



How Heterogeneous Are the Inflation Expectations?

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Abstract

This paper investigates the heterogeneity of inflation expectations among households, firms, and professionals across 14 economies. Using Bayesian model averaging and panel data regressions, we identify key determinants of inflation expectations, assess their stability over time, and evaluate their persistence. Our findings reveal that households and firms rely heavily on past expectations and year-on-year changes in economic variables, whereas professionals are more responsive to monetary policy indicators. The inflation news index emerges as a crucial determinant, especially during high-inflation periods, highlighting the role of media in expectation formation. We find that inflation expectations became more backward-looking during the inflationary period 2022. Additionally, while CPI inflation significantly influences firms and professionals, exchange rates and oil prices appear insignificant.

Keywords

Inflation Expectations, Bayesian Model Averaging (BMA), Panel Data Analysis, Expectations Heterogeneity, Determinants of Inflation Expectations

I. Introduction

Expectations are integral to economic subjects' decision-making process and are among the most important factors influencing economic dynamics. Their importance is particularly evident in periods of high inflation, such as the 1970s, 1980s, and the period from 2021 onwards. However, their nature is still not fully understood, even though they have been researched for several decades. Many researchers have shown that inflation expectations have several features, such as a systematic upward bias and dependence on personal experiences, and are heterogeneous on individual and group levels of economic agents. The recent literature aimed at various determinants and stylised facts of household inflation expectations has been reviewed by D'Acunto et al. (2023) or Candia et al. (2023). Both studies highlight the importance of understanding the fundamentals of inflation beliefs

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for policymakers to adjust their policy and better anchor inflation expectations. Several authors focused on finding what information agents use to form their expectations, whether it was done by using macroeconomic indicators (Ueda, 2010; Beckmann et al., 2022) or microeconomic data (Coibion et al., 2018; Fritzer and Rumler, 2015); however, there is limited research focusing on heterogeneity between different agents' determinants at the international level in various periods and the types of information they might use. This raises the question of whether we can similarly approximate determinants for each economic agent across multiple countries.

Evaluating the heterogeneity of inflation expectations among agents and across countries is also highly relevant for formulating models with heterogeneous expectations. Our paper aims to identify heterogeneity in expectations among households, firms, and professionals, evaluate the primary sources of heterogeneity and underlying determinants of their stability over time, and quantify the level of persistence of inflation expectations. Our paper aims to answer the following questions: Do the determinants of inflation expectations differ across households, firms and professionals? What are the most important factors affecting inflation expectations? How stable are the determinants of inflation expectations over time? How persistent are inflation expectations? To answer these questions, we estimate and evaluate a large set of model specifications for individual countries and agents by employing various variable selection methods. Our robust approach contributes to the existing literature by performing a broader analysis concerning the number of countries and subjects under investigation. Given the many countries analysed, the variables used will be those common to these countries and as similar as possible to those from studies focusing on individual economies. Our analysis also examines the stability of the factors influencing inflation expectations, especially by comparing changes during the high inflation period of 2022. The structure of this paper is outlined as follows. In the second section, we provide a literature review that examines existing methods and approaches for investigating the determinants of inflation expectations. The third section presents the data and methods used to identify inflation expectations' main drivers and evaluate their heterogeneity across three types of agents and investigated countries. The fourth section presents the model estimates and the resulting findings, including a robustness check. Finally, the concluding section summarises the key conclusions drawn from our analysis.

II. Literature Review

Many approaches to studying the role of inflation expectations and their determinants have emerged in the literature. We begin by focusing on studies examining the determinants of inflation expectations among households and firms. We then turn our attention to professional forecasters and briefly address the issue of expectation heterogeneity and its implications for expectation formation models.

Inflation expectations of households and firms

Ueda (2010) employed the Structural Vector Autoregression (SVAR) model to study determinants of quantified inflation expectations of households in the USA and Japan. The main focus was to compare their properties and influence on the economy between 1971

and 2007, thus capturing the high inflation period of the 1970s. Ueda (2010) used the Carlson-Parkin method to quantify inflation expectations and the Hodrick-Prescott filter to estimate the output gap as a key explanatory variable. Other explanatory variables included the short-term nominal interest rate, a core inflation index, changes in food prices, and changes in oil prices. He showed that inflation expectations adjust faster than realised inflation to changes in food and energy prices and monetary policy shocks. In addition, changes in food and energy prices seem more persistent in the USA than in Japan, and the self-fulfilling property of inflation expectations is also more substantial in the USA, which he attributed to a quicker decline in inflation in Japan during the 1980s. Several studies have gone in another direction and studied the determinants using microeconomic data. Moving from macro to micro approaches, Fritzer (2015) conducted an experiment surveying Austrian inflation expectations and perceptions based on their economic and social status. They focused on information about respondents such as age, gender, income, education, financial literacy, and inflation scepticism. Using linear regressions, they showed that people with a disadvantaged socioeconomic background perceive a higher inflation rate and that older people, less educated, and women have significantly higher short-run and long-run inflation expectations. By contrast, people more literate in economic matters and less sceptical of inflation rate measurement tend to have lower and more realistic inflation expectations. Messner and Rumler (2023) expanded the scope by examining expectations among both households and firms. They focused not only on the socioeconomic background of households and their impact on their expectations, but also on the firms and their expectations based on their size and the sector they operate in. Their analysis also shows that smaller firms are pretty similar to households in that they also anticipate higher inflation rates. Larger firms tend to forecast lower inflation rates, which authors explain as a possibility of larger firms having representatives with a better education than smaller firms. Thus, respondents in smaller firms may be less likely to follow economic news closely. According to their study, households exhibit greater rational attention during periods of high inflation. We therefore focus on the high-inflation episode that began in late 2022, as examined in our paper.

D'Acunto et al. (2023) provided a broad literature review on survey experiments studying inflation expectations among households and firms. They highlighted that expectation heterogeneity often arises from differing exposures to price signals. Weber et al. (2022) found that prices of everyday goods like milk, bread, and oil serve as strong inflation signals in the USA. D'Acunto et al. (2023) also emphasised the role of experience and media: while professionals are more hawkish due to occupational exposure, households often rely on less comprehensible media coverage, reducing the effectiveness of monetary policy communication. Candia et al. (2023) focused on inflation expectations among firms, arguing that while firms' expectations share features with both professionals and households, they remain distinct. Firms form expectations based on recent experiences and their views of long-run "natural" levels, which can deviate significantly from reality. Moreover, firms often misunderstand long-term policy objectives, such as central bank inflation targets.

Inflation expectations of professionals

Beckmann et al. (2022) focused on inflation expectations of professionals from G7 and selected Eurozone countries using the Bayesian VAR (BVAR) model. They studied the determinants of those expectations and international spillover effects of the US monetary policy under the hypothesis that there are monetary policy spillover effects between the Eurozone and the US that were suggested by Netšunajev (2014). The analysis included a policy uncertainty index created using the newspaper text-searching methods as a proxy for policy-related movements in economic uncertainty. They found that domestic inflation updates are significantly affected by changing expectations about US inflation and that the importance of these spillover effects increased in recent times, probably due to quantitative easing. Moessner (2022) studied the determinants of professionals' inflation expectations in Euro-area countries through a fixed effects panel regression model. He considered food and energy prices, commodity and oil prices, core inflation, the output gap, and the effects on exchange rates and global freight prices. The data sample spanned from 2000Q1 to 2021Q1, capturing information and dynamics that can be attributed to the coronavirus crisis. He found a significant effect of inflation in food prices on survey-based inflation expectations, greater than the effect of energy CPI inflation and inflation in the oil prices and global commodity prices. In addition, inflation expectations were persistent even though they were of professionals considered the most rational economic agents. Cerisola and Gelos (2009) studied the fundamentals of inflation expectations of surveyed professionals to assess the impact of establishing inflation targeting in Brazil and its ongoing effectiveness through a Vector Error Correction (VEC) model. They showed that the inflation target and fiscal policy were important in shaping inflation expectations. In addition, the credibility of monetary policy and its inflation-targeting framework affected the degree to which inflation expectations were backward-looking. Using an autoregressive distributed lag model, Bulut (2018) focused on the determinants of professionals' 12-month and 24-month ahead inflation expectations in Turkey. He concluded that the longer the anticipated period, the less statistically significant the determinants are. However, for both 12-month and 24-month expectations, the past inflation rate and the exchange rate are important factors.

Heterogeneity in inflation expectations

Heterogeneity in expectations has been studied from different points of view, other than from the view of its fundamentals. Mankiw et al. (2003) introduced the sticky information model as a more realistic alternative to rational expectations, showing significant disagreement between households and professionals in the US. Weber (2007) carried out a similar analysis of households and professionals from five core European economies. Using different adaptive learning models, he shows that professionals update their expectations more frequently than households, and there exists a heterogeneity between the selected European economies and between both agents in each economy. Countries with higher inflation rates update more often, which aligns with Sims' rational inattention hypothesis. He uses a sticky information theory to explain the slower rate of household updates. Łyziak (2013) also focused on understanding the properties of and hypotheses about inflation expectations using survey-based expectations of households, firms, and

professionals from Poland. He focused on the degree of their forward-lookingness (especially by fulfilling the rational expectations hypothesis) and the degree to which they are anchored (i.e., their consistency with the inflation target and insensitivity to current inflation dynamics). Łyziak (2013) also investigated the role of inflation expectations in affecting actual price dynamics in the economy. He showed that consumers are distinct in terms of the efficiency of processing information, while firms and professionals are similar. However, he points out that the survey of firms over-represents large firms. He highlights that no agent in Poland has rational expectations. Households are consistent with near-rationality models, and their expectations become closer to those of professionals when the media coverage of inflation increases, thus becoming more forward-looking and making smaller errors. Another similar study was done by Pfajfar and Santoro (2010), who tested the cross-section heterogeneity of American households' inflation expectations and tested a huge set of models to understand which fits the best. Their results show that households can be divided into three groups based on the approximate model they use. An adaptive learning and sticky information model best fits the first group. In contrast, the second group might use a static or autoregressive model, and the third group, the smallest, could be nearly rational. Lastly, Hommes (2011) performed a laboratory experiment to test theories of expectations and learning in which subjects learned to forecast a market price. The market price is then determined as an aggregation of individual expectations. His results show that no homogeneous expectations model fits the experimental data across various simulated market settings. It suggests that heterogeneity is a crucial aspect of a theory of expectations and that only a heterogeneous model can explain the path dependence recorded in the experiment. These last few studies have shown that previous expectations matter since agents do not update their forecasts, which is either costly or impossible. It is also conditioned by media inflation coverage, although, as Weber et al. (2022) note, people seem to deem them untrustworthy if they do not understand the message. Thus, the media's influence might be a determinant of inflation expectations.

III. Data and Methodology

In this section, we present the data, techniques, and methods we employed to estimate the determinants of inflation expectations for different economic agents across multiple countries. Our goal is to identify the sources of heterogeneity in economic agents' expectations and how they differ from each other not only on the country level but across multiple countries. This way, we can track whether there are patterns in agents' expectational models or whether they tend to be unique depending on the local environment. In addition, we focus on their stability in time to investigate whether there are determinants that tend to be prevalent over time or whether agents might base their expectations on different sets of information in time. We thus estimate linear regression models for each agent and country and perform a regression analysis based on their results.

This paper aims to identify the degree of heterogeneity in determinants of inflation expectations of households, firms, and professionals (professional forecasters or economists) across selected economies. To achieve this goal, we constructed a huge set of regression models with inflation expectations as dependent variables and alternative specifications of explanatory variables representing possible determinants of these expectations. We have estimated the models using data from 14 economies for all three economic agents mentioned above. We have also employed the Bayesian model averaging approach to find the most important determinants and evaluate their heterogeneity. In addition, a robustness check was performed by applying recursive estimates. This approach allowed us to assess the importance of corresponding variables used in regression models and the form of transformation in which they enter the models. Data availability conditioned our choice to focus on a sample of 14 economies. Inflation expectations based on qualitative survey data have been quantified by applying the often-used Carlson-Parkin methodology (Carlson and Parkin, 1975) adjusted for five-question surveys by Batchelor and Orr (1988).

