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What can we learn from the distributions of inflation expectations across European households?

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What can we learn from the distributions of inflation expectations across European households?*

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Abstract

Quite a lot. We use a very large dataset of inflation expectations formed by households across the euro-area over the period 2004:1-2023:11 to assess the degree of existing heterogeneity, and whether features of the households' cross-sectional distribution in these economies are informative for inflation realizations. We summarize the heterogeneity across households using a recent functional data approach, and show that the functional components affect inflation realizations across the euro-area. This points to a role for the distribution of inflation expectations in the Phillips Curve relation, beyond the role of consensus expectations implied by models which do not allow for such heterogeneity. Moreover, we find that the inflationary impact of the functional components differs across high-inflation and low-inflation environments. Importantly, empirical models that account for the distribution of past expectations of current inflation in addition to the distribution of current expectations of future inflation, do better during the period under study as compared to models that include only the forward-looking component, especially during turbulent times. This suggests that rational inattention models with heterogeneity would be a good starting point for building macroeconomic models which can give an empirically relevant Phillips Curve relation.

Keywords: inflation, inflation expectations, heterogeneity, functional regression.

JEL Classification: E31, D84

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1 Introduction

The relation between inflation realizations and inflation expectations is a key component of the New Keynesian Phillips curve but is also interesting in itself for both policy and theory alike. Survey data have been proposed as a direct measure of inflation expectations, see, e.g., Coibion and Gorodnichenko (2012), and come with the advantage of requiring minimum assumptions on the way expectations are formed. Concern for the empirical examination of the above relationship using survey data pertains to how to best summarize agents' beliefs about the future evolution of prices (Mavroeidis et al. (2014)). For example, households' and firms' beliefs are highly heterogeneous around the consensus and cannot be adequately summarized by a simple measure of central tendency. While using dispersion measures can go some distance towards capturing heterogeneity (see Reis (2022)), other features of the cross-sectional distribution of inflation expectations could also be important but remained relatively unexplored until recently.

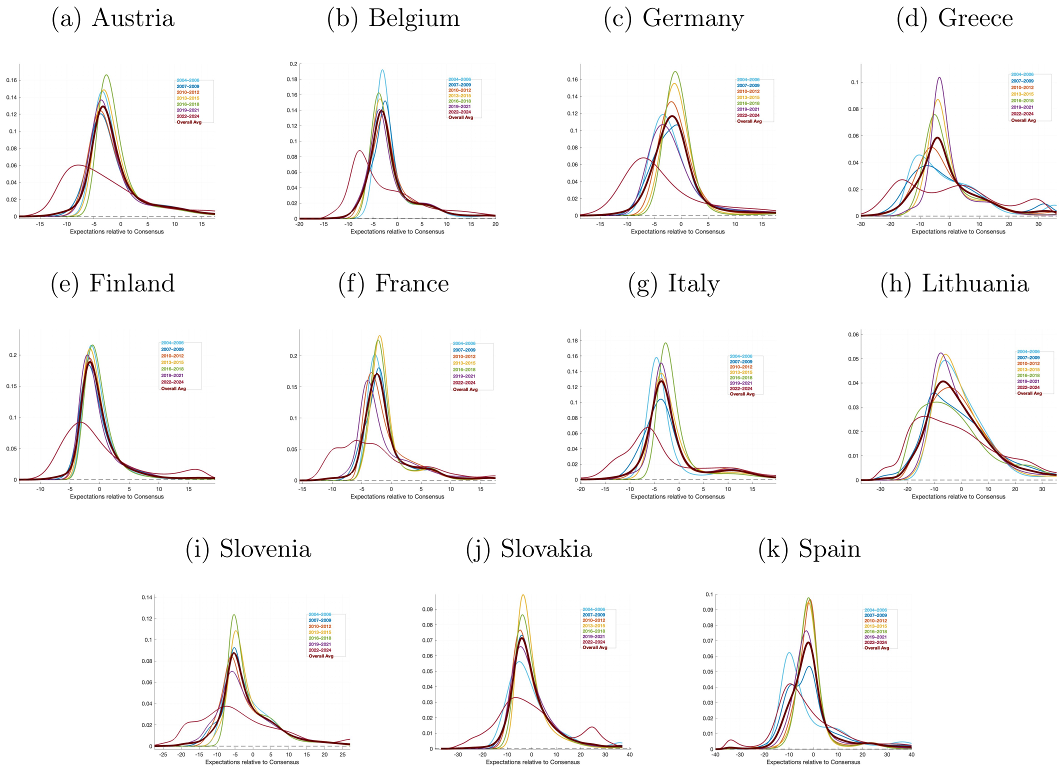
Meeks and Monti (2023) propose using functional data analysis to deal with the aggregation problem of incorporating individual survey forecasts in a macroeconomic model of price-setting behaviour. This method goes beyond using higher moments of the cross-sectional distribution of inflation expectations across households. It treats expectations as a time series of continuous distributions, i.e., a functional time series, summarizing the cross-sectional heterogeneity across household expectations using a set of functional principal components. This makes it possible to summarize and describe the belief dynamics from the cross-section of households and to examine how subjective beliefs can affect inflation dynamics.[1]

The above paper focuses on the US economy. One is thus left to wonder whether, in addition to within country heterogeneity across households, there might be substantial cross-country heterogeneity regarding the belief dynamics which can then affect the inflation dynamics in different ways for different countries. To the best of our knowledge, no work has studied

[1]Close in spirit, Chang et al. (2022) point out the importance of accounting for the whole distribution when studying the impact of various shocks on inflation expectations.

systematically such cross-country differences.[2] In Figure 1, we present a visualization of the degree of cross-country heterogeneity of the distributions of inflation expectations across households. Details of the estimation can be found in subsection 2.1 and subsection 3.1.

Figure 1: Distributions of inflation expectations relative to their within-country sample average (consensus) for Euro area economies. Each subplot illustrates the time heterogeneity of these distributions by showing three-year average densities, along with the overall average density across the entire sample period(dark red).



We pursue our analysis by making use of the quantitative questions regarding price expectations from the Business and Consumers Survey (BCS) of the European Commission available at the household level at a monthly frequency over the period 2004:1-2023:11 across euro-area economies. We find that the cross-sectional distribution of inflation expectations varies over time within each country and across the euro-area. Utilizing the Meeks and Monti (2023) functional data approach to account for variation in the distributions of inflation expectations, we find that this can be summarized by a small number of functional

[2]Utilizing data from different economies as opposed to focusing on a single country also renders any findings more general and potentially more useful for macroeconomic theory, as we show and discuss more extensively towards the end of section 3.5.

factors. We proceed to investigate the relevance of these factors for inflation realizations and show that they affect inflation realizations strongly across these euro-area economies. This points to a role for the distributions of inflation expectations in the Phillips Curve relation, beyond the role of consensus expectations implied by standard models of the macroeconomy which do not allow for such heterogeneity. We also find that the inflationary impact of these functional componets differs across high-inflation and low-inflation environments. Importantly, empirical models that account for the distribution of past expectations of current inflation in addition to the distribution of current expectations of future inflation, do better during the period under study as compared to models that include only the forward-looking component, especially during turbulent times. This suggests that rational inattention models with heterogeneity would be a good starting point for building macroeconomic models which can give an empirically relevant Phillips Curve relation.

The next section presents our data and some preliminary analysis. We then present the functional data approach applied in our paper and present some evidence of cross-country heterogeneity in belief dynamics. Afterward, we present the functional regression analysis that aims to help understand the role of the cross-sectional distribution of households' inflation expectations in determining inflation in these euro-area economies. Finally, we examine the drivers of cross-country heterogeneity in belief dynamics, before briefly concluding.

2 Data and preliminary analysis

2.1 Data description

We make use of the BCS.[3] These surveys are designed to be representative of the population of each country, capturing demographic and socioeconomic heterogeneity, providing us with the ideal foundation for answering questions surrounding the relationship of inflation expectations with inflation. Questions are carried out at a monthly frequency in each coun-

[3]This same dataset is used in Geiger et al. (2025) to investigate the impact of major macroeconomic disruptions on the formation and accuracy of inflation expectations. An earlier edition of this dataset, before it was publicly released, had been utilized for the period May 2003 to December 2016 in Duca-Radu et al. (2021) to study the consumption (intentions) response of households to their beliefs about future inflation.

try during the period under study. For most of the countries, the survey is conducted by computer-assisted telephone interviews.

The BCS offers both qualitative and quantitative questions regarding the households' price expectations. Similar questions are available for households' perceptions of past inflation. Responses are available from January 2004 up to December 2023, offering a common time span for most countries. The BCS also offers a sufficient amount of cross-sectional responses that ranges from 700 to 2000 for each month the surveys are conducted. Our focus will be on Euro area countries that provide data for a sufficient number of years.

The following questions ask respondents to report both qualitatively and quantitatively their perception and expectations regarding prices:

Expected price development over the next 12 months: *"How do you think prices in general will develop over the next 12 months compared to the previous 12 months? They will:"*
Increase more than before; Increase at about the same rate; Increase less strongly than before; Stay about the same; Fall.

Expected inflation rate: *"By how many percent do you expect consumer prices to go up/down in the next 12 months?"*
Consumer prices will increase by _________% / decrease by _________%.

Perceived price development over the past 12 months: *"How do you think prices in general have developed over the past 12 months? They have:"*
Increased strongly; Increased moderately; Increased slightly; Stayed about the same; Fallen.

Perceived inflation rate: *"How many percent do you think prices in general have increased/decreased on average over the past 12 months?"*
Consumer prices have increased by _________% / decreased by _________%.

Some initial data processing is needed before making any estimation. Given the very general nature of the questions about prices, households are allowed to give any point estimate about their price expectations and price perceptions. This has the benefit of not introducing any bias on household responses. However, it comes at a cost of observing many extreme values.

The first step is to define what we consider as an outlier and how to treat it. We cannot simply discard an extreme observation just for estimation purposes. Following Curtin (1996), a person that reports an extremely large value or an "outlier" is still a person that expects a very sharp increase on prices in the future. Given that, instead of discarding extreme values we winsorize them at the highest 99% and bottom 1% of the distributions.

The next issue has to do with the missing values. Those who responded to the qualitative questions that they expect prices to "Stay about the same" were not asked to make a point forecast for prices in the future. Subsequently, their respective value of the quantitative answer is missing and we thus imputed the value of zero as a reasonable approximation

All aggregate variables are in monthly frequency from January 2004 to December 2023. For the calculation of inflation we used the annualized month-on-month percentage change of the seasonally adjusted harmonized consumer price index from the ECB webpage. Seasonal adjustment was made using the x11-toolbox for the countries considered. Monthly seasonally adjusted unemployment rate data were obtained from Eurostat. For the estimation of the unemployment gap for each country we use the difference between the unemployment rate and its time-varying trend which proxies for the natural rate of unemployment. This was estimated using the HP-filter with lambda parameter equal to 14400 for all countries.

In addition,we use the monthly percentage change of oil prices based on the Brent Crude Oil price for Europe and measured in Dollars per Barrel. This series was seasonally adjusted following the same methodology as before. Higher oil prices can directly increase inflation through higher input costs, and indirectly affect inflation via their influence on expectations. Early work of Coibion et al. (2018) show that when estimating the relationship between inflation and household inflation expectations using US data, the effect of household expectations remains significant even after accounting for the direct effect of oil prices on inflation. We adopt a similar approach in all our specifications, by controlling for the current and first lag of oil prices.

We include also, the Global Supply Chain Pressure Index (GSCPI) Benigno et al. (2022)

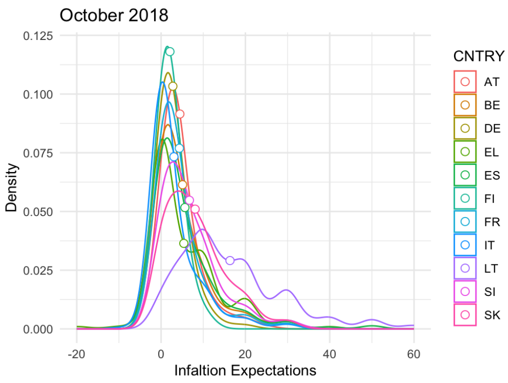
as a control variable in our empirical analysis. The GSCPI captures global supply bottlenecks, transportation costs, and other disruptions that can directly affect domestic price pressures. Incorporating this index allows us to isolate the impact of inflation expectations from supply-side shocks, which is particularly important given the historically high and volatile supply chain pressures observed during and after the COVID-19 pandemic. Prior research has shown that augmenting the Phillips curve with the GSCPI improves its empirical performance Ascari et al. (2024). In this paper, we leverage the GSCPI to account for the direct contribution of global supply disruptions to realized inflation.

2.2 The high inflation period

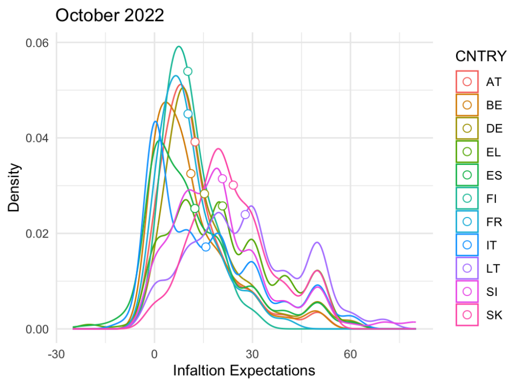
As mentioned before, the available sample covers a time span of twenty years across euro-area countries. Following the expansionary fiscal and monetary policies in response to the Covid-19 pandemic and the Russian invasion of Ukraine, euro-area inflation surged. This was a shift from an environment of low and stable inflation to historically high inflation levels. The surge in inflation potentially undermined the anchoring of inflation expectations.

Figure 2 shows the inflation expectations distributions for the euro-area economies before and after this surge in inflation. This figure displays the uncentered estimated densities across the Euro area countries under both low- and high-inflation regimes. The densities are estimated using kernel density estimation with a rule-of-thumb bandwidth. White spheres represent the sample mean. In October 2018, during a period of low and stable inflation, there was relatively low cross-country heterogeneity in inflation expectations across the euro-area. A very large share of the population expected stable inflation, with a greater mass of the distribution around zero and on low positive values of expected inflation. In October 2022, inflation reached its peak and heterogeneity across countries rose. The cross country heterogeneity is not only evident in the means. Instead, the inflation surge was accompanied by a massive widening of the distributions of inflation expectations in these Euro area economies that appear more disparate as compared with the period of low and stable inflation.

Figure 2: Estimated densities of inflation expectations across euro area countries under low- and high-inflation regimes. The densities are obtained using kernel density estimation with a rule-of-thumb bandwidth. White spheres denote the corresponding sample means.



(a) Inflation Expectations 2018



(b) Inflation Expectations 2022

Table 1: Summary statistics of inflation (infl.) &inflation expectations (exp.) before and after 2020

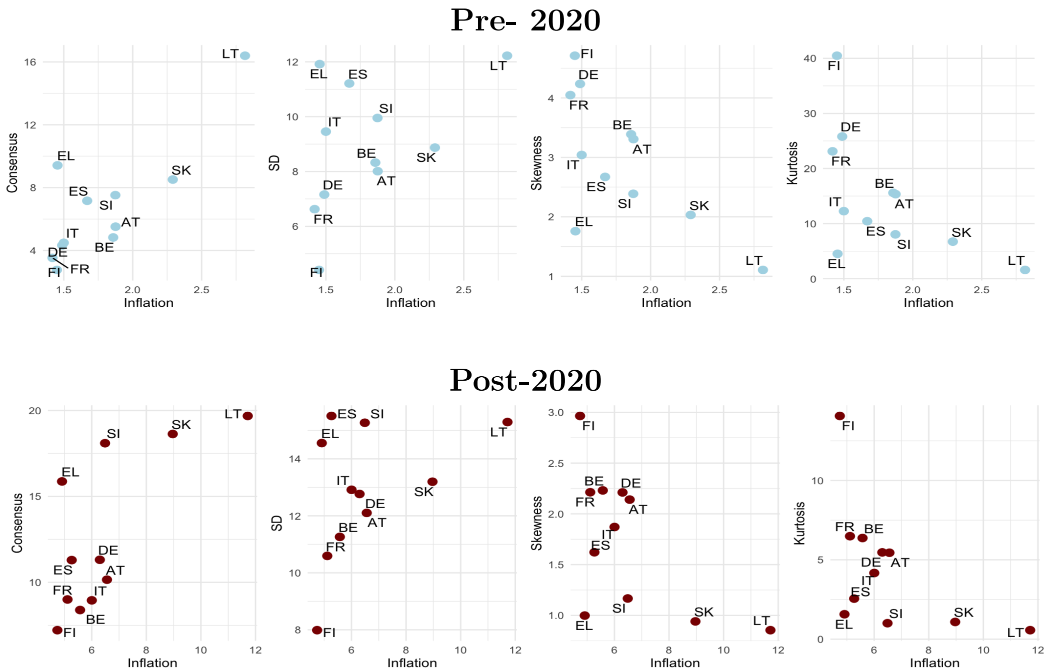
Country	Infl. Pre	Infl. Post	Mean exp. Pre	Mean exp. Post	SD exp. Pre	SD exp. Post	Skew exp. Pre	Skew exp. Post	Kurtosis exp. Pre	Kurtosis exp. Post
AT	1.88	6.56	5.52	10.15	8.01	12.10	3.31	2.14	15.34	5.45
BE	1.86	5.57	4.83	8.39	8.33	11.26	3.39	2.23	15.58	6.37
DE	1.49	6.30	4.33	11.31	7.16	12.77	4.24	2.21	25.81	5.47
EL	1.45	4.91	9.42	15.87	11.92	14.55	1.76	1.00	4.51	1.57
ES	1.67	5.27	7.16	11.29	11.21	15.51	2.67	1.62	10.43	2.56
FI	1.45	4.74	2.76	7.22	4.41	7.99	4.71	2.96	40.47	14.06
FR	1.42	5.11	3.53	9.00	6.63	10.59	4.05	2.21	23.12	6.49
IT	1.50	6.00	4.49	8.95	9.46	12.91	3.04	1.87	12.26	4.17
LT	2.81	11.72	16.40	19.68	12.22	15.29	1.11	0.85	1.59	0.57
SI	1.87	6.49	7.52	18.10	9.95	15.27	2.39	1.17	8.04	1.01
SK	2.29	8.97	8.51	18.63	8.87	13.20	2.03	0.94	6.72	1.09

Table 1 presents summary statistics of inflation and inflation expectations across the Euro area for the pre-2020 and post-2020 sample periods. The statistics include actual inflation, average expectations, and higher moments (standard deviation, skewness, and kurtosis) of the distribution of expectations. We observe that the distributions became more dispersed, left-skewed, and with fatter than normal tails after 2020 as compared to the period of low and stable inflation before 2020.

