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A new model to forecast energy inflation in the euro area

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Abstract

Energy inflation is a major source of headline inflation volatility and forecast errors, therefore it is critical to model it accurately. This paper introduces a novel suite of Bayesian VAR models for euro area HICP energy inflation, which adopts a granular, bottom-up approach – disaggregating energy into subcomponents, such as fuels, gas, and electricity. The suite incorporates key features for energy prices: stochastic volatility, outlier correction, high-frequency indicators, and pre-tax price modelling. These characteristics enhance both in-sample explanatory power and forecast accuracy. Compared to standard benchmarks and official projections, our BVARs achieve better forecasting performance, particularly beyond the very short term. The suite also captures a sizable variation in the impact of commodity price shocks, pointing to higher elasticities at higher levels of commodity prices. Beyond forecasting, our framework is also useful for scenario and sensitivity analysis as an effective tool to gauge risks, which is especially relevant amid ongoing energy market transformations.

JEL Classification: C32, C53, E31, E37

Keywords: Gas prices, Oil prices, HICP, Bayesian VAR

Non-technical summary

This paper proposes a new Short-Term Inflation Projection (STIP) model suite to obtain forecasts of euro area energy inflation. The suite consists of Bayesian VAR (BVAR) models with the following characteristics: (i) a bottom-up approach with a fine disaggregation of energy items; (ii) the inclusion of higher frequency indicators; (iii) modelling of pre-tax prices in absolute (rather than percentage) changes; and (iv) features to account for both abrupt and persistent changes in volatility.

Granular modelling is important because HICP energy components vary substantially in terms of properties: frequency of available explanatory variables, taxation, degree of competition and regulation and main drivers. For instance, consumer car fuel prices are closely linked to developments in refined petroleum and diesel prices, where the pass-through from the latter to the former is full and relatively quick. In contrast, the pass-through from wholesale to consumer gas prices is more delayed, reflecting various shares of regulated prices and rules on price adjustment across the euro area. Electricity prices are also subject to a different share and type of regulation in many countries and are often adjusted less frequently.

The proposed models incorporate a wide range of drivers of consumer energy prices, including crude and refined oil prices, natural gas prices, producer prices of energy and applicable taxes, which could also include carbon prices. In fact, another advantage from implementing a granular modelling strategy is the possibility to better assess the impact of some measures in the Fit-for-55 package, as they affect various components in different ways. For example, EU Emissions Trading System (ETS) 2 will be introduced in 2027 and will affect transport fuels and building heating.

The proposed modelling framework also incorporates features to deal with the relatively unruly behaviour of energy prices. The BVARs feature stochastic volatility in the residuals and also handle extreme observations via "outlier correction". The framework also effectively deals with the so called ragged edge of the data on account of differences in publication delays between the indicators, an important feature in real-time applications. It also allows for seasonal terms in certain energy components.

Modelling HICP energy in a more granular fashion, by specifying models for the various sub-components, brings forecast gains. The STIP forecasts are evaluated using real-time data vintages from beginning 2014 to mid-2023. The forecasts are produced once per quarter at the cut-off dates corresponding to those in the Eurosystem/ECB staff macroeconomic projections. The forecast evaluation ascertains that on average and for the full sample, the newly proposed STIP models outperform the Eurosystem/ECB staff macroeconomic projections, for all forecast horizons except for the very short term. The better performance of the STIP models compared to the projections can be attributed to their better performance after the pandemic. The STIP forecast performance is also better compared to simple model benchmarks, such as an autoregressive model and a simple BVAR including HICP energy inflation and oil price growth.

This modelling framework can be also used to shed light on the transmission of energy price shocks in different markets to consumer energy prices. The estimated responses to oil price shocks are immediate and strong, while responses to wholesale natural gas price shocks tend to be more delayed. In both cases, the strength of the responses varies with the level of the underlying energy commodity prices, with the pass-through being stronger when the level of commodity price is higher.

Our results have important implications for practitioners, but also for policymakers, given that accurate inflation forecasts are key for monetary policy. We show that when it comes to forecasting the energy component of HICP it pays off to implement a granular, bottom-up approach. We underscore the importance of conditioning assumptions for the paths of energy commodity prices, when trying to get the future inflation right. Energy prices have been an important source of forecast errors and will continue to be one. We show that even if a model can accurately explain consumer energy prices *conditional* on the developments in oil and natural gas prices, the challenge comes from predicting the latter. We also stress that even if forecasting energy remains inherently challenging, having a model that does a good job in-sample is useful for scenario and sensitivity analysis as an effective way to gauge risks. It is important for policy makers to grasp the implications of possible paths of oil and gas prices for consumer prices and such exercises are regularly conducted. Furthermore, in the context of the increased pace of the green transition, models for energy prices are key for the quantification of the inflation effects of measures such as carbon taxes under the ETS2.

Finally, the recent energy crisis highlighted the need to continuously adapt forecasting models. We find that features such as outlier corrections and stochastic volatility are important when dealing with post-pandemic data. Looking forward, ongoing structural changes in the energy markets are bound to create new challenges for forecasting energy prices. These structural transformations due for example to carbon prices, renewable energy sources, de-coupling of electricity prices from gas in the long run, can be also incorporated in the proposed STIP models. The models could be also implemented at the country level, in particular for the most challenging components such as electricity and gas, for which the price setting mechanisms differ between countries.

1 Introduction

Energy inflation is volatile and notoriously hard to forecast. This fact makes it the key source of headline inflation forecast errors. This is why a continuous improvement of forecasting models for energy prices is an important task in a central bank and beyond.

Energy is an important driver of total inflation *level*, covering around 10% of HICP basket in the euro area. In certain episodes it has played a dominant role, such as during the global financial crisis of 2008-2009 or at the onset of the COVID-19 pandemic and during the subsequent recovery, see Figure 1. For example, annual rates of change in HICP energy reached an unprecedented level of 44.3% in March 2022, contributing around 60% of headline inflation. At the same time HICP energy has been the key driver of the *volatility* of inflation. Compared to other inflation components, HICP energy is more volatile and linked to movements in international energy commodity prices. This makes HICP energy harder to forecast. In the euro area most of the Eurosystem/ECB staff inflation projections errors come from energy prices, and in particular are related to the assumed (future) paths for energy commodity prices (Chahad et al., 2022, 2023).[1]

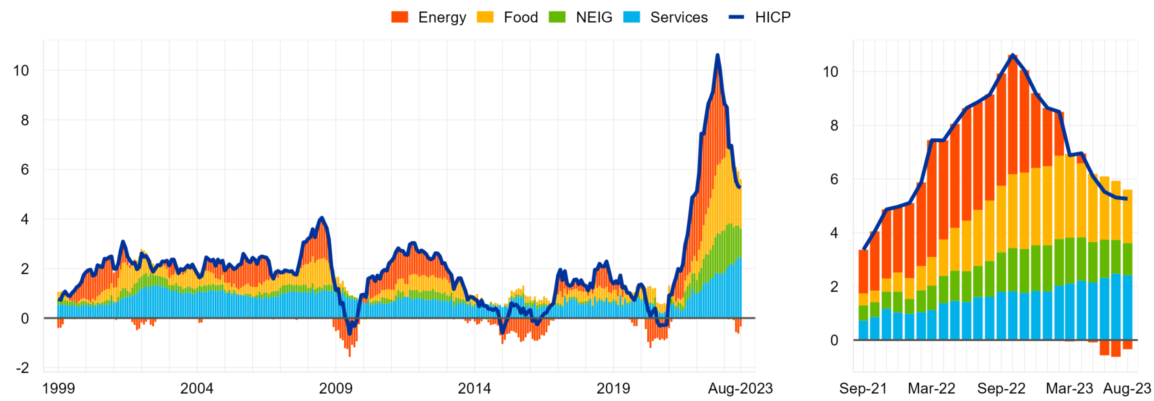


Figure 1: Contribution to euro area HICP annual inflation by main component, in p.p.

We propose a new Short-Term Inflation Projection (STIP) model suite to obtain forecasts of euro area energy inflation. We adopt a granular, bottom-up approach and we fit a Bayesian VAR (BVAR) model to each of 7 subcomponents of HICP energy: petrol, diesel and liquid fuels, gas, electricity, heat energy and solid fuels. The models incorporate key features for energy prices:

[1] The forecast errors in energy prices have also implications for forecast accuracy of other components of inflation given that many goods and services have energy inputs.

the inclusion of higher frequency indicators; modelling of pre-tax prices in absolute (rather than percentage) changes; and stochastic volatility and outlier correction to account for both abrupt and persistent changes in volatility.

We model HICP energy in a bottom-up fashion, as the various components differ substantially in terms of frequency of available explanatory variables, applied taxation, degree of competition and regulation or main drivers. For instance, car fuel prices are closely linked to developments in refined petroleum and diesel prices, whose pass-through to consumer prices is full and relatively quick (Meyler, 2009). In contrast, the pass-through from wholesale to consumer gas prices is more delayed (Cornille and Meyler, 2010; Kuik et al., 2022), as the latter adjust in a more sluggish way, also given a notable share of regulated prices in some countries of the euro area. Electricity prices are also subject to a different share and type of regulation across the euro area and are often adjusted less frequently. Our models incorporate a wide range of drivers of consumer energy prices, including crude and refined oil prices, natural gas prices, producer prices of energy and applicable taxes (which could also include carbon prices).

The framework incorporates several features that are key when modelling energy prices. In order to obtain a timelier signal for the monthly inflation, we exploit information in weekly indicators for car fuels and liquid fuels. We also apply specific transformations to our data in order to establish more robust links between consumer energy prices and their drivers. More precisely, we use pre-tax data where available as excise duties and VAT play a sizeable role for consumer energy prices (unlike for other HICP components).[2] We re-attribute taxes to the forecasts ex-post, assuming constant paths over the future. Furthermore, in line with previous findings (see e.g. Bachmeier and Griffin, 2003; Meyler, 2009) we model *absolute* changes in the price indices as opposed to *percentage* changes as is common for other inflation components. This reflects the observation that refining and distribution margins are broadly stable (and not applied as a percentage of the input cost). This transformation, combined with the fact that excise duties are charged per unit rather than ad valorem, implies that the elasticity of consumer energy prices with regard to oil or natural gas prices depends on the level of the latter. As there is a large share of per unit "add ons" such as excise duties or refining and distribution margins, a certain percentage change in the oil or gas price leads to a lower percentage change in consumer energy prices when oil or gas prices are low compared to when they are high.

[2] Gas and electricity include also other taxes such as system charges, which could become more relevant in the future (Kuik et al., 2022).

Our proposed modelling framework also incorporates features to deal with the relatively unruly behaviour of energy prices. The BVARs feature stochastic volatility in the residuals and also handle extreme observations via "outlier correction" in the spirit of Stock and Watson (2016) and Carriero et al. (2022b). To deal with the so-called ragged edge of the data, which arises in real-time applications on account of differences in publication delays between various indicators, the model is cast in a state space representation and forecasts are obtained using a simulation smoother (see e.g. Durbin and Koopman, 2002; Bańbura et al., 2015). The model also allows for seasonal terms in certain energy components.

Despite the fact that the use of BVARs is now standard in the literature on inflation forecasting (Giannone et al., 2014; Domit et al., 2016; Angelini et al., 2019; Bańbura et al., 2021; Bańbura et al., 2024; Crump et al., 2025, among many others), to our knowledge this is the first study to evaluate the merits of BVARs to forecast HICP energy based on its subcomponents.[3]

Our paper is related to the literature on forecasting inflation using a bottom-up approach, i.e. forecasting inflation subcomponents and aggregating them to construct an overall (headline) inflation forecast (Espasa et al., 2002; Roma et al., 2004; Hubrich, 2005; Hendry and Hubrich, 2011; Bermingham and D'Agostino, 2014; Giannone et al., 2014; Sokol et al., 2020).[4] However, most studies concentrate on analysing forecasts of headline and core HICP inflation and only a limited number of papers evaluates forecasts also for subcomponents. Furthermore, when disaggregation is considered, it usually does not go beyond (total) HICP energy [5]. For instance, Roma et al. (2004) and Hubrich (2005) provide a forecasting evaluation based on five components of headline HICP. In contrast to the evidence provided by academic papers, practitioners often use more granular models to obtain a timelier and more precise signal for the dynamics of consumer energy prices. It is because simple models with total energy and oil prices cannot capture the complexity of energy markets and fully exploit the available information. In addition, more detailed models are needed to evaluate the implications of the ongoing and expected structural changes in energy markets, including the changing relative importance of different

[3] Another class of models popular for forecasting inflation is factor models, see e.g. Stock and Watson (1999), Faust and Wright (2013) or Modugno (2013). In case of HICP energy the set of relevant predictors is however relatively limited. In addition, as shown in e.g. Bańbura et al. (2015), forecasting performance of both classes of models is often similar.

[4] Our paper also contributes to literature on short-term forecasting or nowcasting of inflation using high-frequency data (Bachmeier and Griffin, 2003; Lenza and Warmedinger, 2011; Modugno, 2013; Monteforte and Moretti, 2013; Marsilli, 2017; Knotek and Zaman, 2017, 2023; Aliaj et al., 2023). Baumeister et al. (2015) use weekly data to forecast oil prices.

[5] Knotek and Zaman (2017) and Baumeister et al. (2017) propose models for forecasting gasoline prices in the United States, but they do not consider other energy components.

energy source or the impact of various climate change mitigation measures.

We evaluate the forecast performance and the fit of the models using real-time data vintages covering the period March 2014 to June 2023. We produce forecasts once per quarter, at the cut-off dates corresponding to those in the Eurosystem/ECB staff macroeconomic projections (labelled (B)MPE).[6] This allows us to compare the models' performance to a hard-to-beat benchmark, namely the Narrow Inflation Projection Exercise (NIPE) forecasts. These are monthly forecasts of HICP at disaggregated level prepared as part of the (B)MPEs. They are produced by the National Central Banks of the Eurosystem for their respective country and rely on detailed information, models and judgment (ECB, 2016). We also compare the suite's performance to simple model benchmarks, such as an autoregressive model and a simple BVAR including HICP energy inflation and oil price growth.

We evaluate the models in terms of unconditional forecasts, as well as of forecasts conditioned on (B)MPE assumptions for future paths of oil and gas prices (in euro). The latter setting is relevant when we benchmark the models against the NIPE forecasts, which rely on such conditioning information. In order to evaluate the fit of the models, we also conduct a recursive *counterfactual* exercise in which we condition on the *realised* paths of commodity prices.

The real-time forecast evaluation ascertains that on average and for the full sample, the newly proposed STIP models outperform the NIPE for all forecast horizons except for the very short term. This is interesting as the projections often have an advantage in terms of available information.[7] The better performance of the STIP compared to the NIPE can be attributed to its better performance after the pandemic. On a pre-COVID sample the STIP models beat the simple bi-variate BVAR including oil prices, but they do not outperform the NIPE.

Conditioning on the paths for oil and gas prices assumed in the (B)MPEs does not help apart from the very short term, as unconditional STIP forecasts are better than conditional ones for horizons longer than 3 months. This underscores the importance of the accuracy of such assumptions when forecasting consumer energy prices.

The counterfactual exercise, conditioning on the actual path of oil and wholesale gas prices shows that the model does a good job in explaining consumer energy prices when their determinants are known and going granular pays off compared to a model for total energy inflation.

