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# HOUSEHOLDS' SUBJECTIVE EXPECTATIONS: DISAGREEMENT, COMMON DRIVERS AND REACTION TO MONETARY POLICY (*)

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## Abstract

Using granular data on household subjective expectations for several countries, we uncover a robust positive reaction of inflation expectations to a contractionary monetary policy shock, a result at odds with standard equilibrium theories with nominal rigidities. We then investigate what lies behind such result. Although households disagree, their expectations are correlated in the cross-section. Two principal components account for a significant portion of the variance of all expectations. These components capture households' perceptions of the sources of macroeconomic dynamics, with the first capturing either a supply-side view or an overall dislike for inflation, and the second component reflecting a perception about demand pressures. This structure of disagreement is stable across countries and over time and does not vary with demographic or socioeconomic characteristics. We then use these insights to identify two common factors driving expectations over time. These factors are consistent with a narrative based on perceived supply-side inflationary pressures after the invasion of Ukraine in February 2022, as well as with the overall downward inflation dynamics intensified by the reaction of the ECB.



**Keywords:** survey, expectations, disagreement, monetary policy.

**JEL classification:** D1, D8, E2, E3.

## Resumen

Utilizando datos granulares sobre las expectativas subjetivas de los hogares de varios países de la eurozona, encontramos una robusta reacción positiva de las expectativas de inflación ante un *shock* contractivo de la política monetaria, un resultado que contradice las teorías estándar del equilibrio general con rigideces nominales. A continuación investigamos lo que subyace a tal resultado. Aunque los hogares presentan marcadas divergencias en el nivel de sus expectativas, estas están correlacionadas a lo largo de la muestra. Dos componentes principales explican una parte importante de la varianza de todas las expectativas. Estos componentes capturan las percepciones de los hogares sobre las fuentes de la dinámica macroeconómica: el primero captura una visión del lado de la oferta o un disgusto general por la inflación, mientras que el segundo refleja una percepción de las presiones de la demanda. Esta estructura de divergencias es estable entre países y a lo largo del tiempo y no parece variar en función de las características demográficas o socioeconómicas. Finalmente, utilizamos estos resultados para identificar dos factores comunes que impulsan las expectativas a lo largo del tiempo. Tales factores son consistentes con un discurso basado en las presiones inflacionarias percibidas desde el lado de la oferta después de la invasión de Ucrania en febrero de 2022, así como con la dinámica general de inflación a la baja intensificada por la reacción del Banco Central Europeo.



**Palabras clave:** encuesta, expectativas, divergencias, política monetaria.

**Códigos JEL:** D1, D8, E2, E3.

# 1 Introduction

Researchers and central bankers alike usually agree that household expectations are a critical ingredient in determining macroeconomic dynamics and in shaping the role of monetary policy in the economy. The reason is simple: most household decisions involve making predictions about future outcomes of economic and policy variables. Such household decisions then shape the economic outcomes on which agents form expectations in the first place. The consensus is less clear, however, regarding how households form those subjective predictions, the information they use when doing so, how they react to new information, and their perceptions about (i.e., mental models of) the relationships between the different variables they care about.[1]

This paper aims to shed light on some of those less understood aspects of household expectations and how they can impact the transmission of monetary policy. We address two main questions. First, how do household expectations respond to monetary policy shocks? Second, what is the underlying structure of those expectations, and how can it help us understand the answer to the first question?

To answer these questions we exploit granular data on household expectations about macroeconomic and individual-level variables included in the monthly Consumer Expectations Survey (CES) administered by the European Central Bank (ECB). This survey, which was launched in April 2020 at monthly frequency, comprises a representative panel of around 15,000 households from 6 major European economies.[2] We focus on expectations about ten key variables, including output growth, inflation (over two different horizons), unemployment rate, house price growth, interest rates on mortgages, own income growth, own financial situation, own access to credit, and own spending on durable goods. The advantage of this survey, relative to existing ones, is that most of the above mentioned expectations are quantitative rather than qualitative, i.e. households provide specific numerical values for their responses. Although the survey has a limited time span, commencing in April 2020, it encompasses a monthly four-year timeframe that includes, among other events, the pandemic era, the invasion in Ukraine, the start of the latest tightening cycle by the ECB, and the war between Israel and Palestina.

We start our analysis by estimating the average response of household expectations to identified monetary policy shocks. We find that, as predicted by a standard dynamic New-Keynesian model with nominal rigidity and rational expectations, contractionary monetary policy surprises have a negative effect on the expected growth of the economy

[1]There has been, nonetheless, a recent increase in the number of theoretical and empirical papers proposing and evaluating alternative expectation formation processes; see for example, Bordalo et al. (2022), D'Acunto et al. (2023) and Andre et al. (2023).

[2]The 6 countries included in the survey since the beginning are Belgium, France, Germany, Italy, Spain, and the Netherlands. We only use these 6 countries in our benchmark analysis in order to maximize the time coverage. Five additional countries were added in April 2022: Austria, Finland, Greece, Ireland, Portugal, resulting in an unbalanced panel of around 20,000 households observed in each month.

and on expected own income growth, and a positive impact on expected unemployment rate. We also uncover, however, a *positive effect* on the expected inflation rate one and three years ahead. We show that impulse responses, and in particular the response of inflation expectations, are robust across countries and across different socioeconomic and demographic groups. We confirm these results, an in particular the negative response of unemployment expectations and the positive respone of inflation expectations, using an alternative dataset, namely the aggregated survey household responses provided by the European Commission.

We then explore in detail the structure of expectations within and between households, as well as over time, in order to better understand how people think about the co-movement of inflation with the rest of the economy. We first document that, although households disagree in their predictions of the future, there is significant correlation between household expectations across multiple variables. For example, households expect lower inflation and higher output growth simultaneously; this is in line with previous research findings by Candia et al. (2020) and Kamdar (2019), although our results hold for six different countries. We also find that high inflation expectations correlate with high forecasts for house price growth, while low expected unemployment rates are associated with high expected output growth. Interestingly, household expectations about aggregate-level variables are intertwined with their expectations about individual-level variables. For instance, when households anticipate high output growth, they also tend to expect higher personal income growth. We subsequently explore the common drivers behind the correlated expectations by sequentially imposing more structure on the data, first in the cross-section of households and then across time.

First, we rely on the large cross-sectional dimension of our data and perform a Principal Component Analysis (PCA) on the full set of expectations. Our baseline analysis exploits the cross-sectional variation of household-level expectations (i.e., households' *disagreement* about the future) pooling together all months and countries of the sample, and it reveals that the first two principal components account for more than 40% of the joint variation in all expectations. In other words, disagreement appears to have a defined pattern of co-movement. Judging from the signs of the loadings on expected prices and quantities, we interpret the principal components as household perceived sources of the business cycle. The first component seems to capture unconditional co-movements of beliefs consistent with our results conditional on a monetary policy shock: households anticipate a better economy while expecting lower inflation. This suggests either that they expect the economic dynamics to be driven in that period mainly by supply-side disturbances or, more broadly, that people dislike inflation due to its impact on real purchasing power and the increased complexity in decision-making (Shiller (1996), Stantcheva (2024), Binetti et al. (2024)). The second component, on the other hand, portrays a different story: Households expect higher inflation when they forecast higher output growth. This is consistent with a Phillips curve and more generally with demand-side business cycle.

When we link these perceptions to demographic and socioeconomic characteristics, an interesting result emerges. Principal components for different age and education groups reveal *barely any change* to our baseline results, which is consistent with the estimated impulse responses to a monetary policy shock. This might strike as surprising nonetheless, given the recent literature pointing towards an important role for experiences, purchasing behavior and sophistication in shaping expectations.[3] Note, however, that our exercise is not about levels or changes in single expectations and how they relate to experience and demographics, but about the *joint movement* in expectations.

We also find, similar to what Patton y Timmermann (2010) find for professional forecasters, that households tend to be persistently above or below the consensus expectation in their respective countries. Notwithstanding the results on demographics outlined above, this could still point towards certain unobserved household characteristics shaping the co-movement of expectations. We therefore repeat our analysis using within-household variation in expectations, which is also consistent with the fixed-effects specification used when estimating reactions to monetary policy shocks. The two main underlying drivers are essentially the same to our baseline, reassuring us that household optimism is not driving our results.

Our main cross-sectional results about perceptions are also surprisingly robust to other cuts of the data. Repeating the PCA in each month separately shows that the loadings of the principal components are stable over the months in our sample, pointing to the fact that households across the euro area have been expecting supply-side forces to be more important (in terms of explained variance) than demand-side ones. Similarly, performing the PCA separately by country shows that the loadings are similar across countries, so that no specific country drives our baseline results. We do find, however, that the benchmark results do not hold when using a subset of the expectation. In particular, running the PCA only with expected economic growth, expected inflation and expected interest rates (the main expectations that appear in the standard three-equation New-Keynesian model; see Gali (2015)) fails to extract the two main drivers that emerge from the full set of expectations. This suggests that there is relevant information that can be extracted by analyzing all expectations simultaneously.

Second, we impose additional structure and estimate a factor model exploiting the panel dimension of the data, in order to extract underlying common drivers of expectations *over time*. We use data from September 2020 to November 2023, and our identification strategy relies on the cross-sectional results discussed above. As is well known, factors and loadings in this set-up are only identified up to a rotation. Following the insights in Rubio-Ramírez et al. (2010) and Altavilla et al. (2019), we draw rotations and define as

[3]See, among others, Malmendier y Nagel (2015), Kuchler y Zafar (2019) and D'Acunto et al. (2021b).

valid those which imply loadings that satisfy a set of sign restrictions that are consistent with our cross-sectional principal component results.

Even though we have a short time dimension, the two identified factors present some interesting and intuitive characteristics. First, the trends both prior to and following the invasion in Ukraine of February 2022 align with the narrative of how supply and demand factors influenced prices and quantities during this timeframe. Notably, post-February 2022, perceptions concerning supply indicate increasingly strong inflationary pressures, whereas perceptions regarding demand only indicate mild inflationary pressures. This is in line both with (i) negative supply shocks hitting the euro area in this period (see, for example, Ascari et al. (2023)), and (ii) households unambiguously associating negative news about different topics with an increase in expected inflation. Second, we argue that these drivers of expectations present similar patterns to the drivers behind the observed business cycle (i.e. drivers of *realized* variables) in the euro area since the beginning of 2020. To show this, we correlate the factors driving expectations with different measures of supply and demand forces that shape business cycles. The supply factor, for example, has a very high correlation with the Supply Bottleneck Index (SBI) created by Burriel et al. (2023). This index is constructed from newspaper articles using text-analysis techniques, a dataset very different from the one we use in this paper. The correlation increases when we lag the SBI, and is highest (0.85) at a 6-8 months lag, which is intuitive in our context because of the delay with which one would think households incorporate news into their expectation formation process. This result suggests that households form expectations at least partially based on news they come across, and it reassures us that our measures of perception are connected with fundamental macroeconomic dynamics. We also find that the first factor presents a contemporaneous correlation of 0.85 with the Consumer Confidence Indicator (CCI) from the European Commission (see European Commission (2018)). The CCI is based on survey questions about (i) personal finances / spending and (ii) expectations about macro developments, with questions being mainly categorical with negative and positive options, and the Index is a simple arithmetic sum of replies.

We finally estimate the response of both factors to monetary policy surprises using a very similar specification to the one used for individual expectations. Though noisier than the average response of expectations, both responses seem to be capturing the same surprising movement in inflation expectations: unexpected interest rate increases have a negative impact households' common perceptions about the future state of the economy, which is associated with an increase in price growth.

**Relation to the Literature.** Our aim in this paper is to understand what drives the co-movement of a broad set of households' expectations, and what this implies for perceptions about business cycles as well as for the reaction of expectations to monetary policy. Along the way, we contribute to some strands of literature.

We first contribute to a broad empirical literature that seeks to understand households' expectations formation, the structure of their disagreement and the comparison with expectations from professional forecasters. Recent work by D'Acunto et al. (2024), Fofana et al. (2024) and D'Acunto et al. (2023) has documented several facts about inflation expectations dispersion in the cross-section, over time, and how these relate to different households' characteristics. We share with these the agnostic and non-parametric approach to document what is, by now, suggestive evidence that households have limited and dispersed information sets, limited attention and probably have different mental models about how the economy works.

Another set of papers within this literature seeks to understand the way in which households interpret conditional and unconditional relations between variables such as inflation and unemployment. Candia et al. (2020) and Andre et al. (2022) have recently shown that households tend to think differently than experts or professional forecasters about the transmission of shocks and co-movements of variables such as inflation and unemployment. In particular, while professionals relate low inflation with high unemployment, in line with demand-driven co-movements, households associate low inflation with rising output and decreasing unemployment. Moreover, Shiller (1996), first, and Stantcheva (2024) and Binetti et al. (2024) recently, have documented, using both observational and experimental data, that people tend to *dislike* inflation mainly due to its perceived impact on purchasing power and the complexity in decision making. Inflation is perceived as a negative phenomenon, linked to increased unemployment and lower economic activity. We corroborate this apparent lack of perceived trade-off between inflation and activity, and add value to this recent literature by exploring a broader range of expectations across several different countries, and how can the joint set of expectations be exploited to extract common perceptions about business cycle fluctuations.

These results also speak to the concern of whether households and firms understand policy changes (and its communication) in the intended way, and how such understanding translates into expectations that shape real outcomes and decisions. As mentioned above, results in Binetti et al. (2024) Andre et al. (2023) point to a perceived *lack of trade-off* in monetary policy, which is at odds with the way central banks think about transmission mechanisms. Our results using identified shocks robustly corroborate this fact across the six countries considered. Attention and perceptions about inflation can, however, vary over time and change with an inflation spike such as the recent one. Works such as Carvalho y Nechio (2014), Bottone et al. (2021), Van der Cruijsen et al. (2015), Coibion et al. (2023), De Fiore et al. (2021), D'Acunto et al. (2021a), Coibion et al. (2022) and **?** tend to find that, although households who have a particular interest in tracking monetary policy news – such as mortgagors – might form expectations about monetary policy, inflation, and unemployment in a way consistent with a Taylor-type rule or with standard models used in policy institutions, most households do not react to policy announcements.

Our approach to analyze drivers across time using a factor structure lines up with the literature in macroeconomics and finance that extracts underlying common drivers of asset prices (Fama y French (1993)), demand and supply determinants of inflation dynamics (Stock y Watson (2014), Eickmeier y Hofmann (2022)), as well as surprises to macroeconomic and financial variables (see for example Altavilla et al. (2019) and Andrade y Ferroni (2021)). Kučinskas y Peters (2022) show that many expectation-formation theories can be mapped into a factor structure. Herbst y Winkler (2021) estimate a dynamic factor model on the individual forecasts in the Survey of Professional Forecasters in order to extract the main dimensions along which disagreement co-moves across variables. Along similar lines, Kamdar (2019) finds that a single component or factor, which can be linked to "sentiment", explains the bulk of variation in survey responses on unemployment and inflation expectations in the U.S. during the last 40 years. We complement this literature by relying on insights on identification of factor models from Rubio-Ramírez et al. (2010), Stock y Watson (2016) and Altavilla et al. (2019), in order to exploit the joint cross section of expectations (disagreement) and extract common latent drivers over time. We show how such drivers of expectations, which relate to supply disturbances, a dislike for inflation and demand forces, evolve along the business cycle, capturing the economic and political narrative of the last few years.

# 2 Data

Our main dataset is the novel Consumer Expectations Survey (CES), which is administered by the European Central Bank (ECB). Our sample goes from April 2020 to November 2023.[4] The CES is a representative household-level online survey with a panel dimension, carried out in 11 major European economies and sampling roughly 20,000 survey participants every month. In order to maximize the time coverage, we only use the 6 countries included in the survey since the start, which are also the largest of the euro area: Belgium, France, Germany, Italy, Spain, and the Netherlands. This results in unbalanced panel of around 15,000 households per month.

The large sample size allows the survey to be representative both at the euro area level and at the country level. Respondents complete a background questionnaire upon entering the panel, providing one-time information which hardly changes over time such as age, gender, household size, and housing tenure. Expectations about several variables are asked at monthly frequency, while information about non-durable consumption and savings is provided at quarterly frequency.[5] We next outline the variables we use in our

[4] While the CES had a pilot phase that started in January 2020 (wave 1), the data is only available for analysis since April 2020 (wave 4).

[5] See Christelis et al. (2020), Bańnkowska et al. (2021), and Georgarakos y Kenny (2022) for more information about the survey.

statistical analysis and present some descriptive statistics.

**Descriptive Statistics.** In this paper we use information about household-level demographics, income, spending, and expectations.[6] Disposable income refers to the 12 months preceding the interview and is provided in brackets, so our measure of household income is the median of each bracket.[7] Nondurable spending, which is asked at a quarterly frequency, refers to spending on nondurable goods and services in the month preceding the interview and we annualize it. Precautionary savings is constructed using the quarterly survey question asking households how much they think they need to put aside in total savings to deal with unexpected events. To insure comparability across countries, we perform country-specific purchasing power parity (PPP) adjustment for those three variables. "Spent on Durables (0-1)" is a dummy variable capturing whether households have spent on durable goods in the month preceding the interview and captures spending on cars, home appliances, and luxury items.

Most importantly for our analysis, the survey asks households about their expectations for a range of aggregate-level variables, such as the overall economy, inflation, unemployment rate, house prices growth, and interest rates on mortgages. It also asks about individual-level variables, such as income growth, spending growth, access to credit, financial situation, and plans to buy durables. These expectations are provided as numerical values, except for access to credit and financial situation, which are measured on a 1-5 qualitative scale, and plans to buy durables, which are indicated by a 0-1 variable. All expectations refer to a time horizon of 12 months, except for expected inflation, which is also asked at a 3-year horizon.

Table 1 presents some basic descriptive statistics (mean, 10th percentile, median, 90th percentile, and total number of observations) for the variables under exam. It shows that the median household earns 35,000 euros in annual income, is 42 years old, and spent around 17,000 euros in non-durables over the previous 12 months. Over the following 12 months, the median household expects no growth in the economy and in personal income, 3% inflation, and an unemployment rate of 9%.

**Evolution of expectations over the business cycle.** Figure 1 plots the distribution of expectations about economic growth, inflation, house price growth, unemployment rate, interest rate on mortgages, and own income growth over time, when we pool together households from all countries.[8] Three main features are worth noting: households disagree

[6]To correct for outliers, most quantitative variables are winsorised at the 10th and 90th percentiles of the weighted distribution in each month and country.

[7]Because it is asked in the background questionnaire, disposable income is only provided by each household once.

[8]In Figure 1 we do not plot 3-year ahead inflation expectation for space constraints. Figure A.1 in Appendix A compares 1-year ahead and 3-year ahead inflation expectations over time, and shows that the dispersion of the former is greater than in the latter.

