Inflation forecasts in the euro area: New Insights from Phillips Curve estimates and quantile regressions

First draft version

Sophie Béreau*   Violaine Faubert†   Katja Schmidt‡

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Abstract

Accurate forecasts of inflation are 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 in the light of global disinflationary shocks, such as strong fall in oil prices. In this paper, we build on the recent literature emphasizing the importance of both global and domestic factors for forecasting inflation with the aim (i) to document the relative performance of a large number of alternative measures of global factors for forecasting euro area inflation, as well as (ii) to highlight under which conditions some factors can be expected to outperform the others. We base our analysis on augmented Phillips curve estimates for a forecast horizon of up to one year ahead. Our results show that taking into account global factors significantly improves the accuracy of mean forecasts for euro area inflation, compared to standard benchmarks. However, while adding external supply shock indicators or global inflation improves forecasts, we find little support for introducing global economic slack measures to the Phillips curve. Turning to quantile regressions, our results document the differentiated impact of inflation covariates accross time and economic contexts (low vs. high inflation) and provide evidence that accurately averaging quantile information can also lead to more accurate forecasts of conditional mean inflation.

JEL Classification: E31, E37, C22, C53

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1 Introduction

Accurate forecasts of inflation are of paramount importance for central banks, whose objective is to deliver price stability. Since 2013, both headline and core inflation in the euro area have been lower than the forecasts produced by the Eurosystem and by other institutions. Inflation

*CeReFiM, Université de Namur and CORE, Université catholique de Louvain. E-mail: `sophie.bereau@uclouvain.be`

†Banque de France. E-mail: `violaine.faubert@banque-france.fr`

‡Banque de France. E-mail: `katja.schmidt@banque-france.fr`

was persistently below target in the euro area since 2013, largely due to global disinflationary shocks related to the decline in oil prices, but also to domestic economic slack (Ciccarelli and Osbat, 2017). Within this context, our current contribution is twofold:

First, our study contributes to the growing literature on how global factors affect domestic inflation. Within the framework of augmented backward-looking Phillips curves, we investigate the role of different global factors - commodity prices, exchange rate fluctuations, import prices, global consumer inflation, global economic slack and global demand - in forecasting the mean of euro area inflation. We argue that taking into account global factors improves the accuracy of mean forecasts compared to a range of benchmark models, notably an Autoregressive (AR) model and a standard backward-looking Phillips curve. Global consumer inflation does not seem to contain much additional information for domestic inflation compared to more traditionally used indicators such as commodity prices and import prices. The set of best perfoming models is however not constant over time and some global indicators perform better during some periods than during others. While adding different indicators of global price pressures significantly improves forecasts for the euro area inflation, we find little evidence to support the case for introducing global economic slack in augmented Phillips curves. We also compare the performance of augmented Phillips curves to a more data-rich model in form of a Bayesian VAR, including both global and domestic factors, and conclude that the two perform almost equally well in forecasting euro area inflation. This shows that the Phillips curve remains useful to understand inflation dynamics over a short forecast horizon of up to one year ahead.

Second, we contribute to the scarce literature exploring whether indicators of domestic activity and global factors are useful in predicting the entire conditional distribution of inflation. More specifically, we document the differentiated impact of inflation covariates in general and global factors in particular, accross conditional quantiles of euro area inflation series. For instance, we show that the impact of import prices is predominent over high inflation regimes whereas the influence of oil prices decreases over extreme quantiles (i.e. both high and low). Turning to forecast considerations, we show that quantile regressions can improve forecasts in some periods of persistantly low (or high) inflation. By relying on Zhao and Xiao (2014), we also provide evidence that accurately averaging quantile information can lead to better forecast for the conditional mean.

The remainder of the paper is organized as follows. Section 2 briefly surveys the empirical literature. In Section 3, we examine the role of both domestic and global factors for forecasting the euro area mean inflation in augmented Phillips curves, followed by Section 4 where we implement some testing and review alternative modelling as robustness checks. In Section 5, we explore whether both the domestic and global factors selected in previous sections help in predicting the entire conditional distribution of euro area inflation. We then compare forecast performances of both time series and quantile regression models to evaluate whether quantile regression techniques can hedge against bad forecast performance in particular episodes, such as the subdued inflation period observed between 2013 and 2016. 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 forecast performances of Phillips curves. We also relate to that documenting the role of global factors in domestic inflation dynamics. Finally, we explore quantile regressions applied to forecasting the entire conditional distribution of inflation.

Phillips curves forecast performances. 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 heavily depend on the sample 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 four-quarter random walk benchmark over the period 1984-1999, whereas Stock and Watson (2008) argue that Phillips curves can be useful in some states of the economy, such as the late 1990s. Though comprehensive studies on Phillips curves performances have been undertaken for the U.S., fewer works are available for the euro area. Banbura and Mirza (2013) examine the pseudo out-of-sample performance of a wide range of Phillips curve models for different measures of euro area inflation (headline, core and GDP deflator) over the period 1994-2011. They conclude that, though the best specifications vary substantially depending on the sample period, the best models most often contain either the unemployment rate/gap or GDP growth/gap as an activity variable. The inclusion of a supply shock indicator, such as oil prices, the euro effective exchange rate or import prices, overall improves on the results, although there does not seem to be any clear specification that would systematically beat the others over time.

The role of global factors in explaining domestic inflation. While the role of external supply shock indicators in headline inflation is relatively well documented in the literature, an increasing number of studies looks at the influence of global inflation tendencies and global economic slack on domestic inflation. This strand of literature argues that domestic inflation is being increasingly sensitive to global economic slack which might not only play an indirect role on domestic inflation (via its effect on import prices and domestic output gaps) but also a direct one. One explanation is that globalisation has rendered domestic inflation less responsive to domestic capacity constraints, either because a sudden demand shock would bolster imports rather than increase prices, or because exposure to foreign competitors curtails increases in domestic tradable prices (Guerrieri, Gust, and Lopez-Salido, 2008). 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 exogenous global factors. However, the empirical evidence is mixed, especially regarding the role of global slack. Borio and Filardo (2007) emphasize the role of the global output gap as a determinant of domestic inflation in advanced economies and argue that the role of global factors has been growing over time. Auer, Borio, and Filardo (2017) argue that, as participation in global value chains increases, competition among economies in-

[1] Following Stock and Watson (2008), we interpret Phillips curve forecasts broadly to include forecasts produced using an activity variable, such as the unemployment rate or the output gap, perhaps in conjunction with other variables, such as external supply shock indicators.

creases, making domestic inflation more sensitive to the global ouput 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 that of global slack. However, other studies find conflicting evidence and suggest that Borio and Filardo (2007) results heavily depend on the estimation sample or a particular measurement of the global economic slack. Mikolajun and Lodge (2016) detect no direct effect of global economic slack on domestic inflation for advanced economies. Ciccarelli and Mojon (2010) analyse the role of a global inflation factor when forecasting domestic inflation rates in OECD member countries and conclude that models including a measure of global inflation consistently improve national inflation forecasts. Confirming these results, Medel, Pedersen, and Pincheira (2014), using a sample of OECD countries, conclude that accounting for global inflation improves the inflation forecast for headline and core inflation in most members of the euro area. However, the gains in forecast accuracy are modest: pseudo out-of-sample horse races reveal that, among the euro area members of the sample, only Italy and Slovakia achieve reductions in RMSE that may be considered of economic relevance (i.e. higher than 5%). On the contrary, Mikolajun and Lodge (2016) argue that, with the exception of commodity prices, there is little reason to include global factors into traditional Phillips curves for advanced economies once estimates exclude the volatile inflation period of the 1970s-1980s. Mikolajun and Lodge (2016) find that from the mid-1990s onwards, the coefficients on global inflation are insignificant in most OECD countries: global inflation measures are helpful for forcasting domestic inflation during periods of high and volatile inflation (i.e. the 1970-80s), but less so since inflation has receeded.

Quantile regressions. Much of the inflation forecasting literature focuses on the ability of macroeconomic indicators to predict conditional mean inflation whereas some interesting features may well locate in the tails or at least in areas of the conditional distribution that depart from the center. As such, only very few papers explore whether indicators of domestic activity and global factors are useful in predicting the entire conditional distribution of inflation. Much of this scarce literature focuses on the U.S. Tillmann and Wolters (2012) use quantile regression techniques to examine the persistence of the conditional distribution of US inflation and find evidence for a reduction in persistence at all conditional quantiles. More recently, Korobilis (2017) introduces Bayesian model averaging methods in quantile regressions and finds that different macroeconomic and financial predictors are relevant for each quantile of U.S. inflation. The closest works to ours focus on model selection in quantile regression. In particular, Manzan and Zerom (2013) show that economic activity indicators such as the unemployment rate are useful for forecasting the distribution of U.S. inflation compared with two benchmark models, an autoregressive model and a random walk model. To the best of our knowledge, only one paper (Busetti, Caivano, and Rodano, 2015) relies on dynamic quantile regressions to forecast the conditional distribution of euro-area headline inflation using macroeconomic indicators. The authors adopt a model selection approach to assess whether a Phillips curve augmented with global factors outperforms the benchmark of a trend-cycle model in forecasting year-on-year changes in the euro area HICP.

3 Forecasting mean inflation with augmented Phillips curves

3.1 Methods

Econometric specifications. We investigate the role of global factors for forecasting euro area inflation by augmenting standard Phillips curves with various global factors : *i)* traditionally used external factors such as commodity prices, exchange rates and import prices; *ii)* global factors such as global economic slack, global consumer inflation and global demand. We estimate an aggregate equation for the euro area as a whole, using quarterly data over the period 1996-2016. The model, a backward-looking specification[2] including lagged inflation terms, is closely related to the "triangle" model by Gordon (1988) and corresponds to the type of models considered in Stock and Watson (2008). Our specifications are of the following general form:

$$\pi_t = \alpha + \sum_{l=1}^{MaxL=4} \rho_l \pi_{t-l} + \beta y_{t-1} + \sum_{i=1}^{MaxN=2} \sum_{l=1}^{MaxL=4} \gamma_{i,l} z_{i,t-l} + \varepsilon_t \tag{1}$$

where the dependent variable π is the inflation rate at time t, computed using the first difference in the logarithm of the HICP, y a measure of domestic slack and z a global factor.
In a first step, Phillips curves are augmented with a single global indicator ($N = 1$). Models are estimated by OLS[3], using Heteroskedasticity and Autocorrelation Consistent(HAC) estimates of the covariance matrix to address slight serial correlation in the residuals. The optimal lag order for lagged inflation and global factors is selected on the basis of the three standard information criteria (Akaike [AIC], Schwarz [BIC] as well as Hannan and Quinn criterion [HQ]). Given the limited time span of our data, the maximum number of lags has been limited to four quarters.
In a second step, once the best two-predictors models have been selected, we add a second global indicator to the equation[4].

Benchmarks. We compare the accuracy of the inflation forecasts from of our augmented Phillips curves with those from two benchmark models, namely an AR(1) process and a standard backward-looking Phillips curve (PC hereafter) of the following form:

$$\pi_t = \alpha + \rho \pi_{t-1} + \beta y_{t-1} + \varepsilon_t \tag{2}$$

We test various measures of domestic slack for y. Forecast comparisons show that the best-performing model relies on the output gap, which is consistent with Ciccarelli and Osbat (2017) for euro area hybrid Phillips curves. Therefore, we use the output gap computed by the ECB

[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 test inflation expectations as a regressor in a hybrid Phillips curve (see Model 17 in Section 3), but generally focus on backward-looking specifications.

[3]Following Mikolajun and Lodge (2016), we also estimate Eq. 1 by the generalized method of moments (GMM) using lags as instruments to address possible endogeneity problems notably in the models with global consumer inflation. The J-statistics of the Durbin-Wu-Hausman test do however not signal any endogeneity. We hence maintain OLS estimates given the risk of incorrect inferences by using weak instruments in GMM estimates.

[4]Some of the global indicators are highly correlated. We check the Variance Inflation Factors and choose only those global factors with a limited degree of collinearity. As we are mostly interested in forecasts, which remain basically unbiased even under collinearity, we then proceed as in the standard one factor case.

in Eq. 2 for y.

RMSE. We compare the root mean squared forecast error (RMSE) of different sets of forecasts to select the best performing models.
The RMSE for any forecast 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 Eq. 3, where $\pi^h_{t+h|t}$ is the pseudo out-of-sample forecast of π_{t+h} made using data through date t. We focus on both the one-quarter ($h = 1$) and one-year-ahead forecast horizons ($h = 4$).

$$RMSE(t_1, t_2) = \sqrt{\frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \left(\pi^h_{t+h} - \pi^h_{t+h|t}\right)^2} \tag{3}$$

Following Stock and Watson (2008), we also calculate (bi)weighted rolling estimates of the RMSE (BRMSE hereafter), which correspond to Eq. 4. Rolling estimates are based on a weighted centered 15-quarters windows: bigger (lower) weights are given to errors close to (far from) the center of the window.

$$BRMSE(t) = \sqrt{\frac{\sum_{s=t-7}^{t+7} K\left(\frac{|s-t|}{8}\right)\left(\pi^h_{s+h} - \pi^h_{s+h|s}\right)^2}{\sum_{s=t-7}^{t+7} K\left(\frac{|s-t|}{8}\right)}} \tag{4}$$

where K is the biweight kernel :

$$K(x) = \frac{15}{16}(1 - x^2)^2 I(|x| \leq 1) \tag{5}$$

Sample. The sample covers data over the 1996Q3 to 2016Q4 period, which corresponds to 82 observations at a quarterly frequency. It thus includes episodes of important volatility in the price of oil (which increased dramatically in 2008 and 2011 before decreasing from 2014 onwards), the Great Recession episode, as well as the period of euro area sovereign debt tensions. These major events might have had altered the link between global factors and domestic inflation. Consequently, we compute RMSE over different subsamples and for two different forecast horizons to make sure our models perform well over various periods of time. Our in-sample analysis uses the entire dataset (1996-2016): estimates provided in Appendix are computed on the whole 1996-2016 sample. Our pseudo-out-of-sample 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 identify the importance of the different predictors depending on the time period. Estimates on the longer, 74-quarters window assure that the results are not biased by the small size of the 40-quarters window.

3.2 Data

3.2.1 Dependent variables

We examine 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 inflation data to quarterly data by computing the average value for the three months in the quarter prior to any other transformations[5]. We seasonally adjust quarterly data using the X-12-ARIMA procedure. We evaluate the models for the three measures of consumer price inflation (headline HICP, CORE and HEX). As the policy goal of the ECB is overall price stability, we focus on headline inflation in the main text.

3.2.2 Regressors

Domestic slack. We test different kinds of indicators for the euro area domestic slack, namely: (*i*) the unemployment rate; (*ii*) the output gap; (*iii*) the employment gap; (*iv*) the unemployment gap; and (*v*) the Industrial Production Index (IPI). Most indicators are stationary and are introduced in levels. The IPI is tested both in level and in variation. The output gap estimate heavily depends on the computation method. We hence rely on different measures for the output gap: (*i*) an 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

[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 inflation rates.

macroeconomic projection exercise. As far as output gaps measures are annual, we used cubic splines techniques to interpolate annual figures into quarterly ones.

