WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

Explaining and Forecasting Euro Area Inflation: the Role of Domestic and Global Factors

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February 2018, WP #663

Abstract

In this paper, we study the fit and the predictive performance of the Phillips curve for euro area inflation with regard to different inflation series, time periods and predictor variables, notably different global factors. We compare the relative performance of a large set of alternative global factors in the Phillips curve, such as commodity prices, import prices, global consumer inflation, global economic slack and foreign demand. We find that traditional global indicators such as oil prices and import prices provide more accurate information for euro area headline inflation than global slack measures. In what regards the forecast ability of the Phillips curve for headline inflation, we show that it is unstable and depends strongly on the time period. Global factors provide only limited additional information for forecasting. In addition, we explore whether domestic demand and global factors are useful for analysing the entire conditional distribution of euro area inflation. We find that their impact varies across inflation quantiles (low vs. high inflation) and that inflation is more persistent at the low end of the distribution. We provide evidence that quantile information can lead to more accurate forecasts in periods of persistently low inflation.[4]

Keywords: Inflation; Forecasting; Phillips curve; Quantile regression

JEL classification: E31, E37, C22, C53

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4 We are very grateful to Elena Bobeica for an excellent discussion at the Banque de France seminar. We also thank Marie Aouriri, Yannick Kalantzis, Guy Levy-Rueff, Benoît Mojon, Rolf Scheufele, as well as participants at the 7th IWH/INFER Workshop (2017) on "Inflation Dynamics", the ECB conference (2017) on "Understanding Inflation: lessons from the past, lessons for the future?" and Banque de France seminars (2017, 2018) for helpful comments and insightful discussions. All remaining errors are ours.

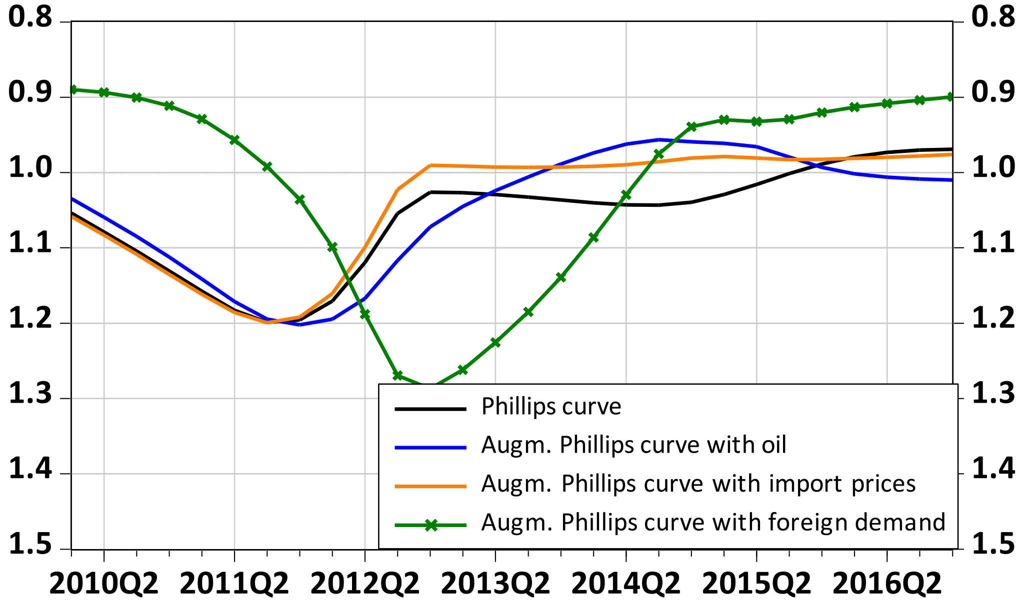
NON-TECHNICAL SUMMARY

Understanding inflation developments and predicting them accurately is of paramount importance for central banks, whose objective is to deliver price stability. Those last years in particular have put standard models into question, given the systematic overprediction of inflation rates. One of these models is the Phillips curve, which remains a workhorse for inflation analysis in most central banks. In this paper, we study the explanatory power and the forecast performance of the Phillips curve for the euro area with respect to different inflation measures (headline and core inflation), time periods and predictor variables. We look in particular at the performance of alternative global indicators in augmented Phillips curve specifications, such as commodity prices, exchange rates, import prices, global consumer inflation and global economic slack measures. We find that traditional commodity price and import price indicators provide a good identification of the augmented Phillips curve for euro area headline inflation, in contrast to global economic slack measures proposed by Borio and Filardo (2007), which do not have a significant influence on euro area inflation. Global factors play a more limited role in the augmented Phillips curve for euro area core inflation.

Turing to forecast considerations, we show that the accuracy of the Phillips curve for headline inflation depends strongly on the time period. The Phillips curve forecast performed significantly better during the most recent period (2015-2016) than on average over the last ten years (2006-2016). The unstable forecast behaviour of the Phillips curve for euro area headline inflation is confirmed by the Giacomini and Rossi (2010) fluctuation test. The forecast ability of the Phillips curve for core inflation is more stable and usually improves the forecast accuracy compared to univariate benchmarks. In what regards the role of global indicators, we argue that they are important for understanding inflation dynamics but that they provide relatively few information for forecasting inflation. One exception is trade-weighted foreign demand, which possesses some leading properties for euro area inflation and provides small improvements for the inflation forecast during some periods, such as the Great Recession or the recent period of low inflation.

Next, we analyse the Phillips curve relationship and the role of global indicators for euro area inflation on the entire conditional distribution of inflation using a dynamic quantile regression approach. We are interested to know whether the impact of the different predictor variables on inflation varies across inflation regimes (high and low inflation) and whether this can be exploited for forecasting. We find that the inflation process is more persistent at the left tail of the distribution, i.e. when inflation is in its lower quantiles. By contrast, domestic activity is found to have a stronger influence on inflation on the right tail of the distribution. This would be broadly consistent with findings in the literature that the Phillips curve might not be linear (see for example Dolado, 2005) and that, as in our case, inflation reacts stronger to the demand situation at higher levels of inflation. Turning to forecast considerations, we show that quantile regressions can improve the forecast ability of the Phillips curve during some periods of persistently low inflation (2014-2015), but this result cannot be easily generalized to other periods when inflation is more dynamic.

Relative forecast performance of the Phillips curve (Rolling BRMSE over 15-quarters window against AR)



Note: The figure shows (bi-weighted) rolling forecast errors (BRMSE) from four Phillips curve specifications against an autoregressive model. The rolling forecasts are realized over 15-quarters windows. A BRMSE ratio smaller (higher) than 1 signifies a better (worse) forecast performance of the respective Phillips curve specification against the autoregressive model. Scales are inverted.

Expliquer et prévoir l'inflation dans la zone euro: le rôle des facteurs domestiques et globaux

Dans ce papier, nous étudions le pouvoir explicatif et la performance prévisionnelle de la courbe de Phillips pour la zone euro à l'égard des différentes mesures de l'inflation (inflation totale et inflation sous-jacente), différentes périodes et différentes variables explicatives. Nous examinons en particulier la performance des différents indicateurs globaux dans les spécifications de la courbe de Phillips augmentée. Nous trouvons que les indicateurs traditionnels comme le prix de pétrole et le prix des importations fournissent une bonne identification de la courbe de Phillips augmentée pour l'inflation totale en zone euro, contrairement aux mesures de l'écart de production global proposées par Borio et Filardo (2007). En ce qui concerne les prévisions avec la courbe de Phillips, nous montrons que l'exactitude des prévisions dépend fortement de la période étudiée. Les prévisions de la courbe de Phillips ont donné des résultats meilleurs au cours de la période récente (2015-2016) qu'en moyenne au cours des dix dernières années (2006-2016). La capacité de prévision de la courbe de Phillips pour l'inflation sous-jacente est plus stable et améliore la précision des prévisions par rapport aux estimations univariées. En ce qui concerne le rôle des indicateurs globaux, nous montrons qu'ils sont importants pour comprendre la dynamique de l'inflation, mais qu'ils fournissent relativement peu d'informations pour la prévision, à l'exception de l'indice de la demandée adressée à la zone euro. En outre, nous analysons la relation Phillips et le rôle des indicateurs globaux sur l'ensemble de la distribution conditionnelle de l'inflation à l'aide d'une approche de régression quantitative dynamique. Nous constatons que le processus d'inflation est plus persistant à la queue gauche de la distribution et que l'activité domestique a une influence plus forte sur l'inflation à la queue droite de la distribution. En période d'inflation durablement faible, il est possible d'en tirer avantage afin d'améliorer la prévision.

Mots-clés : Inflation; prévision; courbe de Phillips; régression quantile.

1 Introduction

Understanding inflation developments and predicting them accurately is of paramount importance for central bank, whose objective is to deliver price stability. After 2012, inflation was very low in the euro area. Forecasts by the Eurosystem and by other institutions were constantly surprised on the downside by inflation developments. According to Ciccarelli and Osbat (2017), both weak domestic demand and negative global shocks were responsible for this. The goal of this paper is to analyse whether the tools used at central banks are still pertinent to understand these developments. One of these tools is the Phillips curve, which in its simplest form links inflation to domestic activity. Augmented with global factors, the Phillips curve provides a convenient tool to assess the role of domestic and global factors in domestic inflation dynamics. In this paper, we want to examine the explanatory power and the forecast ability of the standard and augmented Phillips curve for the euro area with respect to different inflation measures (headline and core inflation), different time periods and different predictor variables, especially different global factors. We distinguish between their explanatory power and their role in forecasting. We aim to address this issue along two dimensions:

First, we re-investigate the goodness-of-fit of the Phillips curve with respect to a large set of different domestic and global indicators. We look at more traditional global indicators, such as commodity prices, exchange rates and import prices, and at indicators proposed more recently in the literature, such as global consumer inflation and global economic slack. We find that traditional commodity and import price indicators provide a good identification of the augmented Phillips curve for euro area headline inflation, in contrast to global slack measures as proposed by Borio and Filardo (2007). We cannot identify a significant impact of global factors on core inflation measures in this reduced-form Phillips curve framework. We then study the forecast behaviour of the Phillips curve over different time periods, including the latest episode of low inflation. We focus on the forecast up to one year ahead. We find a lot of time instability in the forecast performance of the Phillips curve for headline inflation against univariate benchmarks. The Phillips curve forecasts perform better during some period, such as the most recent period, than during other periods. The forecast ability of the Phillips curve for core inflation is more stable and provides generally an improvement to univariate benchmarks. In what regards the role of global indicators, we argue that there are important for understanding headline inflation dynamics *ex post*, but their purpose for forecasting is generally limited. Their influence on headline inflation reflects primarily commodity price movements, which are hard to anticipate. This is also why global indicators capturing wider global price trends, such as global consumer inflation, do not seem to contain additional information for domestic inflation dynamics compared to the more traditional commodity price indicators, such as oil prices. We show however that trade-weighted foreign demand (i.e. the import demand of the euro area trading partners) possesses certain leading properties for euro area inflation and improves the short-term inflation forecast.

Second, we build on the scarce literature on quantile regressions to analyse the Phillips curve relationship and the role of global indicators on the entire conditional distribution of inflation. The goal is to understand whether the impact of these variables on inflation is different on specific areas of the conditional distribution, i.e. during low or high inflation periods. Despite

the extensive literature on inflation analysis and forecasting, little attention has been paid so far to the question whether the different indicators carry useful information for other parts of the conditional distribution than the mean. We find that the inflation process is much more persistent at the left tail of the distribution, i.e. for lower quantiles of inflation. This might explain why mean models have not captured sufficiently the persistency of inflation in the recent period of low inflation. In contrast, domestic activity - and to a lesser extent also global factors - are found to have a stronger impact during periods of higher inflation. Turning to forecast considerations, we show that quantile regressions can improve the short-term forecast ability of the Phillips curve during some periods of persistently low inflation (2014-2015). There are however less useful for forecasting when inflation rebounds.
The remainder of the paper is organized as follows: Section 2 briefly surveys the empirical literature on the Phillips curve and on the quantile regression approach. Section 3 analyses the augmented Phillips curve for mean inflation and presents its in-sample and out-of-sample properties. In Section 4 we implement some testing and explore the forecast ability of the Phillips curve over time. In Section 5, we examine whether the domestic activity variables and global factors selected in the previous sections help in predicting the entire conditional distribution of inflation. We then compare the forecast performance of OLS and quantile regression models to evaluate whether quantile regression techniques can hedge against a bad forecast performance in particular episodes, such as the recent period of subdued inflation. Finally, Section 6 concludes.