**Table 1:** Descriptive statistics of some variables over the whole sample

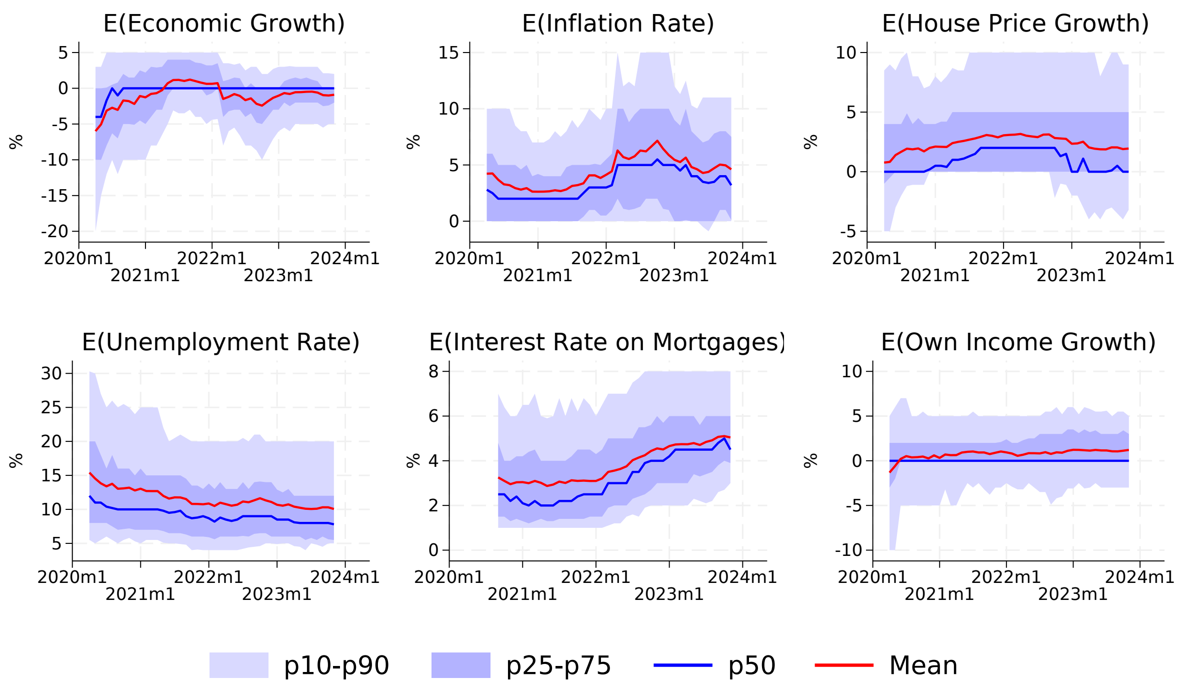
| | Mean | p10 | Median | p90 | N |
|---|---|---|---|---|---|
| Age | 50.78 | 26.00 | 42.00 | 80.00 | 573,051 |
| Disposable Income | 34,860.52 | 12,500.00 | 35,000.00 | 67,500.00 | 573,051 |
| Nondurable Spending | 17,760.69 | 7,548.00 | 17,208.00 | 28,848.00 | 191,006 |
| Spent on Durables (0-1) | 0.18 | 0.00 | 0.00 | 1.00 | 160,914 |
| Precautionary Savings | 7,112.52 | 440.00 | 4,400.00 | 19,600.00 | 173,812 |
| E(Economic Growth) | -1.00 | -7.10 | 0.00 | 4.60 | 573,051 |
| E(Inflation Rate) | 4.37 | 0.00 | 3.00 | 10.00 | 573,025 |
| E(Inflation Rate 3Y) | 3.42 | 0.00 | 2.00 | 10.00 | 567,879 |
| E(House Price Growth) | 2.37 | -1.00 | 1.00 | 10.00 | 573,051 |
| E(Unemployment Rate) | 11.60 | 4.90 | 9.00 | 22.00 | 573,051 |
| E(Interest Rate on Mortgages) | 3.82 | 1.20 | 3.50 | 7.00 | 524,129 |
| E(Own Income Growth) | 0.77 | -3.50 | 0.00 | 5.00 | 573,051 |
| E(Own Spending Growth) | 2.73 | 0.00 | 0.00 | 10.00 | 486,867 |
| E(Own Durable Spending) | 0.29 | 0.00 | 0.00 | 1.00 | 571,632 |
| E(Own Credit Access) | 2.77 | 1.00 | 3.00 | 4.00 | 567,286 |
| E(Own Financial Situation) | 2.80 | 2.00 | 3.00 | 4.00 | 573,051 |

*Note*: "Age" is provided in four brackets ([18-34], [35-49], [50-64], 65+), and we assign to each households the median value in each range. "Disposable Income" refers to the 12 months preceding the interview and it is PPP-adjusted. "Nondurable Spending" is asked at a quarterly frequency, it refers to spending on nondurable goods and services in the month preceding the interview, and it is annualized and PPP-adjusted. "Spent on Durables (0-1)" is asked at a quarterly frequency, and is a dummy variable capturing whether households have spent on durable goods in the month preceding the interview. "Precautionary Savings" is asked at a quarterly frequency, it refers to the amount households think they need to put aside in total savings to deal with unexpected events, and it is PPP-adjusted. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). The sample for all variables in the table covers the period from April 2020 to November 2023, except for the expectation concerning the interest rate, which starts in September 2020.

about the expected future economic outlook, and this disagreement seems to vary over time; households, however, also seem to correctly perceive business cycles, at least in this particular sample period.[9] Households' disagreement, or heterogeneity in expectations, is a well-documented and robust empirical fact in the literature, although most empirical evidence is on inflation expectations; see, for example, Fofana et al. (2024), Andre et al. (2022) and Coibion y Gorodnichenko (2012). This literature tends to find that demographic

[9]As highlighted in the bottom-right graph of Figure 1, households consistently tend to expect no growth when it comes to own income even when they believe the economy will get worse. Figure A.7 in Appendix A shows this is true in each country of our sample.

**Figure 1:** Evolution of household-level expectations over time




*Note*: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of expectations in each month of the sample. All expectations are measured monthly, with a 12-month horizon and reported as numerical values. The sample for the expectations covers the period from April 2020 to November 2023, except for the expectation concerning the interest rate on mortgages, which starts in September 2020.

and socio-economic characteristics explain some, but far from all, the observed heterogeneity in expectations. Conceptually, disagreement about the future can emerge due to households (i) observing *different histories, information and signals* about the state of the economy, (ii) facing *different frictions* in the acquisition and processing of a common information set, and/or (iii) having, for the same information set, *different models (views)* about how relevant variables are determined.[10]

In the first part of the sample, when the first wave of the pandemic was at its peak, the distribution of beliefs for most variables was widest. Households in the 10th percentile of the distribution were expecting a growth of -15% for the overall economy and of -10% for their own income, while those at the 90th percentile were expecting +5% and +7%, respectively. Another episode leading to more disperse distributions, especially regarding expected inflation, is the invasion of Ukraine in February 2022: While households in the 10th percentile of the distribution were expecting inflation to be 0%, those at the 90th percentile were expecting inflation to be 15%.

[10]Dispersion in views or models can arise due to multiple reasons, such as experience, education and memory or selective recall; see, for example, Malmendier y Nagel (2015), Patton y Timmermann (2010), Andre et al. (2023), or Andre et al. (2022).

One might be worried, however, that the dynamics shown in Figure 1 are driven by a composition of heterogeneous behaviour across countries. In order to inspect this, Tables A.1-A.3 in Appendix A present the same descriptive statistics included in Table 1 broken down by country. It is evident that the distributions of income, spending, and expectations can be fairly different across countries. However, these differences manifest themselves mainly in the levels of expectations. Indeed, country-by-country dynamics for the distribution of expectations, as presented in Figures A.2-A.7 in Appendix A, are surprisingly similar.

# 3 The Effect of Monetary Policy on Expectations

During the course of 2022, the European Central Bank (ECB) decided to increase interest rates in order to tame inflation. Although many economists at the time agreed that inflation was mostly supply-driven, one of the main ECB arguments to support rate hikes was related to the risk of inflation expectations de-anchoring. In this vein, ECB President Lagarde stated in a speech during the summer of 2022:

> *"If, for example, we were to see higher inflation threatening to de-anchor inflation expectations, or signs of a more permanent loss of economic potential that limits resource availability, we would need to withdraw accommodation more promptly to stamp out the risk of a self-fulfilling spiral."* (Lagarde (2022))

In this section we ask whether the recent monetary policy tightening has indeed been effective in shaping household inflation expectations over the course of the past few years. We rely on variation from roughly half a million household-month observations and employ panel local projection methods paired with high-frequency identification to study the effect of monetary policy surprises on expectations about aggregate and individual level variables as provided by the Consumer Expectations Survey.

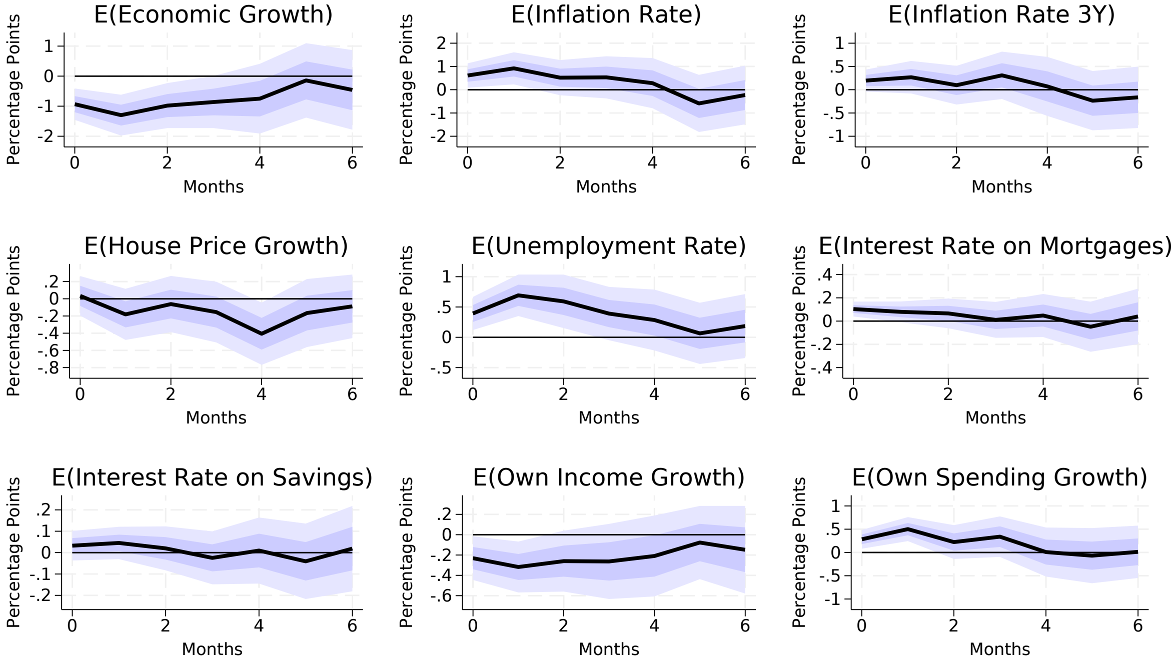
## 3.1 Baseline Average Effect

We use high frequency monetary surprises aggregated at monthly level and panel local projection methods to estimate empirical impulse response functions (IRFs). The baseline specification estimated from April 2020 to October 2023 is the following:

$$\mathbb{E}y^h_{t+hor} - \mathbb{E}y^h_{t-1} = \alpha_h + \beta_{hor}\epsilon^{MP}_t + \sum_{k=1}^{2} \gamma_{hor,k} X_{t-k} + u^h_{hor,t} \tag{1}$$

where $\mathbb{E}y^h_t$ is expectation $\mathbb{E}$ of variable $y$ of household $h$ in time $t$, and $\alpha_h$ are household fixed effects. As a measure of monetary shock $\epsilon^{MP}_t$ we aggregate at monthly frequency the 1-year overnight interest rate swap surprises around the policy announcements computed

**Figure 2:** The response of a contractionary monetary policy shock on household expectations (granular CES data)




*Note*: The figure plots the impulse response functions of the expectations on aggregate and individual level variables to a contractionary monetary surprise that increases the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023 for all variables except for the interest rate expectations whose data starts in September 2020.

in Altavilla et al. (2019), available until October 2023. The parameter of interest, $\beta_{hor}$, captures the *average* effect at horizon *hor* of a monetary policy shock at $t$. Aggregate lagged controls $X_{t-k}$ (with $k = 2$ lags) include the Krippner (2013) shadow short rate, the monetary surprises $\epsilon_t^{MP}$, and euro area price level and industrial production. We run the specification for each horizon $hor = 0, \ldots, 6$ months and cluster the standard error at the month level.

Estimated IRFs from specification (1) to a contractionary monetary surprise that increases the short rate on impact by 25 basis point are presented in Figure 2. Some interesting features are worth commenting. First, even though the sample period only goes from April 2020 to October 2023, point estimates are precisely estimated. The presence of household fixed effects allows to control for individual factors that do not vary over time such as demographic and socio-economic characteristics, country of residence, etc. Second, the monetary shock translates on impact into a one to five pass through to expected interest rates on mortgages: households anticipate that an increase of the short rate of 25 basis points leads to an increases in mortgage interest rates of 5 basis points (center-right panel). Third, households expect an overall prolonged contraction of the economy (top-left panel) associated with a fall in personal income growth and an increase in unemployment rate (middle-center and bottom-center panels). Fourth and finally, households expect an increase in both 1-year ahead and 3-year ahead inflation rate following the monetary shock (top-center and top-right panels). The response of the 1-year ahead inflation is larger than the response of the 3-year ahead, meaning that households adjust their longer-term expectations more slowly to business cycle shocks. The increase in inflation expectations also explains why households anticipate an increase in their nominal spending (bottom-right panel).

Households expecting an increase in inflation following rate hikes is unintuitive in light of the fact that central banks raise interest rates exactly to tame inflation. We validate our results by repeating our analysis on a different survey run by the European Commission about a similar set of household level expectations as the one we use from the CES. The European Commission aggregate surveys responses in the form of balances, which are the difference between the percentages of households giving positive and negative replies. Figure 3 confirms our results: a monetary tightening decreases expectation about the general economic situation but temporarily increases expected inflation.

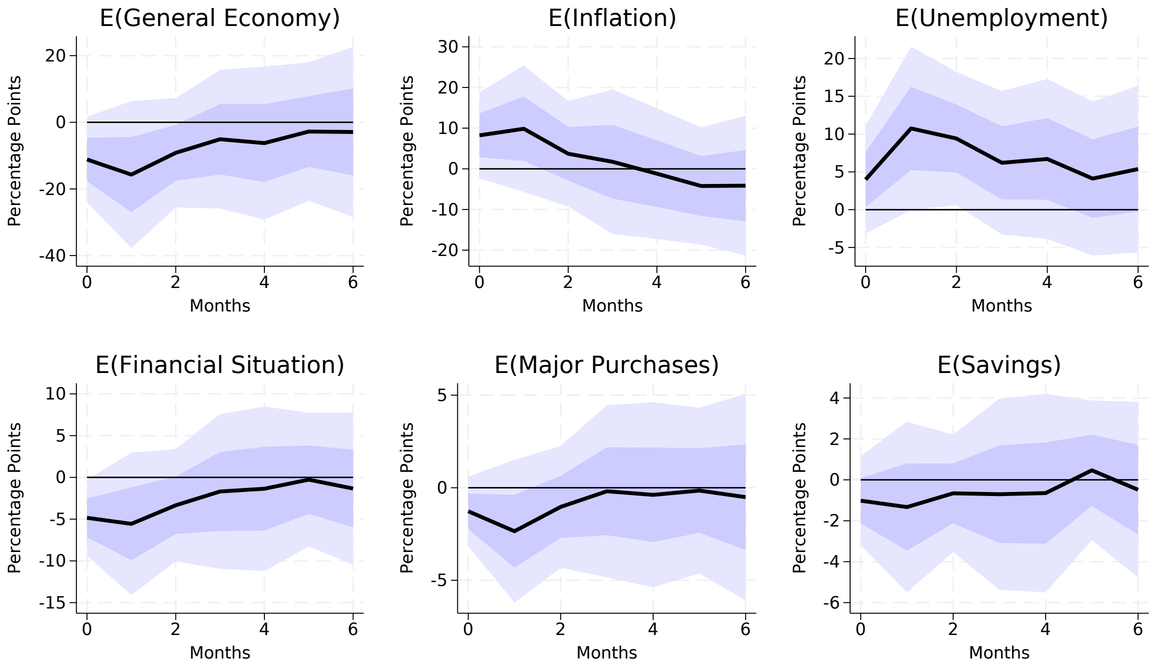
Although to the best of our knowledge we are the first to show an increase in inflation expectations following a monetary policy tightening using dynamic impulse response functions, recent survey evidence for the United States points in the same direction. Using a novel survey on households and experts, Andre et al. (2022) show that while most experts predict a decrease in inflation in response to an unexpected interest rate hike, the majority of households expect the inflation rate to increase instead. The authors further rely on structured questions and vignettes to show that most households mention supply-side mechanisms related to price increases or layoffs due to higher costs. On a similar note, Stantcheva (2024) design a new online survey and find that households believe that managing inflation can be achieved without significant trade-offs in terms of reducing economic activity. This mis-perception about inflation also leads households to support decreasing interest rates in order to fight inflation, which is completely at odds with a central bank mandate.

We next make use of our granular data to explore the household heterogeneity behind our monetary policy results.

## 3.2 Monetary Policy and Household Heterogeneity

One might wonder how much heterogeneity lies behind the baseline monetary policy responses presented in Figure 2. Figures A.8-A.14 in Appendix A present country-by-country responses, with the baseline effects of Figure 2 overlapped in red. It is clear that the euro area results are not driven by any specific country, in that each country response

**Figure 3:** The response of a contractionary monetary policy shock on household expectations (aggregated European Commission data)




*Note*: The figure plots the impulse response function of a set of households expectation measures provided by the European Commission to a contractionary monetary surprise that increases the short rate on impact by 25 basis point. The impulse responses are estimated using the univariate counterpart of specification (1). 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023. The European Commission aggregate surveys responses in the form of balances, which are the difference between the percentages of households giving positive and negative replies.

for most expectations is qualitatively in line with the baseline results. It is however also true that household expectations in Italy and in the Netherlands often respond more strongly to the monetary tightening, especially in terms of expected economic activity, 1-year ahead inflation rate, house price growth, and own income growth.

We additionally study household responses broken down by sociodemographic groups. Specifically, we group households by income, age, employment status, housing tenure status, education, and gender. We only report the impulse responses that show some differences with the baseline responses, and Figures A.15-A.20 in Appendix A present our results. While we do not find any differential responses in terms of gender, above median income households and homeowners holding mortgages tend to adjust their house price growth expectations more strongly than the rest of households (Figures A.15 and A.16). Similarly, renters and less educated households do not tend to adjust their expectations about own income growth following the monetary tightening, while the rest of households expect a sizeable and rather persistent fall in income growth (Figures A.17 and A.18).

Finally, we find that below median income households and households working part-time tend to expect a stronger increase in unemployment rate (Figures A.19 and A.20).

Given the results of monetary policy on household expectations presented in this section, in the the reminder of the paper we exploit the richness and granularity of the data to analyse the drivers behind expectation formation that help uncover the mechanisms behind the impulse responses presented above.

# 4 Latent Drivers of Expectations in the Cross-Section

As a first step towards understanding what lies behind the results uncovered in Section 3, we study the *joint behaviour* of household-level expectations, and the implied *disagreement*. We proceed in two steps. First, we analyze the pairwise co-movement between household-level expectations. Second, we perform a Principal Component Analysis (PCA) exploiting the large cross-sectional dimension of our data.

For our benchmark estimations below, instead of using the level of expectations we work with the residuals from the following regression:

$$y^{\mathbb{E}}_{h,c,t} = \alpha_{c,t} + \epsilon_{h,c,t} \tag{2}$$

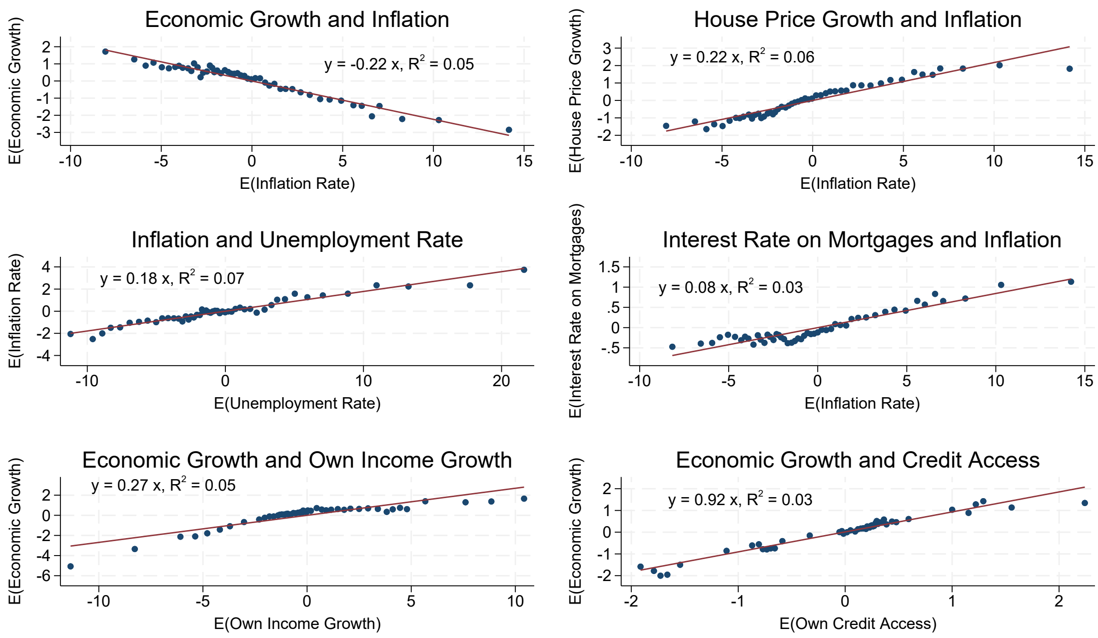
where $y^{\mathbb{E}}_{h,c,t}$ is the the value of the expectation about a variable $y$ for household $h$ in country $c$ and month $t$, and $\alpha_{c,t}$ are country-month fixed effects. The residuals $\hat{\epsilon}_{h,c,t}$ have zero mean in each month and country. These have two important features: First, they capture a household's *disagreement* relative to the average ("consensus") forecast in her country $c$ during a particular month $t$; second, the expectations residuals are comparable when we pool together data across time and countries.

Figure 4 shows strong pairwise co-movement between expectations. The blue circles represent the mean value of the y-axis variable in each of the 50 quantiles of the x-axis variable. To make expectations comparable, we residualize them using equation (2) so that in each month and country, (residualized) expectations have zero mean.

Two such correlations were already noticed in the literature. First, the top-left panel illustrates a negative correlation between expected output growth and expected inflation, a pattern Candia et al. (2020) show holds also in the US from 1978 to 2020 and that they have defined the "supply-side interpretation of inflation". Second, the center-left panel shows the positive correlation between expected inflation and expected unemployment rate, which Kamdar (2019) noticed for the US from 1978 to 2019. A contribution in this paper is to show that similarly strong correlations arise between expectations about many other variables.

The top-right panel reveals a positive correlation between expected inflation and expected house price growth: If households believe inflation is higher over the following 12

**Figure 4:** Pairwise Co-movement Between Expectations




*Note*: The blue circles on the graph represent the mean of the y-axis variable for 50 bins of the x-axis variable, while the red line shows the best fit of the underlying data. All expectations are measured monthly, with a 12-month horizon and reported as numerical values, except for the expectation about own credit access, which is measured on a qualitative scale from 1 to 5. The analysis combines data from all time periods and countries, and the sample for the expectations covers the period from April 2020 to November 2023, except for the expectation concerning the interest rate on mortgages, which starts in September 2020. All expectations are residualized using regression equation (2).

months, they also expect house prices to grow over the same time horizon. The center-right panel shows that households expecting higher inflation also expect higher interest rates, consistent with the presence of a central bank operating a Taylor rule.