[6] For explainers on (Broad) Macroeconomic Projections Excercises, see ECB (2016) and `https://www.ecb.europa.eu/pub/projections/html/index.en.html`.

[7] For example, flash estimates for HICP for certain countries are available before the euro area aggregate data is released. Often also information on future changes in regulated prices or taxes is incorporated.

The in-sample fit worsens in the high inflation period, especially for gas and electricity prices, suggesting the presence of some structural changes, non-linearities or other factors not captured by the model.

The modelling framework can be also used to shed light on the transmission of wholesale energy price shocks in different markets to consumer energy prices. We produce impulse response functions at different levels of oil and natural gas prices. The estimated responses to oil price shocks are immediate and strong, while responses to natural gas price shocks tend to be more delayed and muted. For reasons mentioned above, despite the models being linear, the responses are level dependent whereby a higher level of energy commodity prices implies a stronger pass-through. In particular, during the inflation surge period, the pass-through of gas commodity price changes had on average doubled compared to a pre-pandemic sample.

Our results have important implications for practitioners, but also for policymakers, given that accurate inflation forecasts are key for monetary policy. We show that when it comes to forecasting the energy component of HICP it pays off to implement a granular, bottom-up approach. We underscore the importance of conditioning assumptions for the paths of energy commodity prices, when trying to get the future inflation right. Energy prices have been an important source of forecast errors and will continue to be one. We show that even if a model can accurately explain consumer energy prices *conditional* on oil and natural gas prices, the challenge comes from predicting the latter. In that respect, we find that including information on futures prices of energy commodities does not lead to systematic improvements in forecast accuracy for consumer energy prices. Alternative approaches to derive such conditioning paths could be used, see e.g. Baumeister and Kilian (2014), Van Robays and Belu Mănescu (2014), Baumeister et al. (2024a) or Baumeister et al. (2024b).[8]

We also stress that even if forecasting energy remains inherently challenging, having a model that does a good job in-sample is useful for scenario and sensitivity analysis as an effective way to gauge risks. It is important for policy makers to grasp the implications of possible paths of oil and gas prices for consumer prices and such exercises are regularly conducted.[9] Furthermore,

[8]Baumeister and Kilian (2014) show that VAR models can provide more accurate forecasts for (real) oil prices compared to oil futures prices and no change forecasts. Van Robays and Belu Mănescu (2014) propose a four-model forecast combination approach to deal with instability in relative forecast performance. Baumeister et al. (2024a) provide a comprehensive analysis of the forecastability of the real price of natural gas in the United States and find considerable improvements when using a six-variable BVAR model that includes the fundamental determinants of the supply and demand for natural gas. Baumeister et al. (2024b) propose a model based on Bayesian additive regression trees to evaluate scenarios and risks of tail events in the global crude oil markets.

[9]The Eurosystem/ECB staff macroeconomic projections regularly publish sensitivity analyses with respect to

in the context of the increased pace of the green transition, models for energy prices are key for the quantification of the inflation effects of measures such as carbon taxes under the Emissions Trading System (ETS) 2.[10]

Finally, the recent energy crisis highlighted the need to continuously adapt forecasting models. We find that features such as outlier correction and stochastic volatility are important when dealing with post-pandemic data. Looking ahead, ongoing structural changes in the energy markets are bound to create new challenges in the prediction of energy prices.

2 Econometric framework

The energy block is modelled deploying the same class of models for each individual component, namely a Bayesian Vector Autoregression (BVAR) featuring two key ingredients: (i) stochastic volatility and (ii) model-based adjustment for outliers. These two elements allow for both persistent and transient changes in volatility, which may give rise to extreme realisations.

Modelling stochastic volatility (feature (i)) has been found important for forecasting with BVARs, see e.g. Clark (2011) or Clark and Ravazzolo (2014). Baumeister et al. (2022) find that allowing for stochastic volatility leads to considerable improvements in forecast accuracy for oil prices, especially at longer horizons. In view of the recent volatility, Carriero et al. (2022b) find that allowing for additional transitory changes in variance (feature (ii)) leads to forecast improvements. Bańbura et al. (2024) show the importance of both features when forecasting (total) inflation in the US and in the euro area with BVAR models.

Following Carriero et al. (2022b), stochastic volatility is modelled using the Cholesky factorization of the residual variance-covariance matrix and outliers are handled by introducing a discrete mixture representation originally proposed by Stock and Watson (2016). A similar econometric specification has been applied in Bańbura et al. (2024).

alternative energy commodity price paths whereby the alternative paths are derived from the lower and upper percentiles of the option-implied neutral densities for both oil and gas prices.

[10] The model suite proposed in this paper can be used, for example, to quantify the impact on inflation of the ETS2 under different assumptions on the prices of the emissions, see e.g. Box 2 in the December 2024 report on the Eurosystem staff macroeconomic projections for the euro area (ECB, 2024).

2.1 Model

For any time period $t \in [1, T]$ the VAR reads:

$$y_t = \sum_{i=1}^{p} B_i y_{t-i} + C x_t + \nu_t, \quad \text{with } \nu_t \sim \mathcal{N}(0, \Sigma_t), \tag{1}$$

where y_t is an $n \times 1$ vector of endogenous variables, $B_1, ..., B_p$ are p matrices of dimension $n \times n$ containing the autoregressive coefficients, p is the number of lags, x_t is an $m \times 1$ vector of exogenous variables (e.g., constant terms, seasonal dummies), C is an $n \times m$ matrix of coefficients and ν_t is an $n \times 1$ vector of residuals with zero mean and variance-covariance matrix denoted by Σ_t. Notice that although the BVAR coefficients are assumed to remain constant, the volatility of the residuals is allowed to vary over time, introducing heteroskedasticity. In particular, we assume the volatility to be stochastic and to occasionally take on extreme values, leading to "outliers". Indeed, we decompose the symmetric positive-definite matrix Σ_t as follows:

$$\Sigma_t = A^{-1} O_t \Lambda_t O_t' \left(A^{-1}\right)' \tag{2}$$

where A^{-1} is a time-invariant lower triangular matrix with ones on its main diagonal,[11] Λ_t is a period-specific diagonal matrix of stochastic volatilities with $\text{diag}(\Lambda_t) = (\lambda_{1,t}, ..., \lambda_{n,t})'$, and O_t is a period-specific diagonal matrix of stochastic scale factors with $\text{diag}(O_t) = (o_{1,t}, ..., o_{n,t})'$. Hence the residuals in (1) can be rewritten as:

$$\nu_t = A^{-1} O_t \Lambda_t^{0.5} \epsilon_t \qquad \epsilon_t \sim \mathcal{N}(0, I_n) \tag{3}$$

where ϵ_t may be interpreted as Gaussian structural innovations. The reduced-form residuals ν_t are thus Gaussian conditional on Λ_t and O_t. The model is completed by specifying laws of motion for the unobserved states $\lambda_{j,t}$ and $o_{j,t}$. The vector of logs of the stochastic volatilities, denoted as $\log \lambda_t$, is modelled as a vector of random walks with uncorrelated errors:

$$\log \lambda_t = \log \lambda_{t-1} + e_t \qquad e_t \sim \mathcal{N}(0, \Phi) \tag{4}$$

[11] The main implication of this assumption is that the contemporaneous effect of an innovation to the ith variable on the jth variable is assumed to be constant over time. Indeed, Primiceri (2005) and Carriero et al. (2018) found little variation in such coefficients. Specifying a time-varying A_t would require additional $n(n-1)/2$ state equations to model the evolution of the non-zero off-diagonal entries of such matrix, resulting in a computationally heavier estimation algorithm.

where Φ is diagonal. The scale factors $o_{j,t}$ are mutually *i.i.d.* over all j and t, and follow a mixture distribution that allows distinguishing between regular observations with $o_{j,t} = 1$ and outliers with $o_{j,t} \geq 2$. In particular, in any period t outliers in variable j occur with probability p_j and:

$$o_{j,t} = \begin{cases} 1 & \text{with probability } 1 - p_j \\ \mathcal{U}[2, 20] & \text{with probability } p_j \end{cases} \tag{5}$$

The BVAR is estimated using a Markov Chain Monte Carlo (MCMC) algorithm as in Carriero et al. (2019), Carriero et al. (2022a) and Carriero et al. (2022b), which consists in obtaining draws from the joint posterior distribution by drawing from a sequence of posterior distributions of blocks of parameters conditional on the data and on the remaining blocks.

Priors

The VAR slope coefficients follow a normal distribution and are shrunken towards a white noise such that their unconditional mean is zero. We set a diffuse prior for the constant. The prior for the below-diagonal elements of the correlation matrix A follows a normal distribution. The prior for the variances of the stochastic volatilities contained in the diagonal of Φ is Inverse-Gamma and a normal prior is used for the initial value of $\log \lambda_t$. Finally, Beta prior is used for the outlier probabilities p_j, set to imply a mean outlier frequency of once every 4 years.

Conditional forecasts and impulse response functions

Conditional forecasts are produced using a Kalman filter methodology, see e.g. Bańbura et al. (2015). In fact, the variables for which we do not assume the knowledge of a future path can be considered as time series with missing data. The Kalman filter allows to easily deal with such time series. In particular, we cast the VAR in state-space form, and use a simulation smoother (Durbin and Koopman, 2002) to draw from the posterior distribution of the conditional forecasts. The same approach is used to deal with ragged edges in the data: first, we estimate the model based on a "balanced" data set (excluding the periods at the end of the sample for which not all the variables are available), second we condition our forecasts on the ragged edge so as to avoid discarding information.

The conditional forecast framework can be also used to obtain impulse response functions (see Bańbura et al., 2015). In this paper we use a somewhat unconventional concept of IRF.

Specifically, the impact of shocks in the international commodity prices on consumer prices are computed as the percentage difference between two conditional forecasts, one in which the commodity price is assumed to *permanently* increase by 10% relative to the last value in the sample, and one in which the price is assumed to remain constant at its last observed value throughout the forecast horizon.[12]

2.2 Detailed specifications

We construct and evaluate separate models for six HICP energy components: (i) car fuels, (ii) liquid fuels, (iii) gas, (iv) electricity, (v) heat energy, and (vi) solid fuels.[13] In a second step, we aggregate the forecasts of individual subcomponents to construct predictions for HICP energy, based on consumption basket weights.[14] The need for a more detailed approach in modelling and forecasting energy inflation goes beyond just improving accuracy. It also helps in understanding the factors driving the different energy components and allows for the inclusion of specific explanatory variables for each component. This need became obvious with the energy crisis in the aftermath of the COVID-19 pandemic. Traditionally, energy shocks had been oil-driven, so the main drivers of energy inflation have been car fuels, reflecting their large weight (around 40%) in overall energy consumption. Figure 2 illustrates the role played by the various components of energy inflation over time. Yet the post-pandemic period was atypical with respect to the drivers of the energy inflation - electricity and gas contributed more than usual and accounted for half of energy consumer price inflation at its peak of 44% in early 2022 (their weight in the energy consumption basket were 28% and 20% respectively, based on 2022 weights). Their large contribution reflected various factors. Gas price inflation already surged since the summer of 2021, particularly in Europe, reflecting a combination of supply and demand factors, amid increased uncertainty, including from escalating geopolitical tensions. Supply from Norway was low in the first half of 2021 owing to maintenance work on pipelines, and since the

[12] By contrast, a "traditional" IRF for a recursive scheme can be obtained by a taking a difference between a conditional forecast with appropriate constraints on the shocks on impact and an unconditional forecast, see Bańbura et al. (2015) for details.

[13] This corresponds to disaggregation at four-digit COICOP. In the COICOP terminology the category "car fuels" reads as "fuels and lubricants for personal transport equipment" but we will refer to it with the simplified label. The details, including COICOP codes for each component, are provided in Appendix A. Note that in some publications car fuels and liquid fuels are combined and labelled as "liquid fuels" and are officially defined by Eurostat as "Liquid fuels and fuels and lubricants for personal transport equipment". In this paper, liquid fuels refer to the narrower category (0.7% of the HICP basket) which is included under housing costs (as an example liquid fuels for domestic heating and lighting oils).

[14] The aggregation of the subcomponents to HICP energy is done via chain-linking Laspeyres-type indices.

summer of 2021 supply of gas from Russia to the EU dropped significantly, contributing to the slow replenishment of gas inventories in Europe ahead of the winter season. The Russian invasion of Ukraine in early 2022 had a major aggravating effect. Peak electricity prices in 2022 were mainly driven by gas market developments but were intensified due to supply shortages of other electricity sources, including low hydro power generation due to droughts, and low nuclear generation in France due to maintenance. Heat energy and solid fuels play a negligible role for the euro area aggregate (around 0.5% in total of the HICP basket in 2022) and they are modelled only for the purpose of covering the entire energy basket.

Another advantage from implementing a more granular modelling strategy is the possibility to better assess the impact of some measures in the Fit for 55 package, as they affect various components in different ways. For example, EU Emissions Trading System 2 will be introduced in 2027 and will affect transport fuels and building heating, see e.g. Box 2 in ECB (2024).

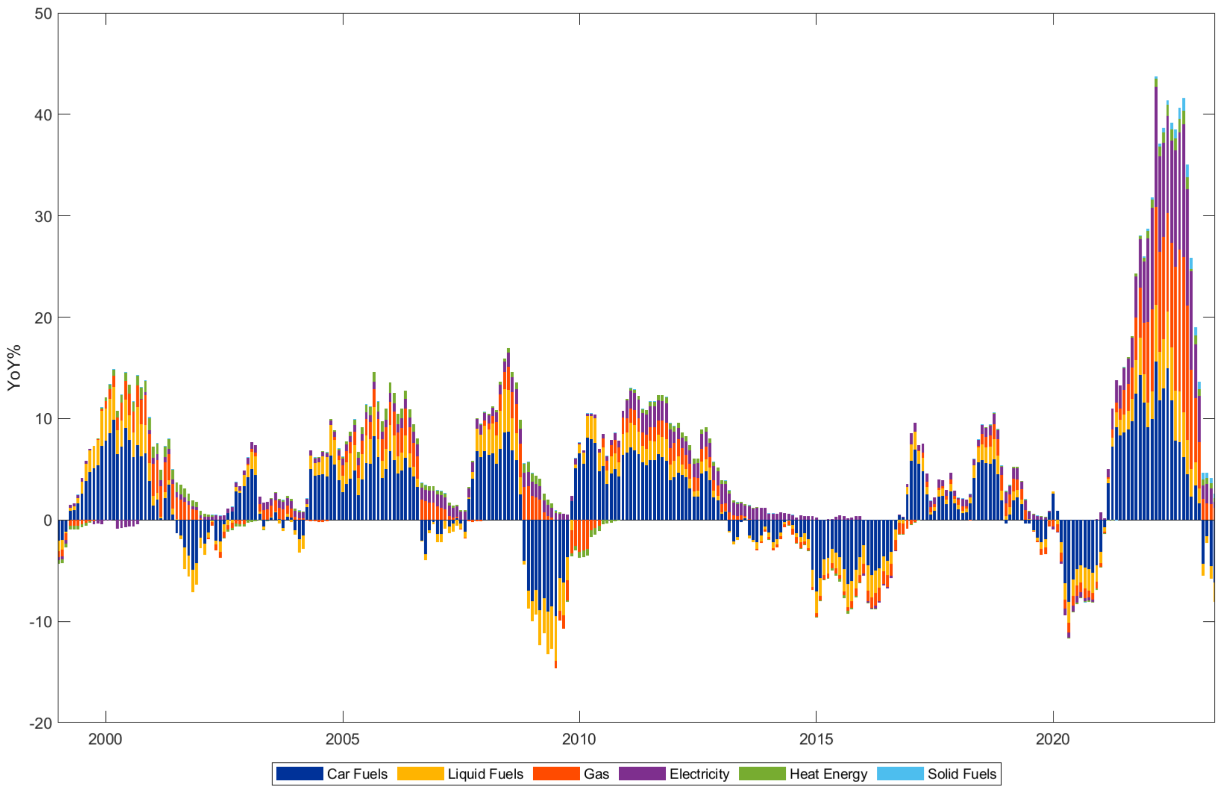


Figure 2: Contribution of subcomponents to annual energy inflation (percentage points).

