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Abstract

The aim of this study is to develop a forecasting framework for household-level inflation in Greece using domestic, global and energy-related predictors for the period 2009-2022. We show that significant forecasts gains are obtained when models incorporate global conditions and energy prices, relative to our benchmark model, the AR(1). More importantly, though, we find that although the global economic activity, global supply chain pressure and geopolitical risk are important predictors for all households, there are other predictors which demonstrate a household-specific forecast performance. Even more, we show that the energy factors are more important predictors for the low-income households. Overall, these results demonstrate (i) that aggregate inflation forecasts are not representative of the Greek households and (ii) the importance of household-specific inflation forecasting, which could be used as an early warning system that identifies the factors that could drive inflation inequality across the different households.

Keywords: Household-level inflation, inflation inequality, Greece, forecasting, DMA, quantile regression.

JEL: C52, C53, D14, E31, E37

1. Introduction

Inflation forecasting is an important tool for the modern monetary policy, which is based on an inflation-targeting framework. This is so given that when monetary authorities place the emphasis of their policy response on inflation forecasts, rather than the current level of inflation, then the recognition, decision and implementation lags of monetary policy become shorter (Bernanke and Woodford, 1997). As such, the monetary policy becomes more effective.

There is a wealth of literature on inflation forecasts and several authors have tried to identify those forecasting methods that would provide the best decision-making tool for policy makers. Early studies in this line of research include those by Bernanke and Woodford (1997) and Stock and Watson (1999), where the former suggest that structural models should be used for inflation forecasts and the latter emphasize on the usefulness of the generalized Philips-curve.

Since then, several other efforts have taken place to develop useful frameworks. The literature uses a battery of different forecasting frameworks for headline and core inflation, ranging from (i) naïve models (such as the autoregressive and random walk models, implemented by Clements and Galvao, 2013; and Atkenson and Ohanian, 2001), (ii) the well-known Philips Curve regression equation (Bańbura and Bobeica, 2023) and (iii) to more sophisticated models, such as stochastic volatility models (Stock and Watson, 2007), VAR-type models (Ang and Piazzesi, 2003; Primiceri; 2005), Bayesian model averaging (Groen et al., 2013), Dynamic model averaging (Koop and Korobilis, 2012), LASSO techniques (Garcia et al. 2017) and computationally intelligent models (Nakamura, 2005; Medeiros et al., 2021).

Apart from the evaluation of inflation forecasts produced by different modelling frameworks, the debate on inflation forecasts is also directed to the predictive gains that could be generated using exogenous predictors. For instance, Stock and Watson (1999) find that exogenous variables (such as, interest rates, commodity prices and other macroeconomic variables) do not really offer any predictive gains for aggregate inflation forecasts, compared to the Phillips curve. More recently, Bańbura and Bobeica (2023) also show that including exogenous variables in their forecasting model does not offer forecasting gains for aggregate inflation. Contrary to the evidence provided thus far, Koop and Korobilis (2012), who investigate the predictive information of a variety of macroeconomic and financial variables such as private residential fixed investment, money supply and treasury bill rates, through the well-known DMA, find that they can indeed offer predictive gains on inflation forecasts. Their findings are in line with the results of previous studies, such as Groen et al. (2009), which conclude that incorporating additional information in the inflation's models can offer forecasting gains when the methodology used can capture statistical properties, such as structural breaks, in the time series of the target variable. Even more, Chen et al. (2014) show that the commodity price index can offer predictive gains over the AR(1) model. Similar findings are also reported Breitung and Roling (2015) who assess the predictive ability of high-frequency data on inflation forecasts, highlighting the usefulness of the commodity price index.

Despite these aforementioned efforts, there is a clear gap in the literature on the household-level inflation forecasts. It is well known since the late 1970s that inflation differs significantly across different households (Michael, 1979; Hagemann, 1982) and since then, a wealth of literature has emerged on this topic (see, for instance, Cardoso,1992; Easterly and Fischer, 2001; Izquierdo *et al*., 2003; Albanesi, 2007; Jaravel, 2021; Strasser *et al*., 2023, among others). Hence, inflation forecasts of the aggregate headline or core inflation may not be useful to alleviate the negative effects of inflation if these "average" measures are not representative of all households within an economy. In the case that the aggregate measure of inflation is not representative of country's households, then this could lead to redistribution of income, which leads to greater income inequality (Doepke and Schneider, 2006; Meh and Terajima, 2008).

Against this backdrop, the aim of the current study is to forecast the household-level inflation, taking Greece as our playfield. The choice of Greece stems from the fact that it is the country that has been heavily impacted by the energy crisis caused by the war in Ukraine and its economy has not been fully recovered from the 2010 debt crisis. We can just highlight that between June and October 2022 Greece's inflation rate was hovering at more than 11%, with the overall inflation rate for the 2022 to land at just below 10%. Anecdotal evidence from various media claims that low-income households experienced more than twice this rate[1]. Thus, the aim of the study is twofold. We aim to conduct an analysis to examine whether Greece has experienced significant household income discrepancies and the magnitude of such potential

[1] See, for instance, https://www.tovima.com/finance/imf-poorer-households-in-greece-experiencing-higher-inflation/, https://www.avgi.gr/oikonomia/407875_ta-ftoha-noikokyria-bionoyn-plithorismo-25-kai-ohi-5 (In Greek), https://www.ot.gr/2024/02/20/oikonomia/dnt-ta-ftoxotera-noikokyria-stin-ellada-vionoun-ypsilotero-plithorismo/ (in Greek).

inequalities among different household categories. Subsequently, we assess how the energy prices have contributed to the Greek households' inflation inequality.

More specifically, in the first stage of our study we generate the inflation rates by household category, where the latter are classified into both social and economic criteria (e.g., income level, household composition, occupational status, etc.). Subsequently, we generate 1-month up to 12-months household-level inflation forecast considering several important predictors and applying three different modelling frameworks (regression-based forecasts, Dynamic model averaging and quantile regressions). Using this framework, we can identify which predictors provide superior forecast gains across the different household categories and over time. This could be used as an early-warning signal for policy makers as our approach answers a very important questions, which has not been answered: "Across different households and over time, what are the key predictive factors that shape household-level inflation?"

Our findings show that the forecasting models that are augmented with the global-specific and energy-related predictors exhibit the highest predictive accuracy, relatively to an AR(1) model. In particular, we find that global economic activity, global supply chain pressure and geopolitical risk are important predictors across households, whereas there is no material difference in the forecast accuracy when these predictors are incorporated in predictive regressions or a DMA model. More importantly, though, we show that there are other predictors that demonstrate a household-specific performance, highlighting the importance of disaggregated inflation forecasting, which has the capacity to operate as an early warning system for the policy makers, should they be interested in identifying those factors that could lead to inflation inequality across households.

The remainder of the paper is structured as follows. Section 2 describes the data used for the calculation of the household-level inflation. Section 3 details the forecasting frameworks used in the study. Section 4 provides a detailed analysis of the empirical findings. Finally, Section 5 concludes the study.

2. Data description

The dataset is based on monthly data from the Household Budget Survey (HBS) of the Hellenic Statistical Authority. More specifically, the HBS contains information according to social and economic criteria. The categories are household i) size (members), ii) composition, iii) geographical location iv) income groups and v) Economic conditions[2]. The inflation per household category is calculated as:

$$CPI^{(i)}_{t,T,TOT} = CPI^{(i)}_{12,T-1,TOT} \sum_{j=1}^{m} w^{(i)}_{j,T} \frac{CPI_{t,T,j}}{CPI_{12,T-1,j}}, \tag{1}$$

$$w^{(i)}_{j,T} = \frac{p_{i,j,T}}{\sum_{j=1}^{m} p_{i,j,T}}, \tag{2}$$

where m is the number of categories of goods and services incorporated to households' basket, the $p_{i,j,T}$ is the value of good or service category j (e.g., food and non-alcoholic beverages) for household's category i, at year T. The $\sum_{j=1}^{m} p_{i,j,T}$ is the total value of purchases for the household's category i, at year T, whereas $CPI^{(i)}_{t,T,j}$ is the sub-group of CPI for the specific category j of good or service at year T. Having computed $CPI^{(i)}_{t,T,TOT}$ for all household categories, the year-on-year (y-o-y) inflation rate per household category is calculated as:

$$infl^{(i)}_t = \log\left(\frac{CPI^{(i)}_t}{CPI^{(i)}_{t-12}}\right). \tag{3}$$

Regarding the predictive variables, we use Greek-specific (domestic) factors, global factors and energy factors. The domestic factors are: Purchasing Managers

[2] **Household size (members):** 1 (HH_1), 2 (HH_2), 3 (HH_3), 4 (HH_4), 5 (HH_5) and 6 or more (HH_6).

Household composition: 1 person under 65 (HH_1PERS_UND65), 1 person over 65 (HH_1PERS_OVER65), childless couple (HH_NOCHILD), couple with 1 child up to the age of 16 (HH_COUPL_1CHILDUP16), couple with 2 children up to the age of 16 (HH_COUPL_2CHILDUP16), couple with 3 children up to the age of 16 (HH_COUPL_3MORECHILDUP16), single parent with 1 or more children up to the age of 16 (HH_1PAR_1MORECHILDUP16), couple or single parent with children aged over 16 (HH_COUPL1PAR_CHILDOVER16), and any other composition (HH_OTHER).

Economic conditions of the households' members: Only the lead member is active (HH_ACT_EXC_WIF_HUS), both the lead member and the partner are active (HH_ACT_WIF_HU), all household members are active (HH_ALL_ACT), retired (HH_RET), and others (HH_OTH_ACT).

Household geographical location: Urban (HH_URB) and rural (HH_RUR).

Household income groups: under 750 euros per month (HH_UP750), 751-1100 (HH_751_1100), 1101-1450 (HH_1101_1450), 1451-1800 (HH_1451_1800), 1801-2200 (HH_1801_2200), 2201-2800 (HH_2201_2800), 2801-3500 (HH_2801_3500) and over 3501 euros (HH_OVER3501) per month.

Index, Consumer Confidence Index, 10-yr Government bond yield, Athens Stock Exchange General Index, Economic Sentiment Index, Employment Expectations Index and the Greek Economic Policy Uncertainty Index. The global factors are the Euro effective exchange rate, Global Economic Policy Uncertainty Index, Geopolitical Risk Index, Global Supply Chain Pressure Index and the Global Economic Activity Index. Finally, the energy factors include the Brent crude oil prices, the EU Natural Gas price and the Greek wholesale electricity prices. Details for the data source and transformations applied for each variable are available in Table 1.

[TABLE 1 HERE]

Figures 1 to 5 exhibit the inflation rates across the different households and socioeconomic characteristics. It is evident that there are material differences on the household-level inflation rates, especially in the income groups, the households' size, households' composition and the economic condition of the households' members. By contrast, we do not observe any inflation inequality between households leaving in rural and urban areas.

[FIGURES 1 - 5]

3. Methodology

3.1 Forecasting framework

Our benchmark model is an autoregressive model of order 1, namely the AR(1), for which the predictive equation is the following:

$$\pi_{t+h|t}^{(i)} = \alpha_i + \delta_i \pi_t^{(i)} + e_{t+h|t}^{(i)}, \tag{4}$$

where $\pi_t^{(i)}$ is the month-on-month inflation rate of household i at time t. We use the month-on-month inflation rate not only due to the strong stationarity of this variable's transformation, compared to the y-o-y series, but also due to the fact that this transformation is widely used by the literature (e.g., Stock and Watson, 1999; Koop and Korobilis, 2012).

We proceed with the estimation of the following individual predictive regression models, as shown in eq. (5-9):

$$\pi_{t+h|t}^{(i)} = \alpha_i + \delta_i \pi_t^{(i)} + \beta_i \boldsymbol{DOM}_t + e_{t+h|t}^{(i)}, \tag{5}$$

$$\pi_{t+h|t}^{(i)} = \alpha_i + \delta_i \pi_t^{(i)} + \gamma_i \boldsymbol{GLO}_t + e_{t+h|t}^{(i)}, \tag{6}$$

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$$\pi_{t+h|t}^{(i)} = \alpha_i + \delta_i \pi_t^{(i)} + \beta_i \boldsymbol{DOM}_t + \gamma_i \boldsymbol{GLO}_t + e_{t+h|t}^{(i)}, \tag{7}$$

$$\pi_{t+h|t}^{(i)} = \alpha_i + \delta_i \pi_t^{(i)} + \theta_i \boldsymbol{ENER}_t + e_{t+h|t}^{(i)}, \tag{8}$$

$$\pi_{t+h|t}^{(i)} = \alpha_i + \delta_i \pi_t^{(i)} + \beta_i \boldsymbol{DOM}_t + \gamma_i \boldsymbol{GLO}_t + \theta_i \boldsymbol{ENER}_t + e_{t+h|t}^{(i)}, \tag{9}$$

where $\boldsymbol{DOM}$ is the vector of the domestic factors, $\boldsymbol{GLO}$ is the vector of the global factors and $\boldsymbol{ENER}$ is the vector of the three energy prices. In our analysis, we estimate the predictive regressions by using specific sets of explanatory variables in order to better reflect the domestic, global and energy environments.

