions of FR-BDF.

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Insee, 2021. *Note de conjoncture – Retour en surface.*

7. Appendix

A - Cointegration tests

The cointegration tests displayed in this section are based on Engle and Granger (1987)

Table A.1 - Private services

	Tau-statistic	Prob*	Z-Statistic	Prob*
0 lag	-3.031255	0.1201	-13.99603	0.1436
1 lag	-3.022408	0.1225	-18.39651	0.0500
2 lags	-2.901505	0.1534	-21.27712	0.0232

*MacKinnon (1996) p-values

Table A.2 - Manufactured products excluding pharmaceutical products

	Tau-statistic	Prob*	Z-Statistic	Prob*
0 lag	-2.747372	0.5628	-10.84064	0.7146
1 lag	-2.825044	0.5243	-15.93804	0.4028
2 lags	-3.838298	0.1283	-40.94552	0.0010

*MacKinnon (1996) p-values

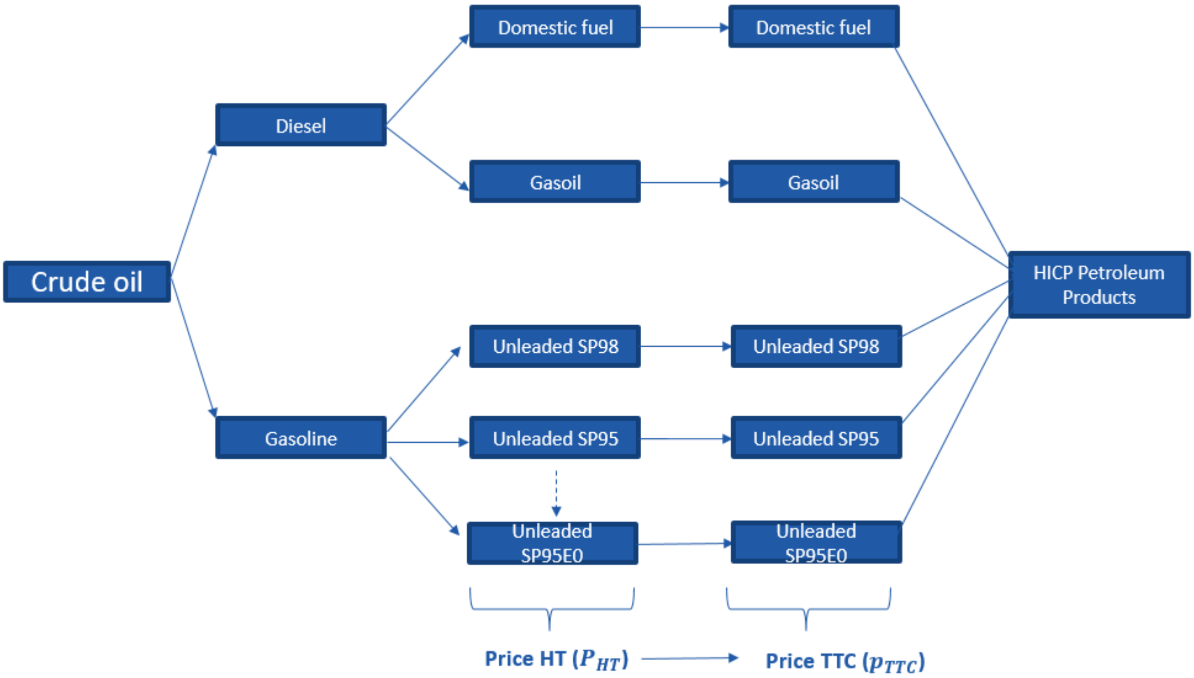
Table A.3 - Processed food excluding tobacco

	Tau-statistic	Prob*	Z-Statistic	Prob*
0 lag	-1.936723	0.7619	-6.820363	0.7948
1 lag	-3.681086	0.0732	-26.25527	0.0309
2 lags	-3.246067	0.1724	-25.16416	0.0393

*MacKinnon (1996) p-values

B - Schematic representation of the process of HICP Petroleum Products

Figure B – Process for forecasting HICP Petroleum Products



$$p_{TTC} = (1 + VAT) \times (P_{HT} + \text{TICPE})$$

C - Comparisons of specifications and input variables in the initial and updated version of MAPI

Table C – Main aggregates of the short and medium run forecasts, and main changes between the initial and updated versions of MAPI