Figure 3 and Table 1 provide an overview of the the explanatory variables, set-up of the models and main features. More details are provided in the next subsections.

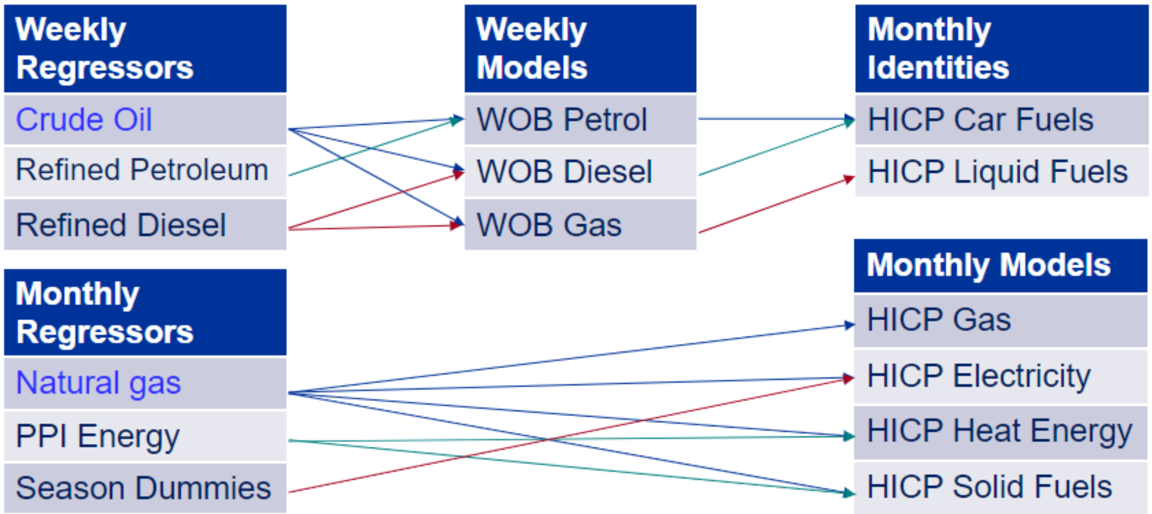


Figure 3: Set-up of the energy inflation forecasting model

Variable	Frequency	Lags	Regressors	Seasonal Dummies
Car fuels, petrol	W	24	Crude oil, refined petroleum	N
Car fuels, diesel	W	24	Crude oil, refined diesel	N
Liquid fuels	W	24	Crude oil, refined diesel	N
Gas	M	12	Natural gas	N
Electricity	M	12	Natural gas	Y
Heat energy	M	12	Natural gas, PPI energy	N
Solid fuels	M	12	Natural gas, PPI energy	N

Table 1: Model specifications

Car fuels

For car fuels and liquid fuels high frequency weekly data is available from the European Commission's Weekly Oil Bulletin (WOB). In order to be able to use up-to-date information with partial monthly data, the models for these two components are specified at a weekly frequency (with 24 lags). Prices of crude oil, refined petroleum and diesel products are all converted to euro. For car fuels WOB data are separately available for petrol and diesel prices, therefore for this HICP energy component we actually construct two models. The weekly BVAR for petrol prices contains WOB petrol, crude oil and refined petroleum prices. The BVAR for diesel prices includes WOB diesel, crude oil and refined diesel prices. The inclusion of refined petroleum and refined diesel prices helps capture developments at different stages of the pricing chain and implicitly obtain forecasts for refining and distribution margins.

Regarding the transformation of the variables, the BVARs include data based on pre-tax prices (also available in the WOB) expressed in weekly absolute differences (as opposed to weekly log differences). As shown in Meyler (2009) the link between consumer prices and oil commodity prices is more stable in that case. In addition, the impact of known future changes to taxes can be easily incorporated when data is expressed in pre-tax terms. Once a forecast is obtained, taxes (i.e. excise and VAT) are "re-attributed" ex-post, assuming unchanged levels over the forecast sample. In order to obtain the monthly forecasts for HICP car fuels, weekly petrol and diesel price forecasts are converted to monthly frequency and aggregated based on their weight.[15] Figure 4 illustrates the importance of taxes and shows the contribution of pre-tax prices and taxes (excise and VAT) for petrol and diesel in the panels (a) and (b).

Liquid fuels

Similarly to car fuels, forecasts for liquid fuels are obtained based on a weekly BVAR model in order to make use of the higher frequency information on consumer prices included in the European Commission's WOB. The model includes the WOB gas oil series, crude oil and refined diesel prices. Otherwise, the same model settings and variable transformations are applied as described for car fuels. We present an overview of the contribution of taxes to WOB gas oil in panel (c) of Figure 4.

Gas

For consumer gas inflation and the remaining HICP energy components the models are specified at monthly frequency (including 12 lags). Again, we include pre-tax consumer gas prices obtained by combining HICP data with the Eurostat (bi-annual) data on gas price level and relevant excise and VAT taxes. The details are provided in Appendix A.1. As for the previously described components, the taxes are re-attributed ex-post to the forecasts using a random walk assumption. Also in this case absolute differences and not log differences are applied to the included variables. As explanatory variable, we consider natural gas wholesale prices (Netherlands TTF Natural Gas Forward Day Ahead - Settlement price).

[15] HICP series for petrol and diesel and associated weights are only available as of December 2016, which does not cover our full estimation sample, which starts in 1994. In order to evaluate the forecasts for the aggregate car fuels component over the entire evaluation sample we use weights estimated via constrained OLS before December 2016.

Electricity

Consumer electricity inflation is forecasted based on a monthly BVAR (12 lags) and includes absolute differences of pre-tax electricity prices and of natural gas wholesale prices. Pre-tax prices are obtained using the Eurostat data as in the case of gas prices. Given that electricity prices tend to be adjusted in specific months (most notably in January) in some countries, seasonal dummies are included as well.

Heat energy

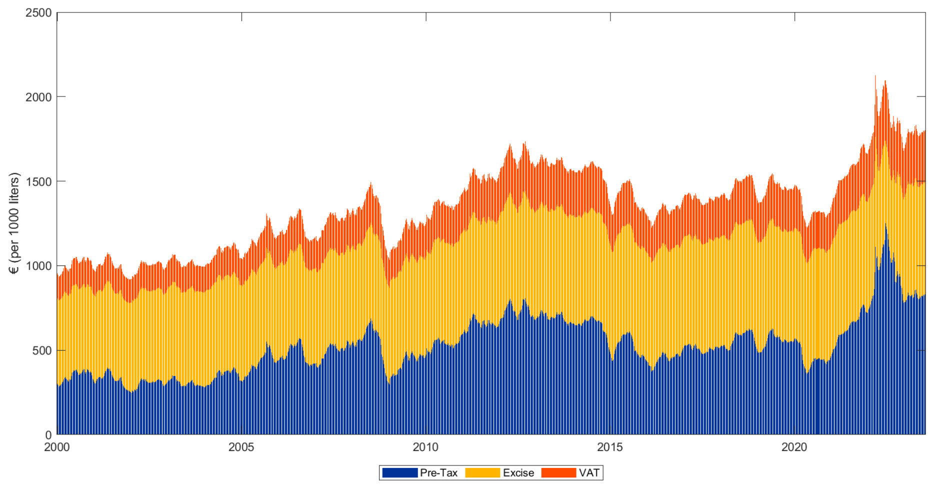
The BVAR is monthly (12 lags) and includes HICP heat energy, natural gas wholesale prices and PPI energy, all expressed in absolute differences.

Solid fuels

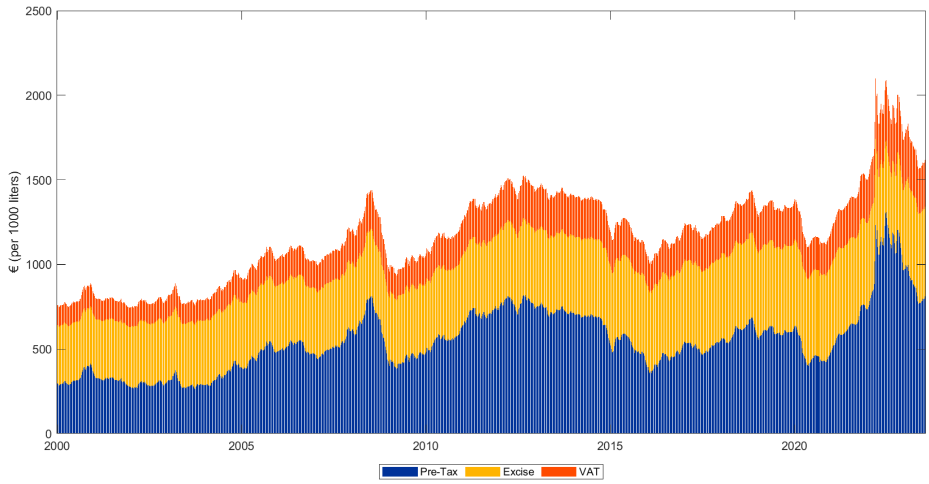
The BVAR is monthly (12 lags) and includes HICP solid fuels, natural gas wholesale prices and PPI energy, all expressed in absolute differences.

2.3 Benchmarks

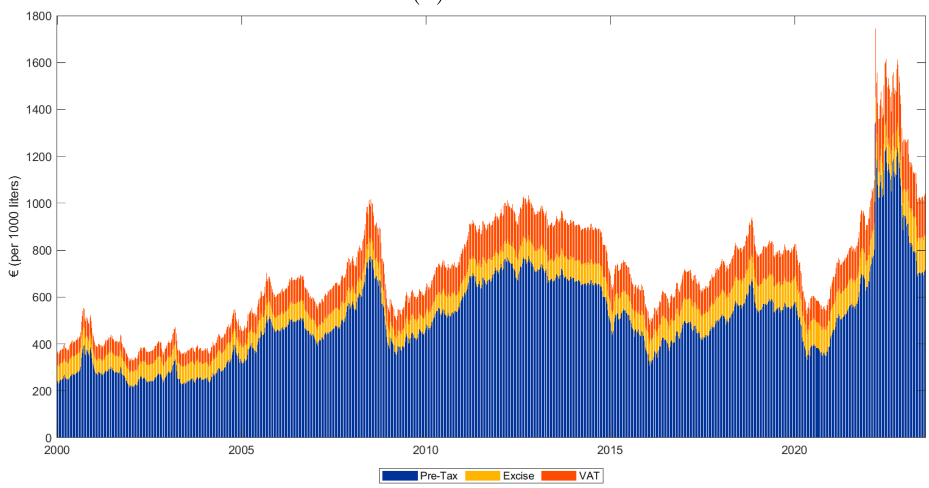
Apart from the short-term inflation projections provided by National Central Banks once per quarter in the Eurosystem staff inflation projections exercise (see ECB (2016)) we compare the models to a univariate Bayesian AR model for HICP energy (in log differences) and a bivariate BVAR including crude oil prices and HICP energy (both variables in log differences). These benchmarks differ in terms of choice of variables and transformations but have the same econometric features.



(a) Petrol



(b) Diesel



(c) Gas

Figure 4: Contributions of excise taxes and VAT to Weekly Oil Bulletin Petrol, Diesel, and Gas prices.

3 Real-time forecast evaluation

3.1 Real-time data

We construct real-time vintages for all the series included in the model, i.e. covering commodity prices, producer prices, EUR/USD exchange rate, WOB series, and the components of HICP energy. To that end we use the vintages stored in the ECB macroeconomic projections database and the Statistical Data Warehouse (SDW). For the bi-annual data on gas price levels and applicable taxes, real-time vintages are not available and we create pseudo real-time vintages.

Wherever applicable the data refers to the changing composition of the euro area. For some series backdating is applied to obtain a longer history. Detailed explanations are provided in Table A1 in the Appendix.

3.2 Design of the evaluation

The models are used to produce forecasts with real-time data vintages. The forecasts are produced once per quarter and the cut-off dates correspond to those in the Eurosystem/ECB staff macroeconomic projections (henceforth (B)MPE, which stands for (Broad) Macroeconomic Projection Exercise). This allows for a fair comparison with the monthly HICP forecast embedded in these projections.

The evaluation sample starts with the (cut-off date of) March 2014 MPE and goes to June 2023 BMPE (38 vintages). The cut-off dates are usually in the second half of the second month of each quarter (see Table A2 in the Appendix). We evaluate the forecasts for one-, three-, six-, nine- and eleven-month ahead horizon. The latter is the longest horizon that is available for the monthly Eurosystem staff inflation projections for the entire evaluation sample.

Model forecasts are evaluated in terms of out-of-sample forecast accuracy and in-sample fit. As measure of accuracy we consider the root mean squared forecast error (RMSFE). To analyse how relative accuracy evolves over time we also look at the RMSFE on a rolling basis of eight quarters. We also check the stability of the forecasts, i.e. forecasts produced by the models should be well-behaved and not exhibit explosive behaviour (an issue particularly relevant in case of large spikes in energy commodity prices).[16]

We produce and evaluate the following forecasts, reflecting different assumptions about paths for crude oil and wholesale gas prices:

[16] To this end we reject parameter draws that result in non-stationary models.

1. *Unconditional forecasts*: we include no additional information after the cut-off date to produce forecasts. Hence, no assumptions on future evolution of any variable are included.

2. *Forecast conditional on (B)MPE assumptions*: the forecasts are conditional on the assumed future paths for crude oil and natural gas prices (in euro) entailed in the (B)MPEs.[17] The Eurosystem staff inflation projections for energy are produced under such conditioning assumptions and thus the STIP conditional forecasts are comparable with the Eurosystem staff inflation projections.[18]

3. *Forecasts conditional on "perfect assumptions"*: the conditioning variables are the same as above, however actual rather then real-time data is used. In other words the forecasts are obtained conditional on the knowledge of future paths of crude oil and wholesale gas prices. This is a highly *counterfactual* rather than *real-time* scenario, however it helps to assess how well the model can replicate the developments in consumer prices given the paths of commodity prices (or how well the model fits the consumer price data).

Whereas the models are fitted to monthly changes or monthly percentage changes, all the results are reported for monthly *year-on-year inflation* rates: $\pi_t^{12} = 100 \times \frac{P_t - P_{t-12}}{P_{t-12}}$, where P_t is the appropriate HICP index.