Global factors. Triangle models of the Phillips curve traditionally capture external cost-push factors via import prices or commodity prices. We test a wide range of these standard external factors including: (*i*) changes in the price of oil; (*ii*) changes in the price of other commodities; (*iv*) changes in the euro area bilateral and effective exchange rates; and (*v*) changes in 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 euro area import deflator for goods and services; (*ii*) the euro area relative import deflator, i.e. the ratio of the euro area import deflator to the GDP deflator; and (*iii*) the euro area competitors' prices on the import side. This latter indicator, which takes into account the euro area trade structure, better reflects the global inflation pressures which are likely to fuel into domestic prices[6].
In order to capture the growing international integration of goods and labour markets and the wider propagation of global cost shocks, we also test indicators of 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 of various groups of countries. 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; (*ii*) output gaps computed by the IMF. Different weighting schemes are applied to compute the output gap of various groups of countries: (*i*) cross countries simple averages; and (*ii*) weighted averages, taking relative GDP as weights.
We consider several groups of countries to compute our global measures: the OECD, 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 (world hereafter), world excluding the euro area and major emerging market economies.
We also test the euro area export foreign demand index[9]. This trade-weighted indicator of global demand is likely to reflect global demand-related price pressures which have an impact on the euro area. Details regarding the variables and their transformations are provided in Appendix A.

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

[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 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 export demand index computed by the ECB (Hubrich and Karlsson, 2010) corresponds to the geometric average of the real imports of the 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 imports.

3.3 Results

Overall, and as summarized in Tables 1 and 2, most of our specifications for headline inflation outperform the benchmarks (AR(1) and PC). However, the set of best-performing models is not constant over time. Focusing on Phillips curves augmented with a single global factor, the best specifications for headline inflation are those that include: (*i*) the euro area output-gap as a measure of domestic slack and (*ii*) variables of either commodity prices or import pices as a global factor. Therefore, if a single global factor was to be selected, we would opt for a traditional indicator of either commodity prices or import prices. When global consumer prices are added as a second global factor, forecast accuracy slightly improves. In contrast, indicators of global economic slack do not increase the forecast performance of the Phillips curve. Hence, contrary to Borio and Filardo (2007) and Auer et al. (2017), we do not find an increasing impact of global slack on domestic inflation.

Turning to core inflation, the best specifications are either (*i*) hybrid Phillips curves, including both inflation expectations and lagged inflation and (*ii*) backward-looking Phillips curves including an indicator for global core inflation.

3.3.1 Headline inflation

The role of global factors. Global factors, such as commmodity prices, import prices and global consumer inflation, improve inflation forecasts for the euro area compared to our benchmarks (for estimation results, see Table 10 in Appendix B). However, forecasts produced by Phillips curves augmented with global consumer prices do not outperform those produced by models augmented with more traditional global factors, such as commodity prices and import prices.

Concerning the coefficient estimate of global consumer inflation (headline CPI), Figure 1 shows that it increased significantly since the Great recession period (2007-2009). It is however only positive and statistically significant when introduced contemporaneously, and not when introduced in lags. As a result, these models are of a lesser use in real-time forecasting exercises: since global inflation measures become only available after the publication of domestic inflation rates, we would need to rely on global consumer price inflation forecasts. The global core CPI measure is not statistically significant in the augmented Phillips curve for headline inflation, which demonstrates that the impact of global headline inflation on domestic inflation should broadly reflect commodity price cycles.

Table 1 presents the ratio of the RMSE between the augmented Phillips curve for a number of selected models and the standard benchmark Phillips curve (Eq. 2) for the two forecast horizons. Compared to our benchmark, seven models achieve reductions in RMSE higher than 5%. The highest reductions in RMSE are achieved by models including the oil price (Model 1) and the import deflator (Model 5). Unsurprisingly, the reduction in RMSE achieved by Model 1 is particularly high for the long estimation sample (reported in the first column of Table 1), as the 2015-2016 forecast period encompasses the sharp decrease in oil prices observed since 2014. Accounting for global consumer inflation (excluding the euro area) in the augmented Phillips curve also improves forecasts relative to our benchmarks (Model 6 and 8). This result is in line with Ciccarelli and Mojon (2010) and Medel et al. (2014), who find modest improvements when

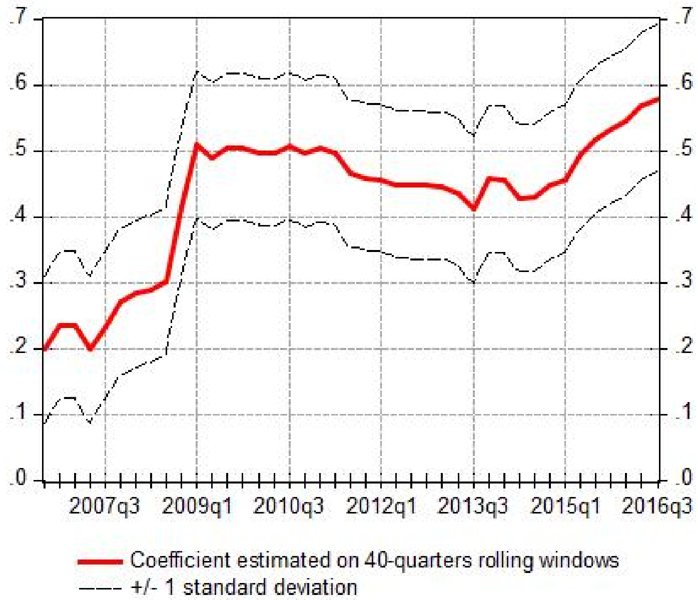

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Figure 1: **Rolling coefficient γ of global inflation in an augmented backward-looking Phillips curve**

Note: The initial estimation sample covers 40 quarters from 1996 to 2006. Coefficients were rolled forward one quarter at a time. The first point on the figure corresponds to the coefficient estimated on the first 40-quarters window (1996-2006). The model estimated corresponds to Model 6: $\pi_t = \alpha + \rho_l \pi_{t-l} + \beta y_{t-1} + \gamma z_t + \varepsilon_t$ with π the first difference in the logarithm of the euro area headline HICP, y the level of the euro area output gap and z the first difference in the logarithm of the CPI of the OECD excluding the euro area (computed as a simple average).

taking into account global inflation measures. However, the reductions in RMSE achieved by our Phillips curves augmented with global consumer price inflation are smaller than those achieved by the models augmented with more traditionally used indicators, such as oil prices (Model 1) and import prices (Model 2 and 5).

The results for Model 18 in Table 1 show that forecast accuracy can be further improved by adding a second global factor to the augmented Phillips curves from above. This works however only for some combinations of global factors, such as the oil price and the OECD CPI index (without the euro area) in a contemporaneous relationship. For this specific model (Model 18), improvements in forecast accuracy are about 15% for the one-quarter-ahead forecast horizon.

The role of global economic slack. To investigate the role of global economic slack in the augmented Phillips curve, we add an indicator of global economic slack to the best-performing models from the previous section. The coefficients of the different measures of global output gaps are however not statistically significant for estimates performed over the whole 1996-2016 sample (see estimation results in Table 11 in Appendix B). For the sake of completeness, relative RMSE are reported in Table 2.

Figure 2 shows that when rolling estimates are performed on 40-quarters rolling windows, the

	Dependent variable	Headline HICP			HICP ex. energy			CORE		
	Estimation window (observations)	74	40		74	40		74	40	
	Forecast period (observations)	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
	Global factor	Backward-looking Phillips curves with one global factor								
PC		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M1	Oil price in EUR	0.43	0.70	0.74	0.98	1.03	1.02	1.03	1.03	1.03
M2	Relative import prices	0.68	0.74	0.75	0.93	0.98	1.00	1.01	1.01	1.01
M3	Competitors' prices in EUR	0.82	0.92	0.90	0.89	0.99	0.98	1.01	1.02	1.02
M4	Non-energy commodity prices	0.87	0.94	0.93	1.01	1.02	1.03	1.01	1.02	1.01
M5	Import prices	0.66	0.71	0.73	0.92	0.97	0.99	1.00	1.00	1.00
M6	OECD CPI ex. EA	0.72	0.78	0.80	1.05	0.94	0.95	0.99	1.00	1.01
M7	Lagged OECD CPI ex. EA	1.04	0.97	0.97	1.00	1.04	1.04	1.02	1.04	1.01
M8	World CPI ex. EA	0.90	0.88	0.98	0.97	1.07	1.01	0.98	1.03	1.09
M9	Lagged World CPI ex. EA	1.03	1.01	1.03	1.01	1.05	1.04	1.02	1.05	1.02
M10	EUR Effective exchange rate	0.99	1.05	1.02	0.97	1.07	1.01	1.03	1.02	1.03
M11	OECD core CPI ex. EA	1.01	1.04	1.11	1.04	1.04	1.08	1.02	1.02	1.03
M12	Lagged OECD core CPI ex. EA	1.00	1.01	0.99	1.02	1.01	0.99	1.02	1.00	0.99
M13	World core CPI ex. EA	1.00	0.99	1.00	1.00	1.00	1.00	1.00	0.98	1.00
M14	Lagged World core CPI ex. EA	1.01	0.98	0.98	0.99	1.00	1.00	1.00	0.99	0.98
M15	World core CPI	0.99	1.00	1.03	0.97	0.98	1.03	0.95	0.92	0.98
M16	Lagged World core CPI	1.01	0.98	0.99	1.00	1.01	1.02	1.01	0.99	1.01
		Hybrid Phillips curve								
M17	Headline inflation expectations	0.97	0.91	0.89	1.14	0.91	0.95	1.06	0.98	1.01
		Backward-looking Phillips curve with two global factors								
M18	Oil price, OECD CPI ex. EA	0.40	0.57	0.55	1.13	0.90	0.87	1.09	0.96	1.00

Ratios below 1 signify a lower RMSE for the augmented Phillips curves 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). Models are estimated on rolling windows of a fixed size of 40 quarters and RMSE are computed over 39 observations for $h = 1$ (second column) and $h = 4$ (third column). Grey shaded cells highlight situations in which the inclusion of a global factors generates a reduction of at least 5% in pseudo out-of-sample RMSE compared to the benchmark Phillips curve.

Table 1: **RMSE ratios between Phillips curves augmented with global factors and the benchmark Phillips curve**

coefficient of global output gaps are positive and statstically significant only over a very specific period (2008-2010), during which the output gap of advanced and emerging countries dropped. Only for this specific period, Phillips curves augmented with global output gaps provide better forecasts than our AR benchmark, but do not outperform our benchmark Phillips curve. Our conclusions are robust to using alternative measures of global slack (i.e. the unemployment rate or output gap measures based on a Hodrick-Prescott filter), and to using both core inflation measures (CORE and HEX) as a dependent variable.

The impact of global output gaps on domestic inflation is hence, at best, episodic, but most of the time insignificant. We therefore find little evidence for augmenting the euro area Phillips curve with global slack measures, once domestic slack and more direct measures of global price pressures are taken into account. 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. Our results are nevertheless in line with Mikolajun and Lodge (2016), which find that measures of global economic slack are rarely significant in standard Phillips curves estimates. In their backward-looking and hybrid Phillips curves for the G7 economies estimated

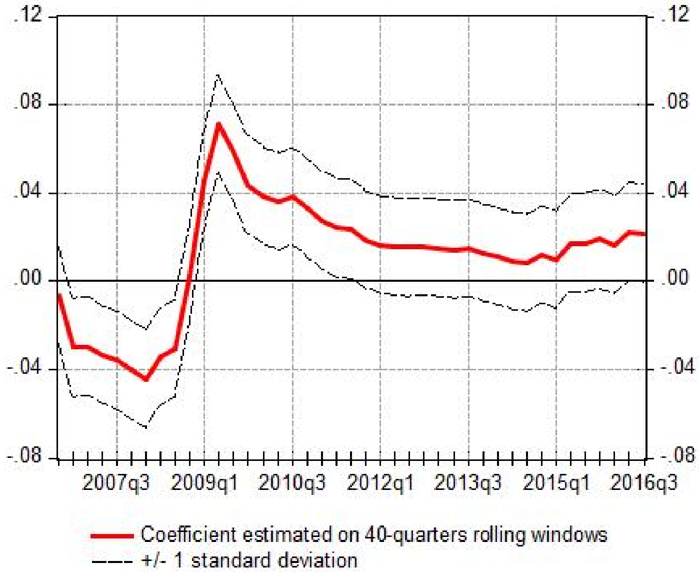

Figure 2: **Rolling coefficient γ of global output gap in an augmented backward-looking Phillips curve**

Note: The initial estimation sample covers 40 quarters from 1996 to 2006. Coefficients are rolled forward one quarter at a time. The first point on the figure corresponds to the coefficient estimated on the first 40-quarters window (1996-2006). The model estimated corresponds to Model 1A: $\pi_t = \alpha + \rho_l \pi_{t-l} + \beta y_{t-1} + \gamma wog_{t-1} + \delta brenteuro_t + \varepsilon_t$ with π the first difference in the logarithm of the euro area headline HICP, y the euro area output gap, wog the lagged output gap of advanced economies excluding the euro area and $brenteuro$ the first difference of the logarithm of the price of oil in EUR.

from the 1990s onwards, Mikolajun and Lodge (2016) find that the coefficients on global output gaps are not significant for France and Germany and significant but negative for Italy and the euro area, while most of the literature (Borio and Filardo, 2007) looks for a positive relationship.

The role of global demand. We augment our best-performing models including a single global factor with the euro area external demand index. This trade-weighted index is likely to better reflect the impact of global demand pressure on the euro area than non-trade-weighted global slack measures. The coefficient of the external demand index is indeed positive and significant in augmented Phillips curves. Table 2 shows the relative RMSE of models augmented with the external demand index and a second global factor and models which only include a single global factor. Models including the external demand index slightly outperform those including a single indicator of global factors (i.e. import prices) for one-quarter-ahead forecasts. However, results are disappointing for one-year ahead forecasts.