Data

Our analysis relies on publicly available data regarding inflation expectations, collected through surveys conducted by public institutions and private companies. The availability and quality of the published expectation data limited the selection of countries. One of the main criteria we adhered to while choosing a country for our analysis was whether there were publicly available data for all three economic agents. The only exceptions to this rule were South Korea and the United Kingdom, which we decided to include to have a broader data set even though they lack publicly available data for firms³. Since most countries have recently gathered surveys about public views on future inflation, all our time series have set a common starting point in the first quarter of 2015 and end in the first quarter of 2023. The list of all series and their sources is in Appendix A, Table A1. In all tables, we use shortcuts or country codes instead of the full names of countries (see Appendix A, Table A2).

Quantification of expectation data

Several series are qualitative and for the analysis were quantified by using the Carlson-Parkin probability method (Carlson and Parkin, 1975), which has become a pretty popular way to use survey data and was modified by a few authors, e.g. Batchelor and Orr (1988), Berk (1999) and Łyziak (2010). However, all the quantified series come from the Business and Consumer survey by the Directorate General for Economic and Financial Affairs of the European Commission, the series for household and firms' expectations, and the National Bank of Poland Quick Monitoring Survey for firms. We followed the approach of the latter two authors. We used either normal or non-central t-distribution. We have also experimented with other distributions, but the dynamics of the series remained pretty much the same, which also is in line with Berk (2002) and Łyziak (2010).

³ In the case of the UK, there are two sources of expectation data for firms. The first is the Business and consumer surveys conducted by the Directorate General for Economic and Financial Affairs of the European Commission, which is qualitative and spans from 1993 to 2019. The second is the Bank of England's Decision Maker Panel survey, which is quantified and is available from the end of 2016 forward. We found the second series too short for our analysis.

The method is built upon answers to two questions about inflation perception and expectations. To describe the method, we will use the responses of consumers. Firstly, respondents are asked, “How do you think that consumer prices have developed over the last 12 months?” and their responses are divided into six response categories (“Risen a lot”, “Risen moderately”, “Risen slightly”, “Stayed about the same”, “Fallen”, “Do not know”). Then there is a follow-up question: “By comparison with the past 12 months, how do you expect consumer prices to develop in the next 12 months?”. The answers to this question are once again divided into six categories (“Increase more rapidly”, “Increase at the same rate”, “Increase at a slower rate”, “Stay about the same”, “Fall”, “Do not know”). Unlike the original Carlson-Parkin method, which imposed an assumption of unbiased expectations, the wording of these questions requires modifications of Batchelor and Orr (1988) that drop the assumption. Since the method uses inflation perception instead of actual inflation, the expectations are usually described as subjectified. Otherwise, expectations quantified on answers in which respondents were told or knew the actual inflation rate are called objectified. The list of quantified subjectified and objectified inflation expectations is in Appendix A, Table A3.

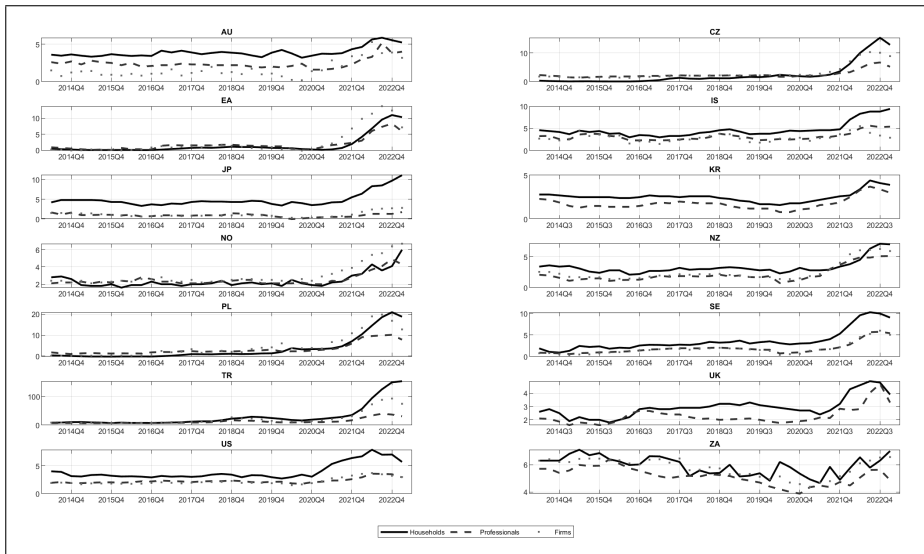
The procedure we used closely follows Łyziak (2010), which approaches the answers regarding sensitivity intervals. For example, it is assumed that respondents reporting expectations of price stability will be assigned an interval centred around zero, $(-l^e, l^e)$. Although the respondent might have expectations about future inflation equal to zero, other individuals will expect inflation close to zero. The same is considered for answers. Likewise, the answers about expected inflation rate, π^e , not deviating from the perceived inflation rate π^p (“Prices will increase at the same rate”) fall into a sensitivity interval $\pi^p - s^e, \pi^p + s^e$. Thus, all answers can be viewed as probabilities of future inflation being in certain intervals of a probability distribution underlying inflation expectations. The same logic applies to inflation perceptions. The answers are denoted as probabilities $(a_1^e, a_2^e, a_3^e, b^e, c^e, d^e)$ and then transformed to account for respondents who answered: “Don’t know”. The transformation is following: $A_1^e = \frac{a_1^e}{1-d^e}, A_2^e = \frac{a_2^e}{1-d^e}, A_3^e = \frac{a_3^e}{1-d^e}, B^e = \frac{b^e}{1-d^e}, C^e = \frac{c^e}{1-d^e}$.

The mean μ_t^e , standard deviation σ_t^e and the sensitivity intervals around zero l_t^e and around perceived inflation s_t^e are then calculated the following way:

$$\begin{aligned}\mu_t^e &= \frac{\pi_t^p \cdot (G_t^e + H_t^e)}{G_t^e + H_t^e - (E_t^e + F_t^e)} \\ \sigma_t^e &= \frac{-2 \cdot \pi_t^p}{G_t^e + H_t^e - (E_t^e + F_t^e)} \\ s_t^e &= \frac{\pi_t^p \cdot (F_t^e - E_t^e)}{G_t^e + H_t^e - (E_t^e + F_t^e)} \\ l_t^e &= \frac{\pi_t^p \cdot (H_t^e - G_t^e)}{G_t^e + H_t^e - (E_t^e + F_t^e)}\end{aligned}\tag{1}$$

where $E_t^e = Nz^{-1}(1 - A_{1t}^e)$, $F_t^e = Nz^{-1}(1 - A_{1t}^e - A_{2t}^e)$, $G_t^e = Nz^{-1}(1 - A_{1t}^e - A_{2t}^e - A_{3t}^e)$, $H_t^e = Nz^{-1}(C_t^e)$, and Nz^{-1} denotes the cumulative distribution function underlying the probabilities. The perceived inflation rate π_t^p is calculated the same way using survey questions on inflation perception and the probabilities are instead compared with a natural rate of inflation π^* which is in our case a 12-month average of inflation rate up to the moment when the questionnaire was taken place. The exception to this is the inflation expectations of firms for the Euro Area and Poland that have been objectified. The resulting time series of inflation expectations are depicted in Figure 1.

Figure 1: Time series of inflation expectations



Source: Own calculations

Explanatory variables

We divide used regressors into three categories that share economic class and methods transformations. Firstly, there is a Business Cycle Indicator (BCI) group consisting of macroeconomic variables, including GDP, unemployment (UNE), interest (INT), and exchange rates (EXR)⁴. This group enters regressions in either a gap form, a yearly percentage change, or a quarterly percentage change. Next, a Price Index (PI) group contains different consumer price indices. In this group, we include CPI, which consists of all items and the core inflation CPI index (CPLC; all items excluding prices of food and energy). We also follow the findings of Weber et al. (2022) and include the consumer price index of all food items (CPLF) and the consumer price index of all dairy products (CPLM). All these series enter regressions as a year-on-year inflation rate, a difference of a year-on-year inflation rate, a quarter-on-quarter inflation rate, a 12-month average of the

⁴ All exchange rates are domestic currency/USD. For the US, it is USD/EUR.

year-on-year inflation rate, and a 6-month average of the year-on-year inflation rate. Lastly, the Other Index (OI) group consists of a relevant local stock price index (SPI)⁵, the price of Brent crude oil (OIL), and a Google Trend index (INN) tracking the frequency of internet searches on the topic of inflation. The Google Trend index serves as a proxy for the general public's interest and media for the topic. It follows the ideas and findings in the inflation expectation literature suggesting that media play a significant role in forming expectations by the general public (Weber et al., 2022; Picault et al., 2022; Łyziak et al., 2013). These variables were transformed into yearly and quarterly percentage changes, except for the Google Trend index, which is in absolute yearly and quarterly changes. Sources of all explanatory variables are available in Appendix A, Table A4.

The classical approach

Firstly, we estimated 84 different model specifications to find determinants of inflation expectations (as dependent variables), using the linear regression and ordinary least squares method for all countries and agents. Model specifications differ in four ways: they either include the variables GDP or unemployment rate; they contain either CPI for all items, CPI for core inflation and CPI for food prices, or CPI for core inflation and CPI for dairy prices; they do or do not lags of GDP, Unemployment rate and price indices are present (some models have only lagged terms of these variables and their non-lagged variants are missing); and whether they include lagged expectations. The term for lagged expectations represents agents' (in)ability to update their expectations, which aligns with the literature on sticky information (Mankiw and Reis, 2002).

All model specifications were estimated based on various combinations of transformations applied to data. In total, we got 100800 estimated models from 2015Q1 to 2023Q1. We obtained this way not only the descriptive statistics about coefficients and their significance but also adjusted coefficients of determination (R^2), which we use in further regressions to find which variables and which transformations lead to better fitting models for various countries and agents. We also estimated all models recursively using an expanding window that gradually expands from 2020Q1 to 2023Q1. Recursive estimations serve two purposes. Firstly, they allow us to analyse whether determinants are stable in time by adding observations from the periods influenced by the coronavirus crisis and the Russian invasion of Ukraine, resulting in a high inflation period. Secondly, by recursively forecasting expectations, we gain two other metrics to measure the quality of a model. The metrics are mean squared prediction error (MSPE) and mean absolute prediction error (MAPE).

⁵ It is a stock price index of the country with the highest level of market capitalisation.

Table 1: Description of variables transformations

Variable group	Shortcut	Description
BCI (Business Cycle Indicators)	gap	cyclical term estimated by the Hodrick-Prescott filter
	q	quarter-on-quarter growth rate
	y	year-on-year growth rate
PI (Price Index group)	lvl	year-on-year inflation rate
	dif	quarter-on-quarter differences of year-on-year inflation rate
	q	quarter-on-quarter inflation rate
	a12	12-month average of y-o-y inflation rates
	a6	6-month average of y-o-y inflation rates
OI (Other Indicators)	q	quarter-on-quarter growth rate
	y	year-on-year growth rate

Source: Own calculations

Note: In the case of the INN variable (the Google Trend index), the q-o-q and y-o-y changes are used.

Regressions using model statistics were estimated to find which variables and transformations improve the performance of a model (increase R² or decrease MSPE and MAPE). The general model formula for these regressions thus contains dummy variables that indicate whether a variable is present in the original regressions (regardless of its transformation) and dummy variables that represent the transformation for each group of variables. The baseline setting contains GDP, no lags in explanatory variables or expectations, and CPI for all items, while BCI variables are in gap form, PI variables are the year-on-year level of inflation, and OI variables use quarterly (relative) changes.

$$\begin{aligned}
 STAT = & \alpha_0 + \alpha_1 D_{EXP_{LAG}} + \alpha_2 D_{UNE} + \alpha_3 D_{CPI^F} + \alpha_3 D_{CPI^M} + \alpha_4 D_{GDP_{LAG}} \\
 & + \alpha_5 D_{UNE_{LAG}} + \alpha_6 D_{CPI_{LAG}} + \alpha_7 D_{CPI_{LAG}^F} + \alpha_8 D_{CPI_{LAG}^M} + \sum_j \alpha_{9,j} D_{BCI_j} \\
 & + \sum_k \alpha_{10,k} D_{PI_k} + \alpha_{11} D_{OI_y},
 \end{aligned} \tag{2}$$

where STAT represents the corresponding model performance statistics, j represents the transformation of BCI variables (y or q), and k represents transformation options for PI variables (*dif*, *q*, *a12*, *a6*). The transformation shortcuts are described in Table 1.

