INTERNATIONAL MONETARY FUND

A Bottom-Up Reduced Form Phillips Curve for the Euro Area

Thomas McGregor and Frederik Toscani

WP/22/260

2022
DEC

WORKING PAPER

 WP/22/260

IMF Working Paper
European Department

A Bottom-Up Reduced Form Phillips Curve for the Euro Area
Prepared by Thomas McGregor and Frederik Toscani

Authorized for distribution by Oya Celasun
December 2022

ABSTRACT: We develop a bottom-up model of inflation in the euro area based on a set of augmented Phillips curves for seven sub-components of core inflation, and auxiliary regressions for non-core items. The disaggregated structure of the model improves on the forecasting performance of a standard one-equation Phillips curve, especially since the onset of the Covid-19 pandemic in early-2020 and the following energy shocks. We find a key role for international energy and food prices in explaining the recent surge in inflation – as of Q2 2022, they account for 75 percent of the increase in headline inflation and 30 percent of the increase in core. Economic slack and inflation expectations explain another 10 percent of headline and 20 percent of core inflation. Around one-third of the increase in core inflation remains unexplained by the model. Out of sample projections show high uncertainty around the inflation path while suggesting that inflation pressures are unlikely to dissipate quickly. We argue that the bottom-up approach offers a useful complement to the forecaster's toolbox–especially in the current environment of sectoral shocks - by improving forecast accuracy, shedding additional light on the drivers of inflation, and providing a framework in which to apply ex-post judgement in a structured way.

RECOMMENDED CITATION: McGregor, T. and F. Toscani (2022), "A Bottom-Up Reduced Form Phillips Curve for the Euro Area", IMF Working Paper WP/22/260.

JEL Classification Numbers:	E31; E37; C32
Keywords:	Euro area; Inflation; Phillips curve
Author's E-Mail Address:	tmcgregor@imf.org; ftoscani@imf.org

WORKING PAPERS

A Bottom-Up Reduced Form Phillips Curve for the Euro Area

Prepared by Thomas McGregor and Frederik Toscani[1]

[1] The authors would like to thank Ravi Balakrishnan and Nir Klein for their guidance on the project. Staff of the IMF provided helpful comments via the internal review process and during various surveillance meetings; and staff of the European Central Bank provided useful suggestions and feedback at several stages of the project, including during a presentation at the ECB in Frankfurt. We also thank seminar participants at the European Commission in Brussels. Projections shown in this paper are illustrative to present the working of the model. They do not reflect the latest projections of the IMF or IMF staff.

Contents

Executive Summary

Since the onset of the Covid-19 pandemic in early-2020, and subsequent energy shocks, inflation developments have consistently surprised forecasters. In this paper we develop a bottom-up model of inflation in the euro area based on a set of augmented Phillips curve models for seven sub-components of core inflation and auxiliary regressions for non-core items. The rationale for such an approach is twofold. First, by decomposing the HICP basket, we hope to exploit the heterogeneous data generation processes of its sub-components and so improve our forecasting accuracy. Second, a bottom-up approach allows for a better understanding of inflation drivers as well as the specific channels of transmission of shocks to core and headline inflation dynamics.

We find that the bottom-up framework improves on the overall forecast accuracy of the canonical top-down Phillips curve model, as well as a set of simple autoregressive processes, in pseudo out of sample forecast evaluations. This is particularly true for headline inflation, where the energy model adds significant value in terms of forecasting accuracy. The outperformance of the headline bottom-up model increases over the 2020-2022 period, given the prevalence of sectoral shocks.

We use the model to estimate that three-quarters of the surge in headline inflation from early 2021 to Q2 2022 was driven by rising commodity prices, while declining slack and increasing inflation expectations explain a further 10 percent. For core inflation, international energy and food prices explain around 30 percent of the increase, slack and inflation expectations account for around 20 percent and other model variables such as non-energy manufactured import prices or house prices for another 20 percent. Unexplained forecast errors account for around one third – or around 1 percentage point – of the increase in core inflation, and also around 1 percentage point of the increase in headline inflation. We discuss the possible drivers of this rather large forecast miss and the general deterioration in forecast performance over the past quarters and identify four salient ones: (i) challenges in measuring economic slack, (ii) policy changes, such as measures to limit the passthrough of energy price increases, (iii) non-linearities in energy pass-through amid an historic natural gas price shock, and (iv) the role of supply-side disruptions. This highlights both the limitations of pure model-based projections, but also the benefits of our bottom-up approach, which contains a more detailed set of transmission channels and provides the forecaster with a structured approach with which to apply judgment to the projections.

Finally, we use the model to explore several scenarios for inflation in the euro area over the coming two years. Uncertainty for any given scenario is large and increasing over time with the confidence band around the end-2024 core inflation projection as wide as 4 percentage points and even wider for headline inflation.

I. Introduction

Over the past decade – from the end of the Global Financial Crisis (GFC) until early-2020 – inflation in the euro area, and around the world, remained stubbornly low. Against this backdrop the use of the workhouse Phillips curve framework for understanding inflation dynamics is being re-examined.[1] A common result is that the Phillips curve continues to have value after accounting for a flattening of the curve in the context of globalization (Mark Carney, 2017). A secular downward trend in tradable goods inflation has also identified as a key driver of low inflation (see, for example, IMF World Economic Outlook October 2016).[2]

The recent inflation narrative has been very different. While the Covid-19 shock initially drove inflation lower – due largely to the collapse in consumer spending and imposition of lockdowns – inflation recovered quickly once economies reopened. A series of large commodity price and supply-side shocks—has continued to drive inflation up in the euro area , and around the world, with repeated historically high inflation prints through most of 2022. The exceptional nature of these shocks has again triggered a debate on the value of standard inflation projections tools based on historical correlations.

Against this backdrop, we re-examine the Phillips curve model and ask if it is still alive and well in the euro area. We have two main goals in this paper. First, given the very different inflation dynamics observed across HICP basket components since the start of 2020 we propose a bottom-up Phillips curve for the euro area to allow for better aggregate forecasting performance. Second, we unpack the drivers of the 2022 inflation surge. We then try to understand what implications we can draw for how to use an empirical projection framework going forward. This allows us to comment much more concretely on the degree to which the current inflationary dynamics do indeed diverge from what history teaches us, and what we can learn from recent experience when it comes to improving our forecasting accuracy.

We build on a rich literature which proposes reduced form bottom-up Phillips curves. There are few theoretical results on whether forecasting at the aggregate level or recovering an aggregate forecast from component level projections is superior. As Bermingham and d'Agostino (2014) point out, theoretical results favor forecast aggregation but it has ultimately been an empirical issue and not all evidence suggests that simply disaggregating inflation into its sub-components improve forecasting performance (Hubrich, 2005). Bermingham and d'Agostino conclude with the view that forecast aggregation (projecting individual components and the aggregating) can lead to substantial improvements in forecasting (particularly when timeseries are sufficiently long). It is in this spirit that we approach our exercise.

Several papers find that the drivers of inflation and inflation dynamics may be very different across sub-components of the consumer price basket, generating heterogeneity in overall inflation which a bottom-up model can exploit. For example, O'Brien et al. (2021) document the importance of domestic factors for services, while Altissimo et al (2004) show that inflation persistence varies dramatically by sub-component and across euro area countries. Recent work by the Bank of International Settlements (BIS) finds evidence of spillovers from shocks across inflation components in the US, that increases in high inflationary environments.[3]

[1] See Koester et al (2019) for a discussion of the low inflation period from 2013 to 2019 in the euro area.
[2] For the euro area, the low inflation in the decade leading up to the pandemic has been explained in part by cyclical developments, including monetary policy being constrained by the effective lower bound, and, to a lesser extent, by underlying structural trends, such as globalization, digitalization, and demographics (Koester et al., 2021).
[3] See BIS 2022 Annual Report Section II.

The papers most closely related to our approach include Peach et al. (2013), Abdih et al. (2016) and Tallman and Zaman (2017) – all of which focus on the US. Abdih et al. (2016) in particular, develop a bottom-up model of inflation for the US and find that it offers improved forecasting performance and a better understanding of inflation dynamics. We follow the approach in these papers in focusing on the split between the drivers of goods and services inflation. Finally, in benchmarking the forecasting performance of our bottom-up model, we construct a top-down model for core and headline inflation in the euro area, similar to that of Abdih et al (2018).

The remainder of the paper proceeds as follows. Section II discusses our methodology, including model specification, and section III presents the estimated model coefficients. Section IV then assesses the model's forecasting performance, both before the pandemic and over the 2020-22 period. Section V studies the drivers of inflation through the lens of the model and section VI presents a set of stylized scenarios for the outlook for inflation until end-2024. Section VI concludes.

II. Methodology

A. The Harmonized Index of Consumer Prices (HICP) Basket

We separate the HICP inflation basket into two non-core components: (1) energy (which in turn is disaggregated into fuels, gas and electricity), and (2) unprocessed food; and seven core components: (1) processed food, (2) durable goods, (3) semidurable and non-durable goods, (4) housing services, (5) recreation services (excl package holidays and accommodation)[4], (6) transport services and (7) other services. We discuss the logic for this breakdown in detail below. In defining these groupings, we focus on differences in the underlying data generation processes that could be explained by different observable explanatory variables that may conceptually matter for one category but not others. We also aimed to minimize the degree of correlation between individual inflation series to justify no further aggregation, except for the non-energy industrial goods categories (durable goods; semi-durable and non-durables goods).[5]

Table 1 shows summary statistics for the key inflation series over the period 2002-2019 and the 2020-Q2 2022 period separately.[6] Figure 1 plots the inflation series to better understand their time-series profiles.

There are a few things to note which will be useful for the modelling section. During the pre-pandemic period, processed food inflation is by far the most volatile core component. Durable goods on average had virtually stable prices (-0.1 percent inflation) and low volatility. Services inflation overall is in fact slightly more volatile than both durable and semi- and nondurable goods in the euro area, an unusual pattern explained by the very low volatility of goods inflation before the pandemic. Transport services inflation – which is influenced rather directly by refined petroleum product prices - has the highest average inflation and the second highest volatility among core components. The two non-core components are more volatile than all core items. In particular, energy inflation has a standard deviation that is 5 times as high as that of processed food and nearly 15 times as high as that of housing services.

[4] The exclusion of package holidays was due to the peculiar behavior of package holidays which are a highly volatile component with a rather different behavior to other recreation services. Package holidays and accommodation are included in "other services" instead.
[5] The correlation between durable and non-durables (incl semi-durable) goods inflation is very high (0.9) but we maintain the split to allow for separate modelling during Covid/post-Covid as needed.
[6] The data start in 2002 due to lack of weights for certain subcomponents before that.

Since the start of 2020, non-core items have seen much higher and more volatile inflation. Average energy inflation has more than doubled, while unprocessed food inflation has nearly doubled; both have become much more volatile. Of the core components, goods inflation has increased significantly, particularly for durable goods. It is worth flagging that five out of the nine categories we study hit their maximum inflation rate since 2002 in Q2 2022. Moreover, three of the categories that did not were only 0.1 percentage point off their maximum (and two of them then significantly exceeded the previous maximum in Q3 2022).

Since we aggregate the individual bottom-up projections, it is important to also consider the component weights. Looking at the averages since the early 2000s, the weights range from 19 percent for semi-and nondurable goods, to 13 percent for processed food and 7 percent for transport services, the smallest core component. Figure 1d plots the weights of individual core components. Core components overall[7] account for slightly below 85 percent of the HICP basket, with energy accounting for about 10 percent and unprocessed food around 7 percent.[8]

Table 1. Summary Statistics for Inflation

YoY inflation (%)	2000Q1-2019Q4				2020Q1-2022Q2			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Core goods								
Processed food	2.3	1.4	0.5	7.0	2.4	1.7	0.8	6.9
Durables	-0.1	0.4	-0.9	0.9	1.8	1.8	-0.1	5.5
Semi- and non-durables	0.9	0.5	0.1	2.3	1.1	1.0	-0.4	3.3
Core services								
Housing	1.9	0.5	1.1	2.7	1.5	0.3	1.2	2.2
Recreation (ex package holidays)	2.3	0.7	1.4	4.3	2.2	0.9	1.6	4.4
Transport	2.5	0.8	0.6	4.6	1.8	1.6	-0.6	4.5
Other	1.3	0.8	0.1	3.1	1.1	1.1	-0.3	3.0
Non-core								
Unprocessed food	2.2	2.0	-2.0	8.3	3.9	2.8	-0.2	9.8
Energy	3.6	6.5	-11.9	15.1	10.0	17.6	-10.3	39.6

Sources: Eurostat and Authors' calculations

Notes: Numbers are based on year-over-year percent changes in the underlying HICP categories.

[7] The ECB defines core inflation as headline excluding energy, food, alcohol, and tobacco while we define it is as headline excluding energy and unprocessed food.

[8] Weights change over time as shown in Figure A.2 in the Appendix, with durable and nondurable and semidurable goods weights trending down over time, for example, while the weight of processed food and certain services has increased. Since 2020 there were some sharp movements (in historical comparison) in weights with energy increasing, for example. For the projections beyond 2022 we will abstract from the future (and thus yet unknown) change in weights when constructing the bottom-up projections.

Figure 1. Year-on-Year Inflation by Components and Core Component Weights

Figure 1a

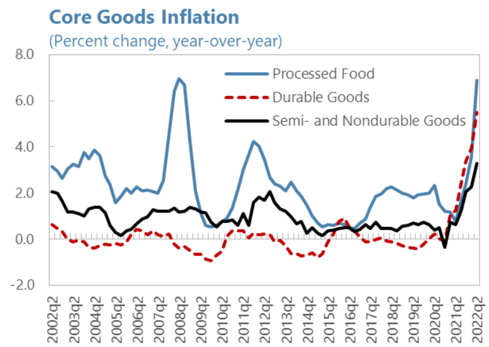


Figure 1b

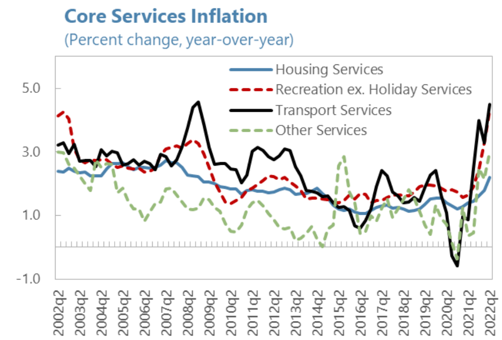


Figure 1c

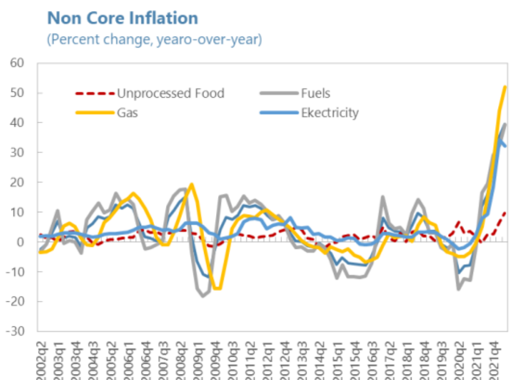
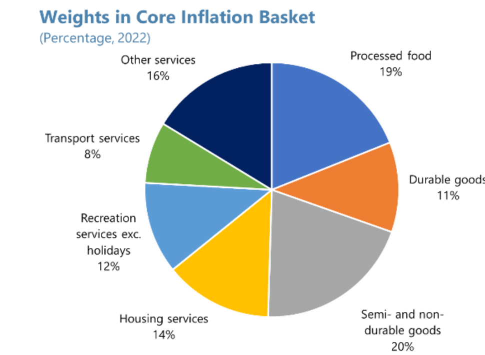


Figure 1d



Sources: Eurostat; and IMF staff calculations.