3.3.2 Core inflation

Regarding the augmented Phillips curve for core inflation (HEX and CORE), the importance of global factors is considerably reduced. We only find small improvements in forecast accuracy for a limited number of global indicators. Improvements are also concentrated over certain forecast

Dependent variable: Headline HICP				
	Estimation window (observations)	74	40	
	Forecast period (observations)	8	39	
Models	Global factors	Forecast horizon		
		h=1	h=1	h=4
Benchmark model: Model 1 (Oil price)				
	Global inflation factor			
Model 1	Oil price	1.00	1.00	1.00
	Global slack factor			
Model 1A	Output gap of adv.economies ex. EA	1.00	1.02	1.24
Model 1B	Output gap for U.S., U.K., Japan and Canada	1.00	1.03	1.27
Model 1C	Output gap of the U.S.	0.99	1.06	1.28
Model 1D	Output gap of advanced countries	1.02	1.03	1.21
Model 1E	EA external demand	1.20	0.95	1.00
Benchmark model: Model 2 (EA relative import prices)				
	Global inflation factor			
Model 2	Relative import prices	1.00	1.00	1.00
	Global slack factor			
Model 2A	Output gap of advanced countries ex. EA	1.00	1.04	1.38
Model 2B	Output gap for U.S., U.K., Japan and Canada	1.00	1.05	1.40
Model 2C	Output gap of the U.S.	0.99	1.08	1.41
Model 2D	Output gap of advanced countries	1.00	1.04	1.33
Model 2E	EA external demand	1.07	0.94	1.04
Benchmark model: Model 5 (EA import prices)				
	Global inflation factor			
Model 5	Import prices	1.00	1.00	1.00
	Global slack factor			
Model 5A	Output gap of advanced countries ex. EA	1.00	1.04	1.47
Model 5B	Output gap for U.S., U.K., Japan and Canada	1.00	1.05	1.49
Model 5C	Output gap of the U.S.	0.99	1.08	1.50
Model 5D	Output gap of advanced countries	1.00	1.04	1.43
Model 5E	EA external demand	1.07	0.95	1.12
Benchmark model: Model 8 (World CPI ex. EA)				
	Global inflation factor			
Model 8	World CPI ex. EA	1.00	1.00	1.00
	Global slack factor			
Model 8A	Output gap of advanced countries ex. EA	0.68	0.84	0.85
Model 8B	Output gap for U.S., U.K., Japan and Canada	0.68	0.84	0.87
Model 8C	Output gap of the U.S.	0.68	0.86	0.87
Model 8D	Output gap of advanced countries	0.69	0.85	0.86
Model 8E	EA external demand	0.72	0.73	0.64

Figures below 1 favor models augmented with two global factors. 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). Models are estimated on rolling windows of a fixed size of 40 quarters and RMSE are computed over 39 observations for $h = 1$ (second column) and $h = 4$ (third column). Grey shaded cells highlight situations in which the inclusion of an indicator of global economic slack generates a reduction of at least 5% in pseudo out-of-sample RMSE compared to the benchmark model, which includes a single global factor.

Table 2: **RMSE ratios between backward-looking Phillips curves augmented with two global factors and backward-looking Phillips curves augmented with a single global factor**

periods, where global factors seem to play a bigger role. The smaller role of global factors in the Phillips curve for core inflation could be due to the fact that the influence of imported core inflation on domestic inflation is much less direct and more gradual than for headline inflation (dominated by commodity price cycles), making it difficult to reveal it in reduced-form Phillips curve type of models.

HICP excluding energy When focusing on HICP excluding energy (HEX) and for models estimated on the whole 1996-2016 sample, the coefficient for changes in the price of oil (Model 1) is unsurprisingly no longer statistically significant. The coefficients for import prices (Model 2 and 5) and competitors' prices (Model 3) remain statistically significant, but their magnitude is considerably reduced. Estimation results are provided in Table 12. Only a handful of models achieve reductions in RMSE higher than 5% (Table 1) compared to the benchmark Phillips curve. The increased forecast accuracy also depends heavily on the forecast period. Three models (Model 2, 3 and 5) achieve reductions in RMSE higher than 5% when forecasts are performed on the most recent period (2015-2016), suggesting that, in addition to domestic slack, global factors played a role in the period of subdued core inflation observed over the last few years. When forecasts are performed on the longer, 39-quarters forecast period, only a single model (Model 6), which includes global headline CPI inflation, achieves a reduction in RMSE higher than 5%. However, the coefficient for the global headline CPI is only statistically significant in estimations over a shorter time period starting in 2003. In contrast, none of the global core indices is significant in the augmented Phillips curve for HICP excluding energy.

HICP excluding food and energy The results are even more disappointing for the Phillips curve for core inflation (exluding energy and food). The coefficients for import prices (Model 2 and 5) and competitors' prices (Model 3) lose their significance for estimates performed over the entire sample (1996-2016), suggesting that these indicators are dominated by commodity price movements. Estimation results are provided in Table 13. The coefficient for global headline consumer inflation is significant (Model 8), but improvements in RMSE are very modest and concentrated over specific forecast periods: Model 8 displays an improvement of 2% over the benchmark for the latest forecast 2015-2016 period. Only a single model (Model 15), which includes the world core CPI (including the euro area) in a contemporaneous relationship, achieves reductions in RMSE higher than 5% (see Table 1) compared to the benchmark Phillips curve. Model 15 is however unsatisfactory, since it relies on world CPI including the euro area.

4 Robustness analysis

4.1 Stability over time

Several papers, notably Stock and Watson (2008), highlight the unstable forecast behaviour of Phillips curve models over time. We therefore compare the predictive performance of our models in different subsamples. Table 3 presents the number of times in which each of the models displays the lowest RMSE in pseudo-ou-of-sample forecasts for each of the inflation measures and forecast horizons. Regarding headline inflation, the models including oil prices, import prices and competitor's prices achieve the lowest RMSE in most of the subsamples. Models including competitors' prices work particularly well at the beginning of the out-of-sample forecast period, i.e. up to 2008. In contrast, Phillips curve models augmented with oil prices display the lowest RMSE at the end of the sample, from 2015 onwards, coinciding with an increased volatility in the price of oil. Models including global consumer inflation display the lowest RMSE for two forecasts during the Great Recession period, coinciding with disinflationary pressures in major advanced countries, especially in the U.S. This is consistent with the findings in Bobeica and Jarocinski (2017) that euro inflation was mainly driven by global factors over the 2008-2011 period. Regarding core inflation (HEX and CORE), models including euro area headline inflation expectations and the world core CPI (including the euro area) have the lowest RMSE in most of the subsamples. Models including world core inflation perform particularly well during the Great Recession, suggesting that global disinflationary tendencies in the core index played a role in the slowdown of domestic core inflation between 2008 and 2010. Models augmented with euro area inflation expectations display the lowest RMSE for forecasts performed during the euro area sovereign tensions, suggesting that domestic factors were preponderant. Figure 3 illustrates that the best models vary over time for headline inflation. We portray relative BRMSE (i.e. weighted RMSE) of six of our preferred models. The models perform relatively similar at the beginning of the forecast interval, while the two models which include measures of global consumer inflation gain in accuracy during the 2012-2014 period (which comprises forecasts performed from 2010 through 2014). At the end of the forecast period, the models with import prices and the oil price outperform the other models. The performance of Model 1, which includes oil prices, is linked to the volatility of the price of oil. In contrast, we find no link between the performance of the different global factors and macroeconomic volatility, as portrayed by the VIX index in figure 3.

Dependent variable	Headline HICP		CORE HICP		HEX HICP	
Global factor	h=1	h=4	h=1	h=4	h=1	h=4
Oil price in EUR	3	7	0	0	0	0
Non energy commodity prices	0	0	0	0	0	0
Commo. price ex. food and energy	0	0	2	0	1	1
Relative import prices	2	1	0	0	0	0
Competitors' prices	7	6	0	0	0	0
Import prices	3	2	0	0	5	0
OECD CPI ex. EA	0	2	0	0	0	0
World CPI ex. EA	0	0	0	0	0	0
World core CPI ex. EA	0	0	0	0	0	0
World core CPI	0	0	9	15	0	1
US CPI	0	0	0	0	0	0
Headline inflation expectations	1	4	11	5	11	16
USD EUR Exchange rate	0	0	1	0	0	0
EUR Effective Exchange rate	0	0	0	0	0	0
Benchmarks (AR1 and PC)	0	0	1	5	3	0

Models are estimated using a rolling scheme with a fixed-size estimation window of 40 quarters. RMSE are computed on 15-quarters forecast periods. 50 pseudo out-of-sample forecast periods are considered, 25 for $h = 1$ and 25 for $h = 4$. The first estimation window spans from 1996Q3 to 2006Q2. The first forecast period spans from 2006Q3 to 2010Q1 for $h = 1$ and from 2007Q2 to 2010Q4 for $h = 4$. The last estimation window spans from 2002Q3 to 2012Q2. The last forecast period spans from 2012Q3 to 2016Q1 for $h = 1$ and from 2013Q2 to 2016Q4 for $h = 4$. Grey shaded cells highlight the models displaying the lowest RMSE on most periods.

Table 3: **Number of times in which each model augmented with a single global factor shows the lowest RMSE**

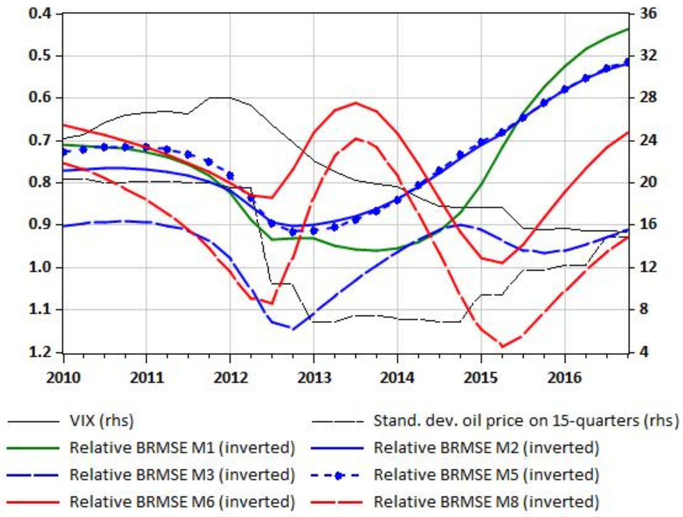

Figure 3: **Relative BRMSE and macroeconomic volatility over 2010-2016**

Note: Relative BRMSE show the ratio of the BRMSE of a specific model to the benchmark Phillips curve, realized over a 15-quarters rollowing forecast period. The date on the time axis represents the end of the 15-quarters rolling forecast period. A smaller (higher) relative BRMSE signifies a better (worse) forecast performance. The VIX Index is the CBOE SPX VOLATILITY Index. The volatility of the oil price is presented by the standard deviation of the oil price in EUR over a 15-quarters rolling window.

4.2 Tests

4.2.1 Diebold-Mariano test

We perform pairwise Diebold-Mariano (DM hereafter) tests (Diebold and Mariano, 1995) to compare : (i) the forecast accuracy of our best performing models with respect to our benchmarks and (ii) the forecast accuracy of alternative specifications including one or two additional global factors presented in Section 3. Models are estimated on 40-quarters rolling windows to evaluate the forecast accuracy over a 39-observations forecast period.
Defining $d_{t(h)}$, the loss-forecast differential, i.e. the difference in mean squared error (MSE) computed from models 1 and 2 given data up to time t, for time horizon h as follows:

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

The Diebold and Mariano testing procedure consists in testing the following null hypothesis:

$$H_0 : \mathbb{E}[d_{t(h)}] \leq 0$$

against the alternative:

$$H_1 : \mathbb{E}[d_{t(h)}] \neq 0$$

The Diebold-Mariano test statistics (DM_h), under the null hypothesis, is given by:

$$\mathsf{DM}_h = \frac{\bar{d}_h}{\sqrt{\sigma^{2,\mathsf{LR}}_{\bar{d}_h}/T}} \tag{6}$$

where $\bar{d}$ stands for the sample mean of the loss differential $d_{t(h)}$ and $\sigma^{2,\mathsf{LR}}_{\bar{d}_h}$ a consistent estimate of the asymptotic long-run variance of $\sqrt{T} \cdot \bar{d}_h$. Diebold and Mariano (1995) show that under the null hypothesis, $\mathsf{DM} \sim \mathcal{N}(0, 1)$. We focus on one-sided tests to detect forecast superiority. Hence, our null hypothesis poses that forecasts generated by model 1 (e.g. our benchmark Phillips curve) perform at least as well as forecasts generated by model 2 (e.g. Phillips curves augmented with global factors). The alternative hypothesis claims superiority of the forecasts generated by model 2. Given the small size of our sample (especially for rolling window estimates), we employ the small-sample bias correction to the DM test proposed by Harvey, Leybourne, and Newbold (1997). Harvey et al. (1997) (HLN) suggest that improved small-sample properties can be obtained by: (i) applying a correction factor to the DM test statistic, and (ii) comparing the corrected statistic to a Student-t distribution with $T - 1$ degrees of freedom, rather than the standard Normal. The corrected test statistic is obtained as follows:

$$\mathsf{HLN} - \mathsf{DM}_h = \sqrt{\frac{T + 1 - 2h + h(h-1)}{T}} \cdot \mathsf{DM}_h \tag{7}$$

with T the forecast period and h the forecast horizon.

Headline inflation. Table 4 reports the $\mathbb{P}$-values of the HLN corrected one-sided DM test. For Phillips curves augmented with oil prices (Model 1), relative import prices (Model 2), import prices (Model 5) and OECD consumer inflation excluding the euro area (Model 6), forecasts are significantly better than our two benchmarks (AR(1) and PC, the standard backward-looking Phillips curve) and than Phillips curves augmented with other global factors at the 10% level. Forecasts from these models are also more accurate than those produced by the hybrid Phillips curve (Model 17). However, none of the forecast produced by one of these four models (Model 1, 2, 5 and 6) outperforms the three others. The augmented Phillips curve with two global factors (Model 18) also produces superior forecasts compared to the benchmark models, which are slightly better than forecasts produced with Model 1, 2 and 5.

Core inflation. Turning to inflation excluding food and energy (CORE), Table 14 in Appendix C shows that only three models (Model 13, 15 and 18) produce a significantly more accurate forecast than the AR(1) but none of the models beats the standard Phillips curve benchmark. Concerning inflation excluding energy (HEX), only Model 6 and 18, which both include the OECD CPI (excluding the euro area), and Model 17, which includes inflation expectations, produce better forecasts than the standard Phillips curve (see Table 15 in Appendix C). However, none of these models beat the AR(1) benchmark. These results confirm that global factors contribute little to the forecast accuracy for core inflation.