To identify general differences across countries and heterogeneity among agents, we estimated fixed-effect panel data regression models while considering the effects of individual agents and countries. It is important to note that the regression results for individual countries align with the overall patterns observed. Therefore, we will present the findings for individual agents while controlling for countries' fixed effects. A country-specific analysis will be addressed using the Bayesian Model Averaging approach discussed in the next subsection.

Bayesian model averaging

Although classical estimates yield interesting results, such as the preferred transformation of explanatory variables, we are aware of possible collinearity problems since it is a common feature between macroeconomic variables. To account for it and to find the determinants more precisely, we employ Bayesian model averaging (BMA) methods adjusted for the possibility of collinearity. Using this methodology, we can determine which explanatory variables have the highest posterior probability, thus indicating which indicators are most likely the true determinants and present in the model of inflation expectations. We follow the approach of Lamnisos et al. (2013), who introduced an adaptive Markov-Chain Monte Carlo (MCMC) algorithm for Bayesian variable selection in linear regression models. The method samples from the model space of 2^K possible models, where K is the number of explanatory variables, to obtain the posterior model probability of each sampled model and the posterior model space. It assumes that the dependent variable, y , follows a normal distribution

$$y \sim N(\alpha + X_\gamma \beta_\gamma, \tau I_n), \quad (3)$$

where parameters $\alpha, \beta_\gamma, \tau, \gamma$ are given prior distributions. The intercept α is set to the noninformative improper prior

$$\pi(\alpha) \propto 1. \quad (4)$$

The regression coefficients have the multivariate normal prior given by

$$\beta_\gamma | \tau, \gamma \sim N_\gamma(0, \tau V_\gamma), \quad (5)$$

where $V_\gamma = c(X_\gamma^T X_\gamma)^{-1}$, c is the scale hyperparameter, and the error variance, τ , is given the noninformative improper prior

$$\pi(\tau) \propto \frac{1}{\tau}. \quad (6)$$

For the model priors, we incorporated the collinearity adjusted dilution prior of George (2010) the probability of a model γ for the collinearity in the matrix of regressors, X_γ . For each model γ , let R_γ be the correlation matrix such that $R_\gamma \propto X_\gamma^T X_\gamma$. Then the determinant of the correlation matrix, $|R_\gamma|$, is a measure of collinearity such as $|R_\gamma| = 1$ when the columns of X_γ are orthogonal, and $|R_\gamma|$ decreases to 0 as the columns of X_γ become more dependent. The model γ prior then takes the following form:

$$\pi(\gamma) \propto h(|R_\gamma|) \prod_{i=1}^K w_i^{\delta_i} (1 - w_i)^{1 - \delta_i}, \quad (7)$$

where h is a monotone function, we set so it satisfies $h(r) = r^{1/2}$, $\delta_i = I(X_i \text{ in } \gamma)$, and $w = \pi(X_i \text{ in } \gamma)$. The priors (4), (5) and (6) results in an analytical form for the marginal

likelihood $\pi(y|\gamma)$ of model γ given by

$$\pi(y|\gamma) \propto |X_\gamma^T X_\gamma + V_\gamma^{-1}|^{-1/2} |V_\gamma|^{-1/2} \left(\tilde{y}^T \tilde{y} - y^T X_\gamma (X_\gamma^T X_\gamma + V_\gamma^{-1})^{-1} X_\gamma^T y \right)^{-(n-1)/2}, \quad (8)$$

where $\tilde{y} = y - \bar{y}$ and $\bar{y}$ is the mean of the dependent variable.

The adaptive Metropolis-Hastings linear regression (ADMH-LR) algorithm with the posterior model distribution $\pi(\gamma|y)$ is then employed to estimate posterior model characteristics. The ADMH-LR algorithm has implemented a tuneable model proposal density $q_{\zeta^{(t)}}(\gamma'|\gamma)$ as proposed by Lamnisos et al. (2009) that controls the mixing of the algorithm. This model proposal draws a new model in the following way. At first, a value $N^{(t)}$ is generated from a binomial distribution with a fixed number, $N - 1$, of trials and success probability ζ which is a scale parameter that is defined by the following function:

$$\rho(\zeta) = \begin{cases} 0 & \text{if } \zeta < 0 \\ \zeta & \text{if } \zeta \in [0, 1] \\ 1 & \text{if } \zeta > 1 \end{cases} \quad (9)$$

Then draw a possible move, “Add”, “Delete”, or “Swap”, from a uniform random distribution. These moves either add $N^{(t)} + 1$ regressors to the previous model, delete $N^{(t)} + 1$ regressors from the previous model, or swap $N^{(t)} + 1$ regressors with those that were excluded from the previous model. However, these moves are conditioned, so there are always regressors in the proposed model. The scale parameter $\zeta^{(t)}$ ensures that either the algorithm explores other parts of the posterior space when the acceptance rate is low or finds its mode when the rate is high. The ADMH-LR algorithm then has the three following steps:

- (1) Draw a proposed model γ' with probability $q_{\zeta^{(t)}}(\gamma'|\gamma)$;
- (2) Accept or reject the proposed model with probability

$$\alpha(\gamma, \gamma') = \min \left\{ 1, \frac{\pi(y|\gamma') \pi(\gamma') q_{\zeta^{(t)}}(\gamma|\gamma')}{\pi(y|\gamma) \pi(\gamma) q_{\zeta^{(t)}}(\gamma'|\gamma)} \right\};$$
- (3) Compute the scale parameter $\zeta^{(t+1)} = \rho(\zeta^{(t)} + s^{(t)}(\alpha(\gamma, \gamma') - \bar{\tau}))$, where $s^{(t)} = \zeta_{0/t}$, ζ_0 is the prior setting of ζ , t is the number of current iteration of the algorithm, and $\bar{\tau}$ is the target acceptance rate of the algorithm, which is set to 0.3.

Similarly to the classical approach, the BMA is also carried out recursively to calculate the change in the regressors' posterior probability as the high inflation period is included in the data. This approach represents an alternative method to test the stability of determinants in time from the view of their significance.

IV. Evaluating Heterogeneity in Inflation Expectations

Using ordinary regressions and panel data regressions estimated with the resulting model statistics (R², MSPE, and MAPE), we find that all agents strongly rely on year-on-year transformations (growth rates or difference) of explanatory variables, as depicted in Table 2 of panel regression of model statistics controlling for countries' fixed-effects. This is also true for these agents at the individual country level. It corresponds to the form of information usually reported by the media, such as GDP growth or the level of annual inflation rate. Our results also show a large impact of the expectation lag on the model performance for all agents, but primarily for households and firms. These results correspond to previous studies showing that expectations are not rational and are either sticky (Mankiw and Reis, 2002) or adaptive (Evans and Honkapohja, 2001).

Including food and dairy prices improves the performance of a model according to R² for all agents, but results using MSPE and MAPE are mixed. However, this result might not indicate that these prices are the driving force of agents' expectations since they both appear in models together with core inflation, which could potentially be the cause of the improvement. Based on the literature, food and milk prices would be more important to households (Weber et al., 2022) since they get these price signals during grocery shopping. Core inflation could be more important for professionals since economists are more often interested in it as a factor of inflation than they would be with food prices. Results show that for professionals and firms, the unemployment rate is a slightly more preferred predictor over GDP based on R² and MAPE. Based on R² and MSPE, they also find the inclusion of lagged CPI inflation statistically significant.

Table 2: Panel regression controlling countries' fixed effects

Variable	Households			Professionals			Firms		
	R ²	MSPE	MAPE	R ²	MSPE	MAPE	R ²	MSPE	MAPE
D_{EXPLAG}	0.104 (0.001)	-54.596 (2.178)	-1.173 (0.026)	0.080 (0.001)	-3.117 (0.102)	-0.299 (0.006)	0.106 (0.001)	-22.474 (0.817)	-0.920 (0.018)
D_{UNE}	0.003 (0.001)	0.370 (2.599)	-0.013 (0.031)	0.006 (0.001)	0.000 (0.122)	-0.015 (0.007)	0.009 (0.001)	-0.095 (0.974)	-0.045 (0.021)
D_{CPI^F}	0.022 (0.001)	0.157 (3.073)	-0.013 (0.037)	0.017 (0.001)	0.030 (0.144)	0.016 (0.008)	0.016 (0.001)	-0.621 (1.152)	-0.042 (0.025)
D_{CPI^M}	0.022 (0.001)	-0.653 (3.073)	0.003 (0.037)	0.019 (0.001)	-0.019 (0.144)	0.012 (0.008)	0.014 (0.001)	-0.945 (1.152)	-0.024 (0.025)
$D_{GDP_{LAG}}$	-0.000 (0.001)	0.700 (2.957)	0.098 (0.035)	0.002 (0.001)	0.249 (0.139)	0.068 (0.008)	0.004 (0.001)	0.539 (1.109)	0.085 (0.024)
$D_{UNE_{LAG}}$	-0.001 (0.001)	0.228 (2.656)	0.017 (0.032)	0.001 (0.001)	-0.011 (0.125)	-0.002 (0.007)	0.002 (0.001)	-0.079 (0.996)	-0.005 (0.021)
$D_{CPI_{LAG}}$	0.008 (0.001)	-5.351 (3.456)	-0.054 (0.041)	0.010 (0.001)	-0.281 (0.162)	-0.007 (0.009)	0.009 (0.002)	-2.738 (1.296)	-0.040 (0.028)

Variable	Households			Professionals			Firms		
	R ²	MSPE	MAPE	R ²	MSPE	MAPE	R ²	MSPE	MAPE
$D_{CPI_{LAG}^F}$	0.016	-3.260	-0.015	0.011	-0.167	0.020	0.011	-1.893	0.010
	(0.001)	(3.176)	(0.038)	(0.001)	(0.149)	(0.008)	(0.002)	(1.191)	(0.026)
$D_{CPI_{LAG}^M}$	0.015	-3.525	-0.005	0.012	-0.167	0.016	0.010	-1.922	0.008
	(0.001)	(3.176)	(0.038)	(0.001)	(0.149)	(0.008)	(0.002)	(1.191)	(0.026)
D_{BCI_y}	0.033	-15.492	-0.221	0.032	-1.286	-0.113	0.044	-7.551	-0.176
	(0.001)	(2.668)	(0.032)	(0.001)	(0.125)	(0.007)	(0.001)	(1.000)	(0.021)
D_{BCI_q}	-0.002	-2.542	0.021	0.005	-0.426	-0.053	0.027	-2.172	-0.057
	(0.001)	(2.668)	(0.032)	(0.001)	(0.125)	(0.007)	(0.001)	(1.000)	(0.021)
$D_{PI_{dif}}$	-0.097	72.500	1.158	-0.075	3.587	0.267	-0.075	28.813	0.834
	(0.001)	(3.444)	(0.041)	(0.001)	(0.161)	(0.009)	(0.002)	(1.291)	(0.028)
D_{PI_q}	-0.049	46.966	0.856	-0.035	1.786	0.162	-0.035	17.471	0.591
	(0.001)	(3.444)	(0.041)	(0.001)	(0.161)	(0.009)	(0.002)	(1.291)	(0.028)
$D_{PI_{a12}}$	-0.007	3.195	0.196	-0.019	1.183	0.118	-0.015	6.756	0.352
	(0.001)	(3.444)	(0.041)	(0.001)	(0.161)	(0.009)	(0.002)	(1.291)	(0.028)
$D_{PI_{a6}}$	-0.004	-0.999	0.057	-0.014	0.795	0.083	-0.013	4.575	0.265
	(0.001)	(3.444)	(0.041)	(0.001)	(0.161)	(0.009)	(0.002)	(1.291)	(0.028)
D_{OI_y}	0.045	-18.561	-0.302	0.046	-1.448	-0.136	0.048	-9.749	-0.372
	(0.001)	(2.178)	(0.026)	(0.001)	(0.102)	(0.006)	(0.001)	(0.817)	(0.018)

Source: Own calculations

Note: Statistically significant estimates at the 10% significance level are bold. Robust standard errors are in parentheses.

Although these results are fruitful, particularly regarding the lag in expectations and the preferred transformation of data, they do not offer a good picture of agents' possible models of inflation expectations. To achieve this goal, we would be required to estimate these regressions on model statistics using the significance of explanatory variables inside the original models as regressors instead of dummies of their presence. However, these results would be potentially heavily biased by the collinearity problem. Thus, we refrained from using this approach. Instead, we chose to find the determinants using the BMA approach, which allows for exploring the model space better while using a collinearity-adjusted model prior to dealing with the potential collinearity problems.