Component	Weight (2021)	Type of model in initial MAPI	Input variables in initial MAPI	Type of model in updated MAPI	Input variables in updated MAPI
Unprocessed food	4,75%	ECM	Farm gate prices - meat	AR (2)	Farm gate prices - fats
Processed food excluding tobacco	15,39%	ECM	Farm gate prices Unit labour costs Production cost in agricultural sector Wages per employee Ratio between prices in the large retail sector and prices in the small retail	ECM	Farm gate prices Wages per hours worked
Tobacco	2,74%	Random walk with expert judgment (tax announcement)	x	Random walk with expert judgment (tax announcement)	x
NEIG excl. pharma. products	23,27%	ECM	Import prices of goods excluding energy Deflator of production of market services Unit labor costs	ECM	Import prices of goods and services (excluding and including energy) Deflator of value-added in the whole economy Nominal effective exchange rate

Pharmaceutical products	1,86%	Random walk with expert judgment	x	Random walk with expert judgment	x
Petroleum products	3,68%	ECM	Crude oil prices in dollars Refined oil prices in dollars Euro dollar exchange rate TICPE	ECM	Crude oil prices in dollars Refined oil prices in dollars Euro dollar exchange rate TICPE
Gas	1,69%	Random walk with expert judgment	x	Single equation with two dummies for tax and shale production	*Futures* of TTF prices
Electricity	3,21%	Random walk with expert judgment	x	Random walk with expert judgment for the annual increase of regulated prices	x
Rents	7,83%	Single equation	Real GDP IRL	Single equation	Real GDP IRL
Private services	30,34%	ECM	Compensation per employee in the market sector Crude oil prices in dollars Euro dollars exchange rate Unemployment rate Minimum wage		Compensation per hours worked in the market sector Crude oil prices in dollars Euro dollars exchange rate Unemployment rate Minimum wage
Health services	2,49%	Random walk with expert judgment	x	Random walk with expert judgment	x
Communication services	2,75%	Random walk with expert judgment	x	Random walk with expert judgment	x

D - Specifications of the Phillips curves

We usually compare our forecast of total HICP to a Phillips curve. Its specification includes an autoregressive term (with two quarters lag), a measure of import prices and the unemployment rate. The explained variable is the seasonally adjusted quarterly rate of change of the total HICP. To be precise, it is regressed on the quarterly rate of change of import prices, the latter being defined as the ratio of the total import deflator to the value added deflator in the economy as a whole, and on the level of the unemployment rate, expressed as a deviation from its long-term average. This specification was chosen for its link with the macroeconomic scenario (through unemployment rate, import prices and value added prices), its good empirical performance and its robustness to revisions in the *slack* measures (which was rather low for the output gap or the NAIRU gap).

$$i_t^{total} = c + \alpha i_{t-2}^{total} + \beta u_{t-1}^{c} + \lambda imp_t^{ratio} + \varepsilon_t$$

Table D.1 – Estimated coefficients of the Phillips curve for total HICP

Sample 1996Q4 – 2019Q4				
c	α	β	λ	R^2
0.31***	0.07	-0.11***	0.02***	0.61

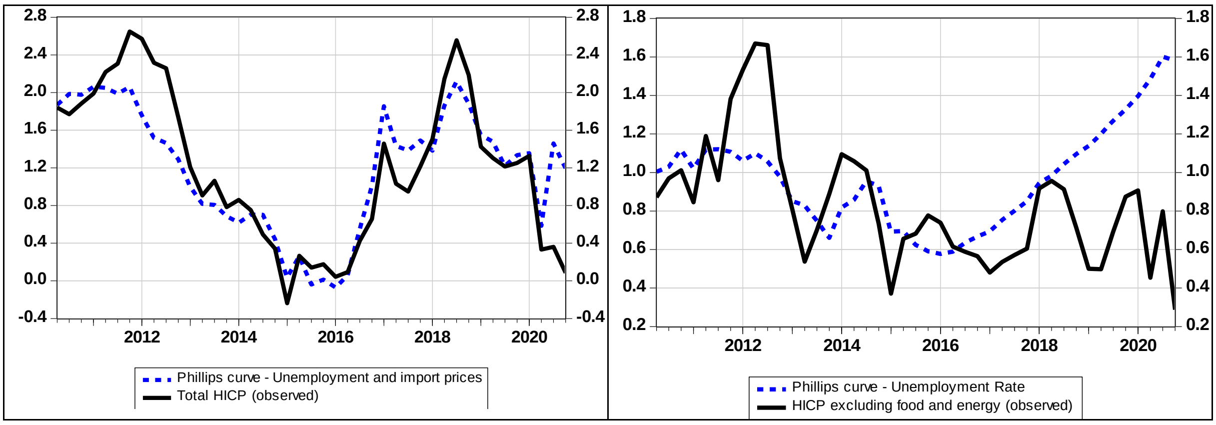
We also use a Phillips curve for HICP excluding food and energy to benchmark our forecast. This specification does not include any measure of import prices. We include a dummy to take into account the increase in VAT in 2014Q1 from 19.6% to 20%.