The estimated model that is explained in eq. (9) assumes that all explanatory variables affect inflation rates over the sample, which may not hold true. Therefore, we proceed with a combination methodology, namely the DMA, which not only allows for parameters' time variation in order to capture potential structural breaks in the targeted series, but it is also developed in a way that the predictive information from the different explanatory variables is incorporated in a "non-equally weighted" fashion. The implementation of this methodology is twofold. In greater detail, we not only generate multi-step ahead inflation forecasts, but we also obtain the time-varying contributions of each explanatory variable to the final aggregated model for inflation per household category.

To proceed with some technical details concerning the DMA model's estimation, it is employed by allowing for K models of different specifications, including domestic, global and energy factors, to generate forecasts that are optimally aggregated over time. The state-space model[3] consists then of the two following equations:

$$\begin{aligned} y_t &= \mathbf{x}_\mathbf{t}^{(\mathbf{k})} \boldsymbol{\alpha}_\mathbf{t}^{(\mathbf{k})} + \varepsilon_t^{(k)} \quad \text{for} \quad \varepsilon_t^{(k)} \sim N\left(0, \boldsymbol{H}_t^{(k)}\right), \\ \boldsymbol{\alpha}_\mathbf{t}^{(\mathbf{k})} &= \boldsymbol{\alpha}_\mathbf{t-1}^{(\mathbf{k})} + \mathbf{u}_\mathbf{t}^{(\mathbf{k})} \quad \text{for} \quad \mathbf{u}_\mathbf{t}^{(\mathbf{k})} \sim N\left(\mathbf{0}, \boldsymbol{\Sigma}_{\mathbf{u_t}}^{(\mathbf{k})}\right), \end{aligned} \tag{10}$$

where $k = 1, \dots, K$, y_t denotes the dependent variable $\pi_t^{(i)}$, $\boldsymbol{\alpha}_\mathbf{t}^{(\mathbf{k})}$ are the regression parameters that constitute each one of the model specifications and the errors $\varepsilon_t^{(k)}$ and $\mathbf{u}_\mathbf{t}^{(\mathbf{k})}$ are mutually independent. Moreover, if there are m predictors in $\mathbf{x}_\mathbf{t}^{(\mathbf{k})}$, the total number of possible combinations of these predictors[4] is $K = 2^m = 2^{16}$. It is noted that

[3] This state space form is based on the model specification of eq.(9).
[4] In the list of predictors, apart from the domestic, global and energy factors, the one lagged inflation rate is also included, which is in line with the literature.

the constant term is included each time at the model specification. This model can be estimated by using the Kalman filter method[5]. One key element that has to be mentioned is that the approximation of the forgetting factor λ, which is used in order to avoid estimating the state covariance matrix $\mathbf{\Sigma}_{\mathbf{u_t}}^{(\mathbf{k})}$ is replaced by the standardized self-perturbed Kalman filter[6] proposed by Grassi *et al.* (2017). It is important to note that we implement the DMA approach with different sets of explanatory variables that represent the domestic, global and energy environments, as mentioned previously. Therefore, we generate multi-step ahead inflation forecasts not only from the DMA-ALL model (this includes the entire set of explanatory variables), but also from the DMA-DOMESTIC (this includes the domestic factors) etc.

Finally, focusing on the income category only, we use a quantile predictive regression so to assess whether the median quantile of the inflation rate at each income category is a better approximation (rather than the average inflation at each income category) and as such it provides better forecasting performance.

Quantile regression has been developed as a generalization of traditional least squares regression by fitting a regression line for each quantile of the distribution of the targeted variable. More specifically, the research question that answers a quantile regression model, initially proposed by Koenker and Bassett (1978) is "*What about the other quantiles?*". Since the symmetry of the absolute value yields the median, perhaps minimizing a sum of asymmetrically weighted absolute residuals—simply giving differing weights to positive and negative residuals—would yield the quantiles. According to Koenker and Hallock (2001), in quantile regression, the estimates of the conditional quantile functions are obtained by solving the following:

$$min \sum \rho_\tau(y_t - \xi(x_t - \beta)) \tag{11}$$

where the function $\rho_\tau(\cdot)$ is the titled absolute value function that yields the τ^{th} sample quantile as its solution and $\xi(x_t - \beta)$ is a parametric function. It is highlighted that in order to solve this minimization problem, when $\xi(x_t - \beta)$ is formulated as a linear function of parameters, linear programming methods can be used very efficiently.

[5] More details for each step of the estimation of time-varying parameter models and the combination of those models through the DMA approach can be found in the Appendix.
[6] This methodological part is motivated by the study of Delis *et al.* (2022), which provides more details on this approximation.

Apart from using the abovementioned classical quantile regression for generating inflation forecasts that reflect different quantiles of its distribution, we also develop Bayesian quantile regression models, proposed by Korobilis (2017) that may lead to more accurate parameters' estimation. In greater detail, the Bayesian framework provides the ability to specify prior distributions for the model parameters. This is considered crucial in cases where limited data is available or when prior information from previous studies is available.

Regarding the linear quantile regression that is estimated using a Bayesian approach, we start with the model representation[7], which is the following:

$$y_t = x_t\beta(\tau) + \sigma(\tau)\varepsilon_t, \tag{12}$$

where $\beta(\tau)$ and $\sigma(\tau)$ are the regression coefficients and the scale parameter, respectively, for each quantile level τ, while ε_t are i.i.d. from a joint Asymmetric Laplace density. Following Kozumi and Kobayashi (2011), we write the Asymmetric Laplace distribution using the following mixture representation as:

$$y_t = x_t\beta(\tau) + \theta(\tau)z_t + \sigma(\tau)\kappa(\tau)\sqrt{z_t(\tau)u_t}, \qquad u_t \sim N(0,1), \tag{13}$$

where $\theta(\tau) = \frac{1-2\tau}{\tau(1-\tau)}$, $\kappa(\tau)^2 = \frac{2}{\tau(1-\tau)}$ and $z_t(\tau) \sim exp(\sigma(\tau)^2)$. From this mixture representation, we write the density of y_t as:

$$\prod_{t=1}^{T} \frac{1}{\sqrt{2\pi z_t(\tau)\sigma(\tau)^2\kappa(\tau)^2}} exp\left\{\frac{(y_t - x_t\beta(\tau) - \theta(\tau)z_t)^2}{2z_t(\tau)\sigma(\tau)^2\kappa(\tau)^2}\right\} \exp\left\{\frac{z_t(\tau)}{\sigma(\tau)^2}\right\}, \tag{14}$$

which conditionally on $z_t(\tau)$ is a normal density, while marginalizing over the unknown $z_t(\tau)$ gives the desired Asymmetric Laplace density. To continue with the priors, the following distributions are assumed:

$$\begin{gathered} \beta(\tau) \sim N\big(0, V(\tau)\big) \\ \sigma(\tau) \sim IG(\rho_1, \rho_2) \\ z_t(\tau) \sim exp\big(\sigma(\tau)\big) \end{gathered} \tag{15}$$

Given these priors, we obtain conditional posteriors of the following form:

$$\begin{gathered} \beta(\tau)|\cdot \sim N((x'Ux + V(\tau)^{-1})^{-1} \\ \times (x'U[y - \theta(\tau)z_t]), (x'Ux + V(\tau)^{-1})^{-1})^{-1}), \end{gathered} \tag{16}$$

[7] For consistency purposes, we use the same notations as in the papers of Korobilis (2017), Korobilis et al. (2021) and Pfarrhofer (2022). In case we want to represent the predictive form of the Bayesian quantile regression, eq. (12) is replaced with $y_{t+h|t} = x_t\beta(\tau) + \sigma(\tau)\varepsilon_{t+h|t}$.

$$\sigma(\tau)|\cdot \sim IG\left(\rho_1 + \frac{3T}{2}, \rho_2 + \sum_{t=1}^{T} \frac{(y_t - x_t\beta(\tau) - \theta(\tau)z_t)^2}{2z_t(\tau)\kappa(\tau)^2} + \sum_{t=1}^{T} z_t(\tau)\right),$$

$$z_t(\tau)|\cdot \sim IG\left(\frac{\sqrt{\theta(\tau)^2 + 2\kappa(\tau)^2}}{|y_t - x_t\beta(\tau)|}, \frac{\theta(\tau)^2 + 2\kappa(\tau)^2}{\sigma(\tau)^2\kappa(\tau)^2}\right),$$

where U is a $T \times T$ diagonal covariance matrix with t^{th} element $(z_t(\tau)\sigma(\tau)^2\kappa(\tau)^2)^{-1}$. For further technical details on the derivation of the posteriors, see Johnson et al. (1994), Kozumi and Kobayashi (2011) and Korobilis et al. (2021).

3.2 Forecast strategy and evaluation

Regarding the generation of multi-step (h) ahead forecasts using the above specified model specifications, the direct approach is used. We follow this approach rather than using its alternative (iterated forecasts) due to the large set of regressors, which would require either the use of auxiliary models for each of them or the inclusion of assumptions for their future values until reaching horizon h. Therefore, by using the direct approach we avoid the complexity in the modelling framework, and we do not rely on assumptions of the explanatory variables, which would add uncertainty in the predictive models. As regards the initial estimation sample, we use the first 60 observations, which reflects the period up to January of 2014. The choice of the initial sample period is justified by the fact that a large enough sample size (5 years) is required for the estimation of the forecasting models but also due to the fact we want to generate forecasts for both low and high volatility periods. The rest months are used for the real out-of-sample forecasting period. We generate inflation forecasts from 1-month up to 12-months ahead. It is also clarified that we employ an expanding window approach, which leads to increased estimation samples, and therefore more accurate estimates.

We proceed with the evaluation of the forecasting performance based on specific loss functions. First, we use a well-established statistical loss function, namely Mean Squared Predictive Error (MSPE), which is expressed as:

$$\Psi_{m,i,t}^{(mspe)} = \left(\pi_{m,t+h|t}^{(i)} - \pi_{t+h}^{(i)}\right)^2 \tag{17}$$

where $\pi_{m,t+h|t}^{(i)}$ denotes the inflation forecast generated from m model and refers to the i household. Moreover, this forecast aims at month t+h and has been estimated with the information that is available at month t.

Second, we use the DMA framework to extract the time-varying contribution of the chosen predictors to each household category. These time-varying contributions allow us to proceed to the economic-based evaluation of our findings, as they indicate the importance of each predictor in forecasting the household-level inflation across time and household category.

4. Analysis of findings

4.1 Household size (members)

We initiate our analysis with the first household category, which relates to the household size, and the results of the relative RMSE is shown in Table 2.

[TABLE 2 HERE]

As shown in Table 2, there are four main forecasting models that provide superior predictive ability across both the forecasting horizons and household's size. More specifically, the results show that the INFL_HH_REG_GLO, INFL_HH_REG_ENER, INFL_HH_DMA_ENER and INFL_HH_DMA_GLO provide predictive gains, relatively to the AR(1) model, ranging from approximately 8% at the 1-month-ahead horizon up to 26% at the 12-months-ahead forecasts. Nevertheless, these gains are not homogeneous across households. The fact that the models that incorporate the global factors (either the regression-based models or the DMA framework) are exhibiting a superior performance, suggests that household-level inflation across Greek households of any category is primarily impacted by global developments rather than Greek-related indicators.

This is also evident from Figure 6, which shows indicatively the time-varying contribution of a given variable to the best performing models from the DMA framework for two households (1-person and 6+-persons for the h=1 and h=12 horizons)[8]. Figure 6 clearly suggests that the most important predictors are the GREA, GSCPI and GPR, whereas ELESI is becoming important only in the longer forecasting horizons. In addition, we observe that not all predictors assume the same level of contribution across the difference households.