The BMA analysis allowed for obtaining posterior probabilities of each model and, thus, posterior probabilities of each variable. Estimated posterior inclusion probabilities of variables for all countries are presented in Table 3, Table 4 and Table 5. The BMA analysis was done using year-on-year growth transformations based on the results from the classical approach.

Table 3: Bayesian model averaging (households, full sample)

Variable	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
GDP_y_dif	.063	.085	.068	.045	.043	.283	.117	.055	<u>.592</u>	.06	.267	.038	.134	.402
CPI	.105	.439	.374	.244	.182	<u>.635</u>	.392	.104	.058	.261	.983	.119	.889	.127
CPL_C	.080	.458	.035	.760	.239	.260	.246	.137	.447	.037	.094	.189	.090	.480
CPL_F	.055	.046	.037	.120	.088	.115	.075	.26	.151	.033	.124	.310	.828	.102
CPL_M	.052	.329	.056	.061	.048	.074	.056	.052	.356	.354	.016	.076	.080	.236
INT_y_dif	.083	.118	<u>.655</u>	.268	.042	.070	.162	.984	.757	.069	.067	.064	.233	.121
EXR_y_dif	.231	.081	.044	.487	.032	.219	.017	.116	.087	.014	.058	.209	.046	.045
UNE_y_dif	.109	<u>.503</u>	<u>.728</u>	.146	.143	.010	.144	<u>.632</u>	.219	.105	.150	.058	.169	.356
OIL_y	.029	.008	.018	.022	.009	.036	.005	.006	.014	.009	.012	.887	.013	.025
INN_y	.998	<u>.551</u>	.999	.042	.153	.042	.029	.015	.400	.971	.018	.036	.115	.321
SPL_y	.022	.331	.027	.018	.008	<u>.724</u>	.051	.079	.281	.050	.030	1.00	.112	.047
EXP_lag	.769	<u>.584</u>	1.00	.399	1.00	.805	.899	<u>.624</u>	.961	.996	1.00	.122	.187	.315
GDP_y_dif_lag	.073	.075	.122	.079	.042	.282	.093	.055	.174	.091	.068	.127	.218	.055
CPL_lag	<u>.748</u>	.983	.033	.048	.087	.424	.141	.252	<u>.625</u>	.144	.059	.124	<u>.739</u>	.146
CPL_C_lag	.369	.053	.054	.052	.232	.809	.290	.174	.189	.066	.047	.328	.091	.468
CPL_F_lag	.063	.380	.035	.055	.054	.147	.063	.144	<u>.717</u>	.039	.172	.086	.109	.075
CPL_M_lag	.058	.032	.110	.045	.061	.077	.228	.058	.305	.080	.033	.031	.059	.495
UNE_y_dif_lag	.105	.372	.229	<u>.602</u>	.149	.009	.386	.302	.145	.126	.137	.014	<u>.594</u>	.080

Source: Own calculations

Notes: Posterior inclusion probabilities greater than 0.5 are underlined, and values greater than 0.75 are in bold.

The analysis shows that lagged expectations (variable EXP_lag) are essential for all agents across most analysed countries, although they are less significant for professionals. This conclusion follows the results based on the classical regression approach. Another vital determinant seems to be the proxy for the inflation news index, which has a high posterior inclusion probability for all agents in several countries. This result is in direct accordance with the findings of Weber et al. (2022), who showed that households are more informed in such countries. Firms are also influenced heavily by the news (INN_y). Suppose firms perceive a general consensus on rising inflation expectations. In that case, they may adjust their pricing strategies upward in anticipation of potential cost increases or take advantage of the prevailing market sentiment by raising prices in line with other firms. As represented by interest rate changes (INT_y_dif), monetary variables are particularly significant in New Zealand, Poland, and the Euro Area.

The similarity between households and firms also relates to the findings in the literature that firms' behaviour is closer to households depending on their size (Candia et al., 2023). However, it is reasonable to assume that for professionals, it is only the result of correlation since across the media in the world, it is usually the professionals (economists from academia and financial institutions) who appear on television and radio to talk about the

inflation levels and so to a certain degree influence the inflation expectations of other agents (Łyziak, 2012). To rule out this effect, we also performed the BMA for professionals without this variable to check for the robustness of other results, but the results remained unchanged.

Table 4: Bayesian model averaging (professionals, full sample)

Variable	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
GDP_y_dif	.079	.062	.061	.039	.843	<u>.999</u>	.105	.086	.294	.187	.081	.140	.146	.110
CPI	.216	.063	<u>.999</u>	.086	.215	.151	.359	<u>.949</u>	.104	<u>.697</u>	<u>.615</u>	.430	.320	.342
CPL_C	.111	.041	.055	.095	.186	.199	.794	.069	<u>.830</u>	.226	.386	.397	<u>.615</u>	.310
CPL_F	.072	.030	.025	.100	.069	.096	.051	.086	.071	.096	.032	.481	<u>.776</u>	.106
CPL_M	.034	.094	.172	<u>.872</u>	.138	<u>.669</u>	.084	.116	.041	.046	.017	.383	.062	.234
INT_y_dif	<u>.728</u>	<u>.850</u>	.119	<u>.996</u>	.054	.108	.487	<u>.849</u>	<u>.976</u>	.059	.109	.152	<u>.541</u>	.099
EXR_y_dif	.285	.033	.014	<u>.949</u>	.024	.233	.019	.070	.053	.039	.063	.187	.088	.032
UNE_y_dif	.219	.215	.102	.072	.280	.011	.107	.339	.218	.169	.233	.014	.169	.128
OIL_y	.382	.039	.003	.009	.005	.070	.006	.011	.094	.199	.017	.088	.223	.012
INN_y	<u>.750</u>	.019	.041	.044	.021	.043	<u>.813</u>	.013	.316	.466	<u>.863</u>	.433	<u>.997</u>	.196
SPL_y	.239	.016	.009	.096	.170	<u>1.00</u>	.022	.012	.215	.186	.067	.134	.172	.111
EXP_lag	.154	.142	.157	.068	<u>.805</u>	.274	.236	.365	.358	<u>.527</u>	<u>.985</u>	.049	.297	<u>.786</u>
GDP_y_dif_lag	.066	.043	.297	.035	.039	.285	.068	.077	.455	.073	.077	.167	.253	.071
CPL_lag	.069	<u>.905</u>	.048	.080	.488	.430	<u>.787</u>	.102	.074	.049	.059	.109	.327	.199
CPL_C_lag	.105	.109	.051	.077	.260	.227	.165	.069	.133	.094	.393	.098	<u>.966</u>	.197
CPL_F_lag	.053	.081	.036	.066	.189	.183	.180	.046	.115	.105	.021	<u>.830</u>	.518	.217
CPL_M_lag	.063	.030	.047	.166	.195	.092	.096	.094	.045	.077	.037	.160	.158	.085
UNE_y_dif_lag	.162	.123	.118	.069	.294	.012	.467	.226	.402	.142	.127	.006	.634	.104

Source: Own calculations

Notes: Posterior inclusion probabilities greater than 0.5 are underlined, and values greater than 0.75 are in bold.

Table 5: Bayesian model averaging (firms, full sample)

Variable	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
GDP_y_dif	.117	.187	.423	.047	.429		.104	.119	.106	.096	.158		.466	.115
CPI	.161	.119	<u>.878</u>	.237	<u>.952</u>		.312	<u>.859</u>	<u>.949</u>	<u>.999</u>	<u>.999</u>		<u>.988</u>	.597
CPL_C	.322	.071	.063	.099	<u>.973</u>		.146	.107	.134	.284	.041		.063	.162
CPL_F	.073	.029	.034	.459	.108		.232	.099	.066	.141	.028		.491	.148
CPL_M	.060	.033	.034	.106	.085		.134	.085	.057	.030	.018		.407	.111
INT_y_dif	.156	.140	.062	.099	.318		.100	.491	.102	.095	.172		.422	.143
EXR_y_dif	.214	.047	.068	.303	.032		.028	.059	.057	.143	.035		.162	.036
UNE_y_dif	<u>.569</u>	.205	.461	<u>.810</u>	.229		.136	<u>.569</u>	.320	.140	.168		.216	.231
OIL_y	.078	.025	.044	.008	.016		.023	.058	.033	.316	.022		.018	.014

Variable	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
INN_y	<u>.963</u>	<u>1.00</u>	<u>.998</u>	.278	.027		.337	<u>.955</u>	<u>1.00</u>	.063	<u>.692</u>		.067	<u>.505</u>
SPL_y	.417	.029	.032	.045	.062		.063	.078	.032	<u>.536</u>	.014		.113	.067
EXP_lag	.151	<u>1.00</u>	<u>.644</u>	<u>.402</u>	<u>1.00</u>		<u>1.00</u>	<u>.927</u>	.093	.249	<u>.998</u>		.272	<u>.982</u>
GDP_y_dif_lag	.093	.077	.104	.117	.117		.095	.119	.110	.124	.124		.485	.118
CPL_lag	.090	.039	<u>.518</u>	.324	.127		.101	.106	.033	.061	.054		.296	.261
CPL_C_lag	.100	.035	.116	.229	.164		.135	.120	.108	.242	.041		.089	.314
CPL_F_lag	.082	.039	.091	.113	.179		.110	.074	.179	.444	.018		.336	.104
CPL_M_lag	.100	.035	.062	.097	.109		.168	.143	.086	.126	.019		.173	.145
UNE_y_dif_lag	.161	.143	.344	.154	<u>.538</u>		.126	.331	.314	.153	.180		.161	.123

Source: Own calculations

Notes: Posterior inclusion probabilities greater than 0.5 are underlined, and values greater than 0.75 are in bold.

Another variable that often has a high posterior probability of inclusion is CPI inflation, especially for firms. However, for households, it is not very significant across the set of countries (it is highly significant in Turkey, a high-inflation country). This result corresponds to the findings of Weber et al. (2022). Professionals seem to use CPI inflation as often as core inflation. In addition, households seem to form their expectations using the lag in CPI inflation, which could indicate that it takes time to gather new information (Mankiw and Reis, 2002). On the other hand, neither core inflation, food prices, nor dairy prices have high posterior probabilities for households, with few exceptions. This contradicts the results of the classical approach and the findings of Weber et al. (2022).

The results show that households and firms seem to use the information about the unemployment rate and, at the same time, prefer it over GDP, which does not seem to be that important at all. Professionals, on average, use interest rates as their determinant, which could correspond to the economic theory. This behaviour may stem from their observation of the central bank, which is perceived as a forward-looking institution that takes proactive measures to combat inflation. Surprisingly, exchange rates are insignificant as determinants, not even for firms. One might expect that firms would find exchange rates significant since they often import materials and intermediate products from abroad, so an increase in costs related to exchange rates is often reflected in selling prices. However, according to the data, this might not be the case. The same applies to oil prices (OIL) and stock prices (SPI). The lags in GDP, the unemployment rate, and price indices, except for the lagged CPI inflation, also tend to be less important predictors.

Stability and persistence in inflation expectations

To evaluate the stability of determinants we found by performing the BMA analysis, we also performed the analysis recursively using expanding windows from 2020Q1 to 2023Q1. After carrying out recursive estimates, we calculated differences between the average of the first four posterior inclusion probabilities (from 2020Q1 to 2021Q1) and the average of the last four posterior inclusion probabilities (from 2022Q1 to 2023Q1). We aimed

to determine if there was a structural change in the posterior probabilities of the studied determinants and, consequently, in their significance. We established a threshold of 0.2 difference in probabilities to indicate a significant change. The results are presented in Tables B1, B2, and B8 in Appendix B.