2 Literature review

This paper is related to three strands of literature: First, we draw on the literature related to the identification and the forecast performance of the Phillips curve. Secondly, we relate to the literature which studies the role of global factors in domestic inflation. Finally, we explore quantile regressions to analyse the entire conditional distribution of inflation.

Phillips curves and its forecast performance. Various forms of Phillips curves have been used to forecast inflation[1]. Stock and Watson (2008) provide an extensive literature review for the U.S. The literature's conclusions on the forecast performance of the Phillips curve strongly depend on the forecast period, the inflation series and the benchmark models. For instance, Atkeson and Ohanian (2001) considered a number of standard Phillips curve forecasting models for U.S. inflation and show that none improve upon a random walk benchmark over the period 1984-1999. In contrast, Stock and Watson (2008) argue that Phillips curves can be useful during some periods, such as the late 1990s.
Though comprehensive studies on the forecast performance of the Phillips curve have been undertaken for the U.S., fewer works are available for the euro area. Banbura and Mirza (2013) examine the forecast ability of a wide range of Phillips curve specifications for different measures of euro area inflation (headline, core and GDP deflator) over the period 1994-2011. As Stock and Watson (2008) they find that the results vary substantially with the forecast period, but that on

[1] Following Stock and Watson (2008), we call Phillips curves those models which include an activity variable, such as the unemployment rate or the output gap, perhaps in conjunction with other variables, such as external supply shock indicators.

average Phillips curve models improve upon univariate benchmarks, notably for core inflation, even if improvements are typically not large. The unemployment rate/gap and the output growth/gap are often part of their best models and the inclusion of supply shock indicators also frequently improves the forecast performance. Ciccarelli and Osbat (2017) confirm that the Phillips curve is still relevant for the euro area and conditional forecasts from some Phillips curve specifications capture well the latest episode of disinflation.

The role of global factors for domestic inflation. While the role of external supply shock indicators, such as commodity prices, for domestic headline inflation is relatively well documented in the literature, an increasing number of studies look at the influence of more general global factors, such as global inflation and global economic slack, on domestic inflation rates. This strand of literature argues that domestic inflation is being increasingly sensitive to global economic conditions which might not only affect domestic inflation indirectly, via its effect on import prices and the domestic output gap, but also directly. One explanation is that globalisation has rendered domestic inflation less responsive to domestic capacity constraints, either because a sudden domestic demand shock would rather bolster imports than increase prices, or because exposure to foreign competitors curtails increases in domestic tradable prices (Guerrieri et al., 2010). Other studies emphasize the role of credible monetary policies that stabilized inflation expectations (Mishkin, 2009): with domestic price expectations well anchored, proportionally more of the variation in domestic inflation rates would be explained by global factors. However, the empirical evidence for the influence of global conditions is at best mixed, especially with regard to the role of global economic slack.

Borio and Filardo (2007) show the importance of the global output gap as a determinant of domestic inflation in advanced economies, stating that the role of global factors has increased over time. Auer et al. (2017) argue that, as participation in global value chains increases, competition among economies increases, making domestic inflation more sensitive to the global output gap. They conclude that the growth of global value chains is associated with both a reduction of the impact of domestic slack on domestic inflation and an increase in the one of global slack. However, other studies, such as Mikolajun and Lodge (2016), find no empirical evidence for a significant impact of global slack on domestic inflation in advanced economies. Ciccarelli and Mojon (2010) analyse the influence of a global inflation factor on domestic inflation in OECD countries and conclude that models including a measure of global inflation consistently outperform univariate benchmarks. This is confirmed by Medel et al. (2014), who conclude that global inflation improves the inflation forecast for headline and core inflation. However, the gains in forecast accuracy are modest: among the euro area members in the sample, only Italy and Slovakia achieve reductions in RMSE that are relevant (i.e. higher than 5%). In contrast, Mikolajun and Lodge (2016) argue that, with the exception of commodity prices, there is little reason to augment the standard Phillips curves for advanced economies with global factors once the volatile inflation period of the 1970s-1980s is excluded from the sample. They find that from the mid-1990s onwards, the coefficients of global inflation are insignificant for most OECD countries: global inflation measures are helpful for forecasting domestic inflation during periods of high and volatile inflation (i.e. the 1970-80s), but less so since inflation has receded.

Quantile regressions. While much of the literature focuses on analysing the conditional mean of inflation, it might be also interesting to examine the relationship between inflation and its determinants in other regions of the conditional distribution and to produce forecasts away from the conditional mean. As such, only very few papers explore whether domestic activity variables and global factors are useful for analysing other moments of the conditional distribution of inflation. Much of this scarce literature focuses on the U.S. Tillmann and Wolters (2014) use quantile regressions to examine the persistence of the conditional distribution of U.S. inflation and find evidence for a reduction in persistence on all conditional quantiles over time. More recently, Korobilis (2017) introduces Bayesian model averaging methods into quantile regressions and finds that different macroeconomic and financial predictors are relevant for each quantile of U.S. inflation. As the closest work to ours, Manzan and Zerom (2013) show that economic activity indicators, such as the unemployment rate and housing starts, are useful for forecasting the distribution of U.S. inflation, especially at the left tail of the distribution. To the best of our knowledge, only one paper (Busetti et al., 2015) relies on quantile regressions to analyse the conditional distribution of euro area headline inflation. They find that quantile regressions provides superior forecasts to those from a benchmark univariate trend-cycle model with stochastic volatility over the very short forecast horizon during the 2010-2014 period. The conditional quantile regression approach also allows them to describe the underlying features of the conditional distribution of inflation, with a higher persistency of the inflation process in the lowest quantiles and a higher reactivity of the inflation process to activity variables at higher quantiles.

3 The augmented Phillips curve for mean inflation

3.1 Methods

Econometric specification. We investigate the importance of global factors for euro area inflation by augmenting standard Phillips curves with various global factors. We estimate an aggregate equation for the euro area as a whole, using quarterly data over the period 1996Q3-2016Q4. The model, a backward-looking specification of the Phillips curve[2] including a lagged inflation term, is closely related to the "triangle" model proposed by Gordon (1988) and is similar to the type of models considered in Stock and Watson (2008). Our equation is of the following general form:

$$\pi_t = \alpha + \rho(L)\pi_{t-1} + \beta(L)y_t + \gamma(L)z_t + \varepsilon_t \tag{1}$$

where the dependent variable π denotes the quarterly rate of inflation at time t, computed as the first difference in the logarithm of the HICP, y a measure of domestic slack, z a global factor and L are lag polynomials.

Models are estimated by OLS[3], using heteroskedasticity and autocorrelation consistent (HAC)

[2] Recent studies on euro area inflation suggest that backward-looking Phillips curves fit inflation better than forward-looking Phillips curves (Mikolajun and Lodge, 2016). We also test inflation expectations in hybrid Phillips curve specifications, but generally focus on backward-looking specifications.

[3] Following Mikolajun and Lodge (2016), we also estimate Equation 1 by the generalized method of moments (GMM) using lags as instruments to address possible endogeneity problems, in particular in the models with global

estimates of the covariance matrix to address slight serial correlation in the residuals. The optimal lag order is selected on the basis of the Schwarz (BIC) information criterium. Given the limited time span of our data, the maximum number of lags has been limited to four quarters.

Forecast setting. We conduct pseudo-out-of-sample forecasts similar to the ones produced in Stock and Watson (2008) to evaluate the forecast performance of the augmented Phillips curves. For this, we use information available up to t for the predictor variables to estimate the model and then compute the h-period ahead forecast for π_{t+h} based on the direct method. The estimation is then rolled forward one quarter at a time over a fixed forecast period (40 and 74 quarters in our case) and the forecast exercise is repeated. We compute both the one-quarter-ahead ($h = 1$) and the four-quarter-ahead forecast ($h = 4$). We use final data and disregard revision issues in this paper. Our forecast equation is hence of the following form:

$$\pi_{t+h} = \alpha + \rho(L)\pi_t + \beta(L)y_t + \gamma(L)z_t + \varepsilon_{t+h} \tag{2}$$

where h denotes the forecast period.

Benchmarks. We compare the accuracy of the inflation forecasts of the augmented Phillips curves to those from two benchmark models[4] namely an autoregressive model of order 1 (AR hereafter) and a standard backward-looking Phillips curve (PC hereafter), both computed using the direct method, where the latter has the following form:

$$\pi_{t+h} = \alpha + \rho(L)\pi_t + \beta(L)y_t + \varepsilon_{t+h} \tag{3}$$

Forecast evaluation. We use the root mean squared forecast error (RMSE) as metric to compare forecasts from the different models. The RMSE corresponds to the square root of the arithmetic average of the squared differences between the actual inflation rate and the predicted inflation rate. The RMSE for a h-period-ahead forecast corresponds to Equation 4, where $\pi_{t+h|t}$ is the pseudo out-of-sample forecast of π_{t+h} made using data up to date t.

$$RMSE(t_1, t_2) = \sqrt{\frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \left(\pi_{t+h} - \pi_{t+h|t}\right)^2} \tag{4}$$

Following Stock and Watson (2008), we also compute (bi)weighted rolling estimates of the RMSE (BRMSE hereafter), which correspond to Equation 5. Rolling estimates are based on weighted centred 15-quarters windows: bigger (lower) weights are given to errors close to (far from) the centre of the window. Rolling RMSE help to distinguish during which specific period the

consumer inflation. However, the J-statistics of the Durbin-Wu-Hausman test do not signal any endogeneity. We hence maintain OLS estimates given the risk of incorrect inferences by using weak instruments in GMM estimates.

[4] We also checked the forecast performance against a random walk. Given the fact that the random walk does not outperform the AR on our fixed forecast windows (it has a similar forecast ability for headline inflation over the longer forecast period and a lower forcast ability over the short forecast period compared to the AR), we decided to use the AR as benchmark.

forecasts performed best.

$$BRMSE(t) = \sqrt{\frac{\sum_{s=t-7}^{t+7} K\left(\frac{|s-t|}{8}\right)\left(\pi_{s+h} - \pi_{s+h|s}\right)^2}{\sum_{s=t-7}^{t+7} K\left(\frac{|s-t|}{8}\right)}} \tag{5}$$

where K is the biweight kernel :

$$K(x) = \frac{15}{16}(1 - x^2)^2 I(|x| \leq 1)$$

Sample. Our sample covers data over the 1996Q3 to 2016Q4 period, which corresponds to 82 observations at a quarterly frequency. It includes episodes of important volatility in oil prices (which increased dramatically in 2008 and 2011 before decreasing from 2014 onwards), the Great Recession period, as well as the euro area sovereign debt crisis. These major events might have had altered the link between global factors and domestic inflation. Consequently, we compute RMSE over different forecast periods to make sure our models perform well during different time periods. Our in-sample analysis is based on the entire sample period from 1996Q3 to 2016Q4. Estimation results are provided in Appendix B. Our pseudo-out-of-sample forecast analysis relies on a fixed size rolling window approach. Three different procedures have been adopted:

- Models are estimated on the longest possible time span, using rolling estimation windows of a fixed length of 74 quarters. Hence, the first one-quarter-ahead forecast starts in 2015Q1 and the last one-quarter-ahead forecast ends in 2016Q4. The RMSE are computed for a forecast period of 8 observations ($t_2 - t_1 + 1 = 8$) for $h = 1$.