Sources: Eurostat and Authors' calculations

B. The Canonical Phillips Curve

The Phillips curve describes an empirical relationship between economic slack and wage or price growth. In its structural form, it is a key component of most standard macroeconomic models used for (monetary) policy making. The structural Phillips curve is usually thought about in its New Keynesian formalization, which links inflation with expected inflation and marginal costs. In the ECB's formulation, the structural Phillips curve is specified as a relationship between the deviation of inflation from target, the output gap (capturing marginal costs), lagged and future deviations of inflation from target, and a markup shock (Eser et al., 2020). Given open economy considerations, the exchange rate and import prices also influence the deviation of inflation from target.

Here we focus on a set of empirical, reduced-form Phillips curves, with the aim of developing a tool that helps us better forecast inflation and understand the drivers of the inflationary process in the euro area. Our starting point for the regression model, broadly following Abdih et al. (2018), is the following relationship[9]:

$$\pi_t^i = \rho\pi_{t-1}^i + \beta_1\tilde{y}_t + \beta_2 mp_t + \beta_3 E\pi^{LR} + \beta_4 cp\_yoy_t + \varepsilon_t^i \qquad [1]$$

where π_t^i denotes YoY inflation at time t of each core HICP component i; $\tilde{y}_t$ is a measure of economic slack, mp_t is the YoY percent change in the non-energy manufacturing import price index (measured in Euro); $E\pi^{LR}$ is the long-run inflation expectation from the ECB's survey of professional forecasters and cp_yoy_t refers to the YoY change in relevant commodity price indices. All data come from Eurostat, ECB and IMF databases.

Note that no constant is included in the Phillips curve models.[10] The stability of the models comes as a result of the fact that, in equilibrium, economic slack is zero and inflation expectations are well anchored at target. In other words, the model would not be well suited for an economy facing expectations that move strongly away from target (i.e become de-anchored). In choosing inflation expectations, we prefer longer-term measures given that shorter-term expectations might be reacting mechanically to current inflation. We considered both the 7-quarter ahead forecast and the 4 to 5 year ahead expectations.[11] Ultimately, the two series have very similar dynamics and we choose the longer-term ones given the anchoring role played by inflation expectations in our econometric model.

Dropping subscript i, and focusing on core inflation, model (1) is a standard top-down Phillips curve model for core inflation. We use this as our benchmark top-down forecasting model, estimated on data covering the period 2002Q2-2022Q2. Our bottom-up core inflation models, take the regression in (1) for each core component and augment them with additional explanatory variables.

Non-core inflation – in our case energy (fuels, electricity and natural gas) and unprocessed food – is not adequately captured by a Phillips curve model, as there are limited, if any, links to euro area slack in exploratory regressions. Instead, we model them by focusing on the role of international commodity prices, as discussed in section II.D below.

C. An Important Aside on Economic Slack

One important modelling choice is the measure of slack we use in the core inflation regressions. The Covid-19 pandemic shock led to a sharp reduction in economic activity as mobility collapsed and whole swathes of the economy were locked down. To prevent large scale unemployment, Europe adopted a forceful policy response in the form of widespread use of short-term work schemes (STWs). The result a much smaller increase in unemployment than in the US for example, where policy support came more in the form of stimulus checks and a temporary increase in unemployment benefits. At the same time, the impact of the pandemic on potential

[9] As with many reduced-form relationships, identification is a key concern. And as discussed in the literature, reduced form Phillips curve estimates could be biased downward – including due to the stabilizing role of monetary policy - providing a lower-bound on the structural relationship.
[10] We do include a constant in the non-core models and auxiliary equations due to the lack of inflation expectations as an anchor.
[11] Longer-term forecasts are four calendar years ahead in the Q1 and Q2 rounds and five calendar years ahead in the Q3 and Q4 rounds.

output is highly uncertain and is still being debated. On top of this, the structural shifts that are taking place due to, or accelerated by the pandemic – both in terms of consumer preferences and the importance of the digital economy – complicate the measurement of slack further.

This of course has repercussions for the choice of slack variable in our Phillips curve specifications. We explore six different aggregate measures of economics slack: (i) the unemployment gap (unemployment rate – NAIRU); (ii) the output gap; (iii) a broader labor market gap including workers marginally attached to the labor market (as proposed by ECB, 2017)[12]; (iv) the deviation of hours worked from trend; (v) the unemployment gap adjusted for job retention schemes (the shadow unemployment gap)[13], and (vi) the deviation of the vacancy-to-unemployment ratio from trend (V/U gap). The vacancy to unemployment ratio in particular has received heightened interest recently, given it signal of very tight labor markets which maps well into the high inflation levels that have been observed.[14]

As Figure 2a shows, prior to the Covid-19 pandemic (2002-2019) these different slack measures tended to co-move, suggesting that they provided similar signals as to the underlying cyclical position of the euro area economy. Over this period, the absolute value[15] of the correlation among the variables was around 0.9 and as high as 0.97 for the correlation between the unemployment gap and hours worked relative to trend. The broad labor market slack variable has a somewhat lower correlation of around 0.7 with other measures of slack. The V/U gap is highly correlated with all other slack variables, especially with the unemployment gap (0.93). Overall, the choice of slack measure, for the pre-pandemic period as a whole does not, materially alter the Phillips curve estimates.

Figure 2. Possible Measures of Euro Area Slack

Figure 2a: Pre-Covid (2002Q1-2019Q4)

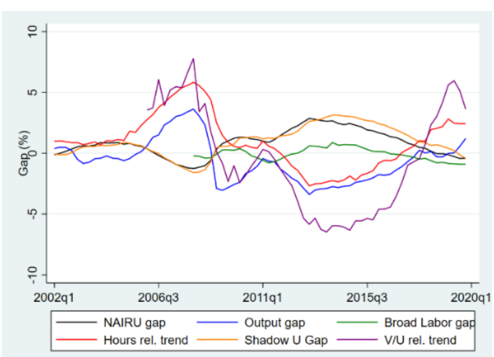
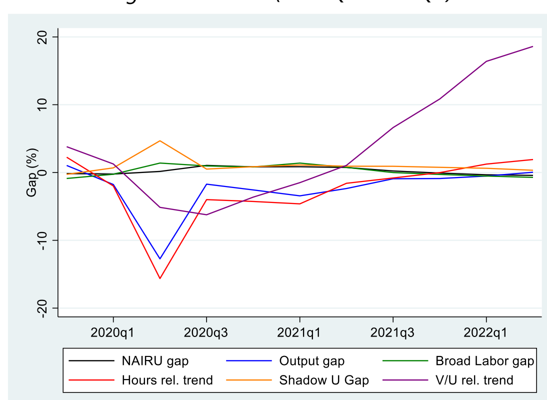


Figure 2b: Covid (2019Q4-2022Q1)



Sources: IMF WEO Nov 2022; Eurostat; Authors' calculations

[12] The broad labor market slack variable is constructed as the sum of the unemployed, underemployed part-time workers and those marginally attached to the labor market (which includes persons available to work but not actively seeking and persons seeking work but not immediately available). Data are available since 2008. To obtain the broad labor market gap, a HP filter is applied to the series.
[13] The shadow unemployment rate is calculated as set out in a IMF European Departmental paper (IMF, 2022). The conceptual approach is to strip out short term work schemes from the unemployment rate. Given the difficulty of doing the adjustment based on exact numbers of short term work scheme users, the authors use a simple econometric approach based on the difference in the unemployment rate and an unemployment rate predicted by Okun's law.
[14] See for example Duval et al. (2022) and Furman and Powell (2021).
[15] As the figure shows, the correlation between a number of slack measures is negative. This is due to how the variables are defined (eg positive unemployment gap implies slack, while a positive output gap implies a tight economy). Here we focus on the absolute value of the correlations.

Since the start of the pandemic, however, the aggregate slack measures have exhibited divergent dynamics (Figure 2b). The unemployment gap was the least volatile measure, showing only limited slack early in the pandemic and a tight labor market in 2022. The broad labor market slack variable showed a steeper increase in slack early in the pandemic and then an even tighter labor market than the unemployment gap by the second quarter of 2022. The output gap, hours worked relative to trend, and the shadow unemployment gap all show very substantial slack early in the pandemic but then recover at different speeds. Last, the V/U gap showed substantial slack early in the pandemic (but less than hours worked or the output gap), followed by a very steep recovery and a very tight labor market in 2022. These divergent dynamics are testament to the difficulty of measuring slack during the last 2 years.

Going even further than exploring different aggregate slack measures, given the possibility of structural shifts since the covid-19 pandemic, and our bottom-up approach, there may be a strong case for allowing for sectoral measures in the regressions. The difficulty is that unlike with aggregate measures of slack, there is very little theoretical underpinning for sectoral measures of slack. Despite some frictions, it is not clear whether a measure such as a sectoral unemployment rate could be meaningful, for example. In addition, even if sectoral slack measures were economically meaningful and could be measured well, projecting these sectoral slack measures forward in order to be able to project inflation out of sample would remain a challenge.

Nevertheless, we study the properties of several available sectoral labor market slack measures: (i) hours worked relative to trend, (ii) job vacancy rates, and (iii) and employment expectations over the next 12 months, taken from the ECB's business and consumer survey. Figure 3 plots these different sectoral slack measures were available, starting in 2015q1. Sectoral slack measures tend to move in similar directions, although to differing degrees. The gap in hours worked relative to trend in the agricultural sector (Figure 3a) declined only modestly at the start of the Covid-19 pandemic and now exceeds pre-crisis levels, while for transport and food services, there is still a significant degree of slack according to this measure. The job vacancy ratio relative to trend behaved very similarly through the pandemic for industry compared to services (Figure 3b). And finally, while there was more heterogeneity in the employment expectations between sectors prior to the pandemic, these measures have moved together during the pandemic, with the exception of retail employment which has lagged other sectors.
We test the properties of these sectoral slack measures in the Phillips curve framework but are faced with imperfect matches to our seven core inflation categories. The coefficient on sectoral slack tend not to be significant when included in the regressions (whether or not we also control for aggregate slack). We therefore focus on measures of aggregate economic slack in the remainder of this paper.

Figure 3. Sectoral Labor Market Slack Measures

Figure 3a Hours relative to trend

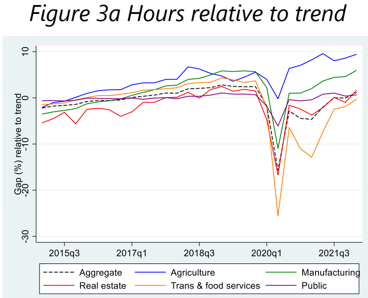


Figure 3b job vacancy rate

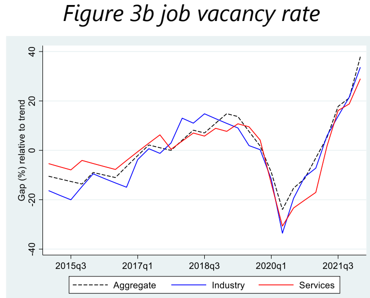
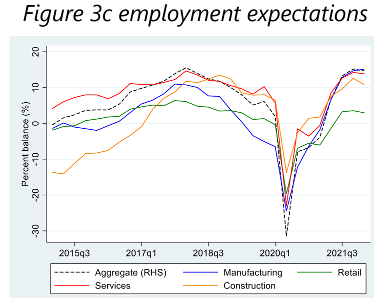


Figure 3c employment expectations

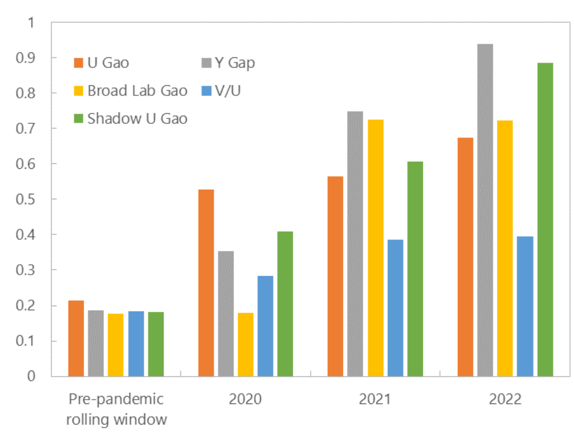


Sources: Eurostat; Authors' calculations

In choosing our preferred aggregate slack measure we adopt an agnostic approach. Figure 4 shows the four quarter ahead root mean square error (RMSE) of the bottom-up core inflation model for different slack measures in the pre-pandemic period (2002-2019), during 2020 and 2021 separately, and finally for the first two quarters of 2022. A first point that stands out is that the RMSEs have increased over time, with the largest errors during 2022. We discuss the model's forecasting performance in detail after laying out the baseline model in the next section. Here, however, we focus on the other dimension of variation in Figure 4, which are the differences in RMSEs across measures of economic slack. In the pre-pandemic period, the choice of slack did not make a material difference in size of forecasting errors. Since 2020, however, forecasting performance differs sharply depending on which measure of slack is used. The vacancy-to-unemployment rate stands out, performing best in two years (2021, 2022) and second best in 2020.

In terms of out-of-sample forecasting, an important practical consideration is that, in our proposed framework, all explanatory variables must be projected exogenously over the forecast horizon in order to produce our final bottom-up inflation projections. The benefit of using a slack measure that relies on the unemployment rate or output gap is that projections exist in the IMF's WEO database – unlike for either the broad labor market slack measure or the vacancy to unemployment rate for example. In addition, data for the vacancy to unemployment rate and broad labor market slack measure are not available for the early 2000s leading to the loss of several years of data. Ultimately, while the simple unemployment gap has many practical advantages, the improvement in forecasting over recent quarters when using the vacancy to unemployment rate in our view justifies relying on it as our preferred measure, with the WEO-based slack measures (unemployment gap and output gap) used in robustness exercises.

Figure 4. RMSE of 4-quarter ahead projection for core inflation



Sources: Authors' calculations

Notes: Root mean squared error (RMSE) calculated over 4-quarter ahead rolling projection windows. The chart presents the average RMSE over each period, using different slack measures in the underlying model.