[FIGURE 6]

Another interesting finding is the fact that the energy factors also materially improve the forecasting performance, vis-à-vis the AR(n) model, primarily for the

[8] The contribution of all predictors for all households' categories are available upon request from the authors.

small-size households and less so for the larger households (see Table 2). This is important, as our framework confirms the premise that inflation forecasts should be performed at household-level, given that the various predictors may impact the households differently. Even more, from Figure 6 we note that since 2020 the Brent crude oil prices, as well as the natural gas price are also important contributors to the best performing models. However, the oil prices seem to be more "important" for the larger households (HH_6), as opposed to the natural gas prices that are having greater contribution for the 1-person households (HH_1).

4.2 Household composition

Next, we continue our analysis with forecasting evaluations, according to the household composition, which are shown in Table 3.

[TABLE 3 HERE]

As in the case of household size category, the best performing models are those that incorporate the global factors, followed by those that incorporate the energy factors. Nevertheless, the magnitude of the predictive gains (relatively to the AR(1) model) of those models vary across the different households and horizons, which further strengthens our premise that these factors may exert a differentiating effect across the different households. This is also exhibited in Figure 7, where we show the time-varying contributions of the predictors to the best performing models.

[FIGURE 7]

4.3 Economic conditions of the households' members and geographical location

The main conclusions drawn from the two previous household categories hold true for the next two categories, namely, the economic conditions of the household's members and the household's geographical location (see Tables 4 and 5 and Figures 8 and 9, respectively).

[TABLES 4 and 5 HERE]

[FIGURES 8 and 9]

Overall, we find that there is indeed a differentiating impact of the different predictors across the different households and household categories. This is an important finding showing that solely generating inflation forecasts based on the average inflation measure may not be representative of all households within the economy. We have left to the end the most important household category which is related to the income categories. The results are presented in Section 4.4.

4.4 Household income groups

As mentioned above, we finalise our forecast evaluation with the household's income category, where the RRMSE are reported in Table 6. The reason for leaving the income category last is that it is the most important household category and for this category we have extended the list of forecasting model with the quantile regressions, so to assess whether the median income could provide superior predictive gains for the income groups, rather than the mean income that is considered in the predictive regressions and DMA framework. Thus, in Table 6 we report the same forecasting models as in the previous household categories, adding the quantile predictive regression for the median quantile (Q50).

[TABLE 6 HERE]

The results on Table 6 clearly suggest that the forecasting models that incorporate the global factors are once again those that exhibit superior predictive gains, relatively to the AR(1) model. However, we further show that the INFL_HH_Q50_B_GLO model is the best performing model across almost all households and horizons. The only exception is the 1-month-ahead horizon where the INFL_HH_DMA_GLO, along with the INFL_HH_DMA_ALL and INFL_HH_REG_GLO seem to perform marginally better than the INFL_HH_Q50_B_GLO. Overall, the predictive gains of the latter model range from 4% up to 25%, depending on the household income category and horizon. Even more, we show that the more material gains are evident in the HH_UP750 income category in all horizons.

Another interesting finding is the fact that the energy factors seem to be more "important" for the low-income households, given that the predictive gains are higher for these households, as shown by the forecasting models that incorporate the energy prices (see, for instance the INFL_HH_Q50_B_ENER model).

Turning our attention to the contribution of each predictor to the best performing models, Figure 10 shows that indeed this is time-varying and household income group dependent. So, for instance for the most vulnerable households (HH_UP750) at the 1-month-ahead horizon, the most important contributors are the GREA, the natural gas, GSCPI, as well as ELESI (until 2020). By contrast, for the wealthier households

(HH_OVER3501) at the same horizon, it is evident that the most important contributor is the Brent crude oil price and ELESI, as well as GPR and GSCPI (towards the latter part of the study). An even clearer distinction as to which are the most important contributors across the income groups is evident at the 12-months-ahead horizon, where the ELESI, EPU_LN, EPU_CURR_GLOBAL_LN and GSCPI are the most important contributors for the HH_UP750, whereas for the HH_OVER3051 the top contributors are ELESI, ELEEI, EFF_EXCHRATE_EUR_MOM and GSCPI.

[FIGURE 10]

5. Conclusion

This aim of this paper is to develop a framework for household-level inflation forecasting across Greek households and socioeconomic categories, for the period 2009-2022. To do so, we employ predictive regressions, DMA and quantile predictive regressions, as well as, a series of predictors, which are grouped in domestic, global and energy-related.

Our findings show that there is indeed a material inflation inequality across Greek households with different socioeconomic characteristics. Even more, we show that although the models that incorporate global factors exhibit superior forecasting performance across all households, there are other factors that demonstrate a household-specific performance. As for the specific variables, our findings highlight the global economic activity, global supply chain pressure and geopolitical risk are the most influential predictors. Nevertheless, we further show that other variables (the energy-factors, for instance) demonstrate a differentiating forecasting performance across different households.

Overall, we find that there is indeed a differentiating impact of the different predictors across the different households and household categories. This is an important finding showing that solely generating inflation forecasts based on the average inflation measure may not be representative of all households within the economy.

These results have important policy implications. First, given the household-specific forecasting performance of various predictors, a release-focused early-warning system for policy makers should be developed that would monitor how and when each factor is relevant for which type of household. Second, given that aggregate inflation is not a sufficient statistic for welfare-relevant policy during economic shocks, the disaggregated inflation forecasts would allow policy makers for more targeted measures (e.g., energy-bill relief and housing cost interventions) that would benefit specific types of households (e.g. low-income households in high energy-price regimes). Finally, given that for the income category the quantile regression offers material predictive gains, authorities should focus not only on the average income of each group, but also on the quantiles within these income groups, for an even higher granularity of the driving factors of inflation inequality.

Further study could assess additional predictors for the added-value in the disaggregated household-level inflation forecasts, as well as, additional forecasting frameworks, so to enhance further the results presented thus far.

Acknowledgement

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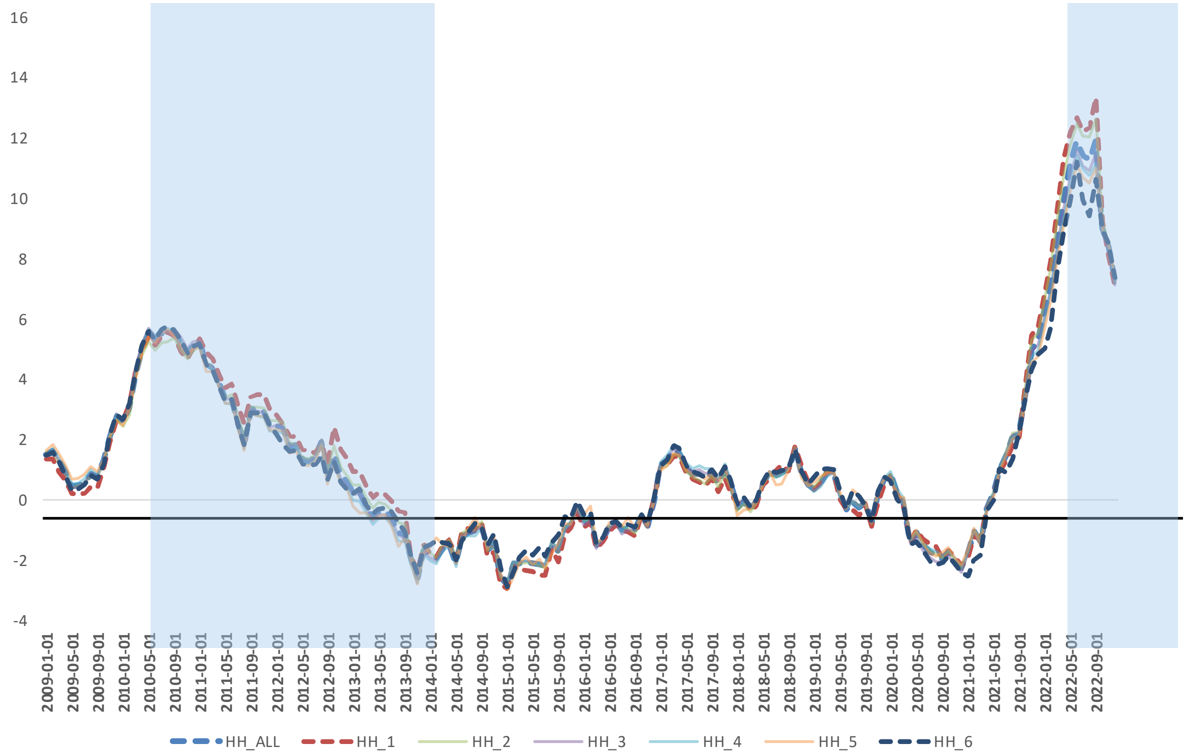
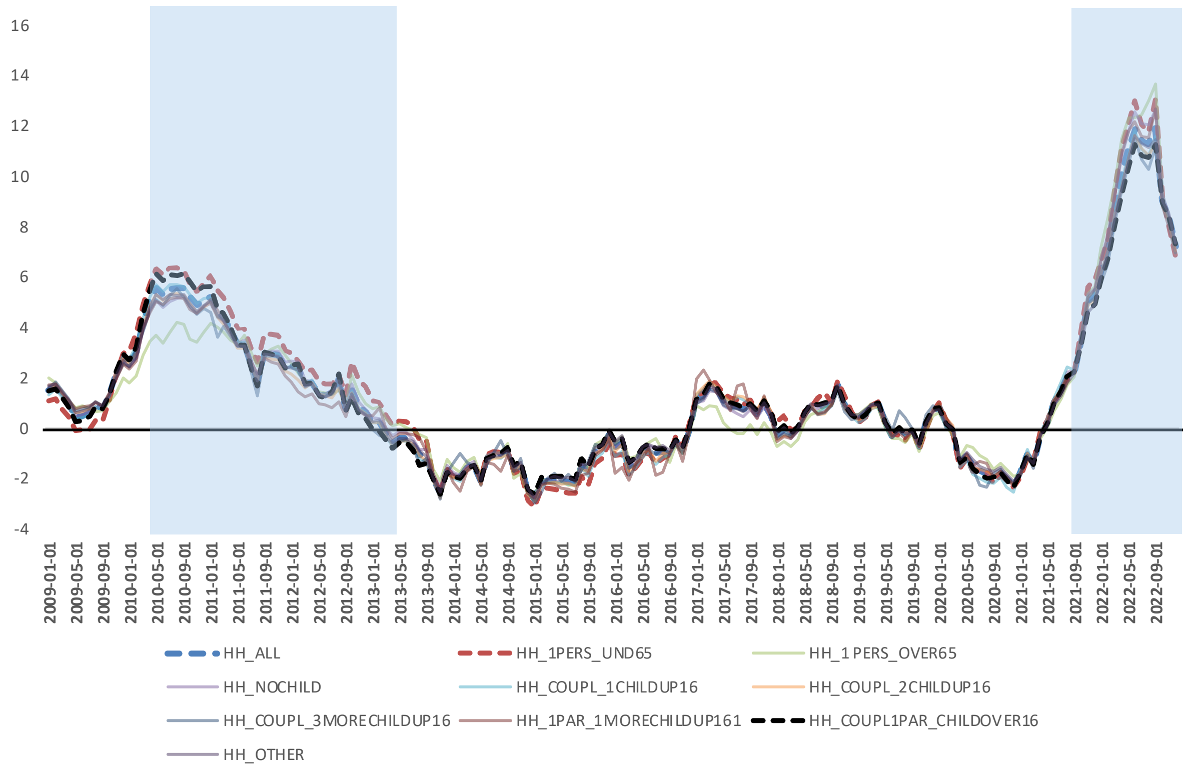
FIGURES

Figure 1: Inflation rate by household size (2009-2022).



Notes: The shaded areas denote periods of significant divergence across the household-level inflation.

Figure 2: Inflation rate by household composition (2009-2022).