All households in the countries where the inflation news proxy (INN) was a significant determinant experienced a rise in significance as the high inflation period started. Even some countries where the BMA on the full sample indicated it to be insignificant experienced a substantial rise. The same is true for firms across most of the studied countries. There was also a more notable rise for professionals. Still, once again, we presume that it is because the media usually interview them on the topic. This finding corresponds to Łyziak (2012), who showed that when the media report more about inflation, the expectations of households and firms become more precise. Although we did not study the forecasting precision of agents, we caught the dynamics that news has in influencing agents' expectations. In addition, due to the possibility of this being a pure correlation for professionals and for a robustness check, we have verified the results by performing BMA recursively without this index for professionals. Interestingly, with the rise in inflation, the significance of lag in expectations has also risen, especially for households and firms. This seems counterintuitive since the literature shows that when inflation becomes a hot topic, economic agents consume more information, lowering the cost of acquiring new information. In the process, they should rely less on their previous forecasts. Such expected results were achieved by Carroll (2003) and Łyziak (2013). However, our results suggest the opposite in several countries. One plausible explanation is that inflation expectations generally become more backward-looking and persistent during high inflation crises, as shown by Cornea-Madeira and Cornea (2022) using the UK inflation expectations during the oil price crises in 1973 and 1979.

Across all agents, the significance of lagged price indices declined. On the other hand, the standard price indices are a mixed bag since there is no evident rise or decline in significance. Only for firms, the importance of CPI inflation across countries rose more than it declined. Similarly, GDP and its lag either stayed stable or their posterior probability declined. The posterior probability of including the unemployment rate has risen significantly in some countries, particularly among households and firms. Its lag mainly remained stable or declined, except for firms for which it was in some countries. Interest rates and exchange rates have different behaviours for each agent. For households, they remain stable, while in the case of firms, they decline in significance. For professionals, interest rates have risen in significance, probably due to their understanding of monetary policy, whilst the exchange rates mainly remained stable, in some countries losing importance. Oil prices and stock price indices remained mostly stable for all agents.

To assess the persistence in inflation expectations, new model specifications were constructed that contain further lags of variables already entered as a lag. The results (based on the classical and BMA approaches) remained similar to those from the previous analysis. We can conclude that there is a strong preference for information in the form of year-on-year changes and that the lag in expectations is essential in forming the expectations. The detailed results based on BMA analysis are presented in Table C1, Table C2 and Table

C3 in Appendix C. In the case of households, the most potent determinants, such as the lag in expectations and inflation news proxy, remained nearly unchanged. For most non-lagged variables, their first-order lag counterparts, or in some cases, even their second-order lag counterparts, became significant. Some countries indicate the strong significance of selected second-order lag variables, such as GDP for the Euro-area and dairy prices in the South African Republic. The only country that prefers multiple second-order lag variables is South Korea, for which GDP and core inflation indicate persistence. The models for inflation expectations of professionals show the prevailing role of the interest rate, and in some countries, the probability of inclusion of this variable has even increased. The significance of removed variables has moved to their first-order lag variant or the inflation news index, which could indicate that they still use the most up-to-date information possible. The second-order lags remained mostly insignificant, except for the GDP growth. Similarly, to professionals, firms seem to have no further persistence in the information they use to form expectations since there are almost no significant second-order lag variables. The inflation news proxy and lag in expectations remain the most significant determinant. In some countries, they even gained significance. As in the case of professionals, removing some non-lagged variables caused some of their first-order lags to become more important as determinants. Finally, all of these results suggest that the most persistent information used for forming expectations is present in the expectations of households.

Tables C4, C5, and C6 in Appendix B show the changes in posterior model inclusion probability of the analysed variables. Our analysis reveals that households' most essential determinants, the lag in expectations and the inflation news index, become more important determinants once high inflation occurs. In most analysed countries, the determinants based on price indices mainly stayed stable or declined in significance. The added second-order lag variables seem to follow a similar trend in instability as the first-order lags, from which the most unstable seem to be GDP, CPI inflation, and unemployment rate variables, with patterns characterised mainly by the negative changes in the probability of inclusion. When considering the additional lags, the determinants in the case of professionals (see Table B5 in Appendix B) were also quite unstable, but there is no clear pattern across countries. The variables can be divided into three groups: those that have risen more than declined, those that have become more irrelevant than increased in significance, and those with approximately the same number of rises and declines. The first group contains the variables related to interest rates, the inflation news index, the lagged core inflation and food inflation. There are more decreases in the probability of inclusion across countries in lagged CPI inflation, lagged GDP, oil prices, and the second-order lag of the unemployment rate. The unstable and undetermined variables are the lag in expectations and exchange rates, and the second-order lag in CPI and core inflation. The remaining analysed variables show only slight probability changes throughout the entire period. After including additional lags, we have observed similar behaviour of most determinants of inflation expectations of the firms (see Table B6 in Appendix B). The importance of interest rates declines over time, and the influence of stock prices is mostly stable. Compared to the original analysis, we can observe a decline in the importance of lagged inflation expectations and an increase in the importance of food price inflation. The impact of oil prices has declined significantly.

The role of the lagged unemployment rate has increased in a period of higher inflation. As before, the lag in the unemployment rate becomes more important in the high-inflation period. In the case of variables with higher lags, we observe a decline in importance only in the case of the lagged CPI inflation variable. The role of the other lagged variables has not changed significantly over time.

Lastly, we were interested in the ratio of the variability of inflation expectations explained by its determinants. This analysis was carried out by computing the relative importance of predictors in models with the highest posterior probability. Although the results are based only on one model for each agent in each country, they show a similar behaviour captured by the posterior probability of inclusion. As for the households, the highest relative importance usually belongs to the lagged expectations, inflation news index, and price indicators (primarily based on CPI or core inflation). The professionals seem to rely more on models that reflect the economic theory, and the key predictors seem to be interest rates, a price indicator, and, to a small degree, lagged expectations. These results reinforce the idea that their expectations are more likely to be formed by following economic theory. There is also a higher occurrence of GDP or unemployment rate variables in the models (in comparison with the households). Finally, the firms tend to form their expectations using CPI inflation, lagged expectations and, to a certain degree, inflation news proxy.

To further test the robustness of our results, we analysed three alternative approaches to the method used to quantify inflation expectations. Using the Carlson-Parking method (Carlson and Parkin, 1975), we quantified the expectations using three modifications: a normal distribution, non-central t-distribution, and logistic distribution. The obtained results remained almost the same, which corresponds to the findings of Berk (2002) and Łyziak (2010).

V. Conclusion

Our findings confirm that inflation expectations exhibit significant heterogeneity across both agents and countries. In particular, households and firms tend to rely heavily on past expectations and year-on-year changes in key economic variables. This observation is consistent with existing theories of sticky expectations (Mankiw and Reis, 2002) and adaptive expectations (Evans and Honkapohja, 2001). CPI inflation emerges as an important determinant for firms; however, it appears to have limited significance for households across the countries studied, with the notable exception of Turkey, where persistently high inflation may heighten sensitivity to such indicators. This result aligns with the findings of Weber et al. (2022). Professionals appear to incorporate both CPI and core inflation to a similar extent in their expectations. Interestingly, households seem to form expectations based on lagged CPI inflation, which may suggest delays in processing or accessing new information (Mankiw and Reis, 2002). By contrast, variables such as core inflation, food prices, and dairy prices generally have low posterior probabilities for households, with a few exceptions. This outcome contrasts with traditional assumptions as well as some of the findings reported by Weber et al. (2022).

Professionals demonstrate greater responsiveness to monetary policy variables, such as interest rate changes, reflecting their more profound understanding of central bank actions.

In the case of households and firms, the importance of monetary policy factors related to the interest rate changes was proved among New Zealand, Poland and the Euro area countries. Following Candia et al. (2023), we can observe similar determinants of forming inflation expectations of households and firms in all investigated countries. Notably, the inflation news index emerges as a crucial determinant across all agents and countries, particularly during periods of high inflation. The increased significance of inflation news suggests that media coverage plays a vital role in shaping expectations. Additionally, our recursive analysis reveals that the persistence of past expectations strengthened during the inflationary period of 2022, implying that inflation expectations became more backward-looking in response to economic uncertainty. While the dynamic of CPI inflation remains an important determinant, its significance varies across agents and economies. Firms appear more responsive to CPI inflation indicators, whereas households rely more on their past values. Interestingly, despite expectations that exchange rates would influence firms due to increased import costs, our analysis finds little evidence supporting this relationship. Similarly, oil prices and stock prices do not play a substantial role in shaping inflation expectations across most agents and countries.

Given the observed heterogeneity in inflation expectations across different groups, there are practical implications for monetary policy. Central banks should consider tailoring their communication strategies accordingly, as pointed out by Weber et al. (2022). For instance, households may respond more strongly to relatable, experience-based narratives or targeted messaging through mass media, while firms and professionals might benefit more from technical, data-driven communication. Understanding the different informational needs and belief-formation processes of each group can help policymakers anchor expectations more effectively and enhance the credibility of monetary policy.

Our findings also contribute to the broader understanding of expectation formation in behavioural economics. The observed reliance on lagged information, particularly among households, supports models of bounded rationality, where agents face cognitive or informational constraints and therefore do not continuously update their expectations in response to new data. Moreover, the differential use of economic indicators across agent types indicates varying capacities for signal extraction, with professionals better able to interpret and integrate complex signals like core inflation, while households respond more to easily observable variables. These patterns underscore the need for expectation models that move beyond the representative agent paradigm and account for heterogeneity in information processing and learning behaviour.

Overall, our paper highlights the complexity of inflation expectations and the dynamic nature of their determinants. The increased reliance on inflation news and past expectations during inflationary periods underscores the importance of clear and effective communication from policymakers. Future research could explore how different forms of media influence expectation formation and whether targeted policy interventions can reduce inflation expectation persistence among households and firms.

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Appendix A: Data description

This appendix provides a detailed description of the data used in the analysis, including sources, variable definitions across countries and agent types.

Table A1: Data sources – inflation expectations

Code	Country	Code	Country
AU	Australia	NZ	New Zealand
CZ	Czechia	PL	Poland
EA	Eurozone	SE	Sweden
IS	Iceland	TR	Turkey
JP	Japan	UK	United Kingdom
KR	South Korea	US	United States
NO	Norway	ZA	South Africa

Source: Own calculations

Notes: Country codes according to ISO 3166-2

Table A2: Data sources – inflation expectations

Country	Agent	Survey Question	Survey (Series Name)	Source
AU	Households	Over the next 12 months	Inflation Expectations – G3	Reserve Bank of Australia
AU	Firms	Over the next 12 months	Inflation Expectations – G3	Reserve Bank of Australia
AU	Professionals	Over the next 12 months	Inflation Expectations – G3	Reserve Bank of Australia
CZ	Households	Over the next 12 months	Economic forecast and surveys	European Commission Consumer Survey
CZ	Firms	Over the next 12 months	Financial market inflation expectations	Czech National Bank
CZ	Professionals	Over the next 12 months	Inflation expectations of corporations	Czech National Bank
EA	Households	Over the next 12 months	Economic forecast and surveys	European Commission Consumer Survey
EA	Firms	Over the next 3 months	Economic forecast and surveys	European Commission Consumer Survey
EA	Professionals	Over the next 12 months	Survey of Professional Forecasters	European Central Bank
IS	Households	Over the next 12 months	Inflation expectations	Central Bank of Iceland/Gallup
IS	Firms	Over the next 12 months	Inflation expectations	Central Bank of Iceland/Gallup
IS	Professionals	Over the next 12 months	Inflation expectations	Central Bank of Iceland/Gallup
JP	Households	Over the next 12 months	Opinion Survey on the General Public's Views and Behavior	Bank of Japan