Expectations about aggregate variables also correlate with expectations about individual-level variables. The bottom-left panel displays the positive correlations between expected output growth and income growth. A percentage-point increase in expected income growth is associated with a 0.27 percentage-point increase in expected output growth. Therefore, households expect their income to grow when they believe the economy will strengthen.[11] Finally, the bottom-left panel shows that households expecting higher output growth also expect improved credit access conditions.

These results together indicate that household expectations about both aggregate-level and individual-level variables are correlated. As they stand, these correlation might emerge

[11]Immordino et al. (2023) use a survey of Italian households administered in November 2021 and show that both expected own income growth and expected output growth are positively correlated with expected consumption growth, which we do not observe in our data. Therefore, the positive correlation between expected income growth and expected output growth also holds in their data.

from either a perception that business cycles are mostly driven by supply-side forces or a strong dislike for price increases given their potential to lower living standards if nominal incomes don't increase as much, as pointed out by Shiller (1996). These correlations are also consistent with households thinking about a "cost channel" in which firms pass on higher costs to consumers – rather than the standard textbook mechanism – when demand shocks, such as the monetary shock of Section 3, hit the economy.

In order to analyze if expectations are indeed jointly determined by some underlying force such as a shock to the economy, we proceed with a more formal analysis of the joint distribution of household expectations and perform a PCA on the cross-section of households. This means that we are not using the time dimension, which we will instead exploit in Section 5 where we estimate a factor model. In Section 4.3 we present a robustness exercise where we repeat our cross-sectional PCA in each month separately and show that the results are consistent over time.

## 4.1 Baseline PCA Results

We have established in Figure 4 that household expectations are correlated. To identify the common drivers behind expectations, we carry out a PCA exploiting the large cross-sectional dimension of our data. The idea is to extract common components that can explain a significant share of the joint variation in expectations and have meaningful economic interpretation.

We use expectations for a range of aggregate-level variables, such as the overall economy, inflation, unemployment rate, house prices growth, and interest rates on mortgages. We also use expectations about individual-level variables such as income growth, access to credit, financial situation, and plans to buy durables. Recall that these expectations are provided as numerical values, except for access to credit and financial situation, which are measured on a 1-5 qualitative scale, and plans to buy durables, which are indicated by a 0-1 variable. All expectations refer to a time horizon of 12 months, except for expected inflation, which is also asked at a 3-year horizon. Because the expectations about interest rate on mortgages only start from September 2020, our effective sample goes from September 2020 to November 2023.

Appendix B formalizes a standard way to decompose the raw data $\boldsymbol{X}$ into principal component scores $\boldsymbol{S}$ and loadings $\boldsymbol{\omega}$. Because our data $\boldsymbol{X}$ is at the household level, the principal component scores will also be at the household level while the loadings $\boldsymbol{\omega}$ represent a vector of loadings attached to each type of expectation. In our baseline analysis, the PCA pools all data across time and countries; i.e. our raw data matrix $\boldsymbol{X}$ has dimensions $(H \times T) \times E$, where $H$ is the total number of households, $T$ is the number of months, and $E$ is the number of expectations about the variables under exam. Again, this means that we are not using the panel dimension, which we will instead exploit in Section 5 where we estimate a factor model.

**Table 2:** Loadings from the PCA that pools data across time and countries

| | Component 1 | Component 2 |
|---|---|---|
| E(Economic Growth) | 0.29 | 0.24 |
| E(Inflation Rate) | -0.46 | 0.24 |
| E(Inflation Rate 3Y) | -0.45 | 0.29 |
| E(House Price Growth) | -0.22 | 0.37 |
| E(Unemployment Rate) | -0.34 | 0.18 |
| E(Interest Rate on Mortgages) | -0.26 | 0.16 |
| E(Own Income Growth) | 0.18 | 0.56 |
| E(Own Financial Situation) | 0.36 | 0.42 |
| E(Own Credit Access) | 0.32 | 0.30 |
| E(Own Durable Spending) | 0.05 | 0.15 |
| Observations | 546404 | 546404 |
| % Variance Explained | 25.4 | 15.4 |

*Note*: The analysis pools together data from all time periods and all countries, and the sample covers the period from September 2020 to November 2023. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). All expectations are residualized using regression (2).

Table 2 presents the findings of our analysis on the first two principal components, which account for more than 40% of the total variance.[12] The first takeaway is that the first principal component offers a supply-side perspective of macroeconomic developments or, more generally, captures a dislike for inflation. Households expecting higher economic and income growth also forecast lower inflation and house prices, indicating that supply-side shocks may be expected in the economy.[13] The second takeaway is that the second principal component is a demand-side view of macroeconomic dynamics. Households forecasting higher economic growth also expect higher inflation and house price growth, suggesting demand-side business cycles.

Our findings also demonstrate that the perceived supply-side source of business cycle fluctuation, as represented by the first principal component, is the most significant factor in explaining the variation in the data. The first component alone explains over 25% of the total variance, indicating the relatively stronger influence of household perceived supply-

[12]The third principal component only contributes with 11% of additional variance and for this reason we only focus on the first two components.

[13]What matters is not the absolute sign of the principal component but the relative one across loadings. Therefore, we interpret the first component as a generic supply-side (e.g., an oil shock) force rather than a "positive" supply-side force (e.g., an oil shock that decreases inflation and improves aggregate activity).

side forces compared to demand-side ones, at least within the sample considered here. The fact that the higher variance of the data is explained by the supply-side component is a direct consequence of the negative correlation in the raw data between expected output growth and expected inflation (top left graph in Figure 4): If households expecting higher economic growth also expect lower inflation on average, then the principal component explaining most of the variance of the data must be indeed related to the supply-side view of economic dynamics. The contribution of our analysis is to show that a second component, related to demand, is also quantitatively relevant in order to understand the cross-sectional variance of the joint distribution of expectations.

**Interpreting the Latent Components** The principal component scores are summary measures of household expectations.[14] A non-parametric way to look at the components in Table 2 is by plotting both the first and second principal component scores against the expectations, and Figure 5 displays such pairwise correlations. The circles show the mean of the y-axis variable (blue for the first principal component scores, red for the second principal component scores) for 50 bins of the x-axis variable (residualized expectations). Notice that the loadings $\boldsymbol{\omega}$ of Table 2 represent the slopes in each of the graphs by construction.

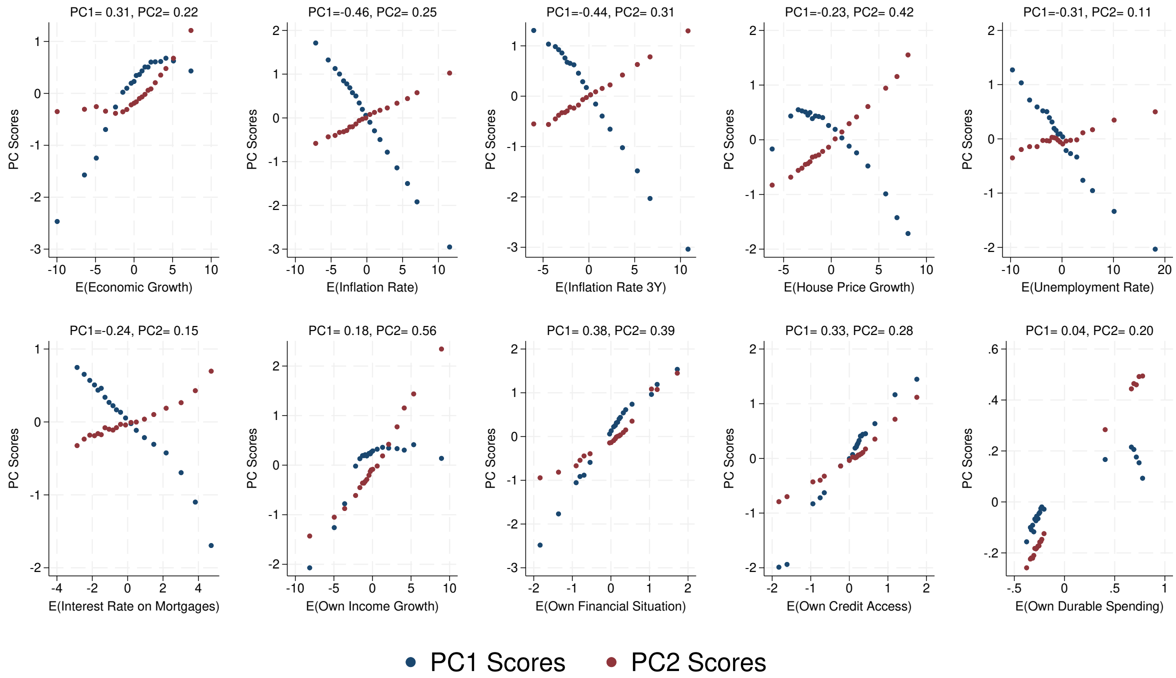
Households with higher values of the first principal component scores tend to expect: a) higher output growth, b) lower inflation and house price growth, c) lower unemployment rate, d) lower interest rates on mortgages, e) higher own income growth, f) higher own financial situation, g) higher probability of accessing credit, and h) higher probability of buying durables. The first principal component scores can therefore be considered as a supply-side force (e.g., an oil shock) hitting the economy over the following 12 months, or as capturing a general dislike for inflation.

Conversely, households with higher values of the second principal component scores tend to expect: a) higher output growth, b) higher inflation and house price growth, c) higher unemployment rate,[15] d) higher interest rates on mortgages, e) higher own income growth, f) higher own financial situation, g) higher probability of accessing credit, and h) higher probability of buying durables. The second principal component score can then be considered a demand-side source of business cycle fluctuations, possibly resulting from factors such as monetary policy shocks. Notice that the two principal component scores are orthogonal to each other by construction, as Figure A.21 in Appendix A shows.

[14]See Equation (B.1) in Appendix B for a basic derivation.

[15]Intuitively, households expecting higher growth of the economy should also be expecting lower unemployment rates. This does not happen with the second principal component, but it is worth mentioning that the loading on unemployment $w_2^U$ in Table 2 is relatively small, meaning that unemployment expectations get very little weight in determining the second principal component scores. Table A.5 in Appendix A shows that this result is mostly driven by Italian households.

**Figure 5:** Pairwise correlations between principal component scores and expectations




*Note*: The circles show the mean of the y-axis variables (first (in blue) and second (in red) household-level principal component scores) for 50 bins of the x-axis variable (household-level expectations residualized using regression (2)). The analysis pools together data from all time periods and all countries, and the sample covers the period from September 2020 to November 2023. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale).

## 4.2 The Role of Household Characteristics

**Demographics.** In order to better understand and interpret the two underlying sources of variation, a natural exercise is to analyze possible links to households' demographic characteristics.

We first repeat the PCA on specific age and education subgroups of the population. This is grounded on the evidence that expectations and disagreement about inflation and house price changes, among other variables, tend to be influenced by age, gender, experience and sophistication; see for example Fofana et al. (2024) and Malmendier y Nagel (2015). Table 4 shows that results of the PCA run separately for younger, older, less educated, and higher educated households. The results for the different subgroups of the population are remarkably similar to the baseline findings of Table 2 in terms of both loadings and variance explained. This is evidence that the PCA results are not driven by either education or age.

**Table 3:** Loadings from PCAs run on specific age and education subgroups of the population

| | Age 18-49 | | Age 50+ | | Lower Education | | Higher Education | |
|---|---|---|---|---|---|---|---|---|
| | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 |
| E(Economic Growth) | 0.27 | 0.26 | 0.32 | 0.24 | 0.27 | 0.30 | 0.31 | 0.17 |
| E(Inflation Rate) | -0.47 | 0.22 | -0.45 | 0.27 | -0.46 | 0.23 | -0.46 | 0.26 |
| E(Inflation Rate 3Y) | -0.46 | 0.26 | -0.43 | 0.33 | -0.45 | 0.28 | -0.44 | 0.30 |
| E(House Price Growth) | -0.26 | 0.34 | -0.19 | 0.42 | -0.23 | 0.38 | -0.22 | 0.37 |
| E(Unemployment Rate) | -0.35 | 0.16 | -0.34 | 0.17 | -0.35 | 0.17 | -0.33 | 0.19 |
| E(Interest Rate on Mortgages) | -0.26 | 0.17 | -0.26 | 0.14 | -0.27 | 0.14 | -0.24 | 0.18 |
| E(Own Income Growth) | 0.14 | 0.56 | 0.22 | 0.54 | 0.15 | 0.57 | 0.22 | 0.54 |
| E(Own Financial Situation) | 0.34 | 0.45 | 0.38 | 0.39 | 0.36 | 0.41 | 0.37 | 0.44 |
| E(Own Credit Access) | 0.32 | 0.32 | 0.32 | 0.28 | 0.33 | 0.29 | 0.32 | 0.32 |
| E(Own Durable Spending) | 0.04 | 0.17 | 0.06 | 0.10 | 0.05 | 0.14 | 0.05 | 0.16 |
| Observations | 292722 | 292722 | 224815 | 224815 | 233704 | 233704 | 283833 | 283833 |
| % Variance Explained | 25.2 | 16.2 | 25.6 | 14.5 | 25.1 | 15.5 | 25.6 | 15.3 |

*Note*: The analysis pools together data from all time periods and all countries but splits the sample by age and education groups. The sample covers the period from September 2020 to November 2023. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). All expectations are residualized using regression (2).

**Table 4:** Loadings from PCAs run on specific age and education subgroups of the population

| | Below Median Income | | Above Median Income | | Low Financial Literacy | | High Financial Literacy | |
|---|---|---|---|---|---|---|---|---|
| | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 |
| E(Economic Growth) | 0.28 | 0.26 | 0.30 | 0.20 | 0.25 | 0.32 | 0.33 | 0.11 |
| E(Inflation Rate) | -0.46 | 0.23 | -0.46 | 0.26 | -0.47 | 0.20 | -0.44 | 0.30 |
| E(Inflation Rate 3Y) | -0.45 | 0.28 | -0.44 | 0.32 | -0.46 | 0.25 | -0.41 | 0.35 |
| E(House Price Growth) | -0.23 | 0.36 | -0.22 | 0.41 | -0.27 | 0.34 | -0.16 | 0.40 |
| E(Unemployment Rate) | -0.34 | 0.18 | -0.33 | 0.19 | -0.35 | 0.14 | -0.32 | 0.20 |
| E(Interest Rate on Mortgages) | -0.27 | 0.19 | -0.23 | 0.11 | -0.27 | 0.17 | -0.24 | 0.18 |
| E(Own Income Growth) | 0.17 | 0.57 | 0.21 | 0.53 | 0.12 | 0.57 | 0.26 | 0.52 |
| E(Own Financial Situation) | 0.36 | 0.42 | 0.38 | 0.42 | 0.34 | 0.43 | 0.40 | 0.40 |
| E(Own Credit Access) | 0.32 | 0.29 | 0.33 | 0.31 | 0.31 | 0.31 | 0.34 | 0.29 |
| E(Own Durable Spending) | 0.05 | 0.16 | 0.03 | 0.14 | 0.03 | 0.15 | 0.07 | 0.18 |
| Observations | 277176 | 277176 | 240361 | 240361 | 241747 | 241747 | 271536 | 271536 |
| % Variance Explained | 25.7 | 15.3 | 24.2 | 15.7 | 25.5 | 15.3 | 25.6 | 14.8 |

*Note*: The analysis pools together data from all time periods and all countries but splits the sample by age and education groups. The sample covers the period from September 2020 to November 2023. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). All expectations are residualized using regression (2).

**Beliefs and Unobserved characteristics.** Figure 1 shows significant household *disagreement* in expectations for all variables at each point in time. A natural question then arises: are some households persistently above or below the "consensus" (median) belief within their country?

To shed light on this question, we exploit the panel and distributional dimension of the data to evaluate how likely it is that a household that has expectations that are in, say, the upper tercile of the distribution of expectations in country $c$ at month $t$, remains in that upper tercile during the next few months. Note that this is *not* about whether a household expects a persistent level of that variable, but about how *persistent is her rank within her country.* Concretely, we estimate non-parametric transition probabilities between $t$ and $t+1$ as well as between $t$ and $t+3$ for each of the ten expectations considered. Households' expectations about a given variable are ranked within a country in each month $t$, and we then count how many remain in the same relative position (tercile) in at $t+1$ and $t+3$. Results for euro area households are shown in Table 5, while country-by-country results are presented in Tables A.6-A.11.[16]

Three results emerge. First, the probability of remaining in the same tercile in the ranking of expectations after one or three months (i.e. the diagonal entries in each matrix) is almost always above 0.7, and higher for those households located in the higher tercile. This is more than twice the value corresponding to no persistence, which would be 0.33. While Patton y Timmermann (2010) find similar (though lower) persistence for professional forecasters in the U.S., we are not aware of studies that report comparable estimates for this type of persistence of household expectations.[17] Second, although persistence between consecutive quarters (from $t$ to $t+3$) is lower than between consecutive months (from $t$ to $t+1$), as one would expect, the difference in transition probabilities is small; in other words, households remain in the same tercile after 3 months with, on average, very high probability. Third, households are less likely to change, *relative* to the rest of households within their country, their expectations about inflation three-years ahead than they are about inflation one-year ahead. This last result, combined with the fact that the disagreement (or dispersion) tends to be larger for 1-year ahead inflation expectations as shown in Figure A.1 in Appendix A, points to a combination of heterogeneity in information and heterogeneity in models as sources of disagreement in the CES survey.

Based on these results, we repeat the baseline PCA after controlling for individual fixed-effects. In particular, instead of residualizing the expectations using equation (2), we use the residuals from the following individual fixed-effect regression:

$$y^{\mathbb{E}}_{h,t} = \alpha_h + \alpha_t + \epsilon_{h,t} \tag{3}$$

[16]Due to space and visualization constraints the tables present transition probabilities for six of the ten expectations considered; results for the remaining four are very similar, and can be obtained upon request.

[17]Country-by-country persistence results presented in Tables A.6-A.11 show that the main findings are robust across countries with a small caveat: households in France and Germany that have expectations about economic growth, 1-year ahead and 3-year ahead inflation in the bottom tercile of the country distribution are much more likely to raise their expectations than bottom tercile households in other countries.

**Table 5:** Persistence in the ranking of a household expectation within her country for the euro area

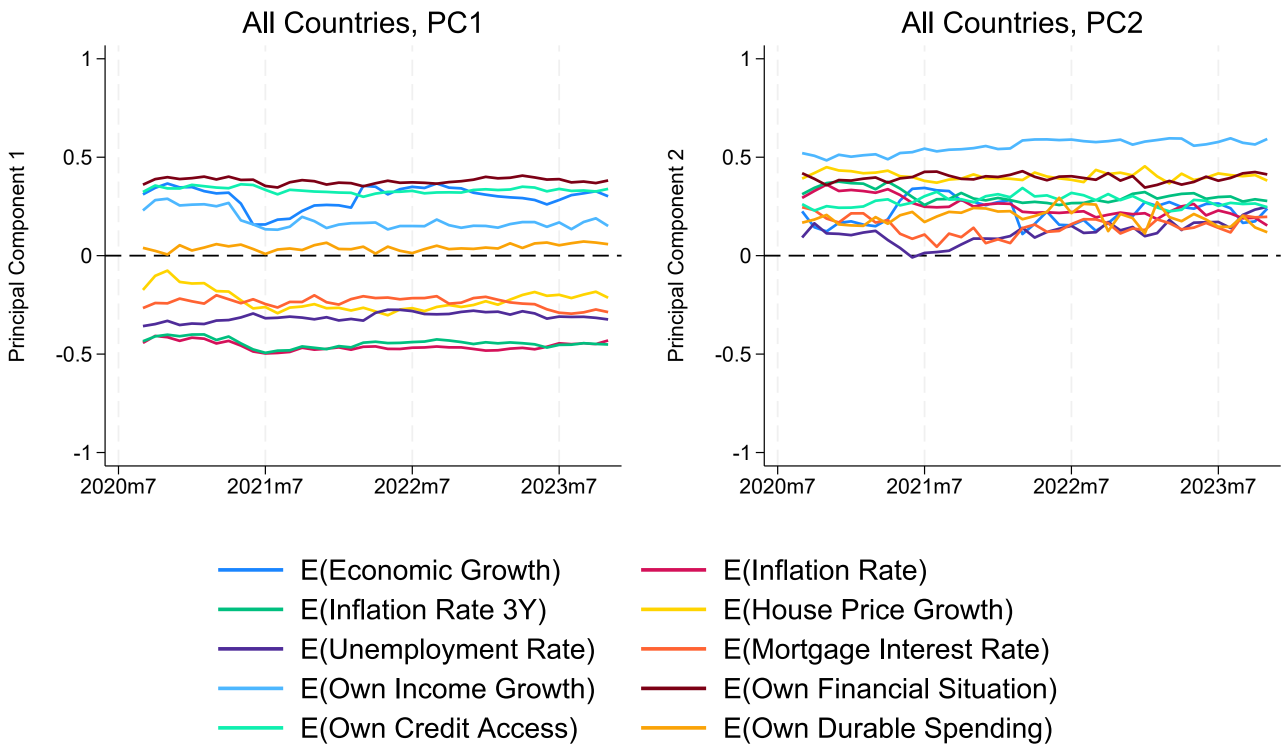
| | | **Persistence $t$ to $t+1$** | | | | **Persistence $t$ to $t+3$** | | |
|---|---|---|---|---|---|---|---|---|
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.71 | 0.09 | 0.05 | $Low_{t+3}$ | 0.69 | 0.1 | 0.05 |
| E(Economic Gr.) | $Mid_{t+1}$ | 0.19 | 0.73 | 0.17 | $Mid_{t+3}$ | 0.2 | 0.71 | 0.18 |
| | $High_{t+1}$ | 0.11 | 0.18 | 0.78 | $High_{t+3}$ | 0.12 | 0.19 | 0.76 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.71 | 0.09 | 0.05 | $Low_{t+3}$ | 0.68 | 0.1 | 0.05 |
| E(Inflation 1yr) | $Mid_{t+1}$ | 0.18 | 0.72 | 0.17 | $Mid_{t+3}$ | 0.2 | 0.7 | 0.18 |
| | $High_{t+1}$ | 0.11 | 0.18 | 0.78 | $High_{t+3}$ | 0.12 | 0.2 | 0.76 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.77 | 0.08 | 0.05 | $Low_{t+3}$ | 0.74 | 0.09 | 0.05 |
| E(Inflation 3yr) | $Mid_{t+1}$ | 0.14 | 0.74 | 0.16 | $Mid_{t+3}$ | 0.16 | 0.72 | 0.18 |
| | $High_{t+1}$ | 0.09 | 0.18 | 0.8 | $High_{t+3}$ | 0.1 | 0.19 | 0.77 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.75 | 0.12 | 0.06 | $Low_{t+3}$ | 0.71 | 0.14 | 0.07 |
| E(House Price Gr.) | $Mid_{t+1}$ | 0.16 | 0.71 | 0.14 | $Mid_{t+3}$ | 0.19 | 0.67 | 0.17 |
| | $High_{t+1}$ | 0.09 | 0.17 | 0.79 | $High_{t+3}$ | 0.1 | 0.19 | 0.77 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.79 | 0.13 | 0.06 | $Low_{t+3}$ | 0.76 | 0.15 | 0.07 |
| E(Unemp. Rate) | $Mid_{t+1}$ | 0.14 | 0.71 | 0.13 | $Mid_{t+3}$ | 0.15 | 0.67 | 0.15 |
| | $High_{t+1}$ | 0.08 | 0.15 | 0.81 | $High_{t+3}$ | 0.09 | 0.17 | 0.79 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.13 | 0.06 | $Low_{t+3}$ | 0.75 | 0.15 | 0.06 |
| E(Own Income Gr.) | $Mid_{t+1}$ | 0.15 | 0.71 | 0.13 | $Mid_{t+3}$ | 0.17 | 0.67 | 0.15 |
| | $High_{t+1}$ | 0.08 | 0.16 | 0.81 | $High_{t+3}$ | 0.08 | 0.18 | 0.79 |

*Note*: The table presents non-parametric estimates of the probability $p^h_{ji}$ that a household's expectation transitions from tercile $i \in \{Low, Mid, High\}$ in the distribution of expectations within her country at $t$ to tercile $j \in \{Low, Mid, High\}$, in the distribution within her country at $t+1$ ($h = 1$, left column) and at $t+3$ ($h = 3$, right column). Each probability is estimated by counting frequencies of each possible transition at the household level in a given month $t$ across the euro area, and then averaging over time. The sample covers the period from April 2020 to November 2023.

where $y^{\mathbb{E}}_{h,t}$ is the value of the expectation about a variable $y$ for household $h$ in month $t$, $\alpha_h$ is an household fixed effect, and $\alpha_t$ is the month fixed effect.