D. Baseline Bottom-Up Model Specification

The specification of each sub-component model is based on a balance between economic theory, empirical performance, and judgment. The overarching approach for the selection of explanatory variables is to obtain parsimonious specifications, with the choice of variables grounded in theory to avoid a “kitchen sink” approach. We discuss each sub-component model below – both core and non-core components – explaining how we augment or adjust the canonical Phillips curve specification in equation (1) as needed, before moving on to the auxiliary regressions for non-core items as well as the auxiliary regressions for exogenous explanatory variables that are needed for forecasting. Given the role for judgement in choosing the final specifications – rather than say a purely statistical approach starting from a large set of possible variables – these specifications are in no way the only possible way to model bottom-up inflation in the euro area. Here we aim to transparently explain how the specifications were reached and why we believe them to be a good approach.

One important consideration is how our model specification might have changed given the Covid-19 pandemic, that is the *ex post* vs *ex ante* model specification. The short answer is that the models are in fact remarkably similar with two exceptions. First, as discussed above, while pre-pandemic (from the early 2000s until 2019) the choice of slack variable did not make an important difference, now it matters. And second, since late 2021, models that include a feedback effect from energy prices to core consumer prices significantly improve model performance. Concretely, this means that we include lagged electricity prices, an important input for several goods and services categories, in several of the bottom-up models as explained below. Other than these two differences, the model specifications would not have been very different before 2020.

Core Sub-components

Processed food

Processed food inflation is characterized by clear peaks and troughs (Figure 1) which, on further inspection, correlate highly with (the lag of) international food prices (see also ECB, 2012). We use model fit and information criteria to choose the lags and settle on a model that includes just the first lag of the YoY growth of the IMF’s international food price index (converted into Euro) as an additional explanatory variable. In addition, as in several other models, we include the lag of electricity inflation as an explanatory variable. Relative to the benchmark model in (1), we drop the non-energy manufacturing import price given no obvious theoretical role for food inflation.

Durable goods

The ECB (Economic Bulletin, Issue 5/2020) find that a large share of purchases of durable goods in the euro area is financed via credit. To capture these dynamics, we augment the durable goods model with data on bank’s self-reported change in lending standards over the past three months. As in the processed food model, we include lagged electricity price inflation. We also explored versions of the model that include credit growth (or alternatively the residual of a regression of credit growth on a measure of economic slack to isolate the supply component). Neither of those variables, however, turns out to be significant. Finally, we add survey responses on firms’ inventories from the European Commission’s business survey aimed at capturing the stock of finished manufacturing products. This variable is statistically significant, and the information criteria suggest inclusion is warranted.

Semidurable and nondurable goods

There are few well-established drivers for semi- and non-durable goods inflation identified in the literature and the benchmark model appears to fit the data well. The only addition is the lag of electricity price inflation[16]

Housing services

Housing services – which consist largely of rents as well as sewage and related utilities[17] – are marked by an indexation component. In many of the largest euro area countries, inflation of the social housing component is mechanically tied to headline CPI inflation of the previous year (ECB, 2019b). While the mapping with headline HICP inflation is not ideal, we nevertheless include a variable, which measures headline HICP inflation in the previous year to capture this indexation. In addition, given possible links between house price inflation and housing services inflation we include a measure of house price growth in the regression.

Recreation services (excl. package holidays and accommodation)

The definition of recreation services is the least standard of our categories, given the exclusion of package holidays and accommodation (which are included in “other services”), and is dominated by restaurants. Thinking about input costs for restaurants, labor stands out, as do utilities, rent and food inputs. The role of labor is already captured though the slack variable. We also include the lag of electricity price inflation. To capture the food component, we include the YoY growth (and one lag) of the IMF’s international food price index (converted to Euro). No statistical association with measures of housing inflation was found.

Transport services

For transport services, a large input cost (besides labor) is fuel. We thus include the YoY growth (and one lag) of the Brent crude oil price (converted to Euro) as an explanatory variable.

Other services

Other services are a somewhat heterogenous group of all remaining services for which it is difficult to identify drivers beyond the standard ones included in the benchmark model. One important point is that the share of administered prices is likely to affect this category in a meaningful way and administered prices can be especially difficult to project, especially at the euro area aggregate level.[18] The methodology to calculate package holiday inflation in Germany (with a large weight in euro area wide package holiday inflation) was changed in 2019 for data starting from 2015 (ECB, 2019a). In 2015, an artificial large jump (and subsequent

[16] We ran versions of both the durables and semi- and nondurables models which include lagged durables PPI but they generally are not significant when import prices and slack variables are also included. Adding key commodity prices to the non-energy industrial goods equations also does not improve the model fit.
[17] It is worth noting that owner occupied housing (OOH) is not included in the euro area HICP index.
[18] In general, administered prices are an important component, accounting for around 12.5 percent of euro area inflation, but their correlation with overall inflation rates is low (ECB Monthly Bulletin, May 2007).

reversal) of package holidays inflation is thus introduced into the data which we correct through the use of the dummy. Lastly, we include lagged electricity price inflation.

Non-core components

We now turn to the specification of the auxiliary regression models for the non-core components of headline inflation. These models do not include the standard Philipps curve variables (slack and inflation expectations) but do include a term to capture persistence. Exogenous variation comes from the link with international commodity prices.

Energy

Within energy, fuels for personal transport equipment make up 40%, electricity 30%, and gas 20%, with the remainder consisting of small categories such as solid fuels. Passthrough from international to retail prices is very different for these different energy sources and also varies substantially across countries depending on specific pricing mechanisms. To better capture some of these dynamics, we estimate separate models for fuel, electricity, and natural gas as follows:

- **Fuel:** Passthrough is relatively fast for personal transport fuels. Overall, inspection of the data suggests a close link with international oil prices at relatively short time horizons. The model thus includes the YoY inflation rate for Brent oil in USD and the EUR-USD exchange rate to capture exchange rate movements.

- **Electricity:** To do the data generation process justice, the role of institutional differences and policies across countries would have to be accounted for. At the aggregate euro area level however, the best model fit is obtained with a simple link from lagged TTF natural gas prices (in Euro) to consumer electricity prices.

- **Natural gas:** The model for natural gas is the same as for electricity, exploiting the lagged link from wholesale natural gas to retail natural gas prices.

Unprocessed Food

Unprocessed food inflation is highly volatile and depends on a host of idiosyncratic factors which are difficult to project. We include the YoY growth of the IMF's international food price index in Euro (as well as its lag) as key determinants in the model. We also include the lag of natural gas inflation, given natural gas is a key input into food production (see Eurostat energy balances, for example).

Benchmark Top-Down Core and Headline Inflation Models

As in the bottom-up modelling choices, the main objective here is to maintain a parsimonious approach while obtaining the best possible model fit. Brent crude oil and food prices are included in both the headline and core model but lagged TTF wholesale gas prices were found to only be (close to) significant in the headline model and are thus dropped from the core inflation model.

Auxiliary Regressions

To be able to run out-of-sample projections – for which the model is ultimately designed – we require projections for all exogenous explanatory variables. Most are available through the IMF's Global Assumptions (GAS) and World Economic Outlook (WEO) databases. The following, however, are not: the vacancy to unemployment rate, US and Chinese PPIs, euro area non-energy manufacturing import prices, euro area house price growth, and euro area manufacturing inventories. We thus estimate regressions to produce projections for these variables. All of the auxiliary models include a constant.

Vacancy-to-unemployment rate

For the vacancy-to-unemployment rate – a key model variable – we exploit its contemporaneous relationship with both the unemployment rate and the output gap to obtain projections. The relationship in 2022 does not hold well – at least based on the output gap and unemployment gap as reflected in the WEO database – as discussed above given different behaviors of slack variables. The model thus includes a dummy for 2022. The informational value from using V/U as the slack variable in out-of-sample projections thus comes mainly from the *level effect* on how tight the labor market is and some persistence given the lagged dependent variable. It does not provide any insights on the future direction of change in economic slack beyond that coming from the unemployment and output gaps.

Non-energy manufacturing import prices

The non-energy manufacturing import price index is a key input for the durable and non-durable goods inflation models and is the most advanced of the auxiliary models. Following Abdih et al. (2016), we model import prices as a function of the EUR-USD exchange rate, and both Chinese and US PPIs. We explored specifications using various commodity prices, but they are never significant, and in the end we drop them.

Chinese and US PPIs, house price growth, and manufacturing inventories

Chinese and US PPIs are modelled as functions of their own lags as well as contemporaneous and lagged US GDP growth and the contemporaneous and lagged oil price. Note that Chinese GDP growth was not found to be significantly related to either the Chinese or US PPI. House price growth is modelled as a function of its own lags and household lending standards while manufacturing inventories are modelled as a pure AR(4) process.[19]

III. Regression Results

We estimate the inflation models (core and non-core) over the period 2002Q2-2022Q2 as a system of seemingly unrelated regressions (SUR) where the errors are assumed to be correlated across equations (this is confirmed ex post). The estimated coefficients are shown in Table 2 (core components) and Table 3 (non-core components). The benchmark top-down model coefficients and auxiliary regressions are estimated

[19] The lending standard variable is not significant when we use four lags of the dependent variables but becomes significant in other specifications, so we opt to keep it in the final specification. Strictly speaking we would now also need to have an auxiliary regression for lending standards but to avoid having another layer of auxiliary regressions we will make ad hoc assumptions on lending standards in the projections.

separately as single equation models with results shown in Table 4 and 5, respectively. Table A1 in the Appendix shows the main regression table when using the unemployment gap as the slack measure as a robustness check. In most cases the coefficients are similar. When they are not, we flag it in the below discussion. Finally, Table A2, also in the appendix, shows coefficients when we estimate the model using the vacancy to unemployment rate as the measure of slack as a further robustness check, but with the regression ending in 2019q4.

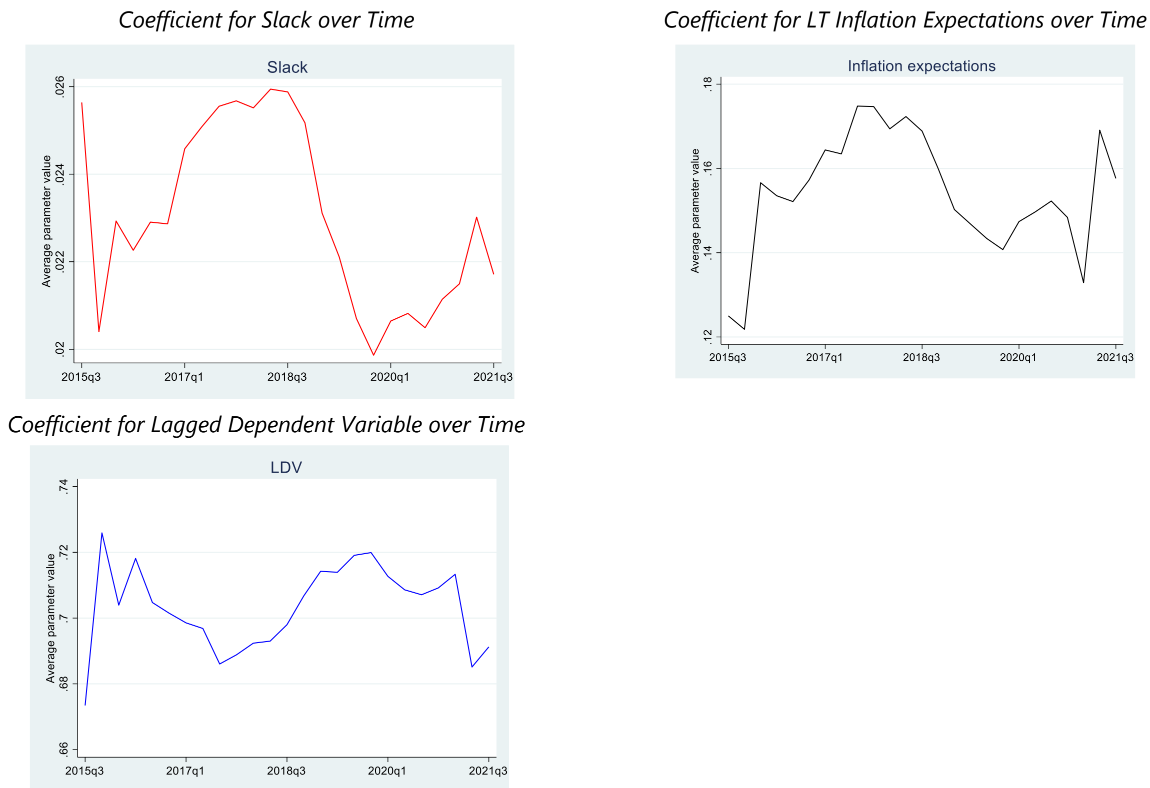
In the core sub-component Phillips curve equations, there is a strong positive relationship between the inflation rate and the deviation of the vacancy to unemployment rate from trend, suggesting that a tighter labor market is associated with higher inflation, except for non-energy industrial goods where the coefficient is not statistically different from zero. Long-term inflation expectations enter with a positive coefficient and are significant in all models except for durable goods and housing services (in the latter they are insignificant and in the former they have a counterintuitive sign). House price growth contributes significantly to housing inflation. The indexation variable is not significant in the specification using the vacancy to unemployment rate to measure slack but highly significant when using the unemployment gap. The respective international commodity price series are significant (either contemporaneous or lagged) in all models where they are included. For durable goods, the inventory growth variable enters with a negative and significantly coefficient. The coefficient on lagged electricity prices is highly significantly with a positive sign where they are included except for other services. Finally, most sub-components exhibit a high degree of persistence, with the AR terms ranging from 0.3 for other services inflation to over 0.9 for durable goods inflation.

Calculating the weighted average core inflation coefficients – what we might call the bottom-up Phillips curve coefficients – gives a slack coefficient of 0.024 for the deviation of the vacancy to unemployment rate from trend, a coefficient on long-term inflation expectations of 0.16, and a coefficient on the lagged dependent variable (persistence) of 0.7. For ease of comparison with the literature, consider that using the unemployment gap as the measure of slack gives a Phillips curve coefficient of around -0.075. Overall, this is a relatively flat Phillips curve, broadly in line with the standard reduced form Phillips curve coefficient retrieved from top-down exercises.

Reassuringly, Figure 5 also shows that these parameters are broadly stable over time (bar some initial volatility in the very early part of the window). The exercise starts with an initial regression window until 2014 and then adds one additional quarter at a time to the regression window. The slack coefficient oscillates between 0.02 and 0.026, the coefficient on long-term inflation expectations ranges between 0.12 and 0.18 and the persistence coefficient between 0.67 and 0.73. It is clear that including the pandemic period leads to *some* change in the parameters but no dramatic movements.[20] We hypothesize that controlling for various supply side factors in a comprehensive way allows for a cleaner estimation of core Phillips curve coefficients.