Country	Agent	Survey Question	Survey (Series Name)	Source
JP	Firms	Over the next 12 months	TANKAN Survey – Inflation outlook of enterprises	Bank of Japan
JP	Professionals	Over the next 12 months	JCER ESP Forecast	Japan Center for Economic Research
KR	Households	Over the next 12 months	Consumer Survey	Bank of Korea
KR	Professionals	Over the next 12 months	Survey of professional forecasters and Consensus economics	Bank of Korea
NO	Households	Over the next 12 months	Expectations survey	Norges Bank
NO	Firms	Over the next 12 months	Expectations survey	Norges Bank
NO	Professionals	Over the next 12 months	Expectations survey	Norges Bank
NZ	Households	Over the next 12 months	Household inflation expectations (H1)	Reserve Bank of New Zealand
NZ	Firms	Over the next 12 months	ANZ Business Outlook survey	ANZ Bank New Zealand Ltd.
NZ	Professionals	Over the next 12 months	Survey of expectations (M14)	Reserve Bank of New Zealand
PL	Households	Over the next 12 months	Economic forecast and surveys	European Commission Consumer Survey
PL	Firms	Over the next 12 months	Inflation expectations of enterprises – NBP Quick Monitoring Survey	Narodowy Bank Polski
PL	Professionals	Over the next 12 months	NBP Survey of Professional Forecasters	Narodowy Bank Polski
SE	Households	Over the next 12 months	Economic tendency survey	Economic Institute of Sweden
SE	Firms	Over the next 12 months	Prospera Swedish inflation expectations survey	Kantar Sifo
SE	Professionals	Over the next 12 months	Prospera Swedish inflation expectations survey	Kantar Sifo
TR	Households	Over the next 12 months	Economic forecast and surveys	European Commission Consumer Survey
TR	Firms	Over the next 12 months	Business tendency survey	Türkiye Cumhuriyet Merkez Bankası
TR	Professionals	Over the next 12 months	Survey of Market participants	Türkiye Cumhuriyet Merkez Bankası
UK	Households	Over the next 12 months	Bank of England/Ipsos Inflation Attitudes Survey	Bank of England
UK	Professionals	Over the next year	Forecasts for the UK economy	HM Treasury
US	Households	Over the next 12 months	Michigan Survey of consumer expectations	University of Michigan

Country	Agent	Survey Question	Survey (Series Name)	Source
US	Firms	Over the next 12 months	Business Inflation Expectations	Atlanta FED
US	Professionals	Over the next 12 months	Survey of Professional Forecasters	Philadelphia FED
ZA	Households	Over the next year	Inflation Expectation Survey	Bureau of Economic Research – Stellenbosch University
ZA	Firms	Over the next year	Inflation Expectation Survey	Bureau of Economic Research – Stellenbosch University
ZA	Professionals	Over the next year	Inflation Expectation Survey	Bureau of Economic Research – Stellenbosch University

Source: Own calculations

Notes: Survey question corresponds to the horizon over which respondents stated their expectations. Over the next 12 (3) months refers to the expected annual (quarter-to-quarter) inflation rate, while over the next year refers to the average inflation rate over the whole following year.

Table A3: Data sources – quantified expectations

Country	Agent	Method of Quantification
CZ	Households	Quantified with CP method (normal distribution), subjectified inflation expectations using 12-month average of previous CPI inflation as the natural rate of inflation for inflation perceptions.
EA	Households	Quantified with CP method (normal distribution), subjectified inflation expectations using 12-month average of previous HICP inflation as the natural rate of inflation for inflation perceptions.
EA	Firms	Quantified with CP method (non-central t distribution), objectified inflation expectations using the previous months' annual inflation rate.
PL	Households	Quantified with CP method (normal distribution), subjectified inflation expectations using 12-month average of previous CPI inflation as the natural rate of inflation for inflation perceptions.
PL	Firms	Quantified with CP method (normal distribution), objectified inflation expectations using the previous months' annual inflation rate.
TR	Households	Quantified with CP method (non-central t distribution), subjectified inflation expectations using 12-month average of previous CPI inflation as the natural rate of inflation for inflation perceptions.

Source: Own calculations

Table A4: Data sources – explanatory variables

Country	Variable	Source	Country	Variable	Source
AU	GDP – Real GDP	Australian Bureau of Statistics	NZ	GDP – Real GDP	Reserve Bank of New Zealand
AU	CPI – Inflation	Australian Bureau of Statistics	NZ	CPI – Inflation	Stats NZ
AU	INT – Interest Rate	Reserve Bank of Australia	NZ	INT – Interest Rate	Reserve Bank of New Zealand
AU	CPLC – Core inflation	Australian Bureau of Statistics	NZ	CPLC – Core inflation	Reserve Bank of New Zealand
AU	EXR – Exchange rate	Reserve Bank of Australia	NZ	EXR – Exchange rate	Reserve Bank of New Zealand
AU	UNE – Unemployment	Australian Bureau of Statistics	NZ	UNE – Unemployment	Reserve Bank of New Zealand
AU	CPLF – CPI Food	Australian Bureau of Statistics	NZ	CPLF – CPI Food	Stats NZ
AU	CPLM – CPI Milk	Australian Bureau of Statistics	NZ	CPLM – CPI Milk	Stats NZ
AU	OIL – Oil price	FRED, Federal Reserve St. Louis	NZ	OIL – Oil price	FRED, Federal Reserve St. Louis
AU	INN – Inflation News Index	Google Trends	NZ	INN – Inflation News Index	Google Trends
AU	SPI – Stock price index	Investing.com	NZ	SPI – Stock price index	Investing.com
CZ	GDP – Real GDP	Czech Statistical Office	PL	GDP – Real GDP	Eurostat
CZ	CPI – Inflation	Czech Statistical Office	PL	CPI – Inflation	Narodowy Bank Polski
CZ	INT – Interest Rate	Czech National Bank	PL	INT – Interest Rate	FRED, Federal Reserve St. Louis
CZ	CPLC – Core inflation	Eurostat	PL	CPLC – Core inflation	Narodowy Bank Polski

Country	Variable	Source	Country	Variable	Source
CZ	EXR – Exchange rate	Czech National Bank	PL	EXR – Exchange rate	FRED, Federal Reserve St. Louis
CZ	UNE _{gap} – Unemployment	Czech Statistical Office	PL	UNE – Unemployment	Statistics Poland
CZ	CPL _F – CPI Food	Czech Statistical Office	PL	CPL _F – CPI Food	FRED, Federal Reserve St. Louis
CZ	CPL _M – CPI Milk	Eurostat	PL	CPL _M – CPI Milk	FRED, Federal Reserve St. Louis
CZ	OIL – Oil price	FRED, Federal Reserve St. Louis	PL	OIL – Oil price	FRED, Federal Reserve St. Louis
CZ	INN – Inflation News Index	Google Trends	PL	INN – Inflation News Index	Google Trends
CZ	SPI – Stock price index	Investing.com	PL	SPI – Stock price index	Investing.com
EA	GDP – Real GDP	Eurostat	SE	GDP – Real GDP	Statistics Sweden
EA	CPI – Inflation	Eurostat	SE	CPI – Inflation	Statistics Sweden
EA	INT – Interest Rate	ECB	SE	INT – Interest Rate	European Central Bank
EA	CPL _C – Core inflation	Eurostat	SE	CPL _C – Core inflation	Eurostat
EA	EXR – Exchange rate	FRED, Federal Reserve St. Louis	SE	EXR – Exchange rate	Sveriges Riksbank
EA	UNE – Unemployment	Eurostat	SE	UNE – Unemployment	Statistics Sweden
EA	CPL _F – CPI Food	Eurostat	SE	CPL _F – CPI Food	Statistics Sweden
EA	CPL _M – CPI Milk	Eurostat	SE	CPL _M – CPI Milk	Statistics Sweden
EA	OIL – Oil price	FRED, Federal Reserve St. Louis	SE	OIL – Oil price	FRED, Federal Reserve St. Louis
EA	INN – Inflation News Index	Google Trends	SE	INN – Inflation News Index	Google Trends
EA	SPI – Stock price index	Investing.com	SE	SPI – Stock price index	Investing.com
IS	GDP – Real GDP	Statistics Iceland	TR	GDP – Real GDP	Eurostat
IS	CPI – Inflation	Statistics Iceland	TR	CPI – Inflation	TURKSTAT
IS	INT – Interest Rate	FRED, Federal Reserve St. Louis	TR	INT – Interest Rate	FRED, Federal Reserve St. Louis

Country	Variable	Source	Country	Variable	Source
IS	EXR – Exchange rate	Central Bank of Iceland	TR	CPLC – Core inflation	TURKSTAT
IS	UNE – Unemployment	Statistics Iceland	TR	EXR – Exchange rate	Turkish Central Bank
IS	CPLF – CPI Food	Statistics Iceland	TR	UNE – Unemployment	TURKSTAT
IS	CPLM – CPI Milk	Statistics Iceland	TR	CPLF – CPI Food	TURKSTAT
IS	OIL – Oil price	FRED, Federal Reserve St. Louis	TR	CPLM – CPI Milk	TURKSTAT
IS	INN – Inflation News Index	Google Trends	TR	OIL – Oil price	FRED, Federal Reserve St. Louis
IS	SPI – Stock price index	Investing.com	TR	INN – Inflation News Index	Google Trends
JP	GDP – Real GDP	Statistics Bureau of Japan	TR	SPI – Stock price index	Investing.com
JP	CPI – Inflation	Statistics Bureau of Japan	UK	GDP – Real GDP	Office for National Statistics
JP	INT – Interest Rate	FRED, Federal Reserve St. Louis	UK	CPI – Inflation	Office for National Statistics
JP	CPLC – Core inflation	Statistics Bureau of Japan	UK	INT – Interest Rate	FRED, Federal Reserve St. Louis
JP	EXR – Exchange rate	FRED, Federal Reserve St. Louis	UK	CPLC – Core inflation	Office for National Statistics
JP	UNE – Unemployment	Statistics Bureau of Japan	UK	EXR – Exchange rate	Bank of England
JP	CPLF – CPI Food	Statistics Bureau of Japan	UK	UNE – Unemployment	Office for National Statistics
JP	CPLM – CPI Milk	Statistics Bureau of Japan	UK	CPLF – CPI Food	Office for National Statistics
JP	OIL – Oil price	FRED, Federal Reserve St. Louis	UK	CPLM – CPI Milk	Office for National Statistics
JP	INN – Inflation News Index	Google Trends	UK	OIL – Oil price	FRED, Federal Reserve St. Louis

Country	Variable	Source	Country	Variable	Source
JP	SPI – Stock price index	FRED, Federal Reserve St. Louis	UK	INN – Inflation News Index	Google Trends
KR	GDP – Real GDP	KOSIS	UK	SPI – Stock price index	Investing.com
KR	CPI – Inflation	KOSIS	US	GDP – Real GDP	Bureau of Economic Analysis
KR	INT – Interest Rate	FRED, Federal Reserve St. Louis	US	CPI – Inflation	U.S. Bureau of Labor Statistics
KR	CPLC – Core inflation	KOSIS	US	INT – Interest Rate	FRED, Federal Reserve St. Louis
KR	EXR – Exchange rate	FRED, Federal Reserve St. Louis	US	CPLC – Core inflation	U.S. Bureau of Labor Statistics
KR	UNE – Unemployment	KOSIS	US	EXR – Exchange rate	FRED, Federal Reserve St. Louis
KR	CPLF – CPI Food	KOSIS	US	UNE – Unemployment	FRED, Federal Reserve St. Louis
KR	CPLM – CPI Milk	KOSIS	US	CPLF – CPI Food	U.S. Bureau of Labor Statistics
KR	OIL – Oil price	FRED, Federal Reserve St. Louis	US	CPLM – CPI Milk	U.S. Bureau of Labor Statistics
KR	INN – Inflation News Index	Google Trends	US	OIL – Oil price	FRED, Federal Reserve St. Louis
KR	SPI – Stock price index	Investing.com	US	INN – Inflation News Index	Google Trends
NO	GDP – Real GDP	Statistics Norway	US	SPI – Stock price index	Investing.com
NO	CPI – Inflation	Statistics Norway	ZA	GDP – Real GDP	FRED, Federal Reserve St. Louis
NO	INT – Interest Rate	FRED, Federal Reserve St. Louis	ZA	CPI – Inflation	Statistics South Africa
NO	CPLC – Core inflation	Statistics Norway	ZA	INT – Interest Rate	FRED, Federal Reserve St. Louis

Country	Variable	Source	Country	Variable	Source
NO	EXR – Exchange rate	Norges Bank	ZA	CPLC – Core inflation	FRED, Federal Reserve St. Louis
NO	UNE – Unemployment	Statistics Norway	ZA	EXR – Exchange rate	FRED, Federal Reserve St. Louis
NO	CPLF – CPI Food	Statistics Norway	ZA	UNE – Unemployment	Statistics South Africa
NO	CPLM – CPI Milk	Statistics Norway	ZA	CPLF – CPI Food	Statistics South Africa
NO	OIL – Oil price	FRED, Federal Reserve St. Louis	ZA	CPLM – CPI Milk	Statistics South Africa
NO	INN – Inflation News Index	Google Trends	ZA	OIL – Oil price	FRED, Federal Reserve St. Louis
NO	SPI – Stock price index	Investing.com	ZA	INN – Inflation News Index	Google Trends

Source: Own calculations

Appendix B: Robustness check based on recursive estimates

This appendix presents the results of a robustness check using recursive estimation. The aim is to assess the stability of the identified determinants of inflation expectations over time. By sequentially updating the estimation sample and re-evaluating posterior inclusion probabilities, we examine whether the key findings remain consistent as new data becomes available.