Figure 3 compares characteristics of the distribution of inflation expectations across euro-area countries before and after 2020. The horizontal axis shows the inflation rate whereas the vertical axis corresponds respectively to each of the four moments of the distribution.

One notable insight we can get from Figure 3 is that complex distributional behaviour is not only found in countries with high inflation. Greece, Spain, Italy and Slovenia are countries that are characterized with low average inflation. The first two have experienced deflation as

Figure 3: Characteristics of the distribution of inflation expectations before and after 2020. The horizontal axis shows the inflation rate and the vertical axes correspond to each of the four moments of the distribution



well. Yet, the distribution of inflation expectations shows high dispersion, excess skewness and kurtosis. This insight is evident even in the sample before 2020. Following year 2020 we observe another distinct feature in the data. Greece, Slovenia, Slovakia and Lithuania not only had the highest level of average inflation expectations, but systematically featured higher dispersion, more positively skewed distributions, and fatter than normal tails.

3 Functional Approach for the distribution of Inflation Expectations

As mentioned in the introduction, recent work including Mavroeidis et al. (2014), has shown significant heterogeneity when estimating the Phillips curve using direct measures of expectations from survey data. The rigorous estimation method from Meeks and Monti (2023) serves as a way to overcome the obstacle of how to best summarize all available information in the surveys, accounting for the significant time-varying heterogeneity in the cross-section.

We describe some key concepts from this method next.[4]

3.1 Functional Regression: explaining inflation realizations with the distribution of inflation expectations

The heterogeneous beliefs PC by Meeks and Monti (2023) is based on a large literature that uses subjective expectations about inflation to estimate the Phillips Curve and forecast inflation. Their approach allows for average expectations to replace their the rational expectations hypothesis and for an additional term to enter the expectations part of the Phillips Curve that describes the differences in opinions about expected inflation. Formally,

$$\pi_t = k\phi_t + \beta\overline{\pi}^e_{t+h} + (1-\theta)\beta\Delta_t$$

where $\overline{\pi}^e_{t+h}$ represent average expected inflation while Δ_t accounts for the heterogeneity of subjective beliefs relative that average.The term ϕ_t captures the real marginal cost and k corresponds to the slope of the Phillips curve. In this framework, E_N denotes the average across a cross-section of N individuals, indexed by j. The additional term that accounts for disagreement in inflation expectations, Δ_t is approximated as an unknown function γ that depends on the differences between individual household-level inflation expectations π^e_t and the consensus expectation $\overline{\pi}^e_t$.

$$\Delta_t \approx E_N[\gamma(\pi^e_t - \overline{\pi^e_t})] \quad \text{or} \quad \lim_{N\to 0} \approx \int \gamma(\pi^e_t - \overline{\pi^e_t})\, dP_t(\pi^e)$$

The empirical relationship between realized inflation and inflation expectations can be represented using a Partial Functional Linear Regression (PFLR) model, following the framework of Ramsay and Silverman (1997). In this empirical model, inflation is a scalar response variable and inflation expectations are modeled through the average expectations plus a functional component. The functional object that enters the regression is used to approximate the unobseved (mean-centered) distribution of inflation expectations. Formally, the model is given by Equation (1):

[4] A more rigorous treatment can be found in Meeks and Monti (2023) and Ramsay and Silverman (1997).

$$\pi_t = \alpha\pi_{t-1} + \beta\overline{\pi}_t^e + \int \gamma(\pi^e - \overline{\pi_t^e})\, dP_c(\pi^e) + kX_t + \epsilon_t, \quad \epsilon_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2) \tag{1}$$

Our focus is not on the estimation of a structural Phillips curve. Instead, we focus on empirically investigating the relationship between inflation and inflation expectations together with other variables that we use as controls in Xt. We also account for a set of lags of past inflation in our models in order for it to be well-specified and so that no autocorrelation remains. Past inflation is commonly used in the empirical literature on the Phillips curve together with expected inflation, in so called hybrid versions of the Phillips curve. Our regression equation is as follows:

The first step when working with functional data is to transform the discrete values from the cross section of survey responses to a continuous distribution. To this purpose, for each month of the survey, we employ the penalized maximum likelihood with a regularization that allows for smoothing in order to obtain consistent estimates of the distribution from which responses are drawn. More details can be found in Meeks and Monti (2023) or in Ramsay and Silverman (1997). That way we create a sequence of continuous distribution functions which are treated as a functional time series object.

Another important step in Functional Data Analysis is that of "average shape". To obtain that, we horizontally translate all functions to a common feature, known as registration. We choose this to be the functional mean or consensus forecast. This way, we center all distributions around the average expectations reported from the survey respondents.

Having obtained the sequence of functions that express time-varying disagreement, we apply functional principal components analysis (FPCA) to express the functional object in terms of its principal component functions (eigen functions), a process known as Karhunen-Loeve expansion. Based on this, the functional regressor, also denoted as $X_t(i)$, is expressed and approximated in terms of its empirical eigen functions truncated at the Kth term and with the term i referred to the cross-sectional heterogeneity of survey responses around their sample average.

$$X_t(i) = \sum_{k=1}^{K} s_{kt} e_k(i)$$

where s_{kt} are the time-varying principal component scores defined as the inner product

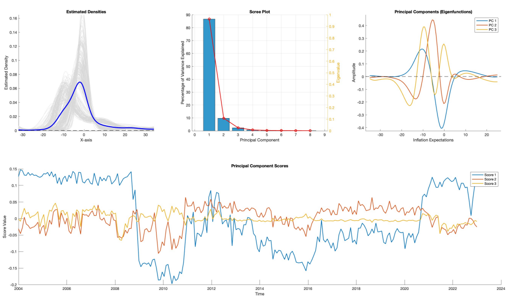
$$s_{kt} = \langle x_t, e_k \rangle,$$

where the following properties hold:

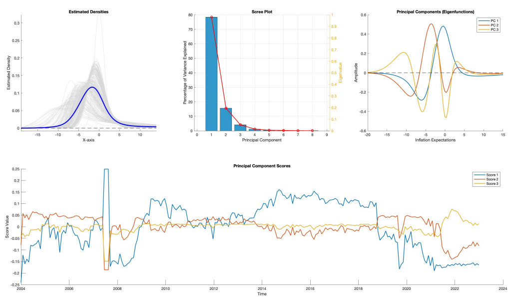
$$E[s_{kt}] = 0, \quad E[s_{kt}^2] = \lambda_k, \quad \text{and} \quad E[s_{kt} s_{k't}] = 0 \quad \text{for } k \neq k'.$$

Figure 4 illustrates a statistical summary from the time series of centered distributions of inflation expectations for the four major Euro area countries. The first graph represents the average distribution (blue) overlaid with grey lines for each period. The scree plot shows the proportion of variation explained by each principal component, the third graph displays the first three eigen functions, and the last panel refers to the time-varying scores.

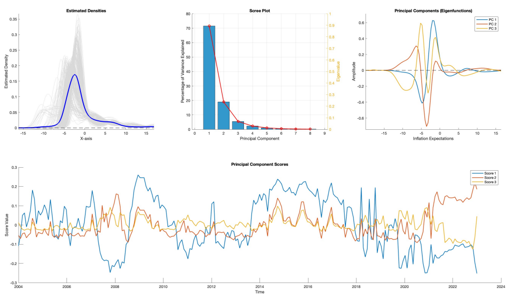
Figure 4: Statistical summary of the time series of centered distributions of inflation expectations.



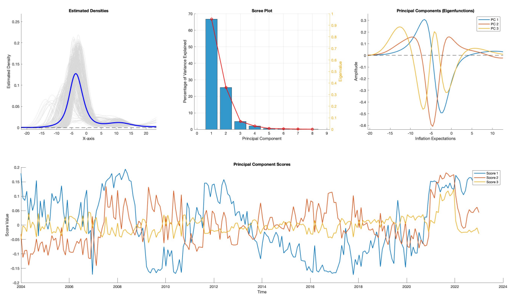
(a) Spain



(b) Germany



(c) France



(d) Italy

Expanding the functional coefficient $\gamma(i)$ in the same orthonormal basis $\{e_k(i)\}$ as the functional regressor:

$$\gamma(i) = \sum_{k=1}^{K} \gamma_k e_k(i),$$

where γ_k are the coefficients associated with the basis functions.

$$\int \gamma(i)\, x_t(i)\, di = \sum_{k=1}^{K} \gamma_k s_{k,t}.$$

$$\int \gamma(i)\, X_t(i)\, di = \int \left(\sum_{k=1}^{K} \gamma_k e_k(i)\right) \left(\sum_{k=1}^{K} s_{k,t} e_k(i)\right) di = \sum_{k=1}^{K} \gamma_k s_{k,t} \int e_k(i)^2\, di = \sum_{k=1}^{K} \gamma_k s_{k,t}$$

The first line follows from the orthogonality condition $\langle e_k, e_{k'} \rangle = 0$, $k \neq k'$, and the second line follows from the normalization condition $\|e_k\| = 1$. Substituting back in the scalar-on-function regression (1) we get:

$$\pi_t = \alpha \pi_{t-1} + \beta \overline{\pi}_t^e + \sum_{k=1}^{K} \gamma_k s_{k,t} + k X_t + \epsilon_t, \quad \epsilon_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2) \tag{2}$$

This model is an approximation of the functional regression model and can be estimated with least squares. However, one important feature of our microdata is that it spans two distinct inflation regimes: one characterized by low and relatively stable inflation across euro-area economies ranging from 2004 to approximately 2020 and the more recent period of high inflation.

For this reason, we will account for structural breaks by allowing both the intercept and slope coefficients of inflation expectations to shift. This approach enables us to investigate whether the shift in the inflation regime was accompanied by a change in the relationship between inflation and inflation expectations. We implement a global Bai-Perron test for structural breaks to detect potential changes in the intercept and permit changes in the slope at the identified breakpoints. Notably, a key breakpoint is found around the end of 2020, coinciding with the onset of the inflation surge.

$$\pi_t = \alpha \pi_{t-1} + (\beta + \beta_D D_t)\, \overline{\pi}_t^e + \sum_{k=1}^{K} (\gamma_k + \gamma_{Dk} D_t)\, s_{k,t} + \kappa X_t + \epsilon_t, \sim \mathcal{N}(0, \sigma^2) \tag{3}$$

Here, the dummy variable takes the value of 1 when there is a change of inflation regime.

$$\pi_t = \begin{cases} \alpha\pi_{t-1} + \beta\,\overline{\pi}^e_{t+h} + \sum_{k=1}^{K} \gamma_k s_{k,t} + \kappa X_t + \epsilon_t, & \text{if } D_t = 0 \\ \\ \alpha\pi_{t-1} + (\beta + \beta_D)\,\overline{\pi}^e_{t+h} + \sum_{k=1}^{K} (\gamma_k + \gamma_{Dk}) s_{k,t} + \kappa X_t + \epsilon_t, & \text{if } D_t = 1 \end{cases} \tag{4}$$

We proceed to statistical testing and inference to assess the significance and stability of the estimated relationships. Our approach combines standard parameter inference with structural break tests to account for potential regime changes. To evaluate the role of average expectations across regimes, we test whether their impact on realized inflation in the high-inflation regime is statistically different from zero. Specifically, we test the null hypothesis against the alternative:

$$H_0 : \beta + \beta_D = 0 \quad \text{vs.} \quad H_a : \beta + \beta_D \neq 0 \tag{5}$$

Under the null hypothesis, the coefficient of average expectations has no influence on realized inflation during the high-inflation regime. Rejecting the null implies that average expectations are informative in this regime. In addition,we test whether average expectations matter at all, regardless of the inflation regime from the following assumtion

$$H_0 : \beta = \beta_D = 0 \quad \text{vs.} \quad H_a : \beta = \beta_D \neq 0 \tag{6}$$

Rejection of the null indicates that average expectations exert a statistically significant effect on realized inflation, either on the low-inflation regime (β) or through the additional shift captured by β_D.

To assess whether a statistical association exists between realized inflation and the cross-sectional distribution of inflation expectations, we employ a Wald test on the coefficients of the functional component of expectations. Since in our analysis we distinguish between low and high inflation regime, the null hypothesis takes the following form:

$$H_0 : \gamma(\pi^e - \overline{\pi^e_t}) = \gamma_D(\pi^e - \overline{\pi^e_t}) = 0$$

with $\gamma(\pi^e - \overline{\pi_t^e})$ captures the effect of the mean-centered cross-sectional distribution of inflation expectations in the low-inflation regime and $\gamma_D(\pi^e - \overline{\pi_t^e})$ represents the additional effect (i.e., the difference) in the high-inflation regime.

To achieve this, we form the following hypothesis:

$$H_0 : \gamma_1 = \cdots = \gamma_K = \gamma_{D1} = ... = \gamma_{DK} = 0 \quad \text{vs.} \quad H_a : \gamma_j \neq \gamma_{DK} \neq 0 \tag{7}$$

Rejecting the null would imply that the distribution of expectations exerts a statistically significant influence on realized inflation, and that models incorporating the distribution are preferred over those relying solely on average expectations.

In addition, we test for the quantitative impact of the cross-sectional distribution on realized inflation for the high ifnlation regime. This is done again using a wald statistic as follows:

$$H_0 : \gamma_1 + \gamma_{D1} = \cdots = \gamma_K + \gamma_{DK} = 0 \quad \text{vs.} \quad H_a : \gamma_j + \gamma_{Dj} \neq 0 \quad \forall j = 1, \ldots, K \tag{8}$$

Rejecting the null indicates that the distribution of expectations matters in periods of high inflation, highlighting the importance of heterogeneity in beliefs in shaping realized inflation outcomes during that period. Practically, this test allows us to isolate the regime-specific contribution of the expectation distribution. While the earlier Wald test assessed whether the distribution is relevant in general, this test focuses specifically on periods of high inflation. In addition, we are interested whether the impact of the distribution is different across high and low inflation regime. This is captured with the coefficient γ_{Dj} which measures the additional effect of the functional components during the high inflation period We test using the following joint hypothesis:

$$H_0 : \gamma_{D1} = \gamma_{D2} = \cdots = \gamma_{DK} = 0 \quad \text{vs.} \quad H_a : \gamma_{Dj} \neq 0 \quad \forall j = 1, \ldots, K \tag{9}$$

Rejecting the null, implies that the distributionâs effect is regime-dependent, i.e., the impact of the cross-sectional heterogeneity plays is statistically different on the high inflation period compared to the low-inflation period.

Respectively for the low-inflation regime we test the following joint hypothesis:

$$H_0 : \gamma_1 = \gamma_2 = \cdots = \gamma_K = 0 \quad \text{vs.} \quad H_a : \gamma_j \neq 0 \text{ for at least one } j,\ 1 \leq j \leq K \tag{10}$$

which assesses whether the mean-centered cross-sectional distribution of inflation expectations has any impact on realized inflation during periods of low inflation. Rejecting the null indicates that at least one component of the distribution significantly influences realized inflation, implying that heterogeneity among agentsâ expectations contributes meaningfully even in stable inflation environments.

For all our specifications, we report the respective Wald statistic as well as the associated p-value in brackets in the tables of results that follow.

For the selection of the number of principal components, we follow a more subjective approach wheere, for each country, the number of principal components is selected to account for approximately 95% of the variaton in the functional regressor.

3.2 Benchmark regression model

We proceed with estimating our benchmark regression model. This involves estimating the impact of inflation expectations on inflation. It's important to note here that, due to the way the survey was conducted, it ameliorates concerns of endogeneity bias of inflation expectations responses given that these are given each month before the corresponding realizations of inflation become known. Thus, we treat expectations as exogenous (see Mavroeidis et al. (2014)).

We estimate regression equation (4) from subsection 3.1 as our benchmark regression model. We include a number of explanatory variables as controls in vector X. This includes the unemployment gap, the past inflation rate (Sum of Inflation lags), percentage change in oil prices (Oil price), and the Global Supply Chain Pressure Index (Supply Chain index). In addition, we include level-shift dummies that capture potential breaks in the intercept identified using the Bai-Perron methodology, as well as outlier dummies that account for extreme observations in the inflation series.

With respect to the functional components we are interested in, $\gamma = \gamma_D = 0$ corresponds to Hypothesis (8) from subsection 3.1, $\gamma + \gamma_D = 0$, to Hypothesis (9), $\gamma_D = 0$ to Hypothesis (10) and $\gamma = 0$ to Hypothesis (11).

Estimates from our benchmark regression are shown in Table 2. As we can see there, the impact of inflation expectations on inflation cannot be captured by the impact of average inflation expectations. We find that the functional components of inflation expectations matter for inflation in addition to average inflation expectations. This is evident from the p-values of the Wald test statistic of the hypothesis that $\gamma = \gamma_D = 0$, which allow us to reject at the one percent level, for all countries except France, the null hypothesis of a model without the functional component of expectations in favor of the alternative.

We find similar results during the low-inflation regime where we typically reject the null hypothesis that $\gamma = 0$ in all countries except France and Slovakia. The rejection of the null hypothesis that $\gamma_D = 0$ in all countries except France and Slovenia, confirms, however, that there is a statistically significant difference regarding the impact of the distribution of inflation expectations on inflation realizations between the high and low inflation regimes. We also reject the null that $\gamma + \gamma_D = 0$ in every country except France, which suggests that the functional components of inflation expectations are especially important in determining inflation in high-inflation environments.

In addition, we document a number of findings with respect to average inflation expectations. To assess their role during the high-inflation regime, we use the Wald test of the null hypothesis $\beta + \beta_D = 0$. The Wald statistics are large, with p-values that allow us to strongly reject the null hypothesis in all countries. This confirms that concensus inflation expectations exert a statistically significant impact on realized inflation in the high-inflation regime. The results are qualitatively similar for the low-inflation regime, whre the average expectations measure retains its significance for explaining realized inflation in all countries except France and Italy. The estimated coefficients on $D_1 \times$ Avg.Expectations suggest, however, that there is a statistically significant change in the estimated impact of average inflation expectations after the identified break, for all countries except France and Slovenia.[5] This provides further evidence that the relationship between inflation and inflation expectations is not constant over time.