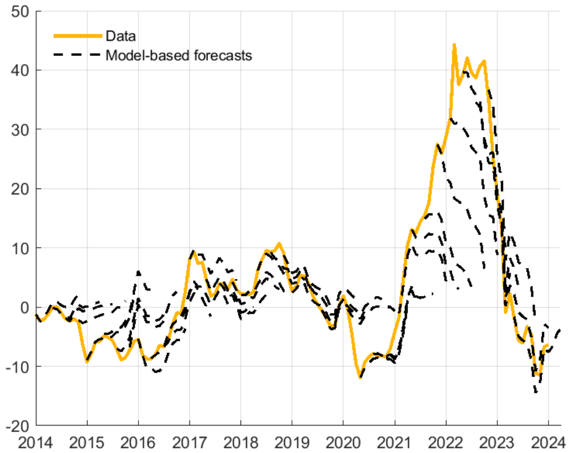
4 Results

Figure 5 shows the real-time forecast paths for HICP energy inflation spanning the period 2014 - 2023 for the 38 vintages and the three types of assumptions on oil and gas described above. There is no systematic bias in forecasting energy inflation, except for the period of the big inflation surge in the post-pandemic environment, when the model under-predicts irrespective of whether one looks at conditional or unconditional forecasts. When forecasts are conditioned on the actual path of the commodity prices (panel (c)) the degree of under-prediction is lower, but there are still some upward dynamics which are missed. One likely explanation for this is that the pass-through of energy commodity shocks has been larger in this period of high inflation and abnormal events, as shown for instance by De Santis and Tornese (2023). Overall, the exercise of conditioning on the actual path of the explanatory variables shows that the model

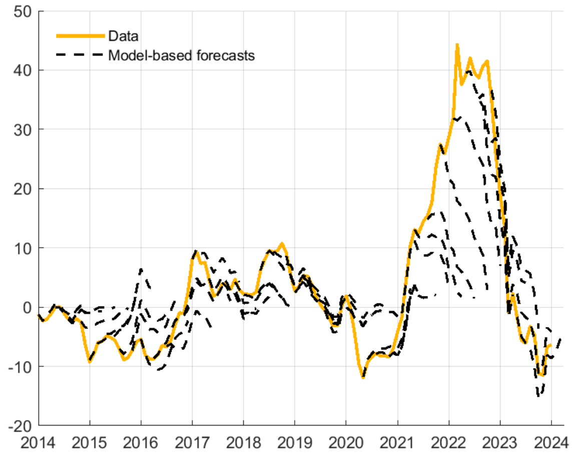
[17] Other explanatory variables such as prices of refined products or producer prices are unrestricted.

[18] In each projection round these conditioning paths are produced based on the latest developments in prices of futures contracts for crude oil and wholesale gas (see ECB, 2016, for details).

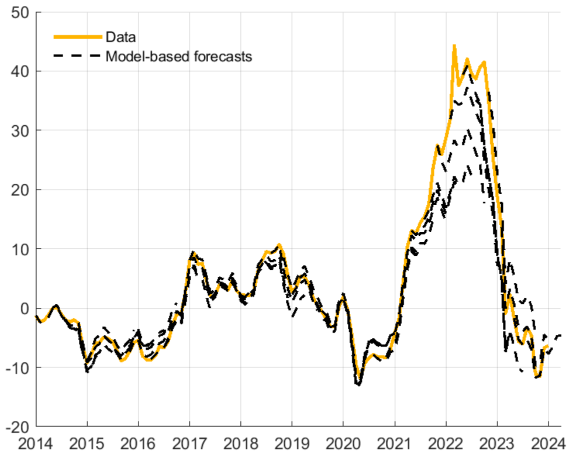
tracks energy inflation quite well and this is valid also for the very last part of the sample when the inflation rates are "normalising".



(a) Real-time unconditional forecasts



(b) Real-time forecasts conditional on (B)MPE assumptions



(c) Counterfactual forecasts conditional on perfect assumptions

Figure 5: HICP energy real-time and counterfactual forecasts

The lessons derived for the aggregate HICP energy inflation also hold across components. Before the invasion of Ukraine unconditional and conditional forecasts track actual data for sub-components reasonably well, but under-predict notably during the post-pandemic inflation surge (Figures 6 - 8). When conditioning on the realised values of the commodity prices, the counterfactual forecasts do a better job in tracking actual inflation compared to unconditional forecasts or those using (B)MPE assumptions, as expected (Figure 8). The fit is almost perfect in the case of car fuels, and it worsens for gas, solid fuels and electricity after the pandemic. Especially for the latter two the model fit is quite poor in the recent period. Country specific factors (such as heterogeneities in price-setting, price composition, retail contract types, electricity mix, taxes, rebates, administered prices, etc.) are likely to play a larger role for electricity and gas prices compared to other components of HICP energy. All in all, forecast errors seem to be to a large extent the result of uncertainty related to commodity price developments, with larger role for other factors in the current high inflation period.

Stochastic volatility and outlier correction render the forecasts overall well-behaved even in this abnormal episode, when lack of such features would yield explosive forecast paths (Lenza and Primiceri, 2020). A strong mean reversion is a feature of all these forecasts, irrespective of whether one conditions or not on the (B)MPE assumptions.

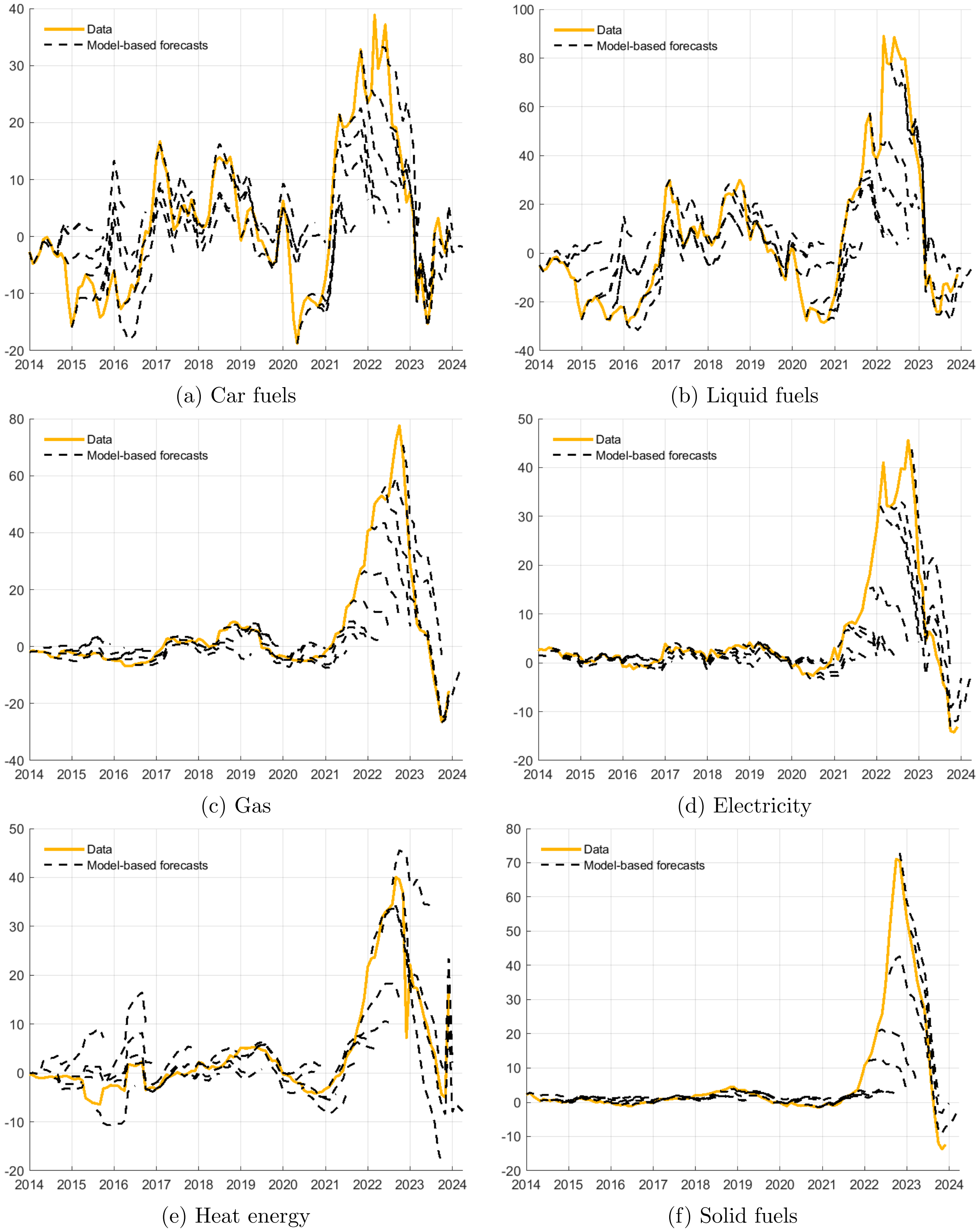
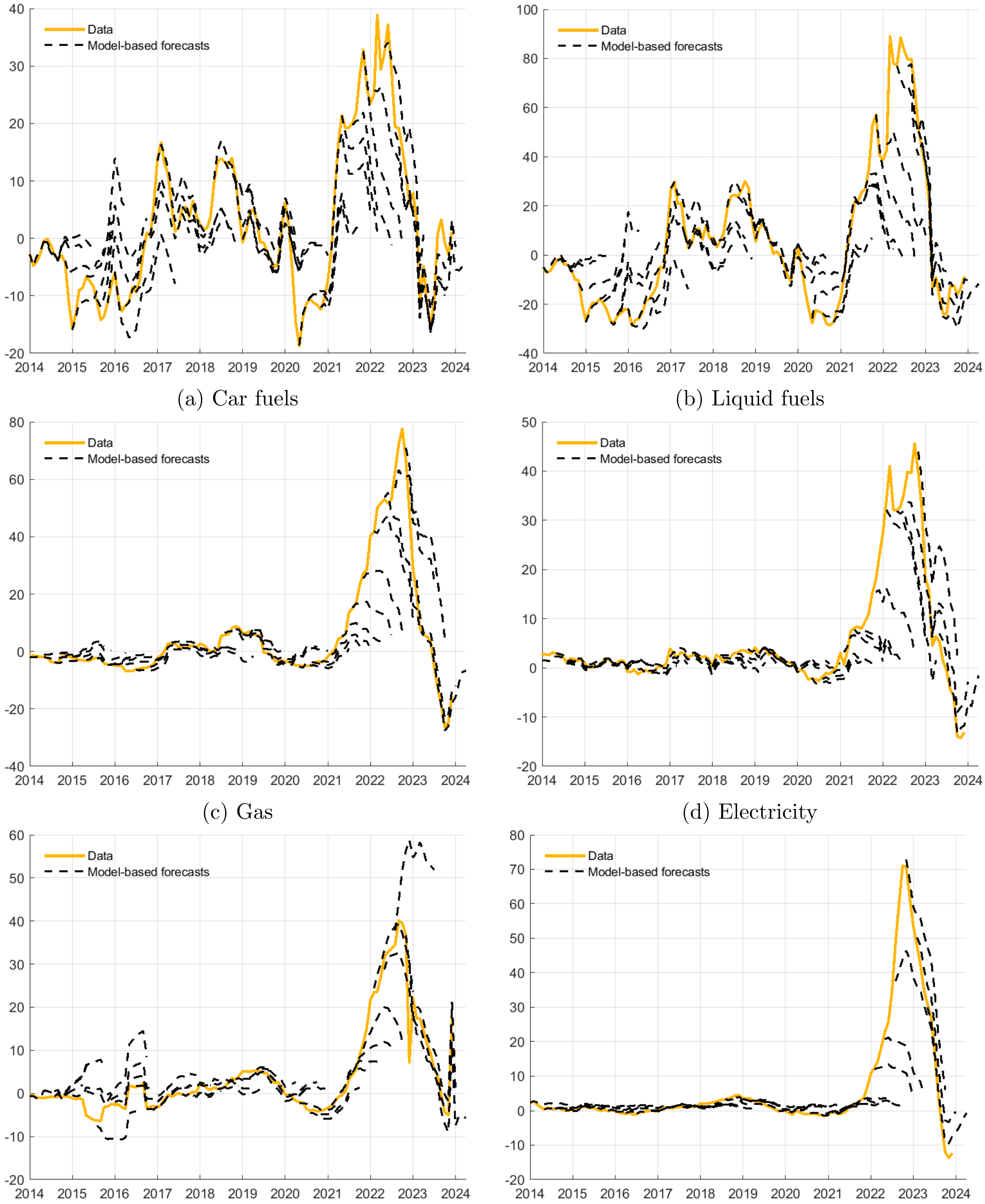


Figure 6: Real-time unconditional forecasts

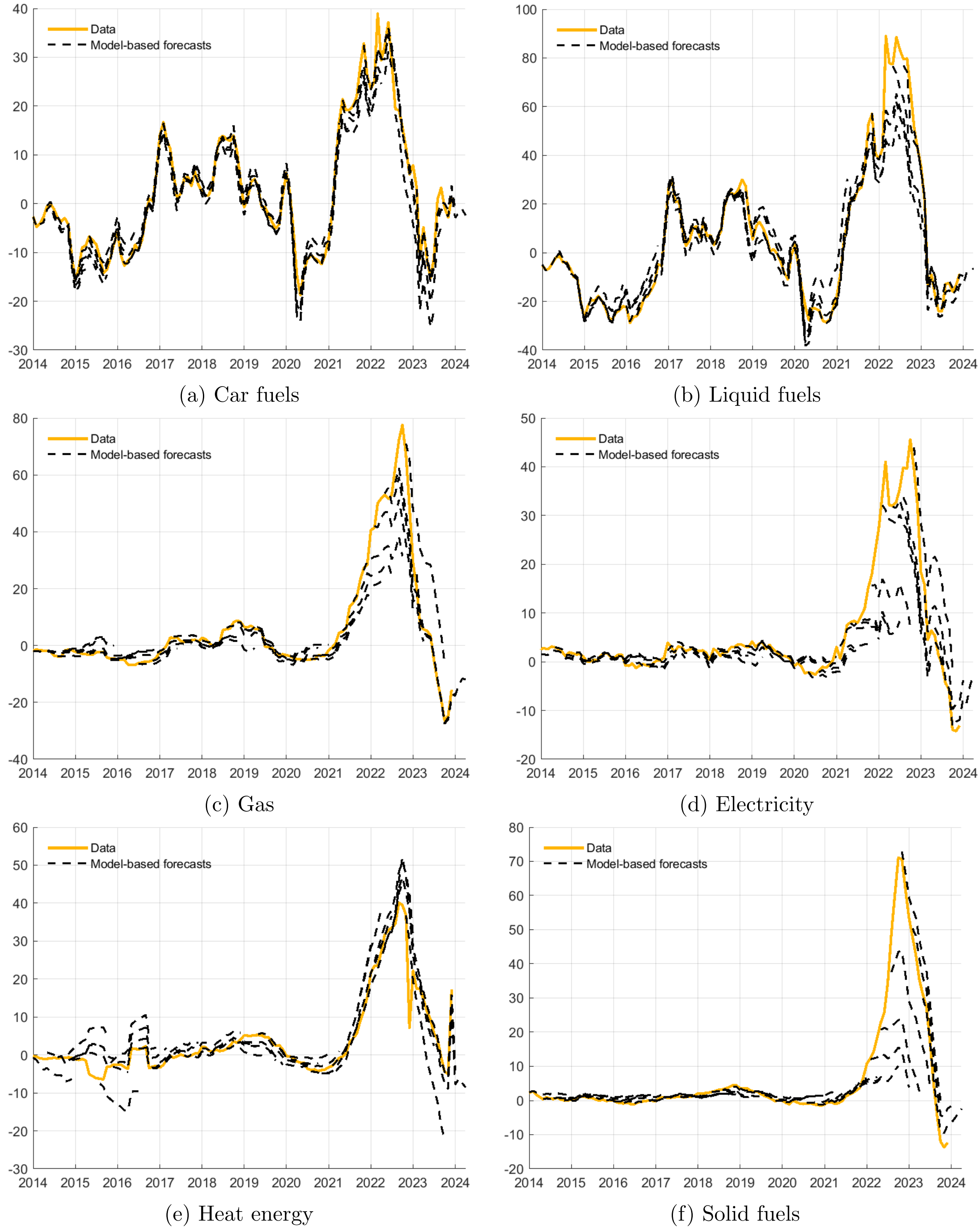


(a) Car fuels (b) Liquid fuels

(c) Gas (d) Electricity

(e) Heat energy (f) Solid fuels

Figure 7: Real-time forecasts conditional on (B)MPE assumptions



(a) Car fuels (b) Liquid fuels

(c) Gas (d) Electricity

(e) Heat energy (f) Solid fuels

Figure 8: Counterfactual forecasts conditional on perfect assumptions

Table 2 shows RMSFEs for the full evaluation sample for five (short-term) forecast horizons (1, 3, 6, 9 and 11 months ahead in line with the monthly Eurosystem staff inflation projections forecast horizon). Over the full sample, the newly proposed STIP models outperform the Eurosystem staff inflation projections for almost all forecast horizons, with the only exception of the one-month ahead horizon.