[20] The observation for 2021q3 is the final one as the four quarter window 2021q3-2022q2 is the final projection window in the four quarter ahead projection exercise explained below and which we leverage to obtain these rolling average coefficient graphs.

Figure 5. Parameter Stability



Sources: Authors' calculations

Turning to the non-core inflation components in Table 3, energy components (fuels, electricity and natural gas) and unprocessed food prices are strongly correlated with international commodity prices, but the overall model fit for energy inflation is significantly better than for unprocessed food.

Table 4 shows the estimated coefficients for the reference top-down regressions which give broadly comparable coefficients for slack but a slightly higher coefficient on the lagged dependent variable for core inflation than in the bottom-up model for. Contemporaneous crude oil price movements are important for headline inflation while food prices are important for core inflation (not surprisingly given processed food is included in the definition of core).

Finally, the auxiliary regressions in Table 5 show the expected reduced form relationships which allow us to construct out of sample inflation projections based solely on explanatory variables included in the GAS or WEO.

Table 2. Baseline Bottom-Up Phillips Curve Regressions

VARIABLES	(1) Processed Food	(2) Durables	(3) Semi- and Nondruables	(4) Housing services	(5) Recreation excl. package holidays	(6) Transport services	(7) Other services
Lagged dependent variable	0.781***	0.959***	0.462***	0.905***	0.838***	0.716***	0.314***
	(0.0498)	(0.0527)	(0.0924)	(0.0255)	(0.0365)	(0.0567)	(0.0947)
V/U rel. to trend	0.0411**	0.00594	0.0117	0.00731**	0.0206***	0.0257**	0.0568***
	(0.0161)	(0.00709)	(0.00820)	(0.00330)	(0.00450)	(0.0122)	(0.0139)
LT Inflation Expectations	0.150**	-0.0752***	0.141***	0.0599**	0.140***	0.313***	0.358***
	(0.0742)	(0.0270)	(0.0414)	(0.0290)	(0.0420)	(0.0741)	(0.0657)
Non-energy manufacturing import price growth		0.0503***	0.0106				
		(0.00851)	(0.0100)				
Manufacturing stocks growth		-0.0242***					
		(0.00457)					
Food price index (in Euros) growth					-0.00212		
					(0.00251)		
Food price index (in Euros) growth, lag	0.0189***				0.00752***		
	(0.00704)				(0.00255)		
House price index growth				0.00748*			
				(0.00438)			
Rent indexator				0.0185			
				(0.0129)			
Brent crude oil (in Euros) growth						0.000624	
						(0.00217)	
Brent crude oil (in Euros) growth, lag						0.00750***	
						(0.00229)	
HICP electricity price growth, lag	0.0392**	0.0152*	0.0499***		0.0171***		0.00502
	(0.0179)	(0.00902)	(0.0116)		(0.00411)		(0.0138)
Dummy for 2015							1.062***
							(0.241)
Observations	66	66	66	66	66	66	66
R-squared	0.953	0.946	0.928	0.997	0.996	0.967	0.869

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations

Notes: The dependent variable is specified as the year over year percent change. Models estimated by system of seemingly unrelated regressions (SUR) where the errors are assumed to be correlated across equations. Regression period is 2006Q1-2022Q2. R-squared refers to adjusted R-squared.

Table 3. Non-Core Inflation Regressions

	(1)	(2)	(3)	(4)
	Energy			
VARIABLES	Fuels	Electricity	Natural gas	Unprocessed Food
Lagged dependent variable	0.432***	0.654***	0.743***	0.450***
	(0.0304)	(0.0574)	(0.0559)	(0.0999)
Food price index (in Euros) growth, lag				0.0380**
				(0.0169)
Brent crude oil growth	0.239***			
	(0.0104)			
Euro-USD exchange rate change	0.293***			
	(0.0356)			
Dutch TTF natural gas price growth, lag		0.0251***	0.0398***	
		(0.00244)	(0.00454)	
HICP natural gas price growth, lag				0.0632***
				(0.0211)
Constant	-0.277	1.007***	0.194	0.886***
	(0.307)	(0.277)	(0.444)	(0.261)
Observations	66	66	66	66
R-squared	0.961	0.921	0.905	0.486

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations

Notes: The dependent variable is specified as the year over year percent change. Models estimated by system of seemingly unrelated regressions (SUR) where the errors are assumed to be correlated across equations. Regression period is 2006Q1-2022Q2. R-squared refers to adjusted R-squared.

Table 4. Top-Down Regressions

	(1)	(2)
VARIABLES	Headline	Core
Lagged dependent variable	0.663***	0.832***
	(0.0672)	(0.0891)
V/U rel. to trend	0.0303**	0.0228***
	(0.0130)	(0.00692)
LT Inflation Expectations	0.206***	0.0906
	(0.0591)	(0.0683)
Non-energy manufacturing import price growth	0.0197	0.0197**
	(0.0217)	(0.00958)
Dutch TTF natural gas price growth, lag	0.00107*	
	(0.000574)	
Brent crude oil (in Euros) growth	0.0131***	0.00142
	(0.00201)	(0.000933)
Food price index (in Euros) growth, lag	0.00608	0.00618**
	(0.00572)	(0.00274)
Observations	66	66
R-squared	0.981	0.985

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations

Notes: The dependent variable is specified as the year over year percent change. Regression period is 2006Q1-2022Q2. R-squared refers to adjusted R-squared. Heteroscedasticity and autocorrelation consistent standard errors.

Table 5. Auxiliary Regressions – Explanatory Variables not in IMF GAS or WEO

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	PPI China growth	PPI US growth	Euro area non-energy manufacturing	House price index growth	Manufacturing stocks growth	V/U
Sum of lagged dependent variables	0.626***	0.803***	0.683***	0.938***	0.568***	0.651**
						(0.0809
US GDP growth	-0.0492	-0.0135				
	(0.0676)	(0.101)				
US GDP growth, lag	0.0129	0.0279				
	(0.0654)	(0.110)				
Oil price growth	0.0678***	0.0698***				
	(0.00402)	(0.00712)				
Oil price growth, lag	-0.0292***	-0.0454***				
	(0.00677)	(0.0126)				
PPI US growth			-0.0343			
			(0.0999)			
PPI US growth, lag			0.126			
			(0.100)			
PPI China growth			0.338***			
			(0.0918)			
PPI China growth, lag			-0.236**			
			(0.117)			
EUR-USD exchange rate change			0.318***			
			(0.0210)			
EUR-USD exchange rate change, lag			-0.197***			
			(0.0380)			
Credit standards change				-0.0217***		
				(0.00793)		
Output Gap						0.330**
						(0.127)
Unemployment Gap						-0.812**
						(0.265)
Dummy for 2022						7.984**
						(1.089)
Constant	0.302**	0.289	0.340*	0.344***	-0.173	0.924**
	(0.153)	(0.198)	(0.198)	(0.111)	(0.308)	(0.323)
Observations	81	81	81	78	81	65
R-squared	0.955	0.936	0.951	0.972	0.801	0.932

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations

Notes: Regression period is 2006Q1-2022Q2. R-squared refers to adjusted R-squared. Heteroscedasticity and autocorrelation consistent standard errors.

IV. Forecasting Performance

In this section we evaluate the forecast accuracy of our bottom-up inflation model in a pseudo-out-of-sample projection exercise and compare it to an augmented top-down model and a simple autoregressive process. We do so by assessing the model's pseudo-out-of-sample forecast performance over a series of rolling 4-quarter ahead windows.

A. Practical Considerations

Top-down and AR benchmarks

To assess the performance of our bottom-up model, we propose two benchmarks against which to compare forecast accuracy: (1) the above discussed top-down PC model for core and headline inflation, and (2) a simple AR process.

Rolling window pseudo-out-of-sample forecasting steps

To avoid the risk of cherry picking a specific time-period for the exercise, we run rolling window regressions and produce 4-quarter ahead forecasts. The exercise involves the following steps:

1. Start with an initial estimation window ending in 2014 over which we estimate all coefficients in our models. The initial window needs to be large enough to get sensible and statistically significant coefficient estimates.

2. Calculate the pseudo-out-of-sample forecast 4-quarters ahead and compute the root mean squared error (RMSE) over this forecast horizon. For the initial window the regression ends in 2014q4 and the forecast is for the four quarters of 2015.

3. Calculate (i) the average RMSEs, (ii) the average normalized RMSE (NRMSE) – normalized by the standard deviation of inflation over the full estimation and projection window to account for volatility of different sub-components – and (iii) the ratio of the RMSE of the full model relative to a simple AR(1) process. The combination of these three metrics shows us (i) which bottom-up model does well in terms of forecast accuracy in an absolute sense; (ii) which model does well in a relative sense (given it is harder to predict more volatile series), and last (iii) which model beats a simple autoregressive process in terms of forecast accuracy.

4. Roll the estimation window and 4-quarter projection window forward by 1 quarter.

5. Repeat steps 2-4. The final step is the one that yields a forecast over (2021q3-2022q2) such that we get 26 partially overlapping projection windows.[21] We then take averages for the key RMSE metrics over the pre-pandemic period (with the last window being 2019q1-2019q4), the period from 2020 onwards, and the overall period.

[21] We also use five non-overlapping windows as an alternative (the non-overlapping windows are for the four quarters of 2015, 2016, 2017, 2018 and 2019, respectively) but results are quantitatively unchanged so we chose to only present one set of graphs.

A. Overall

We begin by assessing the model's performance over the full period before contrasting the pre-pandemic period with the quarters since the start of 2020. Figure 6a compares the overall pseudo-out-of-sample forecasting performance of the bottom-up, top-down, and simple autoregressive models. The bottom-up model does best for both core and headline inflation with the autoregressive model doing worst. While the difference in performance between the bottom-up and top-down model is not statistically significant for core inflation, the difference is large for headline inflation. This is a theme we will return to. Modelling energy inflation separately from the remainder of the HICP basket has clear advantages even if one would prefer to keep the Phillips curve specification as parsimonious as possible.

Figure 6b, 6c, and 6d take a closer look at the performance of the individual bottom-up models. We can broadly divide the HICP component models into three categories based on how well they do.

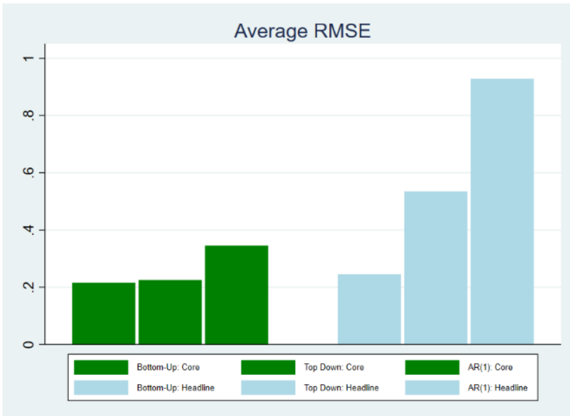
The first group are those models that have a satisfactory forecasting performance: Four of the core component models – processed food, semi- and nondurable goods, housing services, and recreation services – perform well, with low RMSEs and NRMSEs, and outperform the simple AR(1) processes. Out of the non-core components, the fuel and electricity models also have attractive properties. While in an absolute sense the RMSE is large for both models, this is due to the extreme volatility of the underlying inflation series. For both the NRMSE and the relative performance vis-à-vis a simple AR(1) the two energy models do better than most others, with the fuel model the best performer across both criteria.

Next, there are those models that are broadly satisfactory. These include all the remaining core components as well as the natural gas model. The transport, other services, and durable goods models all have worse RMSEs and NRMSEs than other core models, but outperform the AR(1), which is an important criterion. Durable goods have the worst fit out of the core inflation group. The very low volatility in the pre-pandemic period followed by a sharp increase post-2020 is not adequately captured by the model. For non-core items, the natural gas model has very large RMSEs, but once adjusted for the extreme volatility in the series, the NRMSE is less dramatic. We return in more detail to the issues of modelling natural gas inflation, with an important role for policy interventions which the model does not (and cannot) capture.

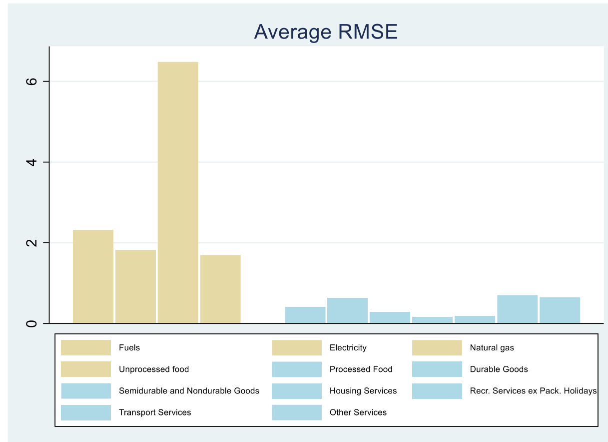
Finally, the unprocessed food model does a poor job at explaining the data generating process looking at both NRMSE and the ratio of the RMSE to that of an AR(1). We explored several alternatives, including more complicated formulations, but given the erratic and volatile nature of the series no satisfactory model was found. We nevertheless keep the two dependent variables included in the model (lagged international food prices and natural gas prices) given the intuitive appeal and statistically significant coefficients.

Figure 6. Forecasting Performance

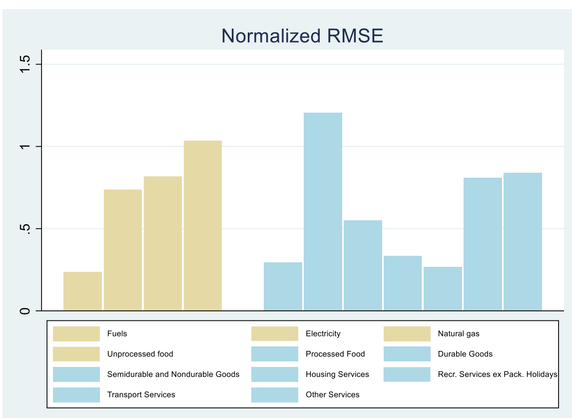
a) RMSE of Bottom-up, Top-down and Simple AR(1)



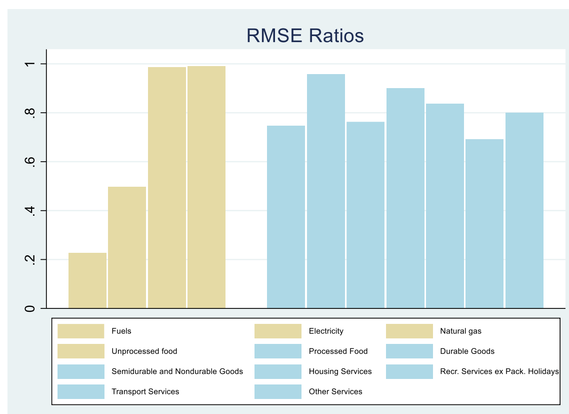
b) Average RMSE for Individual Bottom-Up Models



c) Average normalized RMSE for Individual Bottom-Up Models



d) Average ratio of RMSE to AR(1) RMSE for Individual for Individual Bottom-Up Models



Sources: Authors' calculations

Notes: Root mean squared error (RMSE) calculated over 4-quarter ahead rolling projection windows. The charts present the average RMSE, for different models and inflation sub-components. Normalized RMSE (NRMSEs) normalize based on the standard deviation of inflation for each sub-component over the full estimation and projection window to account for volatility of different subindexes varies and allow comparisons across inflation components. Ratio of RMSE is the RMSE of the respective bottom-up model relative to a simple AR(1) process.