Table 2: Benchmark model

	AT	BE	DE	EL	FI	FR	IT	LT	SI	SK	ES
Avg. Expectations	2.308***	0.691***	0.459**	0.364***	1.670***	0.351	0.777	0.469**	1.492***	0.751***	0.407
	(0.591)	(0.318)	(0.211)	(0.119)	(0.465)	(0.486)	(0.223)	(0.182)	(0.437)	(0.281)	(0.162)
D1*Avg. Expectations	5.219***	2.906***	2.240***	-1.645***	3.214**	0.520	4.397***	1.001**	0.331	1.357***	-3.225***
	(1.226)	(1.046)	(0.360)	(0.509)	(1.250)	(0.596)	(1.232)	(0.390)	(0.590)	(0.365)	(0.597)
$\beta = \beta D = 0$	30.485	19.522	69.225	16.241	29.720	3.843	36.116	9.879	26.968	66.065	29.723
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.146]	[0.000]	[0.007]	[0.000]	[0.000]	[0.000]
$\beta + \beta D = 0$	56.918	25.195	54.555	13.259	34.857	7.430	61.081	18.525	35.027	125.514	39.898
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.024]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Functional coefficient for Expected inflation											
$\gamma = \gamma D = 0$	28.766	24.114	74.649	52.836	36.978	4.746	26.425	86.770	44.668	69.601	108.083
	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.577]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\gamma + \gamma D = 0$	20.402	13.107	34.445	28.162	26.722	4.655	27.923	130.397	7.552	48.370	82.270
	[0.000]	[0.011]	[0.000]	[0.000]	[0.000]	[0.198]	[0.000]	[0.000]	[0.109]	[0.000]	[0.000]
$\gamma = 0$	12.745	18.352	23.347	21.312	6.962	1.992	6.202	21.557	21.717	4.513	13.548
	[0.005]	[0.001]	[0.000]	[0.000]	[0.073]	[0.574]	[0.102]	[0.000]	[0.000]	[0.341]	[0.003]
$\gamma D = 0$	12.821	14.861	49.856	18.272	12.821	0.683	13.767	16.548	6.829	28.936	61.326
	[0.005]	[0.005]	[0.000]	[0.000]	[0.005]	[0.877]	[0.003]	[0.002]	[0.145]	[0.000]	[0.000]
Sum of Inflation Lags [1]	-0.312	-0.945***	0.120	0.093	-0.405**	0.287	-0.066	0.328	-0.197	-0.004	1.166
	(1.908)	(15.134)	(1.026)	(0.248)	(5.106)	(2.165)	(0.226)	(2.664)	(1.223)	(0.001)	(0.280)
Unemployment gap	-0.525*	1.122	-0.044	-0.902*	-1.218*	-0.435	-0.863*	-0.981***	-0.974*	-0.452	-0.379
	(0.311)	(0.766)	(0.760)	(0.462)	(0.670)	(0.645)	(0.508)	(0.358)	(0.568)	(0.374)	(0.255)
Oil price	0.054	0.071*	0.141***	0.095***	0.137***	0.110***	0.046	0.128***	0.135***	0.065***	0.133***
	(0.039)	(0.036)	(0.019)	(0.020)	(0.033)	(0.025)	(0.033)	(0.041)	(0.027)	(0.021)	(0.029)
Lag(1) Oil price	0.091***	0.094***	-0.008	0.071***	0.036*	0.059***	0.061***	0.066	0.147***	0.026	0.071***
	(0.017)	(0.027)	(0.025)	(0.018)	(0.021)	(0.012)	(0.015)	(0.041)	(0.037)	(0.019)	(0.018)
Supply Chain Index	0.202	1.256**	-0.169	1.184	0.442	0.430	0.488*	1.232***	0.514	-0.098	0.668
	(0.228)	(0.485)	(0.247)	(0.738)	(0.377)	(0.317)	(0.259)	(0.468)	(0.442)	(0.420)	(0.581)
Dummy	-46.864***	-23.177***	-9.354**	16.022***	-8.708*	-2.941	-15.298***	-16.509***	-8.434	-15.392***	37.883***
	(11.025)	(7.944)	(4.415)	(3.804)	(4.633)	(2.921)	(5.391)	(5.464)	(10.544)	(3.156)	(7.595)
Variance Explained	0.990	0.960	0.960	0.940	0.930	0.990	0.980	0.950	0.950	0.950	0.990
	[3]	[4]	[3]	[3]	[3]	[3]	[3]	[4]	[4]	[4]	[3]
Observations	239	239	238	239	239	235	234	238	239	238	238
R^2(adjusted)	0.543	0.632	0.788	0.425	0.587	0.419	0.743	0.749	0.525	0.771	0.564
LjungBox(p-value)	0.915	0.179	0.060	0.904	0.380	0.811	0.508	0.351	0.374	0.566	0.122
Wald (p-value, lags jointly zero)	0.040	0.000	0.000	0.034	0.000	0.015	0.000	0.176	0.110	0.001	0.053

Note:*p<0.10, **p<0.05, ***p<0.01. This table presents the regression estimates with heteroscedasticity and autocorrelation-robust standard errors shown in parentheses below the estimates. Where we show hypothesis tests, we present p-values of the Wald test statistic in square brackets below the test statistic value.

[1] Parentheses show the Wald test statistic, while the asterisks indicate the significance level of the corresponding p-value.

It is common practice when estimating the Phillips curve to use an ad-hoc number of lags, as this tends to improve its empirical performance. Controlling for past inflation, allows one to directly test whether and to what extent realized inflation depends on these past values. To evaluate this question, we employ a Wald test of the null hypothesis that the sum of the coefficients on lagged inflation equals zero. Table 2 reports the estimated

[5]Surprisingly, the change in the impact of average expectations is negative for Greece and Spain. A potential explanation for this is that inflation started to decline after October 2022 while inflation expectations of households continued to increase.

sum of lagged coefficients, with the corresponding Wald statistic shown in parentheses and statistical significance indicated by the usual stars. As we can see in Table 2, once we properly aggregate inflation expectations and account for structural breaks, the effect of past inflation becomes insignificant in all countries except Belgium and Finland. This suggests that lagged inflation is generally not a key determinant of realized inflation. In other words, when expectations are appropriately aggregated, the apparent persistence of inflation largely disappears. Inflation is largely driven by expectations rather than past values.

We note that the strong link between inflation and the cross-sectional distribution of inflation expectations remains evident even when we assume that the parameters are constant over time. Table A1 shows that the null of $\gamma = 0$ is rejected for all countries except France. Concensus expectation are also significant for all countries except Greece, France and Spain, confirming that both the mean and the distribution of expectations continue to carry information for realized inflation in this setting.

Our results are also robust to using core inflation instead of the harmonized CPI, which is used as our baseline. Table A4 in the Appendix confirms that the cross-sectional distribution of current expectations about future inflation is informative for realized inflation, rejecting the null for $\gamma = \gamma_D = 0$ for all countries except Italy, implying that the distribution of expectations plays a significant role beyond the role of concensus expectations. We also reject the null for $\gamma + \gamma_D = 0$, except for Italy, highlighting the importance of the cross-sectional distribution during the high-inflation period.

3.3 Higher moments of inflation expectations added to benchmark

A distribution function can in some cases be determined from knowledge of its moments. By allowing for this possibility, we want to see if higher moment can substitute for functional principal components in which case our methodological approach would be rendered redundant. We thus augment our benchmark model with higher moments up to order four.

As we can see in Table 3, the null hypothesis that $\gamma = \gamma_D = 0$ so that the functional components of the distribution of inflation expectations are not informative for current inflation realizations, is still rejected in all countries except Austria and France. We thus infer that the functional component of inflation expectations matters for inflation in addition to higher moments of the distribution.

For the low inflation regime, higher moments hold no additional explanatory power with rare exceptions.[6] We note, however, that the effects of the standard deviation, skewness and kurtosis on inflation, differ significantly between the high and low-inflation regimes in some countries.[7]

By contrast, according to the p-values from the Wald test $\gamma = 0$, the functional principal components are significant in the low-inflation regime for Belgium, Germany, Greece, Lithuania, Slovenia and Spain. We note that, except for Austria, Belgium, France and Slovenia, we reject the null hypothesis $\gamma_D = 0$, which implies a statistically significant difference in the impact of the distribution of inflation expectations on inflation during the high-inflation regime as compared to the low-inflation regime for most countries. As a result, the functional principal components are strongly significant determinants of inflation in the high-inflation regime, in all countries except Austria, Belgium, France and Slovenia.

Our findings indicate that the information embedded in the cross-sectional distribution of inflation expectations is more effectively summarized through functional principal components than by relying on higher-order moments. The functional components of inflation expectations matter for inflation in addition to higher moments of the distribution, for all countries except Austria and France. Moreover, in the low-inflation regime, higher moments are rarely significant whereas functional principal components retain their significance in most countries. The significance of the functional components while controlling for higher moments highlights that functional principal components extract distinct features of the distribution that higher moments cannot fully capture. Consequently, our results strengthen the argument that to better understand the link between inflation and inflation expectations, one

[6]The standard deviation and skewness have a significantly negative impact on inflation at the five percent level for Slovakia and Slovenia respectively, while kurtosis has a statistically significant positive impact at the one percent level for Slovenia.

[7]For the standard deviation and skewness, at the one (five) percent level for three (as many as four) countries, and for kurtosis, at the one (five) percent level for one (three) country (countries).

needs to go beyond a framework restricted to higher moments. Using tools like functional principal components to incorporate additional features of the distribution is thus shown to be essential for understanding this important relation and, by implication, for specifying an empirically relevant Phillips curve.

Table 3: Adding Higher Moments to the benchmark model

	AT	BE	DE	EL	FI	FR	IT	LT	SI	SK	ES
Avg. Expectations	2.186***	1.243*	0.602**	0.384***	2.271***	-0.328	0.976*	0.424**	1.944***	0.727***	0.442
	(0.701)	(0.676)	(0.253)	(0.110)	(0.610)	(0.845)	(0.564)	(0.165)	(0.516)	(0.257)	(0.297)
D1*Avg. Expectations	5.839***	4.439	1.989***	-1.713***	4.410***	0.127	3.343**	0.930**	2.211*	1.435***	-3.057***
	(1.412)	(3.069)	(0.632)	(0.623)	(1.073)	(0.810)	(1.081)	(0.426)	(1.281)	(0.354)	(0.898)
$\beta = \beta_D = 0$	27.792	7.850	23.005	17.713	30.518	0.340	22.87 4	11.586	24.255	64.969	12.095
	[0.000]	[0.019]	[0.000]	[0.000]	[0.000]	[0.844]	[0.000]	[0.003]	[0.000]	[0.000]	[0.002]
$\beta + \beta_D = 0$	53.374	5.416	37.493	9.192	58.205	0.572	41.840	17.790	23.579	122.622	17.755
	[0.000]	[0.019]	[0.000]	[0.010]	[0.000]	[0.751]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Standard Deviation	-1.063	0.601	0.192	0.364	-0.130	0.358	0.202	0.246	0.134	-1.110**	0.045
	(0.949)	(0.755)	(0.293)	(0.374)	(0.565)	(0.237)	(0.339)	(0.450)	(0.638)	(0.550)	(0.192)
Skewness	1.333	0.263	-0.135	-1.848	-0.066	1.161	-0.890	-0.680	-8.002**	2.441	-0.294
	(3.525)	(3.639)	(1.706)	(3.066)	(0.393)	(1.452)	(2.200)	(3.780)	(3.438)	(1.956)	(1.260)
Kurtosis	-0.162	0.020	0.038	0.003	0.012	-0.060	0.246	-0.295	1.313***	-0.267	0.065
	(0.330)	(0.378)	(0.142)	(0.362)	(0.022)	(0.118)	(0.269)	(0.997)	(0.495)	(0.208)	(0.108)
D1 * Standard Deviation	3.087	-4.024	0.843	-1.077*	-5.887***	-0.582	-1.742	-0.250	-5.155*	-3.934***	-2.752*
	(4.022)	(2.934)	(0.722)	(0.602)	(1.664)	(0.959)	(1.155)	(1.366)	(2.652)	(0.819)	(1.537)
D1 * Skewness	-2.243	11.095	3.992	2.718	18.429***	-16.824***	-17.768***	-3.308	33.047**	-4.431	-13.457
	(39.908)	(11.990)	(9.116)	(5.072)	(4.578)	(4.149)	(1.155)	(7.380)	(15.994)	(6.967)	(8.937)
D1 * Kurtosis	0.001	-2.376*	-0.065	-0.422	-1.319***	1.429**	1.237	0.334	-4.278	2.296**	-1.173
	(5.747)	(1.437)	(0.988)	(0.553)	(0.402)	(0.605)	(1.173)	(2.225)	(3.034)	(1.100)	(1.364)
Functional Coefficient of Expected Inflation											
$\gamma = \gamma_D = 0$	5.000	24.427	52.561	28.214	15.368	4.415	28.893	47.248	15.162	111.457	28.945
	[0.544]	[0.002]	[0.000]	[0.000]	[0.018]	[0.621]	[0.000]	[0.000]	[0.056]	[0.000]	[0.000]
$\gamma + \gamma_D = 0$	4.198	1.500	49.431	12.891	13.278	2.754	27.054	36.930	3.056	96.175	22.319
	[0.240]	[0.826]	[0.000]	[0.005]	[0.004]	[0.431]	[0.000]	[0.000]	[0.548]	[0.000]	[0.000]
$\gamma = 0$	1.268	22.538	7.858	10.924	3.560	0.082	1.902	15.829	11.362	2.457	8.286
	[0.737]	[0.000]	[0.049]	[0.012]	[0.313]	[0.994]	[0.592]	[0.003]	[0.023]	[0.652]	[0.040]
$\gamma_D = 0$	4.288	3.079	33.281	17.999	13.581	1.477	19.488	18.202	3.768	63.151	24.468
	[0.232]	[0.544]	[0.000]	[0.000]	[0.004]	[0.688]	[0.000]	[0.001]	[0.438]	[0.000]	[0.001]
Sum of Inflation lags[1]	-0.388*	-0.978***	0.150	0.080	-0.602***	0.251	0.117	0.269	-0.234	0.049	0.169
	(2.871)	(14.841)	(1.720)	(0.181)	(6.969)	(1.397)	(0.985)	(1.644)	(1.913)	(0.166)	(1.315)
Unemployment gap	-0.642*	1.286	-0.096	-0.996**	-0.821*	-0.440	-0.745	-0.940***	-0.709	-0.494	-0.286
	(0.371)	(1.032)	(0.738)	(0.484)	(0.465)	(0.644)	(0.457)	(0.352)	(0.554)	(0.339)	(0.245)
Oil price	0.055	0.076**	0.144***	0.102***	0.128***	0.111***	0.040	0.131***	0.129***	0.066***	0.132***
	(0.038)	(0.037)	(0.020)	(0.022)	(0.030)	(0.025)	(0.028)	(0.040)	(0.026)	(0.020)	(0.031)
lag(1) Oil price	0.089***	0.094***	-0.008	0.077***	0.042**	0.068***	0.066***	0.066	0.156***	0.028	0.072***
	(0.018)	(0.027)	(0.026)	(0.019)	(0.019)	(0.013)	(0.018)	(0.042)	(0.037)	(0.018)	(0.020)
Supply Chain Index	0.365	1.057*	-0.154	1.008	-0.143	0.276	-0.021	1.214**	-0.216	-0.256	0.401
	(0.280)	(0.626)	(0.240)	(0.680)	(0.203)	(0.431)	(0.490)	(0.491)	(0.408)	(0.294)	(0.629)
Dummy	-70.915*	2.392	-29.956	27.405*	-22.086***	39.760***	41.285**	-8.634	5.037	19.440	112.020***
	(39.342)	(46.890)	(24.099)	(14.890)	(5.519)	(13.932)	(16.488)	(15.698)	(26.758)	(13.310)	(28.591)
Variance Explained	0.990	0.960	0.960	0.940	0.930	0.990	0.980	0.950	0.950	0.950	0.990
	[3]	[4]	[3]	[3]	[3]	[3]	[3]	[4]	[4]	[4]	[3]
Observations	239	239	238	239	239	235	237	238	239	238	238
R^2(adjusted)	0.538	0.631	0.785	0.419	0.637	0.461	0.760	0.744	0.547	0.791	0.579
LjungBox(p-value)	0.886	0.228	0.069	0.842	0.371	0.818	0.195	0.316	0.485	0.480	0.695
Wald (p-value, lags jointly zero)	0.043	0.000	0.000	0.115	0.000	0.002	0.000	0.217	0.088	0.000	0.304

Note:*p<0.10,**p<0.05,***p<0.01 This table presents the regression estimates with heteroscedasticity and autocorrelation-robust standard errors shown in parentheses below the estimates. Where we show hypothesis tests, we present p-values of the Wald test statistic in square brackets below the test statistic value.

[1] Parentheses show the Wald test statistic, while the asterisks indicate the significance level of the corresponding p-value

3.4 Adding the perceived inflation rate to the benchmark

Here, we augment our benchmark model with the functional principal components that correspond to the cross-sectional distribution of currrent perceptions regarding past inflation, and with average perceived inflation. The measure of perceived inflation comes from the quantitative question in the survey, described in detail in our data section, that asks about the households' perceived inflation rate. As we cannot directly link perceived inflation with a particular existing theory of price-setting behaviour, we treat this exercise as a robustness check. Nevertheless, it can also help understand whether heterogeneity in perceptions about past inflation realizations explains current inflation realizations directly, beyond any indirect impact it might have through shaping current expectations of future inflation.