Table A.4 in Appendix A displays the outcomes of the PCA after the removal of individual fixed effects from expectations through equation (3). The findings are comparable to the baseline results in Table 2, including the loadings of the two principal components in terms of magnitude. The primary distinction is that the total variance explained decreases to approximately 31%. This is unsurprising as eliminating individual fixed effects reduces the dispersion of expectations, making it more challenging for the two principal components to account for the same amount of total variance.

**Figure 6:** Evolution of the principal components over time




*Note*: The figure plots the evolution of the first principal component (left panel) and the second principal component (right panel) over time after we perform the PCA in each month separately between September 2020 and November 2023.

## 4.3 Robustness

**Results Month-by-Month.** To assess the robustness of our baseline PCA findings where we analyzed all the months in our data together, we examine whether the results remain consistent when we conduct our analysis on each month separately.

Figure 6 plots the loadings over time, as computed from the PCA performed on a monthly basis. Remarkably, the benchmark patterns observed in Table 2 are confirmed and largely stable over time, indicating that in each month since September 2020 households have been expecting supply-side shocks to be more important that demand-side shocks for the evolution of the business cycle. For this reason, these results are not driven by specific events in any particular month such as COVID-related restrictions or the geopolitical tensions following the invasion of Ukraine.

Although all the loadings have the same sign in the whole sample, some of them experience small fluctuations. For instance, when examining the first principal component (left panel), we observe a decline in the loading assigned to expected economic growth during the latter half of 2021, while the loading assigned to expected house price growth has been increasing in magnitude over time. Nonetheless, the majority of loadings remain quantitatively similar across the entire sample period.

**Results Country-by-Country.** We then conduct the PCA in each country separately. Table A.5 in Appendix A displays the results of this analysis, indicating that the principal components, which identify supply- and demand-side sources of macroeconomic developments, are highly consistent across countries both quantitatively and in terms of variance explained.

The results reveal that the interpretation of the components from Section 4.1 remains unchanged in each country. The first component reflects a supply-side perspective of macroeconomic developments, as households anticipate high economic growth with lower inflation. The second component represents a demand-side view of business cycle fluctuations, as households predict higher inflation with an improved economic outlook. Moreover, the variance explained by each factor is comparable across countries, ranging from 24.6% in the Netherlands to 27.6% in Belgium for the supply-side factor, and from 13.8% in Belgium to 16.7% in Spain for the demand-side factor. The total variance explained is approximately 40% in each country. These findings suggest that the country of origin does not drive the household perceived sources of business cycle fluctuations.

**Results by Country-Month.** We finally run the PCA for each month and country separately, and Figure A.22 plots the loadings on expected economic growth and expected inflation separately by country-month. The results are remarkably stable both across countries and over time, confirming that households across countries and in each month perceive the business cycle in an overall similar fashion.

**Results with a Reduced Number of Expectations.** One might wonder if the same information structure can be captured by a reduced number of expectations, namely, those about the main variables present in the stylized New Keynesian three-equation model; see Gali (2015). In order to check this, we run the PCA analysis on the whole sample of households, but now using only expectations about output growth, 1-year ahead inflation rate, and interest rates. The results presented in Table 6 show that while the first component (which now explains 45% of the overall variation) still seems to capture a supply-side perception of inflation and output, movements in these three expectations alone don't seem to be driven by a clear demand-side perception, as it was the case with the benchmark ten-expectations case. We interpret this finding as evidence on the information content present in the joint behavior of an expanded set of relevant expectations.

**Table 6:** PCA run on a reduced set of expectations pooling data across time and countries

| | Component 1 | Component 2 |
|---|---|---|
| E(Economic Growth) | 0.58 | 0.59 |
| E(Inflation Rate) | -0.64 | -0.12 |
| E(Interest Rate on Mortgages) | -0.52 | 0.80 |
| Observations | 524103 | 524103 |
| % Variance Explained | 45.1 | 29.6 |

*Note*: The analysis only uses three expectations and pools together data from all time periods and all countries. The sample covers the period from September 2020 to November 2023. The three expectations are asked on a monthly basis, are based on a 12 months horizon, are provided as numerical values, and are residualized using regression (2).

# 5 Common Latent Perceptions Over Time

In Section 4 we explored the joint *cross-sectional* behavior of a wide range of expectations. Even though households' disagreement (within and across countries) about the future path for the economy is apparent, our analysis has uncovered two underlying common drivers which account between 40% and 50% of the dispersion in expectations. These components present a correlation structure with expectations which suggests a particular perception that households hold about how prices and quantities are determined.

In this section, we turn our focus on the time series properties of the expectations, both within and across households. Using the insights from Section 4, we identify and estimate two common factors, and relate them to different measures of supply and demand forces.

## 5.1 A Factor Structure for Expectations

Based on our cross-sectional results, we conjecture that each household-level expectation can be written as a linear combination of two common factors and an idiosyncratic term. Concretely, collect the expectations $y^{\mathbb{E}}_{h,t}$ about all variables $E$ of all households $H$ as columns of $\boldsymbol{X}_t$, and define the following factor structure:

$$x_{i,t} = \lambda_i' F_t + e_{i,t} \qquad i = 1, \ldots, E \times H \tag{4}$$

where $F_t$ is a $2 \times 1$ vector of common factors, $\lambda_i$ is a $2 \times 1$ vector of household-and-expectation specific loadings, and $e_{i,t}$ is the idiosyncratic component. Specification (4) is quite general, and has been used extensively in the macro literature in order to extract latent drivers or disturbances. Altavilla et al. (2019), for example, estimates such a specification with the objective of extracting monetary policy disturbances that drive the OIS yield curve in the euro area. Kučinskas y Peters (2022) show that, under mild regularity conditions, many expectation-formation theories can be mapped into a factor structure.[18]

Some additional features deserve a brief discussion. First, although a dynamic factor structure can be cast into the static specification (4), in our benchmark exercise we abstract from such dynamics; this is mainly due to the short time-series dimension currently available for the CES. Second, it is apparent from Figure 1 that households disagree about the future path of the economy. It is less obvious whether this disagreement emerges from differences in their information set, or differences in the way they interpret the same information (or both). The specification for expectations underlying Equation (4) assumes that households observe the same common sources of fluctuations (the $F_t$'s), but might a priory interpret their impact differently; i.e. the $\lambda$'s are household and expectation specific.[19] We next turn to our identification strategy.

## 5.2 Identification and Estimation with an Unbalanced Panel

When trying to extract the factors in Equation (4), a standard identification problem arises: Factors and loadings are separately identified only up to a rotation. Concretely, for any orthonormal matrix $Q_{2\times 2}$ such that $Q'Q = I_{2\times 2}$, the following holds:

$$x_{i,t} = \lambda_i' F_t + e_{i,t} = (\lambda_i' Q') \cdot Q F_t + e_{i,t} \equiv \tilde{\lambda}_i \tilde{F}_t + e_{i,t}$$

with $\tilde{\lambda}_i = \lambda_i' Q'$ and $\tilde{F}_t = QF_t$.

Our identification strategy relies on the results of Section 4: We identify rotations that imply loadings which satisfy a set of sign restrictions consistent with the cross-sectional PCA results.[20] We could estimate (4) with a balanced panel of households; however, given the rotating sampling structure of the CES, this would leave us with a selected sample of very few households per country. We therefore use an *unbalanced* panel of households between September 2020 and November 2023, imposing the restriction of at least 12 consecutive monthly answers to all ten expectation questions in order for a household to be included in the panel. We then follow an iterative procedure along the lines of Juodis y Kučinskas (2023) and Bai (2009). First, we get an initial estimate of factors $\hat{F}_t^{init}$ in (4) as the first two principal components of $\boldsymbol{X}_t$ using a *balanced panel* of households. Second, a rotation of $\hat{F}_t^{init}$ is obtained using an orthonormal matrix $\{Q\}$ that results

[18] Juodis y Kučinskas (2023) uses their insights to quantify the noise present in survey expectations.

[19] An alternative specification could assume that the loadings for each expectation are common across households, but each household observes the common drivers with some idiosyncratic noise. Herbst y Winkler (2021) study a factor structure for heterogeneous expectations under this alternative specification.

[20] Identification of factor models by sign restrictions has been used in the literature that uncovers, for example, supply and demand drivers of inflation and business cycles; see, for example, Eickmeier y Hofmann (2022). The approach imposes restrictions on loadings which are consistent with standard theoretical mechanisms in a supply and demand framework. Although our cross-sectional results seem to be in line with the standard perception about how supply and demand shocks affect prices and quantities, we are purposely agnostic in our approach; we don't take a stand about the way in which households perceive aggregate and idiosyncratic dynamics.

from a QR decomposition of random matrix; denote this rotaion $\hat{F}_t^{rot,0}$. Third, for each household-expectation $i = 1, ..., E \times H$ we estimate a *time series* regression

$$x_{i,t} = \lambda_i' \hat{F}_t^{rot,0} + e_{i,t} \tag{5}$$

using those time periods for which household-expectation $i$ is observed; in these regressions, the right hand side variables are the rotated factors $\hat{F}_t^{rot,0}$, common for all households. This provide us with an estimate for household-expectation-specific loadings $\hat{\lambda}_i$. Fourth, we run for each time period $t = 1, ..., T$, *cross-sectional* regressions of the form

$$x_{i,t} = F_t^{rot,1\prime} \hat{\lambda}_i + e_{i,t} \tag{6}$$

using, in a regression for a given time $t$, the $\hat{\lambda}_i$'s of those households with non-missing answers in that same $t$. These regressions provide new estimates $\hat{F}_t^{rot,1}$ of the rotated factors. We iterate on steps 3-4 until the maximum distance between $\hat{F}_t^{rot,1}$ and $\hat{F}_t^{rot,0}$ is smaller than some tolerance level. Once the above iterative procedure has converged, we keep the rotation (denote it as a *valid* rotation) if two conditions hold: (i) the implied estimated loadings $\{\hat{\lambda}_i\}_{i=1}^{E\times H}$ satisfy a set of sign restrictions, described below, and (ii) the estimated factors $\hat{F}_t^{rot,1}$ are *orthogonal*. We repeat these steps for a large number of rotations, and among all the valid ones, we select that which minimizes a standard distance criteria.

**Sign restrictions.** We consider a set of sign restrictions for the rotated loadings imposed on (i) expected 12 months ahead economic growth and (ii) expected 12 months ahead inflation rate. The particular signs we impose for each loading map 1-to-1 to the signs estimated in the PCA results presented in Table 2: we select rotations which imply loadings for expected economic growth and expected inflation that have (i) opposite signs on the first factor ("supply factor") , and (ii) the same sign on the second factor ("demand factor").

As a benchmark, we impose restrictions on the loadings for *average* expectations. In other words, we keep a given rotation matrix if the two loadings for average expected growth and the two loadings for average expected inflation satisfy the restrictions.[21]

## 5.3 Interpreting the Rotated Factors

The two extracted (rotated) common factors from our benchmark identification strategy are presented in Figure 7. The two dark thick lines represent the *optimal* factors as defined

[21]We also consider two alternative ways to identify the rotations: (i) impose sign restrictions on *individual* loadings, and keep a rotation the share of satisfied restrictions is above a threshold; (ii) impose restrictions on the *average loading* across households.

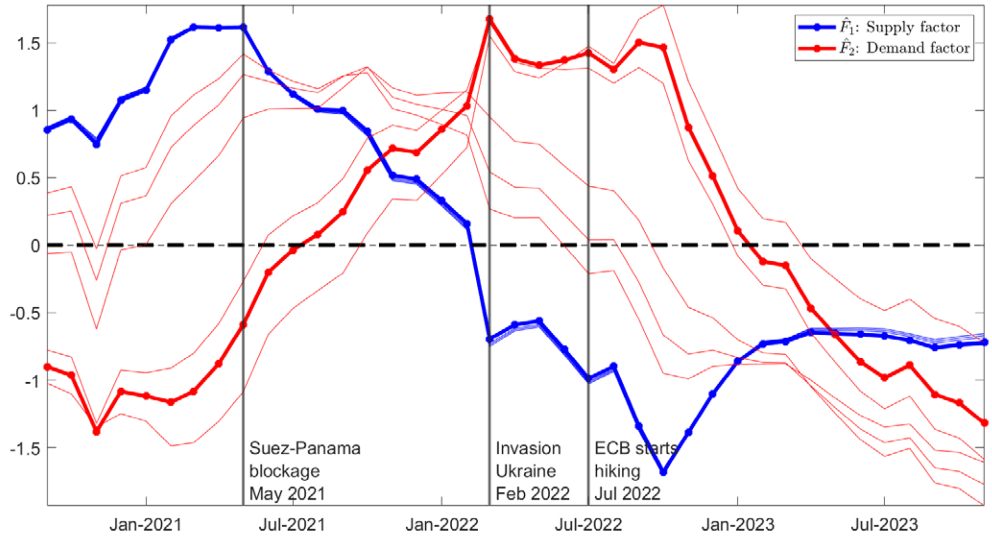
by using a standard euclidean metric. The thinner lines represent different percentiles of the distribution of alternative (valid) models. Blue lines correspond to the first factor, identified based on the signs on loadings that capture opposite correlations between expected economic growth and expected inflation; we label this the "supply factor". Red lines correspond to the second factor, identified with demand-type signs on expected economic growth and expected inflation; this is the "demand factor". The figure also includes several vertical solid lines depicting relevant dates, such as the Russian invasion of Ukraine (February 2022) and the first hike of interest rates by the ECB (July 2022).

Some features are worth mentioning. First, note that the thinner lines capture *model* uncertainty, not estimation (sampling) uncertainty, as captured by alternative valid rotations. Interestingly, all valid models seem to imply a very similar dynamics for the first factor. This is consistent with the fact that this factor captures most of the common variation in the data, and is better identified from sign restrictions. The dynamics for the second factor, in contrast, present more variation across models. Such variation relates mainly to the location of the inflection point around late 2021 and early 2022. Second, the two factors capture perceptions that are in line with a post-2020 narrative based on shifting importance of supply and demand shocks in explaining the perceived business cycle. This is so even though we have a relatively short time series dimension with which to extract the factors. Starting in early 2021, the supply factor captures the perceptions that supply-side disruptions were piling up, implying increasing upward pressure on inflation and downward pressure on economic growth. At the same time, movements of the demand factor capture increasing perceptions about higher inflation and growth of the economy, possibly due to the reopening of euro area economies following lockdowns. The invasion of Ukraine in February 2022 exacerbated perceptions about negative supply disruptions, and started to shift perceptions about demand drivers. The ECB announced its tightening cycle in December 2021, though the first interest rate hike came by July 2022. Household expectations seem to capture this EA-level change.

We also estimate the factor model (i) for each country separately, and (ii) for different age, education and income groups. Figures A.23-A.24 in Appendix A shows that the dynamics of the extracted first factor are very similar across all countries and demographic groups. This might not bee too surprising, given the robustness of the results for different demographic characteristics both in the monetary policy analysis of Section 3 and in the cross-sectional analysis of Section 4. Heterogeneity in the dynamics of the second factor is, however, more noticeable, and this explains the dispersion in valid models captured in Figure 7.

A relevant question at this point is how do these underlying drivers of expectations compare with underlying drivers of the *actual* variables on which households form expectations. Results from two recent papers provide some compelling evidence for a surprising similarity between the two. Eickmeier y Hofmann (2022) estimate a static factor model

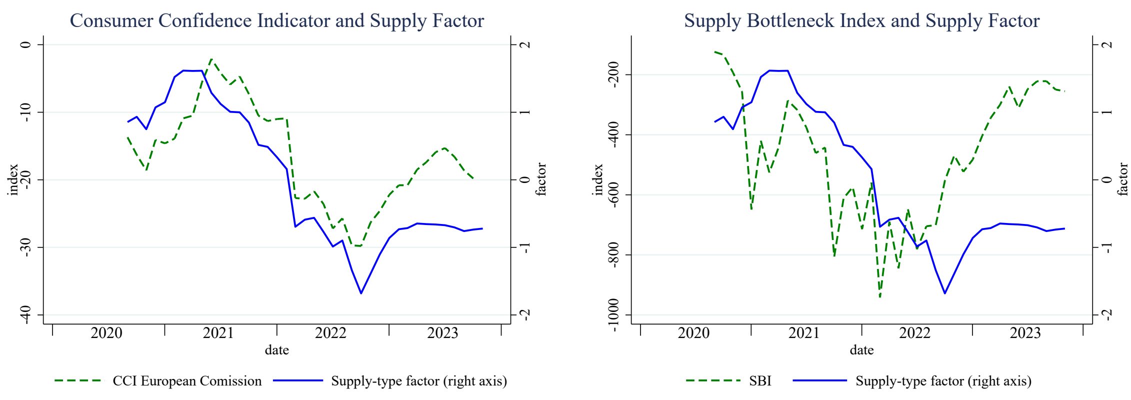
**Figure 7:** Evolution of identified factors over the sample period




*Note*: The figure plots factors estimated from equation (4) that satisfy the sign restriction criteria defined in the main text. The two dark thick lines represent the *optimal* factors as defined using a standard euclidean metric. The thinner lines represent $10^{th}$, $25^{th}$, $50^{th}$, $75^{th}$ and $90^{th}$ percentiles of the distribution of distances for alternative valid models (i.e. rotations). Blue lines correspond to the first factor, identified based on the signs on loadings that capture opposite correlations between expected economic growth and expected inflation. Red lines correspond to the second factor, identified with demand-type signs on expected economic growth and expected inflation. The figure also includes vertical solid lines around the dates of (i) the blockage of the Suez and Panama Canals (May 2021), (ii) the Russian invasion of Ukraine (February 2022), and (iii) the first post-pandemic interest rate hike by the ECB (July 2022).

using different measures of inflation and economic activity, but no data on expectations. Following a similar identification strategy to ours, they extract underlying supply and demand forces driving inflation in the U.S. and the four largest economies in the euro area. The extracted factors since the inflation surge of 2021 for the euro area countries align surprisingly well with the perceptions we extract from expectations: Although both demand and supply pressures have shaped inflation, they find very tight supply conditions driving price increases in 2022. Focusing on inflation and real activity in the euro area since 2020, Ascari et al. (2023) find similar patterns. Using vector auto-regressions identified via sign restrictions, they emphasize combinations of supply and demand forces with signs and intensities that have changed throughout the pandemic, the reopening and the post-reopening of the economy. In particular, during the latter two phases (starting around the end of 2020), they find that inflation and activity were first driven by a combination of strong positive demand recovery and improvement of supply conditions, and then – starting at the end of 2021 – driven by negative supply shocks and mildly positive demand shocks. We find the similarity between our factors and the results in Eickmeier y Hofmann

**Figure 8:** Supply factor and measures of supply disruptions and consumer confidence: the Supply Bottleneck Index from Burriel et al. (2023) and Consumer Confidence Indicator from the European Commission




The figure compares the first factor identified from the model (4) with the Consumer Confidence Indicator (CCI) from the European Commission (left panel) and the newspaper-based Supply Bottleneck Index (SBI) as constructed by Burriel et al. (2023) (right panel) for the sample period for which we have expectations data. Sources: Consumer Confidence Indicator (CCI) is constructed by the European Commission based on questions about (i) personal finances and (ii) expectations about macro developments. The Supply Bottleneck Index (SBI) is constructed by Burriel et al. (2023)) based on text analysis of newspaper articles.