- Models are estimated using a rolling scheme with a shorter rolling estimation window of 40 quarters. RMSE are computed on a 39-quarters forecast period for $h = 1$ and $h = 4$. Hence, the first one-quarter-ahead forecast starts in 2006Q3, and the first one-year-ahead forecast starts in 2007Q2. The last one-quarter-ahead forecast ends in 2016Q1, and the last one-year-ahead forecast ends in 2016Q4.

- Models are estimated on rolling estimation windows of a fixed length of 40 quarters. RMSE and weighted BRMSE are computed on a 15-quarters forecast period for $h = 1$ and $h = 4$. Hence, the first one-quarter-ahead forecast starts in 2006Q3, and the first one-year-ahead forecast starts in 2007Q2.

Rolling estimates on the relatively short-sized 40-quarters window allow us to investigate the importance of the different predictor variables over a longer forecast period. Estimates on the longer, 74-quarters window assure that the results are not biased by the small size of the 40-quarters window and allow us to examine the forecast performance over the latest period of persistently low inflation.

3.2 Data

3.2.1 Dependent variables

We examine the Phillips curve for three measures of consumer price inflation: the euro area headline Harmonized Index of Consumer Prices (HICP), the euro area HICP excluding energy (HEX hereafter) and the euro area HICP excluding food and energy (CORE hereafter). We convert monthly HICP data to quarterly data by computing the average value for the three months in the quarter[5]. We seasonally adjust the quarterly indices using the X-12-ARIMA procedure. We focus on the results on headline inflation in the main text in line with the ECB target of overall price stability.

3.2.2 Regressors

Domestic slack. We test different measures of domestic slack for the euro area, namely: (*i*) the unemployment rate; (*ii*) the output gap; (*iii*) the unemployment gap; and (*iv*) the Industrial Production Index (IPI). Most of the measures are stationary and are introduced in levels. The IPI is tested both in level and in variation. To ensure robustness, we rely on different measures of the euro area output gap, derived from statistical filters and from the production function approach. We test: (*i*) the output-gap computed as the log-difference between actual and potential GDP, the latter being measured by means of a Hodrick-Prescott filter; (*ii*) the output gap computed by the European Commission; as well as (*iii*) the output gap computed by the ECB for the staff macroeconomic projection exercise. As far as output gap measures are annual, we used cubic splines techniques to interpolate annual figures into quarterly ones. Our in-sample and out-of-sample analyses show the best performance for models using the output gap computed by the ECB, which we use hence as our benchmark measure. We also report results based on the unemployment rate as the unemployment rate has the advantage of being less affected by revisions than the output gap.

Global factors. Triangle models of the Phillips curve traditionally capture external cost-push factors via import prices or commodity prices. We test a large number of these traditional used external factors including: (*i*) changes in oil prices; (*ii*) changes in the price of other commodities; (*iii*) changes in the euro area bilateral and effective exchange rates; and (*iv*) changes in euro area import prices, which can influence domestic inflation via the price of imported commodities, the price of imported final consumer goods as well as the price of imported intermediate goods. Concerning the latter, we consider three different indicators of import prices: (*i*) the extra-euro area import deflator for goods and services; (*ii*) the relative import deflator, i.e. the ratio of the extra-euro area import deflator to the GDP deflator; and (*iii*) competitors' prices on the import side[6].

[5]Though year-on-year inflation has no seasonal pattern, using year-on-year rates may introduce a moving average component to inflation. Annual inflation measured by year-on-year rates is approximately equal to the sum of quarterly log HICP differences. As a result, using year-on-year rates can complicate econometric inference, with autocorrelated residuals. We therefore rely on seasonally adjusted quarter-on-quarter rates in our estimations.

[6]The euro area competitors' prices are computed by the ECB as a weighted average of trading partners' export prices (Hubrich and Karlsson, 2010).

In order to capture the growing international integration of goods and labour markets and the wider propagation of global cost shocks, we furthermore test indicators proposed in the recent literature such as global consumer inflation and global economic slack. As a measure of global consumer inflation, we succesively consider: (i) a simple average of cross country inflation rates[7]; and (ii) a weighted average of cross country inflation rates[8], both for the total CPI and the CPI excluding energy and food (CORE). For the global economic slack, we use different measures of the output gap and the unemployment rate. For the output gap, we consider: (i) output gaps computed as the difference between actual and potential GDP, the latter being computed by means of a Hodrick-Prescott filter; and (ii) output gaps computed by the IMF. Different weighting schemes are applied to compute the output gap of various groups of countries: (i) cross-country simple averages; and (ii) weighted averages, taking relative GDP as weights. We consider several groups of countries to compute our global measures: the US, the OECD excluding members from the euro area, major advanced economies (i.e. the U.S., the U.K., Japan and Canada), major emerging and advanced economies excluding members from the euro area (world hereafter) and major emerging market economies.

We also test the euro area trade-weighted foreign demand index (FDR)[9]. This trade-weighted indicator of global demand is likely to reflect global demand-related price pressures that have an impact on the euro area better than non-trade weighted indices.

Details regarding the variables and their transformations are provided in Appendix A.

Inflation expectations. We use two measures of inflation expectations in the hybrid specifications of the Phillips curve: (i) a survey-based measure for households from the monthly European Commission survey; and (ii) a forecast-based measure from the Consensus forecast (more precisely, the one-quarter-ahead and the four-quarter-ahead Consensus forecast).

3.3 Results

3.3.1 In-sample evaluation

In this section, we analyse the in-sample fit of the Phillips curve augmented with the different global factors. Our results show an important role for commodity prices, import prices and global consumer inflation for headline inflation, when entered in a contemporaneous relationship with inflation. The coefficients of these global factors are statistically significant and positive for estimations over the entire sample from 1996Q3 to 2016Q4 (see Appendix B). They strongly improve the in-sample fit compared to the two benchmark models with an adjusted R2 of close to 0.60. The results are robust to different measures of domestic slack in the augmented Phillips curve, such as the output gap, shown in Table 1, and the unemployment rate.

[7] Mikolajun and Lodge (2016) note that a simple average closely follows a common factor of global inflation rates. We hence use the simple average as a proxy for a common global factor in our estimations.

[8] Country weights are computed by the OECD and are based on the previous year's private final consumption expenditure of households and non-profit institutions, expressed in purchasing power parities (PPP).

[9] The euro area foreign demand index computed by the ECB (Hubrich and Karlsson, 2010) corresponds to the geometric average of the real imports of the trading partners of the euro area: real imports of goods and services are weighted by the share of a given trading partner in the euro area total exports.

Dependent variable	HICP		HEX		CORE	
Model	Sign.	Adj. R2	Sign.	Adj. R2	Sign.	Adj. R2
AR		0.20		0.38		0.33
PC-OG		0.23		0.46		0.44
OG+Oil price		0.60	GF insign.	0.45	GF insign.	0.43
OG+Non-energy commodities		0.37	GF insign.	0.46	GF insign.	0.43
OG+Import prices		0.56	GF insign.	0.48	GF insign.	0.43
OG+OECD CPI ex. EA (weight.)		0.59		0.47	GF insign.	0.43
OG+US CPI		0.60		0.47	GF insign.	0.43
OG+FDR		0.41	GF insign.	0.46	GF insign.	0.44
OG+FDR (lag 4)	GF, OG insign.	0.20		0.45		0.44
OG+OG adv. econ. ex. EA (lag 1)	GF, OG insign.	0.23	GF insign.	0.46	GF insign.	0.43
OG+OG US (lag 1)	GF, OG insign.	0.23	GF insign.	0.45	GF insign.	0.44
OG+OECD core CPI ex. EA (weight.)	GF, OG insign.	0.23	GF insign.	0.45	GF insign.	0.43
OG+US core CPI	GF, OG insign.	0.23	GF insign.	0.45	GF insign.	0.43
OG+Consumer inflation exp.	OG insign.	0.30		0.53		0.47
OG+Consensus	OG insign.	0.55		0.55		0.47

Adjusted R2 for Phillips curves with the output gap estimated over the full sample period 1996Q3-2016Q4. "GF insign." stands for an insignificant coefficient of the global factor and "OG insig." for an insignificant coefficient of the domestic slack measure at a 10% significance level. Estimation details are reported in Appendix B.

Table 1: **Adj. R2 for the augmented Phillips curves and benchmark models**

The augmented Phillips curve with oil prices and the one with global consumer inflation[10] perform equally well in-sample, closely followed by the model with import prices[11]. The coefficients of global core inflation measures[12] are not statistically significant in the augmented Phillips curve for headline inflation. This illustrates that the significance of global consumer inflation should principally reflect the role of commodity prices. The coefficients of the different global slack measures are not statistically significant from zero for estimations performed over the full sample, see for instance the results for the GDP-weighted output gap of advanced economies (excluding the EA) and the US output gap provided in Table 1. These results contrast with Borio and Filardo (2007) and Auer et al. (2017), which show a positive and increasing role of global slack measures in domestic inflation rates. They are closer in line with Mikolajun and Lodge (2016), which find that measures of global economic slack are rarely significant (and positively related to domestic inflation) in Phillips curves estimates for the G7 economies. We only find a positive and significant relationship between the global output gap and domestic inflation rates during the small time period of the Great recession (2008-2010), according to rolling window estimates (see Figure 1). But even during this short period, the models with import prices or global consumer headline inflation fit domestic inflation data much better. The coefficient of the global output gap also loses its significance when it is added as a second global factor next to the more traditional global factors. Hence, we find little evidence for augmenting the Phillips curve with (non-trade-weighted) global economic slack measures, once domestic slack and more direct measures of global price pressures are taken into account. This conclusion is robust to using alternative measures of global economic slack (i.e. the unemployment rate or output gap

[10]The weighted OECD headline CPI excluding the EA as well as the US headline CPI.

[11]We tested different import price indicators but only show results for the extra-euro area import deflator here, which has the best in-sample fit.

[12]The weighted OECD core CPI excluding the EA as well as the US core CPI.

estimates derived from statistical filters) and different lags structures.

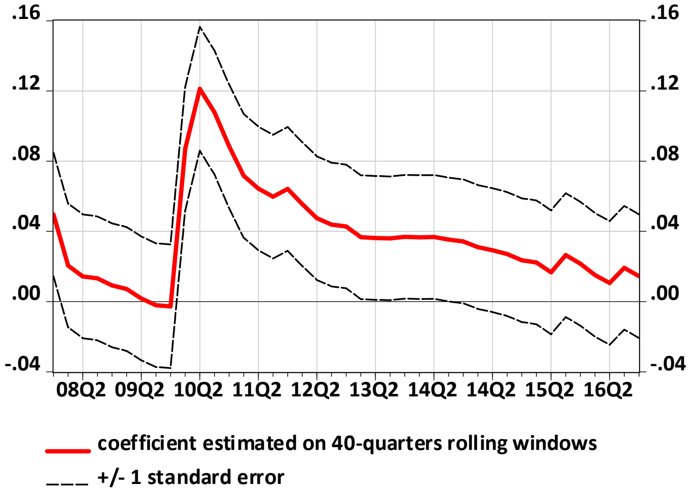


Figure 1: **Rolling coefficient γ of global output gap in an augmented backward-looking Phillips curve**

Note: The initial estimation sample covers 40 quarters from 1996Q3 to 2006Q2. Coefficients are rolled forward one quarter at a time. The model estimated corresponds to Model M8: $\pi_t = \alpha + \rho_l \pi_{t-l} + \beta og_{t-1} + \gamma ogadv_{t-1} + \varepsilon_t$ with π dlog of the headline HICP, og the lagged domestic output gap, $ogadv$ the lagged output gap of advanced economies excluding the euro area.

We find that the coefficient of trade-weighted foreign demand is statistically significant and positive in the augmented Phillips curve, even if the overall fit of the model is lower than the one of our best performing models. It seems that trade-weighted import demand has a more important influence on euro area prices than the general global demand situation, as reflected by non-trade weighted global slack measures. Foreign demand has an additional advantage compared to the commodity price or import price indicators that it seems to possess certain leading properties for domestic inflation. Its coefficient remains statistically significant even when entered with lags, in contrast to the coefficient estimates of other global factors. The hybrid Phillips curve including survey-based or forecast-based measures for inflation expectations explains inflation generally less well than the backward-looking Phillips curve augmented with global factors.