Using the same procedure to transform discrete survey responses for perceived inflation to continuous distribution functions, our model can be written as follows:

$$\pi_t = \beta\overline{\pi}_t^e + \theta\overline{\pi}_t^p + \int \gamma(\pi^e - \overline{\pi_t^e})\, dP_t^c(\pi^e) + \int \delta(\pi^p - \overline{\pi_t^p})\, dP_t^c(\pi^p) + k'X_t + \epsilon_t, \quad \epsilon_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,\sigma^2)] \tag{11}$$

We keep the same set of controls as before and we allow coefficients of both perceived and expected inflation to change between the low and high inflation regime. Thus, equation (11) can be written as:

$$\pi_t = \begin{cases} \beta\,\overline{\pi}_t^e + \theta\,\overline{\pi}_t^p + \sum_{k=1}^{K}\gamma_k s_{k,t} + \sum_{k=1}^{K}\delta_k s_{k,t} + \kappa' X_t + \epsilon_t, & \text{if } D_t = 0 \\ (\beta+\beta_D)\,\overline{\pi}_t^e + (\theta+\theta_D)\,\overline{\pi}_t^p + \sum_{k=1}^{K}(\gamma_k+\gamma_{Dk}) s_{k,t} + \sum_{k=1}^{K}(\delta_k+\delta_{Dk}) s_{k,t} + \kappa' X_t + \epsilon_t, & \text{if } D_t = 1 \end{cases} \tag{12}$$

We present the estimates from this specification in Table 4. Having controlled for the perceived inflation rate, our previous findings remain largely intact. With respect to the functional component of expected inflation, the results indicate that the cross-sectional distribution of inflation expectations remains highly informative in all countries, as shown by the rejection of the null $\gamma = \gamma_D = 0$. The distribution of inflation expectations retains its significance during the low-inflation regime, except in France, Italy and Slovakia. However, for all but one country (Slovenia) we reject the null for $\gamma_D = 0$, implying that the impact of the distribution of expectations differs systematically between the low- and high-inflation regimes.[8] In other words, while expectations are informative in both inflationary environments for the great majority of countries, their quantitative impact is regime dependent.

That said, although perceived inflation is introduced primarily as a robustness check, it is worth noting that we can reject the null that the distribution of current perceptions of past inflation is uninformative for future inflation realizations in the case of Greece, Belgium, Finland, France, Italy, and Slovakia, as well as for Spain, albeit marginally so with a p-value of 0.061 in this case. In the low-inflation regime, we can only reject the null for $\delta = \delta_D = 0$ for two countries (France and Lithuania) and only at the ten percent level of statistical significance. At the same time, we can reject the null of $\delta_D = 0$ for Greece, Finland, Italy and Slovakia at the five percent level and for France and Slovenia at the ten percent level, which implies that the impact of these distributional components on inflation differs across the high and low inflation regimes for these economies. In the high-inflation regime, the impact of the functional components of the distribution of current perceptions of past inflation is significant for Belgium, Greece, Finland, France, Slovenia and Slovakia as implied by the rejection of the null hypothesis that $\delta + \delta_D = 0$.

With respect to average expectations, the results show that they retain strong explanatory power across both regimes, similarly to the benchmark specification. In the high-inflation regime, the null hypothesis $\beta + \beta_D = 0$ is rejected in all countries except Finland, France and Spain. This indicates that, in most cases, average inflation expectations remain highly informative for realized inflation during periods of high inflation. In the low-inflation regime, average expectations are a significant predictor of inflation in all countries except Belgium, Greece and France.

By contrast, average perceived inflation is insignificant in the low-inflation regime except for Belgium. It becomes more relevant in the high-inflation regime where its impact changes significantly for Belgium, Germany, Greece, Finland, Italy and Slovakia so that its impact during the high-inflation regime becomes significant for Germany, Greece, Finland, Italy,

[8]In the high-inflation regime, the functional price components are significant in all countries except Belgium and Slovenia.

and Slovakia as the null hypothesis for $\theta + \theta_D = 0$ is rejected for these countries.

Table 4: Adding perceived inflation to the benchmark model

	AT	BE	DE	EL	FI	FR	IT	LT	SI	SK	ES
Average Expectations	3.012***	0.239	0.856***	0.128	1.891***	-1.048	1.784*	0.636***	1.278***	1.428***	0.787*
	(1.039)	(0.322)	(0.250)	(0.212)	(0.714)	(0.774)	(1.056)	(0.219)	(0.431)	(0.532)	(0.425)
D1 * Average Expectations	2.335	5.135***	1.985***	-1.631**	1.485	1.174*	1.725	1.142*	1.161*	0.067	-3.111*
	(1.641)	(1.437)	(0.468)	(0.677)	(2.349)	(0.683)	(1.711)	(0.690)	(0.654)	(0.667)	(1.709)
$\beta = \beta_D = 0$	14.645	21.197	60.561	5.827	9.025	3.218	15.603	10.868	33.983	15.086	7.043
	[0.001]	[0.000]	[0.000]	[0.054]	[0.011]	[0.200]	[0.000]	[0.004]	[0.000]	[0.001]	[0.030]
$\beta + \beta_D = 0$	21.459	33.801	100.050	10.938	4.470	0.310	19.260	11.827	49.937	19.611	3.415
	[0.000]	[0.000]	[0.000]	[0.004]	[0.107]	[0.856]	[0.000]	[0.003]	[0.000]	[0.000]	[0.181]
Perceived inflation	0.104	0.799**	-0.394	-0.006	1.058	-0.318	0.125	-0.373	0.432	-0.551	-0.192
	(0.627)	(0.362)	(0.410)	(0.250)	(0.671)	(0.503)	(0.098)	(0.312)	(0.421)	(0.480)	(0.266)
D1 * Perceive inflation	-0.222	-1.532***	1.271**	-1.445**	2.058*	0.007	-1.480***	-1.023	-1.005	-2.129*	-0.807
	(0.962)	(0.498)	(0.554)	(0.711)	(1.097)	(0.474)	(0.475)	(0.982)	(0.674)	(1.104)	(0.805)
$\theta = \theta_D = 0$	0.057	9.593	5.308	5.154	19.125	1.486	10.327	3.723	2.224	6.804	3.579
	[0.972]	[0.000]	[0.070]	[0.076]	[0.000]	[0.476]	[0.006]	[0.155]	[0.329]	[0.033]	[0.167]
$\theta + \theta_D = 0$	0.039	6.861	4.826	10.197	30.304	2.888	16.651	4.520	2.936	12.458	4.243
	[0.981]	[0.032]	[0.090]	[0.006]	[0.000]	[0.236]	[0.000]	[0.104]	[0.230]	[0.002]	[0.120]
Functional Coefficient of Expected Inflation											
$\gamma = \gamma_D = 0$	26.855	25.745	25.422	28.480	59.716	18.543	31.255	62.841	31.879	36.585	28.298
	[0.000]	[0.018]	[0.000]	[0.000]	[0.000]	[0.005]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\gamma + \gamma_D = 0$	22.897	7.009	13.994	14.383	55.173	7.175	57.940	18.596	4.218	25.685	15.181
	[0.000]	[0.135]	[0.000]	[0.002]	[0.000]	[0.066]	[0.000]	[0.000]	[0.377]	[0.000]	[0.001]
$\gamma = 0$	8.148	19.977	12.198	12.869	12.146	5.625	3.822	21.238	23.156	6.285	8.463
	[0.043]	[0.000]	[0.007]	[0.005]	[0.007]	[0.131]	[0.281]	[0.000]	[0.000]	[0.179]	[0.037]
$\gamma_D = 0$	21.664	10.402	11.922	11.619	38.753	9.028	8.679	16.423	0.340	18.785	12.252
	[0.000]	[0.034]	[0.008]	[0.009]	[0.000]	[0.029]	[0.034]	[0.003]	[0.987]	[0.001]	[0.007]
Functional Coefficient of Perceived Inflation											
$\delta = \delta_D = 0$	5.840	19.272	6.963	33.710	33.934	48.950	31.002	12.825	12.460	18.304	12.030
	[0.441]	[0.013]	[0.324]	[0.000]	[0.000]	[0.000]	[0.000]	[0.118]	[0.132]	[0.019]	[0.061]
$\delta + \delta_D = 0$	5.311	14.698	1.822	30.516	31.332	37.137	3.718	3.849	9.078	15.898	5.239
	[0.150]	[0.005]	[0.609]	[0.000]	[0.000]	[0.000]	[0.715]	[0.420]	[0.059]	[0.003]	[0.155]
$\delta = 0$	0.214	4.418	4.890	5.339	0.628	6.779	1.050	9.102	3.529	4.773	4.297
	[0.975]	[0.352]	[0.180]	[0.149]	[0.890]	[0.079]	[0.789]	[0.059]	[0.473]	[0.311]	[0.231]
$\delta_D = 0$	3.640	17.342	2.610	10.640	24.490	7.126	26.817	3.349	7.790	16.100	4.437
	[0.303]	[0.000]	[0.456]	[0.014]	[0.000]	[0.068]	[0.000]	[0.501]	[0.100]	[0.003]	[0.218]
Sum of Inflation Lags[1]	-0.667**	-0.941***	0.042	0.017	-0.632***	0.251	0.079	0.327	-0.255	0.075	0.164
	(4.827)	(7.292)	(0.139)	(0.018)	(11.564)	(2.064)	(0.537)	(1.664)	(1.784)	(0.349)	(0.903)
Unemployment gap	-0.962**	0.811	-0.558	-0.518	-0.448	-0.707	-0.712	-0.918***	-0.864	-0.216	-0.218
	(0.422)	(0.939)	(1.597)	(0.496)	(0.353)	(0.910)	(0.484)	(0.330)	(0.623)	(0.417)	(0.304)
Oil price	0.048	0.088**	0.138***	0.079***	0.102***	0.111***	0.040	0.130***	0.127***	0.068***	0.135***
	(0.036)	(0.044)	(0.021)	(0.021)	(0.023)	(0.030)	(0.029)	(0.044)	(0.027)	(0.025)	(0.033)
Lag(1) Oil price	0.088***	0.094***	-0.002	0.057***	0.047***	0.060***	0.054***	0.070*	0.152***	0.036*	0.074***
	(0.018)	(0.026)	(0.022)	(0.020)	(0.014)	(0.015)	(0.016)	(0.042)	(0.040)	(0.021)	(0.023)
Supply Chain Index	0.214	1.148**	-0.230	0.872	-0.275	0.134	0.241	1.155**	-0.642*	-0.276	0.549
	(0.434)	(0.539)	(0.361)	(0.545)	(0.268)	(0.409)	(0.566)	(0.450)	(0.388)	(0.408)	(0.775)
Dummy	-11.857	-18.167	-24.840***	40.670***	-21.658***	1.196	18.205	-1.835	8.752	24.107**	35.515**
	(14.859)	(11.930)	(8.449)	(14.172)	(7.400)	(5.633)	(11.071)	(16.739)	(11.077)	(11.181)	(16.304)
Variance Explained	0.990	0.960	0.960	0.940	0.930	0.990	0.980	0.950	0.950	0.950	0.990
	[3]	[4]	[3]	[3]	[3]	[3]	[3]	[4]	[4]	[4]	[3]
Observations	239	239	238	239	239	235	237	238	239	238	238
R^2(adjusted)	0.540	0.610	0.787	0.491	0.668	0.447	0.764	0.758	0.534	0.785	0.577
LjungBox (p-value)	0.324	0.600	0.013	0.254	0.157	0.522	0.064	0.287	0.377	0.590	0.301
Wald (p-value, lags jointly zero)	0.017	0.000	0.000	0.023	0.000	0.023	0.000	0.123	0.103	0.000	0.012

Note:*p<0.10, **p<0.05, ***p<0.01. This table presents the regression estimates with heteroscedasticity and autocorrelation-robust standard errors shown in parentheses below the estimates. Where we show hypothesis tests, we present p-values of the Wald test statistic in square brackets below the test statistic value.

[1] Parentheses show the Wald test statistic, while the asterisks indicate the significance level of the corresponding p-value

With respect to the impact of past inflation on current inflation, the results are very similar to those found for the benchmark model. Past inflation is significant only for Austria, Belgium, and Finland. This suggests that inflation persistence is better explained by expectations and perceptions of past inflation rather than by purely mechanical autoregressive inflation dynamics. In other words, expectations formation emerges as a key persistence mechanism. People do not simply extrapolate past inflation mechanically; instead, they incorporate past inflation into their subjective expectations and perceptions, which then influence future inflation.

In short, these findings highlight that inflation dynamics are largely expectation-driven, with average inflation expectations and functional components of current expectations of future inflation both playing a role. Perceptions of past inflation provide additional explanatory power in high-inflation environments. Moreover, average inflation expectations remain a strong predictor across regimes, while lagged inflation alone contributes little once expectations are considered.

3.5 Adding past expectations of current inflation to the benchmark

Some theory models, e.g. rational inattention ones, suggest that current inflation is driven both by current expectations of the future inflation rate and by past expectations of the current inflation rate.[9] Motivated by this, we augment our benchmark model to add past expectations of the current inflation rate in addition to current expectations of future inflation. In addition, rather than considering only average past expectations, we allow for the whole cross-sectional distribution of inflation expectations to appear on the right-hand side of our regression equation. With this extension, we want to investigate whether past heterogeneity across households is important so that a shift of the distribution of inflation expectations in the past is informative about current inflation. Thus, our augmented empirical model takes the following form with the two integrals capturing the effect of the distribution of current and past expectations respectively:

[9] Coibion et al. (2018) provide an informative list of theoretical models in their Table 5, along with these models' implications regarding the link between inflation and inflation expectations.

$$\pi_t = \beta\,\overline{\pi}^e_{t|t+1} + \theta\,\overline{\pi}^e_{t-1|t} + \int \gamma\left(\pi^e_{t|t+1} - \overline{\pi}^e_{t|t+1}\right)\,dP^c_t(\pi^e) + \int \delta\left(\pi^e_{t-1|t} - \overline{\pi}^e_{t-1|t}\right)\,dP^c_t(\pi^e) + k'X_t + \epsilon_t \tag{13}$$

where π_t denotes realized inflation at time t, $\overline{\pi}^e_{t|t+1}$ represents the cross-sectional mean of inflation expectations formed at time t for period $t+1$, and $\overline{\pi}^e_{t-1|t}$ captures expectations formed at time $t-1$ for inflation at time t. The integrals reflect the effect of the cross-sectional distribution in expectations, measured as deviations from the mean $\overline{\pi^e}$, and weighted by the functions γ and δ over the distribution $P^c_t(\pi^e)$. The term X_t is a vector of control variables, and ϵ_t is an independently and identically distributed error term with mean zero and variance σ^2.

As the available data on inflation expectations reflect 12-month-ahead forecasts formed at time t, we proxy $\overline{\pi}^e_{t|t+1}$ using expectations at time t for inflation at $t+12$. To approximate the past expectation term $\overline{\pi}^e_{t-1|t}$, which corresponds to expectations at time $t-1$ for inflation at time t, we use the forecast made twelve months earlier for inflation at t.

The results for this specification are reported in Table 5. As we can see there, the null hypothesis for $\gamma = \gamma_D = 0$ is rejected for all countries except France and Belgium. Thus, the distribution of current inflation expectations significantly affects inflation for nearly all countries, as in the benchmark and the other two specifications considered in the previous sub-sections. In the low-inflation regime, the functional components remain important in Austria, Belgium, Germany, Greece, Lithuania, Slovenia and Spain. The null for $\gamma_D = 0$ is rejected for all countries except Belgium, France and Slovenia, implying a statistically significant difference between the impact of the distribution of current expectations on inflation in the high-inflation regime as compared to the low-inflation regime. In the high-inflation regime, the impact of the functional components of the distribution of current expectations of future inflation on current inflation realizations is significant for all countries except Slovenia and Belgium.

Moreover, we find that the distributional components of past expectations (formed 12 months earlier) are statistically significant predictors of the current inflation rate in Belgium, Greece, Finland, France, Italy, Lithuania, Slovenia and Slovakia, where the Wald statistic for the null hypothesis $\delta = \delta_D = 0$ is large so that the respective p-value allow us to reject this null. This result holds while including both current and past average expectations as well as the distribution of current expectations. Thus, the distributional shifts in past expectations appear to contain independent information that is informative about subsequent inflation outcomes.