Table B1: Bayesian model averaging (households, probability changes)

Variables	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
GDP_y_dif	−.06	−.26	−.15	−.01	.00	.13	−.11	−.05	.05	−.07	.20	−.04	−.01	.15
CPI	−.06	−.03	.12	.02	.07	.07	−.14	−.22	−.30	.11	.38	−.28	.43	−.01
CPLC	−.07	.27	−.18	.44	.03	.00	−.09	−.12	.12	−.23	−.21	−.41	−.05	.30
CPLF	−.05	−.16	−.11	−.09	.00	.02	−.32	.10	−.25	−.23	−.01	−.01	.40	.01
CPLM	.00	.03	−.06	−.04	−.02	.02	−.04	−.01	−.03	.33	−.02	−.04	−.03	−.18
INT_y_dif	−.13	−.10	.41	.03	.00	.04	−.04	.01	−.06	−.09	−.03	−.08	.04	−.32
EXR_y_dif	.05	.07	−.04	.10	−.02	.00	.00	−.16	−.13	−.05	.16	−.15	.00	.01
UNE_y_dif	−.12	.30	.57	.00	.11	.00	.05	.27	−.45	−.09	.04	.05	−.03	−.08
OIL_y	.01	−.08	−.05	.01	−.02	−.04	.00	−.01	−.01	−.03	.05	.35	.00	.01
INN_y	.89	−.08	.74	.00	.66	.01	.53	−.26	.11	.78	.02	.00	−.03	.22
SPLY	.00	.05	−.03	−.09	−.01	−.11	−.10	−.01	.07	−.05	−.05	.00	.13	−.05
EXP_lag	.38	−.10	.00	−.11	.33	.45	.25	.19	.00	.72	.00	.00	−.49	−.08
GDP_y_dif_lag	−.59	.00	−.15	.00	−.07	.01	−.06	−.08	−.34	−.22	−.01	−.04	.01	−.10
CPL_lag	.30	.02	−.70	−.07	−.71	.12	−.24	−.05	.48	−.30	−.02	−.30	.26	−.01
CPLC_lag	−.44	−.15	.07	−.11	.02	.33	−.03	.03	.03	−.06	−.07	.18	−.14	−.39
CPLF_lag	−.05	.05	−.02	.00	−.21	.05	−.23	.10	.45	−.68	−.07	−.03	.06	.01
CPLM_lag	.00	−.01	.05	−.13	−.12	−.05	−.17	.01	−.40	−.07	.19	−.10	−.03	.27
UNE_y_dif_lag	−.54	.08	−.59	.42	−.03	.12	−.06	−.01	.01	−.14	−.20	.00	.20	−.12

Source: Own calculations

Notes: Changes in posterior inclusion probability averages greater than 0.2 or less than −0.2 are in bold.

Table B2: Bayesian model averaging (professionals, probability changes)

Variables	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
GDP_y_dif	.20	−.06	.00	−.18	−.04	.03	−.09	−.68	.03	−.39	−.34	.00	.02	−.02
CPI	.38	−.14	.05	−.55	−.07	.06	−.10	.65	−.23	.74	−.42	−.47	.15	.06
CPLC	−.06	.20	−.19	−.11	.01	−.15	.57	−.07	.50	−.03	.07	−.16	.25	−.17
CPLF	−.30	−.12	−.24	−.17	−.13	−.09	−.09	−.30	−.21	−.02	−.82	.13	−.08	.03
CPLM	−.31	.03	.32	.43	−.11	−.08	−.03	.01	−.01	.03	−.04	.13	−.01	−.26
INT_y_dif	.15	.14	.02	.16	−.02	−.86	.12	.24	.67	−.19	−.05	−.19	.41	.20
EXR_y_dif	−.01	−.81	.00	.46	−.04	−.21	.00	−.08	−.01	.01	−.52	−.12	−.01	.01

Variables	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
UNE_y_dif	.25	-.01	-.22	-.16	.20	-.01	-.08	.15	-.04	-.07	-.01	.00	-.04	-.33
OIL_y	.53	-.08	-.06	-.03	-.01	-.12	.00	-.01	.00	-.43	-.04	-.15	.17	-.01
INN_y	-.15	-.22	.33	-.06	-.05	-.11	.58	-.06	.22	-.18	.66	-.34	.33	-.05
SPL_y	.05	-.08	.00	-.67	.02	.00	.01	-.03	.20	.02	-.13	-.03	.07	.01
EXP_lag	.38	-.16	-.09	-.06	.25	-.04	.16	.03	-.17	-.10	.55	-.18	.06	.06
GDP_y_dif_lag	-.20	-.09	-.06	-.07	-.05	-.45	-.06	-.22	-.02	-.04	-.06	-.05	-.49	-.15
CPL_lag	-.09	.22	-.53	-.20	.13	.10	.09	-.80	-.09	-.44	.18	-.56	-.59	-.03
CPL_C_lag	-.63	-.53	-.03	-.39	-.02	-.36	.13	-.02	.01	-.24	-.40	-.10	.60	-.03
CPL_F_lag	.01	-.14	-.05	-.03	.09	.04	.03	-.05	.01	-.34	-.65	.24	-.11	.05
CPL_M_lag	.08	-.04	.00	-.06	-.20	-.05	.03	.03	-.04	.20	-.03	-.20	.03	-.03
UNE_y_dif_lag	.03	-.41	-.12	-.22	.08	-.01	.42	.00	-.12	-.10	-.21	.03	.31	-.26

Source: Own calculations

Notes: Changes in posterior inclusion probability averages greater than 0.2 or less than -0.2 are in bold.

Table B3: Bayesian model averaging (firms, probability changes)

Variables	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
GDP_y_dif	-.03	-.13	-.15	-.02	-.22		-.57	-.25	.16	-.53	-.17		.11	-.07
CPI	-.31	-.59	.53	-.10	.52		-.03	.30	.03	.02	-.04		.01	.39
CPLC	.04	-.11	-.42	-.04	.74		.02	-.19	-.17	-.04	-.03		-.14	.01
CPLF	-.02	-.06	-.04	.30	-.16		-.11	-.03	-.25	-.33	-.88		.04	.04
CPLM	.01	-.07	-.06	-.02	-.25		-.02	-.09	-.02	-.10	-.04		.05	-.08
INT_y_dif	-.30	-.17	.15	-.25	-.19		-.18	-.13	.04	.02	-.48		-.48	-.04
EXR_y_dif	.04	.00	-.67	-.29	-.26		-.05	-.29	-.09	.03	-.03		-.13	-.02
UNE_y_dif	.30	.10	.08	.40	.05		-.15	.32	.10	.11	-.14		.00	-.19
OIL_y	.06	-.01	-.59	-.01	.02		-.11	-.10	-.04	.09	-.04		.04	-.01
INN_y	.83	.85	.30	.05	.03		.30	.73	.51	-.67	.48		.17	.37
SPL_y	.29	-.24	-.03	-.01	-.05		.01	.00	-.06	.20	-.31		-.03	-.03
EXP_lag	-.04	.02	.05	-.01	.32		.78	.37	-.04	.33	.76		-.04	.09
GDP_y_dif_lag	-.09	-.06	-.54	-.02	-.35		-.18	-.55	-.12	-.03	.04		.15	-.04
CPL_lag	-.09	-.05	-.03	-.11	-.67		-.68	-.52	-.11	-.59	-.05		-.02	.15
CPL_C_lag	-.07	-.08	-.16	-.10	.00		-.12	-.07	.06	.06	-.16		-.15	-.54
CPL_F_lag	-.01	-.06	-.11	.09	-.35		-.08	-.24	.10	-.05	-.90		.00	-.01
CPL_M_lag	.02	-.09	-.77	-.05	-.02		.01	.03	-.02	-.07	-.08		-.03	.05
UNE_y_dif_lag	.01	.02	.24	-.11	.32		-.22	.07	.01	-.02	-.17		.35	-.08

Source: Own calculations

Notes: Changes in posterior inclusion probability averages greater than 0.2 or less than -0.2 are in bold.

Appendix C: Models with additional lags

This appendix reports results from alternative model specifications that include additional lags of the explanatory variables. The purpose is to test whether incorporating longer memory effects alters the set of significant determinants of inflation expectations. We compare the posterior inclusion probabilities from these extended models with those of the baseline specification to evaluate the robustness of our findings.

Table C1: Bayesian model averaging (households, full sample, additional lags)

Variable	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
INT_y_dif	.074	.431	.053	.420	.036	.061	.125	<u>.933</u>	<u>.886</u>	.058	.144	.058	.186	.120
EXR_y_dif	.200	.096	.045	.264	.063	.245	.020	.144	.144	.053	.356	.189	.063	.768
OIL_y	.025	.009	.086	.007	.008	.043	.006	.010	.015	.014	.077	.885	.049	.084
INN_y	.999	<u>.604</u>	1.00	.431	.112	.036	.096	.017	.153	.988	.317	.029	.978	.106
SPL_y	.037	.021	.025	.022	.009	.463	.023	.065	.058	.041	.141	1.00	.898	.024
EXP_lag	.805	<u>.525</u>	1.00	.429	1.00	.854	<u>.924</u>	.725	.370	.806	.948	.101	.318	.155
GDP_y_dif_lag	.110	.063	.164	.391	.047	.246	.089	.045	.125	.113	.172	.132	.129	.090
CPL_lag	.437	<u>.646</u>	.053	.283	.130	<u>.914</u>	.107	.076	.324	.478	<u>.746</u>	.177	.087	.308
CPL_C_lag	.207	.424	.091	.628	.216	.800	.210	.080	<u>.565</u>	.065	.101	.320	.820	.276
CPL_F_lag	.054	.243	.048	.098	.054	.209	.053	.082	.173	.066	.201	.082	.248	.106
CPL_M_lag	.046	.033	.032	.059	.050	.088	.153	.056	.076	<u>.502</u>	.044	.036	.285	.080
UNE_y_dif_lag	.110	.202	.856	.375	.155	.013	.184	.406	.111	.140	.172	.008	.118	.080
GDP_y_dif_lag_2	.056	.069	.987	.046	.143	<u>.563</u>	.120	.101	.079	.069	.101	.279	.190	.058
CPL_lag_2	.104	.051	.050	.073	.098	.334	<u>.726</u>	.371	.054	.071	.485	.072	.192	.197
CPL_C_lag_2	.140	.052	.044	.067	.267	<u>.532</u>	.128	.319	.356	.351	.218	.103	.157	.210
CPL_F_lag_2	.076	.056	.123	.153	.112	.112	.072	.210	.103	.200	.123	.061	<u>.649</u>	.435
CPL_M_lag_2	.044	.035	.102	<u>.598</u>	.089	.142	.128	.073	.138	.060	.034	.043	.091	.828
UNE_y_dif_lag_2	.096	.238	.174	.136	.148	.070	.103	.144	<u>.747</u>	.334	.150	.023	.151	.144

Source: Own calculations

Notes: Posterior inclusion probabilities greater than 0.5 are underlined, and values greater than 0.75 are in bold.