Core inflation. The importance of global factors in the augmented Phillips curve for the two core inflation measures (HICP excluding energy and HICP excluding energy and food) is considerably reduced. The coefficients of the different global factors are generally no longer statistically significant for estimations performed over the full sample from 1996Q3 to 2016Q4, except for a weak significance of the OECD CPI measure (excluding the EA) and the US CPI measure in the Phillips curve for the HICP index without energy (see Table 1). The global factors also do not improve the fit compared to the benchmark Phillips curve. This also applies to global core inflation measures[13], which do not show a significant impact on domestic core

[13] The weighted OECD core CPI excluding the EA as well the US core CPI.

inflation. Yet, we would not conclude from these results that global factors do not influence domestic core inflation at all. The impact should however be more gradual and dispersed than for the non-core elements, which are strongly driven by commodity price movements, which makes it difficult to identify it in a significant manner in a reduced-form Phillips curve type of model. For example, Chatelais and Schmidt (2017) find a significant impact of import prices on the core element of manufactured goods when relying on models which allow for a more gradual impact over time (error correction models, VAR). Rolling window estimates over a 40-quarters period suggest nevertheless that the impact of global factors on core inflation has increased lately. The coefficient turned significant over the latest period in rolling window estimates (see Figure 2), which might reflect the increasing share of imports in core consumer goods. As regards inflation expectation, we find that the inflation expectation measures (for total inflation) enhance the fit of the Phillips curve for core inflation.

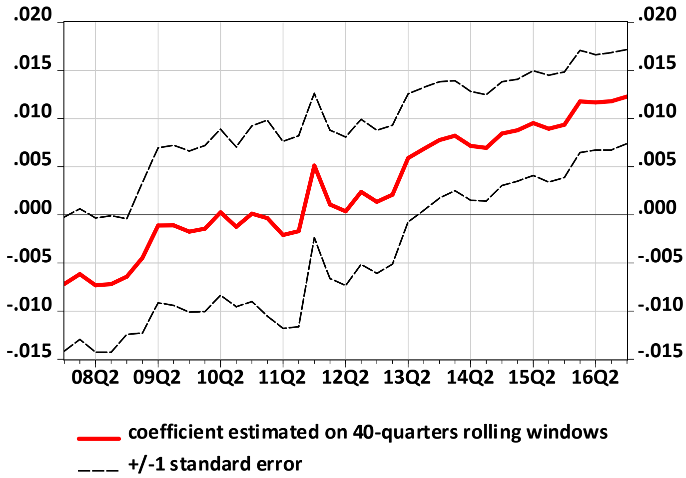


Figure 2: **Rolling coefficient γ of import prices in an augmented backward-looking Phillips curve for core inflation**

Note: The initial estimation sample covers 40 quarters from 1996Q3 to 2006Q2. Coefficients are rolled forward one quarter at a time. The model estimated corresponds to Model M3: $\pi_t = \alpha + \rho_l \pi_{t-l} + \beta og_{t-1} + \gamma z_t + \varepsilon_t$ with π dlog of the HICP excluding energy and food, og the lagged domestic output gap, z the extra-EA import deflator.

3.3.2 Forecast performance

To understand the role of global factors for forecasting inflation, we run the out-of-sample forecast setup outlined in Section 3.1 and compare the root mean squared errors (RMSE) of the augmented Phillips curves to our two benchmarks. Table 2 shows relative RMSE for the standard and the best performing augmented Phillips curve against the AR. Table 3 provides relative RMSE of the augmented Phillips curves against the standard Phillips curve. We report results for two forecast horizons, the one-quarter-ahead and the one-year-ahead forecast. The forecast comparison reveals that the standard Phillips curve for headline inflation only outperforms the AR for the one-quarter-ahead forecast during the most recent period but not during the longer forecast period. For this short period, the improvements in forecast accuracy are noticeable with

RMSE reductions of 7% for the standard Phillips curve with the output gap, 6% for the one with the unemployment rate and 14% for our preferred augmented Phillips curve with the output gap and the foreign demand index.[14] For the longer forecast period of the last ten years, we only find a small improvement in forecast accuracy of 4% for the specification with the output gap and the foreign demand index. No improvements in the forecast performance against the AR are achieved for the one-year-ahead forecast. This result that the forecast performance of the Phillips curve against simple univariate benchmark is episodic and depends on the time period confirms the results for the U.S. in Stock and Watson (2008).

	Dependent variable	Headline HICP			HEX			CORE		
	Estimation window (obs.)	74	40		74	40		74	40	
	Forecast period (obs.)	8	39		8	39		8	39	
	Forecast horizon	h=1	h=1	h=4	h=1	h=1	h=4	h=1	h=1	h=4
	Model									
AR	Autoregressive model	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PC-OG	PC(OG)	0.93	1.05	1.19	0.82	1.03	1.35	0.77	0.93	1.26
PC-U	PC(UR)	0.94	1.05	1.17	0.94	1.02	1.27	0.93	0.92	1.10
M7	OG+FDR	0.86	0.96	1.18	0.82	1.08	1.22	0.78	0.98	1.11
M12	OG+Consensus	0.93	1.09	1.25	1.12	1.00	1.36	0.90	0.90	1.33

Ratios below 1 signify a lower RMSE for the Phillips curve compared to the AR. Models are estimated on rolling windows of a fixed size of 74 quarters and RMSE are computed over 8 observations for $h = 1$ (first column for each inflation series). Models are estimated on rolling windows of a fixed size of 40 quarters and RMSE are computed over 39 observations for $h = 1$ and $h = 4$ (second and third column for each inflation series). Grey shaded cells highlight situations in which the achieved reductions in the RMSE is at least 3%. OG stands for output gap and UR for unemployment rate.

Table 2: **RMSE ratios between Phillips curves and the autoregressive model**

Table 3 shows that global factors generally do not improve the forecast ability for headline inflation compared to the standard benchmark Phillips curve. While commodity prices, import prices or global consumer inflation help to explain domestic inflation rates *ex post*, they are less powerful *ex ante* for forecasting purposes. This is even true for the very short next-quarter forecast horizon. Likewise, global core inflation measures or global slack measures do not lead to a better forecast compared to the benchmark Phillips curve. There are only two global indicators, the non-energy commodity price index and the trade-weighted foreign demand index, that achieve reductions in RMSE that are higher than 3%, both over the shorter (2015Q1-2016Q4) and the longer forecast sample (2006Q3-2016Q1) for the one-quarter-ahead forecast. The foreign demand index leads to the biggest gain in forecast accuracy of about 8% for the Phillips curve with the output gap. The usefulness of the foreign demand index is confirmed in the specification which uses the unemployment rate instead of the output gap as a measure of domestic slack. This leads us to conclude that trade-weighted import demand (the foreign demand index) is a useful leading indicator for the short-term domestic inflation forecast. On the

[14] Phillips curve with other global factors, such as oil prices or import prices, also achieve reductions in RMSE compared to the AR over the short forecast sample. Results are not shown here as this is basically due to the inclusion of the output gap. These other global factors do not improve the forecast compared to the standard Phillips curve or in a model without the output gap in comparison to the AR.

contrary, we do not find global consumer inflation to be useful for the domestic inflation forecast as in Ciccarelli and Mojon (2010), nor global slack measures as in Borio and Filardo (2007) and Auer et al. (2017). None of the global indicator improves the forecast ability for the one-year-ahead forecast. The hybrid Phillips curve specification including inflation expectations also does not outperform the standard benchmark Phillips curve according to this forecast exercise.

	Dependent variable	Headline HICP			HEX			CORE		
	Estimation sample (obs.)	74	40		74	40		74	40	
	Forecast period (obs.)	8	39		8	39		8	39	
	Forecast horizon	h=1	h=1	h=4	h=1	h=1	h=4	h=1	h=1	h=4
	Model	Backward-looking Phillips curve with the OG								
PC-OG	PC(OG)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M1	Oil price	1.01	1.00	1.05	1.02	1.17	1.06	1.08	1.08	1.01
M2	Non-energy commodities	0.92	0.96	1.01	0.97	1.03	1.03	0.97	1.03	1.02
M3	Import prices	1.00	1.00	1.04	1.00	1.08	1.04	1.04	1.06	0.99
M4	OECD CPI ex. EA (simple)	1.04	0.98	0.99	1.00	1.04	1.01	1.02	1.04	1.01
M5	OECD CPI ex. EA (weight.)	1.01	1.07	1.08	1.05	1.09	1.12	1.01	1.13	1.06
M6	US CPI	1.00	1.05	1.11	1.04	1.09	1.09	1.01	1.18	1.01
M7	FDR	0.92	0.92	0.99	1.01	1.05	0.90	1.01	1.05	0.88
M8	OG adv. econ. ex. EA	1.00	1.02	1.01	1.01	1.11	1.02	1.00	1.14	1.05
M9	OECD core CPI ex. EA (w.)	1.00	1.01	1.02	1.02	1.01	0.97*	1.02	1.00	0.97*
M10	US core CPI	1.00	1.02	1.05	1.05	1.02	0.96	1.03	1.02	0.97*
		Hybrid Phillips-curve with the OG								
M11	Consumer inflation exp.	1.00	1.02	1.00	0.99	0.97	1.04	1.01	1.02	1.11
M12	Consensus	1.00	1.04	1.05	1.37	0.97	1.01	1.16	0.97	1.06
		Phillips-curve with unemployment								
PC-U	PC(UR)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M13	FDR	0.95	0.93	0.98	0.98	1.11	0.89	0.99	1.08	0.87
M14	Consensus	0.99	1.04	1.11	1.17	0.97	1.05	0.97	0.96	1.09

Ratios below 1 signify a lower RMSE for the augmented Phillips curve compared to the benchmark Phillips curve. Models are estimated on rolling windows of a fixed size of 74 quarters and RMSE are computed over 8 observations for $h = 1$ (first column for each inflation series). Models are estimated on rolling windows of a fixed size of 40 quarters and RMSE are computed over 39 observations for $h = 1$ and $h = 4$ (second and third column for each inflation series). Grey shaded cells highlight situations in which the achieved reductions in the RMSE is at least 3%. OG stands for output gap and UR for unemployment rate. An asterisk marks the case where the coefficient of the global factor has an unexpected (i.e. negative) sign compared to what could be expected from economic theory.

Table 3: **RMSE ratios between augmented Phillips curves and the benchmark Phillips curve**

Core inflation. Regarding the out-of-sample forecast performance of the Phillips curves for core inflation (HICP without energy and HICP without energy and food), we find that they outperform the AR for the one-quarter-ahead forecast, both for the shorter forecast sample and, in the case of the HICP index without energy and food, also for the longer forecast sample (see Table 2). Average gains in forecast accuracy are higher than for headline inflation, with reductions in the RMSE of up to 8% for the HICP index excluding energy and 23% for the one excluding energy and food. This conclusion is robust to different indicators of domestic slack, such as the output gap and the unemployment rate. The specification with the output gap performs however slightly better than the one with the unemployment rate in this pseudo out-of-sample setting.[15] As could be expected from the limited significance of global factors in the in-sample analysis, global factors generally do not improve the forecast ability of the standard benchmark Phillips curve (see Table 3). An exception is the specification with the non-energy commodity price index (Model 2), which achieves small reductions in the RMSE of 3% for the one-quarter-ahead forecast for the most recent forecast period. We find more important reductions in the forecast error of around 10% for the models augmented with the foreign demand index (Model 7 and 13) for the four-quarter-ahead forecast. Similarly, we also detect smaller improvements in the forecast ability of the Phillips curve augmented with the two global core measures (Model 9 and 10) for the four-quarter-ahead forecast. These models are however unsatisfactory from an economic point of view, as the coefficient estimates (of the fourth lag) of the global core indices have a negative sign (which is non-significant over the full 1996Q3-2016Q4 sample), while economic theory would rather suggest a positive relationship between global and domestic inflation (see also Mikolajun and Lodge (2016)). This renders the interpretation of these forecast results challenging. In contrast to the results for headline inflation, we also find that inflation expectation measures in hybrid Phillips curve specifications contain useful information for forecasting core inflation.