Table 5: Adding past expectations of current inflation to the benchmark model

	AT	BE	DE	EL	FI	FR	IT	LT	SI	SK	ES
Average Expectations	3.059***	0.745***	0.544	0.324*	2.047***	0.051	0.285	0.584**	1.628***	0.832***	0.795 **
	(0.755)	(0.217)	(0.352)	(0.183)	(0.653)	(0.707)	(0.752)	(0.225)	(0.508)	(0.265)	(0.383)
D1 * Average Expectations	-0.087	3.796***	2.264*	-1.548***	6.474	0.313	4.522***	0.132	0.119	0.464	-4.163***
	(2.111)	(1.329)	(1.151)	(0.302)	(4.554)	(0.778)	(1.666)	(0.364)	(0.685)	(0.380)	(0.558)
$\beta = \beta_D = 0$	21.365	17.164	10.555	26.480	10.916	0.917	10.542	6.725	20.733	28.497	52.700
	[0.000]	[0.000]	[0.005]	[0.000]	[0.004]	[0.632]	[0.005]	[0.034]	[0.000]	[0.000]	[0.000]
$\beta + \beta_D = 0$	3.503	21.609	14.137	42.055	6.629	1.835	20.819	5.099	24.283	40.504	81.955
	[0.173]	[0.000]	[0.001]	[0.000]	[0.010]	[0.175]	[0.000]	[0.024]	[0.000]	[0.000]	[0.000]
Lag(12) Average Expectations	-1.332**	-0.561**	-0.354**	-0.404**	1.192**	-1.931*	0.173	-0.285**	0.261	-0.379	0.141
	(0.622)	(0.263)	(0.168)	(0.187)	(0.497)	(1.005)	(0.675)	(0.132)	(0.450)	(0.398)	(0.264)
D1*Lag(12)Average Expectations	2.200	-0.956	-0.973	0.748**	-0.939	-0.146	-3.280***	-1.135***	-0.568	0.581	-0.299
	(2.160)	(1.733)	(0.997)	(0.357)	(2.131)	(0.996)	(0.985)	(0.432)	(0.730)	(0.720)	(0.642)
$\theta = \theta_D = 0$	5.865	5.068	6.005	6.286	6.021	24.527	14.772	10.592	0.621	0.990	0.595
	[0.053]	[0.079]	[0.050]	[0.043]	[0.304]	[0.000]	[0.000]	[0.005]	[0.733]	[0.609]	[0.743]
$\theta + \theta_D = 0$	0.624	1.533	3.594	2.248	0.032	47.787	28.138	18.767	0.583	0.246	0.153
	[0.732]	[0.215]	[0.166]	[0.325]	[0.857]	[0.000]	[0.000]	[0.000]	[0.445]	[0.619]	[0.926]
Functional coefficient for current expectations of future inflation											
$\gamma = \gamma_D = 0$	47.946	13.332	33.742	68.819	15.286	10.415	24.835	50.489	33.621	75.431	76.906
	[0.000]	[0.101]	[0.000]	[0.000]	[0.018]	[0.108]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\gamma + \gamma_D = 0$	21.837	4.522	13.147	52.213	9.214	8.585	11.278	40.478	5.352	67.452	58.906
	[0.000]	[0.339]	[0.004]	[0.000]	[0.026]	[0.047]	[0.010]	[0.000]	[0.252]	[0.000]	[0.000]
$\gamma = 0$	24.167	10.224	24.587	15.719	7.286	2.656	5.431	13.289	16.312	3.960	11.873
	[0.000]	[0.036]	[0.000]	[0.001]	[0.063]	[0.447]	[0.142]	[0.009]	[0.002]	[0.411]	[0.008]
$\gamma_D = 0$	22.397	4.182	13.778	59.531	12.134	3.456	9.952	29.216	3.151	55.134	52.826
	[0.000]	[0.381]	[0.000]	[0.000]	[0.006]	[0.326]	[0.019]	[0.000]	[0.352]	[0.000]	[0.000]
Functional Coefficient for past expectations of current inflation											
$\delta = \delta_D = 0$	9.073	79.528	8.060	33.329	21.485	129.246	13.946	34.435	17.187	51.551	9.503
	[0.170]	[0.000]	[0.234]	[0.000]	[0.001]	[0.000]	[0.030]	[0.000]	[0.028]	[0.000]	[0.147]
$\delta + \delta_D = 0$	4.016	68.530	2.467	33.426	3.478	119.799	9.481	22.618	12.856	42.457	5.320
	[0.259]	[0.000]	[0.481]	[0.000]	[0.323]	[0.000]	[0.023]	[0.000]	[0.012]	[0.000]	[0.149]
$\delta = 0$	5.682	2.263	9.230	6.063	13.038	6.059	4.507	14.661	4.262	5.597	2.352
	[0.128]	[0.622]	[0.101]	[0.026]	[0.004]	[0.108]	[0.211]	[0.005]	[0.371]	[0.231]	[0.502]
$\delta_D = 0$	4.833	52.331	3.078	27.647	3.367	11.359	4.966	14.603	6.808	33.931	4.296
	[0.184]	[0.000]	[0.380]	[0.000]	[0.338]	[0.000]	[0.009]	[0.000]	[0.146]	[0.000]	[0.231]
Sum of Inflation Lags [1]	-0.685**	-0.956***	-0.056	-0.460*	-0.688***	0.121	0.129	0.118	-0.232	-0.338**	0.193
	(4.116)	(11.649)	(0.287)	(3.279)	(17.358)	(0.407)	(0.587)	(0.232)	(1.097)	(5.009)	(1.515)
Unemployment gap	-0.740**	-0.395	0.830	-1.409***	-1.439*	-0.239	-0.976*	-0.711*	-1.013	-0.733**	-0.624**
	(0.367)	(1.007)	(0.910)	(0.536)	(0.872)	(0.883)	(0.562)	(0.389)	(0.731)	(0.336)	(0.256)
Oil price	0.048	0.080**	0.131***	0.090***	0.110***	0.145***	0.053	0.123***	0.131***	0.061***	0.131***
	(0.039)	(0.037)	(0.021)	(0.019)	(0.027)	(0.020)	(0.040)	(0.043)	(0.029)	(0.022)	(0.037)
Lag(1) Oil price	0.090***	0.107***	0.005	0.052***	0.058**	0.066***	0.052***	0.095***	0.150***	0.024	0.085***
	(0.015)	(0.024)	(0.019)	(0.018)	(0.021)	(0.020)	(0.015)	(0.035)	(0.039)	(0.020)	(0.020)
Supply Chain Index	-0.024	0.492	-0.730**	0.577	0.344	-0.242**	0.091	0.709	0.106	-0.115	0.427
	(0.520)	(0.541)	(0.296)	(0.504)	(0.537)	(0.406)	(0.632)	(0.437)	(0.565)	(0.388)	(0.517)
Dummy	-8.182	-20.171	-5.422	3.967	-31.440	-6.376	-2.104	15.257*	7.302	-0.702	40.858***
	(23.435)	(19.544)	(9.755)	(4.178)	(22.780)	(6.418)	(9.192)	(7.787)	(11.160)	(14.314)	(7.324)
Variance Explained	0.990	0.960	0.960	0.940	0.930	0.990	0.980	0.950	0.950	0.950	0.990
	[3]	[4]	[3]	[3]	[3]	[3]	[3]	[4]	[4]	[4]	[3]
Observations	227	227	226	226	227	223	225	226	227	227	226
R^2(adjusted)	0.528	0.618	0.798	0.508	0.609	0.481	0.750	0.766	0.509	0.802	0.572
LjungBox (p-value)	0.276	0.086	0.008	0.853	0.541	0.300	0.441	0.208	0.614	0.529	0.232
Wald (p-value, lags jointly zero)	0.087	0.009	0.000	0.020	0.000	0.021	0.000	0.565	0.044	0.001	0.259

Note:*p<0.10,**p<0.05,***p<0.01 This table presents the regression estimates with heteroscedasticity and autocorrelation-robust standard errors shown in parentheses below the estimates. Where we show hypothesis tests, we present p-values of the Wald test statistic in square brackets below the test statistic value.

[1] Parentheses show the Wald test statistic, while the asterisks indicate the significance level of the corresponding p-value

During the low-inflation regime, we observe noticeable differences across countries. Noting that rejecting the null of $\gamma = 0$ for current expectations and $\delta = 0$ for past expectations implies that the impact of the distribution of the respective expectations is statistically significant, we find that for Austria, Germany, Belgium, Slovenia and Spain, the cross-sectional distribution of current expectations is significant while for past expectations it is not. For Lithuania, Greece and Finland we observe a statistically significant impact of the distribution of both current and past expectations on inflation. On the contrary, the distribution of current and past expectations is insignificant for France, Italy and Slovakia.

Finally, for Belgium, Greece, France, Italy, Lithuania and Slovakia, the p-value of the Wald statistic for the null hypothesis $\delta_D = 0$ allow us to reject the null, which implies again a statistically significant difference between the impact of the distribution of past expectations on inflation in the low and high-inflation regimes. As a result, in the high-inflation regime, the impact of the functional components of the distribution of past expectations of current inflation on current inflation realizations is significant for Belgium, Greece, France, Italy, Lithuania, Slovenia and Slovakia as the null hypothesis $\delta + \delta_D = 0$ is rejected there.

Moreover, we find strong evidence that average current expectations play a significant role for most countries in the high-inflation regime: the Wald statistic for the null hypothesis $\beta + \beta_D = 0$ is large and the corresponding p-value close to zero for all countries except Austria and France, leading us to reject this null hypothesis in favor of the alternative. Past average expectations are not as important as current expectations for the high-inflation regime. Considering the p-values of the Wald statistic for $\theta + \theta_D = 0$, we see that this null cannot be rejected for all countries except France, Italy and Lithuania.

Focusing on the low-inflation regime, both current and past average expectations are statistically significant for Austria, Belgium, and Lithuania. In these countries, current expectations exert a positive effect on inflation, while past expectations have a negative impact, albeit of smaller absolute magnitude. For Greece, the impact of both current and past expectations is also significant: current expectations display the same positive sign as in the aforementioned countries, but their effect is weaker in magnitude and only marginally significant at the 10 % level, whereas past expectations exert a relatively stronger influence. In the case of Finland, both current and past expectations are statistically significant, with each exerting a positive effect on current inflation.

Moreover, average current expectations are significant determinants of inflation in Spain, Slovenia, and Slovakia, whereas average past expectations are statistically insignificant. By contrast, for Germany and France, only past inflation expectations are informative for current inflation.

It is noteworthy that both the average and the functional components of past expectations of current inflation are strong determinants of current inflation realizations for France. By contrast, as we have seen for our benchmark empirical model in section 3.2 and for the models in sections 3.3 and 3.5, France is the single country where (the average and the functional components of) current expectations of future inflation are consistently insignificant for determining current inflation. This suggests a mechanism more in line with sticky information models of expectation formation as compared to any other euro-area economy. This uniqueness of France calls into question the generality of the findings in studies relying exclusively on French inflation expectations data, such as Andrade et al. (2023) or Savignac et al. (2024). Conversely, the utilization of microeconomic data of inflation expectations across several economies is an important advantage of our analysis.

Across countries, our findings confirm that current expectations about future inflation, both the average and the distribution, are key drivers of realized inflation, particularly in high-inflation regimes. Past expectations about current inflation also influence inflation outcomes, indicating that shifts in the cross-sectional distribution of past expectations can foreshadow current inflation. In low-inflation regimes, there is greater heterogeneity: in some cases, both current and past expectations help determine inflation, while in others, past expectations better explain inflation outcomes. This suggests a more sluggish adjustment of expectations when inflation is low and stable. Overall, these findings reveal significant regime dependence and substantial cross-country heterogeneity in the relationship between inflation and inflation expectations.

3.6 Comparison across models: Evidence from Rolling regressions.

Based on our earlier findings, the relationship between inflation and the functional components of the distribution of inflation expectations is significant and varies substantially across countries but also across inflation regimes. Building on these findings, we now compare the different model specifications by re-estimating our models using a rolling regression approach which allows us to account for any possible instability over time in the relationship between inflation and inflation expectations in a parsimonious and flexible manner.

We estimate six different models using rolling regressions, applying a fixed-size window that moves across the sample period[10]. For each window and each model, we compute the root mean square error (RMSE). To compare the empirical performance of each model across countries we use the following approach. First, we compute the average RMSE over time and use them to compare the in-sample performance across models (Figure 5). Second, we plot the RMSE paths to evaluate the models' performance over time and to highlight periods when particular specifications achieve superior explanatory power for inflation, as indicated by lower RMSEs (Figure 6).

Model 0: $\pi_t = \beta \overline{\pi}_t^e + k' X_t + \epsilon_t$

Model 1: $\pi_t = \beta \overline{\pi}_t^e + \int \gamma \left(\pi^e - \overline{\pi_t^e}\right) \, dP_t^c(\pi^e) + k' X_t + \epsilon_t$

Model 2: $\pi_t = \beta \overline{\pi}_t^e + \int \gamma \left(\pi^e - \overline{\pi_t^e}\right) \, dP_t^c(\pi^e) + \theta' Moments_t + k' X_t + \epsilon_t$

Model 3: $\pi_t = \beta \overline{\pi}_t^e + \theta \overline{\pi}_t^p + \int \gamma \left(\pi^e - \overline{\pi_t^e}\right) \, dP_t^c(\pi^e) + \int \delta \left(\pi^p - \overline{\pi_t^p}\right) \, dP_t^c(\pi^p) + k' X_t + \epsilon_t$

Model 4: $\pi_t = \beta \, \overline{\pi}^e_{t|t+1} + \theta \, \overline{\pi}^e_{t-1|t} + \int \gamma \left(\pi^e_{t|t+1} - \overline{\pi}^e_{t|t+1}\right) \, dP_t^c(\pi^e) + \int \delta \left(\pi^e_{t-1|t} - \overline{\pi}^e_{t-1|t}\right) \, dP_t^c(\pi^e) + k' X_t$

Model 5: $\pi_t = \beta \overline{\pi}^e_{t-1|t} + \int \gamma \left(\pi^e_{t-1|t} - \overline{\pi}^e_{t-1|t}\right) \, dP_t^c(\pi^e) + k' X_t + \epsilon_t$

Model 0 is equivalent to the hybrid version of the Phillips curve that includes lags of inflation and the average one-year-ahead inflation expectations. We compare all other models to Model 0 to assess whether incorporating the distributional component of inflation ex-

[10] Each window covers a three-year period, corresponding to a total of 36 observations.

pectations leads to better in-sample performance. Model 1 is our benchmark model from sub-section 3.2 which adds the distributional functional components to Model 0, Model 2 adds higher moments to the benchmark model as described in sub-section 3.3, Model 3 adds the perceived past inflation rate to the benchmark as in sub-section 3.4, Model 4 (described in section 3.4) adds past expectations of current inflation to the benchmark in line with rational inattention theory models, while Model 5, results for which are shown in the appendix, (is not nested and) uses only past expectations about current inflation in line with sticky information models going back to Mankiw and Reis (2002). We estimate these models with the same control variables included in each case. These are: the unemployment gap, past inflation, Oil prices, and Supply Chain Index.

In Figure 5, we compare the average (over time) RMSE across models. There are noticable differences in the empirical empirical performance of each model across countries. First, we can see that, for all countries, Model 0 yields a higher average RMSE as compared to Models 1 to 4 considered in sections 3.2 to 3.5 respectively. This provides strong evidence that the cross-sectional heterogeneity in the expectations of future inflation is highly informative for realized inflation, and that a measure of central tendency is not a sufficient statistic to capture households' subjective beliefs about inflation.

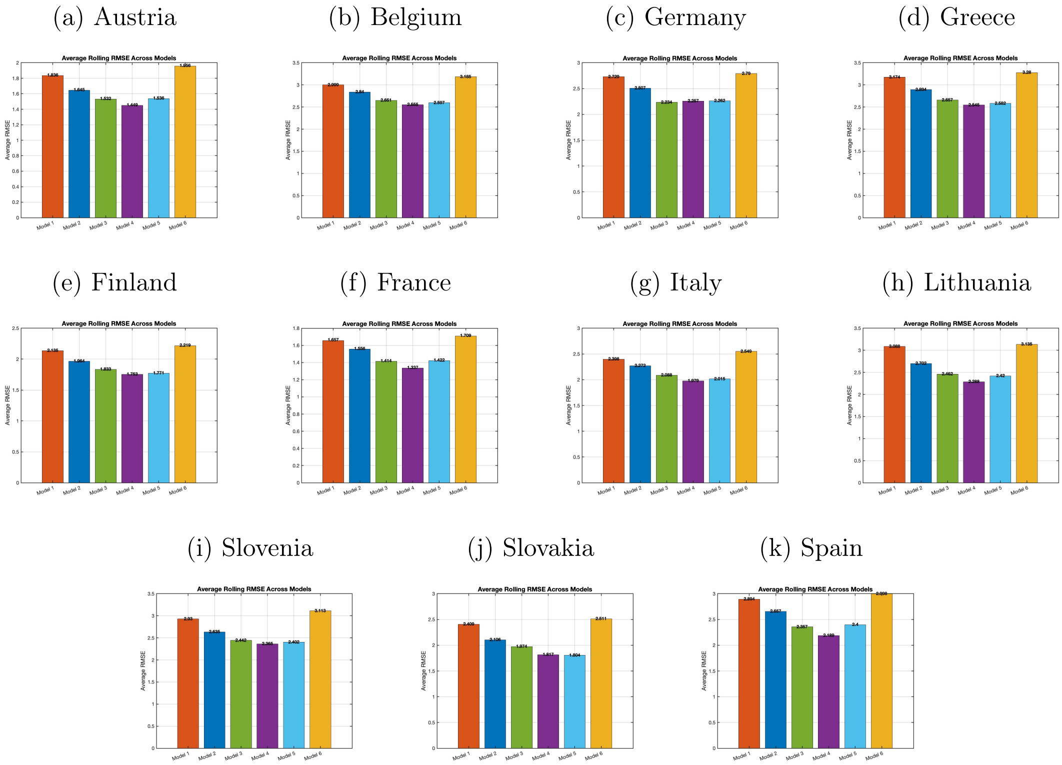
Furthermore, accounting for higher moments in Model 2 improves on the benchmak specification in Model 1 as it further reduces the RMSE for all countries. Models 3 and 4 provide, which respectively add the perceived past inflation rate and past expectations of current inflation to the benchmark, have the lowest average RMSE among all models for all countries. These two models suggest only minor differences in performance among them where, for some countries, the average RMSEs are almost the same.[11]

Model 5 which uses only past expectations of current inflation performs worse than Models 1 to 4 which utilize the distribution of expectations regarding future inflation. It also performs worse than Model 0 for all countries. As we can see in Table A2 in the Appendix, this is due to the low explanatory power of past average expectations of current inflation which are

[11]It is likely that expectations formed 12 months ago regarding current inflation are closely related to current perceptions of how prices changed over the past 12 months.

found to be insignificant in most of these EU countries.[12] This is the case, even though the distribution of past expectations of current inflation appears to matter for current inflation realizations as we can see in Table A2 where the null hypothesis that $\delta = \delta_D = 0$ is rejected at (least at) the five percent level for all countries except Germany.

Figure 5: Average rolling RMSE across models.



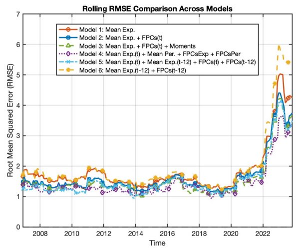
(a) Austria (b) Belgium (c) Germany (d) Greece (e) Finland (f) France (g) Italy (h) Lithuania (i) Slovenia (j) Slovakia (k) Spain

Having used the rolling regression approach we are left with an available sample that starts from 2007-M1 and ends at 2023-M11. With this we can plot over time and across countries the RMSE across the different models and observe the differences. We do so in Figure 6. One major finding from Figure 6 is that there is a considerable increase in the RMSE for all models during the high inflation period. For many countries, among them the major euro area economies, the RMSEs were initially relatively low and stable between values of 1 and 2, whereas after 2020 there was a sharp increase in them. This offers some additional justification regarding the need to account for breaks in our analysis.

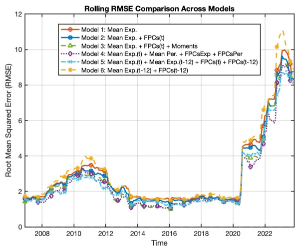
[12] In fact, the worse model, not shown here for the sake of bravity but available upon request, is one with only past average expectations, i.e., excluding the past distribution of inflation expectations and current average inflation expectations. This directly refutes sticky information models.