$$i_t^{wxb} = c + \alpha i_{t-2}^{wxb} + \beta u_{t-1}^{c} + \lambda dummy^{VAT} + \varepsilon_t$$

Table D.2 – Estimated coefficients of the Phillips curve for HICP excluding food and energy

	Sample 1996Q4 – 2019Q4			
c	α	β	λ	R^2
0.19***	0.31***	-0.08***	0.21***	0.46

Figure D – Estimated coefficients of the Phillips curve for total HICP and HICP excluding food and energy



E - Distribution of forecast errors in the updated equations

Figure E.1: Distribution of forecast errors on y-o-y variations, private services (2006-2018)

Figure E.1.a – 4 quarters ahead

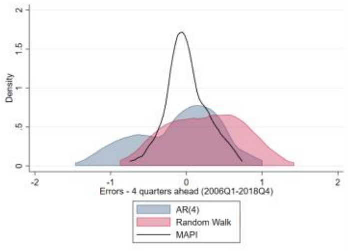


Figure E.1.b – 8 quarters ahead

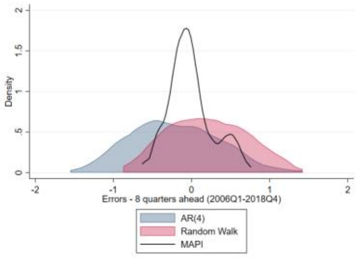


Figure E.1.c – 12 quarters ahead

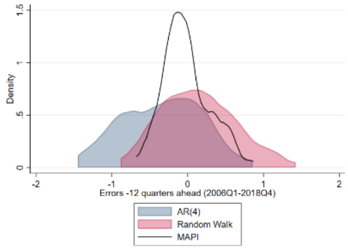


Figure E.2: Distribution of forecast errors on y-o-y variations, petroleum products (2006-2018)

Figure E.2.a – 4 quarters ahead

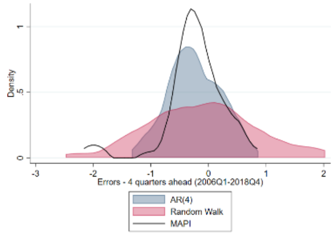


Figure E.2.b – 8 quarters ahead

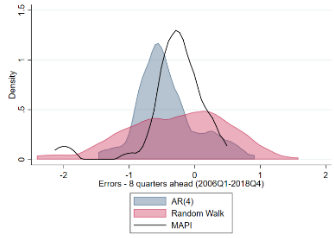


Figure E.2.c – 12 quarters ahead

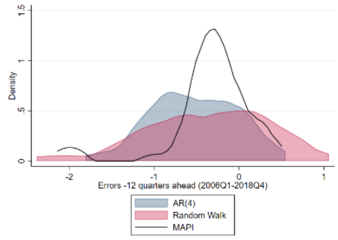


Figure E.3: Distribution of forecast errors on y-o-y variations, manufactured products excluding pharmaceutical products (2006-2018)

Figure E.3.a – 4 quarters ahead

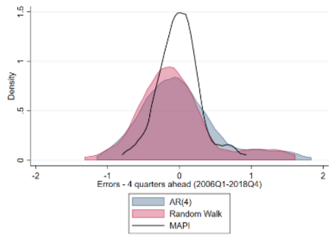


Figure E.3.b – 8 quarters ahead

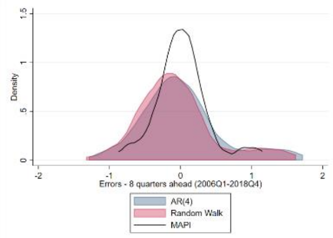


Figure E.3.c – 12 quarters ahead

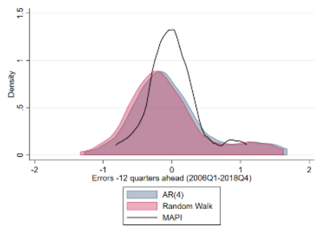


Figure E.4: Distribution of forecast errors on y-o-y variations, processed food excluding tobacco (2006-2018)