4 Robustness analysis

4.1 Forecast performance over time

Stock and Watson (2008) highlight the unstable forecast behaviour of the Phillips curve for the U.S. over time. We want to verify this result for the euro area and compute forecast errors of the Phillips curve over rolling forecast samples of 15 quarters. Figure 3 shows these rolling forecast errors of the standard Phillips curve and some of our preferred augmented Phillips curve specifications for the one-quarter-ahead forecast for the period from 2006Q3 to 2016Q4[16]. It reports relative BRMSE (i.e. weighted RMSE) of the different models compared to the AR benchmark. The BRMSE allows to distinguish the period during which the forecast performed better by assigning bigger weights for forecast errors in the centre of the forecast window. The figure shows that the standard Phillips curve improves in its forecast ability compared to the AR from 2012 onwards (i.e. over the forecast sample 2009-2012). This is the period where the euro area output gap deteriorated sharply. Its forecast ability increases further during the euro area debt crisis and surpasses the forecast performance of the AR at the end of our sample, i.e. for forecasts from mid-2012 to 2016. The augmented Phillips curve with trade-weighted foreign demand (Model 7) works particularly well at the beginning of the forecast sample (i.e. during the Great recession period 2006-2010 where global demand fell significantly) and also at the end of the sample. The model with oil prices (Model 1) improves in its forecast ability compared to the AR - and also to the standard Phillips curve - during the period of the strong fall of oil prices (i.e. over the forecast sample 2012-2015). This fluctuating pattern of the forecast error confirms that the forecast performance of the Phillips curve for the euro area is unstable and

[15] The unemployment rate benefits however from the fact that it is only little revised, while the output gap estimates can be revised quite substantially, which might give an advantage to the unemployment rate in a real-time forecast environment.

[16] The date on the time axis of Figure 3 represents the end of the rolling 15-quarters forecast sample.

depends strongly on the forecast sample. During some time periods domestic activity variables and global factors provide however a clear forecast advantage to univariate benchmarks such as the AR. This seems to be especially the case when we observe strong movements in the predictor variables.

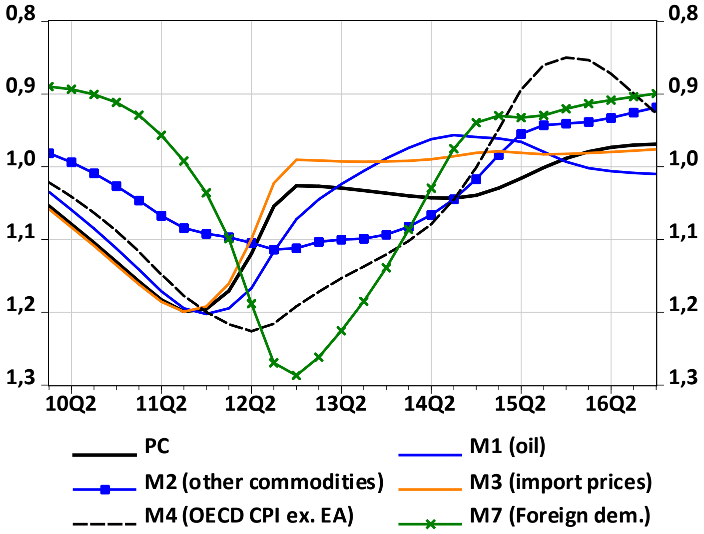


Figure 3: **Relative BRMSE between Phillips curves and the AR**

Note: Relative BRMSE are computed as the ratio of the BRMSE of the standard Phillips curve (PC) and the augmented Phillips curves (Model 1, 2, 3, 4 and 7) to the AR, realized over 15-quarters rollowing forecast windows for the one-quarter-ahead forecast $h = 1$. The date on the time axis represents the end of the 15-quarters forecast window. A smaller (higher) relative BRMSE signifies a better (worse) forecast performance. Scales are inverted.

Giacomini and Rossi (2010) provide a formal test, the so called fluctuation test, to examine whether two models have an equal forecast performance at each point of time of the rolling subsamples. We implement the fluctuation test for the standard Phillips curve to establish more formally whether it outperformed the AR during one of the 15-quarters rolling forecast periods over the 2006q3 to 2016Q4 sample for the one-quarter-ahead forecast. The test is based on the standardised local relative RMSE and we implement it as one-sided test with Clark-West critical values (see Section 4.2 for a discussion). The test results, which are shown in Appendix C, broadly confirm the results from the graphical analysis: (i) the test statistic shows a strongly fluctuating pattern and signals an unstable relative forecast performance of the two models; and (ii) the relative performance of the standard Phillips curve increases strongly towards the end of the sample (i.e. for the 2013-2016 period); however, it does not significantly outperform the AR.[17]

[17] Smaller rolling forecast windows of 8-quarters lead to a rejection of the null hypothesis of equal predictability of the two models at the end of the sample, meaning that the Phillips curve outperforms the AR over the last two years of the forecast sample, which is in line with the results in Section 3.3.2.

4.2 Test

We perform pairwise Clark-West tests [Clark and McCracken (2001) and Clark and West (2007)] (CW hereafter) to evaluate whether the small gains in forecast accuracy of the Phillips curve reported in Section 3.3.2 are statistically significant. CW propose this test for forecast comparisons in the case of nested models in order to control for the noise in the forecast evaluation coming from additional parameter estimates. The CW-test hence evaluates whether additional parameters - such as the domestic activity variable and the global factors in the Phillips curve - improve the accuracy of the forecast compared to the more parsimonious benchmark. We use the AR as benchmark for the standard Phillips curve and the standard Phillips curve as a benchmark for the augmented and hybrid Phillips curve specifications. We concentrate our analysis on the longer, 39-quarters forecast sample.

Defining the loss-forecast differential given data up to time t for horizon h as:

$$c_{t(h)} = \left(\pi_{t+h} - \pi_{1,t+h|t}\right)^2 - \left[\left(\pi_{t+h} - \pi_{2,t+h|t}\right)^2 - \left(\pi_{1,t+h|t} - \pi_{2,t+h|t}\right)^2\right]$$

with indices 1 and 2 standing, respectively, for the parcimonious benchmark and the larger model. The null hypothesis of the CW-test is then given by:

$$H_0 : \mathbb{E}[c_{t(h)}] = 0$$

vs. the alternative:

$$H_1 : \mathbb{E}[c_{t(h)}] > 0$$

The test is one-sided, as we are trying to establish whether model 2 is superior to model 1, or whether we cannot distinguish upon their forecast performance. In the latter case, model 1 is said to encompass model 2. Under the null hypothesis, the test statistic is defined as follows:

$$\mathsf{CW}_h = \frac{\bar{c}_h}{\sqrt{\sigma^{2,\mathsf{LR}}_{\bar{c}_h}/T}} \qquad (6)$$

where $\bar{c}_h$ stands for the sample mean of $c_{t(h)}$ and $\sigma^{2,\mathsf{LR}}_{\bar{c}_h}$ is a consistent estimate of the asymptotic long-run variance of $\sqrt{T} \cdot \bar{c}_h$. Given the small sample size in the rolling window estimates, we compare the test statistic to critical values from a Student-t distribution instead of asymptotically normal critical values, as proposed in Clark and West (2007). The test requires that multistep forecasts are conducted with the direct method, as it is the case in our forecast exercise.

Table 4 reports the $\mathbb{P}$-values of the CW-test. The standard PC significantly outperforms the AR for core inflation (HEX and CORE), but not for headline inflation. The Phillips curve augmented with foreign demand (Model 7) is significantly better than the AR both for headline inflation and for core inflation (for the CORE measure). As regards the comparison to the standard Phillips curve, only the augmented Phillips curve with foreign demand provides significantly better forecasts for all three inflation series: over the two forecast horizons for headline inflation

	Dependent variable	Headline HICP			HEX			CORE		
	Benchmark	AR	PC		AR	PC		AR	PC	
	Forecast horizon	h=1	h=1	h=4	h=1	h=1	h=4	h=1	h=1	h=4
	Model									
PC-OG	PC(OG)	0.51			0.07			0.00		
M7	OG+FDR	0.01	0.01	0.03	0.12	0.63	0.00	0.02	0.72	0.00
M1	OG+Oil price		0.26	0.96		0.97	1.00		0.68	0.57
M2	OG+Non-energy comm.		0.07	0.82		0.58	0.99		0.59	0.58
M5	OG+OECD CPI ex.EA		0.93	0.37		0.92	0.99		0.82	1.00
M6	OG+US CPI		0.88	0.80		0.94	0.99		0.74	0.61
M9	OG+OECD core CPI ex.EA		0.24	0.00*		0.56	0.01*		0.43	0.02*
M10	OG+US core CPI		0.61	0.08*		0.90	0.02*		0.99	0.06*
M11	OG+Consumer exp.		0.73	0.40		0.00	0.37		0.02	0.56
M12	OG+Consensus		1.00	0.74		0.03	0.59		0.01	0.99

Models are estimated over rolling windows of a fixed size of 40 quarters and forecast errors are computed over 39 quarters for $h = 1$ and $h = 4$. Grey shaded cells highlight situations in which the null hypothesis that the small nested model performs as well as the larger model is rejected at the 10% level. The standard PC and Model 7 are compared to the AR while the augmented PC and the hybrid PC are compared to the standard PC. An asterisk marks the case where the coefficient of the global factor has an unexpected (i.e. negative) sign compared to what could be expected from economic theory.

Table 4: **Pairwise Clark-West test ($\mathbb{P}$-values)**

and over the one-year-horizon for core inflation (HEX and CORE). The inclusion of non-energy commodity prices also provides a significant, if weak, improvement of the forecast ability of the Phillips curve for headline inflation for the one-quarter-ahead forecast. The CW-test also demonstrates that the global core measures significantly improve the forecast ability of the Phillips curve for core inflation (HEX and CORE). However, as highlighted in Section 3.3.2, the results are driven by negative sign estimates of the global core measures, which complicates the economic interpretation of these results.

5 Quantile regressions

In this section, we investigate the relationship between inflation and its determinants on the entire conditional distribution of inflation and not just on the conditional mean. The aim is to understand whether the impact of the dependant variables varies across inflationary regimes and if this can be used for forecasting. For this, we rely on the dynamic quantile regression approach. Our quantile regressions are motivated by Phillips curve arguments from Section 3, i.e. they include a domestic slack measure and global factors. The quantile regression approach has the advantage that it allows to model non-linearities or asymmetries in the Phillips curve relationship. There is indeed an intensive discussion in the literature about possible non-linearities in the reaction of inflation to domestic activity (see Musso et al. (2007) and Dolado et al. (2005) for a good overview on non-linearity issues). The quantile regression approach is a relative flexible approach in this sense. It allows for a non-linear reaction of inflation to domestic activity without having a prior assumption of the exact form of the asymmetry.

5.1 Methods and specification

Methods. In this paragraph, we briefly review the quantile regression approach, for further details see Koenker (2005).