Figure 6: Dynamic in-sample performance: RMSE from Rolling Regressions

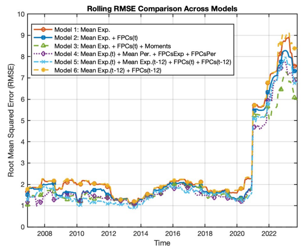
(a) Austria



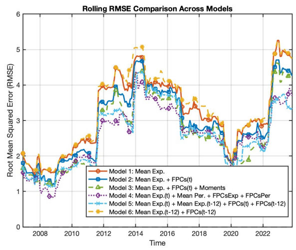
(b) Belgium



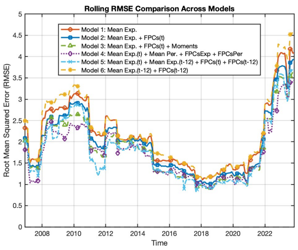
(c) Germany



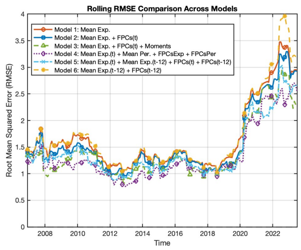
(d) Greece



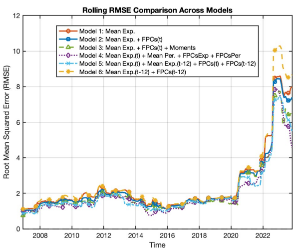
(e) Finland



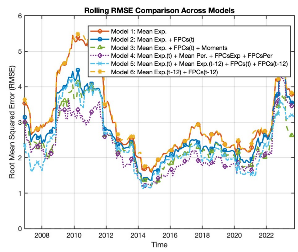
(f) France



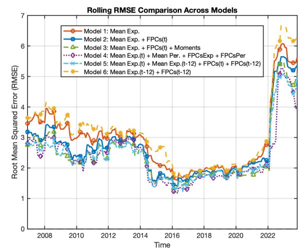
(g) Italy



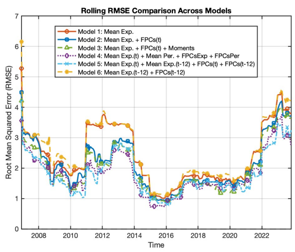
(h) Lithuania



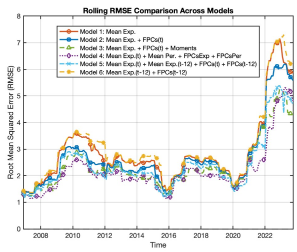
(i) Slovenia



(j) Slovakia



(k) Spain



Focusing on the high inflation period, we see that controlling for the distributional component of inflation expectations gives better empirical performance in terms of reducing the RMSE relative to Model 0. Models 3 and 4 appear to describe the data better during the high-inflation period for all countries. Importantly, the performance gains are not limited to high-inflation periods. During the global financial crisis and the subsequent Eurozone sovereign debt crisis (2008-2014), the distributional components of inflation expectations also contribute to lowering the RMSE. Models 3 and 4 once again deliver superior in-sample performance during those turbulent times.

4 Interpreting the factors

A natural question that arises is: what is behind the evident cross-country heterogeneity in the distribution of inflation expectations? To address this, we begin with a descriptive approach that explores how the distributional characteristics of each country's inflation expectations relate to various macroeconomic aggregates and to higher-order moments derived from the same distributions. We then explore the cross-country correlations between these distributional characteristics to assess how much of the variation in inflation expectations is shared across countries. Lastly, we combine the functional response model with rolling regressions in order to calculate a measure of fit known as functional R^2. This helps assess how much of the cross-sectional heterogeneity in the distribution of inflation expectations can be explained by macroeconomic aggregates.

4.1 Descriptive Analysis

We begin by considering how macroeconomic aggregates such as the annual inflation rate, the unemployment rate and other supply-side factors summarized by the Global Supply Chain Pressure Index, that were utilized in our benchmark model, correlate with the functional components of the distribution of inflation expectations across households. In Table 6, we can see that the dominant component of the distribution of inflation expectations across households (Score 1) and the measure of average expectations, are highly correlated with inflation in all countries and with unemployment in most countries. For several countries, they are also correlated with supply-side factors. Moreover, the second and third scores exhibit non-negligible correlation with inflation in most countries and with unemployment in some countries, but obviously weaker than is the case for the primary component. There is no evident correlation of these scores with supply-side factors.

With respect to the correlation with higher moments, the standard deviation, skewness and kurtosis of the distribution of inflation expectations across households, correlate strongly with the dominant functional principal component of this distribution. The second and third scores do not correlate with higher moments of the distribution in most countries. Last but not least, we observe evident heterogeneity among countries regarding the correlation of the functional principal component with macroeconomic aggregates.

Table 6: Correlation of concensus and functional principal components of inflation expectations with macro aggregates and with higher moments of the expectations' distribution

Score	**Variable**	**AT**	**BE**	**DE**	**ES**	**FI**	**FR**	**EL**	**IT**	**SI**	**SK**	**LT**
Average Expectations	Inflation	0.91	0.73	0.85	0.69	0.89	0.84	0.83	0.78	0.79	0.95	0.78
	Unemployment Rate	-0.48	-0.48	-0.12	-0.70	-0.55	-0.64	-0.70	-0.41	-0.50	-0.24	-0.31
	Supply Factors	0.32	0.42	0.37	0.06	0.32	0.16	-0.02	0.33	0.51	0.29	0.12
Score 1	Inflation	0.76	0.48	-0.48	0.63	0.78	-0.50	0.74	0.63	0.60	-0.77	0.53
	Unemployment Rate	-0.45	-0.46	-0.26	-0.66	-0.55	0.56	-0.61	-0.45	-0.37	0.13	-0.12
	Supply Factors	0.34	0.32	-0.34	0.04	0.33	-0.33	-0.15	0.10	0.45	-0.32	0.08
	Standard Deviation	0.93	0.33	0.79	0.92	0.91	0.86	-0.59	0.90	0.93	0.86	-0.84
	Skewness	-0.94	-0.55	-0.87	-0.92	-0.87	-0.65	0.63	-0.92	-0.68	-0.88	0.82
	Kurtosis	-0.94	-0.50	-0.89	-0.84	-0.87	-0.67	0.63	-0.94	-0.84	-0.90	0.84
Score 2	Inflation	-0.47	0.29	0.40	-0.26	-0.22	0.49	-0.23	0.36	-0.09	0.42	0.23
	Unemployment Rate	0.07	-0.09	-0.17	0.24	-0.06	-0.31	0.34	0.07	0.05	-0.12	-0.15
	Supply Factors	0.14	0.16	0.15	0.04	0.19	0.01	-0.19	0.20	-0.06	-0.09	-0.04
	Standard Deviation	-0.22	0.23	-0.33	-0.02	-0.04	-0.41	0.52	-0.17	-0.02	-0.09	0.41
	Skewness	0.03	-0.22	0.38	-0.09	0.12	0.19	-0.35	0.12	-0.16	0.02	-0.25
	Kurtosis	-0.12	-0.16	0.26	-0.29	-0.14	0.05	-0.28	-0.05	-0.02	-0.09	-0.04
Score 3	Inflation	-0.20	0.43	-0.32	-0.09	0.00	-0.48	-0.21	0.31	0.30	0.25	0.49
	Unemployment Rate	-0.07	-0.24	0.39	-0.10	-0.18	0.24	-0.10	-0.08	-0.28	-0.12	-0.19
	Supply Factors	0.05	0.22	-0.09	-0.14	0.19	0.08	-0.14	0.44	0.20	-0.10	0.21
	Standard Deviation	-0.20	0.22	0.39	-0.17	-0.23	0.13	-0.31	0.17	0.23	0.43	0.26
	Skewness	0.11	-0.19	-0.07	0.16	0.29	-0.12	0.30	-0.23	-0.14	-0.25	-0.14
	Kurtosis	0.12	-0.19	0.03	0.20	0.22	-0.12	0.25	-0.17	-0.01	-0.25	-0.11

We extend our analysis by exploiting the cross-country dimension of our data, namely the fact that we observe the distribution of inflation expectations over time for multiple countries. The characteristics of these cross-sectional distributions summarized by a finite number of functional principal components, also exhibit significant correlation across countries. These are particularly pronounced for the dominant functional principal component (Score 1), suggesting a high degree of shared variation in this component across countries. The second principal component (Score 2) also exhibits notable cross-country correlations, although lower than that of the dominant component, indicating some common structure but with more country-specific variation. Finally, correlations among countries are relatively weak for the third principal component (Score 3), reflecting that this component captures more idiosyncratic country-specific features.

Even though the analysis so far is primarily descriptive, the high correlation of the principal components with macroeconomic aggregates in most countries, the substantial heterogeneity of these correlations across countries, and the significant cross-country correlation of the functional components, underscore the need to go beyond this preliminary analysis. More analysis is required to better understand the functional principal components of the distribution of inflation expectations across households and their role in driving inflation realizations.

Figure 7: Cross-country correlations for the functional components

	BE	DE	ES	FI	FR	EL	IT	SI	SK	LT
AT	0.35	0.60	0.48	0.89	0.66	0.42	0.72	0.79	0.64	0.30
BE		0.25	0.30	0.29	0.49	0.10	0.47	0.49	0.40	0.04
DE			0.66	0.58	0.57	0.30	0.61	0.62	0.73	0.05
ES				0.42	0.44	0.55	0.76	0.51	0.70	0.06
FI					0.69	0.29	0.64	0.75	0.58	0.17
FR						0.12	0.62	0.83	0.68	0.03
EL							0.53	0.24	0.45	0.41
IT								0.72	0.70	0.04
SI									0.73	0.11
SK										0.14

(a) Score 1

	BE	DE	ES	FI	FR	EL	IT	SI	SK	LT
AT	0.01	0.45	0.12	0.82	0.47	0.06	0.41	0.31	0.50	0.18
BE		0.17	0.12	0.04	0.28	0.05	0.30	0.00	0.02	0.10
DE			0.34	0.57	0.58	0.36	0.49	0.31	0.57	0.04
ES				0.28	0.35	0.17	0.26	0.12	0.38	0.16
FI					0.64	0.16	0.47	0.43	0.65	0.16
FR						0.29	0.56	0.46	0.61	0.09
EL							0.15	0.20	0.34	0.15
IT								0.34	0.34	0.15
SI									0.36	0.05
SK										0.06

(b) Score 2

	BE	DE	ES	FI	FR	EL	IT	SI	SK	LT
AT	0.07	0.14	0.00	0.45	0.39	0.05	0.25	0.20	0.14	0.43
BE		0.03	0.08	0.20	0.19	0.11	0.12	0.13	0.05	0.05
DE			0.36	0.14	0.24	0.47	0.23	0.39	0.38	0.17
ES				0.05	0.12	0.38	0.32	0.19	0.10	0.41
FI					0.10	0.00	0.02	0.23	0.14	0.15
FR						0.25	0.29	0.22	0.37	0.22
EL							0.29	0.37	0.36	0.28
IT								0.20	0.00	0.45
SI									0.24	0.18
SK										0.02

(c) Score 3

4.2 Understanding Distributional factors: Functional response model

In this section, we utilize a functional response model to better understand the functional principal components of the distribution of inflation expectations across households. We thus consider a functional linear model with the distribution of inflation expectations as the dependent variable and a set of macroeconomic aggregates as our independent variables. This approach allows us to assess how much of the cross-sectional heterogeneity in inflation expectations can be explained by macroeconomic fundamentals.

One concern, however, is that of time heterogeneity of the effect of each variable on the cross-sectional distribution of inflation expectations. In order to account for possible time heterogeneity on the effect of macroeconomic aggregates, we combine the functional response model with a rolling regression approach. Formally, Let $\mathcal{T}_\tau = \{\tau, \tau+1, \ldots, \tau+W-1\}$ denote the subsample of size $W < T$ starting at time τ. For each window, the model is re-estimated as:

$$\mathbf{p}_{\mathcal{T}_\tau}(\cdot) = \mathbf{w}_{\mathcal{T}_\tau}\,\beta(\cdot) + \mathbf{u}_{\mathcal{T}_\tau}(\cdot), \tag{14}$$

where $\mathbf{p}_{\mathcal{T}_\tau}(\cdot)$ correspond to the cross-sectional distribution for window $\mathcal{T}_\tau$ and $\mathbf{w}_{\mathcal{T}_\tau}$ stacks the regressors over the same period. A more detailed treatment of the rolling functional response model is provided in Section A.5 of the Appendix. In practice we select the number of principal components to summarize the functional variation on the cross-sectional distribution of expectations and we estimate the following rolling regression models for each of the selected principal components as dependent variables.

Since survey participants report their expectations before the realized values of the macroeconomic aggregate are known, we use the first lag of all independent variables. The selection of exogenous macroeconomic aggregates follows our benchmark regression and includes the inflation rate, the unemployment rate, and the supply chain index.

We estimate four models, progressively extending the specification:

Model (I): Baseline specification

$$s_{k,t} = \beta_{t,k}\, Inflation_t + \epsilon_t \tag{15}$$

Model (II): Adding unemployment

$$s_{k,t} = \beta_{k,t}\, Inflation_t + \gamma_{k,t}\, Unemployment_t + \epsilon_t \tag{16}$$

Model (III): Adding Supply Chain Index

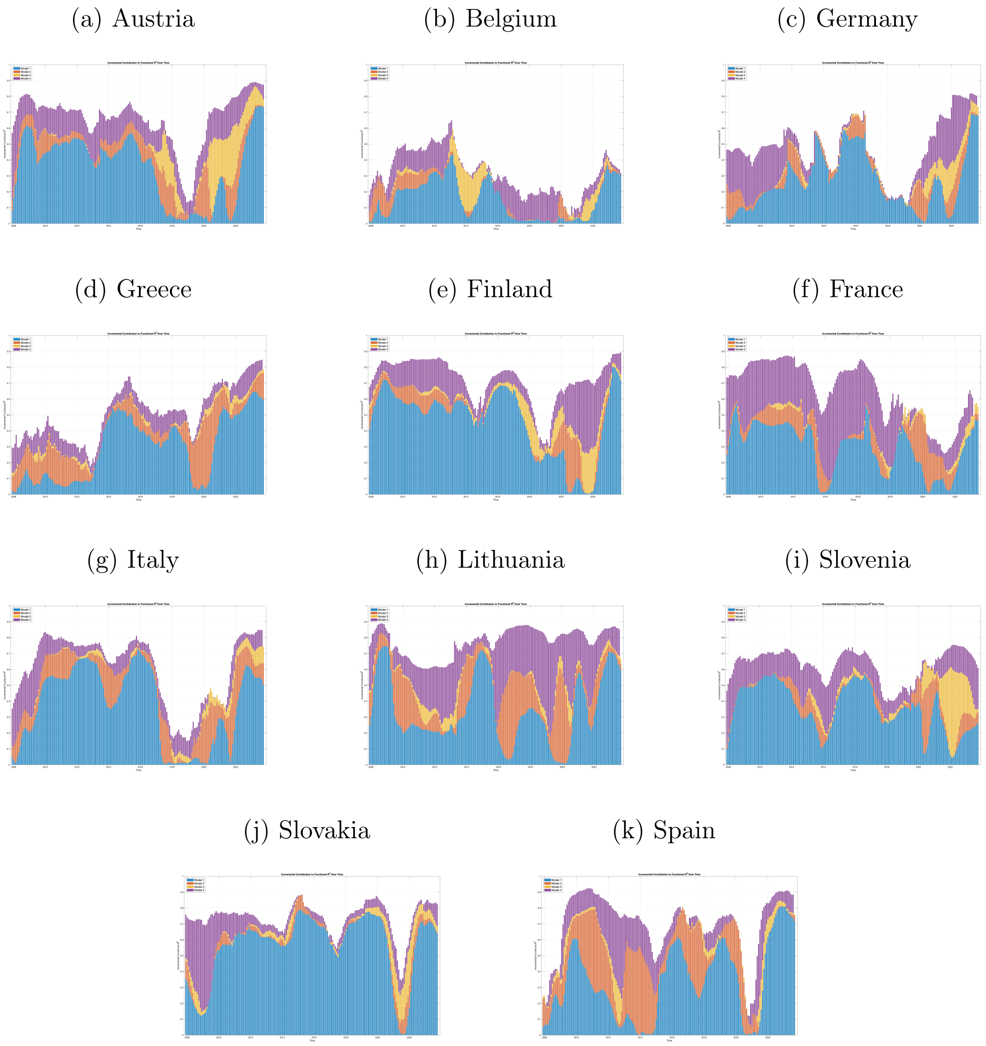
$$s_{k,t} = \beta_{k,t}\, Inflation_t + \gamma_{k,t}\, Unemployment_t + \delta_{k,t}\, SupplyChainIndex_t + \epsilon_{k,t} \tag{17}$$

Model (IV): Dynamic specification

$$s_{k,t} = \alpha_t\, s_{k,t-1} + \beta_{k,t}\, Inflation_t + \gamma_{k,t}\, Unemployment_t + \delta_{k,t}\, SupplyChainIndex_t + \epsilon_{k,t} \tag{18}$$

Further empirical results are presented in Section A.6 of the Appendix where we estimate the dynamic specification of Model (IV).

Figure 8: Rolling Functional R^2



(a) Austria (b) Belgium (c) Germany

(d) Greece (e) Finland (f) France

(g) Italy (h) Lithuania (i) Slovenia

(j) Slovakia (k) Spain

For interpretation, we compute and plot the rolling functional R^2 in Figure 8. The functional R^2 is used to measure how much of the total variation in the cross-sectional distribution of inflation expectations is explained by the existing macroeconomic aggregates. Using a rolling regression approach we compute and plot the functional R-squared for each partition of the sample. In Figure 8, we compare the rolling functional R-squared obtained when explaining the cross-sectional distribution of survey responses using different sets of macroeconomic aggregates. The vertical axis adds up to 1 while the x axis starts from January 2008 up to November 2023. The rolling functional R2 from the baseline specification is depicted with blue, showing how much of the cross-sectional variation in the distribution of inflation expectations can be explained from past inflation rate realizations. The orange area depicts the additional variance explained when adding the unemployment rate, while the yellow area shows the incremental explanatory power of including the supply chain index. Finally, the purple area corresponds to the contribution of the dynamic term.

Some interesting findings are observed by plotting the rolling functional R2 in Figure 8. To begin with, past inflation accounts for a large proportion of the total variation on the cross-sectional distribution of inflation expectations. This finding is consistent across countries. The unemployment rate appears to be of major importance for selected countries. For instance, in the case of Greece, unemployment accounted for a large proportion of the explained variation between 2008 and 2013, a period marked by a sovereign debt crisis, severe recession, and major, initially painful, structural reforms. Unemployment also emerges as an important driver of the distribution of inflation expectations in Spain and Lithuania. It also played a noticeable role during the COVID period, though to varying degrees across countries. As expected, supply factors became a key driver in some countries, notably Austria and Slovenia, from 2018 onward.

Furthermore, we observe in many countries that during the Covid period (2018-2020), the functional R^2 was relatively small in some countries. This is the case for Belgium, France, Italy, Slovakia and Spain. This suggests that factors other than past macroeconomic fundamentals were probably driving the heterogeneity of inflation expectations across households in some euro-area countries during this particular period.