Bringing in information from the (B)MPE assumptions for oil and gas prices (see STIP Conditional) helps only for the very short term (up to three months ahead), while further ahead the unconditional STIP is better than the conditional one. This result holds across components, where one can see that by and large conditioning on (B)MPE assumptions does not help apart from the very short term. Hence, the model itself "extrapolates" better at longer horizons than when aided with (B)MPE assumptions.

The proposed STIP model outperforms the simple BVAR specification with aggregate energy inflation, highlighting the advantage of going more granular when forecasting energy.

The counterfactual exercise where we condition on the actual outcomes of crude oil and wholesale gas prices (labeled as STIP perfect) yields a sizeably lower RMSFE. This is not relevant in real-time but tells us something about the fit of the model. For example, the forecast performance of the STIP is much better than of the simple BVAR with energy inflation and oil price growth, suggesting that also in-sample a disaggregated model has a much better fit.[19]

The lower RMSFE of the STIP compared to the Eurosystem staff inflation projections can be attributed to its better performance after the pandemic. On a pre-COVID sample (see Table B1 in the Appendix) while the STIP models beat the simple bi-variate BVAR including oil prices, they are worse than the Eurosystem staff inflation projections, but only slightly. This means that the STIP models are already a good benchmark in normal times, if we consider the information advantage of the official projections in terms of announced changes in regulated prices and taxes. In addition to this, STIP models have the advantage of improving the performance compared to the Eurosystem staff inflation projections in periods of exceptional volatility.

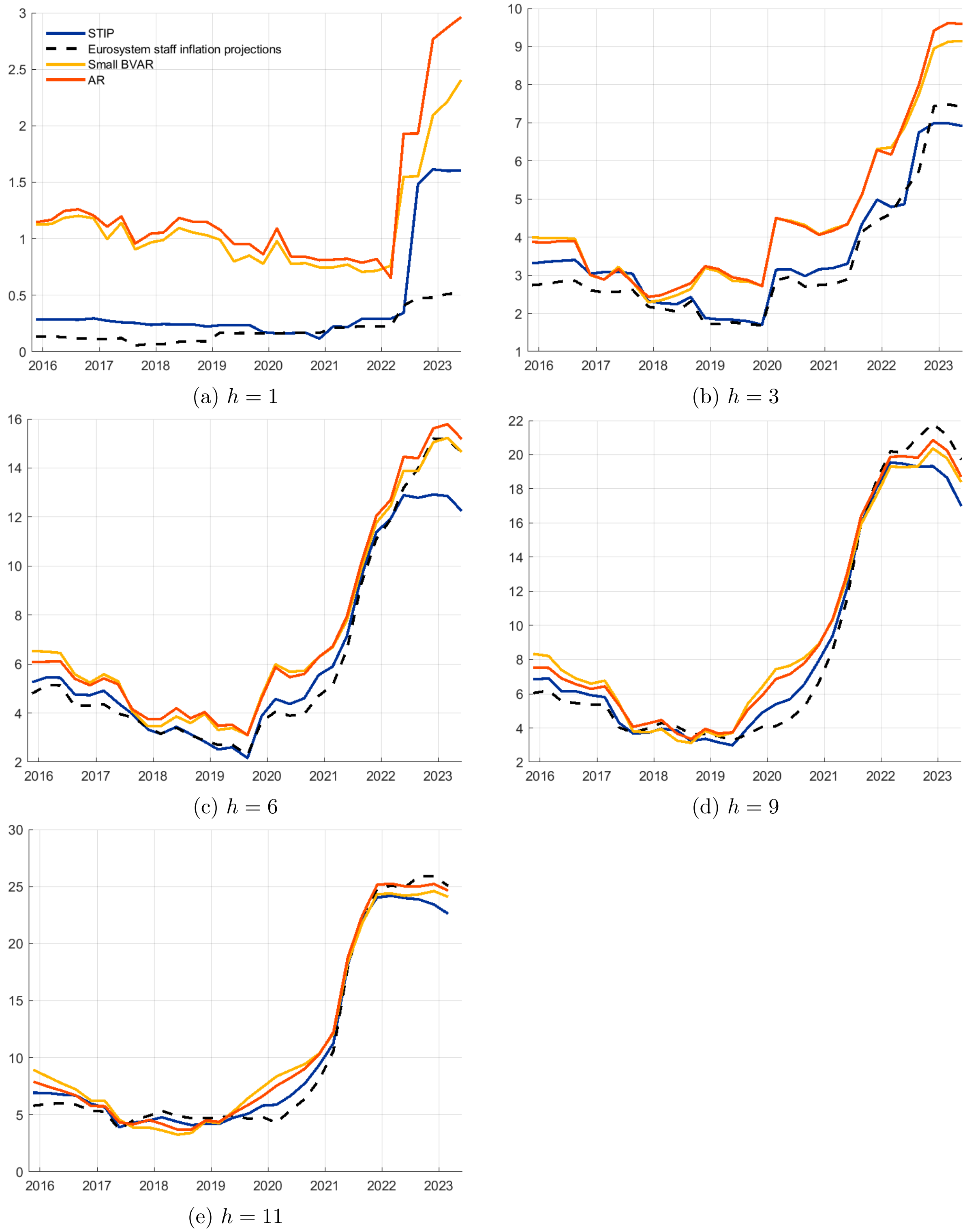
[19] A similar BVAR which includes also gas price (assumptions) would slightly improve the forecasts over the full sample compared with the BVAR with only oil and HICP energy, except for one-month ahead horizon. In the pre-COVID sample the forecasts of the BVAR with three variables would be, however, slightly worse. In any case, the performance of the three-variable BVAR would be overall worse compared to the proposed suite.

	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 11$
HICP Energy					
Eurosystem staff inflation projections	0.28	4.06	7.90	11.03	13.20
STIP Unconditional	0.77	4.05	7.17	10.28	12.42
BVAR (oil) Unconditional	1.38	5.25	8.45	11.18	13.42
BAR Unconditional	1.62	5.41	8.63	11.26	13.54
STIP Conditional	0.67	3.65	7.33	10.65	12.84
BVAR (oil) Conditional	1.01	4.60	7.67	10.40	12.76
STIP Perfect assumptions	0.66	2.87	4.34	5.59	6.45
BVAR (oil) Perfect assumptions	1.20	4.12	5.47	7.06	8.76
Car fuels					
STIP Unconditional	0.43	4.34	7.60	10.17	12.30
STIP Conditional	0.40	4.08	7.98	10.44	12.53
STIP Perfect assumptions	0.40	2.35	3.15	3.36	4.18
Liquid fuels					
STIP Unconditional	1.33	9.74	16.82	23.39	27.44
STIP Conditional	1.14	8.77	17.38	24.22	28.34
STIP Perfect assumptions	1.18	6.60	9.41	11.32	13.06
Gas					
STIP Unconditional	1.71	6.00	11.07	15.56	16.55
STIP Conditional	1.58	5.30	11.55	16.06	17.23
STIP Perfect assumptions	1.53	5.44	8.03	10.38	10.22
Electricity					
STIP Unconditional	1.65	4.53	7.39	9.70	11.31
STIP Conditional	1.58	4.38	7.44	9.87	11.52
STIP Perfect assumptions	1.55	4.60	6.91	8.59	9.70

Heat energy					
STIP Unconditional	1.51	2.89	5.74	8.03	9.46
STIP Conditional	1.46	3.21	6.74	9.17	11.18
STIP Perfect assumptions	1.43	3.08	4.07	5.26	8.13
Solid fuels					
STIP Unconditional	1.97	5.65	10.40	13.88	15.21
STIP Conditional	1.95	5.39	10.29	13.95	15.40
STIP Perfect assumptions	1.94	5.37	9.94	13.05	14.43

Table 2: RMSFE. Notes: root mean squared forecast errors (RMSFEs) are computed for monthly annual growth rates of HICP energy and components. The model forecasts are computed with real-time data at projection cut-off dates: i) unconditional ii) conditional on (B)MPE assumptions iii) conditional on realized oil and wholesale assumptions (perfect assumptions). Evaluation sample includes March 2014 (B)MPE to June 2023 (B)MPE. The latest outcome in the evaluation is June 2023.

In terms of time variation in the forecasting performance (see Figures 9-11 showing the RMSFE calculated over a rolling window of 8 exercises) all models have deteriorated in terms of accuracy at the onset of the pandemic, also under perfect assumptions. The Eurosystem staff inflation projections cannot be beaten for the one-month ahead horizon, but it is worth mentioning that in many cases the HICP flash release for certain countries is available before the euro area aggregate data is released. Beyond the shortest horizon, the figures show a clear deterioration of the Eurosystem staff inflation projections performance relative to the model in the recent period, while before 2022 the official projection was performing slightly better than the STIP in most cases.

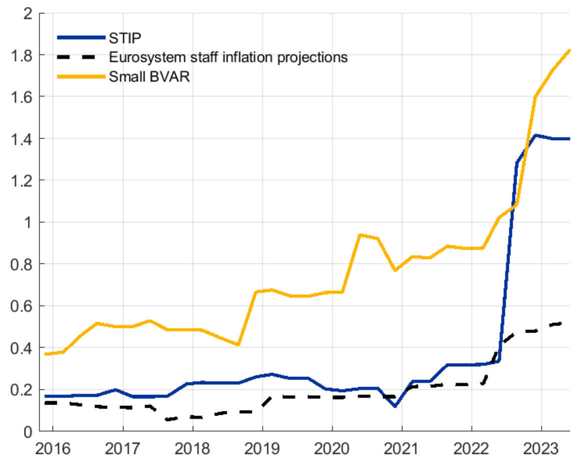


(a) $h = 1$ (b) $h = 3$

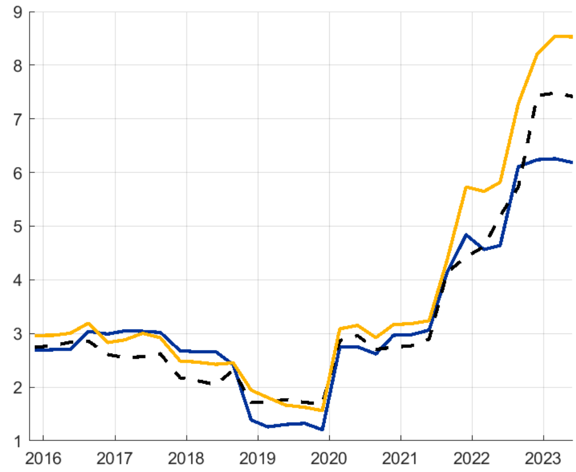
(c) $h = 6$ (d) $h = 9$

(e) $h = 11$

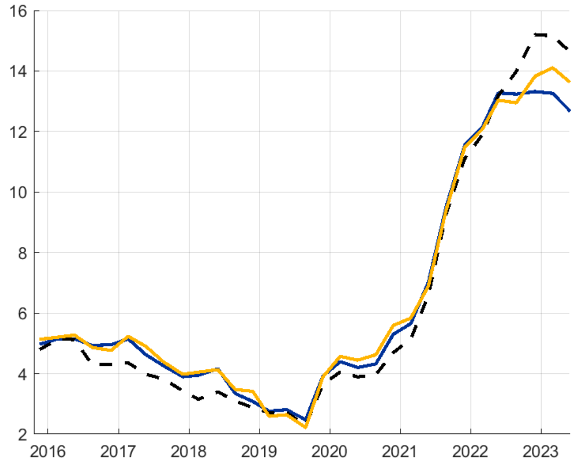
Figure 9: Rolling RMSFE: Unconditional model forecasts compared to the Eurosystem staff inflation projections.
Notes: the rolling window includes 8 projection rounds.



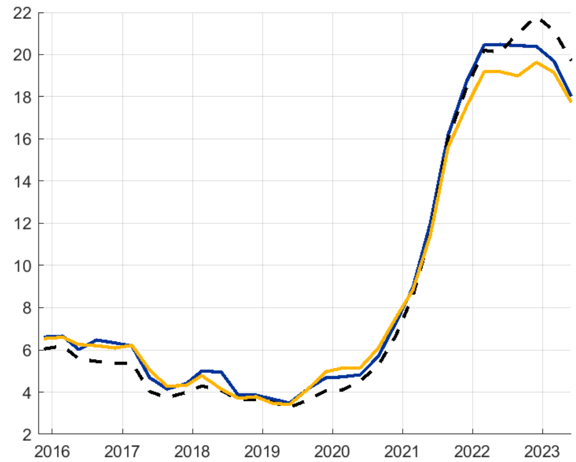
(a) $h = 1$



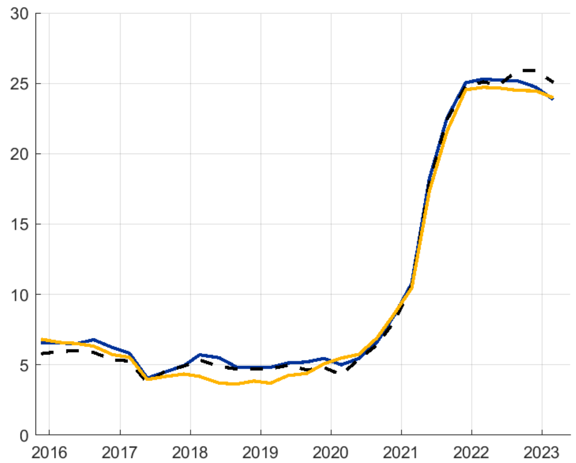
(b) $h = 3$



(c) $h = 6$



(d) $h = 9$



(e) $h = 11$

Figure 10: Rolling RMSFE: Model forecasts conditional on (B)MPE assumptions compared to the Eurosystem staff inflation projections.
Notes: the rolling window includes 8 projection rounds.