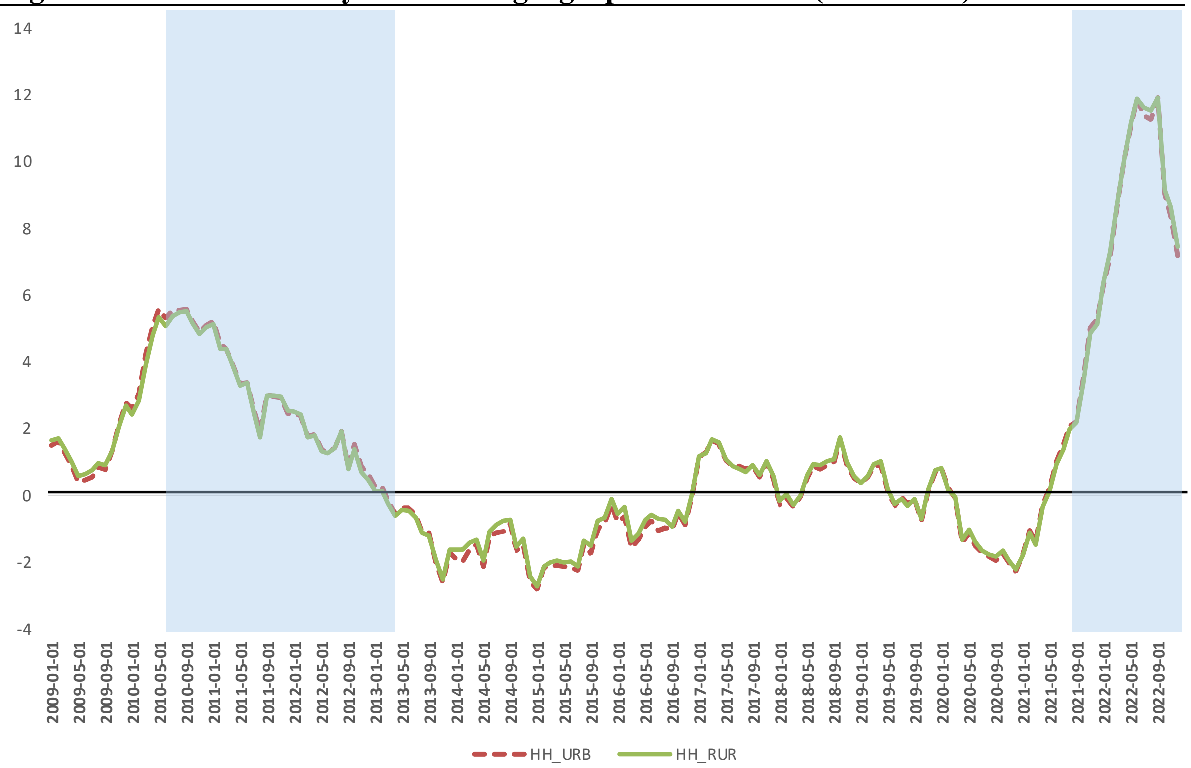


Notes: The shaded areas denote periods of significant divergence across the household-level inflation.

Figure 3: Inflation rate by economic conditions of the households' members (2009-2022).

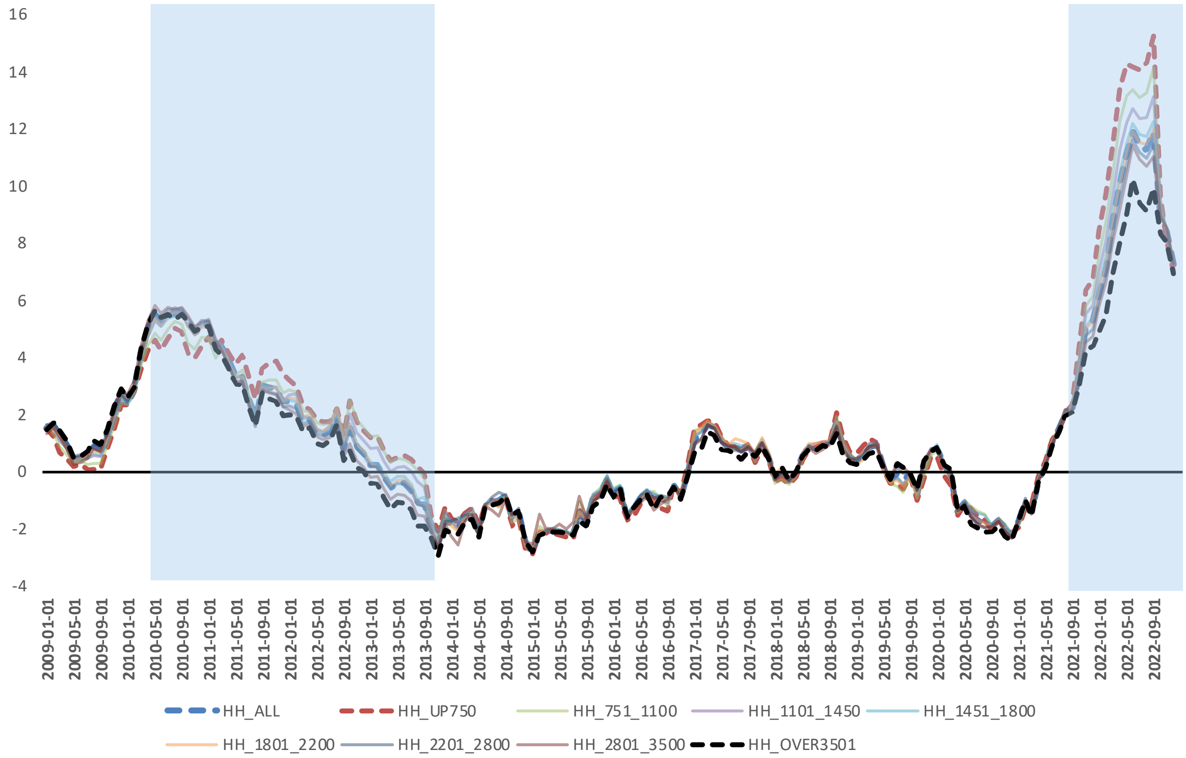
Notes: The shaded areas denote periods of significant divergence across the household-level inflation.

Figure 4: Inflation rate by household geographical location (2009-2022).



Notes: The shaded areas denote periods of significant divergence across the household-level inflation.

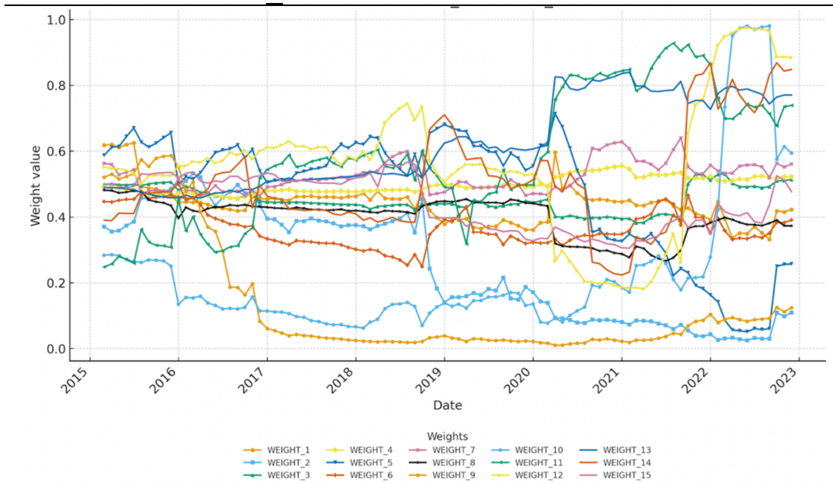
Figure 5: Inflation rate by household income category (2009-2022).



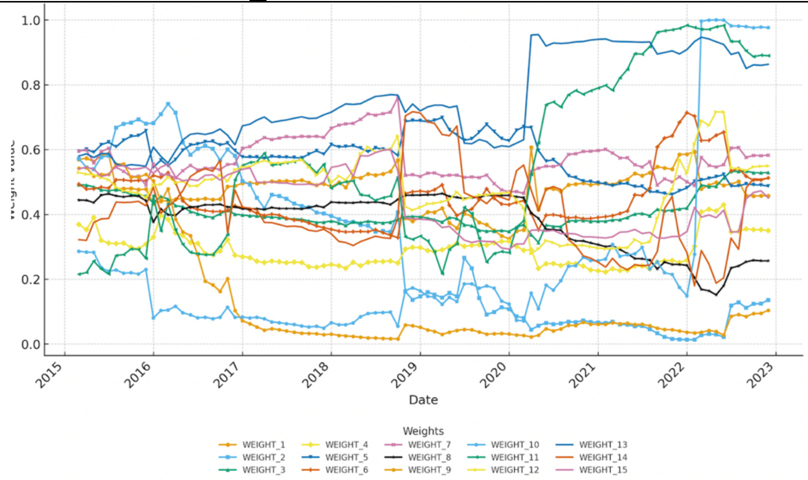
Notes: The shaded areas denote periods of significant divergence across the household-level inflation.

Figure 6: Predictors' time-varying contributions for household size category

HH_1 – 1-month-ahead horizon

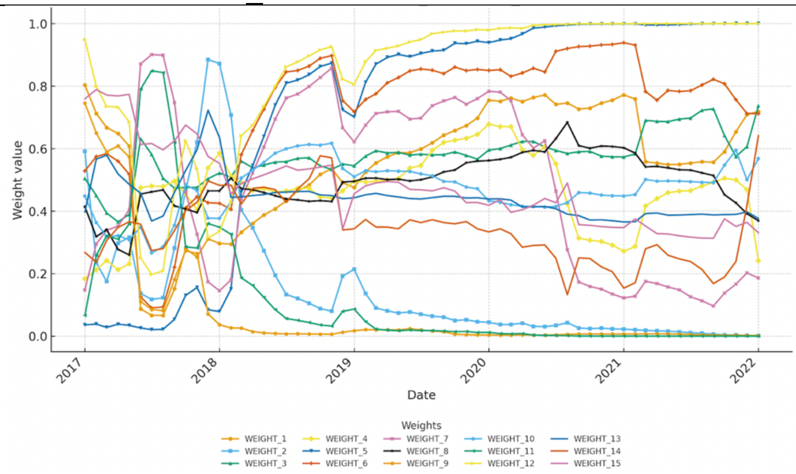


HH_6 – 1-month-ahead horizon



HH_1 – 12-month-ahead horizon

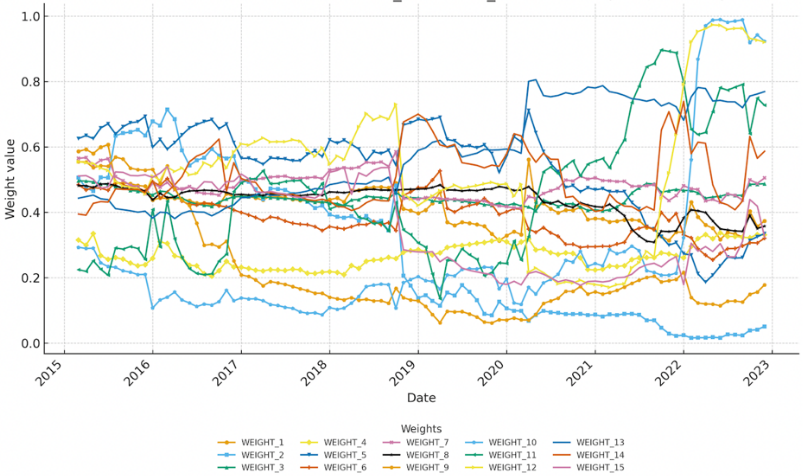
HH_6 – 12-month-ahead horizon



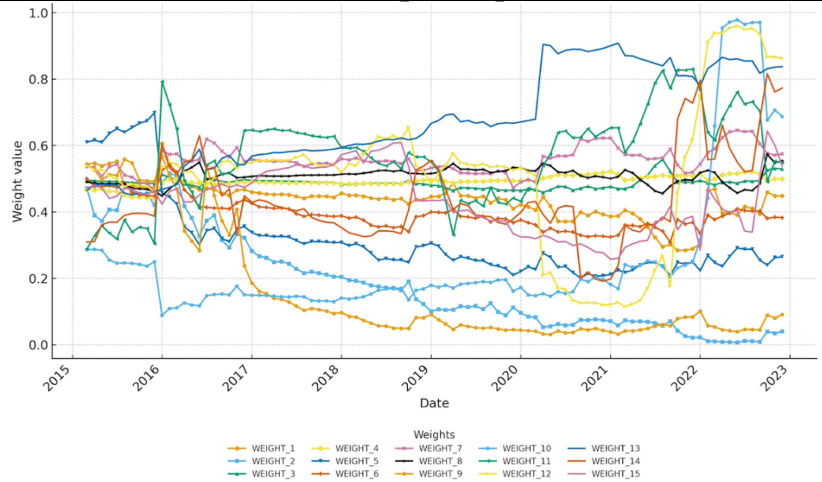
Note: WEIGHT_1=GR_PMI, WEIGHT_2=GR_CCI, WEIGHT_3=GR_10YR_BOND, WEIGHT_4=GR_INDEX, WEIGHT_5=GR_ESI, WEIGHT_6=GR_EEI, WEIGHT_7=GR_EPU, WEIGHT_8=EFF_XRATE, WEIGHT_9=GLOBAL_EPU, WEIGHT_10=GPR, WEIGHT_11=GREA, WEIGHT_12=GSCPI, WEIGHT_13=UKBRENT, WEIGHT_14=NG, WEIGHT_15=ELECTR.