Dependent variable: Headline HICP

External factor	h	AR1	PC	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17
		Benchmarks																		
1 Oil price in EUR	1	0.02	0.03		0.30	0.02	0.01	0.49	0.46	0.01	0.03	0.01	0.02	0.01	0.04	0.03	0.03	0.02	0.03	0.03
	4	0.06	0.01		0.35	0.04	0.01	0.55	0.36	0.01	0.01	0.00	0.01	0.00	0.03	0.01	0.02	0.01	0.02	0.05
2 Relative imp. prices	1	0.01	0.01	0.70		0.00	0.01	0.88	0.61	0.00	0.06	0.00	0.01	0.00	0.03	0.01	0.01	0.01	0.02	0.02
	4	0.06	0.00	0.65		0.01	0.00	0.88	0.44	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.02
3 Competitors' prices	1	0.33	0.13	0.98	0.99		0.40	0.99	0.97	0.12	0.68	0.06	0.07	0.03	0.19	0.16	0.19	0.10	0.19	0.57
	4	0.40	0.07	0.96	0.99		0.33	0.99	0.97	0.07	0.14	0.02	0.03	0.01	0.15	0.08	0.12	0.03	0.12	0.52
4 Commo. ex. energy	1	0.45	0.24	0.99	0.99	0.60		0.99	0.97	0.28	0.72	0.18	0.13	0.12	0.24	0.28	0.31	0.25	0.30	0.66
	4	0.54	0.14	0.99	0.99	0.67		0.99	0.95	0.14	0.34	0.07	0.11	0.03	0.18	0.15	0.19	0.08	0.16	0.71
5 Import prices	1	0.01	0.02	0.51	0.12	0.00	0.01		0.46	0.01	0.03	0.01	0.02	0.00	0.03	0.02	0.02	0.01	0.02	0.02
	4	0.03	0.01	0.45	0.12	0.00	0.00		0.30	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.01	0.00	0.01	0.02
6 OECD CPI ex.EA	1	0.02	0.03	0.54	0.39	0.03	0.03	0.54		0.02	0.00	0.02	0.03	0.01	0.06	0.04	0.04	0.02	0.05	0.03
	4	0.06	0.02	0.64	0.56	0.03	0.05	0.70		0.02	0.00	0.01	0.01	0.00	0.05	0.02	0.03	0.01	0.04	0.07
7 l.OECD CPI ex.EA	1	0.66	0.30	0.99	0.99	0.88	0.72	0.99	0.98		0.81	0.11	0.09	0.13	0.34	0.41	0.52	0.33	0.46	0.92
	4	0.76	0.38	0.99	0.99	0.93	0.86	0.99	0.98		0.60	0.08	0.25	0.06	0.46	0.42	0.58	0.19	0.45	0.99
8 World CPI ex.EA	1	0.24	0.18	0.97	0.94	0.32	0.28	0.97	0.99	0.19		0.14	0.12	0.07	0.21	0.21	0.22	0.16	0.22	0.34
	4	0.67	0.35	0.99	0.99	0.86	0.66	0.99	0.99	0.40		0.25	0.28	0.04	0.40	0.37	0.43	0.20	0.39	0.85
9 l.World CPI ex.EA	1	0.82	0.58	0.99	0.99	0.94	0.82	0.99	0.98	0.89	0.86		0.21	0.28	0.50	0.70	0.77	0.60	0.70	0.95
	4	0.90	0.73	0.99	0.99	0.98	0.93	0.99	0.99	0.92	0.75		0.62	0.18	0.74	0.76	0.85	0.50	0.77	0.99
10 EUR EER	1	0.83	0.98	0.98	0.99	0.93	0.87	0.98	0.97	0.91	0.88	0.79		0.59	0.85	0.98	0.98	0.91	0.99	0.95
	4	0.81	0.74	0.99	0.99	0.97	0.89	0.99	0.99	0.75	0.72	0.38		0.05	0.67	0.74	0.84	0.29	0.71	0.99
11 OECD core ex.EA	1	0.87	0.84	0.99	0.99	0.97	0.88	0.99	0.99	0.87	0.93	0.72	0.41		0.67	0.87	0.92	0.96	0.87	0.98
	4	0.87	0.98	0.99	0.99	0.99	0.97	0.99	0.99	0.94	0.96	0.82	0.95		0.95	0.98	0.98	0.99	0.96	0.99
12 l.OECD core ex.EA	1	0.68	0.58	0.96	0.97	0.81	0.76	0.97	0.94	0.66	0.79	0.50	0.15	0.33		0.69	0.75	0.57	0.75	0.82
	4	0.70	0.42	0.97	0.99	0.85	0.82	0.98	0.95	0.54	0.60	0.26	0.33	0.05		0.46	0.66	0.21	0.50	0.92
13 World core ex.EA	1	0.66	0.11	0.97	0.99	0.84	0.72	0.98	0.96	0.59	0.79	0.30	0.02	0.13	0.31		0.82	0.38	0.61	0.86
	4	0.74	0.35	0.99	0.99	0.92	0.85	0.99	0.98	0.58	0.63	0.24	0.26	0.02	0.54		0.85	0.06	0.57	0.98
14 l.World core ex.EA	1	0.62	0.04	0.97	0.99	0.81	0.69	0.98	0.96	0.48	0.78	0.23	0.02	0.08	0.25	0.18		0.26	0.32	0.84
	4	0.70	0.10	0.98	0.99	0.88	0.81	0.99	0.97	0.42	0.57	0.15	0.16	0.02	0.34	0.15		0.26	0.32	0.84
15 World core CPI	1	0.72	0.45	0.98	0.99	0.90	0.75	0.99	0.98	0.67	0.84	0.40	0.09	0.04	0.43	0.62	0.74		0.64	0.92
	4	0.83	0.93	0.99	0.99	0.97	0.92	0.99	0.99	0.81	0.80	0.50	0.71	0.01	0.79	0.94	0.94		0.85	0.99
16 l.World core CPI	1	0.63	0.12	0.97	0.98	0.81	0.70	0.98	0.95	0.54	0.78	0.30	0.01	0.13	0.25	0.39	0.68	0.36		0.83
	4	0.71	0.37	0.98	0.99	0.88	0.84	0.99	0.96	0.55	0.61	0.23	0.29	0.04	0.50	0.43	0.78	0.15		0.96
17 Expectations	1	0.27	0.10	0.97	0.98	0.43	0.34	0.98	0.97	0.08	0.66	0.05	0.05	0.02	0.18	0.14	0.16	0.08	0.17	
	4	0.40	0.01	0.95	0.98	0.48	0.29	0.98	0.93	0.00	0.15	0.00	0.00	0.00	0.08	0.02	0.03	0.01	0.04	
18 Oil price in EUR,	1	0.01	0.02	0.06	0.09	0.02	0.01	0.10	0.04	0.01	0.00	0.01	0.02	0.01	0.04	0.03	0.03	0.02	0.03	0.02
OECD CPI ex.EA	4	0.00	0.02	0.07	0.09	0.02	0.02	0.09	0.03	0.01	0.00	0.01	0.01	0.01	0.03	0.02	0.02	0.01	0.02	0.03

Models are estimated on rolling windows of a fixed size of 40 quarters. Forecast errors are computed over 39 observations for $h = 1$ and $h = 4$. Grey shaded cells highlight situations in which the null hypothesis is rejected at the 10% level. The abbreviation l. stands for lagged.

Table 4: **Pairwise one-sided Diebold-Mariano test ($\mathbb{P}$-values)**

4.2.2 Clark-West test

Clark and West (2007) propose an alternative test for forecast comparison in presence of nested models, which controls for the noise in the forecast coming from additional parameter estimates in a larger model compared to a more parcimonious one. The Clark-West test hence evaluates whether additional parameters - such as global factors in the augmented Phillips curves - help to better predict inflation, compared to more parcimonious benchmarks. In other words, we compare model adequacy here, instead of forecast accuracy as in the previous section.

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 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 both models cannot be discriminated on forecast performances. In that latter case, model 1 is said to encompass model 2. Under the null hypothesis, the test statistic is defined as follows:

$$\mathsf{CW}_h = \frac{\bar{c}_h}{\sqrt{\sigma^{2,\mathsf{LR}}_{\bar{c}_h}/T}} \tag{8}$$

where $\bar{c}_h$ stands for the sample mean of $c_{t(h)}$ and $\sigma^{2,\mathsf{LR}}_{\bar{c}_h}$ 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 suggested in Clark and West (2007). The test requires that multistep forecasts are produced with the direct method, which we use in our forecast exercise, in contrast to the iterated method.

Table 5 shows that the Phillips curves augmented with commodity prices (Model 1 and 4) and import prices (Model 2, 3 and 5) are superior to the benchmark Phillips curve[10]. The same applies to the model including inflation expectations(Model 17). The conclusions are however less straightworward for models augmented with global consumer price inflation. The models which include contemporaneous OECD and world consumer inflation (Model 6 and 8) are superior to the benchmark Phillips curve. This is however no longer true when lagged consumer inflation

[10]This confirms results by Medel et al. (2014) that the CW test will be able to show more rejections of the null hypothesis than the DM test

Dependent variable: Headline HICP		
Benchmark: PC		
	h=1	h=4
M1	0.00	0.00
M2	0.00	0.00
M3	0.03	0.01
M4	0.09	0.07
M5	0.00	0.00
M6	0.00	0.00
M7	0.12	0.09
M8	0.02	0.04
M9	0.29	0.31
M10	0.97	0.61
M11	0.64	0.99
M12	0.24	0.05
M13	0.03	0.24
M14	0.01	0.00
M15	0.26	0.85
M16	0.00	0.10
M17	0.01	0.01
M18	0.00	0.00

Models are estimated on rolling windows of a fixed size of 40 quarters and forecast errors are computed over 39 observations 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. Models 1 to 17 are compared to the benchmark Phillips curve, while Model 18 is compared to Model 1.

Table 5: **Pairwise Clark-West test ($\mathbb{P}$-values)**

is introduced instead of contemporaneous one (Model 7 and 9), which makes this conclusion sensitive to the time lags. Model 18, which includes two global factors, is superior to both the benchmark Phillips curve and Model 1, which includes a single global factor in form of the oil price.

4.3 Comparison to a BVAR

As an ultimate exercise, we compare the forecast performance of our best performing augmented Phillips curves (Model 1, 2 and 5 with one global factor and Model 18 with two global factors) to a more data-rich model structure in the form of a Bayesian VAR. The BVAR includes a large number of variables which are likely to impact inflation, namely: euro area external demand, the oil price in USD, total non-energy commodity prices, the EUR nominal effective exchange rate, real GDP, real investment, the unemployment rate, compensation per employee, the short-term interest rate (3-month EURIBOR) as well as lending rates to non-financial corporations. Data are quarterly in log-levels (except for interest rates and the unemployment rate) and are included with 4 lags. We estimate the Bayesian VAR assuming a Normal-inverse Wishart prior structure[11] with dummy initial observation extension, which allows for cointegration of the variables (i.e. the unconditional forecast being mean reverting in the long-run). We rely here on the ECB's BEAR toolbox for the estimation (Dieppe, van Roye, and Legrand, 2016). Rolling estimates on 40-quarters windows are carried out to calculate out-of-sample conditional forecasts (i.e. conditional on global factors and the interest rate), using the algorithm developed by Waggoner and Zha (1999). These conditional forecasts are then compared to observed inflation as well as to the forecasts from the augmented Phillips curves selected in Section 3.

Table 6 shows that the median of the conditional forecast distribution of the Bayesian BVAR has a slightly lower RMSE than the best performing augmented Phillips curve with one global factor (Model 1). This result is insofar not surprising as the data environment of the BVAR is much richer and accounts for endogenous reactions of the variables in the forecast. However, the improvement in forecast accuracy is relatively modest and has to be weighed against the cost of a more complex model. The augmented Phillips curve with two global factors (Model 18) performs as well as the BVAR for the one-quarter-ahead forecast and even slighty better for the four-quarter-ahead forecast. This confirms the conclusion in Ciccarelli and Osbat (2017) that the Phillips curve remains a useful tool in understanding and predicting inflation dynamics even if compared to more sophisticated models.

Forecast horizon	BVAR	Model 1	Model 2	Model 5	Model 18
h=1	0.20	0.22	0.27	0.26	0.20
h=4	0.22	0.25	0.28	0.27	0.20

Notes: The RMSE is calculated as the difference between the actual outcome for total HICP inflation and the h-step forecast from the two models estimated on a rolling window of a fixed length of 40 quarters. One-quarter-ahead forecasts are performed on a 39-quarters forecast period, from 2006Q3 to 2016Q1. One-year-ahead forecasts are performed on a 39-quarters forecast period, from 2007Q2 to 2016Q4. For the BVAR, we use the median of the conditional forecast distribution to compare it to the actual outcome.

Table 6: RMSE for headline inflation forecasts from the Bayesian VAR (median) and the best-performing Phillips curves

5 Quantile regressions

5.1 Quantile regression results

Methods. In this paragraph, we briefly review the quantile regression approach as well as our empirical strategy.

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,

[11] The prior's hyperparameters are selected using a grid search procedure.

denoted $q_\tau(Y)$ is defined by: $q_\tau(Y) := \mathsf{inf}\,\{y : F(y) \geq \tau\}$, which simplifies to the following relationship when the variable of interest Y (as in our case, inflation) is continuous:

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

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.[12] Alternatively, it can be shown that the estimator corresponds to the solution of the following minimization problem (see Koenker and Basset, 1978):

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

with $\rho_\tau(u) = (\tau - 1_{\{u<0\}}) \cdot u$, the check function with $1_{\{\mathsf{Condition}\}}$ the indicator function that takes value 1 if the condition in brackets is satisfied, 0 otherwise. For further details, see Koenker (2005).

Quantile regressions, as introduced by Koenker and Basset (1978), aim to assess how conditional quantiles $q_\tau(Y|X) = F_{Y|X}^{-1}(\tau)$ change with respect to changes in the explanatory 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 heterogenous specifications. Doing so, they provide an alternative to nonlinear modelling by allowing for differentiated impact of the covariates on specific areas of the conditional distribution of the endogenous variable (inflation in our context), since it is not necessarily expected that those effects remain stable accross quantiles. In our study, we thus consider specifications as follows:

$$q_\tau(\pi_t|X_t) = \alpha^{(\tau)} + \sum_{l=1}^{Max=4} \rho_l^{(\tau)} \pi_{t-l} + \beta^{(\tau)} y_{t-1} + \sum_{i=1}^{Max=2} \sum_{l=1}^{Max=4} \gamma_{i,l}^{(\tau)} z_{i,t-l} + \varepsilon_t^{(\tau)} \tag{9}$$

with $X_t = (\pi_{t-l}, y_{t-1}, z_{i,t})'$ the set of explanatory variables, namely: π_{t-l}, lagged inflation, y_{t-1} lagged measures of domestic slack, and $z_{i,l}$ the set of exogenous factors previoulsy defined. As all our specifications include past inflation, that is the lagged endogeneous variable, we talk about "dynamic quantile regressions", for which standard techniques and metrics still apply. Given the limited size of our sample, we employ resampling techniques (bootstrap) to derive inference, as suggested by Koenker and Xiao (2002) .

5.1.1 Descriptive analysis of quantile regression results

Headline inflation. The graphs in Appendix D show the semi-parametric estimation of density functions related to the residuals stemming from linear regressions of our best performing models (namely Model 1, 2 and 5, as well as some variations of these models using different measures of domestic slack) as in comparison with the standard Normal distribution. For the residual series stemming from Model 1 (and variations of Model 1), it shows clear and signifi-

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

cant departure from the Gaussian norm, especially in the tails, motivating the interest to explore more widely the entire conditional distribution of inflation. For residuals stemming from the other two models (Model 2, 5 and its variations), non-Normalities are of lesser extent, but we still observe extreme realizations in the upper quantiles.

Quantile regression estimates (parameter estimates, bootstrapped standard deviations), are summarized into graphical representations of quantile-specific slopes in Appendix E. We see important variations in the impact of inflation covariates over different quantiles, even if they are not always significantly different from the mean. Concerning global factors, we observe a lower impact of oil prices (Model 1 and variations) on the low end of the conditional distribution (i.e. for low levels of inflation), which increases strongly towards the median, before falling back again at higher quantiles (i.e. for high levels of inflation). For the models with import prices (Models 2 and 5 and variations), the impact grows with increasing quantile. Such patterns imply that when assuming mean coefficients for external factors, we may either over- or underestimate their impact on future inflation. In the case of the model with oil prices, if past inflation was located at the extremes of the historical distribution, the effect will probably be overvalued with OLS. On the contrary, observing past realizations located in the middle of the historical distribution may generate forecasts which are too low. Quantile information can thus be useful for forecasting purposes in adjusting the covariates' impact.