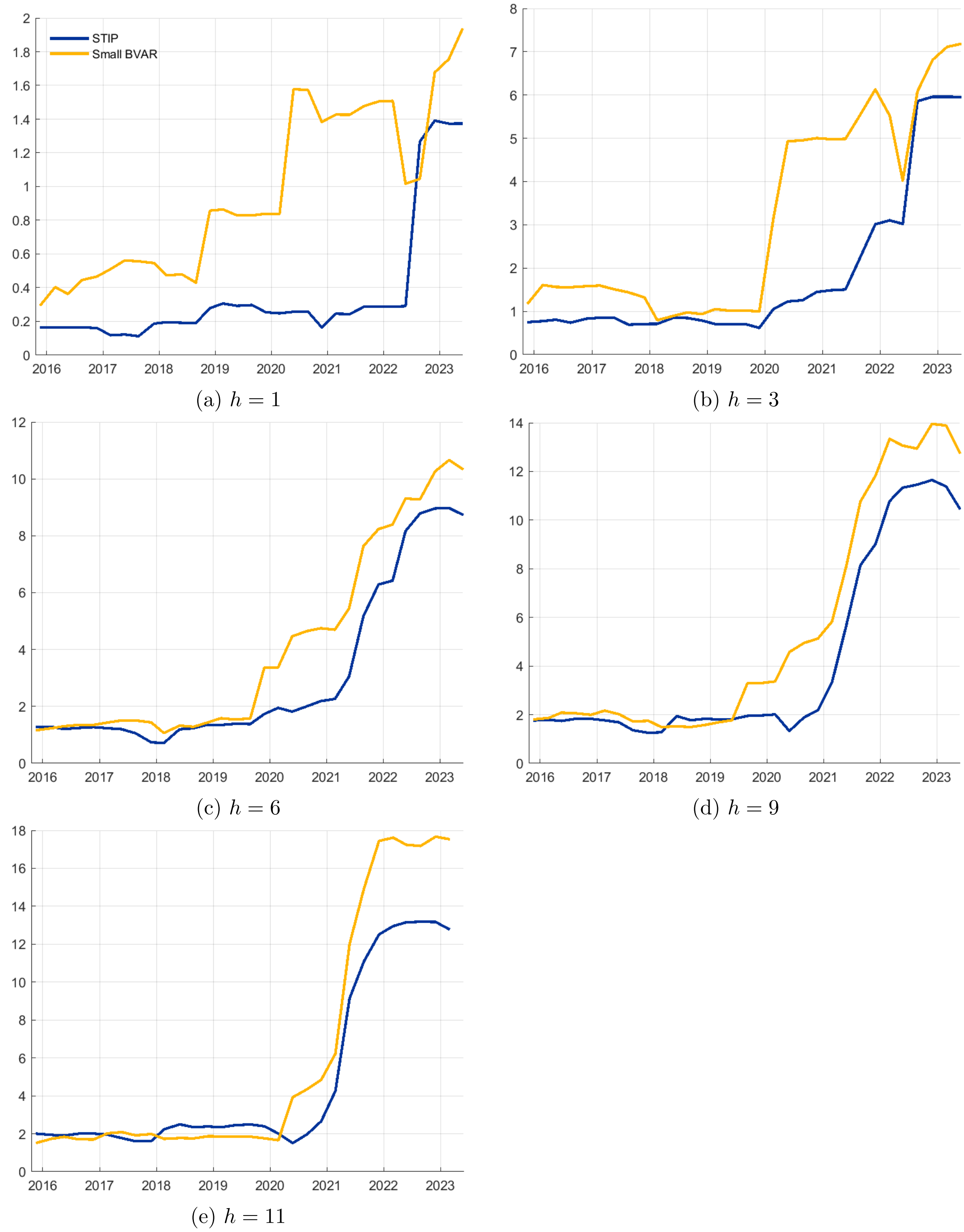


Figure 11: Rolling RMSFE: Model forecasts conditional on perfect assumptions.
Notes: the rolling window includes 8 projection rounds.

Figure 12 depicts a decomposition of one-quarter ahead forecast errors into a component due to errors in the conditioning ((B)MPE) assumptions on wholesale commodity prices and a residual component. Errors in the assumptions explain most of the forecast errors in the first part of the evaluation sample until the recent inflation surge, when exceptionally large swings in commodity prices have likely altered the pass-through of the respective shocks to consumer prices, causing misspecification issues.

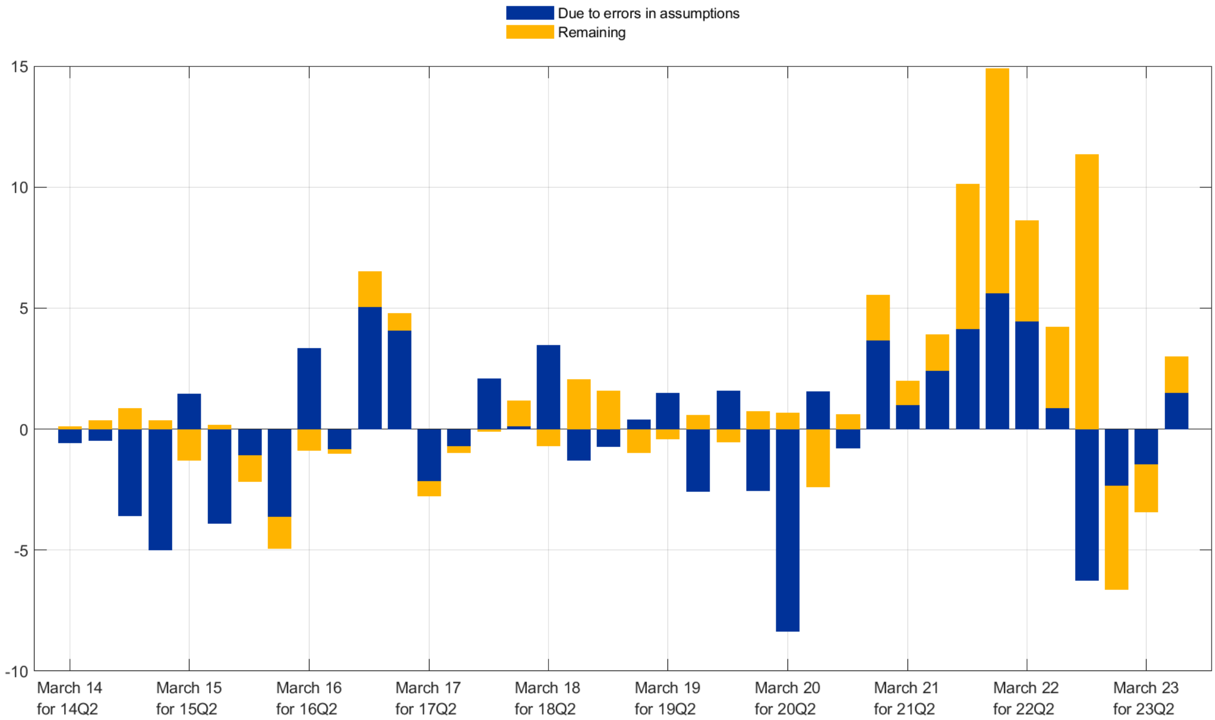


Figure 12: Decomposition of one-quarter ahead forecast errors

Finally, Appendix B reports robustness checks to some of the specification choices. In particular, Tables B2-B3 show the results when error correction terms (the margins) are included in the BVARs for car fuels, liquid fuels and gas.[20] Including those additional terms does not lead to improvements in forecast accuracy over the full sample, and to marginal improvements in the pre-Covid sub-sample. Therefore we opt for the simpler specification. Tables B4-B5 show the results when after-tax data are used (as opposed to pre-tax in the baseline specification). They indicate that using pre-tax data overall improved the accuracy in the pre-Covid sample, while slightly deteriorating over the full sample. Considering the limited difference between

[20]More precisely, in the models for WOB data we include the difference between the consumer price and the price of refined product (the "distribution margin") and the difference between the price of refined product and the price of crude oil (the "refining margin"). In the model for gas we include the difference between the consumer price and the wholesale price. Similar error correction terms have been considered in e.g. Meyler (2009), Cornille and Meyler (2010) or Knotek and Zaman (2017).

tax-corrected and tax-uncorrected and the importance for scenario analysis of modelling tax changes, we prefer to maintain the tax correction in the main specification. Finally, table B6 compares the performance of a monthly version[21] of our model to a medium-scale monthly BVAR that jointly includes all the components of HICP energy (car fuels, liquid fuels, gas, electricity, heating energy, and solid fuels) and the two wholesale commodity prices (crude oil and natural gas)[22]. Over the full sample, the medium-scale BVAR's performance is inferior to that of STIP across all forecasting modalities. Interestingly, the deterioration in relative performance is particularly severe when conditioning on realized values of the two energy commodities, which provides evidence in favour of disaggregated modelling for better capturing commodities' pass-through dynamics. The result is mainly driven by the fuels components over the high inflation period. Specifically, the strong correlation between oil and gas prices in the years preceding the inflationary episode of 2021-2022 leads to too high forecasts for fuels when gas prices are included in the (joint) model, indicating some identification issues in the latter. When limiting the comparison to the pre-pandemic period (Table B7) differences in performance are less pronounced.

5 Sensitivity of energy inflation to energy commodity prices

A strong feature of the chosen model setup is the opportunity to analyse the sensitivity of the different energy sub-components to wholesale energy price changes. To do so, we conduct an analysis of the responses given by the models to changes in the oil and natural gas prices. The exercises are designed so that the responses can be benchmarked against the Eurosystem Basic Model Elasticities (BMEs, see paragraph 3.4 in ECB, 2016). BMEs provide a mechanical "rule of thumb" assessment of the impact on the economy from *changes* in various *variables*, including commodity prices, rather than from *structural shocks*.[23]

Figure 13 shows the estimated responses of HICP energy to a 10% *permanent* increase in either crude oil prices (panel (a)) or wholesale natural gas prices (panel (b)) estimated over all the data vintages.[24] While the pass-through of a change in oil price is quick (see also Meyler,

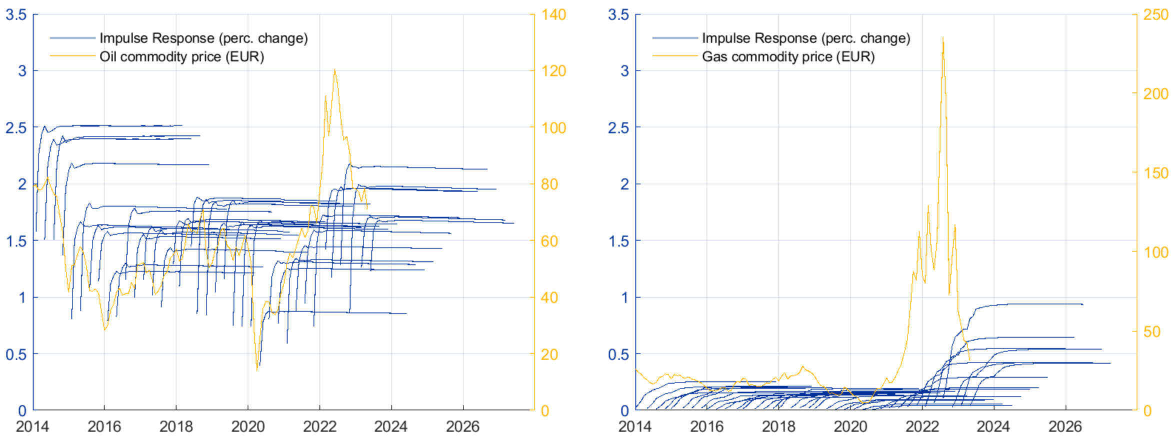
[21] Car and liquid fuels are modelled at monthly frequency, using monthly crude oil as explanatory variable.

[22] The treatment of taxes is aligned across the two models – transport and liquid fuels are tax-corrected directly at monthly frequency, following a procedure similar to that used for HICP gas and HICP electricity.

[23] The BMEs are used e.g. to assess the sources of inflation forecast errors by Chahad et al. (2022, 2023).

[24] As explained in Section 2.1, we evaluate the sensitivity to commodity prices by looking at the difference

2009), a wholesale gas price change takes roughly a year to be fully absorbed. Although more clear for crude oil than for wholesale gas, the elasticities are level dependent with respect to price levels of both commodities. For the case of natural gas the level dependence seems to be more relevant after 2021, most likely associated to high swings in the price level. The result of level-dependent elasticities in this linear model is a consequence of the fact that the variables enter as *absolute* rather than as *percentage* changes and in pre-tax terms. The refining and distribution margins tend to be broadly stable and do not depend on the level of the input price. In addition, there is typically a large share of per unit (litre) excise duty in the price of fuels (similarly for gas). These two factors imply that a certain percentage change in the euro price of oil triggers a lower percentage change in consumer energy prices when oil prices are low compared with when they are at high levels. This is because the above mentioned margins and excise taxes have a larger share in the consumer price in the former case and thus dampen the impact of changes in input prices to a larger extent (see also Meyler, 2009, for a discussion on this point).



(a) Oil (b) Natural gas

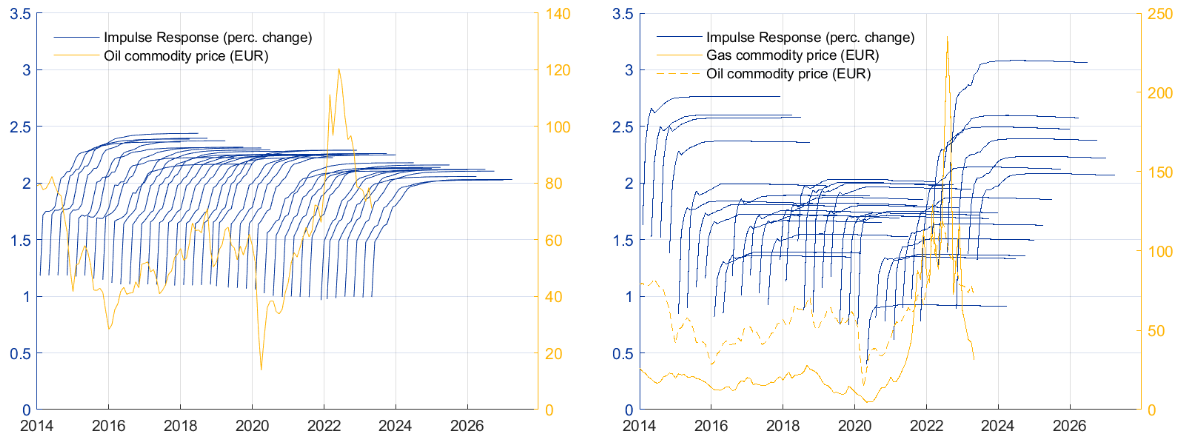
Figure 13: HICP energy response to 10% permanent shocks, based on the STIP models

Note: The blue lines (left-side axis) represent the (median) responses of HICP energy to a permanent 10% increase in oil (panel (a)) and natural gas (panel (b)) price. The yellow lines (right-side axis) show the evolution of the corresponding commodity prices. The responses associated to oil shocks are aggregated using the responses of car fuels and liquid fuels, while the responses associated to natural gas shocks are constructed from gas, electricity, heat energy and solid fuels.