5 Conclusion

Based on the aforementioned results, a set of conclusions can be drawn regarding the relation between inflation and inflation expectations in the euro-area. The functional components of the cross-sectional distribution of current expectations of future inflation across households are found to be important drivers of current inflation realizations in the euro-area. This result remains even after accounting for higher moments of the distribution or for the distribution of current perceptions of past inflation. The importance of features of the distribution of current expectations of future inflation in explaining current inflation realizations, suggests that empirically relevant Phillips Curves should account for heterogeneity in inflation expectations across households. Thus, heterogeneity across households emerges as a necessary ingredient for theoretical models that imply a Phillips Curve linking inflation to inflation expectations to be consistent with the empirical findings documented here.

Forward-looking expectations appear to be more important for driving current inflation realizations across the euro-area, as compared to past expectations of current inflation. Importantly, however, we find that empirical models that account for the distribution of past expectations of current inflation in addition to the distribution of current expectations of future inflation, do better during the period under study as compared to models that include only the forward-looking component, especially during turbulent times. This suggests that models of noisy information such as rational inattention would be an appropriate starting point for understanding the empirical findings documented here, since they produce a Phillips Curve relation where inflation relates to both current expectations of future inflation and to past expectations of current inflation rather than one or the other. Again, such models would also need to incorporate heterogeneity across households in this case, so that the implied Phillips Curve could possibly allow for the cross-sectional distribution of inflation expectations to play a role in determining current inflation realizations. Our findings here are inconsistent with sticky information or sticky price models as these do not produce a Phillips Curve where both current expectations of future inflation and past expectations of current inflation can play a role for determining inflation.

Finally, we also find substantial cross-country heterogeneity in the relation between inflation and inflation expectations in the euro-area, suggesting that future work would need to account for cross-country heterogeneity in addition to heteregeneity across households.

Overall, our work suggests an important role for heterogeneity as captured by the functional components of the distribution of inflation expectations across households, in determining inflation. This suggests a role for the distribution of inflation expectations in the Phillips

Curve relation for individual economies, beyond the role of consensus expectations implied by standard models of the macroeconomy which do not allow for such heterogeneity. Furthermore, the large degree of heterogeneity we uncover across economies comprising the euro-area, suggests that macroeconomic models should also allow for this additional form of heterogeneity to play a role in the Phillips Curve relation.

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Appendix

A.1 Robustness - Model with constant slope

Table A1 reports the results from Model 0, estimated without allowing for parameter breaks.

Table A1: Benchmark model wth constant parameters

	AT	BE	DE	EL	FI	FR	IT	LT	SI	SK	ES
Avg. Expectations	2.742***	1.378***	0.813**	0.056	1.998***	0.380	1.726***	0.263*	1.553***	0.939***	-0.810
	(0.665)	(0.473)	(0.354)	(0.165)	(0.432)	(0.330)	(0.532)	(0.158)	(0.309)	(0.199)	(0.833)
Functional coefficients for Expected Inflation											
$\gamma = 0$	22.216	8.701	24.800	13.076	11.095	6.033	10.983	24.081	35.321	18.917	6.279
	[0.000]	[0.069]	[0.000]	[0.004]	[0.011]	[0.109]	[0.011]	[0.000]	[0.000]	[0.000]	[0.098]
Sum of Inflation Lags	-0.417	-0.567***	0.234*	0.204	-0.137	0.365**	-0.002	0.736***	-0.206	0.180	0.050
	(2.323)	(8.255)	(2.840)	(1.369)	(0.798)	(4.449)	(0.002)	(25.839)	(1.429)	(1.438)	(0.113)
Unemployment gap	-0.733*	1.634	0.127	-1.288***	-1.139*	-0.482	-0.382	-0.612	-0.789	-0.954**	-0.998**
	(0.385)	(0.992)	(0.884)	(0.422)	(0.663)	(0.466)	(0.433)	(0.382)	(0.548)	(0.462)	(0.402)
Oil price	0.061	0.084**	0.150***	0.110***	0.141***	0.112***	0.047***	0.125***	0.130***	0.066***	0.136***
	(0.040)	(0.035)	(0.018)	(0.018)	(0.036)	(0.027)	(0.017)	(0.040)	(0.026)	(0.021)	(0.034)
lag(1) Oil price	0.086***	0.087***	-0.016	0.069***	0.037*	0.060***	0.051***	0.056	0.150***	0.016	0.079***
	(0.020)	(0.029)	(0.028)	(0.019)	(0.021)	(0.012)	(0.018)	(0.043)	(0.032)	(0.020)	(0.023)
Supply Chain Index	0.450**	1.739***	0.173	0.493	0.663**	0.444	0.745***	1.127***	0.604	0.697	0.476
	(0.185)	(0.501)	(0.261)	(0.527)	(0.311)	(0.325)	(0.221)	(0.336)	(0.470)	(0.472)	(0.558)
Variance Explained	0.990	0.960	0.960	0.940	0.930	0.990	0.980	0.950	0.950	0.950	0.990
	[3]	[4]	[3]	[3]	[3]	[3]	[3]	[4]	[4]	[4]	[3]
Observations	239	239	238	239	239	235	237	238	239	238	238
R^2(adjusted)	0.493	0.588	0.776	0.386	0.564	0.422	0.722	0.730	0.525	0.729	0.498
LjungBox(p-value)	0.735	0.449	0.094	0.969	0.516	0.879	0.192	0.577	0.515	0.192	0.006
WaldEqual	0.021	0.000	0.000	0.091	0.000	0.008	0.008	0.000	0.112	0.018	0.075

Note:*p<0.10, **p<0.05, ***p<0.01. This table presents the regression estimates with heteroscedasticity and autocorrelation-robust standard errors shown in parentheses below the estimates. Where we show hypothesis tests, we present p-values of the Wald test statistic in square brackets below the test statistic value.

[1] Parentheses show the Wald test statistic, while the asterisks indicate the significance level of the corresponding p-value

Looking at the results for our Benchmark model we understand that the inflation expectations parameters are not constant over time. The recent inflation surge was accompanied with a change of the relationship between inflation and inflation expectations.

However, our results remain robust even if we assume that parameters remain constant over time. The null for $\gamma = 0$ is rejected for all countries except France while it is rejected at 10% level of significance for Belgium and Spain. That said, we confirm that the heterogeneity on subective beliefs about inflation hold additional explanatory power for inflation that cannot be captured by a measure of central tendency like average expectations. Moreover, average expectations remain an important determinant of inflation, with their effect statistically significant for most countries. There are, however, some notable exceptions: in Greece, Spain, and France, the impact of average expectations on inflation is insignificant. his finding for Greece and Spain can partially be explained by the results of the benchmark model, which indicate that the effect of average expectations shifted from positive before the structural break to negative afterward.

We again observe that, after accounting for the cross-sectional heterogeneity of inflation expectations, past inflation no longer appears as a significant determinant of the inflation series. Past inflation(Sum of Inflation Lags) is insignificant for all countries except from Belgium, France and Lithouania.

A.2 Using past expectations of current inflation instead of current expectations of future inflation

Models of sticky information Mankiw and Reis (2002) suggest that the lags of expectations should be used instead of current expectations. For that reason we estimate again our benchmark mode but this time using past expectations. $\overline{\pi}^e_{t-1|t}$ captures expectations formed at time $t-1$ for inflation at time t. Since the question on the survey asks about the prices twelve months in the future, we approximate $\overline{\pi}^e_{t-1|t}$ taking the twelve month lag of current expectations

$$\pi_t = \theta\overline{\pi}^e_{t-1|t} + \int \delta\left(\pi^e_{t-1|t} - \overline{\pi}^e_{t-1|t}\right) dP^c_t(\pi^e) + k'X_t + \epsilon_t, \quad \epsilon_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,\sigma^2) \quad (5)$$

As before we allow for coefficitents to change across inflation regimes. Taking the model to the data we get the following results

Table A2: Using past expectations of current inflation instead of current expectations of future inflation.

	AT	BE	DE	EL	FI	FR	IT	LT	SI	SK	ES
Lag(12) Average Expectations	-0.7642	-0.076	0.1401	-0.0734	-0.0586	-1.3938	0.0065	-0.2975**	-0.0365	-0.187	-0.0866
	(0.5205)	(0.192)	(0.3925)	(0.1583)	(0.6093)	(0.8615)	(0.6068)	(0.1461)	(0.3925)	(0.4021)	(0.2273)
D1 * Lag(12) Average Expectations	2.0958	-0.204	0.4657	-0.4776	-2.8947*	-0.2578	-1.5283	-1.1857**	-0.9926	1.3013	-0.8079
	(2.0947)	(0.622)	(0.8122)	(0.3963)	(1.6868)	(0.914)	(0.9869)	(0.5638)	(0.7655)	(1.2468)	(0.7718)
$\theta = \theta_D = 0$	2.609	0.431	0.922	6.852	3.326	29.776	9.552	5.655	3.274	1.098	1.992
	[0.806]	[0.191]	[0.630]	[0.032]	[0.190]	[0.000]	[0.008]	[0.059]	[0.195]	[0.577]	[0.369]
$\theta + \theta_D = 0$	0.855	0.475	1.527	12.481	5.032	54.097	8.154	10.585	5.391	1.833	2.976
	[0.355]	[0.490]	[0.216]	[0.000]	[0.081]	[0.000]	[0.017]	[0.005]	[0.068]	[0.175]	[0.086]
Functional Regressor											
$\delta = \delta_D = 0$	14.630	32.195	8.948	42.665	15.1826	103.488	45.268	102.956	23.777	14.633	15.691
	[0.023]	[0.000]	[0.176]	[0.000]	[0.037]	[0.000]	[0.000]	[0.000]	[0.002]	[0.066]	[0.015]
$\delta + \delta_D = 0$	10.084	21.184	3.256	18.185	1.988	103.488	22.530	46.682	21.021	12.301	14.609
	[0.017]	[0.000]	[0.353]	[0.000]	[0.574]	[0.000]	[0.000]	[0.000]	[0.000]	[0.015]	[0.002]
$\delta = 0$	4.821	8.685	6.576	18.781	12.192	6.049	12.136	74.251	5.267	1.981	1.233
	[0.185]	[0.069]	[0.086]	[0.000]	[0.016]	[0.109]	[0.007]	[0.000]	[0.261]	[0.739]	[0.744]
$\delta_D = 0$	7.305	26.946	3.336	18.171	3.625	20.337	41.634	87.908	9.293	13.134	14.286
	[0.062]	[0.000]	[0.343]	[0.000]	[0.305]	[0.000]	[0.000]	[0.000]	[0.054]	[0.054]	[0.003]
Sum of Inflation Lags	0.028	-0.247*	0.336***	0.281*	0.244	0.400***	0.500***	0.460***	0.320**	0.599.**	0.031
	(0.024)	(3.301)	(11.888)	(3.381)	(2.254)	(10.108)	(25.271)	(11.315)	(4.714)	(12.174)	(0.040)
Unemployment gap	-2.124***	-1.277	-0.565	-1.486	-1.596*	0.118	-0.896*	-1.206***	-0.597	-0.488**	-1.044**
	(0.626)	(1.037)	(0.941)	(0.919)	(0.850)	(0.827)	(0.493)	(0.364)	(0.701)	(0.204)	(0.404)
Oil Price	0.060	0.095**	0.147***	0.115***	0.116***	0.135***	0.050	0.127***	0.137***	0.074***	0.157***
	(0.047)	(0.040)	(0.022)	(0.019)	(0.028)	(0.020)	(0.040)	(0.044)	(0.029)	(0.022)	(0.047)
lag(1) Oil Price	0.105***	0.110***	-0.014	0.046**	0.072***	0.048**	0.054***	0.067	0.157***	0.028	0.082***
	(0.019)	(0.034)	(0.029)	(0.019)	(0.018)	(0.021)	(0.013)	(0.042)	(0.035)	(0.020)	(0.023)
Supply Chain Index	-0.115	1.015*	-0.384	0.085	0.163	0.485*	0.202	-0.052	0.234	0.125	0.089
	(0.371)	(0.570)	(0.245)	(0.507)	(0.375)	(0.260)	(0.473)	(0.459)	(0.716)	(0.236)	(0.348)
Dummy	-41.336**	1.591	-6.890	3.009	16.828**	0.418	2.804	22.081**	8.443	-20.145*	12.787**
	(19.119)	(6.446)	(4.982)	(2.664)	(6.879)	(3.395)	(6.059)	(9.144)	(6.916)	(9.645)	(4.917)
Variance Explained	0.990	0.960	0.960	0.940	0.930	0.990	0.980	0.950	0.950	0.950	0.990
	[3]	[4]	[3]	[3]	[3]	[3]	[3]	[4]	[4]	[4]	[3]
Observations	227	227	226	226	227	223	225	226	227	227	226
R^2(adjusted)	0.440	0.526	0.761	0.394	0.529	0.495	0.730	0.744	0.456	0.734	0.490
LjungBox(p-value)	0.576	0.225	0.009	0.969	0.657	0.632	0.252	0.504	0.311	0.330	0.001
Wald (p-value, lags jointly zero)	0.001	0.186	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.136

Note:*p<0.10, **p<0.05, ***p<0.01. This table presents the regression estimates with heteroscedasticity and autocorrelation-robust standard errors shown in parentheses below the estimates. Where we show hypothesis tests, we present p-values of the Wald test statistic in square brackets below the test statistic value.

[1] Parentheses show the Wald test statistic, while the asterisks indicate the significance level of the corresponding p-value

The most noteable result is that the cross-section distribution of past expectations about current inflation is in general informative for realized inflation. More precisely, we can reject the null for $\delta = \delta_D = 0$ for all countries except from Germany and Slovakia [1]. In addition, we rejecting the null for $\delta + \delta_D = 0$ for all countries except Germany and Finland which means that past expectations was particulary relevant for actual inflation during the high-inflation period. For the low inflation regime, the functional componets are mostly insignificant with notable exceptions Greece, Lithouania and Italy, rejecting the null $\delta = 0^2$. On the contrary, average expectations are in general uninformative for realized inflation across both inflation

[1]We reject at 5 % level of significance for Austria, Finland and Spain

[2]We can reject the null for Belgium at 10% level of significance

regimes

What we notice is that past average expectations are generally insignificant, for the majority of countries, across both inflation regimes.

A.3 Using past expectations for current inflation together with current perceptions of past inflation

We now control for Current Expectations, Past Expectations and Perceived Inflation in the same specification. Comparing average root mean squared errors across different specifications, we find that using perceived past inflation or past expectations of current inflation, produces very similar in-sample results. Therefore, another robustness check of our main findings is to control for perceived inflation and past expectations together.

First,the functional coefficient of current expected inflation are still very informative in the high inflation regime while it remains signifinant for most countries in the low inflation regime.

The interest lies in comparing the impact of the distribution of currently perceived past inflation with that of past expectations of current inflation. We reject the null hypothesis for $\kappa = \kappa_D = 0$ in all countries except Austria, Germany, and Spain, where the distribution of past expected inflation is not statistically significant. With respect to the functional components of perceived inflation, we can reject the null for $\pi = \pi_D = 0$ for Belgium, Finland, Italy, and Spain, and at lower levels of significance for Austria, Greece, France, Slovenia, and Slovakia. In Austria and Spain, the distribution of current perceptions of past inflation appears more relevant for current inflation realizations than past expectations. By contrast, in Lithuania the opposite holds. Taken together, the evidence suggests that in most countries both perceived past inflation and past expectations of current inflation serve as highly informative predictors of current inflation outcomes

Table A3: Adding past expectations and perceptions of past inflation to the Benchmark