(2022) and Ascari et al. (2023) reassuring about the interpretation of our identified factors as supply- and demand-driven perceptions.

We next compare the dynamics of our extracted factors with measures of supply disruptions and consumer confidence that have recently been identified in the literature.

**Co-movement of the supply factor with existing measures of supply disruptions and consumer confidence.** The Supply Bottleneck Index (SBI) is a measure of supply disruptions recently developed by Burriel et al. (2023) and based on high-frequency newspaper data for the U.S., U.K., Germany, France, Italy, Spain, and China. Supply disruptions in their framework are defined as a negative event related to supply provision or functioning of supply chains. While there are other measures of supply shocks developed recently,[22] this SBI is particularly useful in our set-up because it covers the four largest countries (out of six) in our sample. The Consumer Confidence Indicator (CCI) is constructed by the European Commission (see European Commission (2018)) based on survey questions about (i) personal finances / spending and (ii) expectations about macro developments. Questions are mainly categorical with negative and positive options, and the Index is a simple arithmetic sum of replies.

Figure 8 compares our supply factor with the Consumer Confidence Indicator (CCI) in the left panel, and the (negative of the) euro area SBI in the right panel, while figure A.25 plots the correlation of the first factor with different lags of the SBI; i.e. $Corr\left(\hat{F}_{1,t}, SBI_{t-j}\right)$

[22]See for example Shapiro et al. (2022), Benigno et al. (2022), Ascari et al. (2023), and De Santis y Stoevsky (2023).

for $j = 1, ..., 10$. Two interesting patterns emerge. First, the structure of correlations with SBI has an inverted U-shape: The contemporaneous correlation is around 0.33, increases monotonously up to around 0.77 when the SBI is lagged six months, and decreases with longer lags. This suggests that households pay attention to news (newspapers) and adjust their expectations with some delays; in other words, media might be shaping expectations about future events and/or the explanations (i.e. narratives) that people entertain to arrive at a particular expectation given the available data. Although purely a correlation, the time lags might be suggestive of a causal direction.[23] Second, as can be seen from the left panel of Figure 8, the contemporaneous correlation with the CCI is around 0.85. This is surprising, even if the type of questions asked by the European Commission is similar to the ones in the CES; after all, the construction of the index follows a different methodology, and the expectation questions we use from the CES cover more variables (including inflation which is not considered in the Index).

**Response of factors to a monetary policy shock.** Figure 9 plots the impulse response of both factors to an identified monetary policy shock, estimated from the following specification similar to the one used in Section 3:

$$F_{t+h,f} - F_{t-1,f} = \alpha^{h,f} + \beta^{h,f}\epsilon_t^{MP} + \Sigma_{k=1}^{2}\gamma_k^{h,f}\epsilon_{t-k}^{MP} + u_t^{h,f} \tag{7}$$

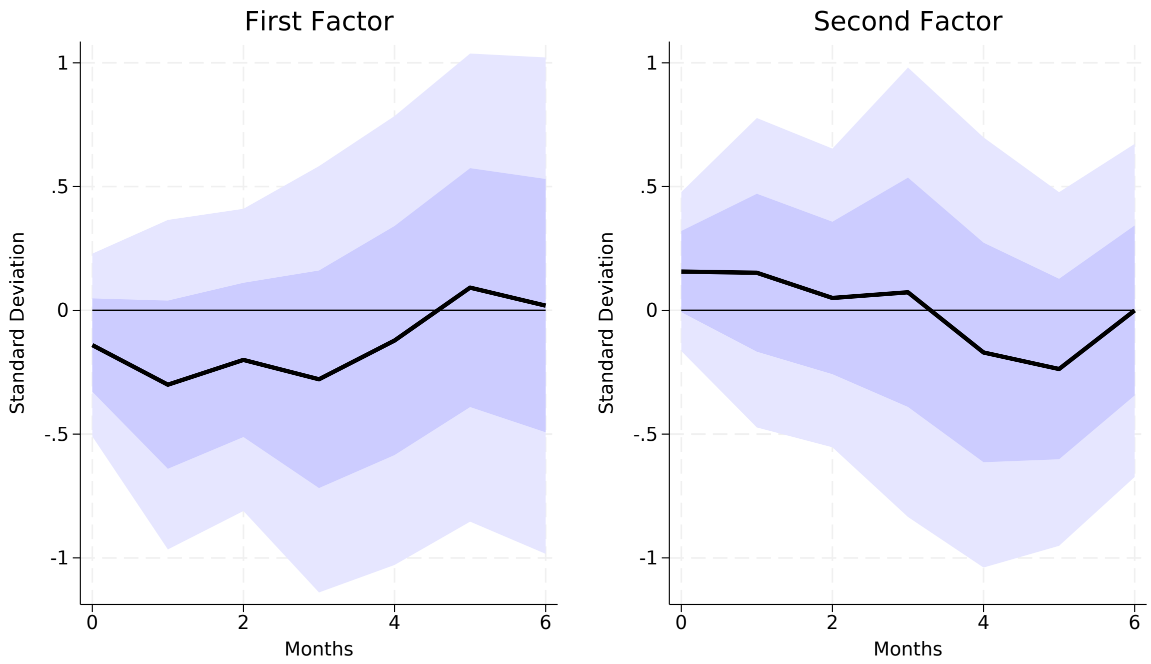
Two features evident in the figure are worth discussing. First, the point estimates are consistent with the response of expectations and the findings in Section 3. An unexpected monetary policy tightening drives the common perceptions of households in the direction of an implied *increase* of expected inflation. This is perhaps not surprising, given how these factors are constructed and identified. Second, the estimates are much more noisy than the ones for individual expectations presented in Figure 2. This is also not surprising: the factors capture the joint variation of all individual expectations.

# 6 Conclusions

In this paper we have exploited a very rich panel of expectation questions from the newly available Consumer Expectation Survey (CES), carried out in the six largest euro area countries since April 2020. Our main results show a robust positive reaction of inflation expectations to a contractionary monetary policy shock. We have also shown that although households disagree, they do so with a rich underlying structure. Two principal components explain a large fraction of the variance of the joint distribution of expectations in the cross-section. The first component reflects a supply-side view of future macroeconomic

[23]Interestingly, this is also consistent with evidence in Andre et al. (2023) that media shapes *backward looking narratives*, i.e. cause and effects explanations that people entertain about past events, which in turn affects their expectation formation.

**Figure 9:** The response of a contractionary monetary policy shock on identified factors




*Note*: The figure plots the impulse response functions of the first (left panel) and second (right panel) factors to a monetary surprise that increases the short rate on impact by 25 basis point. The impulse responses are estimated using the local projection specification (7). The factors are estimated from equation (4) using the sign restrictions described in the main text. The estimation sample goes from September 2020 to October 2023.

developments or, more generally, a dislike for inflation, whereby households associate higher expected growth of the economy with lower expected inflation. The second component, instead, reflects a demand-side view, leading households to forecast an improve of the economy together with an increase in inflation.

We further rely on these cross-sectional findings in order to identify a structural factor model which allow us to extract common latent drivers of expectations across time, both within and between households. The two identified factors align well with the narrative pre- and post- invasion of Ukraine in February 2022. In particular, they point to time-varying perceptions that assign strong inflationary pressures to dire economic growth prospects right after the the Russian invasion, and mildly inflationary pressures to later improvements in growth expectations. Moreover, the factors correlate strongly with different measures of supply and demand disruptions.

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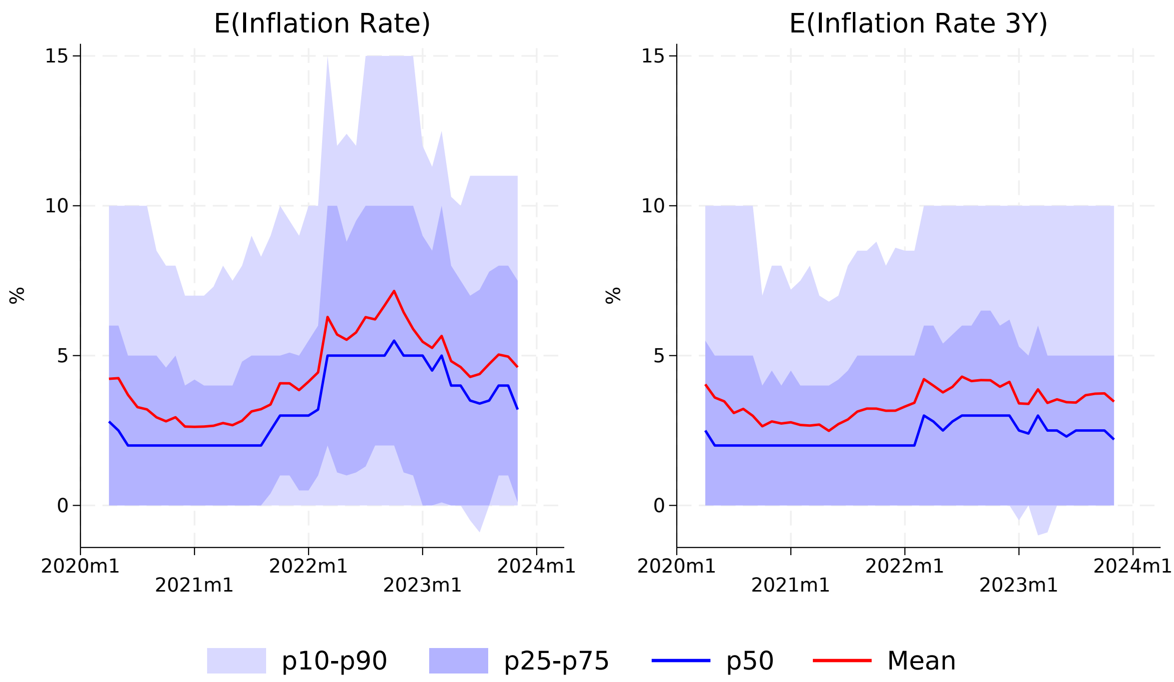
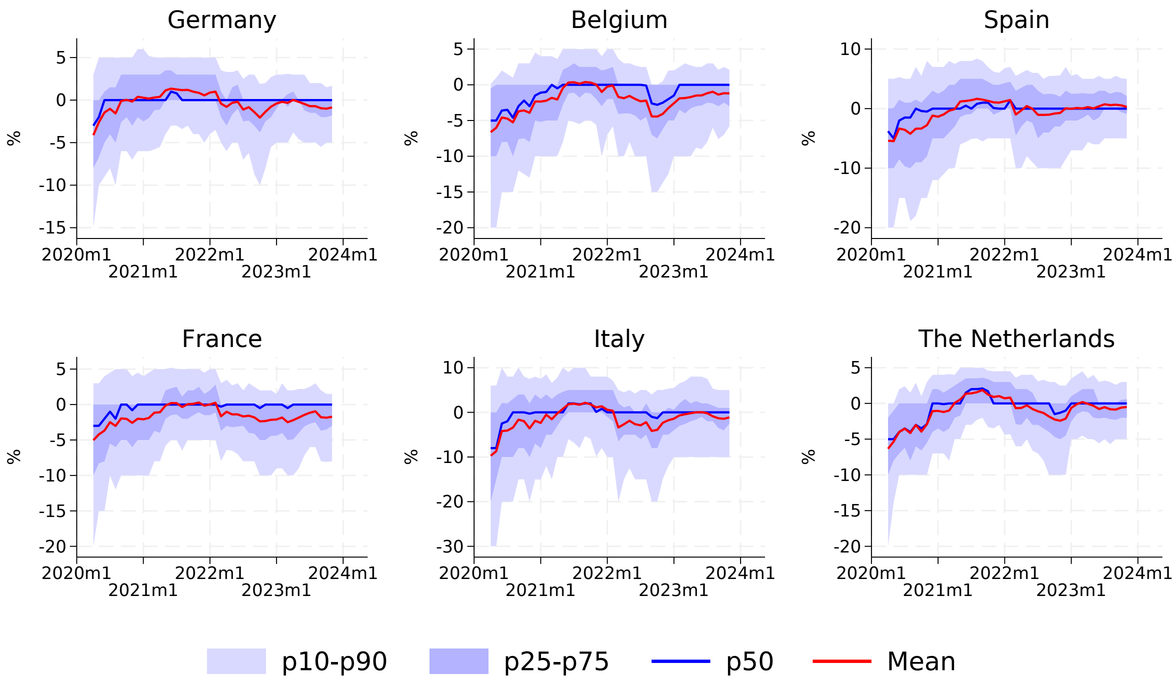
# Appendix A Additional Figures and Tables

**Figure A.1:** Evolution of household-level inflation expectations over time in the euro area



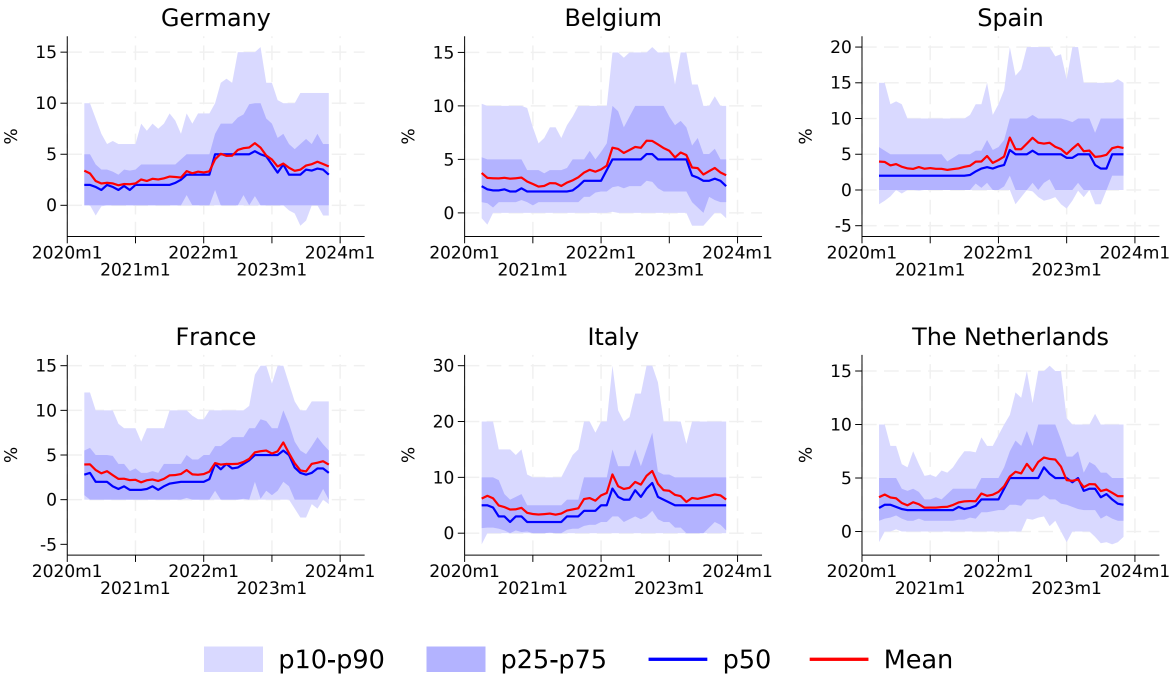

*Note*: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about 1-year ahead and 3-year ahead inflation expectation in each month of the sample. The expectations are measured monthly and reported as numerical values. The sample covers the period from April 2020 to November 2023.

**Figure A.2:** Evolution of household-level expectations over time, country-by-country: **E(Economic Growth)**



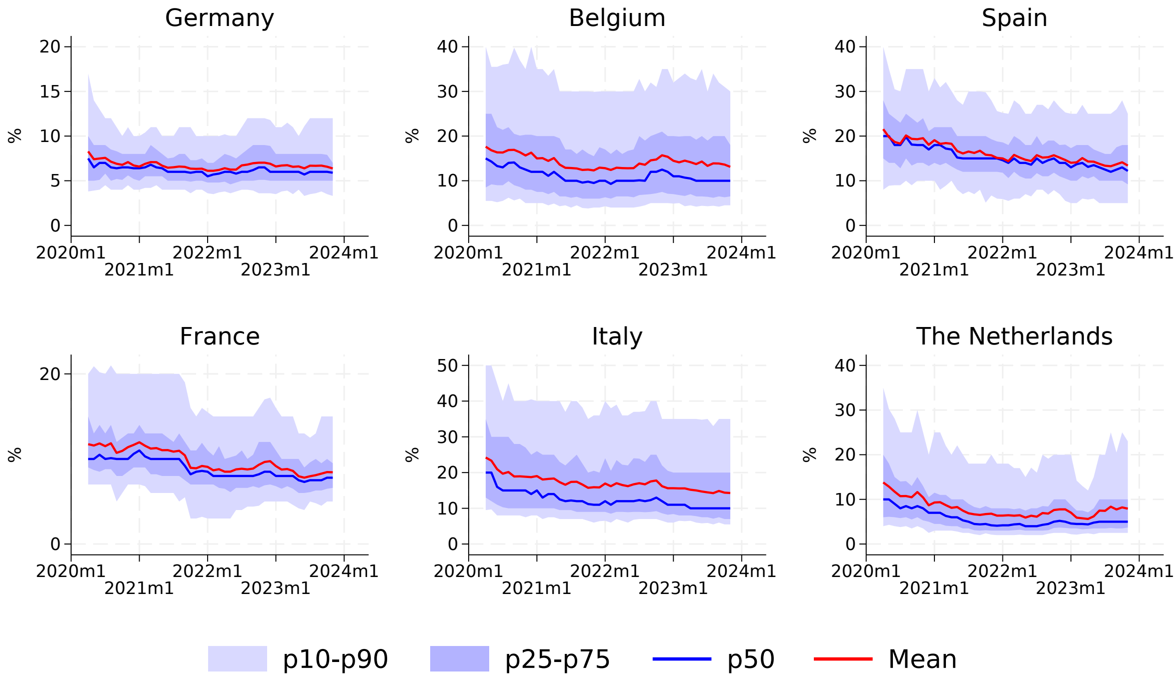

*Note*: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about economic growth in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April 2020 to November 2023.

**Figure A.3:** Evolution of household-level expectations over time, country-by-country: **E(Inflation Rate)**



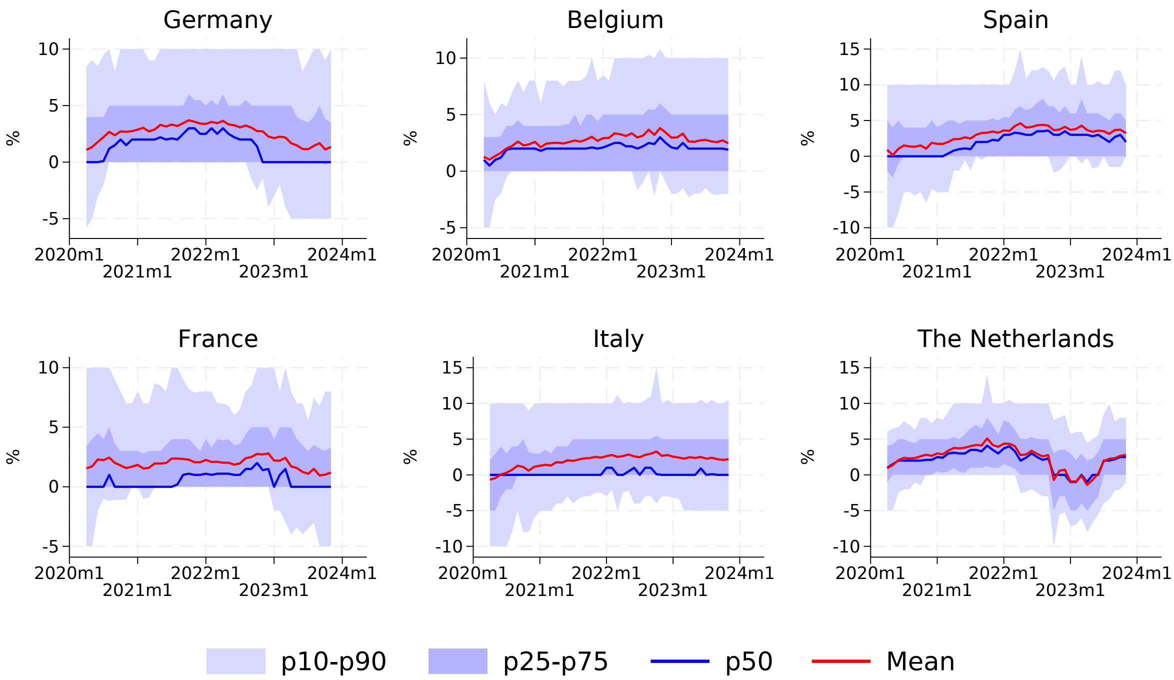

*Note*: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about the inflation rate in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April 2020 to November 2023.