Let $F_Y(y) := \mathbb{P}[Y \leq y]$ be the cumulative distribution function of a random variable Y. As recalled by D'Haultfoeuille and Givord (2014), for any $0 < \tau < 1$, the τ-th quantile of Y, denoted $q_\tau(Y)$ is defined by: $q_\tau(Y) := \inf\{y : F(y) \geq \tau\}$, which simplifies to the following relationship when the variable of interest Y (as in our case, inflation) is continuous:

$$\mathbb{P}[Y < q_\tau(Y)] = \tau \Leftrightarrow q_\tau(Y) := F_Y^{-1}(\tau)$$

Let $(Y_t)_{t=1,\dots,T}$ be a set of i.i.d. observations for Y. An intuitive way to provide an estimator for $q_\tau(Y)$, denoted $\widehat{q_\tau}(Y)$, consists in ordering those T observations by ascending order, the τ-th quantile corresponding to the $[T * \tau]$-th observation.[18] Alternatively, it can be shown that the estimator corresponds to the solution of the following minimization problem (Koenker and Bassett, 1978):

$$\widehat{q_\tau}(Y) = \mathsf{argmin}_q \left\{ \sum_{t=1}^{T} \rho_\tau (Y_t - q) \right\} = \mathsf{argmin}_q \left\{ \sum_{y_t - q \geq 0} \tau |Y_t - q| + \sum_{y_t - q < 0} (1-\tau)|Y_t - q| \right\}$$

with $\rho_\tau(u) = (\tau - \mathbb{I}_{\{u<0\}}) \cdot u$, the loss function with $1_{\{\mathsf{Condition}\}}$ the indicator function that takes value 1 if the condition in brackets is satisfied, 0 otherwise.
For example, for $\tau = 0.5$, the sample median is obtained as the solution to the problem of minimising a sum of equally weighted absolute residuals: $\widehat{q}_{0.5}(Y) = \mathsf{argmin}_q \sum_{t=1}^{T} |Y_t - q|$.
For $\tau \neq 0.5$, quantiles other than the median can be obtained by minimising a sum of asymmetrically weighted absolute residuals, i.e. giving differing weights to positive and negative residuals, where the weights are asymmetric functions of τ.

Specifications. Quantile regressions aim to assess how conditional quantiles $q_\tau(Y|X) = F^{-1}_{Y|X}(\tau)$ change with respect to changes in the dependant variables X. As such, and as recalled by Koenker (2005), they can be viewed as an extension of classical least square estimation method of conditional mean models, in the way that they provide estimates for a set of conditional quantile functions assuming potentially heterogeneous specifications. We consider the following general quantile specification:

$$q_\tau(\pi_t|X_t) = \alpha^{(\tau)} + \rho^{(\tau)}\pi_{t-1} + \beta^{(\tau)}y_{t-1} + \sum_{l=0}^{Max=4} \gamma_l^{(\tau)} z_{t-l} + \varepsilon_t^{(\tau)} \tag{7}$$

with $X_t = (1, \pi_{t-1}, y_{t-1}, z_{t-l})'$ the set of dependant variables as defined in Section 3.1. As all our specifications include past inflation, we talk about "dynamic quantile regressions", for which standard techniques and metrics apply. Given the limited size of our sample, we employ resampling techniques (bootstrap) to derive inference, as suggested by Koenker and Xiao (2002).

[18] $[T * \tau]$ here characterizes the smallest integer being greater or equal to $T * \tau$.

Models are estimated for different quantile orders.[19] Estimation results for the full sample period from 1996Q3 to 2016Q4 are reported in Appendix E.1. As a measure of goodness-of-fit for quantile regression, we rely on the pseudo R^2 proposed by Koenker and Machado (1999), based on the residual absolute sum of weighted differences (RASW):

$$RASW_\tau = \sum_{y_t - \widehat{q}_{\tau,t}(y) \geq 0} \tau |y_t - \widehat{q}_{\tau,t}| + \sum_{y_t - \widehat{q}_{\tau,t} < 0} (1-\tau)|y_t - \widehat{q}_{\tau,t}|$$

where $\widehat{q}_{\tau,t}$ is the fitted τ-quantile at time t. The pseudo R^2 is constructed as the coefficient of determination in OLS and is defined as:

$$R^2_\tau = 1 - \frac{RASW_\tau}{TASW_\tau}$$

where $TASW_\tau$ is the total sum of weighted differences and with R^2_τ ranging between 0 and 1.

5.2 Estimation results

In a first step, we compute residual densities from linear OLS for the augmented Phillips curves with the best in-sample fit (respectively Model 1 and 3, each with the output gap and the unemployment rate as a measure of domestic slack) in order to compare it to the standard normal distribution. The density functions and normal Q-Q-plots[20] in Appendix D show clear departure of the residuals from the Gaussian norm, especially for Model 1 and especially in the tails. Non-normalities are of lesser extent for Model 3, but we still observe extreme realizations in the upper quantiles. This motivates our interest to further explore the conditional distribution of inflation. In the case of non-normal errors, non-linear estimators might be more efficient estimators than OLS.

Quantile regression estimates for Models 1 and 3 are reported in Appendix E.2. Slope equality tests based on Koenker and Bassett (1982) reveal that coefficients differ across quantiles, especially for Model 1.[21]

Quantile regression estimates are summarized into graphical representations of quantile-specific slopes in Figure 4 (see Appendix E.1 for the quantile slopes of the other specifications). We see important variations in the impact of the dependent variables over different quantiles, even if they are not always significantly different from the mean impact. We observe notably a - significantly - higher impact of lagged inflation on current inflation at the left tail of the distribution. This implies that inflation is more persistent during low inflation times. This is in line with the findings in Busetti et al. (2015). Regarding the output gap, we find an increasing response of inflation to (lagged) domestic slack at the right tail of the distribution, i.e. domestic slack measures seem

[19] We experimented with different quantile orders, i.e. $\tau = 0.1, 0.25, 0.5, 0.75, 0.9$ and $\tau = 0.1, 0.2, 0.4, 0.6, 0.8$. The maximum quantile order is however restricted to 10 given the limited sample size.

[20] Normal Q-Q-plots compare the sample quantiles on the vertical axis to the theoretical quantiles of the standard normal distribution on the horizontal axis

[21] This result is somewhat sensitive to the chosen quantile order. The Chi-square test rejects the null hypothesis of equal quantile coefficients at the 5%-level for quantile order $\tau = 0.1, 0.2, 0.4, 0.6, 0.8$ but not for quantile order $\tau = 0.1, 0.25, 0.5, 0.75, 0.9$ for Model 1. But even for the latter, pairwise comparison tests across quantiles still reveal significant differences in the quantile coefficients for some of the quantiles.

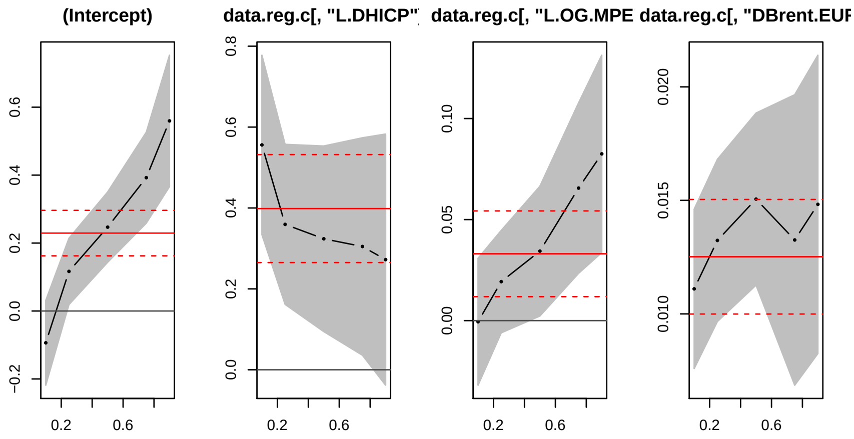


Figure 4: **Quantile slopes for the dependent variables for Model 1 for headline inflation**

to play a stronger role during high inflation times. The (contemporaneous) impact of the global factor on inflation varies somewhat less over the conditional inflation quantiles. For the model with oil prices (Model 1), the impact increases towards the median, before falling back again at higher quantiles. For the model with import prices (Model 3), the impact is relatively stable and close to the median across the conditional distribution before jumping up abruptly at the very high end of the distribution (i.e. for high levels of inflation). This diverging impact of the dependant variables on inflation across conditional quantiles implies that when assuming mean coefficients, we may either over- or underestimate their impact on inflation. If inflation was located at the lower end of the conditional distribution, we might notably underestimate the impact of past inflation. Also, during low inflation periods, the impact of domestic slack and global factors might be somewhat smaller than during normal and high inflation times. The higher persistency of the inflation process at the left tail of the distribution could also explain why Ciccarelli and Osbat (2017) find an increase of the persistency of inflation over the most recent period of low inflation from 2014 to 2016.

5.3 Forecast performance

Quantile regressions are generally used to derive forecast distributions based on the forecast quantiles. We consider an alternative approach to evaluate whether the quantile regression results can be useful for forecasting purposes. We conduct point forecasts from quantile regressions based on specific quantiles and compare it to the forecasts from OLS.[22] We concentrate our analysis on the most recent period of low inflation from 2014 to 2016 and use the quantile regression model corresponding to the quantile of past observed inflation. Hence, to forecast inflation for $t+1$ with quantile regressions, we rely on the model corresponding to the quantile of observed inflation at date t, based on the historical distribution of inflation up to date t. For instance, in 2013Q4, headline inflation was located at the extreme left of the distribution (first quantile). We then conduct the one-quarter-ahead forecast for 2014Q1 based on the model corresponding to the first quantile and compare it to observed inflation. We then roll the estimation one quarter forward, recalculate the historical distribution up to 2014Q1 and make forecasts based on the

[22]We focus on the one-quarter-ahead forecast for which the quantile models are better identified.

model for the observed inflation quantile in 2014Q1, and so forth. We analyse two forecast periods: (i) the period from 2014 to 2015, where inflation was persistently low and located most of the time in the first quantile of the distribution (except for the one quarter in 2015Q3), and (ii) the period from 2014 to 2016, where inflation rebounded.

	Dependent variable	Headline HICP	
	Forecast period	2014-2015	2014-2016
	Model		
PC-OG	OG	0.78	1.17
M1	OG+oil price	0.74	1.11
M3	OG+import prices	0.77	1.17
M5	OG+OECD CPI ex. EA (weight.)	0.68	1.01
M7	OG+FDR	0.74	1.17

Models are estimated on rolling windows of a fixed size of 71 quarters. Mean absolute forecast errors (MAE) for $h = 1$ are computed over two forecast periods: 2014Q1 to 2015Q4 (8 observations) and 2014Q1-2016Q4 (12 observations). Ratios below 1 signify a lower MAE for the quantile regressions compared to OLS. OG stands for output gap.

Table 5: **MAE ratios between quantile regressions and OLS for headline HICP ($h = 1$)**

Table 5 reports the relative mean-absolute forecast errors (MAE) for quantile regressions compared to the corresponding OLS estimates. For the period of persistently low inflation from 2014 to 2015, forecasts produced by quantile regressions are superior to the corresponding OLS forecasts for all of the specifications. The gains in forecast accuracy are quite large, with improvements in the MAE of between 22% and 32%. The best overall forecast model for this period (Quantile Model 7 with the foreign demand index) has a MAE of 0.20 compared to 0.27 for the corresponding OLS estimate with Model 7 (the best OLS model) and to 0.30 for the OLS estimate of the standard Phillips curve. We also find that most of the quantile models augmented with global factors (Model 1, 5 and 7) outperform the quantile model including only the domestic slack variable. These results change however when we look at the longer forecast period from 2014 to 2016, which includes the pick-up of inflation in 2016. For this period, quantile regressions no longer outperform the forecast ability of the corresponding OLS estimates. The lowest forecast error of 0.26 is achieved with the OLS Model 7, compared to a MAE of 0.29 for the quantile model with the lowest MAE (Model 5) and of 0.30 for the quantile model 7. These results leave us to conclude that quantile regressions can be a useful addition to OLS for forecasting short-term headline inflation in periods of persistently low (or high) inflation. Quantile regressions are of lesser use for forecasting during periods of volatile inflation. In such periods, quantile regressions do not provide better forecast results than OLS.