Core inflation. Turning to core inflation measures (HEX and CORE), quantile regression estimates appear less convincing. Most of the test do not reject the null hypothesis of non significantly different slopes across quantiles for our baseline models [13].

5.2 Forecasts performance

How can we use quantile regressions to better forecast headline inflation? To address this question, we use two approaches: *i)* we investigate whether forecasts from quantile regressions produce more accurate forecasts than OLS regressions by comparing usual metrics such as RMSE; *ii)* we adopt a weighted quantile average estimator approach following Zhao and Xiao (2014) to accurately combine quantile information.

5.2.1 Forecast performances of OLS versus quantile regressions

In this section, we investigate whether forecasts from quantile regressions produce more accurate forecasts than OLS regressions using usual metrics such as RMSE. We focus on the most recent period of low inflation (from 2014 onwards) and use the model corresponding to the quantile of past observed inflation. Hence, to forecast inflation in $t + h$ with quantile regressions, we rely on the model corresponding to the quantile of observed inflation at date t, computing 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). Hence, we forecast one-quarter and one-year-ahead inflation based on the model corresponding to the first quantile. We perform

[13] For both measures (HEX and CORE), the tested specifications are Models 1, 2 and 5 as well as those models incorporating proxies for global consumer inflation (Model 6, 8 and 11 to 16). Results are available upon request from the authors.

pairwise Diebold-Mariano tests (Diebold and Mariano, 1995) presented in Section 4 to compare the forecast accuracy of the model estimated by quantile regressions with respect to the models estimated by OLS presented in Section 3. Our null hypothesis, which we want to invalidate, poses that forecasts generated by model 1 (i.e. models estimated with OLS) perform at least as well as forecasts generated by model 2 (i.e. models estimated by quantile regressions).
In a first step, we focus on the period of subdued inflation from 2014 through 2015 to produce one-quarter and one-year-ahead forecasts for a period of 4 quarters. Hence, the first one-quarter-ahead forecast starts in 2014Q1, and the first one-year-ahead forecast starts in 2014Q4. The last one-quarter-ahead forecast ends in 2014Q4, and the last one-year-ahead forecast ends in 2015Q3. We chose this period in order to demonstrate how quantile regressions can be useful in a period of persistenly low (or high) inflation. From the first quarter 2014 to the third quarter 2015, observed inflation was most of the time located at the extreme left (first quantile) of the distribution (except for the second and third quarter 2015, where it was located at the center of the distribution).
Table 7 reports the $\mathbb{P}$-values of the HLN corrected one-sided DM test. For this specific period of low inflation, forecasts produced by quantile regressions are superior to the corresponding OLS estimates for $h = 1$ for all models except for Model 1. However, for $h = 4$, forecasts from quantile regressions no longer outperform forecasts produced by OLS. No quantile model can however beat forecasts from Model 1 with OLS. These results confirm the pattern of quantile slopes in Appendix E, which showed notably for Model 2 and 5 a below average impact on smaller quantiles. Quantile regressions might hence be a useful addition to OLS model estimates in a period of persistantly low (or high) information. They might however be of a lesser use to forecast a pick-up in inflation.

In a second step, we check wether the results presented in Table 7 are robust to extending the forecast period to episodes of higher inflation. We look at a forecast period of 9 quarters from 2014 to 2016. Hence, the first one-quarter-ahead forecast starts in 2014Q1, and the first one-year-ahead forecast starts in 2014Q4. The last one-quarter-ahead forecast ends in 2016Q1, and the last one-year-ahead forecast ends in 2016Q4. The forecast period includes quarters during which observed inflation was close to the center of the distribution as well as quarters where inflation was located at the extreme left of the distribution. The $\mathbb{P}$-values of the HLN corrected one-sided DM test in Table 8 show that quantile regressions do not provide significantly better forecasts than OLS estimates over the period where inflation was more volatile. In such periods, quantile regressions do not provide better forecast results than OLS.

5.2.2 Weighted quantile average

As an ultimate exercise, we follow Zhao and Xiao (2014) weighted quantile average estimator (WQAE hereafter) approach, as an alternative to model averaging techniques[14]. According to those authors, in the context of non-Gaussian variables, it is possible to accurately combine quantile information in order to obtain more efficient estimates of the regression parameters from a linear specification than those obtained from standard OLS techniques. We claim here

[14]See Korobilis (2017) for a recent review on those techniques applied to inflation forecasting.

Dependent variable: Headline HICP

	Benchmarks: forecasts from OLS estimates											
	M1 OLS		M2 OLS		M3 OLS		M5 OLS		M6 OLS		M18 OLS	
	h=1	h=4	h=1	h=4	h=1	h=4	h=1	h=4	h=1	h=4		
PC OLS	0.97	0.99	0.99	0.99	0.37	0.66	0.99	0.99	0.95	0.99	0.95	0.99
PC QR	0.36	0.98	0.06	0.66	0.03	0.27	0.06	0.67	0.05	0.83	0.34	0.99
M1 OLS			0.16	0.02	0.07	0.02	0.18	0.04	0.01	0.00	0.24	0.99
M1 QR	0.64	0.90	0.20	0.45	0.06	0.17	0.20	0.47	0.30	0.59	0.96	0.92
M2 OLS	0.84	0.98			0.03	0.03	0.34	0.73	0.65	0.69	0.80	0.99
M2 QR	0.12	0.98	0.03	0.52	0.03	0.14	0.04	0.55	0.00	0.70	0.12	0.99
M3 OLS	0.93	0.98	0.97	0.97			0.98	0.99	0.90	0.90	0.91	0.99
M3 QR	0.52	0.98	0.05	0.75	0.03	0.13	0.06	0.76	0.10	0.79	0.48	0.98
M5 OLS	0.82	0.96	0.66	0.27	0.02	0.01			0.65	0.64	0.78	0.98
M5 QR	0.13	0.98	0.02	0.50	0.02	0.11	0.03	0.53	0.01	0.69	0.13	0.99
M6 OLS	0.99	0.99	0.35	0.31	0.10	0.10	0.35	0.35			0.95	0.99
M6 QR	0.26	0.90	0.08	0.61	0.04	0.32	0.09	0.62	0.03	0.73	0.23	0.92
M18 OLS	0.76	0.01	0.20	0.01	0.09	0.01	0.22	0.02	0.05	0.00		
M18 QR	0.63	0.91	0.20	0.29	0.05	0.09	0.19	0.33	0.31	0.42	0.59	0.95

Models are estimated on rolling windows of a fixed size of 71 quarters. Forecast errors are computed over 4 observations for $h = 1$ and $h = 4$. Grey shaded cells highlight situations in which the null hypothesis is rejected at the 10% level. The first one-quarter-ahead forecast starts in 2014Q1, and the first one-year-ahead forecast starts in 2014Q4. The last one-quarter-ahead forecast ends in 2014Q4, and the last one-year-ahead forecast ends in 2015Q3.

Table 7: **Pairwise one-sided Diebold-Mariano test ($\mathbb{P}$-values)**

Dependent variable: Headline HICP

	Benchmarks: forecasts from OLS estimates											
	M1 OLS		M2 OLS		M3 OLS		M5 OLS		M6 OLS		M18 OLS	
	h=1	h=4	h=1	h=4	h=1	h=4	h=1	h=4	h=1	h=4		
PC OLS	1.00	1.00	1.00	1.00	0.85	0.89	1.00	1.00	1.00	1.00	1.00	1.00
PC QR	0.90	1.00	0.78	0.72	0.56	0.27	0.79	0.79	0.78	0.78	0.89	0.99
M1 OLS			0.01	0.00	0.01	0.02	0.01	0.01	0.01	0.01	0.55	0.78
M1 QR	0.86	0.91	0.34	0.31	0.05	0.10	0.39	0.39	0.38	0.38	0.83	0.90
M2 OLS	0.99	1.00			0.03	0.07	0.93	0.93	0.52	0.52	0.98	1.00
M2 QR	0.82	0.96	0.40	0.37	0.07	0.08	0.45	0.45	0.43	0.43	0.79	0.95
M3 OLS	0.99	0.98	0.97	0.93			0.98	0.98	0.86	0.86	0.98	0.98
M3 QR	0.89	0.98	0.61	0.63	0.18	0.11	0.64	0.64	0.60	0.60	0.86	0.97
M5 OLS	0.99	1.00	0.07	0.07	0.02	0.06			0.45	0.45	0.98	0.99
M5 QR	0.81	0.96	0.38	0.34	0.06	0.07	0.42	0.42	0.41	0.41	0.78	0.95
M6 OLS	0.99	1.00	0.48	0.52	0.14	0.19	0.55	0.55			0.99	1.00
M6 QR	0.85	0.99	0.30	0.71	0.07	0.32	0.35	0.35	0.30	0.30	0.83	0.99
M18 OLS	0.44	0.22	0.02	0.00	0.02	0.02	0.02	0.02	0.01	0.01		
M18 QR	0.85	0.91	0.17	0.15	0.02	0.05	0.22	0.22	0.25	0.25	0.80	0.90

Models are estimated on rolling windows of a fixed size of 71 quarters. Forecast errors are computed over 9 observations for $h = 1$ and $h = 4$. Grey shaded cells highlight situations in which the null hypothesis is rejected at the 10% level. The first one-quarter-ahead forecast starts in 2014Q1, and the first one-year-ahead forecast starts in 2014Q4. The last one-quarter-ahead forecast ends in 2016Q1, and the last one-year-ahead forecast ends in 2016Q4.

Table 8: **Pairwise one-sided Diebold-Mariano test ($\mathbb{P}$-values)**

that we can make use of that information to obtain more accute forecasts for inflation series. A tentative (and still preliminary) horse race based on a selection of our set of best-performing models estimated by OLS (Model 1, 2 and 5 plus some variations from these baselines, as described below) for the one-step-ahead forecast is presented below in Table 9. For Model 1 and its variations, it leads to systematic reduction of the RMSE (computed on the left on fixed window estimates and on the right on rolling window estimates). For other models, the quantile information does not seem to lead to more accurate forecasts since in all cases the computed weighted average RMSE lead to higher figures than those obtained by OLS.

Models	RMSE.OLS	RMSE.WQAE	RMSE.ROLS	RMSE.RWQAE
M1	0.17	0.17	0.17	0.16
M1'	0.19	0.19	0.19	0.18
M1"	0.18	0.19	0.18	0.16
M1"'	0.20	0.19	0.20	0.17
M2	0.25	0.27	0.26	0.27
M2'	0.27	0.28	0.27	0.28
M2"	0.28	0.29	0.28	0.29
M2"'	0.26	0.27	0.26	0.28
M5	0.25	0.27	0.25	0.26
M5'	0.26	0.27	0.26	0.27
M5"	0.26	0.26	0.25	0.27
M5"'	0.28	0.28	0.27	0.28

Notes: RMSE is calculated as the difference between the actual outcome for total HICP inflation and the 1-step ahead forecast from the alternative baseline models (as well as variations described below) estimated by means of OLS vs. averaged quantile regressions over 0.1, 0.25, 0.5, 0.75, 0.9 quantiles relying on Zhao and Xiao (2014) procedure. Fixed vs. rolling estimations over the 1996Q3-2014(16)Q4(Q2) period are considered for both estimation techniques (OLS vs. WQAE, ROLS vs. RWQAE resp.). Variations of baseline models 1, 2 and 5 include alternative domestic slack proxy (lagged unemployment rate or alternative measures of the output gap) as well as alternative measure for oil price (in USD in M1' and M1"' vs. EUR in M1 and M1").

Table 9: Root-mean squared error (RMSE) for forecasts from the OLS vs. weighted quantile estimates over best-performing Phillips curve models

6 Conclusion

In this paper, we examined the role of different global indicators for forecasting euro area inflation based on augmented Phillips curve estimates. We show that headline inflation forecasts for up to one year can be improved by taking into account global factors. The set of best-performing models is not constant over time and seems to be retated to the volatility of the global indicators. On longer time spans, traditionally used indicators such as commodity prices or import prices perform slightly better than global consumer prices, but adding global consumer prices as a second global indicator to the augmented Phillips curve can be useful. We find only limited support for introducing global economic slack measures into euro area inflation forecasts. Regarding core inflation measures, the importance of global factors is considerably reduced and improvements are only observed for some periods. Overall, Phillips curves are still a useful tool for studying inflation dynamics and they perform almost as good as more sophisticated models. Turning to quantile considerations, our results confirm the interest of exploring the entire conditional distribution of euro area inflation series in addition to standard conditional mean estimation by OLS. We show that the tail behaviour of some of the inflation covariates such as the domestic slack or oil prices and import prices do matter. Forecasts from quantile regressions might be a useful addition to standard OLS estimates in periods of persistantly low or high inflation. We also provide pieces of evidence that accurately averaging quantile information can lead to better forecasts of the conditional mean in some contexts. These results still need to be confirmed by further analysis and extended to larger time periods. This paper also still leaves open questions which indicators perform better in which specific macroeconomic contexts (crisis vs. normal times, high vs. low inflation context, high vs. low volatility of external factors), which calls for further conditioning on our regressions and identifying recurrent patterns in the way domestic or global covariates influence inflation.