**Figure A.4:** Evolution of household-level expectations over time, country-by-country: **E(Unemployment Rate)**



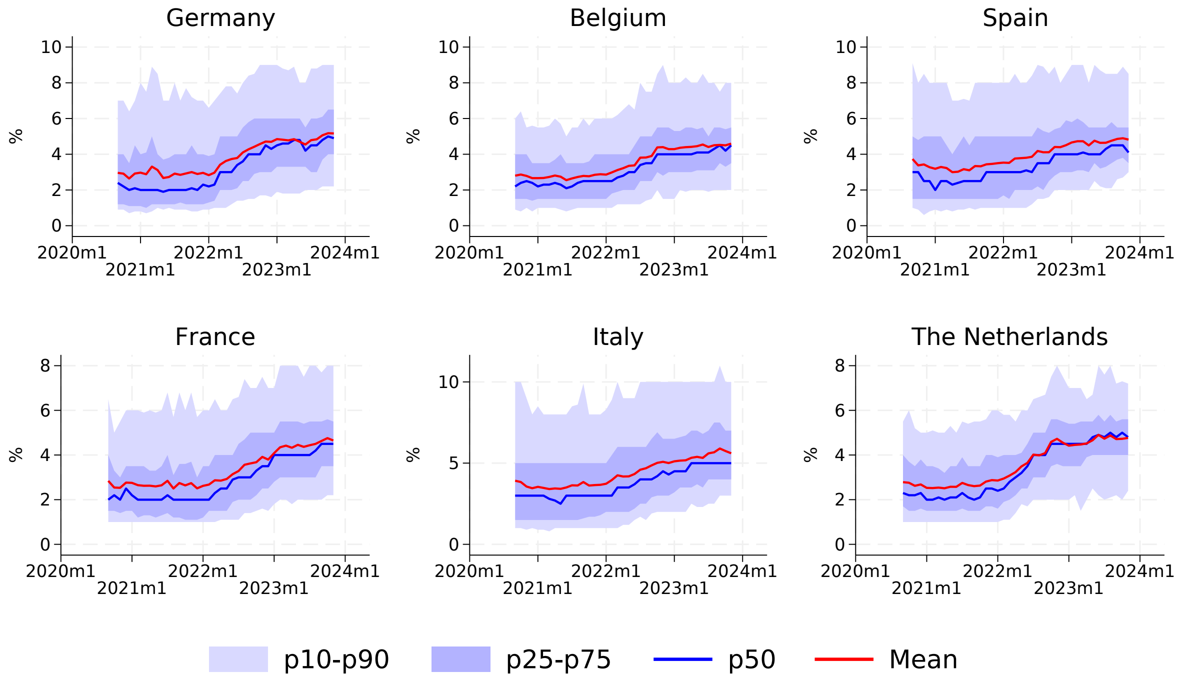

*Note*: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about the unemployment rate in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April 2020 to November 2023.

**Figure A.5:** Evolution of household-level expectations over time, country-by-country: **E(House Price Growth)**



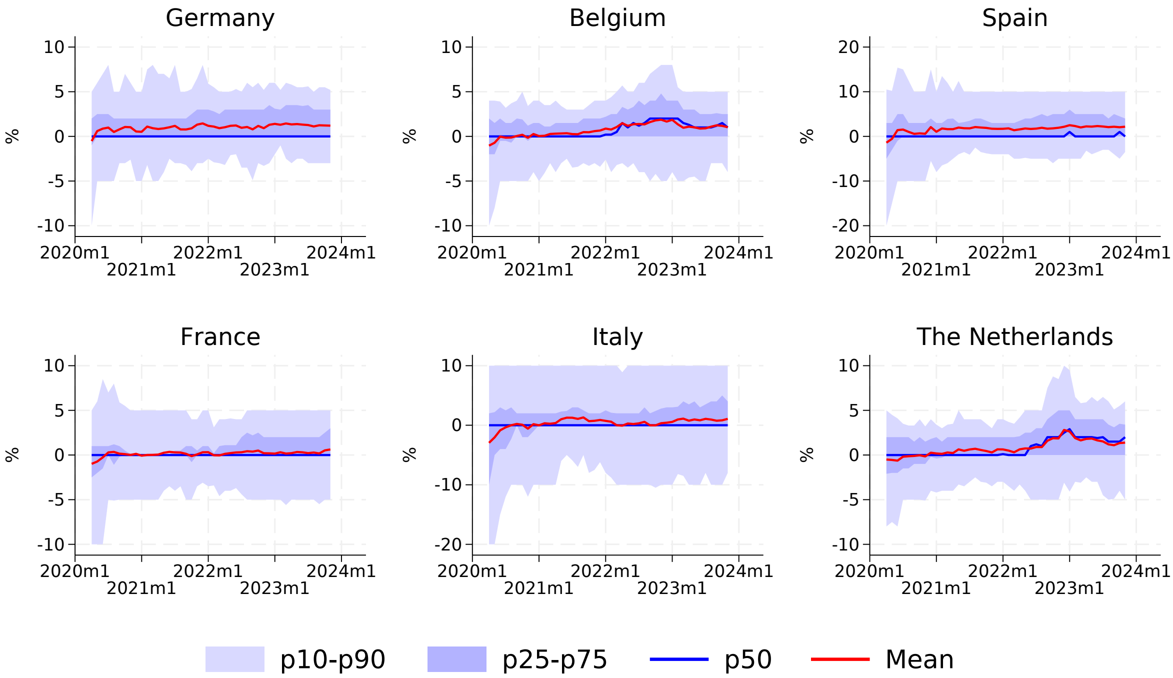

*Note*: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about house price growth in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April 2020 to November 2023.

**Figure A.6:** Evolution of household-level expectations over time, country-by-country: **E(Interest Rate on Mortgages)**



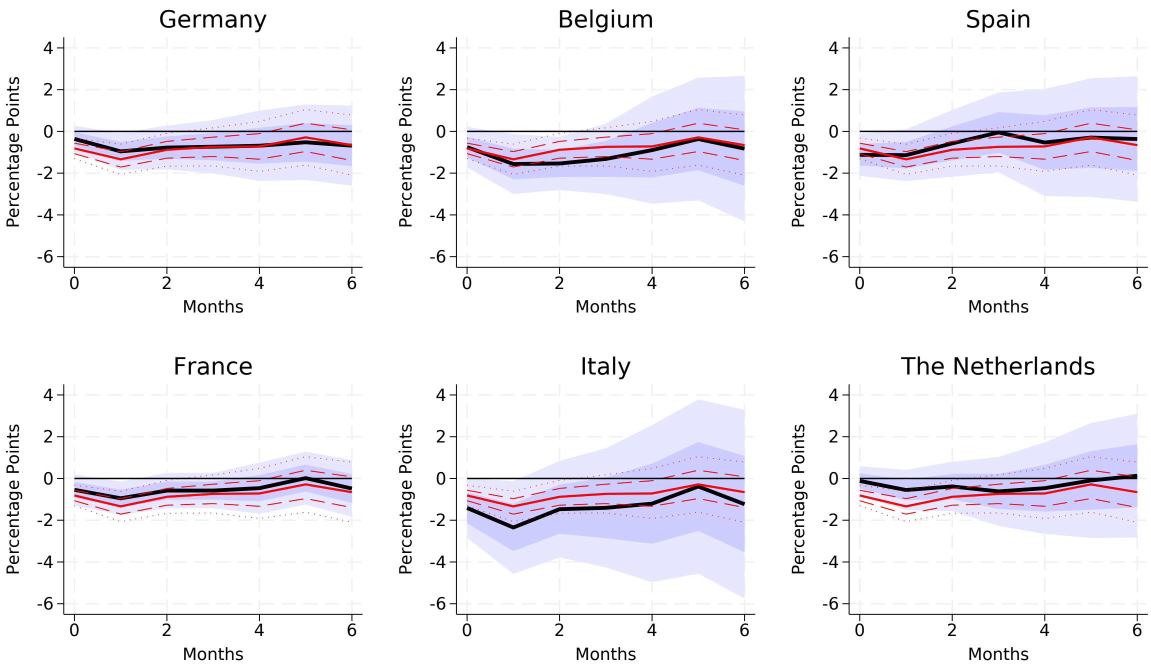

*Note*: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about the interate rate on mortgages in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from September 2020 to November 2023.

**Figure A.7:** Evolution of household-level expectations over time, country-by-country: **E(Own Income Growth)**



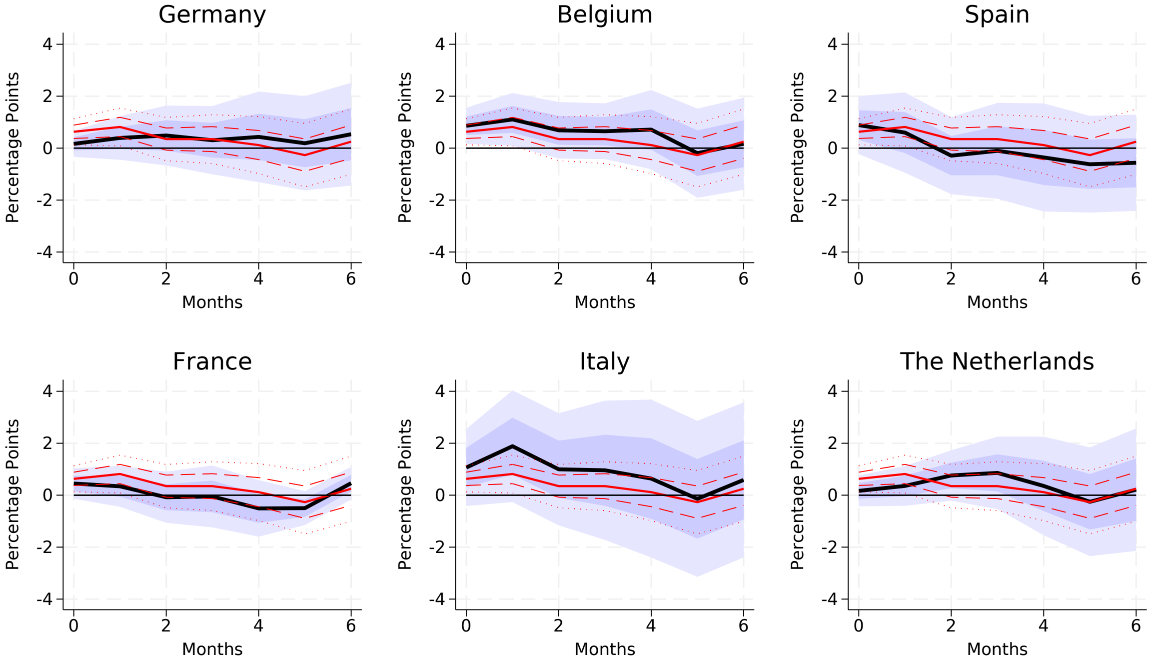

*Note*: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about own income growth in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April 2020 to November 2023.

**Figure A.8:** The country-by-country response of a contractionary monetary policy shock on **E(Economic Growth)**



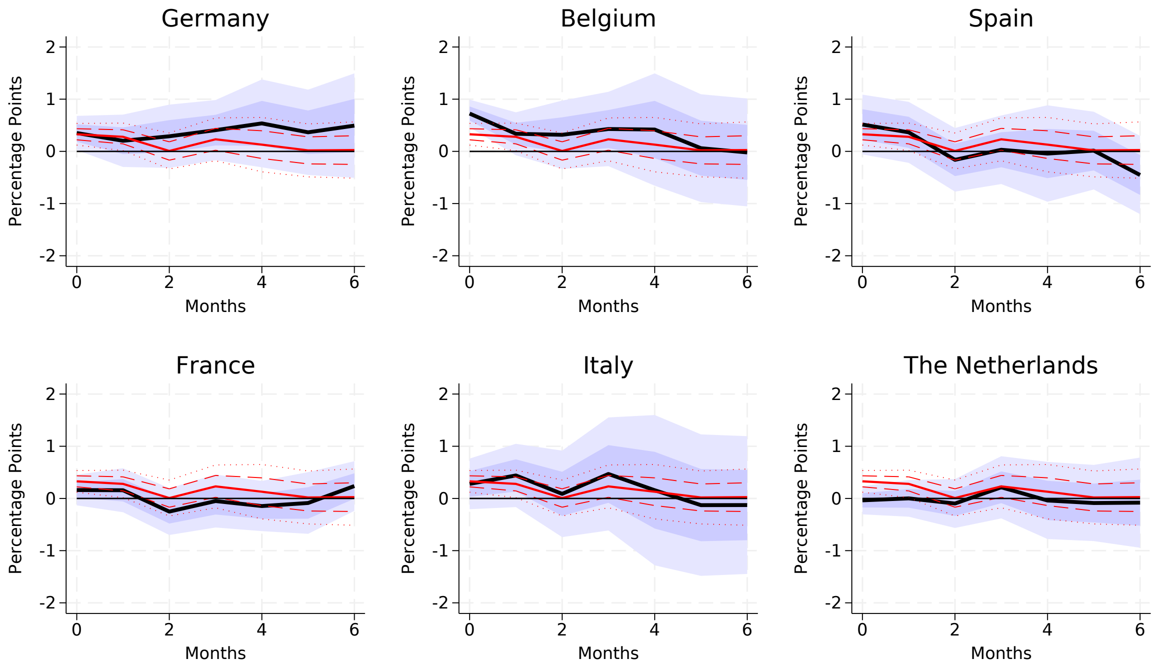

*Note*: The figure plots the country-by-country impulse response functions of monetary policy shocks on economic growth expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.9:** The country-by-country response of a contractionary monetary policy shock on **E(Inflation Rate)**



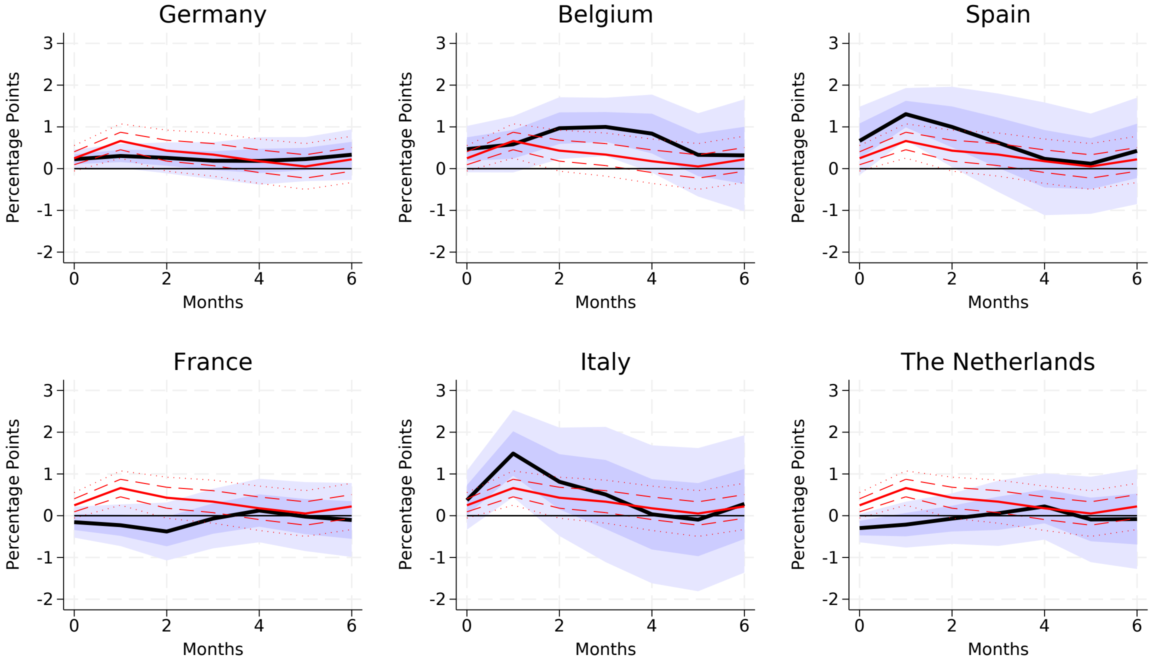

*Note*: The figure plots the country-by-country impulse response functions of monetary policy shocks on inflation expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.10:** The country-by-country response of a contractionary monetary policy shock on **E(3Y Inflation Rate)**



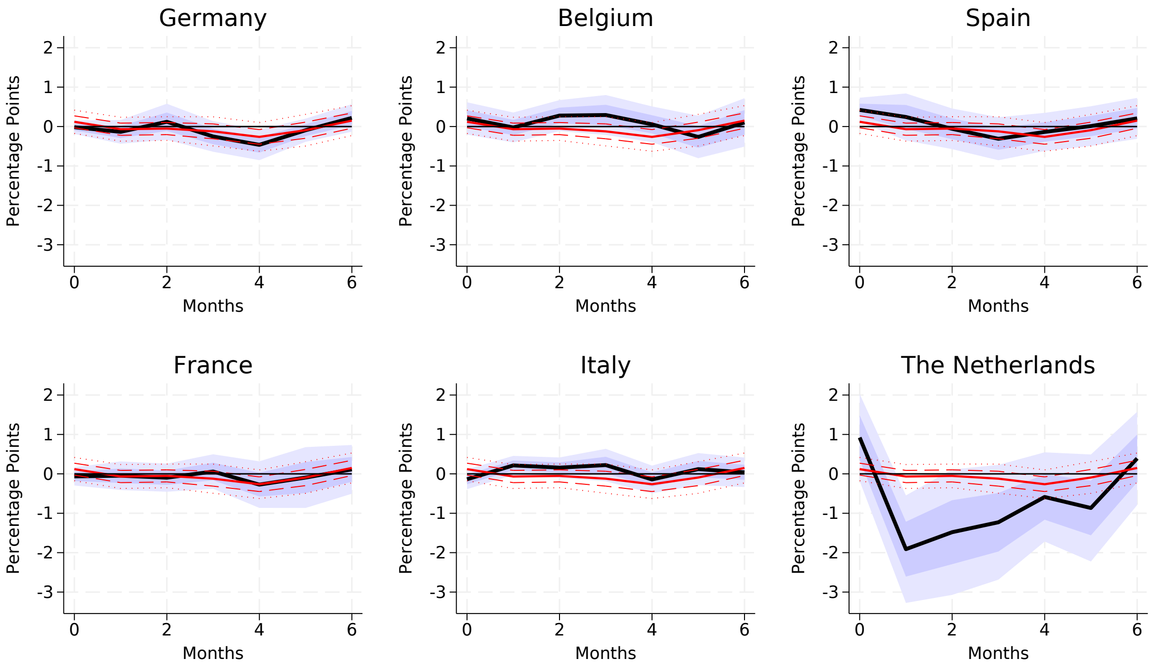

*Note*: The figure plots the country-by-country impulse response functions of monetary policy shocks on 3-year ahead inflation expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.11:** The country-by-country response of a contractionary monetary policy shock on **E(Unemployment Rate)**



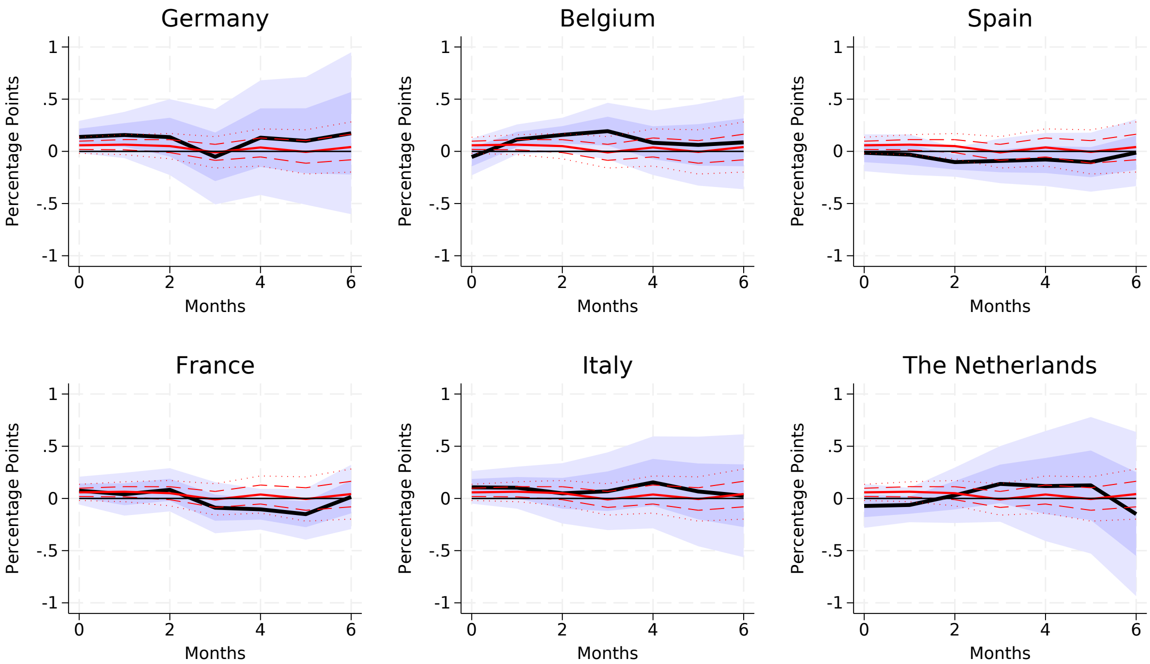

*Note*: The figure plots the country-by-country impulse response functions of monetary policy shocks on unemployment rate expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.12:** The country-by-country response of a contractionary monetary policy shock on **E(House Price Growth)**