To contrast the previous results, we also construct the responses of HICP energy to oil shocks

between two conditional forecasts, one in which the commodity price is assumed to permanently increase by 10% and one in which the price is assumed to remain constant at its last observed value throughout the forecast horizon.

based on the bi-variate BVAR model (see panel (a) in Figure 14). The responses based on this model do not capture the level dependencies evidenced in Figure 13. This result highlights the merits of modelling HICP energy on a more granular basis and with less "standard" transformations. To better compare this and our specification, we combine our model responses of HICP energy to shocks in both commodity markets in panel (b) of Figure 14. While the average responses to a "synthetic" energy shock for our model are similar to those for the simpler model, we can see clear differences across different levels of commodity prices for the former.



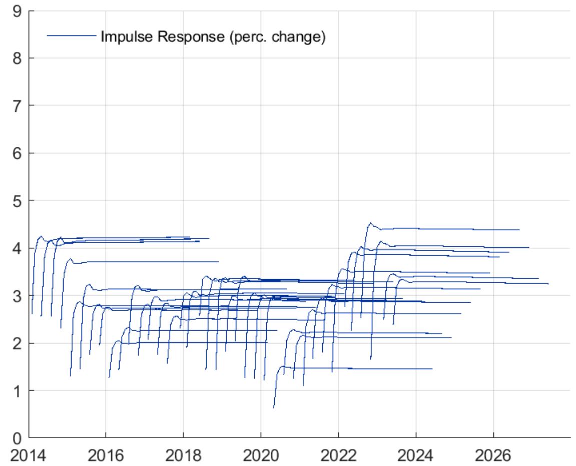
(a) Impulse responses to shock in oil price, produced by BVAR with HICP energy and crude oil in log-differences.

(b) Impulse responses to shocks to oil and gas prices, produced by the STIP.

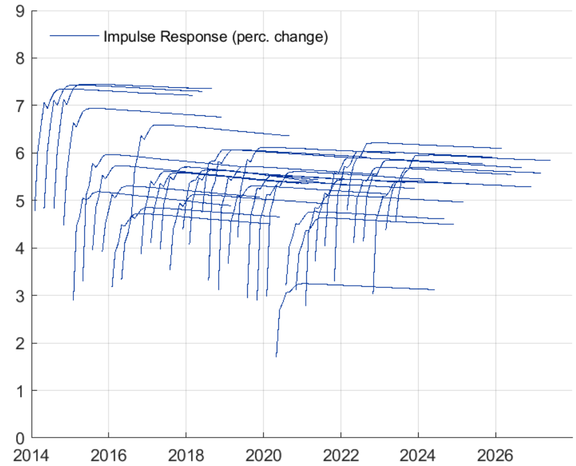
Figure 14: HICP energy response to 10% permanent shocks: BVAR vs STIP

Note: The blue lines represent the (median) responses of HICP energy to shocks in oil (panel (a)) and in oil and natural gas (panel (b)) markets. The yellow lines show the evolution of the corresponding commodity prices. In the right-hand panel we assume 10% increase for both oil and gas prices and we aggregate the responses of car and liquid fuels to the former and of the remaining HICP energy components to the latter.

Taking a granular approach, we also show the individual responses of oil-sensitive (car and liquid fuels) and gas-sensitive (gas, electricity, heat energy and solid fuels) items to both commodity shocks in Figure 15 and Figure 16, respectively. Liquid fuels react more strongly to oil prices than car fuels, due likely to a difference in weight of taxes and refining and distribution margins between the two components. A 10% shock to wholesale gas prices affects mainly heat energy and gas, while the impact on electricity and solid fuels is limited and was almost null before 2022.

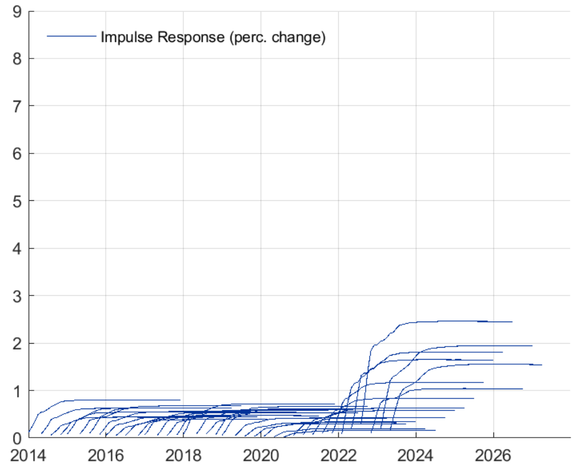


(a) Car fuels

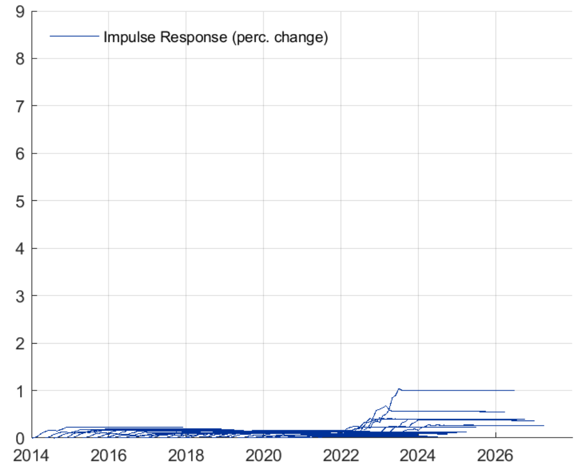


(b) Liquid fuels

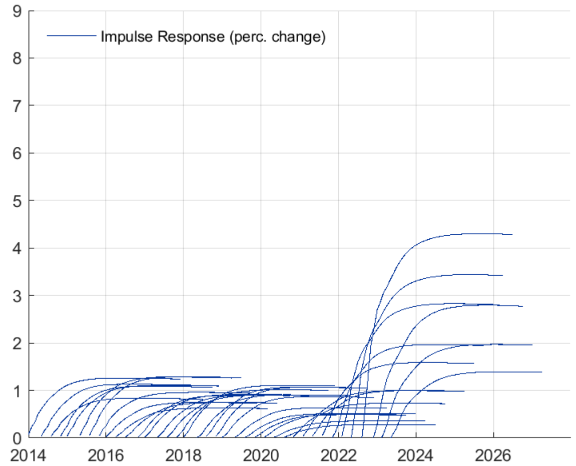
Figure 15: Permanent 10% oil commodity shock



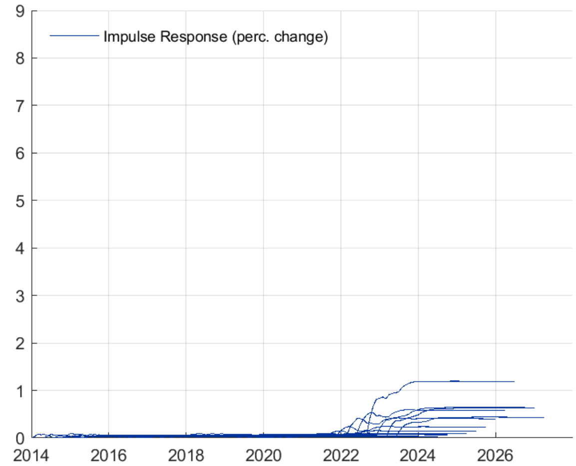
(a) Gas



(b) Electricity



(c) Heat energy



(d) Solid fuels

Figure 16: Permanent 10% gas commodity shock

6 Concluding remarks

The paper proposes a framework for forecasting energy inflation by modelling various energy components individually. It consists of Bayesian Vector Autoregressions (BVARs) that can handle various features of the data, in particular its extreme volatility in post-COVID times, seasonal patterns and ragged edges related to differences in publication delays. It incorporates a wide range of drivers of consumer energy prices, including crude and refined oil prices, natural gas prices and producer prices of energy. A real-time forecast evaluation ascertains that it is beneficial to model individual energy components separately, as the bottom-up approach is superior to a top-down simpler benchmark, namely a bi-variate BVAR containing aggregate energy inflation and oil prices. In sample, the model fits the data quite well, with the exception of the post-pandemic surge episode and with the notable exception of electricity, which appears harder to model. All in all, forecast errors seem to be the result not of the poor underlying model, but of the inability of forecasting the key explanatory variables, namely wholesale commodity prices as observed on the international or European markets.

This modelling framework can be also used to shed light on the transmission of energy commodity price shocks in different markets to consumer energy prices. We produce impulse response functions at different levels of oil and natural gas prices. We show that responses to oil price shocks are immediate and strong, while responses to wholesale natural gas price shocks tend to be more delayed. In both cases, the strength of the responses varies with the level of the underlying energy commodity prices, with the pass-through being stronger when the level of commodity price is higher.

The proposed model could be applied at the country level, to better reflect and understand differences in the price setting mechanisms between the countries, in particular for the most "difficult" components like electricity and gas. The structural transformation in energy markets due to carbon prices, biofuels, de-coupling of electricity prices from gas in the long run (due for example to renewable energy sources) can be also reflected and analysed in the model.

In general, the structural change and the resulting time variation in forecast performance highlights the need to continuously adapt the available battery of models.

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Appendix A Data availability and construction

Table A1: Data description and availability

Variable	Description	Source	Freq.	Span
WOB Petroleum CPR WTAX	Consumer price, all taxes and duties included, per thousand litres, Euro Super 95, automotive motor fuel (light distillate), euro	EC	W	12-01-1998 - present
WOB Petroleum CPR NTAX	Consumer price, taxes and duties not included, per thousand litres, Euro Super 95, automotive motor fuel (light distillate), euro	EC	W	03-01-1994 - present
WOB Petroleum IDT	Indirect taxes, per thousand litres, Euro Super 95, automotive motor fuel (light distillate), euro	EC	W	03-01-1994 - present
WOB Petroleum VAT	Value added tax, per thousand litres, Euro Super 95, automotive motor fuel (light distillate), percentage	EC	W	03-01-1994 - present
WOB Diesel CPR WTAX	Consumer price, all taxes and duties included, per thousand litres, Diesel, automotive gas oil, euro	EC	W	12-01-1998 - present
WOB Diesel CPR NTAX	Consumer price, taxes and duties not included, per thousand litres, Diesel, automotive gas oil, euro	EC	W	03-01-1994 - present
WOB Diesel IDT	Indirect taxes, per thousand litres, Diesel, automotive gas oil, euro	EC	W	03-01-1994 - present
WOB Diesel VAT	Value added tax, per thousand litres, Diesel, automotive gas oil, percentage	EC	W	03-01-1994 - present
WOB Gas CPR WTAX	Consumer price, all taxes and duties included, per thousand litres, heating gas oil, euro	EC	W	11-01-1999 - present
WOB Gas CPR NTAX	Consumer price, taxes and duties not included, per thousand litres, heating gas oil, euro	EC	W	03-01-1994 - present
WOB Gas IDT	Indirect taxes, per thousand litres, heating gas oil, euro	EC	W	03-01-1994 - present
WOB Gas VAT	Value added tax, per thousand litres, heating gas oil, percentage	EC	W	03-01-1994 - present

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Table A1: Data description and availability (Continued)

Variable	Description	Source	Freq.	Span
HICP Car Fuels	harmonised index of consumer prices, fuels and lubricants for personal transport equipment, CP0722	Eurostat	M	01-1995 - present
HICP Liquid Fuels	harmonised index of consumer prices, liquid fuels, CP0453	Eurostat	M	01-1995 - present
HICP Gas	harmonised index of consumer prices, gas, CP0452	Eurostat	M	01-1995 - present
HICP Electricity	harmonised index of consumer prices, electricity, CP0451	Eurostat	M	01-1995 - present
HICP Heat Energy	harmonised index of consumer prices, heat energy, CP0455	Eurostat	M	01-1995 - present
HICP Solid Fuels	harmonised index of consumer prices, solid fuels, CP0454	Eurostat	M	01-1995 - present
Natural Gas Price WTAX	Gas prices for domestic consumers, all taxes included, euro	Eurostat	B	1991S1 - 2022S2
Natural Gas Price NTAX	Gas prices for domestic consumers, no taxes included, euro	Eurostat	B	1991S1 - 2022S2
Natural Gas Price VAT	Gas prices for domestic consumers, value added taxes, percentage	Eurostat	B	1991S1 - 2022S2
Natural Gas Price EXC	Gas prices for domestic consumers, excise tax, euro	Eurostat	B	1991S1 - 2022S2
Electricity Price WTAX	Electricity prices for domestic consumers, all taxes included, euro	Eurostat	B	1991S1 - 2022S2
Electricity Price NTAX	Electricity prices for domestic consumers, no taxes included, euro	Eurostat	B	1991S1 - 2022S2
Electricity Price VAT	Electricity prices for domestic consumers, value added taxes, percentage	Eurostat	B	1991S1 - 2022S2
Electricity Price EXC	Electricity prices for domestic consumers, excise tax, euro	Eurostat	B	1991S1 - 2022S2
Oil	European Dated Brent Forties Oseberg Ekofisk (BFOE) Crude Oil Spot Price, Historical close	Bloomberg	D	16-05-1983 - present
Refined Petroleum	NWE Eurobob Oxy Barge Balance of the Month, Historical close	Bloomberg	D	02-06-1986 - present

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Table A1: Data description and availability (Continued)

Variable	Description	Source	Freq.	Span
Refined Diesel	Gas oil 0.1% Sulphur Antwerp-Rotterdam-Amsterdam - Unit 7.44 bbl/tonne, Historical close	Refinitiv	D	30-03-1987 - present
Gas Spot (backcasted with border gas)	Netherlands TTF Natural Gas Forward Day Ahead - Historical close, average of observations through period	Refinitiv	M	02-2006 - present
Border Gas	European Border Gas Prices, Average (€/MMBtu)	Energy Intelligence	M	01-1990 - present
Gas Futures	ICE Endex TTF Natural Gas Monthly Futures Chain, Historical close	Reuters	D	31-08-2016 - present
PPI Energy	Producer Price Index, domestic sales, MIG Energy, NACE Rev2	Eurostat	M	01-1985 - present (available from I6)
FX Euro-dollar	US DOLLARS/1 EUR, SPOT AT 2:15 PM (CET)D & W,M,Q,A-AVG	BIS	D	28-06-1975 - present

Notes: EC: European Commissi
by purpose (COICOP) four-digi

A.1 Pre-tax consumer gas and electricity prices

In order to obtain monthly consumer pre-tax gas (electricity) prices we combine (after-tax) HICP gas (electricity) with bi-annual data on consumer gas (electricity) prices and applicable excise and VAT taxes. In order to do so we transform bi-annual data to monthly frequency assuming they remain constant over the periods of 6 months. Then we rescale HICP to match the after-tax bi-annual data. Finally we remove VAT and excise takes. Specifically, pre-tax gas price series is obtained from the following formula:

$$GAS_t^{pre-tax} = \frac{GAS_t^{HICP} \times \hat{\gamma}}{1 + VAT_t^{BI}} - EXC_t^{BI}$$

where

- $GAS_t^{pre-tax}$ is the *pre-tax* gas price level at time t (to be included in the model).

- GAS_t^{HICP} is HICP gas at time t, with mean μ^{HICP} and standard deviation σ^{HICP}.