Figure 7: Predictors' time-varying contributions for household composition category

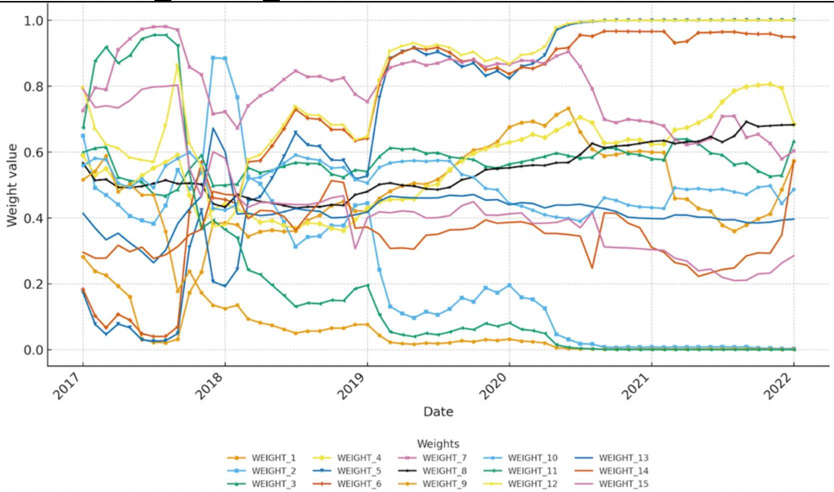
HH_1PERS_UND65 – 1-month-ahead horizon



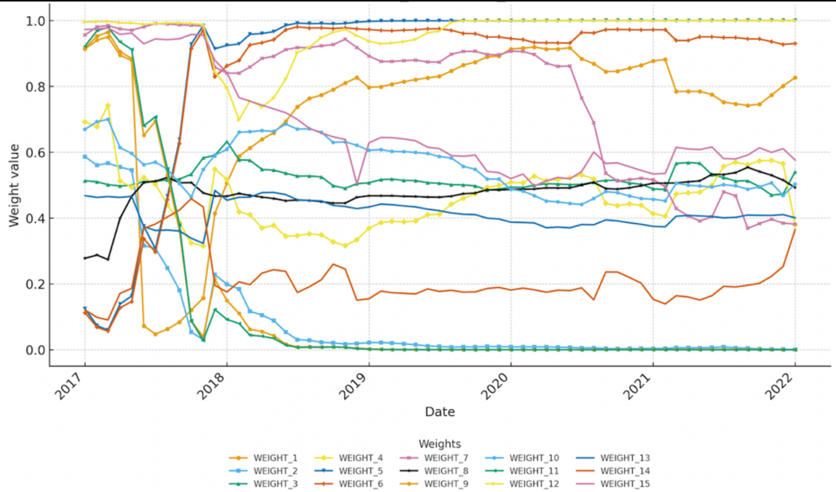
HH_COUPL1PAR_CHILDOVER16 – 1-month-ahead horizon



HH_1PERS_UND65 – 12-month-ahead horizon



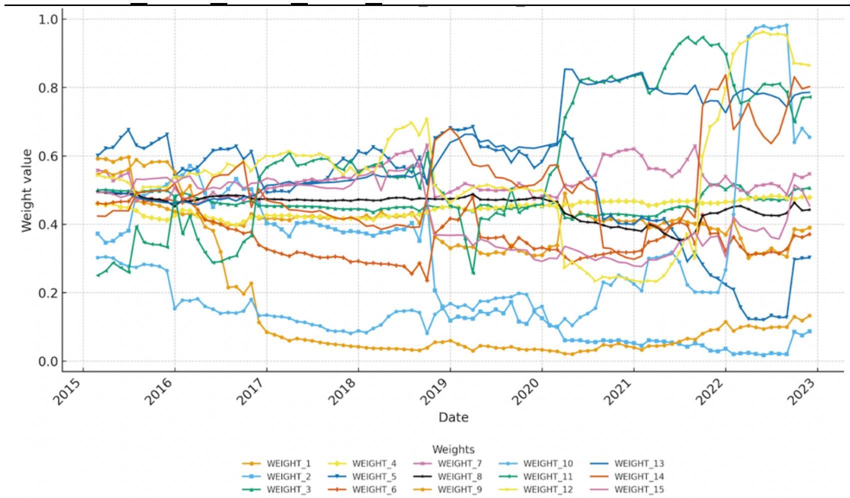
HH_COUPL1PAR_CHILDOVER16 – 12-month-ahead horizon



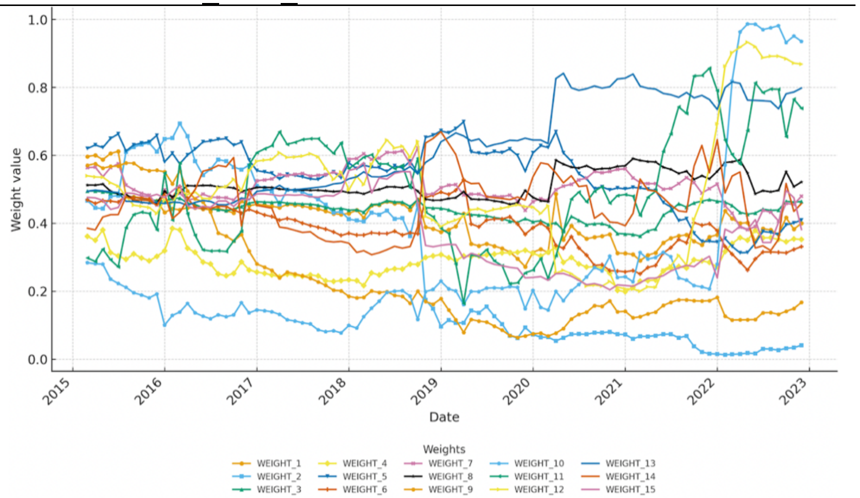
Note: WEIGHT_1=GR_PMI, WEIGHT_2=GR_CCI, WEIGHT_3=GR_10YR_BOND, WEIGHT_4=GR_INDEX, WEIGHT_5=GR_ESI, WEIGHT_6=GR_EEI, WEIGHT_7=GR_EPU, WEIGHT_8=EFF_XRATE, WEIGHT_9=GLOBAL_EPU, WEIGHT_10=GPR, WEIGHT_11=GREA, WEIGHT_12=GSCPI, WEIGHT_13=UKBRENT, WEIGHT_14=NG, WEIGHT_15=ELECTR.

Figure 8: Predictors' time-varying contributions for household's economic conditions category

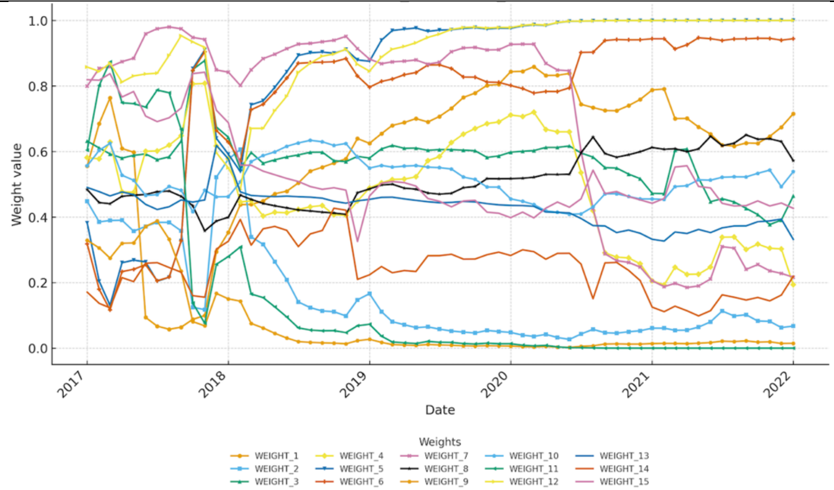
HH_ACT_EXC_WIF_HUS – 1-month-ahead horizon



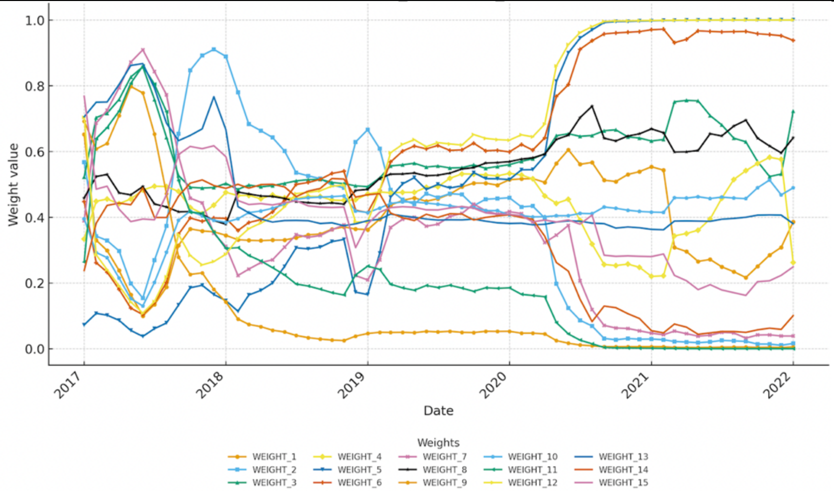
HH_ALL_ACT – 1-month-ahead horizon



HH_ACT_EXC_WIF_HUS – 12-month-ahead horizon



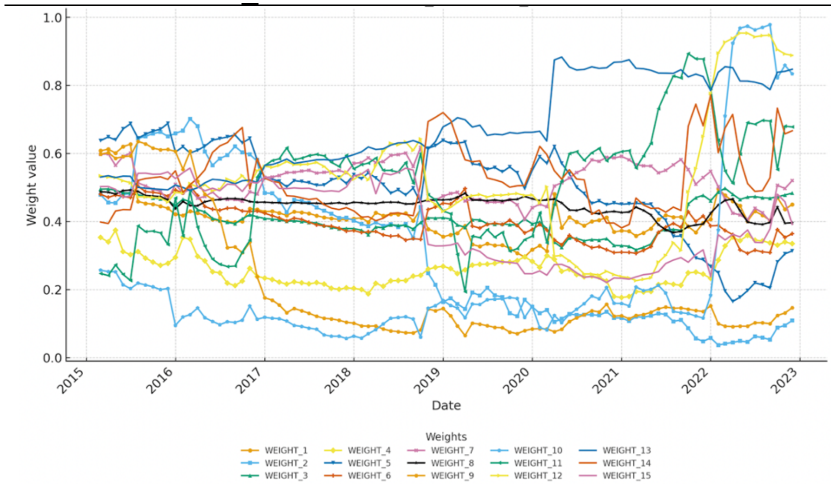
HH_ALL_ACT – 12-month-ahead horizon



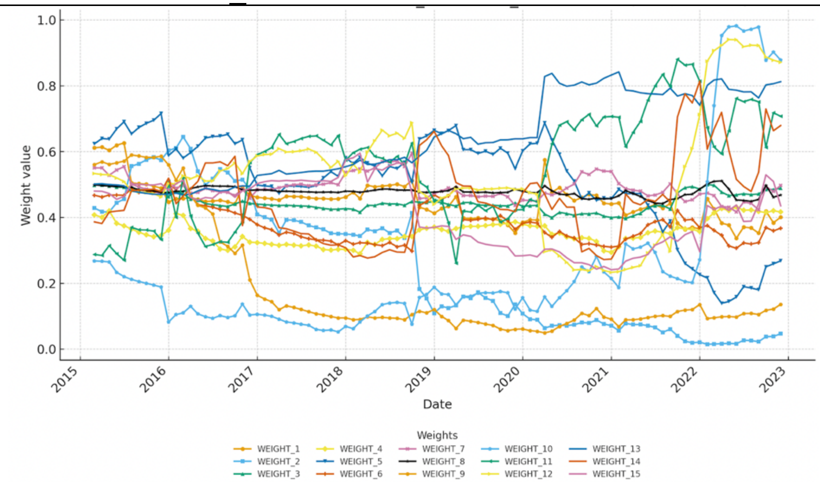
Note: WEIGHT_1=GR_PMI, WEIGHT_2=GR_CCI, WEIGHT_3=GR_10YR_BOND, WEIGHT_4=GR_INDEX, WEIGHT_5=GR_ESI, WEIGHT_6=GR_EEI, WEIGHT_7=GR_EPU, WEIGHT_8=EFF_XRATE, WEIGHT_9=GLOBAL_EPU, WEIGHT_10=GPR, WEIGHT_11=GREA, WEIGHT_12=GSCPI, WEIGHT_13=UKBRENT, WEIGHT_14=NG, WEIGHT_15=ELECTR.