Table C2: Bayesian model averaging (professionals, full sample, additional lags)

Variable	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
INT_y_dif	.283	.751	.666	.999	.183	.113	.366	.942	.827	.059	.296	<u>.573</u>	.976	.153
EXR_y_dif	.245	.042	.014	.961	.035	.423	.045	<u>.729</u>	.046	.035	<u>.621</u>	.304	.122	.120
OIL_y	.160	.042	.023	.008	.037	.185	.009	.878	.014	.819	.242	.086	.146	.119
INN_y	<u>.688</u>	.020	.050	.050	.013	.040	.994	.013	.858	.999	.916	<u>.505</u>	1.00	.450
SPL_y	.161	.020	.009	.116	.012	1.00	.017	.015	.116	.141	.030	.267	.187	.085
EXP_lag	.153	.210	.036	.077	.983	.162	.114	.113	.228	.943	1.00	.119	.082	.903
GDP_y_dif_lag	.169	.061	.044	.117	.052	.261	.086	.307	.147	.066	.138	.209	.344	.090

Variable	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
CPL_lag	.076	.904	.992	.220	.204	.100	.930	.319	.265	.073	.032	.460	.063	.137
CPL_C_lag	.384	.119	.066	.164	.278	.146	.225	<u>.716</u>	.375	.060	.113	.114	.976	.208
CPL_F_lag	.075	.254	.032	.092	.386	<u>.566</u>	.841	.104	.094	<u>.557</u>	.040	<u>.578</u>	.778	.110
CPL_M_lag	.185	.070	.030	.446	.041	.150	.181	.475	.038	.058	.018	.065	.121	.083
UNE_y_dif_lag	.452	.202	.180	.109	.154	.008	.185	.424	<u>.710</u>	.354	.339	.005	.435	.108
GDP_y_dif_lag_2	.131	.057	.495	.064	.044	.100	.765	.046	.065	.237	.091	.832	.161	.090
CPL_lag_2	<u>.513</u>	.054	.030	.163	.133	.179	.340	.060	.055	.034	.111	.169	.086	.255
CPL_C_lag_2	.230	.061	.046	.092	.111	.426	.162	.086	.194	.181	.039	.164	.279	.189
CPL_F_lag_2	.077	.044	.095	.103	.084	.126	.126	.155	.114	.263	.022	.128	.178	.219
CPL_M_lag_2	.059	.035	.138	.245	.049	.046	.099	.098	.035	.131	.059	.229	.171	.169
UNE_y_dif_lag_2	<u>.558</u>	.164	.223	.106	.144	.055	.165	.173	.158	.263	.133	.135	.880	.235

Source: Own calculations

Notes: Posterior inclusion probabilities greater than 0.5 are underlined, and values greater than 0.75 are in bold.

Table C3: Bayesian model averaging (firms, full sample, additional lags)

Variable	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
INT_y_dif	.343	.491	.062	.267	.097		.088	.934	.772	.117	.085		<u>.540</u>	.246
EXR_y_dif	.175	.063	.116	.101	.137		.033	.311	.072	.102	.117		.044	.042
OIL_y	.081	.024	<u>.698</u>	.014	.310		.022	.383	.301	.900	.075		.866	.014
INN_y	.100	.100	.999	.297	.108		.184	.995	.100	.958	.919		.161	.683
SPL_y	.776	.040	.057	.051	.069		.079	.073	.044	.482	.043		.181	.060
EXP_lag	.127	.100	.100	.801	.100		.100	.186	.268	.273	.993		.923	.996
GDP_y_dif_lag	.100	.094	.165	.172	.154		.087	.235	.313	.094	.158		.136	.109
CPL_lag	.119	.037	.123	.083	.450		.139	<u>.675</u>	.148	<u>.710</u>	.039		.074	<u>.566</u>
CPL_C_lag	.109	.047	.075	.084	<u>.727</u>		.141	.399	<u>.688</u>	.102	.047		.143	.303
CPL_F_lag	.071	.047	.132	.063	.131		.078	.085	.070	.159	.025		.724	.116
CPL_M_lag	.056	.043	.076	.062	.150		.164	.786	.089	.069	.023		.096	.150
UNE_y_dif_lag	.231	.196	.288	.315	.193		.138	.483	<u>.500</u>	.244	.146		.118	.123
GDP_y_dif_lag_2	.076	<u>.508</u>	.256	.055	.168		.083	.150	.116	.090	.105		.494	.127
CPL_lag_2	.128	.042	.105	.112	.128		.124	.098	.051	.044	.183		<u>.716</u>	.120
CPL_C_lag_2	.094	.038	.214	.167	.207		.148	.098	.150	.071	.836		.070	.218
CPL_F_lag_2	.084	.048	.108	.096	.175		.394	.108	.068	.161	.051		.195	.115
CPL_M_lag_2	.074	.036	.161	.223	.205		.184	.153	.069	.296	.024		.044	.331
UNE_y_dif_lag_2	.183	.148	.296	.248	.248		.310	.377	.232	.278	.118		.214	.172

Source: Own calculations

Notes: Posterior inclusion probabilities greater than 0.5 are underlined, and values greater than 0.75 are in bold.

Table C4: Bayesian model averaging (households, probability changes, additional lags)

Variables	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
INT_y_dif	-.42	.27	.03	.13	.01	.00	-.06	.00	-.46	.01	-.68	-.11	-.06	-.44
EXR_y_dif	.01	.09	.01	-.51	.11	-.02	-.01	-.02	-.05	-.48	.16	-.01	.02	.38
OIL_y	.01	.01	.19	.00	-.03	-.07	.00	.00	-.04	-.03	.01	.64	.07	.05
INN_y	.87	.71	.82	.31	.57	-.01	.65	-.12	.35	.89	.29	.00	.51	.03
SPL_y	.01	-.01	-.03	-.01	.00	-.20	-.06	-.01	-.49	-.21	.17	.12	.51	-.12
EXP_lag	.29	.22	.00	.17	.45	.21	.23	.28	.38	.57	-.01	-.03	-.18	-.02
GDP_y_dif_lag	-.58	-.01	-.32	.25	-.18	.06	-.07	-.06	-.18	.00	-.05	-.03	-.18	-.14
CPL_lag	.11	.06	-.76	.07	-.34	.66	-.21	-.31	.06	-.19	.08	-.18	-.09	.18
CPL_C_lag	-.63	-.27	.14	.52	.09	.53	.07	-.06	.13	-.13	-.18	.05	.39	.04
CPL_F_lag	-.06	.05	-.10	.01	-.13	.09	-.20	.02	.05	-.31	.07	-.01	.02	-.11
CPL_M_lag	-.01	-.01	-.04	-.34	-.06	.00	-.25	.01	-.14	.27	-.06	-.03	.07	-.24
UNE_y_dif_lag	-.52	.14	-.22	.04	.02	.02	.06	.11	-.20	-.01	-.07	.00	-.10	-.08
GDP_y_dif_lag_2	-.21	-.33	.26	-.06	.14	.42	-.03	-.18	-.08	-.21	-.39	-.06	-.10	-.12
CPL_lag_2	-.34	-.36	.13	-.09	-.35	.03	.05	.10	.55	-.03	.17	-.05	-.07	.04
CPL_C_lag_2	.24	-.03	-.04	-.15	.15	-.38	-.03	.14	.11	-.15	.03	-.07	.02	-.24
CPL_F_lag_2	.00	-.01	.07	.09	-.13	-.11	-.11	.09	-.49	-.28	.04	.01	.28	.14
CPL_M_lag_2	-.01	-.01	.08	.54	.00	-.08	.03	.03	.01	-.14	.06	.01	-.10	.20
UNE_y_dif_lag_2	-.02	-.53	.04	-.02	-.02	-.01	-.03	-.03	.26	.22	.02	.25	-.05	-.08

Source: Own calculations

Notes: Changes in posterior inclusion probability averages greater than 0.2 or lesser than -0.2 are in bold.

Table C5: Bayesian model averaging (professionals, probability changes, additional lags)

Variables	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
INT_y_dif	-.03	.51	.14	.11	.08	-.60	.09	.38	.09	.00	.17	-.23	.68	.47
EXR_y_dif	.05	-.77	-.03	.08	-.01	.04	.02	.49	-.71	-.01	.44	.00	-.09	.13
OIL_y	.06	-.30	-.74	-.01	-.02	.06	.00	.35	-.71	.19	.20	-.25	-.10	.06
INN_y	-.01	-.10	-.28	-.05	-.02	-.02	.90	-.10	.65	.88	-.01	.00	.70	.08
SPL_y	.06	-.31	.00	.03	-.03	.01	.00	-.03	-.61	.02	.00	.03	.05	.01
EXP_lag	.21	-.14	-.02	-.12	.32	-.02	-.16	-.30	.04	.35	.00	-.21	-.12	-.36
GDP_y_dif_lag	.05	-.30	-.08	.01	-.14	-.19	-.13	-.10	-.10	-.20	.03	.08	-.44	-.21
CPL_lag	-.03	.31	.00	.09	-.07	.53	-.05	-.10	-.52	-.50	-.02	-.27	-.14	-.25
CPL_C_lag	.36	.42	-.13	-.03	.05	-.26	.33	.51	.09	-.22	.04	-.06	.14	.21
CPL_F_lag	.00	-.25	-.06	-.01	.16	.32	.29	-.01	-.66	-.09	-.06	.22	.28	-.01
CPL_M_lag	-.06	-.08	-.03	.00	-.03	.01	.07	.40	.00	-.05	-.06	-.04	-.12	.00
UNE_y_dif_lag	.39	-.07	-.15	-.04	-.03	-.16	.04	.16	-.18	-.02	.30	.06	.06	.15
GDP_y_dif_lag_2	-.08	-.14	.06	-.05	-.13	.56	.31	-.16	-.68	.01	.03	.01	-.21	-.09

Variables	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
CPL_lag_2	.25	-.08	-.04	-.22	-.06	.08	.27	-.23	-.08	-.12	.07	.03	-.11	.28
CPL_C_lag_2	-.01	-.10	-.07	-.16	-.01	.38	.25	-.06	.05	-.28	.01	.00	.22	-.14
CPL_F_lag_2	.01	-.09	-.08	.00	.00	-.22	.00	-.02	.06	.20	.02	.00	-.45	.09
CPL_M_lag_2	.01	-.04	.00	-.10	-.13	-.01	.02	.03	-.06	.05	.02	-.14	-.04	.14
UNE_y_dif_lag_2	.16	-.77	.01	-.20	-.07	-.05	-.05	-.30	-.57	-.19	-.14	.02	.58	-.22

Source: Own calculations

Notes: Changes in posterior inclusion probability averages greater than 0.2 or lesser than -0.2 are in bold.

Table C6: Bayesian model averaging (firms, probability changes, additional lags)

Variables	AU	CZ	EA	IS	JP	KR	NO	NZ	PL	SE	TR	UK	US	ZA
INT_y_dif	-.05	-.07	-.26	-.03	-.28		-.58	-.06	.19	-.49	-.17		.10	-.12
EXR_y_dif	-.24	-.58	.20	-.10	.73		.06	.01	-.03	.03	-.02		.04	.28
OIL_y	.01	-.06	-.21	-.04	.79		.03	-.45	-.22	-.02	-.05		-.14	.01
INN_y	-.02	-.03	-.07	.34	-.05		-.20	.03	-.13	-.29	-.83		.06	.05
SPL_y	.03	-.05	-.06	-.01	-.04		.04	-.05	-.02	-.08	-.04		.05	-.15
EXP_lag	-.30	-.15	.08	-.28	.09		-.17	-.31	.18	.03	-.43		-.51	-.12
GDP_y_dif_lag	.04	.01	-.60	-.34	-.10		-.03	-.15	-.01	.03	-.04		-.10	-.02
CPL_lag	.33	.12	.12	.47	.06		-.12	.21	.09	.09	-.13		.02	-.17
CPL_C_lag	.05	.00	-.25	-.01	.02		-.08	.03	.00	.08	-.05		.04	-.01
CPL_F_lag	.83	.80	.37	.11	.05		.25	.74	.55	-.58	.43		.19	.35
CPL_M_lag	.25	-.17	-.03	.00	.00		.01	.02	-.02	.18	-.28		-.03	-.13
UNE_y_dif_lag	-.04	.02	.22	-.01	.13		.78	.57	-.05	.30	.75		-.04	.11
GDP_y_dif_lag_2	-.10	-.05	-.56	-.02	-.17		-.18	-.50	-.03	-.04	.04		.13	-.08
CPL_lag_2	-.08	-.03	-.09	-.09	-.77		-.70	-.66	-.13	-.53	-.06		-.01	.11
CPL_C_lag_2	-.10	-.05	-.20	-.17	.12		-.09	-.01	.03	.06	-.16		-.19	-.52
CPL_F_lag_2	-.02	-.03	-.13	.10	-.16		-.06	-.15	.10	-.06	-.86		-.01	.00
CPL_M_lag_2	.04	-.08	-.72	-.05	.03		.01	.11	-.04	-.05	-.08		-.02	.04
UNE_y_dif_lag_2	.00	.02	.35	-.12	.33		-.19	.19	.10	-.02	-.18		.31	-.09

Source: Own calculations

Notes: Changes in posterior inclusion probability averages greater than 0.2 or lesser than -0.2 are in bold.