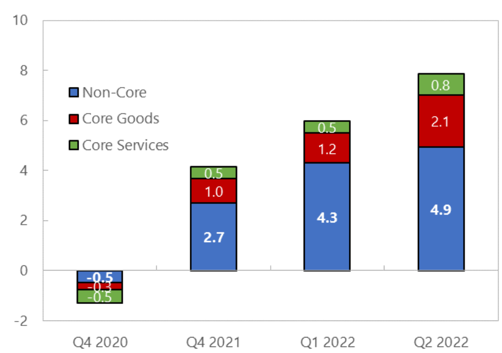
B. Pre-Pandemic Period vs 2020-2022

In this section we look at how the model's forecasting performance changed since the onset of the Covid-19 pandemic in early-2020 and the repeated energy shocks of 2021 and 2022. We also assess how relevant the model remains, what specific factors outside the model are important in explaining model performance, and explore whether *ex post* adjustments to model-based projections are warranted at the current juncture.

The different inflation dynamics since 2020 can be seen clearly by looking back to Figure 1 and considering Figure 7 below. Core goods inflation – processed food, durable goods and, to a lesser degree, semi- and non-durable goods – broke sharply with pre-pandemic behavior. With the onset of the Covid-19 pandemic, and widespread shutdowns, inflation declined into negative territory across most of these components. From the start of 2021, inflation began to increase and quickly rose above pre-pandemic levels, driven mainly by energy inflation, but more and more by core goods inflation. For services, the picture is more nuanced with an unusual negative print early in the pandemic for two of the four components and some upward pressure in the latest quarters. In Q2 2022, however, all services components except housing saw an unusually high print (by historic standards), suggesting strong re-opening effects and a re-adjustment in relative prices. Nevertheless, services remain the smallest contributor to the surge in inflation (relative to contributions in the pre-pandemic period). Finally, for non-core items, the surge in energy prices in recent quarters of course stands out – note the different scale relative to the other charts in Figure 1.

Figure 7. Contribution to Headline Inflation Relative to Pre-Pandemic

(Quarter on X-Axis vs 2019q4)



Sources: Eurostat; Authors' calculations

Notes: Contributions of sub-components to headline year-over-year inflation in selected quarters relative to 2019Q4.

With this background in mind, we now turn to our assessment of the model's forecasting performance over the period 2020Q1-2022Q2, through rolling 4-quarter window pseudo-out-of-sample projections. To give a visual sense of how the model projects inflation over this period we plot the projection for headline and core inflation over 2020, 2021, and 2022 from the bottom-up and top-down models, with the model estimation always ending the quarter prior to the projection start.[22]

As can be seen in Figures 8a and 8b, the bottom-up model tends to outperform the top-down model. The difference is minimal in the early pandemic but the bottom-up model does a much better job at capturing the upswing since 2021, especially for headline inflation. At the same time, it is worth flagging that the bottom-up model misses headline inflation by 1.4 percentage points in Q2 2022 for the model estimated through Q4 2021 – a large miss for a two quarter ahead projection.

Figure 7c compares forecasting performance more formally between the bottom-up and top-down models across different windows. In the pre-pandemic period, there is no difference between model performance for

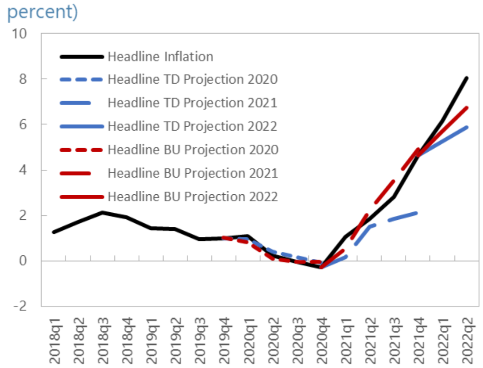
[22] Figure A.3 in the appendix shows the bottom-up, top-down and AR(1) projection for core and headline inflation over the entire period from 2020q1-2022q2.

core inflation. But for core inflation since 2020, and in all periods for headline inflation, the bottom-up model outperforms the top-down model. The figure also shows how all models have seen worsening forecast errors over recent quarters, with errors particularly large during 2022. Figure 7d looks across individual HICP components to see which ones have driven the deterioration in RMSEs. In short, only the housing services model did not see a deterioration since 2020 (housing is also the only inflation series not to have seen a significant increase in volatility). Perhaps unsurprisingly, natural gas, followed by fuels and durable goods stand out with the largest deterioration in the RMSE (fourfold increase for natural gas). These are the categories were the pandemic and energy shocks of the last two and a half years have been concentrated.

Figure 8. Forecast Accuracy (RMSE) since 2020 vs Pre-Pandemic Period

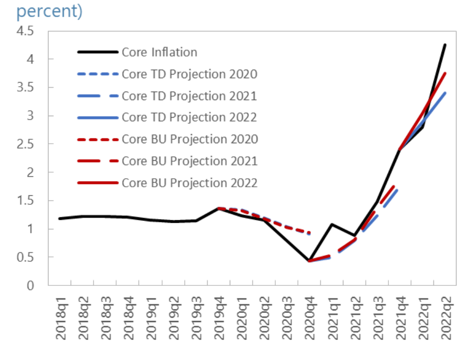
a) Headline Projection since 2020: Bottom-Up vs Top-down Top-down

Top Down vs Bottom Up headline Inflation Projections for 2020, 2021 and 2022 (yoy, percent)



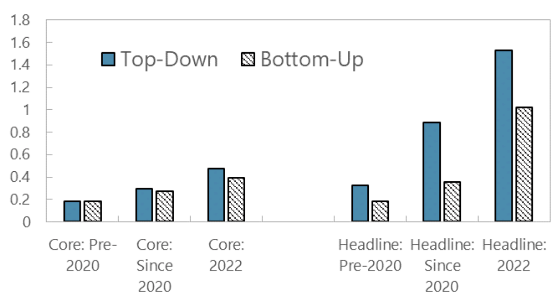
b) Core Projection since 2020: Bottom-Up vs Top-down

Top Down vs Bottom Up Core Inflation Projections for 2020, 2021 and 2022 (yoy, percent)



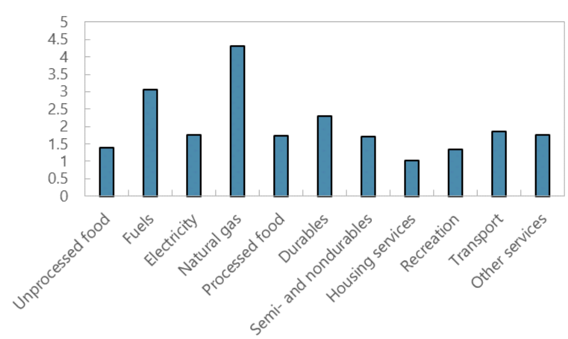
c) RMSE over different forecast windows

Bottom-Up vs Top-Down RMSE over Different Windows



d) Individual HICP components: 2020-2022 vs Pre-2020

Ratio of RMSE (pre-pandemic vs 2020-2022)



Sources: Authors' calculations

Notes: Root mean squared error (RMSE) calculated over 4-quarter ahead rolling projection windows. The charts present the average RMSE over each period, for different models and inflation sub-components.

C. What explains the increase in forecast errors?

As discussed, the model's forecast performance deteriorated significantly since 2020. There are several important factors that contributed to this:.

1. **Measurement difficulties:** Measuring economic slack became particularly difficult during the Covid-19 pandemic. As discussed in section II.C, different slack variables showed strongly diverging patterns during the pandemic making it hard to discern to true level of slack as relevant for inflation pressures. The V/U gap, which shows a very tight labor market in recent quarters, does the best job at forecasting inflation over the past quarters, and this could point towards an overall assessment of a tight labor market. Nevertheless, the fundamental issue of diverging signals from different slack variables reduces confidence in the assessment of demand side pressures on inflation and could be contributing to a worse forecast performance.

2. **Policy changes:** Another important consideration is that policy makers responded to the pandemic and subsequent energy shocks with a range of economic support measures. The two most relevant policy changes for inflation dynamics were the temporary VAT cut in Germany in H2 2020 and the various policy interventions to limit the passthrough of wholesale natural gas and electricity prices introduced since mid-2021.

    - Figure 9a shows a counter-factual core inflation path using a crude adjustment for the VAT change. What is clear is that the model forecast performance for the 8-quarter ahead projection improves substantially against this counter-factual inflation path.[23] In fact the model performance against this counterfactual is nearly as good as the pre-pandemic one.

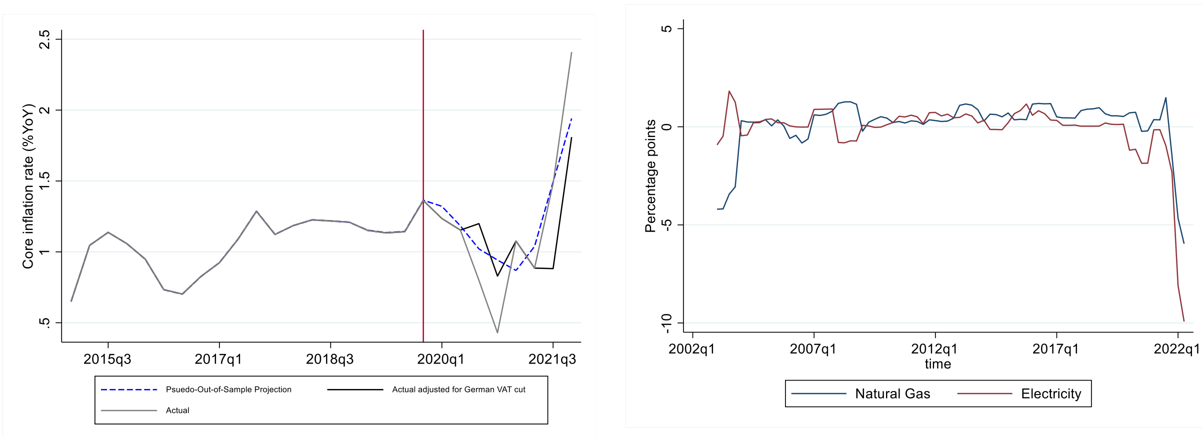
    - Figure 9b plots the difference between observed natural gas and electricity inflation and Eurostat's calculation for inflation at constant tax rates. In recent quarters the gap has been very large, with indirect tax changes subtracting as much as 10 percentage points from electricity inflation in Q2 2022. These calculations do not cover additional, non-tax measures, governments have taken to limit passthrough.

[23] We include a dummy in the regression and then construct a counterfactual by first adding it in 2020 and then subtracting it again in 2021. Despite the extremely simple approach, the estimated VAT impact of 0.4 p.p. is close to an assessment by the ECB.

Figure 9. The impact of policy interventions on inflation

Panel a: no German VAT cut in 2020 counterfactual

Panel b: Difference between observed energy inflation and energy inflation at constant tax rates



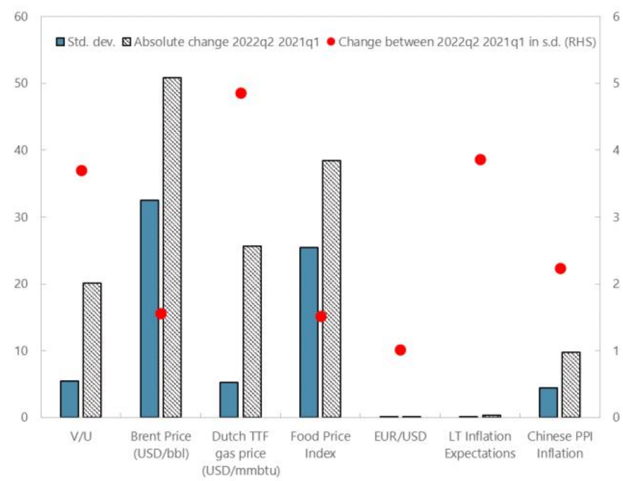
Sources: Eurostat; Authors' calculations

Notes: Panel a presents inflation projections (in year-over-year percent terms) from the baseline model relative to actual inflation and a counterfactual without the 2020 German VAT cut. Panel b presents energy inflation (in year-over-year percent terms) using the Eurostat series at current vs constant tax rates.

3. **Energy pass-through, especially from the European natural gas shock:** The rise of energy prices over recent quarters has been very sharp. But while similar oil price movements have been observed in the past, the movements in European gas prices are without precedent – the increase in oil prices between Q1 2021 and Q2 2022 was a one standard deviation event while the increase in natural gas prices was a five standard deviation shock (Figure 10).[24] Comparing the model coefficients from an estimation window through Q2 2022 (Tables 2 and 3) with the coefficients estimated only until Q4 2019 (Table A2 in the Annex) shows generally limited changes. Two exceptions are the coefficients on the TTF wholesale natural gas price in the electricity and natural gas inflation regressions. The coefficients in the electricity price regression is somewhat larger when extending the sample through the recent energy shock, but it is 70 percent smaller in the natural gas equation. The result is that when the coefficient from the regression ending in Q4 2019 is used to project natural gas inflation over Q1 2020 – Q2 2022, it yields a significant overestimation of inflation (with natural gas inflation peaking at close to 100 percent relative to the 60 percent observed so far). On the other hand, when the smaller coefficient is used, natural gas inflation in Q2 2022 is underestimated. This points to a possible structural break in the energy inflation relationship. Simply put, the relationship between wholesale natural gas and both retail natural gas and electricity prices has been highly unstable – likely due to the policy interventions mentioned above, but also due to the very large size of the shock, which means that importers are not able to smooth the shock the way they might have for smaller changes. A plausible explanation for a structural break include also the greater share of LNG (purchased at spot prices) in natural gas imports. Last, the large shock has brought to the fore the complex institutional differences that exist across countries in the way passthrough operates making an aggregate euro area analysis more difficult.

[24] European natural gas prices increased substantially more during Q3 following a sharp reduction in Russian natural gas deliveries to Europe and dropped back somewhat during Q4.