Figure 9: Predictors' time-varying contributions for household's geographical location category

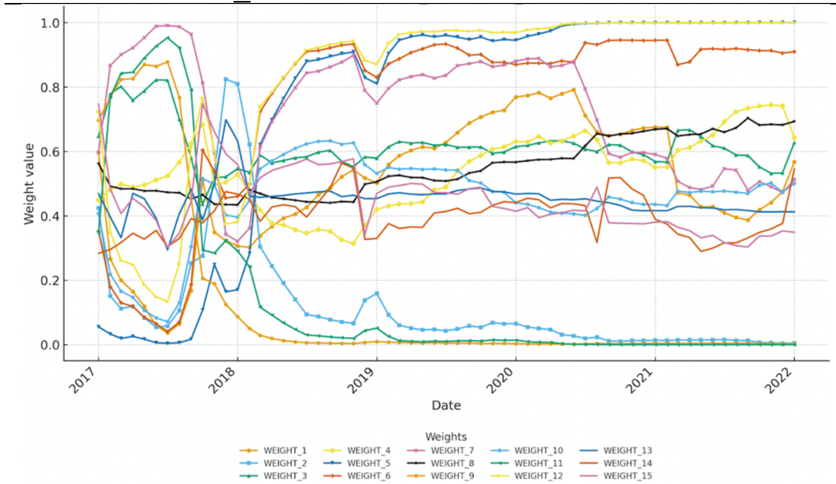
HH_RUR – 1-month-ahead horizon



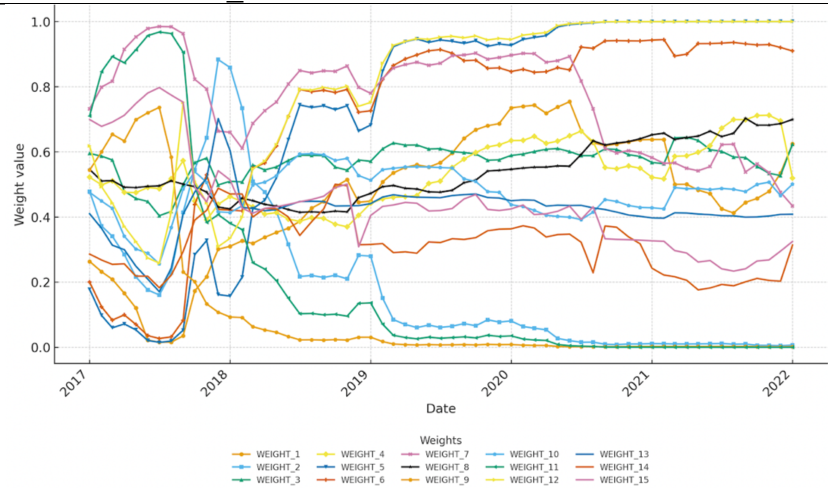
HH_URB – 1-month-ahead horizon



HH_RUR – 12-month-ahead horizon



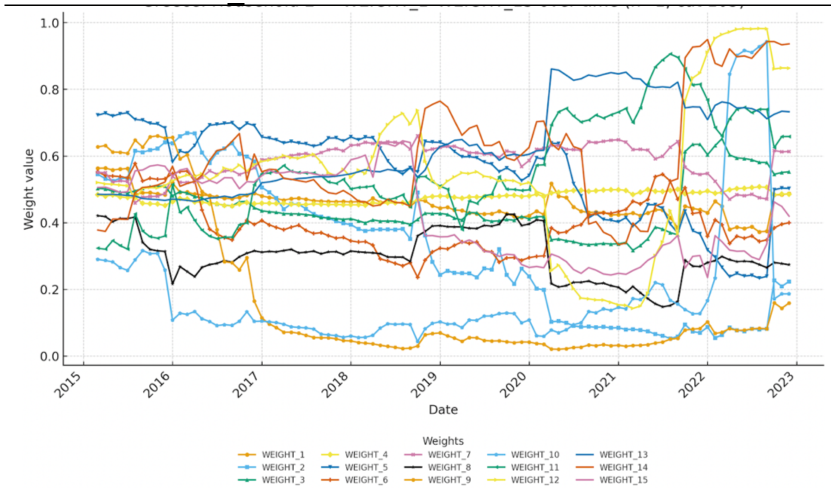
HH_URB – 12-month-ahead horizon



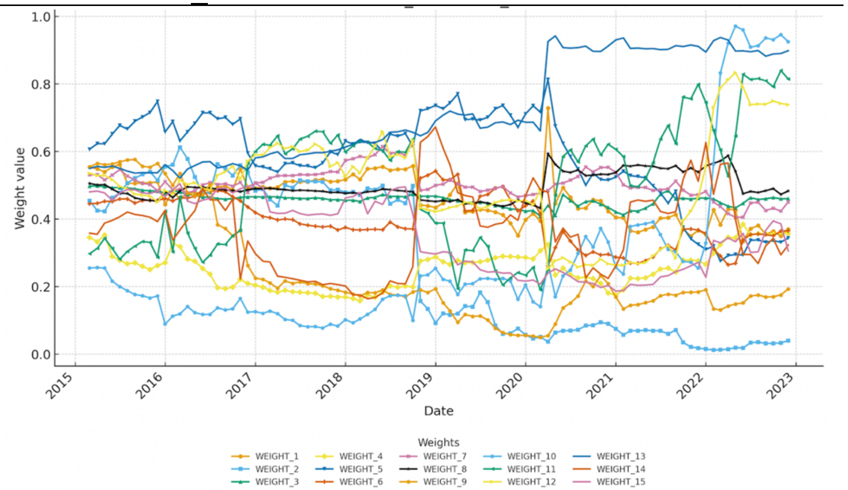
Note: WEIGHT_1=GR_PMI, WEIGHT_2=GR_CCI, WEIGHT_3=GR_10YR_BOND, WEIGHT_4=GR_INDEX, WEIGHT_5=GR_ESI, WEIGHT_6=GR_EEI, WEIGHT_7=GR_EPU, WEIGHT_8=EFF_XRATE, WEIGHT_9=GLOBAL_EPU, WEIGHT_10=GPR, WEIGHT_11=GREA, WEIGHT_12=GSCPI, WEIGHT_13=UKBRENT, WEIGHT_14=NG, WEIGHT_15=ELECTR.

Figure 10: Predictors' time-varying contributions for household's income category

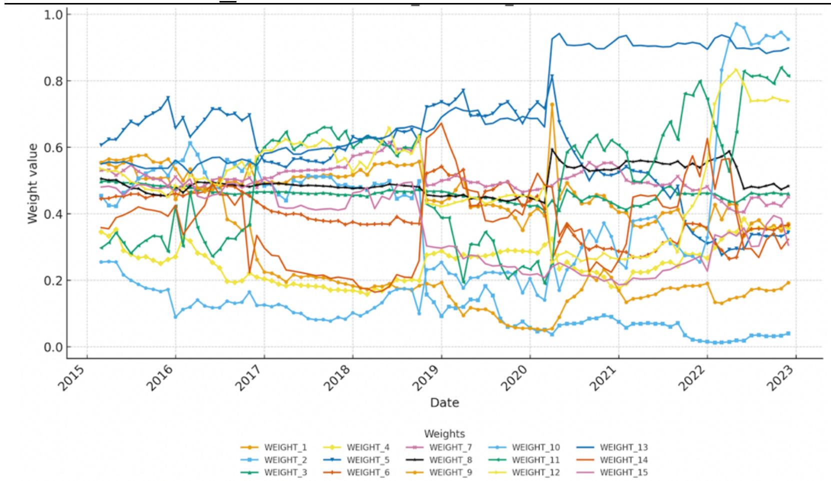
HH_UP750 – 1-month-ahead horizon



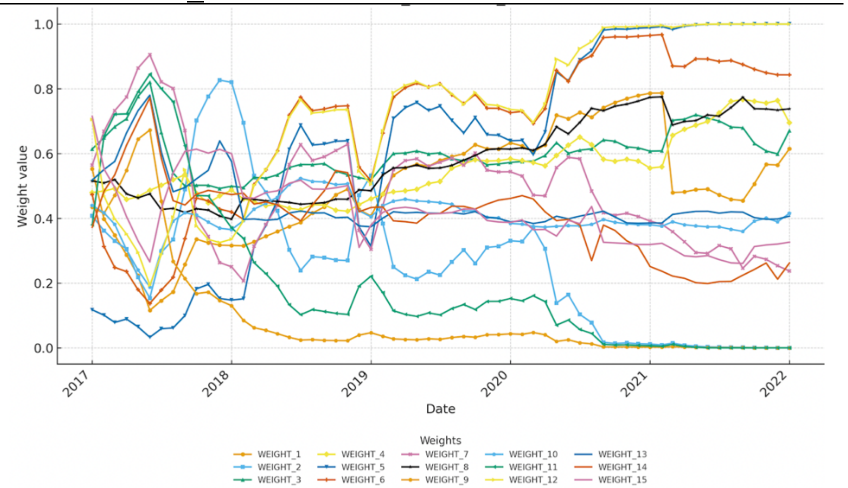
HH_OVER3501 – 1-month-ahead horizon



HH_UP750 – 12-month-ahead horizon



HH_OVER3501– 12-month-ahead horizon



Note: WEIGHT_1=GR_PMI, WEIGHT_2=GR_CCI, WEIGHT_3=GR_10YR_BOND, WEIGHT_4=GR_INDEX, WEIGHT_5=GR_ESI, WEIGHT_6=GR_EEI, WEIGHT_7=GR_EPU, WEIGHT_8=EFF_XRATE, WEIGHT_9=GLOBAL_EPU, WEIGHT_10=GPR, WEIGHT_11=GREA, WEIGHT_12=GSCPI, WEIGHT_13=UKBRENT, WEIGHT_14=NG, WEIGHT_15=ELECTR.

TABLES

Table 1: Data sources and transformations of the predictors.

Group	Variable	Acronym	Data source	Transformation
Domestic	Economic Sentiment Index	GR_ESI	European Commission/Business and consumer surveys	Level
	Consumer Confidence Index	GR_CCI	European Commission/Business and consumer surveys	Level
	Employment Expectations Index	GR_EEI	European Commission/Business and consumer surveys	Level
	Purchasing Managers Index	GR_PMI	S&P Global	Level
	Greek Economic Policy Uncertainty Index	GR_EPU	Economic Policy Uncertainty/Gikas Hardouvelis website	Logarithmic
	10-yr government bond yield	GR_10YR_BOND	Federal Reserve Bank of St. Louis	Logarithmic first difference
	Athens Stock Exchange General Index	GR_INDEX	WSJ Market data	Logarithmic first difference
Global	Global Economic Policy Uncertainty Index	GLOBAL_EPU	Economic Policy Uncertainty website	Logarithmic
	Euro effective exchange rate	EFF_XRATE	Federal Reserve Bank of St. Louis	Logarithmic first difference
	Geopolitical Risk Index	GPR	Matteo Iacoviello website	Level
	Global Supply Chain Pressure Index	GSCPI	Federal Reserve Bank of New York	Level
	Global Economic Activity Index	GREA	Federal Reserve Bank of Dallas	Level
Energy	Brent crude oil prices	UKBRENT	IMF Primary Commodity Prices	Logarithmic first difference
	EU Natural Gas prices	NG	World Bank Commodity Price Data (The Pink Sheet)	Logarithmic first difference
	Greek wholesale electricity prices	ELECTR	Hellenic Energy Exchange	Logarithmic first difference

Table 2: Relative RMSE across different households' size.