6 Conclusion

In this paper, we examined the fit and the forecast ability of the Phillips curve augmented with different global indicators for euro area inflation. We show that global factors generally improve the fit of the Phillips curve for headline inflation but that they are less relevant for forecasting, with one notable exception of trade-weighted foreign demand. While introducing traditional global indicators such as commodity prices and import prices or global consumer inflation into the Phillips curve improves its fit, we find little support for introducing global slack measures into the Phillips curve, once domestic slack and more direct measures of global price pressures have been taken into account. Regarding core inflation, the importance of global factors is considerably reduced and difficult to establish in a significant manner in a Phillips curve framework. Anticipation measures from surveys or forecasts contain more useful information for explaining core inflation. Overall, we conclude that the Phillips curve remains a useful tool for studying and forecasting inflation. The forecast behaviour of the Phillips curve in its standard or augmented form is however not stable over time, especially as regards headline inflation, and it performs better during some periods such as the recent period of low inflation than during others. Turning to quantile considerations, our results confirm the interest of exploring the entire conditional distribution of inflation in addition to standard conditional mean estimation by OLS. We show that the tail behaviour of some of the predictors such as the lagged inflation term and domestic slack do matter and that there exists asymmetries in the reaction of inflation to these predictors. Forecasts from quantile regressions can be a useful addition to forecasts from OLS in periods of persistently low inflation. This result could be exploited further by extending the analysis to different time periods or contexts. Further alleys to investigate concern notably a more exhaustive description of the macroeconomic environment (crisis vs. normal time, high vs. low volatility of the global factors), in addition to the inflationary regime, which determines the forecast ability of the Phillips curve.

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A Data sources and descriptions

Description	Source	Details
	Euro area inflation	
HICP headline	Eurostat	sa(X12)
HICP ex. energy and food	Eurostat	sa(X12)
HICP ex. energy	Eurostat	sa(X12)
Household's inflation expectations	European Commission	sa, price trends over next 12 months
Consensus forecast	Consensus Economics	One quarter and four quarters ahead forecast
	Euro area slack	
EA Unemployment rate	Eurostat	sa
EA unemployment gap	ECB & authors' calc.	Difference between NAIRU and unemployment rate
EA OG	European Commission	Cubic spline
EA OG	ECB	Cubic spline
EA OG	Eurostat & authors' calc.	Real GDP sa, HP filtered
EA industrial production	Eurostat	sa
	Global factors	
	Commodities	
Oil price, USD	ECB	Brent crude oil price in USD
Oil price, EUR	ECB	Brent crude oil price in EUR
Price of non-energy commodities, EUR	ECB	
	Exchange rates	
USD/EUR exchange rate	ECB	Exchange rate against euro, spot (mid)
Nominal effective exchange rate	ECB	Exchange rate against 12 trading partners
Nominal effective exchange rate	ECB	Exchange rate against 19 trading partners
Nominal effective exchange rate	ECB	Exchange rate against 38 trading partners
	Foreign demand and global slack	
Foreign demand index (FDR)	ECB	Trade-weighted imports of EA trading partners
OG, US	IMF	Cubic spline
OG, advanced economies*	IMF & authors' calc.	GDP-weighted, cubic spline
OG, adv. economies ex. EA	IMF & authors' calc.	GDP-weighted, cubic spline
OG, emerging markets	IMF & authors' calc.	GDP-weighted, cubic spline
OG, US-JPN-UK-CAN	IMF & authors' calc.	GDP-weighted, cubic spline
OG, world	IMF	Cubic spline
OG, world ex. EA	IMF & authors' calc.	GDP-weighted, cubic spline
US unemployment rate	OECD	sa
OECD unemployment rate	OECD	Unemployment rate of advanced economies, sa
Unemployment rate, OECD ex. EA	OECD & authors' calc.	sa, GDP-weighted
Unemployment rate, US-JPN-UK-CAN	OECD & authors' calc.	sa, GDP-weighted
	Global inflation	
OECD CPI ex. EA	OECD & authors' calc.	Simple or weight. avg., exp.-weighted, sa(X12)
CPI, US-JPN-UK-CAN	OECD & authors' calc.	Simple or weight. avg., exp.-weighted, sa(X12)
US CPI	OECD & authors' calc.	sa(X12)
World** CPI ex. EA	OECD & authors' calc.	Simple or weight. avg., exp.-weighted, sa(X12)
OECD CPI (ex. EA) ex. food & energy	OECD & authors' calc.	Simple or weight. avg., exp.-weighted, sa(X12)
World CPI (ex. EA) ex. food & energy	OECD & authors' calc.	Simple or weight. avg., exp.-weighted, sa(X12)
CPI ex. food & energy, US-JPN-UK-CAN	OECD & authors' calc.	Simple or weight. avg., exp.-weighted, sa(X12)
US CPI ex. food & energy	OECD & authors' calc.	sa(X12)
Competitors' prices, USD	ECB	Export prices of extra EA trading partners in USD
Competitors' prices, EUR	ECB	Export prices of extra EA trading partners in EUR
Import deflator, EUR	Eurostat	Extra EA import deflator
Relative import deflator, EUR	Eurostat & authors' calc.	Extra EA Import deflator against GDP deflator

*Australia, Canada, Denmark, Japan, Korea, New Zealand, Norway, Sweden, the United Kingdom, the United States and the euro area.
**Members of the G20 and members of the OECD (Australia, Brazil, Canada, Chile, China, Colombia, Denmark, Hungary, Iceland, India, Indonesia, Israel, Japan, Korea, Lithuania, Mexico, New Zealand, Norway, Poland, Russia, Saudi Arabia, South Africa, Sweden, Switzerland, Turkey, the United Kingdom, the United States and EA).
Note: CPI stands for Consumer price index, HICP for Harmonized index of consumer prices, OG for output gap, sa for seasonally adjusted

B OLS estimates of augmented Phillips curves

						Headline inflation					
Models	AR1	PC(OG)	PC(UR)	M1	M2	M3	M4	M5	M6	M7	M8
Intercept	0.22***	0.27***	0.89**	0.24***	0.28***	0.31***	-0.06	0.04	0.13***	0.24***	0.38***
Lagged inflation	0.45***	0.36**	0.34***	0.38***	0.30**	0.20**	0.20*	0.18**	0.20*	0.20**	0.34***
Lagged EA OG / UR		0.04*	-0.06*	0.03*	0.04*	0.05***	0.02	0.04**	0.03*	0.06***	0.03
Oil price EUR				0.01***							
Non-energy commodity prices					0.02***						
Import prices						0.08***					
OECD CPI ex. EA (simple)							0.55***				
OECD CPI ex. EA (weight.)								0.54***			
US CPI									0.38***		
FDR										0.07***	
Lagged OG adv. ex. EA											0.00
Adjusted R2	0.20	0.23	0.24	0.60	0.37	0.56	0.49	0.59	0.60	0.41	0.23
Observations	82	82	82	82	82	82	82	82	82	82	82
Models	M9	M10	M11	M12	M13	M14					
Intercept	0.30	0.17	0.25**	0.12*	1.03***	0.09					
Lagged inflation	0.35**	0.35**	0.33**	-0.36***	0.22**	-0.37***					
Lagged EA OG / UR	0.04	0.03*	0.04	0.00	-0.08***	-0.02					
OCDE CORE CPI ex. EA	-0.06										
US CORE CPI		0.18									
Consumer infl. expectations			0.00								
Consensus				0.41***		0.39***					
Foreign demand					0.07***						
Adjusted R2	0.23	0.23	0.23	0.55	0.40	0.55					
Observations	82	82	82	82	82	82					

Notes: Stars *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively. Models are estimated over the 1996Q3-2016Q4 sample. Commodity prices and import prices are in EUR. Variables are in log-difference, except for the output gap, which is introduced in levels.

Table 6: Estimation results for Phillips curves for headline infation

Dependent variable: HICP excluding energy (HEX)

Models	AR1	PC(OG)	PC(UR)	M1	M2	M3	M4	M5	M6	M7	M8
Intercept	0.14***	0.23***	0.64***	0.22***	0.23***	0.21***	0.16**	0.19***	0.20***	0.21***	0.23***
Lagged inflation	0.63***	0.10***	0.45***	0.41***	0.40***	0.43***	0.39***	0.40***	0.41***	0.40***	0.40***
Lagged EA OG / UR		0.03**	-0.04***	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03***	0.03*
Oil price EUR				0.00							
Non-energy commodity prices					0.00						
Import prices						0.01					
OECD CPI ex. EA (simple)							0.10*				
OECD CPI ex. EA (weight.)								0.07*			
US CPI									0.04*		
FDR										0.01	
Lagged OG adv. ex. EA											0.00
Adjusted R2	0.38	0.46	0.45	0.45	0.46	0.48	0.49	0.47	0.47	0.46	0.46
Observations	82	82	82	82	82	82	82	82	82	82	82

Models	M9	M10	M11	M12	M13	M14
Intercept	0.23***	0.20**	0.20***	0.15***	0.63***	0.20**
Lagged inflation	0.40***	0.40***	0.25*	0.20*	0.45***	0.40***
Lagged EA OG / UR	0.03**	0.03**	0.03***	0.02**	-0.04***	-0.03**
OCDE CORE CPI ex. EA	-0.01					
US CORE CPI		0.05				
Consumer infl. expectations			0.01**			
Consensus				0.09***		0.05***
Foreign demand					0.01	
Adjusted R2	0.45	0.45	0.53	0.55	0.45	0.45
Observations	82	82	82	82	82	82

Notes: Stars *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively. Models are estimated over the 1996Q3-2016Q4 sample. Commodity prices and import prices are in EUR. Variables are in log-difference, except for the output gap, which is introduced in levels.

Table 7: Estimation results for Phillips curves augmented for inflation excluding energy

Dependent variable: HICP excluding energy and food CORE)

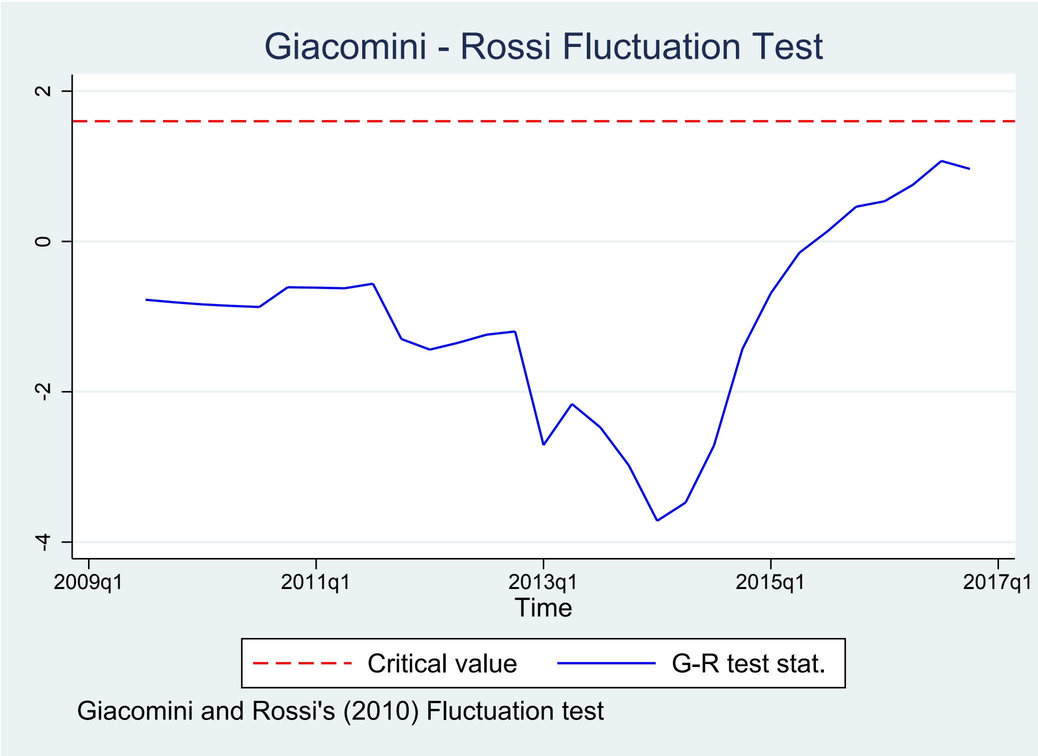
Models	AR1	PC(OG)	PC(UR)	M1	M2	M3	M4	M5	M6	M7	M8
Intercept	0.14***	0.24***	0.60***	0.24***	0.24***	0.23***	0.20***	0.23***	0.21***	0.23***	0.24***
Lagged inflation	0.58***	0.31***	0.37***	0.30***	0.31***	0.32***	0.32***	0.31***	0.31***	0.31***	0.31***
Lagged EA OG / UR		0.03***	-0.04***	0.03**	0.03***	0.03***	0.03**	0.03***	0.03**	0.03***	0.03***
Oil price EUR				0.00							
Non-energy commodity prices					0.00						
Import prices						0.00					
OECD CPI ex. EA (simple)							0.05				
OECD CPI ex. EA (weight.)								0.02			
US CPI									0.01		
FDR										0.00	
Lagged OG adv. ex. EA											0.00
Adjusted R2	0.33	0.44	0.43	0.43	0.43	0.43	0.44	0.43	0.43	0.44	0.43
Observations	82	82	82	82	82	82	82	82	82	82	82