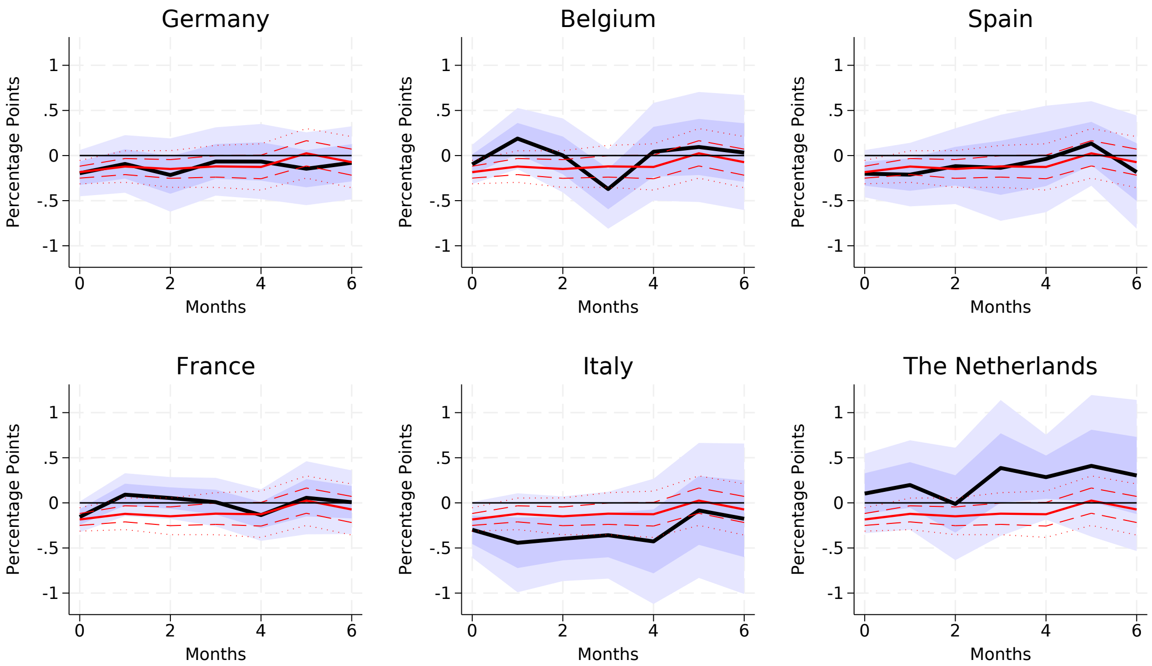

*Note*: The figure plots the country-by-country impulse response functions of monetary policy shocks on house price growth expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.13:** The country-by-country response of a contractionary monetary policy shock on **E(Interest Rate on Mortgages)**



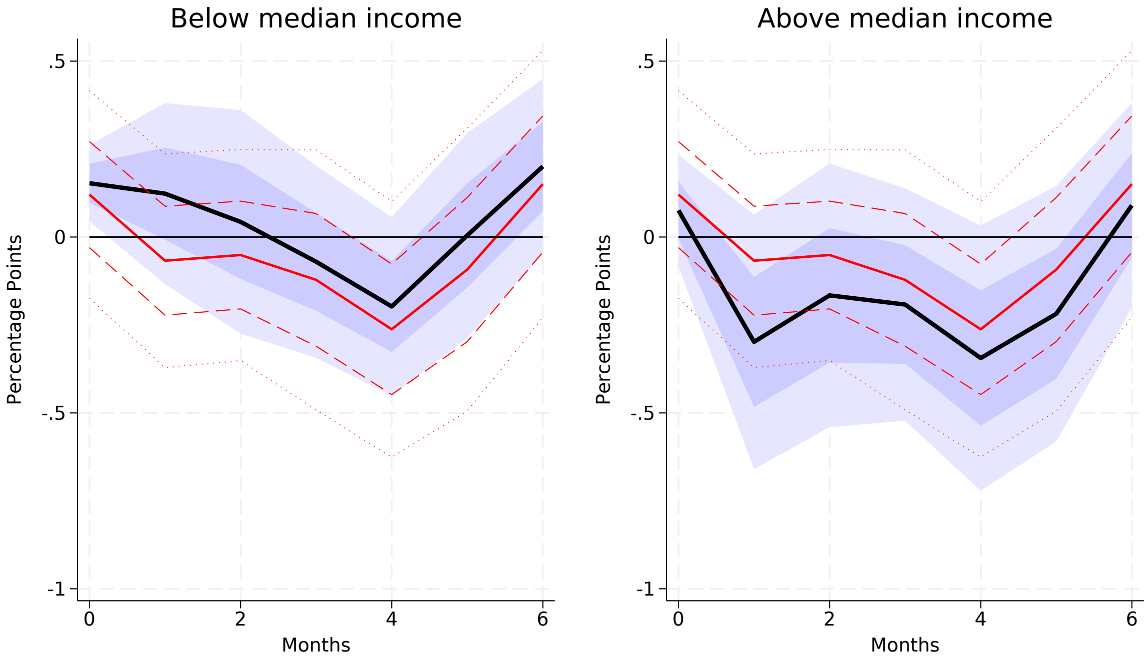

*Note*: The figure plots the country-by-country impulse response functions of monetary policy shocks on mortgage interest rate expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from September 2020 to October 2023.

**Figure A.14:** The country-by-country response of a contractionary monetary policy shock on **E(Own Income Growth)**



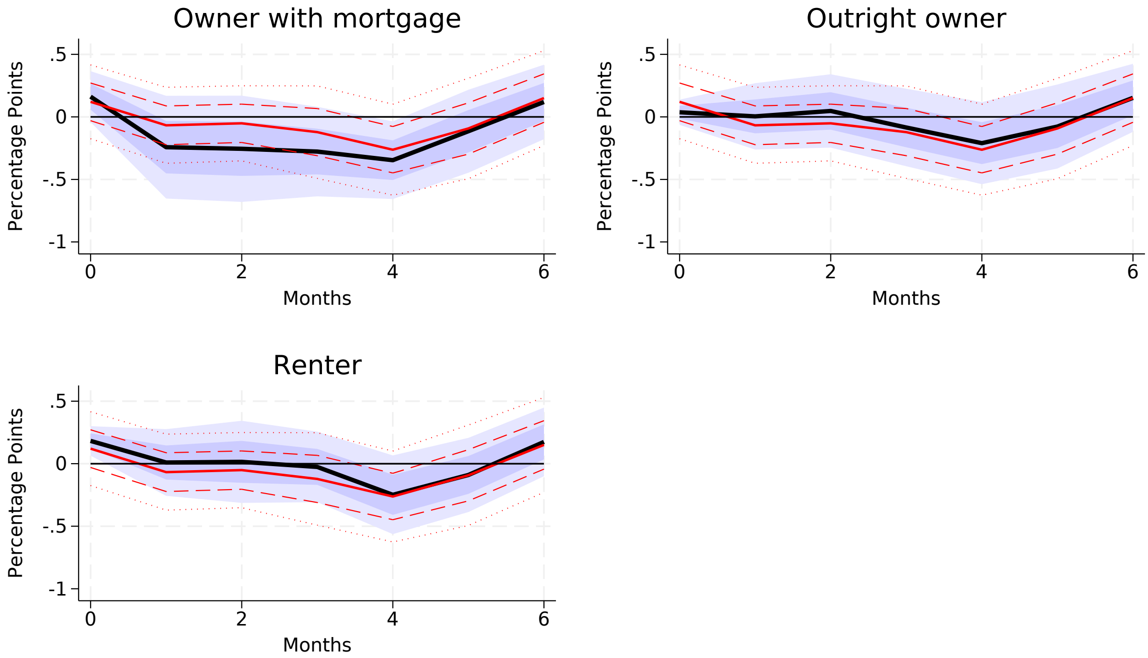

*Note*: The figure plots the country-by-country impulse response functions of monetary policy shocks on own income growth expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.15:** The response of a contractionary monetary policy shock by income group on **E(House Price Growth)**



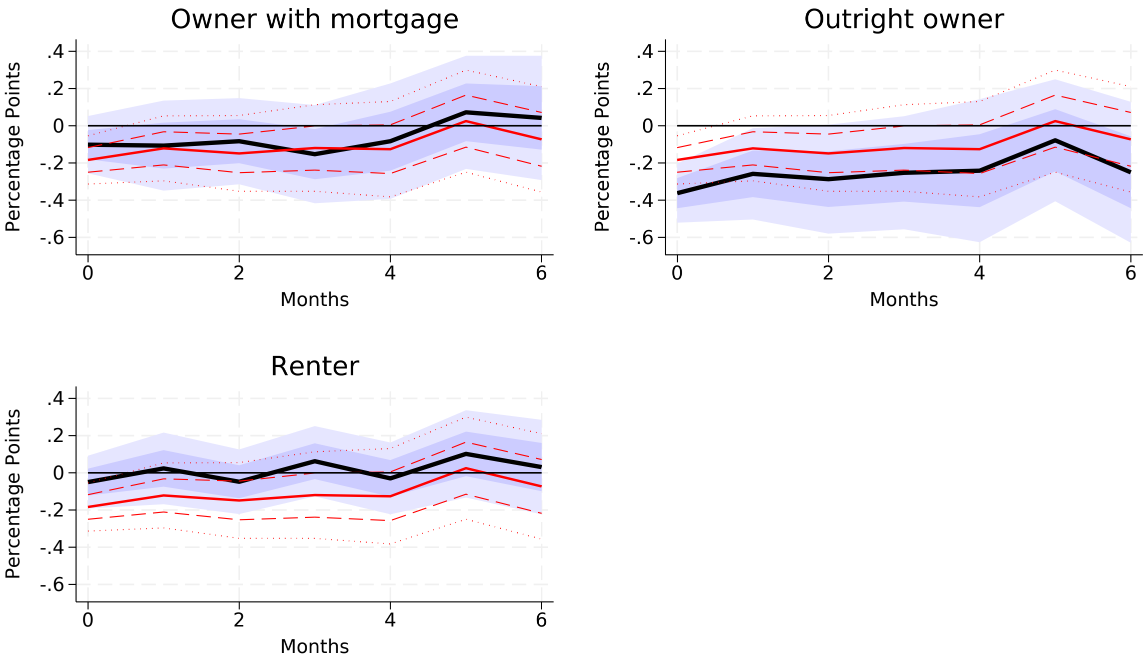

*Note*: The figure plots the impulse response functions of monetary policy shocks by income groups on own house price growth expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.16:** The response of a contractionary monetary policy shock by housing tenure status on **E(House Price Growth)**



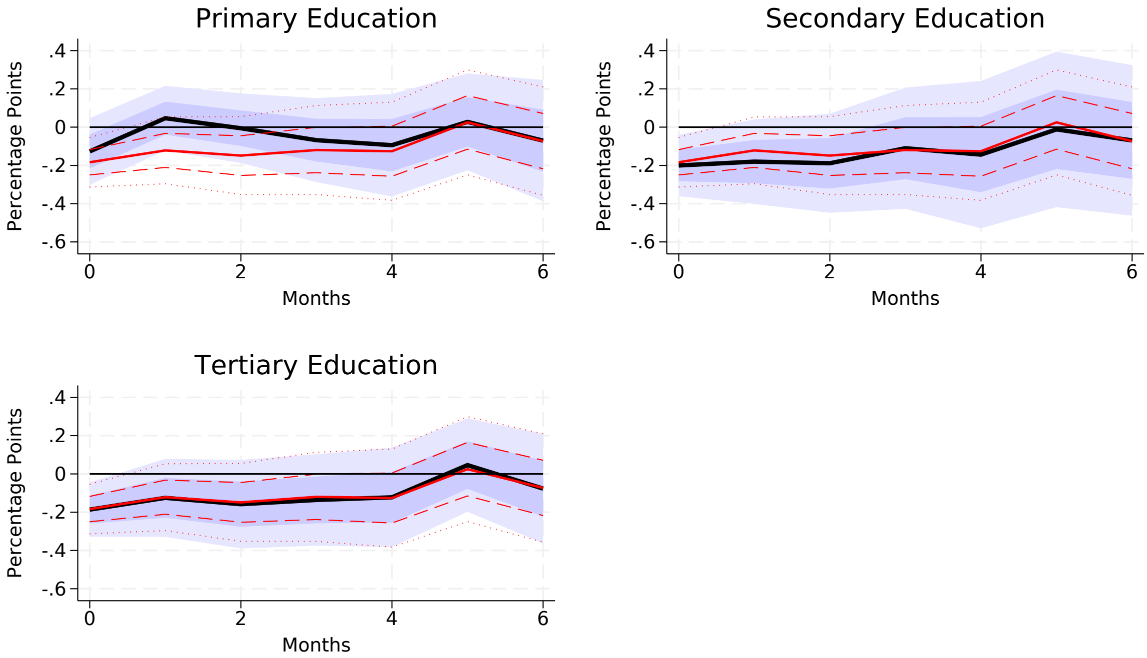

*Note*: The figure plots the impulse response functions of monetary policy shocks by housing tenure status on house price growth expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.17:** The response of a contractionary monetary policy shock by housing tenure status on **E(Own Income Growth)**



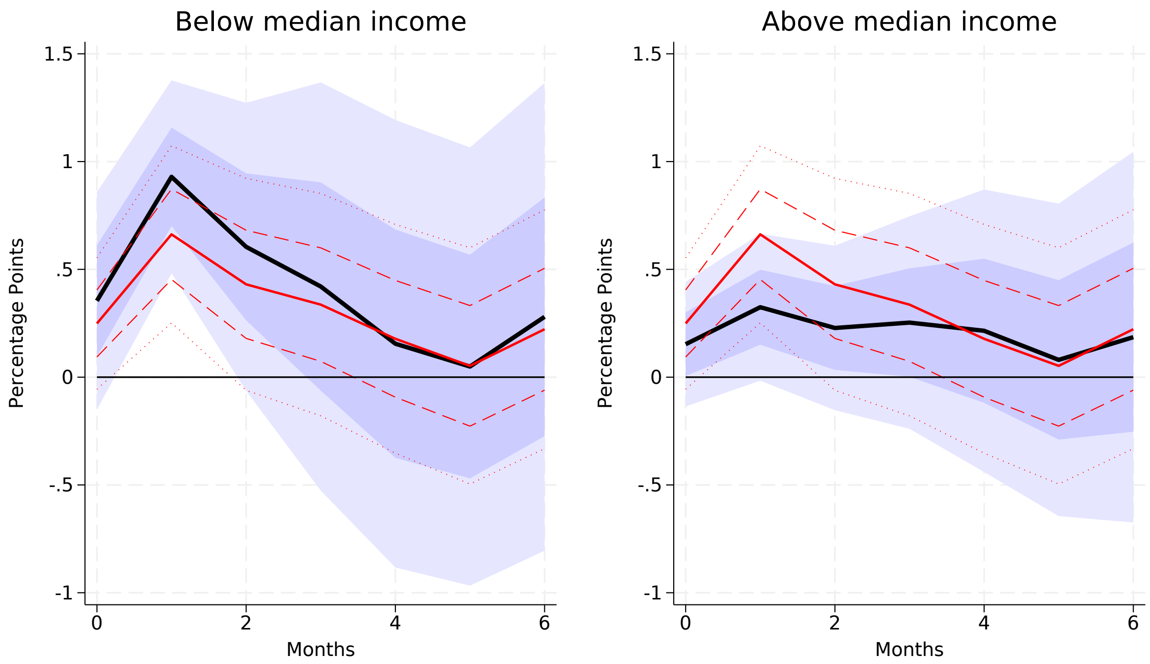

*Note*: The figure plots the impulse response functions of monetary policy shocks by housing tenure status on own income growth expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.18:** The response of a contractionary monetary policy shock by education status on **E(Own Income Growth)**



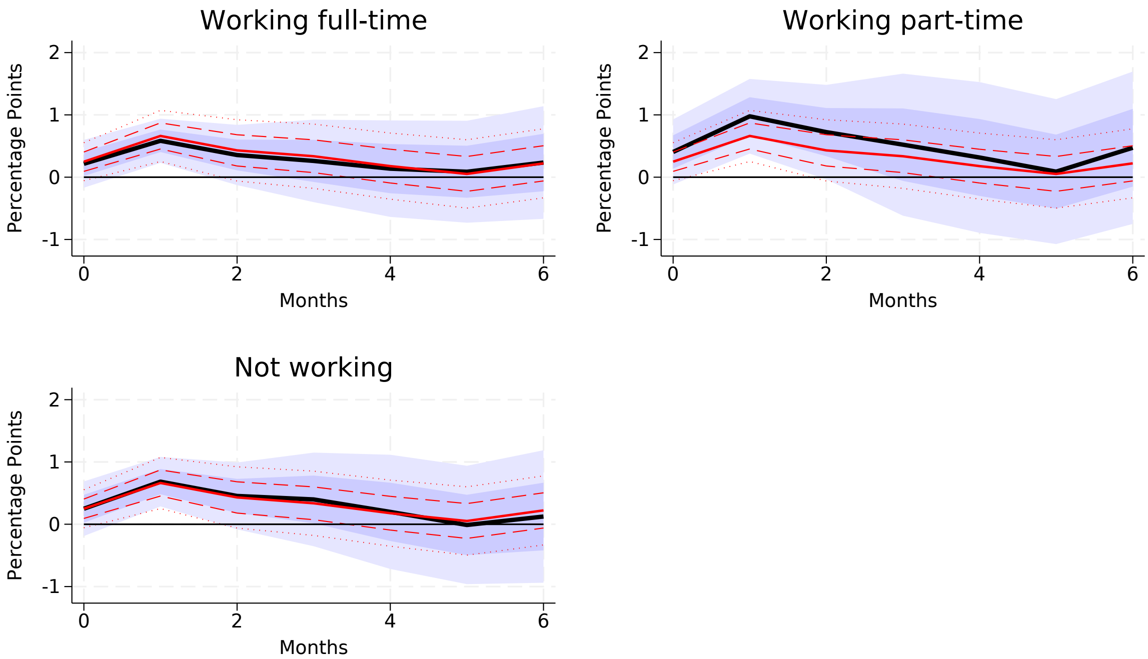

*Note*: The figure plots the impulse response functions of monetary policy shocks by education status on own income growth expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.19:** The response of a contractionary monetary policy shock by income groups on **E(Unemployment Rate)**



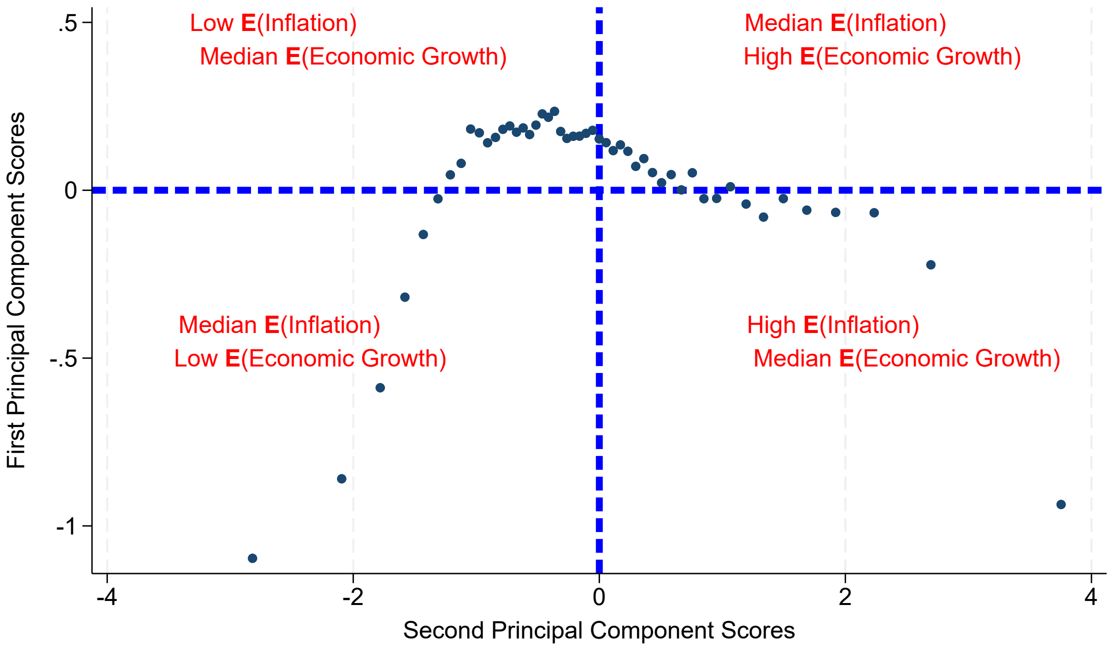

*Note*: The figure plots the impulse response functions of monetary policy shocks by income groups on unemployment rate expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.20:** The response of a contractionary monetary policy shock by employment situation on **E(Unemployment Rate)**



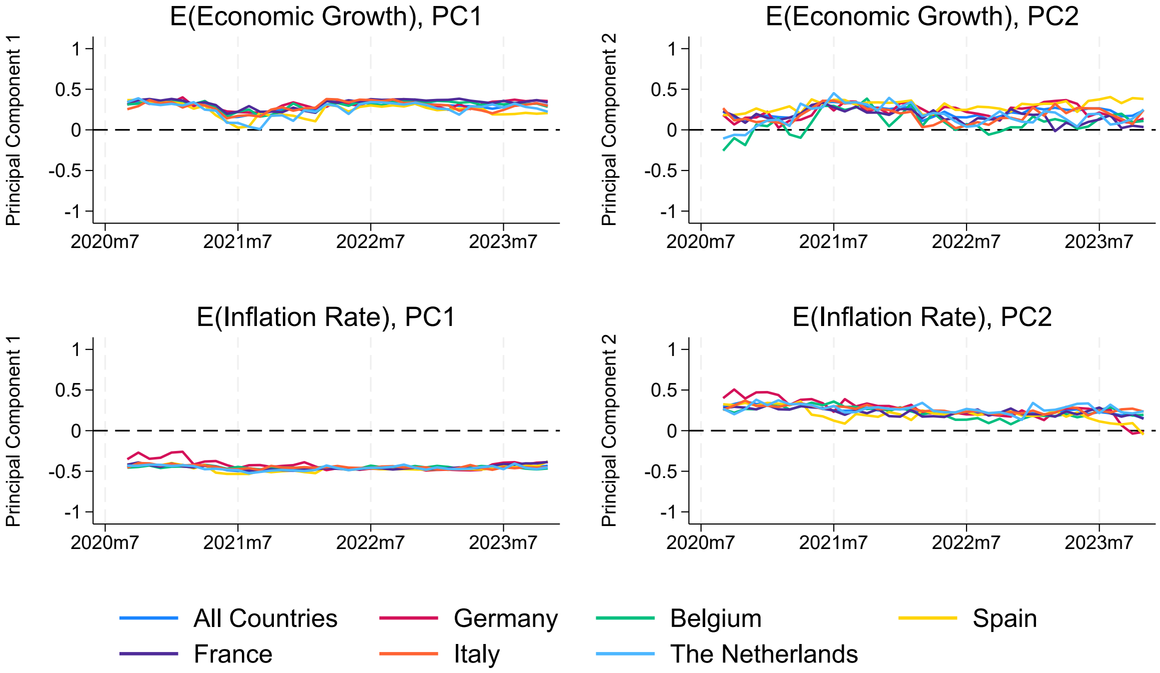

*Note*: The figure plots the impulse response functions of monetary policy shocks by employment situation on unemployment rate expectations. Red lines represent the baseline responses (at the euro area level). The monetary surprises are normalized to an increase in the short rate on impact by 25 basis point. The impulse responses are estimated using the panel local projection specification (1) where standard errors are clustered at the month level. 95% confidence intervals are in light blue while 68% confidence intervals are in dark blue. The estimation sample goes from April 2020 to October 2023.