Figure E.4.a – 4 quarters ahead

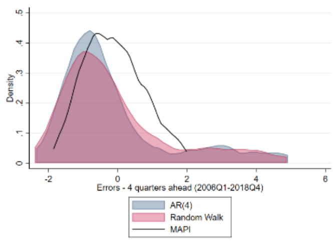


Figure E.4.b – 8 quarters ahead

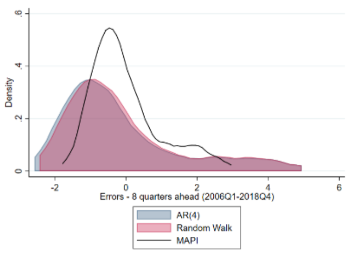


Figure E.4.c – 12 quarters ahead

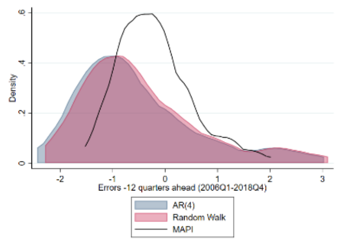


Figure E.5: Distribution of forecast errors on y-o-y variations, unprocessed food (2006-2018)

Figure E.5.a – 4 quarters ahead

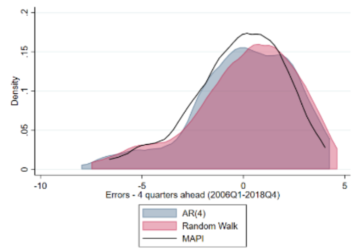


Figure E.5.b – 8 quarters ahead

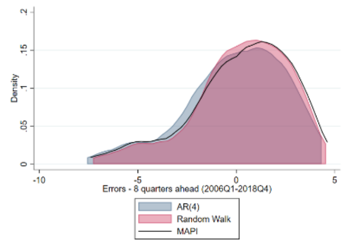


Figure E.5.c – 12 quarters ahead

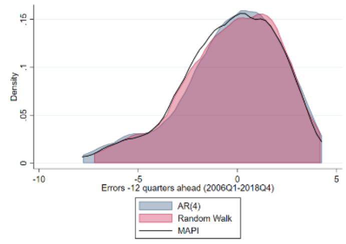


Figure E.6: Distribution of forecast errors on y-o-y variations, petroleum products (2006-2018)

Figure E.6.a – 4 quarters ahead

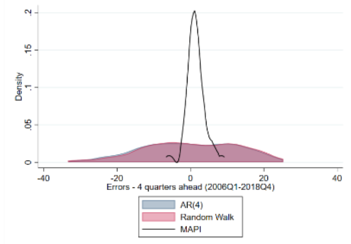


Figure E.6.b – 8 quarters ahead

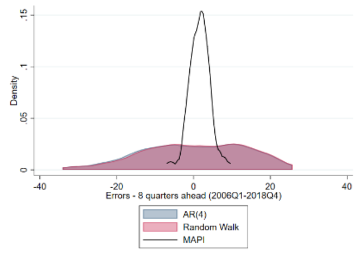


Figure E.6.c – 12 quarters ahead

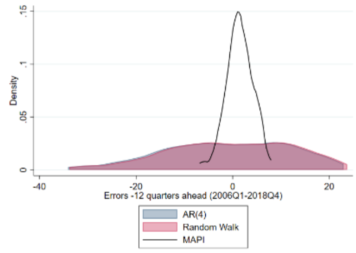


Figure E.7: Distribution of forecast errors on y-o-y variations, gas and other combustibles (2006-2018)

Figure E.7.a – 4 quarters ahead

Figure E.7.b – 8 quarters ahead

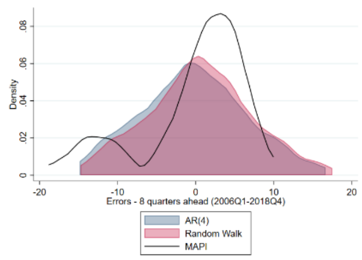


Figure E.7.c – 12 quarters ahead