Figure 10. Historical Standard Deviation and Peak Change in Explanatory Variables between 2022q2 and 2021q1



Sources: Authors' calculations

Notes: Standard deviation of underlying explanatory variables using quarterly data over 1991 (or earliest data available) -2022

4. **Supply disruptions:** The sharp deterioration in the durable goods model performance also stands out. There has been a lot of focus, both in the media and amongst policy makers, on supply bottlenecks (caused by a likely combination of worldwide demand switches to goods and pandemic induced supply disruption). Celasun et. al (2022) estimate that supply disruptions might have increased core inflation by 0.3-0.4pp. While the durable goods model includes a variable measuring manufacturing stocks (with lower stocks associated with greater supply bottlenecks), the large forecast errors for the durable goods model show that this does not adequately capture the whole supply bottlenecks story.

It is unavoidable that some of the above factors that explain the deterioration in forecast performance since the pandemic will, by construction, always remain outside a model which is estimated over a longer period. This does not mean, however, that we should disregard model forecasts. Instead, it reinforces the need for a careful analysis on where factors outside the model need to be considered *ex post* in arriving at a final forecast. Using alternative measures of slack as a cross check might be warranted at the current juncture for example. Ultimately, what adjustments should be made to the pure model-based projections, and how, requires the judgment of the forecaster. On energy pass-through, for example, both the size of the energy shock and the strong policy response have likely contributed to a change in pass-through of wholesale oil and gas prices to electricity and energy inflation, with knock-on effects for inflation in other components. One option to deal with this is to re-run the natural gas and electricity models for the inflation series at constant tax rates to try and recover something closer to the non-policy distorted passthrough coefficient. One could then use these coefficients in the out of sample projection exercise to project natural gas and electricity inflation, allowing for future policy changes to subtract or add to estimated inflation based on judgement. Similarly, on supply bottlenecks, an explicit *ex post* adjustment to the durable goods model could be considered if the forecaster has information which suggests the high persistence embedded in the model is not appropriate as bottlenecks unwind.

V. The Drivers of Inflation

A. Impact of Standardized Changes in Explanatory Variables

To get a better sense of how different explanatory variables impact inflation in the model, we study the impact of standardized changes to key explanatory variables. Figure 11 shows the impact of a one standard deviation change to (i) the EUR-USD exchange rate, (ii) crude oil prices, (iii) food prices, (iv) the vacancy to unemployment rate, (v) long-term inflation expectations, (vi) Chinese PPI inflation and (vii) natural gas prices. The sign of all changes are chosen to be inflationary but the model is symmetric and would simply yield the opposite impact for deflationary shocks. Each shock is assumed to dissipate over four quarters but does not reverse for those variables that enter the model as growth rates (in other words, a 10 percent increase in crude oil prices does not lead to negative oil price growth in the following year).

For core inflation, a one standard deviation in economic slack has the largest impact, peaking at over 0.15 percentage points after three quarters before declining relatively gradually over the following quarters. The impact of a one standard deviation shock to the exchange rate is similar.[25] Natural gas prices have a very large and delayed impact on core inflation, peaking after 7 quarters at about 0.25 percentage points. The long lag is due to the way natural gas shocks works their way through the system – impacting retail natural gas and electricity prices with a lag, and these in turn impact a number of core components with a lag. Food price and crude oil price increases have a slightly smaller impact on core inflation. Shocks to inflation expectations and Chinese PPI inflation have the smallest impact.

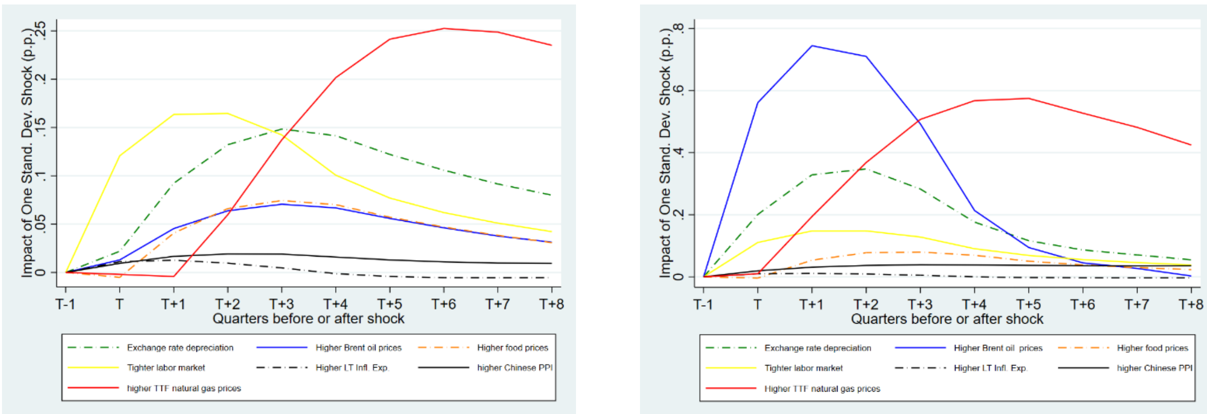
For headline inflation, the large impact of oil price shocks is clear., although the impact is estimated to unwind almost fully after 5 quarters. Again, natural gas price shocks also have a large, albeit delayed, and persistent impact. The exchange rate, and to a lesser degree economic slack also have meaningful and persistent effects.

To put the impact of these one standard deviation changes into context with what has been happening recently, it is instructive to re-consider the magnitude of changes in key explanatory variables shown in Figure 10. As mentioned before, the increase in natural gas prices stands out at five standard deviations. The second largest changes were to long-term inflation expectations and the vacancy to unemployment rate (roughly four standard deviations) followed by Chinese PPI inflation (two standard deviations). All other variables increased by between one and two standard deviations.

[25] The exchange rate result can be translated into a simple passthrough metric – one standard deviation corresponds roughly to a 10 percent depreciation here which leads to a 0.15 percentage point increase in core inflation after 4 quarters.

Figure 11. Impact of a One Standard Deviation Change in Key Explanatory Variables

Core Inflation *Headline Inflation*



Sources: Authors' calculations

Notes: Figures present the impact on inflation (in percentage ppoint year-over-year terms) of a one standard deviation increase in selected explanatory variables. Y-axis refers to quarters with the shock occurring in quarter T.

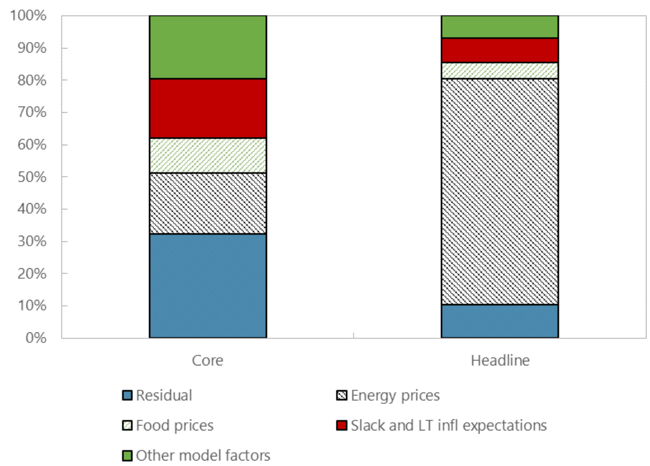
B. Decomposing the Drivers of the Recent Inflation Surge

In this section we implement a decomposition exercise in the spirit of IMF (2022b), aimed at quantifying the contribution of several factors to the surge in inflation observed over the past quarters. These include: international energy prices, food prices, economic slack, the expectations channel, "other" model factors (such as house prices) and finally the unexplained component. We calculate dynamic pseudo out of sample projections over two horizons (2020q1-2022q2, 2021q3-2022q2) given that the exact breakdown depends to some degree on the starting point. The contribution of any one factor is recovered by assuming no change in that explanatory variable during the forecast horizon and comparing the projection in that scenario with that obtained using the actual observed values for all explanatory variables.

Figure 12 shows that commodity prices (energy and food prices, including the exchange rate component of these price changes) are estimated to account for 75 percent of the increase in headline inflation in Q2 2022 (relative to Q2 2021 and Q4 2019) while they account for roughly 30 percent of the increase in core inflation. The reduction in slack and increase in inflation expectations, on the other hand, are estimated to be responsible for 10 percent of the higher headline, and 20 percent of the higher core inflation. Other model variables – such as house price growth, manufacturing stocks, imported manufacturing prices – account for close to 20 percent of core inflation.

All in all, recent movements in headline inflation are heavily dominated by commodity prices. Even for core inflation they have played an important role, but so too have domestic factors. Around one-third of the increase in core inflation – 1 percentage point – and slightly over 10 percent of headline inflation – close to 1 percentage point – remain unexplained by the model.[26]

Figure 12. Decomposition of the Inflation Surge



Sources: Authors' calculations

Notes: Contribution of selected explanatory variables to inflation surge. The contribution of any one factor is recovered by assuming no change in that explanatory variable during the forecast horizon and comparing the projection in that scenario with that obtained using the actual observed values for all explanatory variables. The average of contributions recovered from pseudo out of sample projections over 2021q3-2022q2 and 2020q1-2022q2 are shown.

VI. Projecting Inflation[27]

A. The role of model uncertainty

An important benefit of the bottom-up framework outlined in this paper is the ability to produce inflation projections under a range of different assumptions and scenarios. Given the large and successive shocks that have hit the euro area economy over the last two years, and the highly uncertain outlook, producing a range of inflation projections, and assessing the importance of certain assumptions for the inflation outlook, is a particularly useful exercise at the current juncture.

Before turning to scenario analysis, we illustrate the substantial uncertainty around model-based forecast at the current juncture. To do so, we assume an entirely stylized "neutral" economy starting in Q4 2022 – in other words, we assume no slack as of Q4, long-term expectations at target and no change in commodity prices or the exchange rate relative to the previous year – and calculate confidence intervals for model inflation

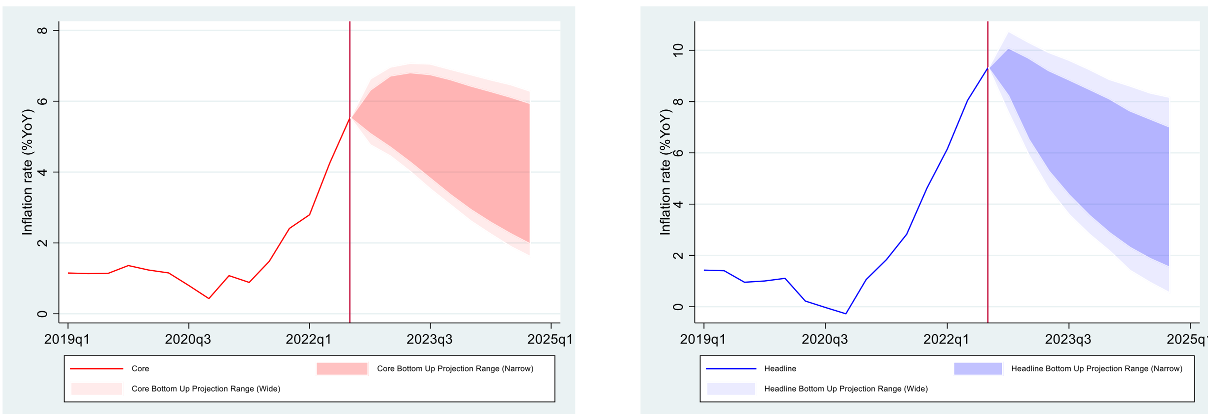
[26] The fact that the unexplained part is slightly smaller for headline that for core is perhaps a quirk of the specific circumstances and should not carry too much weight – the energy models overestimated inflation in many instances, to some degree offsetting part of the undershooting of core inflation.

[27] Projections shown here are illustrative to present the working of the model. They do not reflect the latest projections of the IMF or IMF staff.

projections based on parameter uncertainty and residual uncertainty. The darker shaded area in Figure 13 indicates the 95 percent confidence interval considering only parameter uncertainty, while the lighter shaded area also incorporates uncertainty due to model residuals. Uncertainty is high even in 2022q4 and by end-2024, the confidence band for core inflation spans from around 2 to 6 percent and for headline inflation from around 1 to 8 percent.

Figure 13. Stylized "Neutral Economy" Projection

Core Inflation *Headline Inflation*



Sources: Authors' calculations

Notes: Projections based on a "neutral" economy starting in Q4 2022. That is slack is set to zero from Q4 2022 onward, long-term expectations are at target, and there is no year-on-year change in commodity prices or the exchange rate. The darker shaded area in indicates the 95 percent confidence interval considering only parameter uncertainty, while the lighter shaded area also incorporates uncertainty due to model residuals.

B. Scenario Analysis

Beyond the model-related sources of uncertainty incorporated in the stylized neutral economy benchmark, a key additional source of uncertainty is the path of the explanatory variables, which we treat as exogenous. The systematic upside surprises to inflation in the euro area in recent quarters have, in part, been driven by upside surprises to commodity prices (themselves driven often by unforeseen events, such as the Russian invasion of Ukraine). Here we study three illustrative scenarios for the euro area and World economy – (i) a scenario based on the macroeconomic assumptions in the October IMF World Economic Outlook combined with recent futures prices for commodities, (ii) a scenario which assumes a sharp slowdown in euro area and World demand and (iii) a scenario with additional commodity prices shocks, leading to persistent euro area stagflation. We focus on the midpoint of the projection for each scenario[28].

- **The October 2022 WEO scenario:** Under the published October WEO, the euro are economy was expected to enter 2023 with both a small negative output gap and small negative unemployment gap. Based on recent futures prices, Brent crude oil prices were expected to sit around 90 USD/bbl during 2023 with natural gas prices slightly above the levels seen in the first half of 2022. International food prices were expected to drop slightly from elevated levels. Based on latest survey of professional

[28] Given the WEO only includes quarterly data until end-2023 the WEO based scenario has projections until end-2023 while for the other two scenarios projections go until end-2024.

forecasters data, long term inflation expectations are 2.1 percent. We apply an ex-post adjustment to the durable good model to allow for some expected unwinding of supply bottlenecks

- **The demand reduction scenario:** US growth is assumed to turn marginally negative on an annual basis in 2023. The unemployment rate in the Euro Area gradually increases by 3 p.p. and the output gap is assumed to show significant slack as of 2023 with a worsening of 2p.p. Oil prices drop to 70 bbl/USD in 2023 and stabilize there in 2024 while gas prices stabilize at the level observed in 2021Q4 and 2022Q1. Food prices drop five percentage points and the Euro appreciated 10 percent as the Federal Reserve has room to limit or reverse monetary policy tightening. Inflation expectations are anchored at 2 percent. We apply an ex-post adjustment to the durable good model to allow for some expected unwinding of supply bottlenecks

- **The stagflation scenario:** A sharp reversal of the recent easing in key wholesale energy prices drives this scenario as TTF natural gas prices return to the record levels observed in Q3 2022 and stabilize there. Oil prices climb to 100 USD/bbl, growth in the US is broadly unchanged but the unemployment and output gap in the euro area weaken by 2p.p. each. Finally, long term inflation expectations move up to 3 percent.