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A Data

Description	Transformation	Source
	Euro area inflation	
HICP headline	SA (X12)	Eurostat
HICP ex. food and energy	SA(X12)	Eurostat
HICP ex. energy	SA (X12)	Eurostat
HICP expectations (household infl. expectations)		European Commission
	Euro area slack	
Unemployment rate		Eurostat
Whole economy employment (heads)		Eurostat
EA unemployment gap		ECB & authors' computation
EA output gap	Cubic splines	European Commission
EA output gap		ECB
EA output gap	HP filter	Eurostat & authors' computation
EA Industrial production index		Eurostat
	Global factors	
	Commodities	
Brent crude oil price, USD		ECB
Brent crude oil price, EUR		ECB
Non-energy commodity price, EUR		ECB
Commodity price ex. energy and agriculture		ECB
	Exchange rates and financial variables	
EUR USD exchange rate, USD per EUR		ECB
EUR effective exchange rate, 12 currencies		ECB
EUR effective exchange rate, 19 currencies		ECB
EUR effective exchange rate, 38 currencies		ECB
EURIBOR 3 months		ECB
	Global slack	
EA foreign demand index		ECB
Output gap of the US	Cubic splines	IMF or ECB & authors' computation
Output gap of advanced economies*	Cubic splines	IMF or ECB& authors' computation
Output gap of adv. economies ex. EA	Cubic splines	IMF & authors' computation
Output gap of emerging markets	Cubic splines	IMF & authors' computation
Output gap for US, Japan, UK, Canada	Cubic splines	IMF & authors' computation
World output gap	Cubic splines	IMF
World output gap ex. EA	Cubic splines	IMF or ECB & authors' computation
US unemployment rate		OECD
OECD unemployment rate		OECD
Unemployment rate of adv. economies ex. EA	GDP-weighted avg	OECD & authors' computation
Unemployment rate for US, Japan, UK, Canada	GDP-weighted avg	OECD & authors' computation
	Global inflation	
OECD CPI	Cross country avg, SA (X12)	OECD & authors' computation
G7 countries CPI	Cross country avg, SA (X12)	OECD & authors' computation
G20 countries CPI	Cross country avg, SA (X12)	OECD & authors' computation
G20 countries CPI ex. EA	Cross country avg, SA (X12)	OECD & authors' computation
CPI for US, Japan, UK, Canada	Cross country avg, SA (X12)	OECD & authors' computation
US CPI	SA (X12)	OECD & authors' computation
World** CPI	Cross country avg, SA (X12)	OECD & authors' computation
World CPI ex. EA	Cross country avg, SA (X12)	OECD & authors' computation
OECD CPI ex. food & energy	Cross country avg, SA (X12)	OECD & authors' computation
OECD CPI ex. food & energy (ex. EA)	Cross country avg, SA (X12)	OECD & authors' computation
World** CPI ex. food & energy	Cross country avg, SA (X12)	OECD & authors' computation
World CPI ex. food & energy (ex. EA)	Cross country avg, SA (X12)	OECD & authors' computation
CPI ex. food & energy for US, Japan, UK, Canada	Cross country avg, SA (X12)	OECD & authors' computation
US CPI ex. food & energy	SA (X12)	OECD & authors' computation
Extra EA competitors' prices, USD		ECB & authors' computation
Extra EA competitors' prices, EUR		ECB
EA import deflator, extra EA, EUR		Eurostat
EA import deflator to EA GDP deflator, EUR		Eurostat & authors' computation

*Australia, Canada, Denmark, Japan, Korea, New Zealand, Norway, Sweden, the United Kingdom, the United States and the euro area.

**This aggregate encompasses 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 the euro area).

B OLS estimates of augmented Phillips curves

	Headline inflation										
Models	AR1	PC	M1	M2	M3	M4	M5	M6	M7	M8	M9
Intercept	0.23***	0.27***	0.24***	0.33***	0.29***	0.28***	0.31***	0.04	0.33***	-0.06	0.32***
Lagged inflation	0.46***	0.36***	0.38***	0.23***	0.28***	0.30***	0.21***	0.24***	0.46***	0.25**	0.45***
Lagged EA Output gap		0.04**	0.03***	0.05***	0.05***	0.04***	0.05***	0.02	0.04**	0.03*	0.04***
Oil price EUR			0.01***								
Relative import prices				0.08***							
Competitors' prices					0.04***						
Non-energy commodity prices						0.02***					
Import prices							0.08***				
OECD CPI ex. EA								0.39***			
Lagged OECD CPI ex. EA									-0.14		
World CPI ex. EA										0.40***	
Lagged World CPI ex. EA											-0.11
Adjusted R2	0.20	0.24	0.60	0.53	0.38	0.37	0.56	0.46	0.25	0.38	0.24
Observations	82	82	82	82	82	82	82	82	82	82	82
Models	M10	M11	M12	M13	M14	M15	M16	M17			
Intercept	0.27***	0.29**	0.35***	0.31***	0.40***	0.21*	0.39***	0.36***			
Lagged inflation	0.35***	0.36***	0.36***	0.35***	0.34***	0.34***	0.36***	0.15			
Lagged EA Output gap	0.04**	0.04**	0.04**	0.04**	0.04**	0.03*	0.05**	0.05***			
EUR Effective exchange rate (EER38)	-0.02										
OCDE CORE CPI ex. EA		-0.04									
Lagged OCDE CORE CPI ex. EA			-0.16								
World CORE CPI ex. EA				-0.06							
Lagged World CORE CPI ex. EA					-0.18						
World CORE CPI						0.10					
Lagged World CORE CPI							-0.21				
Headline inflation expectations								0.01***			
Adjusted R2	0.24	0.22	0.23	0.23	0.24	0.23	0.24	0.35			
Observations	82	82	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. The OECD CPI and world CPI are computed as simple averages of cross countries inflation rates. Commodity prices and imports prices are in EUR. Variables are in log-difference, except for the output gap, which is introduced in levels.

Table 10: Estimation results for Phillips curves augmented with a single external factor

Dependent variable: Headline inflation

	M1A	M1B	M1C	M1D	M1E	M18
Intercept	0.24***	0.24***	0.24***	0.25***	0.23***	0.07
Lagged inflation	0.38***	0.38***	0.38***	0.37***	0.33***	0.30***
Lagged EA Output gap	0.03**	0.03***	0.04***	0.03**	0.04***	0.02
Oil price EUR	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
Lagged output gap of advanced countries ex. EA	0.00					
Lagged output gap for U.S., Japan, U.K., Canada		0.00				
Lagged output gap of the U.S.			0.00			
Lagged output gap of advanced countries				0.01		
EA external demand					0.02*	
OECD CPI ex. EA						0.32***
Adjusted R2	0.60	0.60	0.60	0.60	0.61	0.66
Observations	82	82	82	82	82	82

	M2A	M2B	M2C	M2D	M2E
Intercept	0.33***	0.33***	0.33***	0.33***	0.31***
Lagged inflation	0.23***	0.23***	0.23***	0.23***	0.19**
Lagged EA Output gap	0.05***	0.06***	0.06***	0.06***	0.06***
EA relative price	0.08***	0.08***	0.08***	0.08***	0.07***
Lagged output gap of advanced countries ex. EA	0.00				
Lagged output gap for U.S., Japan, U.K., Canada		0.00			
Lagged output gap of the U.S.			0.00		
Lagged output gap of advanced countries				0.00	
EA external demand					0.03***
Adjusted R2	0.53	0.53	0.53	0.53	0.55
Observations	82	82	82	82	82

	M5A	M5B	M5C	M5D	M5E
Intercept	0.30***	0.30***	0.30***	0.30***	0.29***
Lagged inflation	0.21***	0.21***	0.21**	0.21***	0.18**
Lagged EA Output gap	0.05***	0.05***	0.06***	0.05***	0.06***
EA imports deflator	0.09***	0.09***	0.09***	0.09***	0.07***
Lagged output gap of advanced countries ex. EA	-0.01				
Lagged output gap for U.S., Japan, U.K., Canada		-0.01			
Lagged output gap of the U.S.			0.00		
Lagged output gap of advanced countries				0.00	
EA external demand					0.03*
Adjusted R2	0.56	0.56	0.56	0.56	0.57
Observations	82	82	82	82	82

	M8A	M8B	M8C	M8D	M8E
Intercept	-0.02	-0.02	-0.02	-0.02	-0.02
Lagged inflation	0.20**	0.20**	0.20**	0.20**	0.12
Lagged EA Output gap	0.02	0.02	0.02	0.02	0.04***
World CPI	0.45***	0.45***	0.45***	0.45***	0.38***
Lagged output gap of advanced countries ex. EA	0.00				
Lagged output gap for U.S., Japan, U.K., Canada		-0.00			
Lagged output gap of the U.S.			0.00		
Lagged output gap of advanced countries				0.00	
EA external demand					0.05***
Adjusted R2	0.50	0.50	0.50	0.50	0.60
Observations	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. The OECD CPI and world CPI are computed as simple averages. Commodity prices and imports prices are in EUR. Variables are in log-difference, except the output gap, which is introduced in levels.

Table 11: Estimation results for Phillips curves augmented with two external factors

Dependent variable: HICP excluding energy (HEX)

Models	AR1	PC	M1	M2	M3	M4	M5	M6	M7	M8	M9
Intercept	0.14***	0.23***	0.22***	0.22***	0.21***	0.23***	0.21***	0.16***	0.23***	0.14***	0.25***
Lagged inflation	0.63***	0.40***	0.41***	0.43***	0.44***	0.41***	0.43***	0.39***	0.40***	0.38***	0.42***
Lagged EA Output gap		0.03***	0.03***	0.03***	0.03***	0.03***	0.03*	0.03***	0.03***	0.03***	0.03***
Oil price EUR			0.04								
Relative import prices				0.01*							
Competitors' prices					0.01*						
Non-energy commodity price						0.00					
Import prices							0.01*				
OECD CPI ex. EA								0.10**			
Lagged OECD CPI ex. EA									0.00		
World CPI ex. EA										0.14**	
World CPI ex. EA											-0.03
Adjusted R2	0.38	0.46	0.45	0.47	0.47	0.46	0.48	0.49	0.45	0.48	0.46
Observations	82	82	82	82	82	82	82	82	82	82	82

Models	M10	M11	M12	M13	M14	M15	M16	M17	M18
Intercept	0.22***	0.23***	0.21***	0.24***	0.26***	0.19***	0.24***	0.25***	0.15***
Lagged inflation	0.42***	0.40***	0.40***	0.40***	0.40***	0.39***	0.40***	0.35***	0.42***
Lagged EA Output gap	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
EUR Effective exchange rate (EER38)	0.00								
OCDE core CPI ex. EA		0.00							
Lagged OCDE core CPI ex. EA			0.04						
World CORE CPI ex. EA				-0.2					
Lagged World core CPI ex. EA					-0.04				
World core CPI						0.07			
Lagged World core CPI							-0.03		
Headline inflation expectations								0.003***	
Oil price in EUR									0.00
World CPI ex. EA									0.11**
Adjusted R2	0.46	0.45	0.45	0.46	0.46	0.46	0.45	0.51	0.48
Observations	82	82	82	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. The OECD CPI and world CPI are computed as simple averages of cross countries inflation rates. The OECD CORE CPI is computed as a weighted average of cross-countries inflation rates. Commodity prices and import prices are in EUR. Variables are in log-difference, except for the output gap, which is introduced in levels.

Table 12: Estimation results for Phillips curves augmented with external factors

Dependent variable: HICP excluding food and energy (CORE)

Models	AR1	PC	M1	M2	M3	M4	M5	M6	M7	M8	M9
Intercept	0.14***	0.24***	0.24***	0.24***	0.24***	0.23***	0.20***	0.24***	0.24***	0.20***	0.25***
Lagged inflation	0.56***	0.31***	0.37***	0.31***	0.31***	0.31***	0.32***	0.32***	0.31***	0.32***	0.32***
Lagged EA Output gap		0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
Oil price in EUR			0.00								
Non-energy commodity price						0.02					
Relative import prices				0.00							
Competitors' prices						-0.03					
Import prices							0.00				
OECD CPI ex. EA								0.05			
Lagged OECD CPI ex. EA									0.16		
World CPI ex. EA										0.06*	
Lagged World CPI ex. EA											-0.02
Adjusted R2	0.32	0.44	0.44	0.43	0.43	0.43	0.43	0.45	0.43	0.44	0.43
Observations	82	82	82	82	82	82	82	82	82	82	82

Models	M10	M11	M12	M13	M14	M15	M16	M17	M18
Intercept	0.24***	0.24***	0.21***	0.22***	0.24***	0.18***	0.23***	0.23***	0.17***
Lagged inflation	0.30***	0.31***	0.31***	0.30***	0.31***	0.29***	0.31***	0.33***	0.37***
Lagged EA Output gap	0.03***	0.03***	0.03***	0.03***	0.03***	0.02***	0.03***	0.03***	0.02***
EUR Effective exchange rate (EER38)	0.00								
OCDE core CPI ex. EA		0.00							
Lagged OCDE core CPI ex. EA			0.05						
World CORE CPI ex. EA				0.03					
Lagged World core CPI ex. EA					0.00				
World core CPI						0.11*			
Lagged World core CPI							0.01		
Headline inflation expectations								0.002***	
Oil price in EUR									0.00
World CPI ex. EA									0.08**
Adjusted R2	0.43	0.43	0.43	0.44	0.43	0.46	0.43	0.45	0.46
Observations	82	82	82	82	82	82	82	82	0.82

Notes: Stars *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively. Models are estimated over the 1996Q3-2016Q4 sample. The OECD CPI and world CPI are computed as simple averages of cross countries inflation rates. The OECD CORE CPI is computed as a weighted average of cross-countries inflation rates. Commodity prices and import prices are in EUR. Variables are in log-difference, except for the output gap, which is introduced in levels.