Models	M9	M10	M11	M12	M13	M14
Intercept	0.23***	0.21***	0.20***	0.19***	0.60***	0.47***
Lagged inflation	0.31***	0.31***	0.29**	0.25*	0.37***	0.27***
Lagged EA OG / UR	0.03***	0.03***	0.02***	0.02***	-0.04***	-0.03***
OCDE CORE CPI ex. EA	0.00					
US CORE CPI		0.04				
Consumer infl. expectations			0.00**			
Consensus				0.04**		0.04***
Foreign demand					0.00	
Adjusted R2	0.43	0.43	0.47	0.47	0.42	0.47
Observations	82	82	82	82	82	82

Notes: Stars *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively. Models are estimated over the 1996Q3-2016Q4 sample. Commodity prices and import prices are in EUR. Variables are in log-difference, except for the output gap, which is introduced in levels.

Table 8: Estimation results for Phillips curves for inflation excluding energy and food

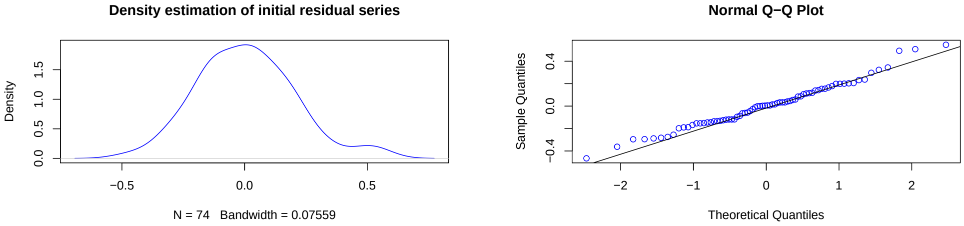
C Giacomini and Rossi's fluctuation test



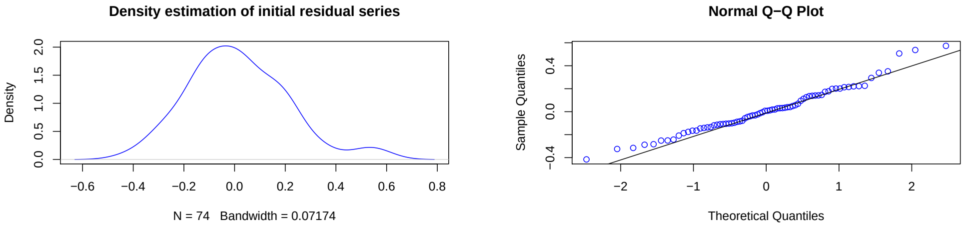
Note: Giacomini and Rossi's one-sided fluctuation test for the standard Phillips curve and the AR over 15-quarters rolling forecast window for $h = 1$. The test rejects the null hypothesis of equal predictive ability when the test statistic is above the band line.

D Residual densities

Density plots of residuals from estimated model M1 and variations

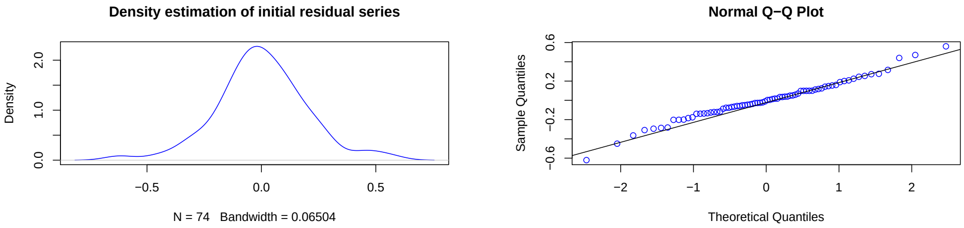


Model 1 with OG

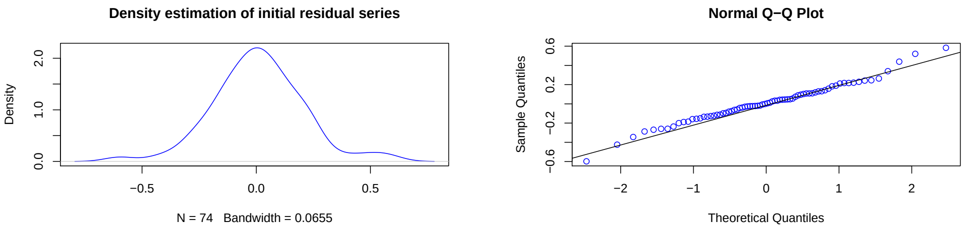


Model 1 with UR

Density plots of residuals from estimated model M3 and variations



Model 3 with OG



Model 3 with UR

E Quantile inference

E.1 Quantile slopes

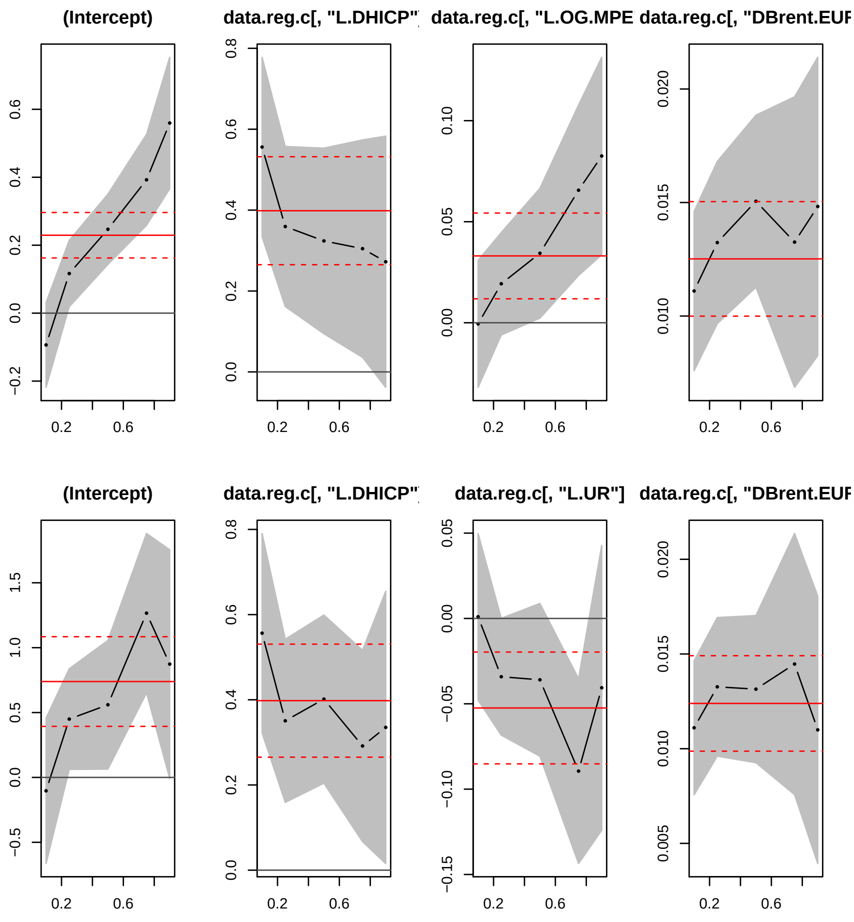
E.2 Quantile regression estimates

Table 9: Quantile regression estimates for headline inflation

	Dependent variable: Headline inflation				
Quantile τ	0.10	0.25	0.50	0.75	0.90
			PC1		
Intercept	-0.113 (0.108)	0.087 (0.093)	0.243 (0.089)	0.400 (0.098)	0.701(0.141)
Lagged inflation	0.516 (0.207)	0.500 (0.202)	0.448 (0.176)	0.362 (0.193)	0.059 (0.255)
Lagged EA Output gap	0.004 (0.041)	0.041 (0.026)	0.038 (0.024)	0.047 (0.027)	0.064 (0.038)
Pseudo R2	0.15	0.18	0.17	0.15	0.16
			Model 1 Oil price in EUR		
Intercept	-0.076 (0.077)	0.117 (0.059)	0.242 (0.082)	0.425 (0.072)	0.557 (0.103)
Lagged inflation	0.531 (0.128)	0.366 (0.124)	0.337 (0.163)	0.247 (0.142)	0.265 (0.170)
Lagged EA Output gap	-0.002 (0.022)	0.018 (0.016)	0.032 (0.024)	0.058 (0.024)	0.063 (0.031)
Oil price EUR	0.011 (0.002)	0.013 (0.002)	0.014 (0.002)	0.013 (0.003)	0.013 (0.003)
Pseudo R2	0.52	0.45	0.38	0.32	0.32
			Model 3 Import prices		
Intercept	0.075 (0.087)	0.161 (0.066)	0.322 (0.070)	0.436 (0.075)	0.589 (0.098)
Lagged inflation	0.224 (0.158)	0.297 (0.142)	0.211 (0.143)	0.179 (0.162)	0.105 (0.186)
Lagged EA Output gap	0.043 (0.031)	0.041 (0.015)	0.055 (0.019)	0.057 (0.025)	0.069 (0.033)
EA import prices	0.085 (0.020)	0.082 (0.024)	0.074 (0.023)	0.088 (0.021)	0.093 (0.025)
Pseudo R2	0.39	0.38	0.35	0.32	0.32
			Model 5 OECD CPI ex.EA (weighted average)		
Intercept	-0.151 (0.094)	-0.088 (0.062)	-0.007 (0.065)	0.176 (0.073)	0.264 (0.123)
Lagged inflation	0.191 (0.174)	0.277 (0.128)	0.268 (0.137)	0.091 (0.140)	0.059 (0.179)
Lagged EA Output gap	0.025 (0.023)	0.027 (0.017)	0.030 (0.019)	0.028 (0.021)	0.034 (0.026)
OECD inflation ex. EA	0.511 (0.117)	0.500 (0.092)	0.575 (0.097)	0.611 (0.129)	0.623 (0.185)
Pseudo R2	0.42	0.41	0.37	0.33	0.33
			Model 7 Foreign demand index		
Intercept	-0.111 (0.010)	0.007 (0.072)	0.181(0.052)	0.334 (0.117)	0.687 (0.141)
Lagged inflation	0.277 (0.200)	0.304 (0.133)	0.374 (0.117)	0.349 (0.165)	0.250 (0.187)
Lagged EA Output gap	0.043 (0.032)	0.046 (0.018)	0.044 (0.016)	0.046 (0.023)	0.055 (0.040)
FDR	0.099 (0.025)	0.108 (0.022)	0.057 (0.015)	0.031 (0.027)	-0.046 (0.053)
Pseudo R2	0.38	0.32	0.28	0.18	0.14

Notes: Estimated coefficients for quantile orders $\tau = 0.10, 0.25, 0.50, 0.75, 0.90$. Estimation period: 1996-2016. Standard errors computed by bootstrap are reported in brackets.

Estimated parameters, Model M1 and variations



Estimated parameters, Model M3 and variations