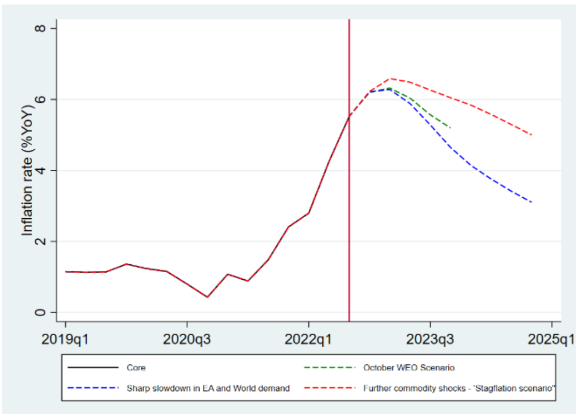
As Figure 14 shows, by early-2023 the model expects inflation to be on a downward trajectory but significantly above target in all scenarios. The key difference is in the speed of decline. Under the demand slowdown scenario, the disinflationary process in 2023 is nearly as steep as the inflationary one was in 2022. In the stagflation scenario, both core and headline remain substantially above target even at end 2024.

Looking at the individual HICP categories sheds some further light on how the scenarios impact inflation dynamics (see figure 15).

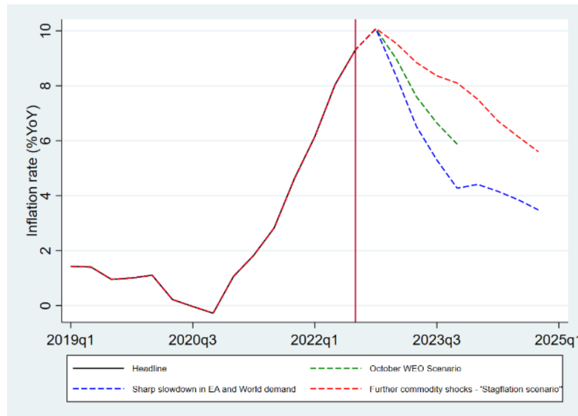
- Oil prices make an important difference as the graph for fuel inflation shows - given the direct and large passthrough, a scenario with Brent crude at 70 USD/bbl leads to large negative fuel inflation in 2023 supporting a fast drop in transport services also.
- Assumptions on gas prices lead to large level differences in natural gas and electricity inflation between scenarios. But interestingly both retail gas and electricity inflation are projected to remain high but drop in both scenarios as there is more passthrough to come but at the same time the new commodity shock in the stagflation scenario would not be large enough to lead to a renewed peak in retail energy price (note, however, the implicit assumption that measures to limit passthrough are being maintained).
- For a number of services categories which are sensitive to the level of economic slack, the dynamics across scenario are relatively similar given a worsening of labor markets in both the demand reduction and persistent stagflation scenarios. The level difference at end-2024 is driven in part by higher inflation expectations in the stagflation scenario but importantly also by higher electricity prices.
- The current high food prices are expected to be rather persistent, with processed food for example staying above 5 percent in all scenarios. Last, durable goods have a peculiar pattern given the importance of adjusting – or not – the model implicit assumption of continued supply bottlenecks.

Figure 14. Scenario Analysis

Core Inflation



Headline Inflation

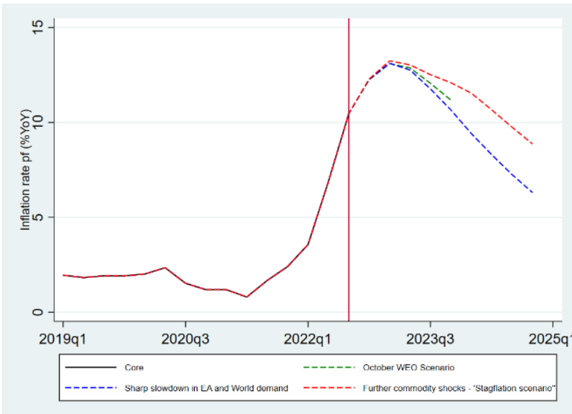


Sources: Authors' calculations

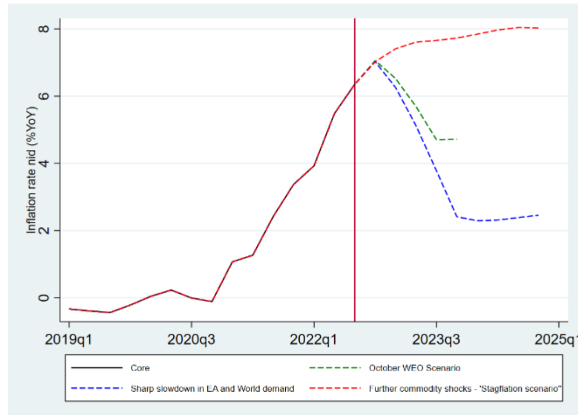
Notes: Figures show projections for headline and core inflation under three scenarios: (i) October 2022 WEO scenario (green dashed), (ii) a demand reduction scenario (blue dashed), and (iii) stagflation scenario (red dashed).

Figure 15 Scenario Analysis – Individual HICP Components

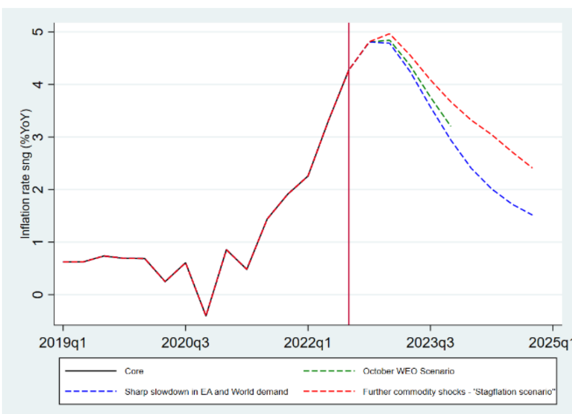
Processed Food



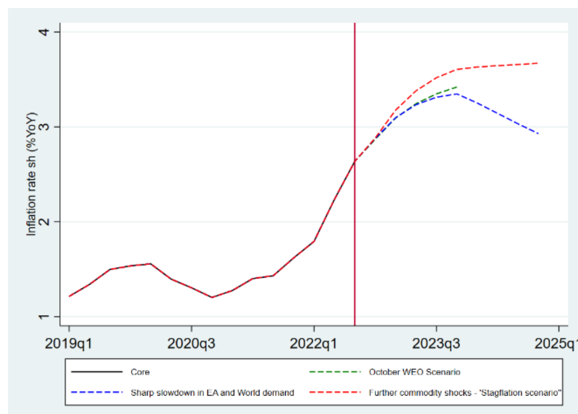
Durable Goods



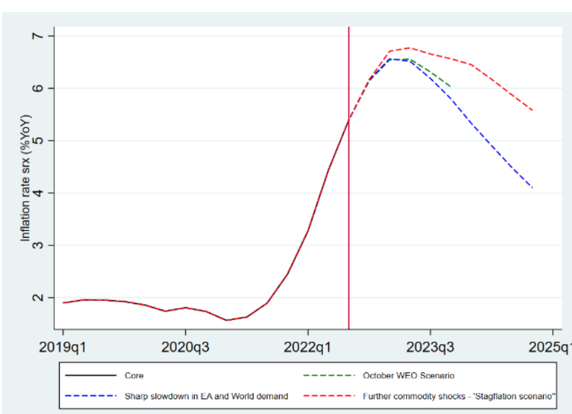
Semi- and Nondurable Goods



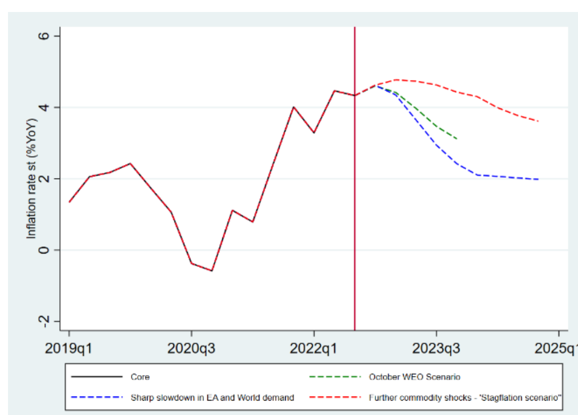
Housing Services



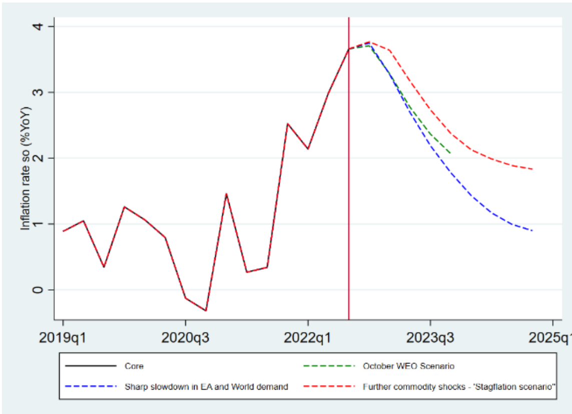
Recreation Services



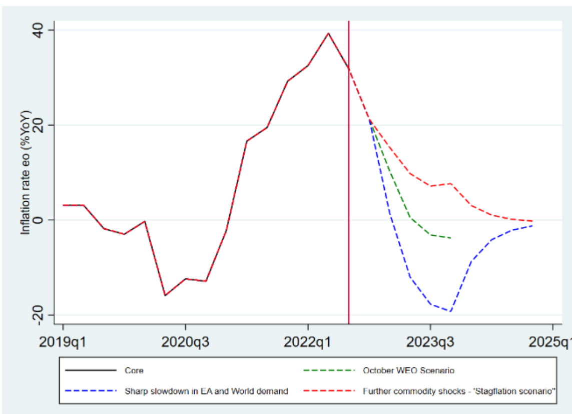
Transport Services



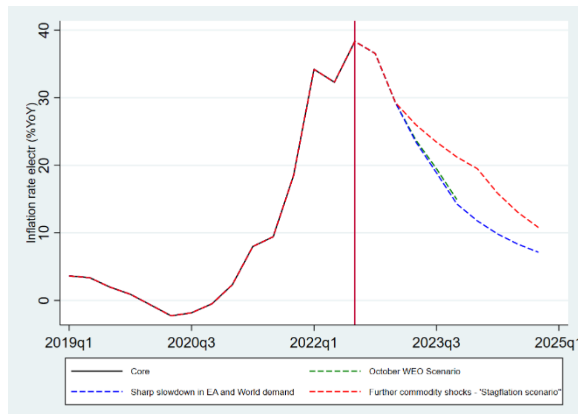
Other Services



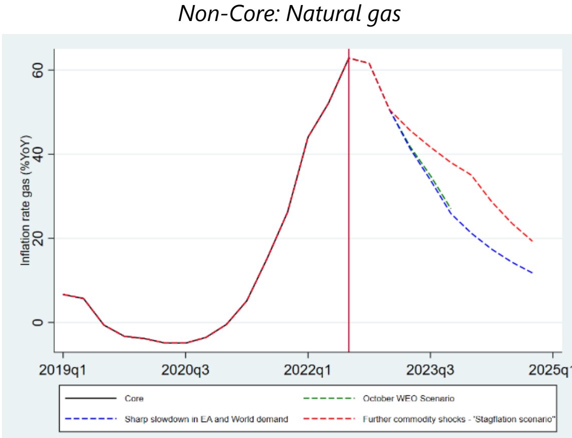
Non-Core: Fuels



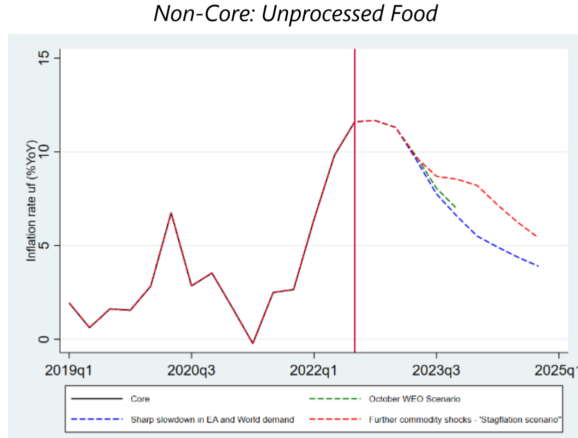
Non-Core: Electricity



Non-Core: Natural gas



Non-Core: Unprocessed Food



Sources: Authors' calculations

Notes: Figures show inflation projections for each sub-componet under three scenarios: (i) October 2022 WEO scenario (green dashed), (ii) a demand reduction scenario (blue dashed), and (iii) stagflation scenario (red dashed).

VII. Conclusion

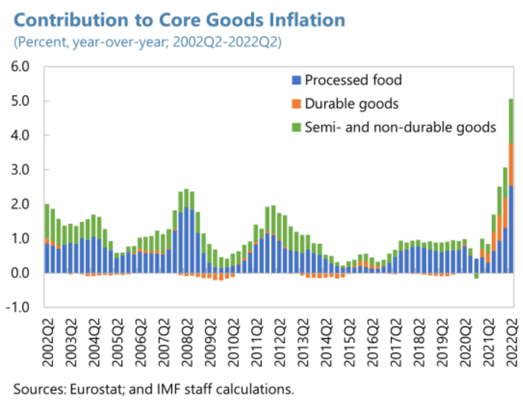
Forecasting macroeconomic variables is always challenging and particularly so at times when temporary or structural shifts are taking place. This has been the case since early 2020 when the Covid-19 pandemic and then the war in Ukraine led to a series of large shocks, both on the supply and demand side. Our work shows that when taking a bottom-up approach, the key Phillips curve relationships (including the relationship between inflation and economic slack and inflation and inflation expectations) does not seem to have changed dramatically. At the same time, a number of supply side shocks – most prominently the increase in European gas prices – have been unprecedented in size and have likely changed the passthrough to specific consumer prices relative to previous periods. In addition, the rotation in demand from services to goods, and currently back to services, has led to unusual demand-supply imbalances at the sectoral level. Modelling inflation in a bottom-up way improves forecast accuracy and seems a particularly pertinent tool for modeling inflation dynamics at the current juncture given these dislocations.

Annex I.