Table 13: Estimation results for Phillips curves augmented with external factors

C Pairwise one-sided Diebold-Mariano tests

Dependent variable: CORE HICP

External factor		AR1	PC	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17
		Benchmarks																		
M1 Oil price in EUR	h=1	0.27	0.81		0.83	0.63	0.59	0.84	0.75	0.42	0.47	0.28	0.68	0.60	0.76	0.87	0.86	0.91	0.84	0.88
	h=4	0.25	0.83		0.78	0.58	0.73	0.79	0.60	0.60	0.25	0.53	0.46	0.44	0.88	0.81	0.90	0.78	0.70	0.60
M2 Relative import prices	h=1	0.18	0.59	0.17		0.09	0.31	0.77	0.56	0.03	0.19	0.05	0.37	0.35	0.54	0.75	0.74	0.85	0.68	0.82
	h=4	0.20	0.60	0.22		0.15	0.44	0.73	0.45	0.35	0.17	0.34	0.23	0.28	0.71	0.61	0.83	0.65	0.46	0.45
M3 Competitors' prices	h=1	0.23	0.86	0.37	0.91		0.51	0.95	0.79	0.22	0.33	0.17	0.63	0.51	0.75	0.89	0.94	0.90	0.91	0.94
	h=4	0.23	0.90	0.42	0.85		0.76	0.87	0.58	0.58	0.22	0.49	0.35	0.38	0.92	0.79	0.98	0.74	0.77	0.59
M4 Commo. ex. energy	h=1	0.22	0.97	0.41	0.69	0.49		0.73	0.84	0.34	0.28	0.27	0.66	0.50	0.80	0.90	0.99	0.91	0.95	0.88
	h=4	0.19	0.98	0.27	0.56	0.24		0.60	0.47	0.44	0.15	0.40	0.09	0.23	0.93	0.75	0.98	0.71	0.54	0.49
M5 Import prices	h=1	0.17	0.55	0.16	0.23	0.05	0.27		0.53	0.04	0.16	0.05	0.33	0.33	0.51	0.72	0.72	0.84	0.65	0.81
	h=4	0.20	0.56	0.21	0.27	0.13	0.40		0.42	0.31	0.16	0.32	0.21	0.27	0.67	0.58	0.81	0.64	0.41	0.42
M6 OECD CPI ex.EA	h=1	0.17	0.54	0.25	0.44	0.21	0.16	0.47		0.17	0.00	0.15	0.25	0.28	0.48	0.77	0.78	0.87	0.70	0.77
	h=4	0.25	0.65	0.40	0.55	0.42	0.53	0.58		0.48	0.04	0.45	0.34	0.35	0.74	0.72	0.85	0.72	0.55	0.51
M7 l.OECD CPI ex.EA	h=1	0.32	0.85	0.58	0.97	0.78	0.66	0.96	0.83		0.53	0.18	0.74	0.64	0.78	0.90	0.91	0.91	0.89	0.94
	h=4	0.24	0.67	0.40	0.65	0.42	0.56	0.69	0.52		0.24	0.40	0.38	0.38	0.73	0.66	0.81	0.69	0.58	0.56
M8 World CPI ex.EA	h=1	0.32	0.92	0.53	0.81	0.67	0.72	0.84	0.99	0.47		0.36	0.78	0.65	0.84	0.96	0.97	0.94	0.96	0.96
	h=4	0.51	0.88	0.75	0.83	0.78	0.85	0.84	0.96	0.76		0.71	0.77	0.74	0.90	0.92	0.94	0.91	0.87	0.79
M9 l.World CPI ex.EA	h=1	0.40	0.86	0.72	0.95	0.83	0.73	0.95	0.85	0.82	0.64		0.79	0.71	0.81	0.90	0.91	0.91	0.89	0.94
	h=4	0.25	0.68	0.47	0.66	0.51	0.60	0.68	0.55	0.60	0.29		0.44	0.44	0.74	0.66	0.79	0.69	0.60	0.59
M10 EUR EER	h=1	0.18	0.93	0.32	0.63	0.37	0.34	0.67	0.75	0.26	0.22	0.21		0.41	0.73	0.90	0.96	0.91	0.90	0.84
	h=4	0.25	0.98	0.54	0.77	0.65	0.91	0.79	0.66	0.62	0.23	0.55		0.47	0.98	0.89	0.98	0.81	0.83	0.62
M11 OECD core ex.EA	h=1	0.18	0.79	0.40	0.65	0.49	0.50	0.67	0.72	0.36	0.35	0.29	0.59		0.79	0.93	0.86	0.96	0.83	0.80
	h=4	0.24	0.87	0.56	0.72	0.62	0.77	0.73	0.65	0.62	0.26	0.56	0.53		0.94	0.93	0.90	0.91	0.75	0.62
M12 l.OECD core ex.EA	h=1	0.12	0.57	0.24	0.46	0.25	0.20	0.49	0.52	0.22	0.16	0.19	0.27	0.21		0.82	0.77	0.90	0.69	0.70
	h=4	0.12	0.23	0.12	0.29	0.08	0.07	0.33	0.26	0.27	0.10	0.26	0.02	0.06		0.38	0.65	0.58	0.13	0.34
M13 World core ex.EA	h=1	0.09	0.23	0.13	0.25	0.11	0.10	0.28	0.23	0.10	0.04	0.10	0.10	0.07	0.18		0.40	0.89	0.28	0.50
	h=4	0.16	0.44	0.19	0.39	0.21	0.25	0.42	0.28	0.34	0.08	0.34	0.11	0.07	0.62		0.70	0.67	0.27	0.40
M14 l.World core ex.EA	h=1	0.11	0.10	0.14	0.26	0.06	0.01	0.28	0.22	0.09	0.03	0.09	0.04	0.14	0.23	0.60		0.82	0.35	0.59
	h=4	0.13	0.10	0.10	0.17	0.02	0.02	0.19	0.15	0.19	0.06	0.21	0.02	0.10	0.35	0.30		0.52	0.01	0.27
M15 World core CPI	h=1	0.03	0.14	0.09	0.15	0.10	0.09	0.16	0.13	0.09	0.06	0.09	0.09	0.04	0.10	0.11	0.18		0.14	0.23
	h=4	0.12	0.36	0.22	0.35	0.26	0.29	0.36	0.28	0.31	0.09	0.31	0.19	0.09	0.42	0.33	0.48		0.30	0.36
M16 l.World core CPI	h=1	0.12	0.29	0.16	0.32	0.09	0.05	0.35	0.30	0.11	0.04	0.11	0.10	0.17	0.31	0.72	0.65	0.86		0.66
	h=4	0.20	0.77	0.30	0.54	0.23	0.46	0.59	0.45	0.42	0.13	0.40	0.17	0.25	0.87	0.73	0.99	0.70		0.48
M17 Inflation exp.	h=1	0.13	0.27	0.12	0.18	0.06	0.12	0.19	0.23	0.06	0.04	0.06	0.16	0.20	0.30	0.50	0.41	0.77	0.34	
	h=4	0.26	0.59	0.40	0.55	0.41	0.51	0.58	0.49	0.44	0.21	0.41	0.38	0.38	0.65	0.60	0.73	0.64	0.52	
M18 Oil price in EUR,	h=1	0.02	0.21	0.04	0.21	0.12	0.14	0.23	0.25	0.12	0.13	0.09	0.13	0.07	0.15	0.34	0.08	0.73	0.26	0.38
OECD CPI ex.EA	h=4	0.00	0.11	0.03	0.14	0.06	0.08	0.16	0.17	0.12	0.09	0.10	0.03	0.01	0.15	0.15	0.08	0.27	0.11	0.20

Models are estimated on rolling windows of a fixed size of 40 quarters. Forecast errors are computed over 39 observations for $h = 1$ and $h = 4$. Grey shaded cells highlight situations in which the null hypothesis is rejected at the 10% level. The abbreviation l. stands for lagged.

Table 14: **Pairwise one-sided Diebold-Mariano tests ($\mathbb{P}$-values)**

Dependent variable: HEX HICP

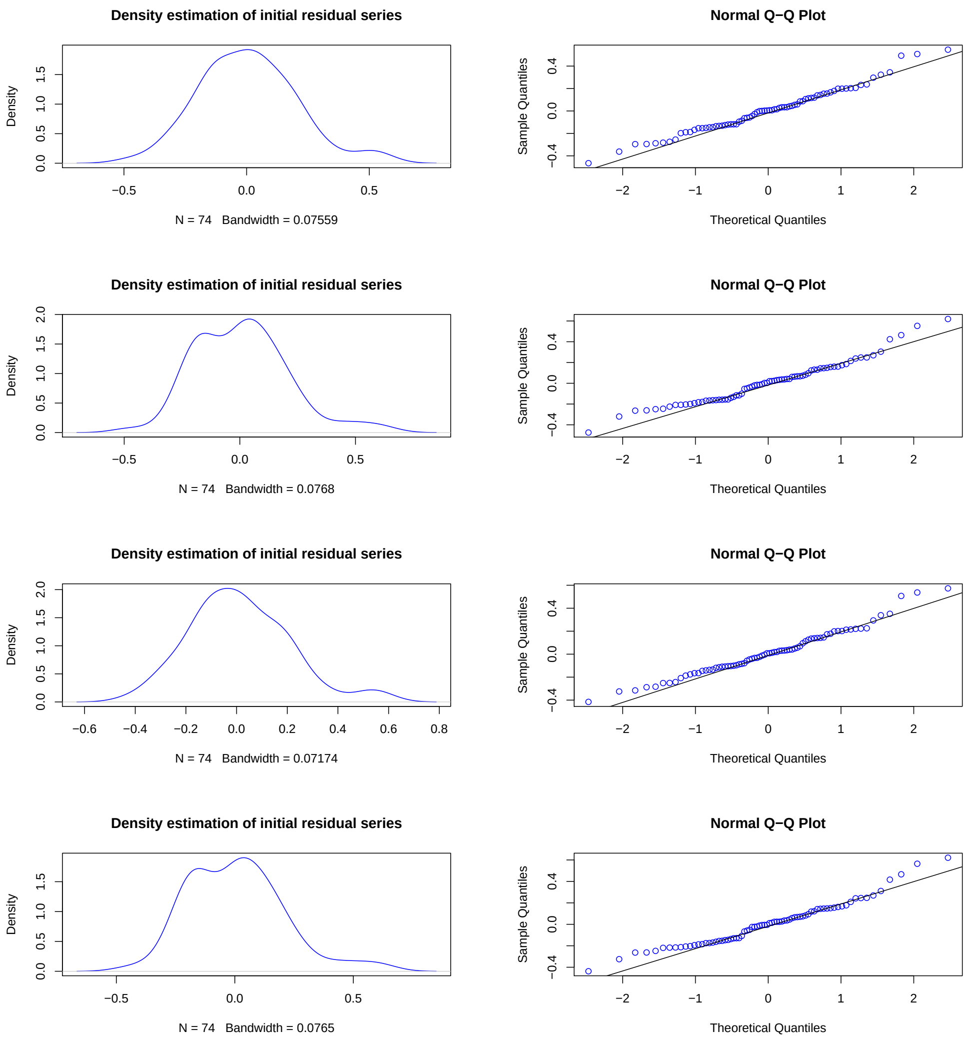
External factor	h	AR1	PC	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17
								Benchmarks												
M1 Oil price in EUR	1	0.69	0.81		0.95	0.81	0.54	0.95	0.91	0.34	0.76	0.28	0.49	0.43	0.75	0.84	0.82	0.76	0.73	0.96
	4	0.72	0.80		0.88	0.85	0.25	0.91	0.86	0.33	0.57	0.30	0.44	0.23	0.85	0.83	0.81	0.42	0.58	0.94
M2 Relative import prices	1	0.55	0.26	0.05		0.42	0.15	0.92	0.80	0.12	0.52	0.11	0.08	0.25	0.17	0.27	0.36	0.51	0.17	0.90
	4	0.65	0.44	0.12		0.61	0.06	0.91	0.74	0.11	0.44	0.14	0.24	0.19	0.51	0.45	0.41	0.28	0.21	0.86
M3 Competitors' prices	1	0.58	0.34	0.19	0.58		0.19	0.80	0.89	0.20	0.56	0.17	0.09	0.25	0.23	0.37	0.42	0.55	0.23	0.94
	4	0.66	0.21	0.15	0.39		0.05	0.44	0.77	0.15	0.37	0.12	0.02	0.12	0.32	0.27	0.24	0.17	0.11	0.76
M4 Commo. ex. energy	1	0.73	0.80	0.46	0.85	0.81		0.91	0.93	0.35	0.75	0.29	0.44	0.40	0.73	0.82	0.83	0.72	0.68	0.96
	4	0.77	0.94	0.75	0.94	0.95		0.96	0.91	0.46	0.64	0.39	0.61	0.28	0.92	0.92	0.94	0.52	0.80	0.97
M5 Import prices	1	0.50	0.14	0.05	0.08	0.20	0.09		0.76	0.11	0.43	0.10	0.04	0.21	0.07	0.13	0.24	0.44	0.09	0.87
	4	0.64	0.37	0.09	0.09	0.56	0.04		0.72	0.09	0.42	0.11	0.19	0.17	0.43	0.38	0.33	0.24	0.14	0.84
M6 OECD CPI ex.EA	1	0.31	0.08	0.09	0.20	0.11	0.07	0.24		0.12	0.01	0.11	0.04	0.05	0.07	0.09	0.10	0.17	0.07	0.69
	4	0.52	0.16	0.14	0.26	0.23	0.09	0.28		0.14	0.04	0.13	0.07	0.05	0.20	0.14	0.17	0.05	0.12	0.51
M7 l.OECD ex.EA	1	0.72	0.82	0.66	0.88	0.80	0.65	0.89	0.88		0.76	0.19	0.63	0.51	0.78	0.83	0.84	0.79	0.77	0.93
	4	0.76	0.83	0.67	0.89	0.85	0.54	0.91	0.86		0.63	0.35	0.59	0.30	0.87	0.83	0.85	0.54	0.73	0.97
M8 World CPI ex.EA	1	0.55	0.35	0.24	0.48	0.44	0.25	0.57	0.99	0.24		0.22	0.18	0.16	0.31	0.36	0.38	0.50	0.28	0.92
	4	0.73	0.54	0.43	0.56	0.63	0.36	0.58	0.96	0.37		0.35	0.39	0.20	0.57	0.55	0.53	0.35	0.44	0.78
M9 l.World CPI ex.EA	1	0.75	0.84	0.72	0.89	0.82	0.71	0.90	0.89	0.81	0.78		0.69	0.55	0.82	0.86	0.87	0.81	0.81	0.93
	4	0.79	0.86	0.70	0.86	0.88	0.61	0.88	0.87	0.65	0.65		0.66	0.34	0.90	0.84	0.86	0.60	0.77	0.95
M10 EUR EER	1	0.73	0.97	0.51	0.92	0.91	0.56	0.96	0.96	0.37	0.82	0.31		0.42	0.91	0.95	0.96	0.81	0.92	0.98
	4	0.79	0.96	0.56	0.76	0.98	0.39	0.81	0.93	0.41	0.61	0.34		0.22	0.91	0.88	0.88	0.46	0.65	0.93
M11 OECD core ex.EA	1	0.81	0.73	0.57	0.75	0.75	0.60	0.79	0.95	0.49	0.84	0.45	0.58		0.69	0.73	0.76	0.93	0.68	0.93
	4	0.90	0.86	0.77	0.81	0.88	0.72	0.83	0.95	0.70	0.80	0.66	0.78		0.86	0.86	0.85	0.87	0.78	0.91
M12 l.OECD core ex.EA	1	0.65	0.74	0.25	0.83	0.77	0.27	0.93	0.93	0.22	0.69	0.18	0.09	0.31		0.76	0.74	0.67	0.39	0.97
	4	0.67	0.34	0.15	0.49	0.68	0.08	0.57	0.80	0.13	0.43	0.10	0.09	0.14		0.37	0.32	0.20	0.08	0.87
M13 World core ex.EA	1	0.62	0.38	0.16	0.73	0.63	0.18	0.87	0.91	0.17	0.64	0.14	0.05	0.27	0.24		0.56	0.62	0.14	0.95
	4	0.69	0.45	0.17	0.55	0.73	0.08	0.62	0.86	0.17	0.45	0.15	0.12	0.14	0.63		0.42	0.20	0.13	0.91
M14 l.World core ex.EA	1	0.61	0.35	0.18	0.64	0.58	0.17	0.76	0.90	0.16	0.62	0.13	0.04	0.24	0.26	0.44		0.61	0.10	0.93
	4	0.69	0.5	0.19	0.59	0.76	0.06	0.67	0.83	0.15	0.47	0.14	0.12	0.15	0.68	0.58		0.25	0.03	0.90
M15 World core CPI	1	0.55	0.36	0.24	0.49	0.45	0.28	0.56	0.83	0.21	0.50	0.19	0.19	0.07	0.33	0.38	0.39		0.29	0.85
	4	0.79	0.77	0.58	0.72	0.83	0.48	0.76	0.95	0.46	0.65	0.40	0.54	0.13	0.80	0.80	0.75		0.62	0.92
M16 l.World core CPI	1	0.66	0.85	0.27	0.83	0.77	0.32	0.91	0.93	0.23	0.72	0.19	0.08	0.32	0.61	0.86	0.90	0.71		0.96
	4	0.73	0.87	0.42	0.79	0.89	0.20	0.86	0.88	0.27	0.56	0.23	0.35	0.22	0.92	0.87	0.97	0.38		0.95
M17 Inflation exp.	1	0.26	0.04	0.04	0.10	0.06	0.04	0.13	0.31	0.07	0.08	0.07	0.02	0.07	0.03	0.05	0.07	0.15	0.04	
	4	0.51	0.10	0.06	0.13	0.23	0.03	0.16	0.49	0.03	0.22	0.05	0.07	0.09	0.13	0.09	0.10	0.08	0.05	
M18 Oil price in EUR,	1	0.11	0.06	0.07	0.13	0.06	0.04	0.15	0.14	0.09	0.04	0.01	0.03	0.01	0.03	0.07	0.06	0.07	0.05	0.38
OECD CPI ex.EA	4	0.11	0.07	0.08	0.14	0.08	0.05	0.15	0.13	0.08	0.07	0.06	0.03	0.01	0.08	0.08	0.08	0.03	0.07	0.24

Models are estimated on rolling windows of a fixed size of 40 quarters. Forecast errors are computed over 39 observations for $h = 1$ and $h = 4$. Grey shaded cells highlight situations in which the null hypothesis is rejected at the 10% level. The abbreviation l. stands for lagged.