	AT	BE	DE	EL	FI	FR	IT	LT	SI	SK	ES
Current average expectations											
Average Expectations	2.858***	0.135	0.651	0.402	1.226	-1.236	1.049	0.862**	1.602***	1.456***	1.590***
	(1.053)	(0.243)	(0.459)	(0.320)	(0.781)	(0.930)	(0.825)	(0.335)	(0.587)	(0.504)	(0.490)
D1 * Average Expectations	2.392	5.577***	1.657	-2.058***	4.321	1.558	3.084**	-0.378	1.562**	-0.573	-3.141**
	(1.951)	(1.411)	(1.140)	(0.508)	(3.752)	(1.020)	(1.538)	(0.501)	(0.679)	(0.834)	(1.429)
$\beta = \beta_D = 0$	10.071	27.019	10.538	15.906	5.179	1.641	11.634	11.384	48.173	10.606	10.135
	[0.014]	[0.000]	[0.043]	[0.000]	[0.179]	[0.311]	[0.000]	[0.034]	[0.000]	[0.008]	[0.000]
$\beta + \beta_D = 0$	10.576	36.045	9.235	28.911	4.015	0.951	22.793	2.098	88.903	3.283	2.077
	[0.001]	[0.000]	[0.002]	[0.000]	[0.045]	[0.329]	[0.000]	[0.147]	[0.000]	[0.070]	[0.149]
Average past expectations											
Lag(12) Average Expectations	-1.499	-0.782**	-0.250	-0.197	0.148	-2.104**	-0.229	-0.272*	-0.099	-0.513	-0.251
	(0.916)	(0.382)	(0.504)	(0.152)	(0.580)	(0.960)	(0.848)	(0.159)	(0.397)	(0.341)	(0.348)
D1* Lag(12) Average Expectations	1.071	-0.493	-1.278	1.257***	1.463	-0.683	-3.177**	-1.547***	1.132**	1.273	0.418
	(2.256)	(1.371)	(1.350)	(0.462)	(3.211)	(1.028)	(1.578)	(0.432)	(0.561)	(1.148)	(0.658)
$\delta = \delta_D = 0$	1.745	10.157	1.695	5.440	0.372	14.225	6.845	13.665	12.087	4.575	0.074
	[0.418]	[0.006]	[0.429]	[0.066]	[0.830]	[0.001]	[0.033]	[0.001]	[0.002]	[0.102]	[0.964]
$\delta + \delta_D = 0$	0.041	4.514	3.087	9.399	0.408	26.973	2.832	25.965	20.828	0.971	0.142
	[0.980]	[0.105]	[0.214]	[0.009]	[0.816]	[0.000]	[0.243]	[0.000]	[0.000]	[0.615]	[0.932]
Average Perception	0.868	1.191***	-0.031	-0.168	0.988	0.316	0.317	-0.696	0.263	-0.385	-0.790***
	(0.616)	(0.422)	(0.542)	(0.372)	(0.615)	(0.465)	(0.198)	(0.459)	(0.509)	(0.520)	(0.242)
D1 * Average Perceptions	-1.539*	-2.456***	1.095*	0.156	1.984*	0.690	-1.932**	0.727	-1.299	-0.625	1.337*
	(0.814)	(0.858)	(0.636)	(0.523)	(1.118)	(0.898)	(0.746)	(0.689)	(0.859)	(1.150)	(0.767)
$\zeta = \zeta_D = 0$	1.984	7.970	0.003	0.204	2.583	0.462	2.563	2.297	0.258	0.546	10.680
	[0.159]	[0.005]	[0.954]	[0.652]	[0.108]	[0.497]	[0.109]	[0.130]	[0.612]	[0.460]	[0.001]
$\zeta + \zeta_D = 0$	1.915	6.732	12.944	0.002	22.635	2.285	11.167	0.009	1.859	1.879	1.133
	[0.166]	[0.009]	[0.000]	[0.969]	[0.000]	[0.131]	[0.001]	[0.924]	[0.173]	[0.170]	[0.287]
Functional Coefficient for Current Expected Inflation											
$\gamma = \gamma_D = 0$	30.300	20.472	13.299	45.773	39.634	20.000	42.900	45.726	35.467	70.656	19.973
	[0.000]	[0.008]	[0.038]	[0.000]	[0.000]	[0.006]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]
$\gamma + \gamma_D = 0$	21.538	5.487	9.307	27.297	36.582	10.504	20.573	21.251	7.043	50.786	4.790
	[0.000]	[0.241]	[0.025]	[0.000]	[0.000]	[0.014]	[0.000]	[0.000]	[0.133]	[0.000]	[0.187]
$\gamma = 0$	3.357	16.127	6.051	10.517	8.225	10.875	6.042	17.044	21.918	9.938	12.786
	[0.339]	[0.002]	[0.109]	[0.014]	[0.041]	[0.012]	[0.109]	[0.002]	[0.000]	[0.041]	[0.005]
$\gamma_D = 0$	20.641	4.810	7.625	24.623	37.801	10.454	14.222	24.474	1.416	33.034	3.349
	[0.000]	[0.307]	[0.054]	[0.000]	[0.000]	[0.015]	[0.002]	[0.000]	[0.841]	[0.000]	[0.341]
Functional Coefficient for Past Expected inflation											
$\kappa = \kappa_D = 0$	8.600	21.890	9.777	37.801	60.223	33.167	15.009	24.369	17.633	30.347	7.885
	[0.197]	[0.005]	[0.134]	[0.000]	[0.000]	[0.000]	[0.020]	[0.002]	[0.024]	[0.000]	[0.264]
$\kappa + \kappa_D = 0$	0.840	19.409	2.054	33.289	21.963	31.900	9.547	20.017	7.585	27.101	6.818
	[0.839]	[0.000]	[0.561]	[0.000]	[0.000]	[0.000]	[0.022]	[0.000]	[0.108]	[0.000]	[0.077]
$\kappa = 0$	4.906	7.900	5.195	7.845	10.967	5.306	9.111	20.069	4.238	16.321	8.698
	[0.093]	[0.517]	[0.032]	[0.013]	[0.000]	[0.063]	[0.297]	[0.073]	[0.127]	[0.508]	[0.691]
$\kappa_D = 0$	1.600	16.936	2.132	24.343	11.920	19.743	5.695	14.229	4.528	29.278	7.473
	[0.659]	[0.002]	[0.545]	[0.000]	[0.008]	[0.000]	[0.127]	[0.007]	[0.339]	[0.000]	[0.058]
Functional coefficient for Perception											
$\pi = \pi_D = 0$	14.220	22.514	4.777	10.968	33.434	11.727	65.012	11.752	19.888	15.797	21.342
	[0.027]	[0.004]	[0.573]	[0.089]	[0.000]	[0.068]	[0.000]	[0.163]	[0.011]	[0.045]	[0.002]
$\pi + \pi_D = 0$	6.913	7.391	4.475	6.969	31.552	5.869	61.234	7.171	12.737	11.934	3.203
	[0.075]	[0.117]	[0.215]	[0.073]	[0.000]	[0.118]	[0.000]	[0.127]	[0.013]	[0.018]	[0.361]
$\pi = 0$	5.582	7.852	0.475	3.939	0.481	6.125	5.779	4.271	9.309	5.310	13.591
	[0.093]	[0.517]	[0.032]	[0.013]	[0.000]	[0.063]	[0.297]	[0.073]	[0.000]	[0.508]	[0.691]
$\pi_D = 0$	3.574	12.060	4.648	5.428	27.715	10.041	46.411	9.898	6.074	13.530	1.585
	[0.311]	[0.017]	[0.199]	[0.143]	[0.000]	[0.018]	[0.000]	[0.042]	[0.194]	[0.009]	[0.663]
Lagged Inflation	-0.717**	-1.328***	-0.111	-0.514*	-0.640***	0.099	-0.230	0.119	-0.242	0.000	0.085
	(4.331)	(10.738)	(0.804)	(3.811)	(10.699)	(0.290)	(1.585)	(0.229)	(1.035)	(0.000)	(0.229)
Unemployment gap	-0.833*	-0.035	0.969	-1.268**	-0.700	-0.223	-0.666	-0.552	-0.079	-0.399	-0.613**
	(0.437)	(0.988)	(1.252)	(0.596)	(0.488)	(1.061)	(0.580)	(0.342)	(0.619)	(0.343)	(0.297)
Oil Price	0.048	0.085*	0.136***	0.083***	0.102***	0.154***	0.040	0.114**	0.132***	0.064**	0.137***
	(0.041)	(0.049)	(0.022)	(0.025)	(0.022)	(0.022)	(0.028)	(0.048)	(0.032)	(0.028)	(0.037)
lag1. Oil	0.094***	0.082***	0.001	0.055***	0.055***	0.053***	0.052***	0.099***	0.159***	0.038*	0.085***
	(0.017)	(0.021)	(0.023)	(0.017)	(0.015)	(0.019)	(0.018)	(0.038)	(0.045)	(0.020)	(0.024)
Supply Factors	-0.234	0.486	-0.709*	0.191	-0.068	0.993**	0.054	0.469	-0.563	-0.542*	0.481
	(0.524)	(0.533)	(0.413)	(0.401)	(0.361)	(0.465)	(0.568)	(0.485)	(0.432)	(0.287)	(0.668)
Variance Explained	0.990	0.960	0.960	0.940	0.930	0.990	0.980	0.950	0.950	0.950	0.990
	[3]	[4]	[3]	[3]	[3]	[3]	[3]	[4]	[4]	[4]	[3]
Observations	227	227	226	226	227	223	225	226	227	227	226
R^2 (adjusted)	0.575	0.669	0.802	0.540	0.681	0.509	0.779	0.778	0.540	0.813	0.601
Ljung-Box (p-value)	0.492	0.402	0.013	0.601	0.399	0.150	0.244	0.176	0.465	0.176	0.120
Wald (p-value, lags jointly zero)	0.048	0.000	0.000	0.023	0.000	0.037	0.000	0.647	0.074	0.000	0.005

Note:*p<0.10, **p<0.05, ***p<0.01. This table presents the regression estimates with heteroscedasticity and autocorrelation-robust standard errors shown in parentheses below the estimates. Where we show hypothesis tests, we present p-values of the Wald test statistic in square brackets below the test statistic value.

[1] Parentheses show the Wald test statistic, while the asterisks indicate the significance level of the corresponding p-value

A.4 Robustness - using core inflation instead of harmonized CPI inflation

Here we repeat our analysis from Table 2 with the Benchmark model but this time using the core inflation rate rather than the harmonized CPI inflation rate.

Table A4: Benchmark model - Core inflation

	AT	BE	DE	EL	FI	FR	IT	LT	SI	SK	ES
Average Expectations	0.116	0.244	-0.122	0.261*	0.651**	-0.913	-0.814	0.588***	0.171	0.641***	0.606**
	(0.388)	(0.201)	(0.337)	(0.134)	(0.313)	(0.644)	(0.575)	(0.130)	(0.369)	(0.217)	(0.292)
D1 * Average Expectations	3.095***	-0.234	2.663***	-1.101**	0.835	1.702**	0.281	-0.636***	-0.376	0.458*	-0.835
	(0.821)	(0.568)	(0.663)	(0.516)	(0.691)	(0.734)	(0.774)	(0.188)	(0.426)	(0.267)	(0.542)
$\beta = \beta_D = 0$	15.911	0.901	20.092	7.542	12.348	8.359	2.220	24.947	1.551	34.268	4.459
	[0.000]	[0.637]	[0.000]	[0.023]	[0.002]	[0.015]	[0.330]	[0.000]	[0.461]	[0.000]	[0.108]
$\beta + \beta_D = 0$	31.154	0.01	39.967	5.247	13.117	13.909	1.255	0.125	2.920	60.691	0.542
	[0.000]	[0.982]	[0.000]	[0.073]	[0.001]	[0.001]	[0.534]	[0.939]	[0.232]	[0.000]	[0.763]
Functional Regressor											
$\gamma = \gamma_D = 0$	21.027	21.670	21.374	36.636	27.950	17.660	7.976	60.250	35.732	57.158	12.658
	[0.002]	[0.005]	[0.002]	[0.000]	[0.000]	[0.007]	[0.240]	[0.000]	[0.000]	[0.000]	[0.049]
$\gamma + \gamma_D = 0$	20.178	14.821	20.730	25.451	22.908	11.774	6.046	37.817	35.581	53.567	11.438
	[0.000]	[0.005]	[0.000]	[0.000]	[0.000]	[0.000]	[0.109]	[0.000]	[0.000]	[0.000]	[0.009]
$\gamma = 0$	1.326	2.720	0.830	7.640	1.469	3.000	6.351	30.274	1.304	5.952	6.194
	[0.723]	[0.605]	[0.842]	[0.054]	[0.689]	[0.392]	[0.096]	[0.000]	[0.861]	[0.203]	[0.103]
$\gamma_D = 0$	16.213	8.909	19.371	27.553	16.771	15.899	4.020	56.771	14.699	31.147	8.107
	[0.001]	[0.063]	[0.000]	[0.000]	[0.001]	[0.001]	[0.259]	[0.000]	[0.005]	[0.000]	[0.044]
Sum of Inflation Lags	-0.251	-0.256	-0.511***	-0.812***	-0.515**	-0.702**	-0.965*	-0.273**	0.349*	-0.454*	-0.423
	(0.920)	(0.248)	(8.974)	(16.109)	(6.366)	(4.256)	(3.499)	(5.407)	(3.714)	(3.771)	(1.509)
Unemployment gap	-0.292	0.481	-2.582***	-1.561***	-0.346	-0.679	-1.543**	-1.222***	0.734	-0.658**	-0.183
	(0.326)	(0.483)	(0.825)	(0.552)	(0.307)	(0.669)	(0.624)	(0.262)	(0.502)	(0.255)	(0.355)
Oil Prices	-0.011	-0.035***	0.009	0.002	0.012	0.016	0.012	0.049***	0.007	0.024	0.015**
	(0.021)	(0.012)	(0.016)	(0.022)	(0.012)	(0.014)	(0.008)	(0.012)	(0.022)	(0.015)	(0.007)
lag(1) Oil Prices	0.022	0.006	-0.010	-0.103***	-0.012	0.015	-0.008	0.012	0.004	0.002	0.002
	(0.023)	(0.013)	(0.015)	(0.036)	(0.019)	(0.011)	(0.015)	(0.030)	(0.014)	(0.014)	(0.012)
Supply Chain Index	-0.221	-0.137	-0.063	1.410***	-0.455*	0.372	-0.396	1.619***	0.452	0.050	0.179
	(0.299)	(0.295)	(0.397)	(0.469)	(0.244)	(0.242)	(0.333)	(0.248)	(0.311)	(0.268)	(0.190)
Dummy	-11.887**	-3.914	2.398	4.214	-8.174***	-3.538	-0.608	12.734***	1.108	-10.295***	6.650*
	(4.709)	(4.354)	(10.662)	(4.987)	(2.212)	(3.172)	(3.608)	(3.382)	(3.231)	(3.307)	(3.697)
Variance Explained	0.990	0.960	0.960	0.940	0.930	0.990	0.980	0.950	0.950	0.950	0.990
	[3]	[4]	[3]	[3]	[3]	[3]	[3]	[4]	[4]	[4]	[3]
Obs	239	239	238	238	239	235	238	238	239	239	238
R^2(adjusted)	0.403	0.779	0.436	0.453	0.268	0.334	0.488	0.682	0.316	0.634	0.369
LjungBox(p-value)	0.613	0.001	0.002	0.900	0.276	0.371	0.530	0.594	0.932	0.325	0.996
WaldEqual	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.036	0.004	0.000

Note:*p<0.10, **p<0.05, ***p<0.01. This table presents the regression estimates with heteroscedasticity and autocorrelation-robust standard errors shown in parentheses below the estimates. Where we show hypothesis tests, we present p-values of the Wald test statistic in square brackets below the test statistic value.

[1] Parentheses show the Wald test statistic, while the asterisks indicate the significance level of the corresponding p-value

A.5 Statistical background for functional R^2

This section reports the functional response model used to link inflation realizations with the distribution of inflation expectations. The basic specification is:

$$p_{t,h}(\cdot) = w_t^\top \beta(\cdot) + u_t(\cdot), \tag{A1}$$

where $p_{t,h}(\cdot)$ is the functional outcome, w_t is a $p \times 1$ vector of regressors, $\beta(\cdot)$ is the unknown coefficient function, and $u_t(\cdot)$ is an error term.

Stacking the observations by time at horizon h, the model becomes:

$$p(\cdot) = W\beta(\cdot) + u(\cdot) \tag{A2}$$

where the dimensions are: $T \times 1$, $T \times p$, $p \times 1$, and $T \times 1$, respectively.

To estimate the coefficient function, we expand the functional elements in terms of an empirical basis. Thus:

$$p_t(\cdot) = \sum_k s_{t,k} e_k(\cdot), \qquad \beta(\cdot) = \sum_k b_k e_k(\cdot), \qquad u_t(\cdot) = \sum_k u_{t,k} e_k(\cdot),$$

where $\{s_{t,k}, b_k, u_{t,k}\}$ are scores associated with the k-th eigenvalue of the covariance function of u (see Section A). Substituting, the model for each component k becomes:

$$s_{\cdot k} = W b_k + u_{\cdot k} \tag{A3}$$

with dimensions $T \times 1$, $T \times p$, $p \times 1$, and $T \times 1$.

The static model in Eq. (D.1)–(D.2) is estimated over the full sample of length T, implicitly assuming stability of the relationship between inflation and expectations. To allow for time variation, we extend the framework using a rolling window.

Let $\mathcal{T}_\tau = \{\tau, \tau+1, \ldots, \tau+W-1\}$ denote the subsample of size $W < T$ starting at time τ.

For each window, the model is re-estimated as:

$$\mathbf{p}_{\mathcal{T}_\tau}(\cdot) = \mathbf{w}_{\mathcal{T}_\tau}\,\beta(\cdot) + \mathbf{u}_{\mathcal{T}_\tau}(\cdot) \tag{A4}$$

where $\mathbf{p}_{\mathcal{T}_\tau}(\cdot)$ collects $\{p_t(\cdot) : t \in \mathcal{T}_\tau\}$ and $\mathbf{w}_{\mathcal{T}_\tau}$ stacks the regressors over the same period. Similarly, we can expand the functional element in term of his empirical basis finctions For each principal component k and each rolling window $\mathcal{T}_\tau = \{\tau, \tau+1, \ldots, \tau+W-1\}$, we estimate:

$$s_{\cdot k,\mathcal{T}_\tau} = \mathbf{W}_{\mathcal{T}_\tau} b_{k,\tau} + u_{\cdot k,\mathcal{T}_\tau} \tag{A5}$$

where $\mathbf{s}_{\cdot k,\mathcal{T}_\tau}$ denotes the $W \times 1$ vector of scores of principal component k over window $\mathcal{T}_\tau$, $\mathbf{W}_{\mathcal{T}_\tau}$ is the $W \times m$ matrix of independent variables, $\mathbf{b}_{k,\tau}$ is the $m \times 1$ vector of regression coefficients for principal component score k in window τ, and $\mathbf{u}_{\cdot k,\mathcal{T}_\tau}$ is the corresponding $W \times 1$ vector of residuals.

with corresponding coefficient estimates:

$$\hat{b}_{k,\tau} = \left(\mathbf{w}_{\mathcal{T}_\tau}^\top \mathbf{w}_{\mathcal{T}_\tau}\right)^{-1} \mathbf{w}_{\mathcal{T}_\tau}^\top s_{\cdot k,\mathcal{T}_\tau}. \tag{A6}$$

Rolling estimates $\hat{b}_{k,\tau}$ across $\tau = 1, \ldots, T-W+1$ yield a sequence of time-varying coefficient functions that track how the impact of inflation expectations evolves over time. This approach allows us to account for possible time heterogeneity on the impact of the selected macroeconomic aggregates on the cross-sectional distribution of inflation expectations.

We can then define for each window $\mathcal{T}_\tau$ the residual sum of square errors as:

$$\mathrm{RSS}_{\mathcal{T}_\tau} = \sum_{k=1}^{K} s_{\cdot k,\mathcal{T}_\tau}^\top\, \mathbf{P}_{\mathbf{w}_{\mathcal{T}_\tau}}^\perp\, s_{\cdot k,\mathcal{T}_\tau}, \qquad \mathbf{P}_{\mathbf{w}_{\mathcal{T}_\tau}} = \mathbf{w}_{\mathcal{T}_\tau}\left(\mathbf{w}_{\mathcal{T}_\tau}^\top \mathbf{w}_{\mathcal{T}_\tau}\right)^{-1}\mathbf{w}_{\mathcal{T}_\tau}^\top, \quad \mathbf{P}_{\mathbf{w}_{\mathcal{T}_\tau}}^\perp = \mathbf{I} - \mathbf{P}_{\mathbf{w}_{\mathcal{T}_\tau}}. \tag{A7}$$

The coefficient of determination R^2 for each window of our rolling functional response model is computed by the sum-of-squares residulas from (A4) with the respective total sum-of-squares defined as $TSS_{\mathcal{T}_\tau} = \sum_{k=1}^{K} s_{\cdot k,\mathcal{T}_\tau}^\top\, s_{\cdot k,\mathcal{T}_\tau}$