	HH_1	HH_2	HH_3	HH_4	HH_5	HH_6
	1-month-ahead horizon					
INFL_HH_REG_ALL	0.939	0.952	0.958	0.963	0.973	0.926
INFL_HH_REG_DOM	1.065	1.071	1.079	1.077	1.069	1.056
INFL_HH_REG_DOMGLO	0.984	0.984	0.982	0.982	0.982	0.957
INFL_HH_REG_ENER	0.946	0.958	0.961	0.973	0.979	0.978
INFL_HH_REG_GLO	0.932	0.929	0.927	0.929	0.935	0.926
INFL_HH_DMA_ALL	0.919	0.936	0.931	0.943	0.954	0.925
INFL_HH_DMA_DOM	1.016	1.026	1.022	1.034	1.016	1.005
INFL_HH_DMA_DOMGLO	0.954	0.958	0.952	0.957	0.967	0.941
INFL_HH_DMA_ENER	0.944	0.962	0.958	0.971	0.972	0.960
INFL_HH_DMA_GLO	0.921	0.926	0.922	0.919	0.936	0.931
	3-months-ahead horizon					
INFL_HH_REG_ALL	1.076	1.033	1.042	1.030	1.029	1.022
INFL_HH_REG_DOM	1.198	1.163	1.185	1.160	1.181	1.181
INFL_HH_REG_DOMGLO	1.036	1.001	1.014	1.003	1.001	1.002
INFL_HH_REG_ENER	1.006	0.981	0.981	0.963	0.987	0.975
INFL_HH_REG_GLO	0.922	0.910	0.922	0.906	0.917	0.918
INFL_HH_DMA_ALL	1.056	1.041	1.079	1.058	1.070	1.040
INFL_HH_DMA_DOM	1.205	1.212	1.228	1.212	1.203	1.169
INFL_HH_DMA_DOMGLO	1.043	1.043	1.065	1.051	1.045	1.025
INFL_HH_DMA_ENER	1.033	1.073	1.031	1.123	1.113	1.059
INFL_HH_DMA_GLO	0.935	0.980	0.959	0.939	0.948	0.936
	6-months-ahead horizon					
INFL_HH_REG_ALL	1.039	0.998	1.029	1.04	1.046	1.036
INFL_HH_REG_DOM	1.188	1.176	1.226	1.224	1.262	1.264
INFL_HH_REG_DOMGLO	1.017	0.980	1.010	1.017	1.019	1.007
INFL_HH_REG_ENER	0.924	0.930	0.958	0.964	0.985	1.013
INFL_HH_REG_GLO	0.849	0.836	0.862	0.862	0.871	0.876
INFL_HH_DMA_ALL	1.138	1.071	1.132	1.183	1.236	1.155
INFL_HH_DMA_DOM	0.969	0.976	0.994	0.979	1.008	1.004
INFL_HH_DMA_DOMGLO	1.113	1.013	1.056	1.124	1.172	1.133
INFL_HH_DMA_ENER	0.839	0.858	0.935	0.948	0.938	0.933
INFL_HH_DMA_GLO	1.169	1.167	1.191	1.178	1.275	1.233
	12-months-ahead horizon					
INFL_HH_REG_ALL	1.154	1.158	1.213	1.238	1.238	1.227
INFL_HH_REG_DOM	1.253	1.269	1.307	1.316	1.348	1.315
INFL_HH_REG_DOMGLO	1.154	1.162	1.216	1.239	1.241	1.233
INFL_HH_REG_ENER	0.984	0.986	0.989	1.000	1.003	0.977
INFL_HH_REG_GLO	0.930	0.923	0.951	0.957	0.933	0.924
INFL_HH_DMA_ALL	1.016	1.013	1.045	1.062	1.094	1.032

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INFL_HH_DMA_DOM	1.049	1.062	1.077	1.076	1.068	1.101
INFL_HH_DMA_DOMGLO	1.038	1.027	1.069	1.080	1.111	1.057
INFL_HH_DMA_ENER	1.021	1.024	1.038	1.039	1.026	1.037
INFL_HH_DMA_GLO	0.959	0.842	0.966	1.004	0.981	0.879

Note: The table reports the relative RMSE vis-à-vis the AR(1) model. REG denotes the predictive regressions and DMA denotes the Dynamic Model Averaging. DOM=domestic factors, GLO=global factors, ENER=energy factors.

Table 3: Relative RMSE across different households' composition.

	HH_ 1PERS_ UND65	HH_ 1PERS_ OVER65	HH_NO CHILD	HH_COU PL_1CHI LDUP16	HH_COU PL_2CHI LDUP16	HH_COUPL _3MORECH ILDUP16	HH_1PAR_ 1MORECH ILDUP16	HH_COUPL 1PAR_CHIL DOVER16	HH_ OTHER
	1-month-ahead horizon								
INFL_HH_REG_ALL	0.932	0.952	0.954	0.955	0.964	0.981	0.947	0.960	0.964
INFL_HH_REG_DOM	1.057	1.060	1.071	1.070	1.069	1.079	1.053	1.089	1.076
INFL_HH_REG_DOMGLO	0.968	1.004	0.986	0.983	0.984	1.000	0.987	0.982	0.975
INFL_HH_REG_ENER	0.946	0.950	0.958	0.953	0.971	0.969	0.949	0.965	0.984
INFL_HH_REG_GLO	0.928	0.939	0.930	0.936	0.938	0.944	0.953	0.920	0.925
INFL_HH_DMA_ALL	0.917	0.911	0.938	0.939	0.943	0.958	0.928	0.932	0.946
INFL_HH_DMA_DOM	1.006	1.014	1.028	1.029	1.033	1.012	0.998	1.022	1.023
INFL_HH_DMA_DOMGLO	0.948	0.955	0.961	0.966	0.964	0.979	0.954	0.946	0.952
INFL_HH_DMA_ENER	0.946	0.946	0.964	0.950	0.965	0.963	0.943	0.963	0.980
INFL_HH_DMA_GLO	0.919	0.925	0.929	0.929	0.926	0.944	0.935	0.914	0.923
	3-months-ahead horizon								
INFL_HH_REG_ALL	1.086	1.034	1.030	1.031	1.031	1.029	1.004	1.045	1.040
INFL_HH_REG_DOM	1.209	1.156	1.159	1.175	1.150	1.190	1.117	1.194	1.175
INFL_HH_REG_DOMGLO	1.051	0.993	0.999	1.007	1.002	1.008	0.981	1.018	1.005
INFL_HH_REG_ENER	0.997	1.010	0.977	0.980	0.975	0.989	0.992	0.970	0.973
INFL_HH_REG_GLO	0.939	0.896	0.909	0.927	0.919	0.942	0.917	0.911	0.901
INFL_HH_DMA_ALL	1.064	1.046	1.035	1.056	1.032	1.038	0.983	1.104	1.091
INFL_HH_DMA_DOM	1.207	1.196	1.209	1.210	1.201	1.186	1.150	1.239	1.203
INFL_HH_DMA_DOMGLO	1.060	1.015	1.038	1.060	1.041	1.047	0.994	1.076	1.080
INFL_HH_DMA_ENER	1.006	1.083	1.070	1.078	1.001	1.092	1.124	1.070	0.979
INFL_HH_DMA_GLO	0.982	0.912	0.963	0.950	0.936	0.949	0.915	0.948	0.963
	6-months-ahead horizon								
INFL_HH_REG_ALL	1.096	1.008	0.990	1.002	0.988	0.935	1.020	1.030	1.020

INFOR

INFL_HH_REG_DOM	1.187	1.085	1.110	1.138	1.112	1.132	1.097	1.173	1.139
INFL_HH_REG_DOMGLO	1.104	1.035	1.011	1.033	1.015	0.968	1.037	1.054	1.041
INFL_HH_REG_ENER	0.969	0.921	0.937	0.953	0.948	0.971	0.947	0.963	0.947
INFL_HH_REG_GLO	0.998	0.950	0.946	0.960	0.941	0.953	0.952	0.958	0.938
INFL_HH_DMA_ALL	1.088	1.104	1.043	1.017	1.061	1.036	0.984	1.152	1.125
INFL_HH_DMA_DOM	0.976	0.992	0.992	0.959	0.926	0.969	0.954	1.000	0.963
INFL_HH_DMA_DOMGLO	1.099	1.112	1.017	1.016	1.027	1.012	0.993	1.176	1.134
INFL_HH_DMA_ENER	0.962	0.854	0.943	0.995	0.936	0.983	0.888	1.011	0.955
INFL_HH_DMA_GLO	1.205	1.145	1.183	1.136	1.157	1.162	1.109	1.221	1.178
	12-months-ahead horizon								
INFL_HH_REG_ALL	1.208	1.064	1.150	1.216	1.213	1.186	1.189	1.250	1.200
INFL_HH_REG_DOM	1.278	1.198	1.264	1.285	1.275	1.303	1.219	1.355	1.304
INFL_HH_REG_DOMGLO	1.207	1.064	1.154	1.218	1.214	1.192	1.190	1.253	1.204
INFL_HH_REG_ENER	0.986	0.972	0.985	0.993	1.002	0.979	1.018	0.992	0.991
INFL_HH_REG_GLO	0.965	0.890	0.921	0.971	0.962	0.925	0.965	0.946	0.926
INFL_HH_DMA_ALL	1.024	1.041	1.012	1.013	1.024	1.013	1.003	1.045	1.073
INFL_HH_DMA_DOM	1.068	1.077	1.060	1.077	1.083	1.074	1.006	1.071	1.069
INFL_HH_DMA_DOMGLO	1.051	1.056	1.030	1.035	1.039	1.036	1.036	1.091	1.097
INFL_HH_DMA_ENER	1.033	1.007	1.023	1.048	1.044	1.034	1.057	1.034	1.024
INFL_HH_DMA_GLO	0.970	1.006	0.834	0.941	0.855	0.970	0.990	1.013	0.896

Note: The table reports the relative RMSE vis-à-vis the AR(1) model. REG denotes the predictive regressions and DMA denotes the Dynamic Model Averaging. DOM=domestic factors, GLO=global factors, ENER=energy factors.

Table 4: Relative RMSE across different households' economic condition.

	HH_ACT_ EXC_WIF_ HUS	HH_ACT_ WIF_HU	HH_ ALL_ACT	HH_ RET	HH_ OTH_ACT
	1-month-ahead horizon				
INFL_HH_REG_ALL	0.944	0.953	0.96	0.938	0.968
INFL_HH_REG_DOM	1.071	1.074	1.085	1.058	1.083
INFL_HH_REG_DOMGLO	0.982	0.982	0.975	0.971	0.983
INFL_HH_REG_ENER	0.954	0.957	0.973	0.951	0.973
INFL_HH_REG_GLO	0.928	0.929	0.920	0.924	0.927
INFL_HH_DMA_ALL	0.924	0.927	0.934	0.923	0.947
INFL_HH_DMA_DOM	1.019	1.022	1.021	1.027	1.023
INFL_HH_DMA_DOMGLO	0.951	0.955	0.945	0.949	0.962
INFL_HH_DMA_ENER	0.953	0.952	0.971	0.943	0.975
INFL_HH_DMA_GLO	0.919	0.924	0.915	0.913	0.927
	3-months-ahead horizon				
INFL_HH_REG_ALL	1.073	1.037	1.054	1.042	1.047
INFL_HH_REG_DOM	1.191	1.167	1.199	1.184	1.183
INFL_HH_REG_DOMGLO	1.033	1.007	1.025	1.009	1.013
INFL_HH_REG_ENER	0.998	0.981	0.969	0.998	0.997
INFL_HH_REG_GLO	0.918	0.923	0.910	0.917	0.925
INFL_HH_DMA_ALL	1.066	1.042	1.115	1.088	1.079
INFL_HH_DMA_DOM	1.223	1.217	1.24	1.187	1.197
INFL_HH_DMA_DOMGLO	1.044	1.040	1.085	1.079	1.075
INFL_HH_DMA_ENER	1.028	0.977	1.022	1.071	0.978
INFL_HH_DMA_GLO	0.932	0.945	1.007	0.992	1.008
	6-months-ahead horizon				
INFL_HH_REG_ALL	1.042	1.006	1.073	0.99	1.026
INFL_HH_REG_DOM	1.197	1.191	1.279	1.156	1.198
INFL_HH_REG_DOMGLO	1.020	0.989	1.049	0.972	1.002
INFL_HH_REG_ENER	0.929	0.944	0.978	0.926	0.944
INFL_HH_REG_GLO	0.839	0.849	0.867	0.859	0.863
INFL_HH_DMA_ALL	1.146	1.048	1.268	1.003	1.101
INFL_HH_DMA_DOM	0.955	0.977	1.004	1.041	0.997
INFL_HH_DMA_DOMGLO	1.136	0.974	1.262	0.981	0.994
INFL_HH_DMA_ENER	0.803	0.913	0.950	0.873	0.875
INFL_HH_DMA_GLO	1.169	1.140	1.292	1.149	1.183
	12-months-ahead horizon				
INFL_HH_REG_ALL	1.186	1.185	1.264	1.123	1.183
INFL_HH_REG_DOM	1.284	1.277	1.369	1.211	1.266
INFL_HH_REG_DOMGLO	1.186	1.188	1.267	1.126	1.184
INFL_HH_REG_ENER	0.988	0.990	0.996	0.972	0.979