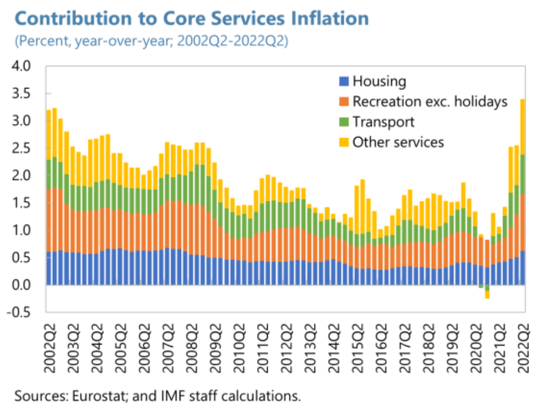
Additional Figures

Figure A.1. Contribution to Year-on-Year Inflation Subindices

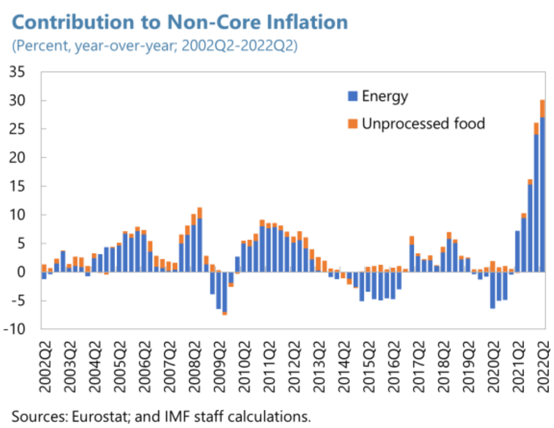
Good goods



Core services

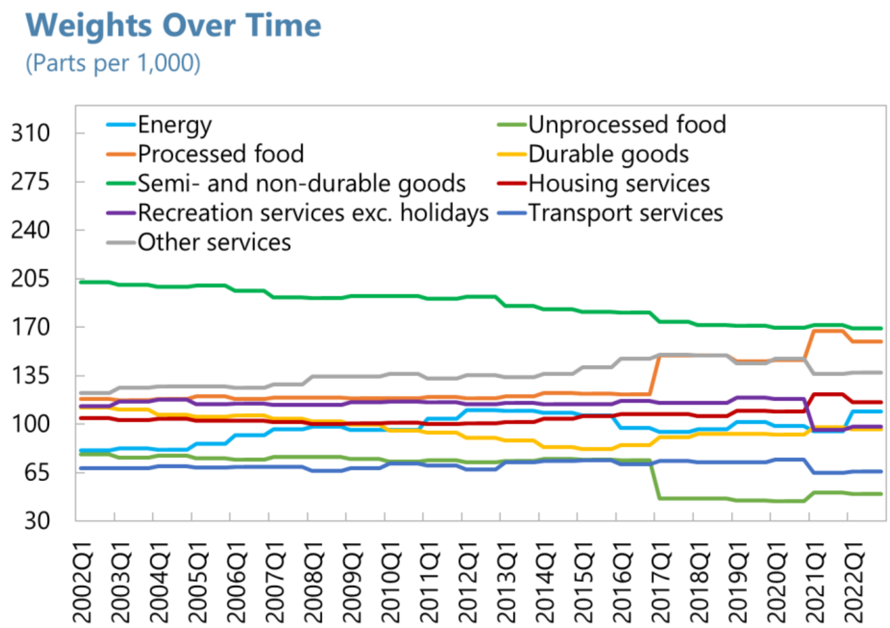


Non-core items



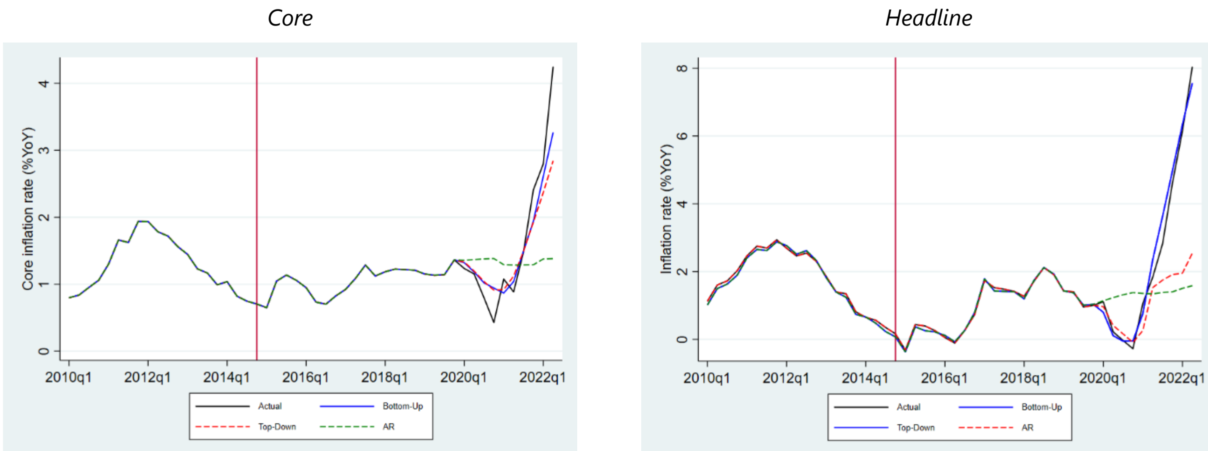
Sources: Eurostat; Authors' calculations

Figure A.2. HICP Weights (2002-2022)



Sources: Eurostat; Authors' calculations

Figure A.3. 9-Quarter Ahead Pseudo out of Sample Projections During the Pandemic



Sources: Eurostat; Authors' calculations

Table A1. Bottom-Up Phillips Curve Regressions with the Unemployment Gap as the Measure of Slack

VARIABLES	(1) Processed Food	(2) Durables	(3) Semi- and Nondruables	(4) Housing services	(5) Recreation excl. package holidays	(6) Transport services	(7) Other services	(8) Fuels	(9) Electricity	(10) Natural gas	(11) Unprocesse Food
Lagged dependent variable	0.763***	0.969***	0.606***	0.917***	0.877***	0.727***	0.608***	0.425***	0.658***	0.749***	0.440***
	(0.0463)	(0.0453)	(0.0705)	(0.0230)	(0.0323)	(0.0505)	(0.0694)	(0.0299)	(0.0524)	(0.0534)	(0.0832)
Slack	-0.191***	-0.0254	-0.0552*	0.00233	-0.0697***	-0.105**	-0.171***				
	(0.0596)	(0.0251)	(0.0326)	(0.0120)	(0.0212)	(0.0477)	(0.0591)				
LT Inflation Expectations	0.239***	-0.0531**	0.133***	0.0187	0.116***	0.355***	0.313***				
	(0.0786)	(0.0226)	(0.0408)	(0.0253)	(0.0451)	(0.0753)	(0.0721)				
Non-energy manufacturing import price growth		0.0454***	0.00754								
		(0.00686)	(0.00959)								
Manufacturing stocks growth		-0.0211***									
		(0.00428)									
Food price index (in Euros) growth					0.00316						
					(0.00269)						
Food price index (in Euros) growth, lag	0.0153**				0.00384						0.0337**
	(0.00600)				(0.00282)						(0.0147)
House price index growth				0.0154***							
				(0.00317)							
Rent indexator				0.0382***							
				(0.0113)							
Brent crude oil (in Euros) growth						0.000838					
						(0.00192)					
Brent crude oil (in Euros) growth, lag						0.00679***					
						(0.00204)					
HICP electricity price growth, lag	0.0613***	0.0162**	0.0409***		0.0239***		0.00767				
	(0.0146)	(0.00786)	(0.00987)		(0.00462)		(0.0118)				
Dummy for 2015							0.673***				
							(0.243)				
Brent crude oil growth								0.229***			
								(0.00970)			
Euro-USD exchange rate change								0.269***			
								(0.0310)			
Dutch TTF natural gas price growth, lag									0.0250***	0.0401***	
									(0.00221)	(0.00437)	
HICP natural gas price growth, lag											0.0706***
											(0.0188)
Constant								-0.115	0.968***	0.381	0.827***
								(0.282)	(0.233)	(0.385)	(0.219)
Observations	81	81	81	81	81	81	81	81	81	81	81
R-squared	0.959	0.945	0.923	0.997	0.995	0.972	0.886	0.953	0.919	0.897	0.471

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations

Notes: Bottom-up models using unemployment gap as slack measure. Estimated by system of seemingly unrelated regressions (SUR) where the errors are assumed to be correlated across equations. Regression period is 2002Q2-2022Q2. R-squared refers to adjusted R-squared.

Table A2. Bottom-Up Phillips Curve Regressions with V/U relative to Trend as Slack Measure estimated until 2019Q4

VARIABLES	(1) Processed Food	(2) Durables	(3) Semi- and Nondruables	(4) Housing services	(5) Recreation excl. package holidays	(6) Transport services	(7) Other services	(8) Fuels	(9) Electricity	(10) Natural gas	(11) Unprocesse Food
Lagged dependent variable	0.761***	0.828***	0.490***	0.937***	0.867***	0.819***	0.333***	0.358***	0.700***	0.427***	0.529***
	(0.0636)	(0.0498)	(0.0918)	(0.0272)	(0.0383)	(0.0530)	(0.103)	(0.0271)	(0.0634)	(0.0900)	(0.101)
Slack	0.0543***	0.00315	0.00738	0.000977	0.0178***	0.0208**	0.0562***				
	(0.0185)	(0.00515)	(0.00711)	(0.00408)	(0.00463)	(0.0101)	(0.0141)				
LT Inflation Expectations	0.236***	-0.0455	0.0598	0.0136	0.145***	0.210***	0.377***				
	(0.0862)	(0.0280)	(0.0434)	(0.0320)	(0.0405)	(0.0704)	(0.0799)				
Non-energy manufacturing import price growth		0.0400***	0.0146								
		(0.00690)	(0.00991)								
Manufacturing stocks growth		-0.0121***									
		(0.00402)									
Food price index (in Euros) growth					-0.00422						
					(0.00267)						
Food price index (in Euros) growth, lag	0.0188**				0.00814***						0.0153
	(0.00769)				(0.00262)						(0.0160)
House price index growth				0.0119**							
				(0.00495)							
Rent indexator				0.0288*							
				(0.0159)							
Brent crude oil (in Euros) growth						8.69e-05					
						(0.00203)					
Brent crude oil (in Euros) growth, lag						0.00403**					
						(0.00204)					
HICP electricity price growth, lag	0.00908	-0.00744	0.0814***		-0.00438		-0.00703				
	(0.0410)	(0.0115)	(0.0188)		(0.00873)		(0.0261)				
Dummy for 2015							1.019***				
							(0.240)				
Brent crude oil growth								0.258***			
								(0.0104)			
Euro-USD exchange rate change								0.300***			
								(0.0320)			
Dutch TTF natural gas price growth, lag									0.0199***	0.108***	
									(0.00391)	(0.0185)	
HICP natural gas price growth, lag											0.0212
											(0.0229)
Constant								-0.375	0.874***	0.631	0.815***
								(0.256)	(0.260)	(0.486)	(0.238)
Observations	56	56	56	56	56	56	56	56	56	56	56
R-squared	0.951	0.861	0.938	0.998	0.996	0.983	0.891	0.965	0.758	0.789	0.420

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sources: Authors' calculations

Notes: Bottom-up models using V/U relative to trend as slack measure. Estimated by system of seemingly unrelated regressions (SUR) where the errors are assumed to be correlated across equations. Regression period is 2006Q1-2019Q4. R-squared refers to adjusted R-squared.

References

Abdih, Y., R. Balakrishnan and B. Shang, 2016, “What is Keeping US Core Inflation Low: Insights from a Bottom-Up Approach”, IMF Working Paper, WP/16/124, International Monetary Fund.

Abdih, Y., L. Lin, and A. C. Paret, 2018, “Understanding Euro Area Inflation Dynamics: Why So Low for So Long?”, IMF Working Paper, WP/18/25, International Monetary Fund.

Altissimo, F., Bilke, L., Levin, A., Mathä, T. and Mojon, B., 2006. “Sectoral and aggregate inflation dynamics in the euro area”. Journal of the European Economic Association, 4(2-3), pp.585-593.

Bank of International Settlements (BIS) Annual Economic Report 2022.

Bermingham, C. and A. D’Agostino, 2014. “Understanding and Forecasting Aggregate and Disaggregate Price Dynamics”. Empirical Economics, 46: 765-788..

Celasun, O., Hansen, N, J, H., Mineshima, A., Spector, M., and Zhou, J.., 2022. “Supply Bottlenecks: Where, Why, How Much, and What Next?”, IMF Working Paper, WP/22/031, International Monetary Fund.

Duval, R. Y. Ji, L. Li, M. Oikonomou, C. Pizzinelli, I. Shibata, A. Sozzi, and M. M. Tavares, 2022, “Labor Market Tightness in Advanced Economies”, Staff Discussion Note, SDN/2022/001, International Monetary Fund.

European Central Bank, 2012, “Recent Developments in Food Commodity Prices and their Implications for Consumer Food Prices in the Euro Area”, ECB Economic Bulletin, Issue 09/2012.

European Central Bank, 2014, “The Responsiveness of HICP Items to Changes in Economic Slack”, ECB Economic Bulletin, Issue 09/2014.

European Central Bank, 2017, “Assessing labor market slack”, ECB Economic Bulletin, Issue 3/2017

European Central Bank, 2019a, “A new method for the package holiday price index in Germany and its impact on HICP inflation rates”, ECB Economic Bulletin, Issue 2/2019.

European Central Bank, 2019b, “Rent inflation in the euro area since the crisis”, ECB Economic Bulletin, Issue 4/2019.

European Central Bank, 2020, “Consumption of durable goods in the euro area”, ECB Economic Bulletin, Issue 5/2020.

Furman, J., W. Powell III, 2021, “What is the best measure of labor market tightness”, PIIE blog (November 22), Peterson Institute for International Economics.

International Monetary Fund, 2021, World Economic Outlook (October).

International Monetary Fund, 2022a, “European Labor Markets and the COVID-19 Pandemic: Fallout and the Path Ahead”, IMF European Departmental Paper

International Monetary Fund, 2022b, Regional Economic Outlook for Europe (October).

Hubrich, K., 2005. “Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy?”. International Journal of Forecasting, 21(1), pp.119-136.

Koester, G., Lis, E., Nickel, C., Osbat, C., and F. Smets (2021), “Understanding low inflation in the euro area from 2013 to 2019: cyclical and structural drivers”, ECB Occasional Paper Series.

Niskanen, W.A., 2002. On the death of the Phillips curve. Cato J., 22, p.193.

O’Brien, D., C. Dumoncel and E. Gonçalves, 2021, “The role of demand and supply factors in HICP inflation during the COVID-19 pandemic – a disaggregated perspective”, ECB Economic Bulletin, 1.

Peach, R., R. Rich, and H.M. Lindner, 2013, “The Parts are More than the Whole: Separating Goods and Services to Predict Core Inflation”, Current Issues in Economics and Finance, 19(7), Federal Reserve Bank of New York.

Stock, J. and M. Watson, 2019, “Slack and Cyclically Sensitive Inflation”, NBER Working Paper Series, WP 25987.

Tallman, E. and S. Zaman, 2017, “Forecasting Inflation: Phillips Curve Effects on Services Price Measures”, International Journal of Forecasting 33(2), 442-457

PUBLICATIONS

[Title of Working Paper: Subtitle (As Needed)]

Working Paper No. [WP/YYYY/###]