- $\hat{\gamma}$ is a scaling factor estimated via OLS regressing the bi-annual gas price including all taxes and levies on HICP gas in real-time.

- VAT_t is the value added tax on consumer gas.

- EXC_t is the excise tax on consumer gas.[25]

Analagous operations are applied in order to obtain pre-tax prices for electricity.

[25] Where the database displays clear errors, i.e. negative or very large excise numbers, we reconstruct these entries by using the three remaining Eurostat series: $EXC_t = GAS_t^{WTX} / (1 + VAT_t) - GAS_t^{NTAX}$. The same is applied for WOB data in case of large discrepancies.

A.2 Cut-off dates for real-time vintages

Table A2: (B)MPE cut-off dates

Vintage	Latest Information	Assumptions
March 2014	2014-02-20	2014-02-12
June 2014	2014-05-21	2014-05-14
September 2014	2014-08-21	2014-08-13
December 2014	2014-11-20	2014-11-13
March 2015	2015-02-20	2015-02-11
June 2015	2015-05-20	2015-05-12
September 2015	2015-08-21	2015-08-12
December 2015	2015-11-19	2015-11-12
March 2016	2016-02-25	2016-02-15
June 2016	2016-05-18	2016-05-10
September 2016	2016-08-18	2016-08-11
December 2016	2016-11-24	2016-11-17
March 2017	2017-02-20	2017-02-14
June 2017	2017-05-23	2017-05-16
September 2017	2017-08-21	2017-08-14
December 2017	2017-11-30	2017-11-22
March 2018	2018-02-19	2018-02-13
June 2018	2018-05-31	2018-05-22
September 2018	2018-08-29	2018-08-21
December 2018	2018-11-28	2018-11-21
March 2019	2019-02-21	2019-02-12
June 2019	2019-05-22	2019-05-15
September 2019	2019-08-29	2019-08-19
December 2019	2019-11-27	2019-11-19
March 2020	2020-02-24	2020-02-18
June 2020	2020-05-25	2020-05-18
September 2020	2020-08-27	2020-08-18
December 2020	2020-11-25	2020-11-18
March 2021	2021-02-24	2021-02-16

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Table A2: (B)MPE cut-off dates (Continued)

Vintage	Latest Information	Assumptions
June 2021	2021-05-26	2021-05-18
September 2021	2021-08-26	2021-08-16
December 2021	2021-12-01	2021-11-25
March 2022	2022-03-02	2022-02-28
June 2022	2022-05-24	2022-05-17
September 2022	2022-08-25	2022-08-22
December 2022	2022-11-30	2022-11-23
March 2023	2023-03-01	2023-02-15
June 2023	2023-05-31	2023-05-23

Appendix B Robustness

B.1 Sub-sample analysis: pre-covid sample

	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 11$
HICP Energy					
Eurosystem staff inflation projections	0.13	2.24	4.01	4.79	5.19
STIP Unconditional	0.24	2.53	4.23	5.31	5.82
BVAR (oil) Unconditional	0.97	3.09	5.06	6.44	7.07
BAR Unconditional	1.03	3.07	4.91	6.05	6.50
STIP Conditional	0.20	2.30	4.29	5.32	5.69
BVAR (oil) Conditional	0.52	2.41	4.37	5.35	5.51
STIP Perfect assumptions	0.21	0.69	1.31	1.69	2.03
BVAR (oil) Perfect assumptions	0.60	1.17	2.21	2.39	1.76
Car fuels					
STIP Unconditional	0.41	4.19	7.04	8.35	8.73
STIP Conditional	0.36	3.81	7.12	8.17	8.19
STIP Perfect assumptions	0.33	1.14	2.25	2.22	2.53
Liquid fuels					
STIP Unconditional	1.04	7.56	12.02	15.93	17.39
STIP Conditional	0.84	6.62	11.90	15.64	16.41
STIP Perfect assumptions	0.91	2.25	4.99	4.91	5.44
Gas					
STIP Unconditional	0.79	1.91	3.13	4.02	4.20
STIP Conditional	0.79	1.76	2.91	3.96	4.24
STIP Perfect assumptions	0.77	1.62	2.49	3.01	3.23
Electricity					
STIP Unconditional	0.65	1.04	1.52	1.67	1.49

STIP Conditional	0.65	1.03	1.52	1.70	1.49
STIP Perfect assumptions	0.67	1.03	1.46	1.63	1.37
Heat energy					
STIP Unconditional	1.44	2.58	3.91	5.26	5.13
STIP Conditional	1.43	2.42	3.53	4.91	5.39
STIP Perfect assumptions	1.42	2.49	3.69	4.82	5.09
Solid fuels					
STIP Unconditional	0.32	0.60	0.95	1.34	1.65
STIP Conditional	0.31	0.59	0.95	1.39	1.70
STIP Perfect assumptions	0.27	0.56	0.85	1.20	1.51

Table B1: RMSFE - Pre-Covid sub-sample

B.2 Error-corrected weekly models

Main specification						Error-correction				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$
Car fuels										
Unconditional	0.43	4.34	7.60	10.17	12.30	0.39	4.42	8.18	10.98	14.01
Conditional	0.40	4.08	7.98	10.44	12.53	0.38	4.10	8.39	11.04	13.57
Perfect assumptions	0.40	2.35	3.15	3.36	4.18	0.39	3.03	5.10	6.10	6.82
Liquid fuels										
Unconditional	1.33	9.74	16.82	23.39	27.44	1.35	10.21	17.09	23.07	27.81
Conditional	1.14	8.77	17.38	24.22	28.34	1.17	9.53	18.36	25.07	29.59
Perfect assumptions	1.18	6.60	9.41	11.32	13.06	1.24	8.35	12.16	13.67	14.69
Gas										
Unconditional	1.71	6.00	11.07	15.56	16.55	1.77	6.06	11.05	15.46	16.44
Conditional	1.58	5.30	11.55	16.06	17.23	1.65	5.35	11.53	15.97	17.14
Perfect assumptions	1.53	5.44	8.03	10.38	10.22	1.60	5.50	8.01	10.19	9.92

Table B2: RMSFE - Main specification vs. error-correction, full sample

Main specification						Error-correction				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$
Car fuels										
Unconditional	0.41	4.19	7.04	8.35	8.73	0.36	3.98	7.11	8.05	9.25
Conditional	0.36	3.81	7.12	8.17	8.19	0.34	3.65	6.98	7.63	8.11
Perfect assumptions	0.33	1.14	2.25	2.22	2.53	0.33	1.64	3.90	4.59	4.88
Liquid fuels										
Unconditional	1.04	7.56	12.02	15.93	17.39	1.03	7.29	11.35	14.56	16.88
Conditional	0.84	6.62	11.90	15.64	16.41	0.87	6.57	11.55	14.46	15.73
Perfect assumptions	0.91	2.25	4.99	4.91	5.44	0.94	2.24	5.36	5.91	6.72

Gas										
Unconditional	0.79	1.91	3.13	4.02	4.20	0.78	1.90	3.10	3.98	4.16
Conditional	0.79	1.76	2.91	3.96	4.24	0.78	1.75	2.83	3.78	4.03
Perfect assumptions	0.77	1.62	2.49	3.01	3.23	0.77	1.63	2.45	2.84	3.05

Table B3: RMSFE - Main specification vs. error-correction, Pre-Covid sub-sample

B.3 Tax-corrected vs. tax-uncorrected

Main specification						Tax-uncorrected				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 11$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 11$
HICP Energy										
Unconditional	0.77	4.05	7.17	10.28	12.42	0.71	3.97	6.99	10.11	12.26
Conditional	0.67	3.65	7.33	10.65	12.84	0.65	3.58	7.17	10.48	12.67
Perfect assumptions	0.66	2.87	4.34	5.59	6.45	0.64	2.73	3.99	5.11	6.02
Car fuels										
Unconditional	0.43	4.34	7.60	10.17	12.30	0.42	4.33	7.61	10.20	12.28
Conditional	0.40	4.08	7.98	10.44	12.53	0.39	4.06	7.96	10.43	12.44
Perfect assumptions	0.40	2.35	3.15	3.36	4.18	0.39	2.31	3.04	3.18	4.00
Liquid fuels										
Unconditional	1.33	9.74	16.82	23.39	27.44	1.37	9.82	16.77	23.30	27.29
Conditional	1.14	8.77	17.38	24.22	28.34	1.16	8.79	17.32	24.15	28.25
Perfect assumptions	1.18	6.60	9.41	11.32	13.06	1.20	6.55	9.19	11.07	12.74
Gas										
Unconditional	1.71	6.00	11.07	15.56	16.55	1.50	5.70	10.76	15.25	16.35
Conditional	1.58	5.30	11.55	16.06	17.23	1.44	4.89	11.31	15.88	17.17
Perfect assumptions	1.53	5.44	8.03	10.38	10.22	1.37	4.76	7.17	9.35	9.58
Electricity										
Unconditional	1.65	4.53	7.39	9.70	11.31	1.73	4.63	7.12	9.31	10.83
Conditional	1.58	4.38	7.44	9.87	11.52	1.68	4.54	7.27	9.54	11.12
Perfect assumptions	1.55	4.60	6.91	8.59	9.70	1.66	4.64	6.63	7.95	8.93

Table B4: RMSFE - Main specification vs. tax-uncorrected, full sample

Main specification						Tax-uncorrected				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$
HICP Energy										
Unconditional	0.24	2.53	4.23	5.31	5.82	0.23	2.56	4.35	5.55	6.05
Conditional	0.20	2.30	4.29	5.32	5.69	0.19	2.28	4.37	5.50	5.86
Perfect assumptions	0.21	0.69	1.31	1.69	2.03	0.19	0.72	1.31	1.68	1.98
Car fuels										
Unconditional	0.41	4.19	7.04	8.35	8.73	0.40	4.19	7.13	8.54	8.93
Conditional	0.36	3.81	7.12	8.17	8.19	0.35	3.77	7.14	8.28	8.32
Perfect assumptions	0.33	1.14	2.25	2.22	2.53	0.33	1.17	2.19	2.08	2.36
Liquid fuels										
Unconditional	1.04	7.56	12.02	15.93	17.39	1.05	7.59	12.02	16.01	17.44
Conditional	0.84	6.62	11.90	15.64	16.41	0.83	6.59	11.90	15.68	16.44
Perfect assumptions	0.91	2.25	4.99	4.91	5.44	0.91	2.27	5.00	4.85	5.41
Gas										
Unconditional	0.79	1.91	3.13	4.02	4.20	0.81	1.85	3.08	4.04	4.21
Conditional	0.79	1.76	2.91	3.96	4.24	0.82	1.69	2.86	4.01	4.31
Perfect assumptions	0.77	1.62	2.49	3.01	3.23	0.79	1.58	2.41	2.90	3.13
Electricity										
Unconditional	0.65	1.04	1.52	1.67	1.49	0.64	1.41	2.18	2.22	1.78
Conditional	0.65	1.04	1.52	1.70	1.49	0.64	1.41	2.20	2.26	1.84
Perfect assumptions	0.67	1.04	1.47	1.64	1.39	0.64	1.39	2.11	2.13	1.63

Table B5: RMSFE - Main specification vs. tax-uncorrected, Pre-Covid sub-sample

B.4 Medium-sized BVAR including all sub-components at monthly frequency and crude oil and nautral gas prices

Monthly STIP						BVAR incl. all monthly components				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$
HICP Energy										
Conditional	0.73	3.82	7.52	10.73	12.85	2.56	3.53	7.89	11.45	13.80
Perfect assumptions	0.78	2.80	4.18	5.44	6.34	2.70	4.25	5.22	5.56	5.45
Unconditional	1.14	4.56	7.93	10.86	12.89	2.69	4.34	7.53	10.81	13.27
Car fuels										
Conditional	1.47	4.08	7.77	10.16	12.26	4.96	5.72	9.73	12.50	14.33
Perfect assumptions	1.55	2.30	2.63	3.16	4.08	5.53	6.49	9.04	10.53	11.87
Unconditional	2.47	5.82	8.40	10.63	12.82	4.78	6.77	9.91	12.11	14.77
Liquid fuels										
Conditional	2.75	9.88	17.24	24.10	28.40	11.13	12.23	22.80	29.87	33.32
Perfect assumptions	3.19	6.80	7.96	10.22	11.94	11.28	12.67	17.66	20.57	20.58
Unconditional	3.61	11.97	18.46	24.42	28.60	11.25	15.24	23.28	28.94	33.05
Gas										
Conditional	1.56	5.30	11.56	16.08	17.24	1.80	5.89	12.22	16.47	18.35
Perfect assumptions	1.50	5.46	8.04	10.41	10.26	1.84	6.36	7.61	7.63	7.67
Unconditional	1.67	5.97	11.06	15.53	16.52	1.88	6.20	11.21	15.30	16.65
Electricity										
Conditional	1.57	4.39	7.45	9.86	11.51	1.64	4.17	7.95	10.23	11.89
Perfect assumptions	1.57	4.61	6.89	8.58	9.71	1.70	4.72	7.01	7.52	8.21
Unconditional	1.67	4.56	7.41	9.74	11.35	1.71	4.51	7.71	10.03	11.69

Table B6: RMSFE - Main specification vs. medium-sized BVAR including all monthly components, full sample

Monthly STIP						BVAR incl. all monthly components				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$	$h=1$	$h=3$	$h=6$	$h=9$	$h=11$
HICP Energy										
Conditional	0.52	2.34	4.16	5.04	5.46	0.60	2.56	4.61	6.02	6.69
Perfect assumptions	0.64	0.93	1.29	1.75	2.03	0.62	1.68	2.82	3.70	4.14
Unconditional	0.69	2.92	4.39	5.30	5.88	0.65	2.90	4.45	5.84	6.40
Car fuels										
Conditional	1.06	3.75	6.76	7.63	7.82	1.60	4.32	7.20	9.05	9.75
Perfect assumptions	1.18	1.55	2.16	2.67	2.84	1.54	2.90	4.56	5.63	6.09
Unconditional	1.64	4.89	7.16	8.30	8.91	1.83	4.97	6.81	8.84	9.54
Liquid fuels										
Conditional	2.58	6.83	11.07	14.02	15.34	2.60	8.09	13.27	17.49	19.18
Perfect assumptions	3.06	2.45	4.40	4.61	5.62	2.67	5.09	7.18	9.50	10.75
Unconditional	2.66	7.94	11.82	15.14	17.01	3.13	9.06	13.16	17.44	19.03
Gas										
Conditional	0.79	1.76	2.90	3.96	4.24	0.63	1.51	2.80	4.10	4.54
Perfect assumptions	0.77	1.62	2.48	3.01	3.23	0.68	1.50	2.29	3.12	3.49
Unconditional	0.79	1.91	3.12	4.02	4.19	0.68	1.67	2.88	4.00	4.28
Electricity										
Conditional	0.65	1.05	1.53	1.70	1.48	0.66	1.03	1.64	1.89	1.66
Perfect assumptions	0.67	1.04	1.47	1.65	1.39	0.66	0.97	1.42	1.57	1.39
Unconditional	0.65	1.05	1.52	1.67	1.49	0.65	1.02	1.63	1.82	1.57

Table B7: RMSFE - Main specification vs. medium-sized BVAR including all monthly components, pre-covid sample

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