INFOR

INFL_HH_REG_GLO	0.924	0.941	0.950	0.955	0.938
INFL_HH_DMA_ALL	1.049	1.024	1.054	1.002	0.997
INFL_HH_DMA_DOM	1.055	1.067	1.075	1.059	1.066
INFL_HH_DMA_DOMGLO	1.062	1.046	1.105	1.03	1.018
INFL_HH_DMA_ENER	1.024	1.035	1.034	1.025	1.028
INFL_HH_DMA_GLO	0.851	0.844	1.036	0.943	0.981

Note: The table reports the relative RMSE vis-à-vis the AR(1) model. REG denotes the predictive regressions and DMA denotes the Dynamic Model Averaging. DOM=domestic factors, GLO=global factors, ENER=energy factors.

Table 5: Relative RMSE across households' geographical location

	HH_RUR	HH_URB
	1-month-ahead horizon	
INFL_HH_REG_ALL	0.961	0.951
INFL_HH_REG_DOM	1.080	1.076
INFL_HH_REG_DOMGLO	0.986	0.980
INFL_HH_REG_ENER	0.971	0.958
INFL_HH_REG_GLO	0.928	0.924
INFL_HH_DMA_ALL	0.939	0.926
INFL_HH_DMA_DOM	1.024	1.021
INFL_HH_DMA_DOMGLO	0.958	0.951
INFL_HH_DMA_ENER	0.967	0.954
INFL_HH_DMA_GLO	0.928	0.917
	3-months-ahead horizon	
INFL_HH_REG_ALL	1.036	1.048
INFL_HH_REG_DOM	1.171	1.180
INFL_HH_REG_DOMGLO	1.005	1.016
INFL_HH_REG_ENER	0.974	0.980
INFL_HH_REG_GLO	0.906	0.915
INFL_HH_DMA_ALL	1.078	1.070
INFL_HH_DMA_DOM	1.213	1.221
INFL_HH_DMA_DOMGLO	1.060	1.052
INFL_HH_DMA_ENER	0.973	1.033
INFL_HH_DMA_GLO	0.958	0.952
	6-months-ahead horizon	
INFL_HH_REG_ALL	1.017	1.026
INFL_HH_REG_DOM	1.202	1.211
INFL_HH_REG_DOMGLO	0.994	1.006
INFL_HH_REG_ENER	0.949	0.948
INFL_HH_REG_GLO	0.844	0.852
INFL_HH_DMA_ALL	1.177	1.127
INFL_HH_DMA_DOM	0.997	0.976
INFL_HH_DMA_DOMGLO	1.120	1.074
INFL_HH_DMA_ENER	0.897	0.906
INFL_HH_DMA_GLO	1.243	1.167
	12-months-ahead horizon	
INFL_HH_REG_ALL	1.185	1.201
INFL_HH_REG_DOM	1.294	1.296
INFL_HH_REG_DOMGLO	1.190	1.203
INFL_HH_REG_ENER	0.986	0.991

INFL_HH_REG_GLO	0.925	0.941
INFL_HH_DMA_ALL	1.065	1.042
INFL_HH_DMA_DOM	1.063	1.070
INFL_HH_DMA_DOMGLO	1.087	1.067
INFL_HH_DMA_ENER	1.024	1.032
INFL_HH_DMA_GLO	0.838	0.908

Note: The table reports the relative RMSE vis-à-vis the AR(1) model. REG denotes the predictive regressions and DMA denotes the Dynamic Model Averaging. DOM=domestic factors, GLO=global factors, ENER=energy factors.

Table 6: Relative RMSE across households' income groups

	HH_ UP750	HH_ 751_1100	HH_ 1101_1450	HH_ 1451_1800	HH_ 1801_2200	HH_ 2201_2800	HH_ 2801_3500	HH_ OVER3501
	1-month-ahead horizon							
INFL_HH_REG_ALL	0.940	0.945	0.952	0.948	0.957	0.960	0.962	0.960
INFL_HH_REG_DOM	1.055	1.058	1.070	1.070	1.082	1.073	1.076	1.076
INFL_HH_REG_DOMGLO	0.996	0.998	0.993	0.979	0.987	0.978	0.970	0.968
INFL_HH_REG_ENER	0.944	0.944	0.951	0.963	0.960	0.968	0.980	0.972
INFL_HH_REG_GLO	0.946	0.945	0.939	0.926	0.925	0.928	0.911	0.926
INFL_HH_DMA_ALL	0.923	0.926	0.940	0.930	0.924	0.940	0.939	0.941
INFL_HH_DMA_DOM	1.017	1.014	1.020	1.015	1.017	1.021	1.028	1.037
INFL_HH_DMA_DOMGLO	0.968	0.961	0.965	0.945	0.952	0.958	0.942	0.958
INFL_HH_DMA_ENER	0.946	0.952	0.965	0.963	0.957	0.966	0.970	0.964
INFL_HH_DMA_GLO	0.943	0.933	0.937	0.919	0.918	0.931	0.902	0.914
INFL_HH_Q50_B_ALL	0.899	0.927	0.953	1.013	1.013	1.056	1.035	1.002
INFL_HH_Q50_B_DOM	0.980	0.997	1.007	1.004	1.074	1.069	1.109	1.079
INFL_HH_Q50_B_DOMGLO	0.953	0.957	1.018	1.018	1.072	1.035	1.053	1.099
INFL_HH_Q50_B_ENER	0.958	0.984	0.980	0.997	0.998	1.019	1.010	0.959
INFL_HH_Q50_B_GLO	0.913	0.932	0.980	0.929	1.010	0.953	0.946	1.008
	3-months-ahead horizon							
INFL_HH_REG_ALL	1.037	1.038	1.035	1.031	1.044	1.037	1.019	1.049
INFL_HH_REG_DOM	1.165	1.164	1.169	1.160	1.177	1.176	1.161	1.205
INFL_HH_REG_DOMGLO	1.003	1.007	1.006	1.002	1.015	1.010	0.993	1.023
INFL_HH_REG_ENER	1.020	0.999	0.986	0.973	0.974	0.975	0.978	0.973
INFL_HH_REG_GLO	0.916	0.910	0.912	0.900	0.909	0.925	0.912	0.945
INFL_HH_DMA_ALL	1.049	1.057	1.055	1.044	1.063	1.076	1.114	1.119
INFL_HH_DMA_DOM	1.169	1.206	1.195	1.212	1.221	1.234	1.213	1.233
INFL_HH_DMA_DOMGLO	1.045	1.057	1.051	1.029	1.061	1.059	1.075	1.107
INFL_HH_DMA_ENER	0.977	1.072	1.047	0.999	1.103	0.975	1.142	0.987

INFOR								
INFL_HH_DMA_GLO	0.985	0.951	0.949	0.940	0.938	0.936	0.979	0.998
INFL_HH_Q50_B_ALL	1.025	1.034	0.998	1.010	1.025	1.098	1.080	1.110
INFL_HH_Q50_B_DOM	1.051	1.155	1.286	1.231	1.294	1.231	1.244	1.241
INFL_HH_Q50_B_DOMGLO	0.960	0.964	0.939	0.954	1.016	1.021	1.033	1.072
INFL_HH_Q50_B_ENER	0.963	0.956	0.963	0.985	0.983	1.015	1.025	1.088
INFL_HH_Q50_B_GLO	0.873	0.831	0.899	0.809	0.828	0.882	1.061	0.958
	6-months-ahead horizon							
INFL_HH_REG_ALL	0.967	0.995	1.003	1.013	1.030	1.030	1.019	1.065
INFL_HH_REG_DOM	1.091	1.126	1.168	1.183	1.207	1.232	1.228	1.309
INFL_HH_REG_DOMGLO	0.953	0.980	0.987	0.993	1.010	1.009	0.997	1.038
INFL_HH_REG_ENER	0.876	0.896	0.923	0.939	0.947	0.966	0.973	1.003
INFL_HH_REG_GLO	0.827	0.833	0.838	0.845	0.859	0.864	0.848	0.905
INFL_HH_DMA_ALL	1.007	1.007	1.019	1.150	1.099	1.087	1.005	1.258
INFL_HH_DMA_DOM	0.934	0.963	0.979	0.987	0.992	1.006	1.007	1.039
INFL_HH_DMA_DOMGLO	0.953	0.968	0.986	1.106	1.027	1.014	0.946	1.148
INFL_HH_DMA_ENER	0.819	0.888	0.912	0.903	0.933	0.932	0.948	0.980
INFL_HH_DMA_GLO	1.066	1.097	1.152	1.185	1.184	1.230	1.153	1.299
INFL_HH_Q50_B_ALL	0.932	0.954	1.019	0.991	1.000	1.076	1.025	1.072
INFL_HH_Q50_B_DOM	1.007	1.117	1.169	1.142	1.178	1.175	1.221	1.260
INFL_HH_Q50_B_DOMGLO	0.904	0.995	1.000	0.999	0.995	1.046	1.014	1.066
INFL_HH_Q50_B_ENER	0.889	0.920	0.952	0.972	0.969	0.987	1.006	1.002
INFL_HH_Q50_B_GLO	0.745	0.856	0.903	0.871	0.847	0.911	0.855	0.951
	12-months-ahead horizon							
INFL_HH_REG_ALL	1.088	1.122	1.165	1.178	1.195	1.219	1.229	1.264
INFL_HH_REG_DOM	1.173	1.217	1.263	1.275	1.284	1.323	1.326	1.376
INFL_HH_REG_DOMGLO	1.091	1.126	1.171	1.182	1.198	1.222	1.229	1.265
INFL_HH_REG_ENER	0.971	0.980	0.985	0.988	0.992	0.991	0.990	0.991
INFL_HH_REG_GLO	0.938	0.930	0.927	0.934	0.952	0.938	0.934	0.956
INFL_HH_DMA_ALL	0.999	1.032	1.025	1.050	1.037	1.046	0.994	0.994

INFOR

INFL_HH_DMA_DOM	1.068	1.072	1.060	1.062	1.070	1.060	1.080	1.086
INFL_HH_DMA_DOMGLO	1.029	1.057	1.046	1.067	1.061	1.066	1.048	1.024
INFL_HH_DMA_ENER	1.024	1.026	1.028	1.028	1.032	1.030	1.037	1.042
INFL_HH_DMA_GLO	1.083	1.049	0.908	0.886	0.910	0.827	1.056	1.050
INFL_HH_Q50_B_ALL	0.956	0.996	1.067	1.054	1.119	1.126	1.140	1.208
INFL_HH_Q50_B_DOM	1.119	1.195	1.301	1.300	1.305	1.358	1.367	1.414
INFL_HH_Q50_B_DOMGLO	0.940	0.980	1.045	1.034	1.102	1.100	1.130	1.211
INFL_HH_Q50_B_ENER	1.013	1.020	0.987	1.008	1.024	1.006	1.000	1.030
INFL_HH_Q50_B_GLO	0.838	0.842	0.898	0.916	0.931	0.954	0.968	1.046

Note: The table reports the relative RMSE vis-à-vis the AR(1) model. REG denotes the predictive regressions, DMA denotes the Dynamic Model Averaging and Q50 denotes the median quantile from the quantile predictive regressions. DOM=domestic factors, GLO=global factors, ENER=energy factors.