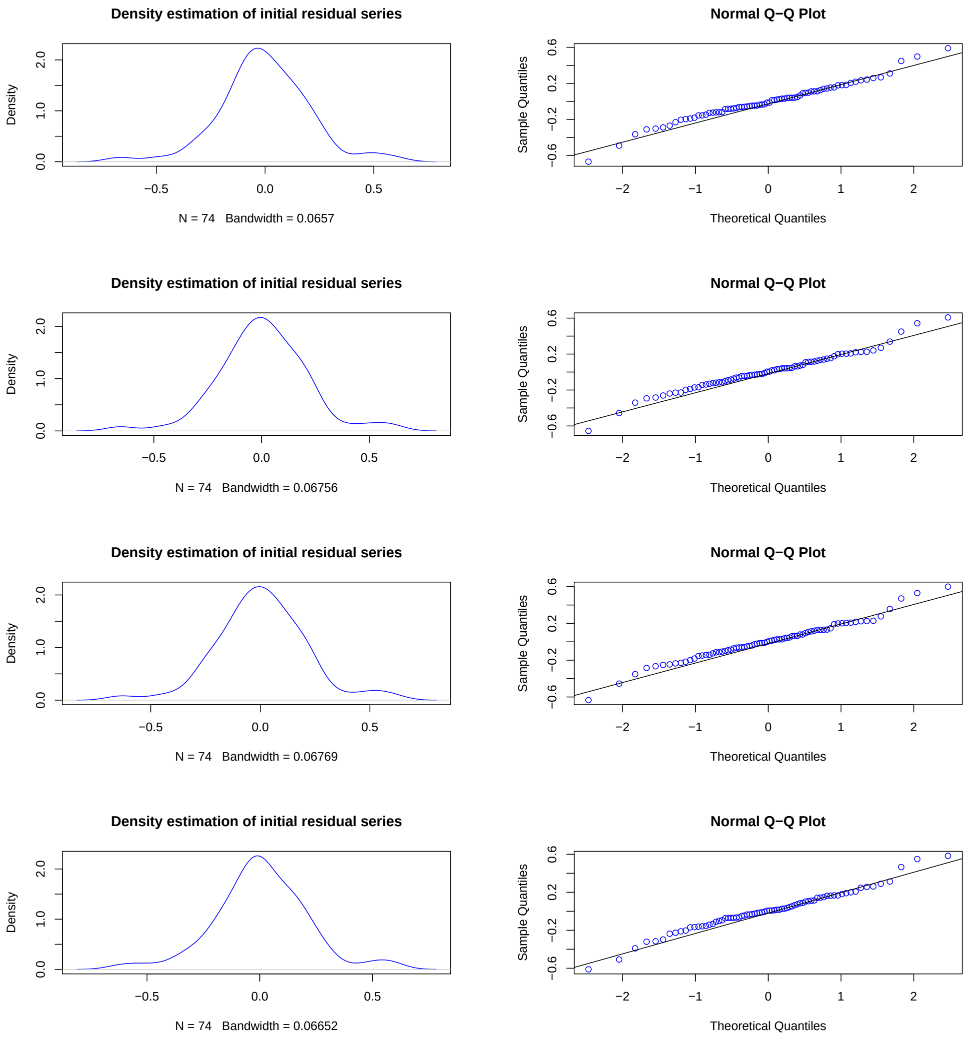
Table 15: **Pairwise one-sided Diebold-Mariano tests ($\mathbb{P}$-values)**

D Semi-parametric estimation of residual densities

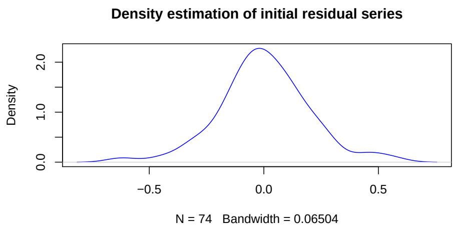
Density plots of residuals from estimated models M1 and variations

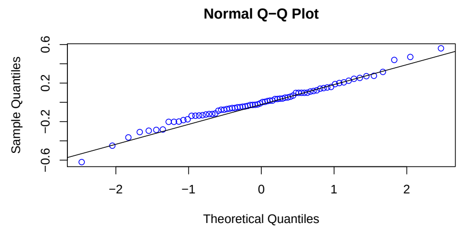


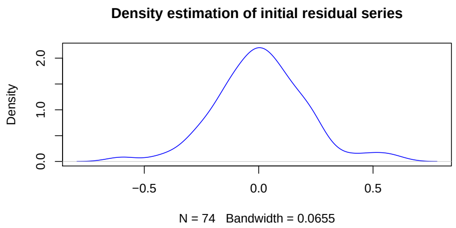
Density plots of residuals from estimated models M2 and variations

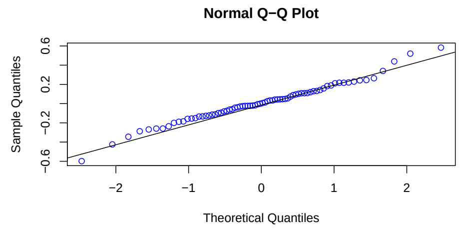


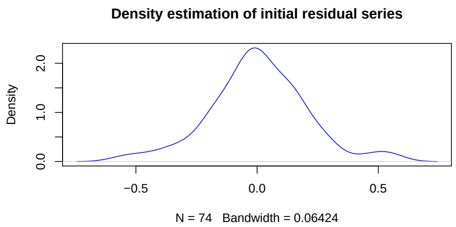
Density plots of residuals from estimated models M5 and variations

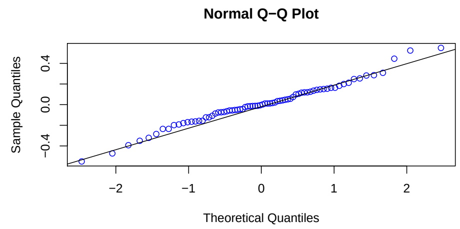


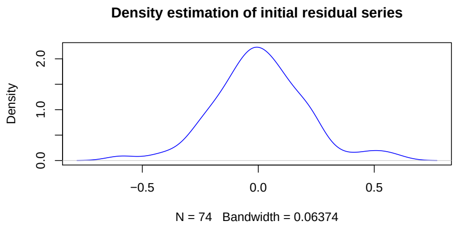


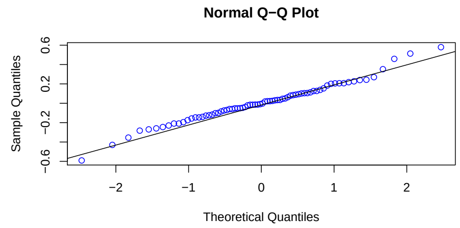








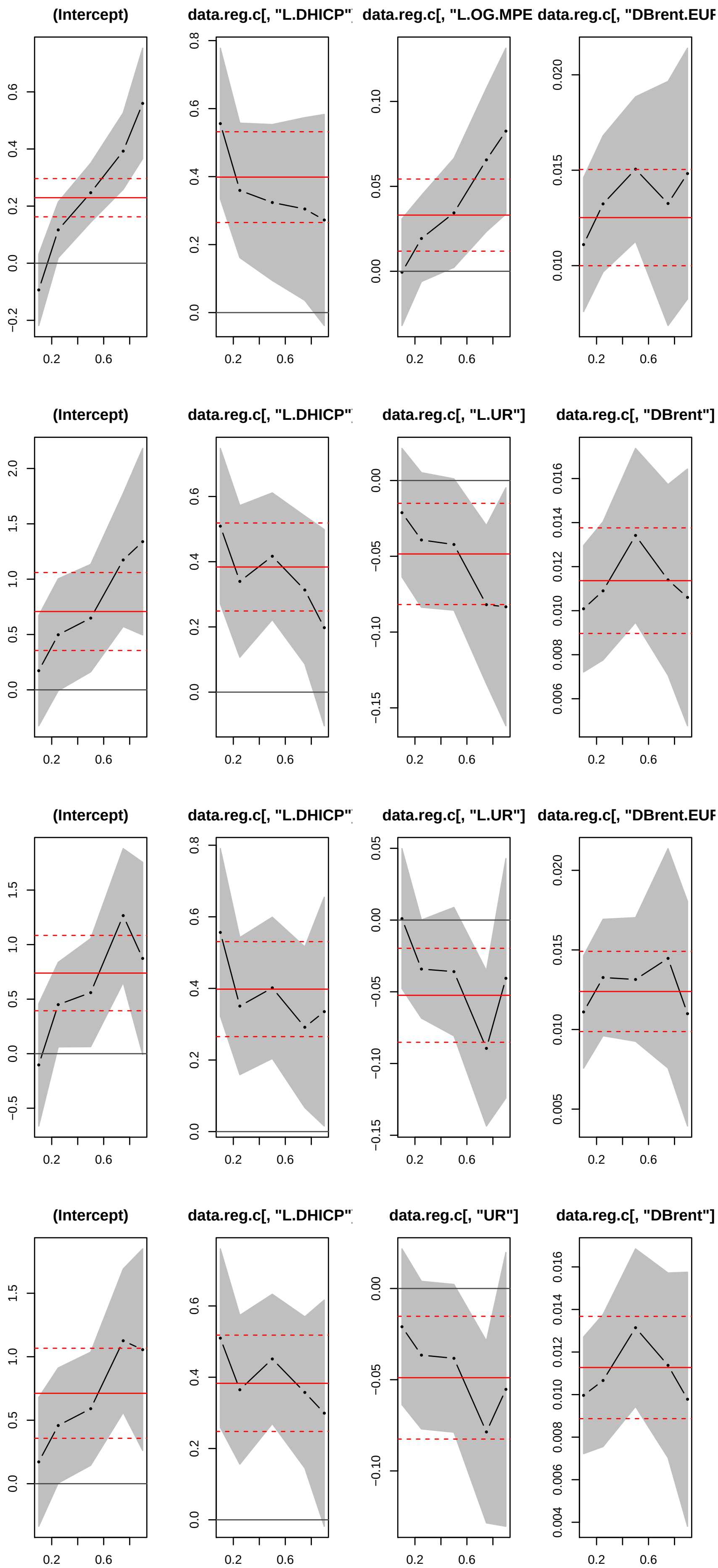


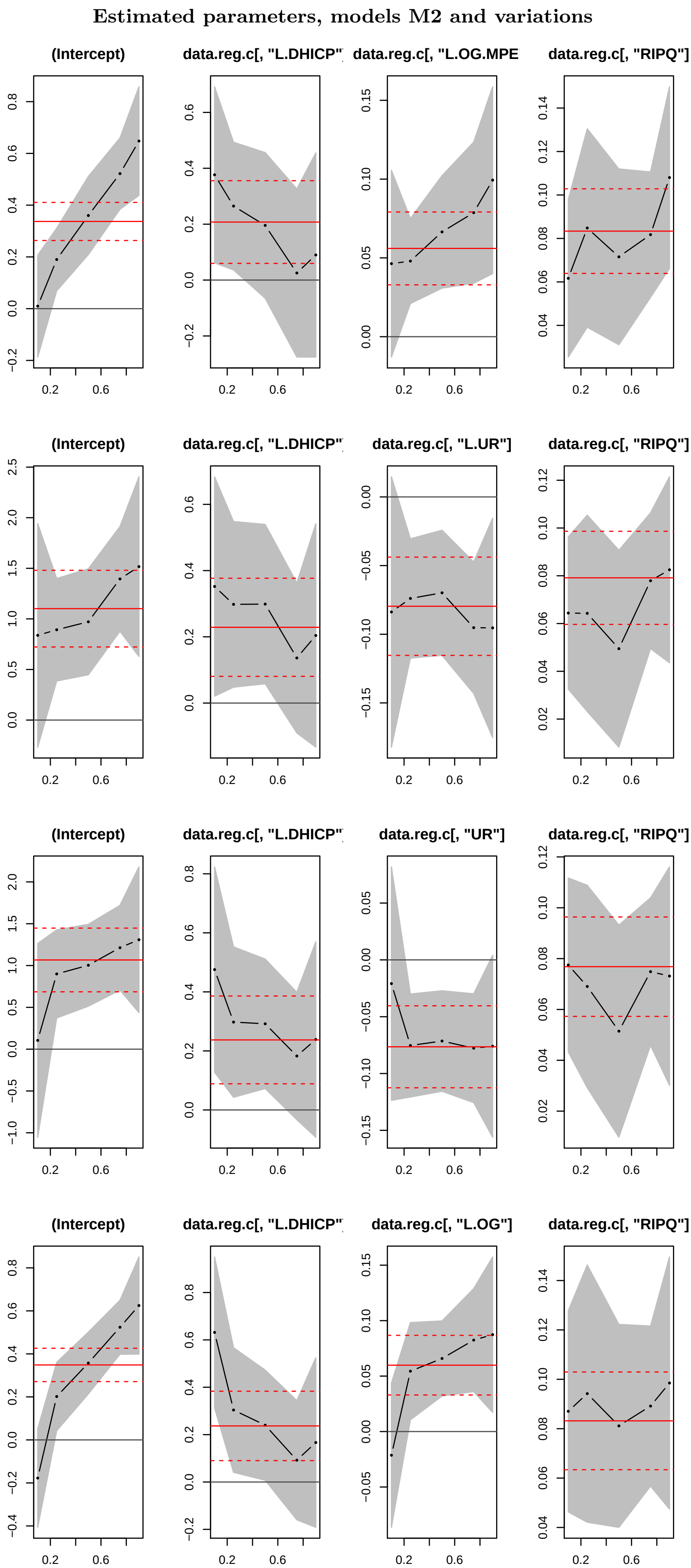


E Quantile inference

E.1 Graphs

Estimated parameters, models M1 and variations




Estimated parameters, models M2 and variations
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data.reg.c[, "L.OG.MPE
data.reg.c[, "RIPQ"]
(Intercept)
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data.reg.c[, "L.UR"]
data.reg.c[, "RIPQ"]
(Intercept)
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data.reg.c[, "UR"]
data.reg.c[, "RIPQ"]
(Intercept)
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data.reg.c[, "L.OG"]
data.reg.c[, "RIPQ"]

Estimated parameters, models M5 and variations