**Figure A.21:** Diagram of PC scores and relation to expected inflation and economic growth



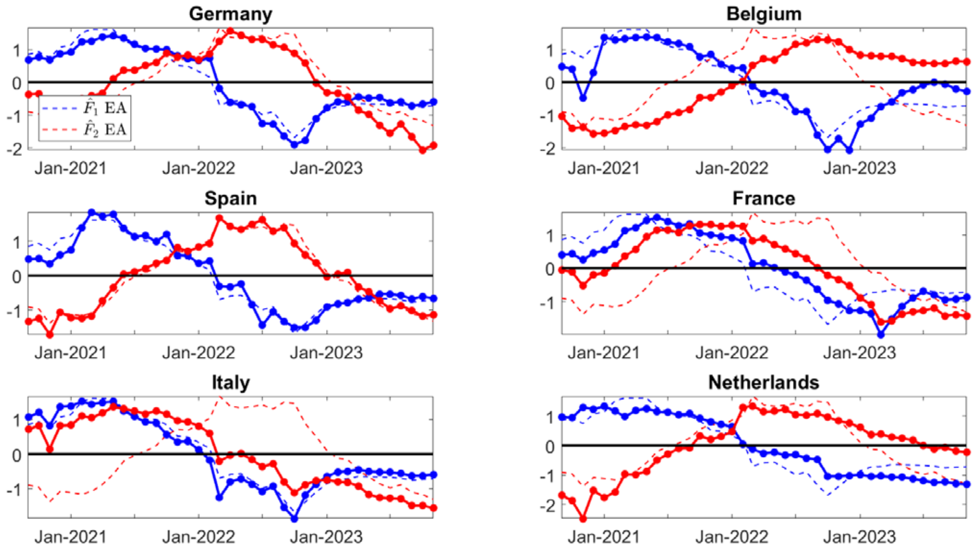

*Note*: The blue circles show the mean of the y-axis variables (first principal component score) for 50 bins of the x-axis variable (second principal component score). The scores divide the graph into four quadrants, which relates to the joint distribution of expectations. By "High" we mean higher than the median, "Medium" close to the median, and "Low" below the median.

**Figure A.22:** Evolution of specific loadings of the principal components over time in each country



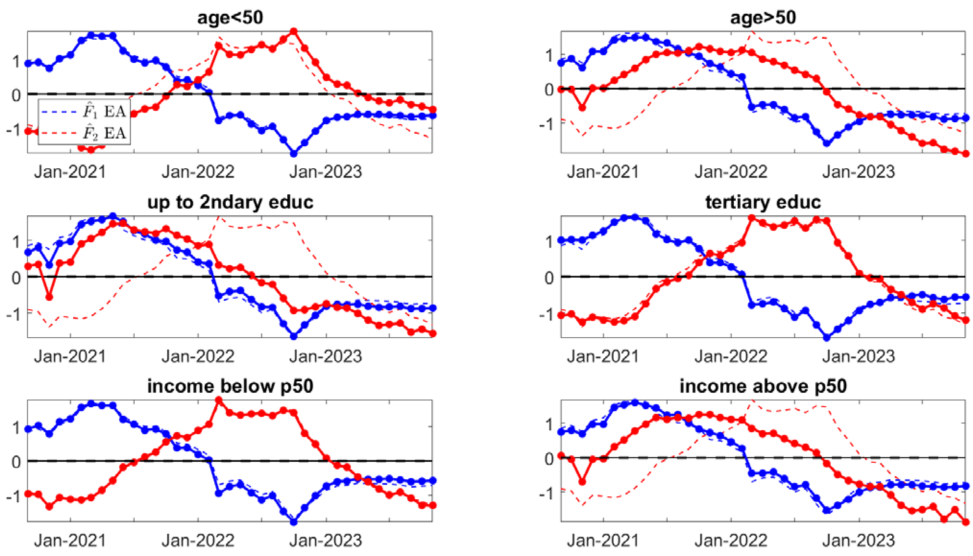

*Note*: The figure plots the evolution of the loadings of expected economic growth (top panels) and expected inflation rate (bottom panels) in the first principal component (left panels) and the second principal component (right panels). The loadings results from a PCA run for each month and country separately between September 2020 and November 2023.

**Figure A.23:** Evolution of identified factors over the sample period estimated separately for each country



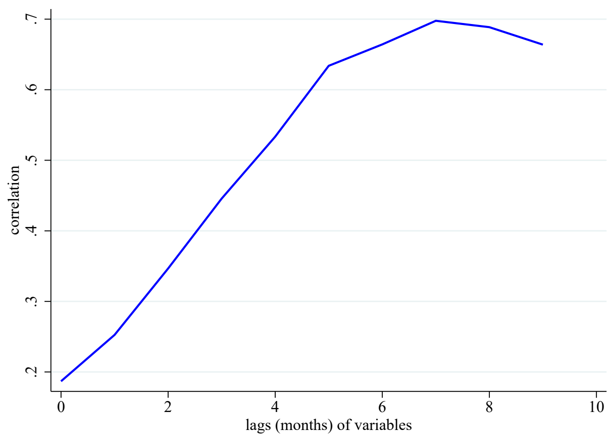

*Note*: The figure plots the *optimal* valid factors (i.e. factors that satisfies the sign restriction criteria defined in the main text and are optimal in terms of a standard euclidean metric) as estimated from (4) separately for each country. Blue lines correspond to the first factor, identified based on the signs on loadings that capture opposite correlations with expected economic growth and expected inflation. Red lines correspond to the second factor, identified with demand-type sings on expected economic growth and expected inflation.

**Figure A.24:** Evolution of identified factors over the sample period estimated separately for different demographic groups, pooling all countries together




*Note*: The figure plots the *optimal* valid factors (i.e. factors that satisfies the sign restriction criteria defined in the main text and are optimal in terms of a standard euclidean metric) as estimated from (4) separately for age, education and income groups. Blue lines correspond to the first factor, identified based on the signs on loadings that capture opposite correlations with expected economic growth and expected inflation. Red lines correspond to the second factor, identified with demand-type sings on expected economic growth and expected inflation. The shaded area represents the p10-p90 of the distribution of distances of models (i.e. rotations)

**Figure A.25:** Correlation structure between the supply factor and the SBI




The figure plots the correlation structure of the supply-type factor with different lags of the SBI; i.e. $Corr\left(\hat{F}_{1,t}, SBI_{t-j}\right)$ for $j = 1, ..., 10$, where the number of lags (in months) are represented in the x-axis. Sources: the Supply Bottleneck Index (SBI) is constructed by Burriel et al. 2023) based on text analysis of newspaper articles.

**Table A.1:** Descriptive statistics over the whole sample for Belgium and France

| | Mean | p10 | Median | p90 | N |
|---|---|---|---|---|---|
| *Belgium* | | | | | |
| Age | 49.87 | 26.00 | 42.00 | 80.00 | 45,611 |
| Disposable Income | 37,258.43 | 17,500.00 | 35,000.00 | 67,500.00 | 45,611 |
| Nondurable Spending | 17,701.65 | 6,600.00 | 17,520.00 | 28,620.00 | 15,394 |
| Spent on Durables (0-1) | 0.17 | 0.00 | 0.00 | 1.00 | 12,247 |
| Precautionary Savings | 7,786.76 | 400.00 | 5,000.00 | 19,600.00 | 14,224 |
| E(Economic Growth) | -2.13 | -10.00 | 0.00 | 2.50 | 45,611 |
| E(Inflation Rate) | 4.23 | 0.00 | 3.00 | 10.00 | 45,605 |
| E(Inflation Rate 3Y) | 3.41 | 0.00 | 2.50 | 10.00 | 45,099 |
| E(House Price Growth) | 2.67 | 0.00 | 2.00 | 8.00 | 45,611 |
| E(Unemployment Rate) | 14.28 | 5.00 | 11.00 | 30.00 | 45,611 |
| E(Interest Rate on Mortgages) | 3.50 | 1.20 | 3.10 | 6.00 | 40,363 |
| E(Own Income Growth) | 0.72 | -3.00 | 0.00 | 4.00 | 45,611 |
| E(Own Spending Growth) | 3.50 | 0.00 | 2.00 | 10.00 | 36,983 |
| E(Own Durable Spending) | 0.24 | 0.00 | 0.00 | 1.00 | 45,465 |
| E(Own Credit Access) | 2.54 | 1.00 | 3.00 | 3.00 | 44,433 |
| E(Own Financial Situation) | 2.64 | 1.00 | 3.00 | 4.00 | 45,611 |
| *France* | | | | | |
| Age | 50.44 | 26.00 | 42.00 | 80.00 | 121,175 |
| Disposable Income | 35,982.55 | 17,500.00 | 35,000.00 | 67,500.00 | 121,175 |
| Nondurable Spending | 18,400.48 | 7,800.00 | 17,964.00 | 29,820.00 | 39,875 |
| Spent on Durables (0-1) | 0.16 | 0.00 | 0.00 | 1.00 | 34,034 |
| Precautionary Savings | 7,503.92 | 480.00 | 5,000.00 | 20,000.00 | 35,198 |
| E(Economic Growth) | -1.58 | -8.00 | 0.00 | 3.00 | 121,175 |
| E(Inflation Rate) | 3.58 | 0.00 | 2.50 | 10.00 | 121,172 |
| E(Inflation Rate 3Y) | 2.84 | 0.00 | 2.00 | 8.60 | 120,146 |
| E(House Price Growth) | 1.96 | 0.00 | 0.00 | 7.00 | 121,175 |
| E(Unemployment Rate) | 9.78 | 5.50 | 9.00 | 15.00 | 121,175 |
| E(Interest Rate on Mortgages) | 3.35 | 1.10 | 3.00 | 6.00 | 111,664 |
| E(Own Income Growth) | 0.16 | -4.00 | 0.00 | 5.00 | 121,175 |
| E(Own Spending Growth) | 2.23 | 0.00 | 0.00 | 9.00 | 99,532 |
| E(Own Durable Spending) | 0.24 | 0.00 | 0.00 | 1.00 | 120,846 |
| E(Own Credit Access) | 2.67 | 1.00 | 3.00 | 4.00 | 120,064 |
| E(Own Financial Situation) | 2.72 | 1.00 | 3.00 | 4.00 | 121,175 |

*Note*: "Age" is provided in four brackets ([18-34], [35-49], [50-64], 65+), and we assign the median value to each household. "Disposable Income" refers to the 12 months preceding the interview and it is PPP-adjusted. "Nondurable Spending" is asked at a quarterly frequency, it refers to spending on nondurable goods and services in the month preceding the interview, and it is annualized and PPP-adjusted. "Spent on Durables (0-1)" is asked at a quarterly frequency, and is a dummy variable capturing whether households have spent on durable goods in the month preceding the interview. "Precautionary Savings" is asked at a quarterly frequency, it refers to the amount households think they need to put aside in total savings to deal with unexpected events, and it is PPP-adjusted. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). The sample for all variables in the table covers the period from April 2020 to November 2023, except for the expectation concerning the interest rate on mortgages, which starts in September 2020.

**Table A.2:** Descriptive statistics over the whole sample for Germany and Italy

| | Mean | p10 | Median | p90 | N |
|---|---|---|---|---|---|
| *Germany* | | | | | |
| Age | 50.79 | 26.00 | 57.00 | 80.00 | 116,778 |
| Disposable Income | 38,926.12 | 12,500.00 | 35,000.00 | 67,500.00 | 116,778 |
| Nondurable Spending | 19,498.53 | 9,000.00 | 19,200.00 | 31,020.00 | 38,847 |
| Spent on Durables (0-1) | 0.19 | 0.00 | 0.00 | 1.00 | 32,940 |
| Precautionary Savings | 7,381.51 | 500.00 | 4,400.00 | 20,000.00 | 34,628 |
| E(Economic Growth) | -0.32 | -5.00 | 0.00 | 3.50 | 116,778 |
| E(Inflation Rate) | 3.56 | 0.00 | 3.00 | 9.50 | 116,777 |
| E(Inflation Rate 3Y) | 2.62 | 0.00 | 2.00 | 7.00 | 115,701 |
| E(House Price Growth) | 2.58 | 0.00 | 1.50 | 9.50 | 116,778 |
| E(Unemployment Rate) | 6.73 | 4.00 | 6.00 | 10.00 | 116,778 |
| E(Interest Rate on Mortgages) | 3.78 | 1.10 | 3.40 | 7.10 | 107,405 |
| E(Own Income Growth) | 1.02 | -2.50 | 0.00 | 5.00 | 116,778 |
| E(Own Spending Growth) | 2.78 | 0.00 | 0.00 | 8.80 | 100,543 |
| E(Own Durable Spending) | 0.28 | 0.00 | 0.00 | 1.00 | 116,532 |
| E(Own Credit Access) | 2.93 | 2.00 | 3.00 | 4.00 | 115,702 |
| E(Own Financial Situation) | 2.88 | 2.00 | 3.00 | 4.00 | 116,778 |
| *Italy* | | | | | |
| Age | 51.94 | 26.00 | 57.00 | 80.00 | 125,234 |
| Disposable Income | 30,755.89 | 12,500.00 | 27,500.00 | 55,000.00 | 125,234 |
| Nondurable Spending | 15,997.43 | 6,240.00 | 15,600.00 | 25,872.00 | 41,920 |
| Spent on Durables (0-1) | 0.20 | 0.00 | 0.00 | 1.00 | 35,769 |
| Precautionary Savings | 8,012.35 | 440.00 | 4,800.00 | 22,000.00 | 38,726 |
| E(Economic Growth) | -1.50 | -10.00 | 0.00 | 5.50 | 125,234 |
| E(Inflation Rate) | 6.21 | 0.00 | 5.00 | 15.10 | 125,230 |
| E(Inflation Rate 3Y) | 4.84 | 0.00 | 3.00 | 15.00 | 124,166 |
| E(House Price Growth) | 1.95 | -3.20 | 0.00 | 10.00 | 125,234 |
| E(Unemployment Rate) | 17.16 | 7.00 | 12.00 | 35.00 | 125,234 |
| E(Interest Rate on Mortgages) | 4.39 | 1.30 | 4.00 | 8.30 | 115,030 |
| E(Own Income Growth) | 0.37 | -8.00 | 0.00 | 10.00 | 125,234 |
| E(Own Spending Growth) | 3.04 | -1.00 | 0.00 | 10.00 | 108,261 |
| E(Own Durable Spending) | 0.34 | 0.00 | 0.00 | 1.00 | 124,991 |
| E(Own Credit Access) | 2.72 | 1.00 | 3.00 | 3.00 | 124,307 |
| E(Own Financial Situation) | 2.74 | 2.00 | 3.00 | 4.00 | 125,234 |

*Note*: "Age" is provided in four brackets ([18-34], [35-49], [50-64], 65+), and we assign the median value to each household. "Disposable Income" refers to the 12 months preceding the interview and it is PPP-adjusted. "Nondurable Spending" is asked at a quarterly frequency, it refers to spending on nondurable goods and services in the month preceding the interview, and it is annualized and PPP-adjusted. "Spent on Durables (0-1)" is asked at a quarterly frequency, and is a dummy variable capturing whether households have spent on durable goods in the month preceding the interview. "Precautionary Savings" is asked at a quarterly frequency, it refers to the amount households think they need to put aside in total savings to deal with unexpected events, and it is PPP-adjusted. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). The sample for all variables in the table covers the period from April 2020 to November 2023, except for the expectation concerning the interest rate, which starts in September 2020.

**Table A.3:** Descriptive statistics over the whole sample for Spain and the Netherlands

| | Mean | p10 | Median | p90 | N |
|---|---|---|---|---|---|
| *Spain* | | | | | |
| Age | 50.38 | 26.00 | 42.00 | 80.00 | 120,403 |
| Disposable Income | 29,625.94 | 12,500.00 | 27,500.00 | 55,000.00 | 120,403 |
| Nondurable Spending | 15,889.12 | 7,020.00 | 15,240.00 | 25,800.00 | 40,018 |
| Spent on Durables (0-1) | 0.18 | 0.00 | 0.00 | 1.00 | 33,974 |
| Precautionary Savings | 5,371.43 | 360.00 | 3,400.00 | 15,000.00 | 37,155 |
| E(Economic Growth) | -0.54 | -8.00 | 0.00 | 5.30 | 120,403 |
| E(Inflation Rate) | 4.66 | 0.00 | 3.00 | 12.00 | 120,398 |
| E(Inflation Rate 3Y) | 3.93 | 0.00 | 2.50 | 10.50 | 119,345 |
| E(House Price Growth) | 2.99 | -0.20 | 2.00 | 10.00 | 120,403 |
| E(Unemployment Rate) | 16.17 | 8.00 | 15.00 | 25.30 | 120,403 |
| E(Interest Rate on Mortgages) | 3.92 | 1.20 | 3.50 | 8.00 | 110,779 |
| E(Own Income Growth) | 1.65 | -4.00 | 0.00 | 10.00 | 120,403 |
| E(Own Spending Growth) | 2.61 | 0.00 | 0.00 | 10.00 | 103,933 |
| E(Own Durable Spending) | 0.30 | 0.00 | 0.00 | 1.00 | 120,119 |
| E(Own Credit Access) | 2.75 | 1.00 | 3.00 | 4.00 | 119,886 |
| E(Own Financial Situation) | 2.92 | 2.00 | 3.00 | 4.00 | 120,403 |
| *Netherlands* | | | | | |
| Age | 49.59 | 26.00 | 42.00 | 80.00 | 43,850 |
| Disposable Income | 38,312.57 | 17,500.00 | 35,000.00 | 67,500.00 | 43,850 |
| Nondurable Spending | 18,378.95 | 8,040.00 | 18,000.00 | 29,040.00 | 14,952 |
| Spent on Durables (0-1) | 0.20 | 0.00 | 0.00 | 1.00 | 11,950 |
| Precautionary Savings | 5,587.69 | 200.00 | 3,600.00 | 15,000.00 | 13,881 |
| E(Economic Growth) | -1.00 | -5.70 | 0.00 | 3.20 | 43,850 |
| E(Inflation Rate) | 3.94 | 0.00 | 3.00 | 9.20 | 43,843 |
| E(Inflation Rate 3Y) | 2.99 | 0.00 | 2.50 | 7.00 | 43,422 |
| E(House Price Growth) | 2.37 | -2.40 | 2.00 | 8.00 | 43,850 |
| E(Unemployment Rate) | 7.96 | 2.70 | 5.50 | 18.00 | 43,850 |
| E(Interest Rate on Mortgages) | 3.57 | 1.50 | 3.50 | 6.00 | 38,888 |
| E(Own Income Growth) | 0.80 | -3.10 | 0.20 | 4.20 | 43,850 |
| E(Own Spending Growth) | 2.94 | 0.00 | 2.00 | 8.00 | 37,615 |
| E(Own Durable Spending) | 0.30 | 0.00 | 0.00 | 1.00 | 43,679 |
| E(Own Credit Access) | 2.63 | 1.00 | 3.00 | 3.00 | 42,894 |
| E(Own Financial Situation) | 2.73 | 2.00 | 3.00 | 4.00 | 43,850 |

*Note*: “Age” is provided in four brackets ([18-34], [35-49], [50-64], 65+), and we assign the median value to each household. “Disposable Income” refers to the 12 months preceding the interview and it is PPP-adjusted. “Nondurable Spending” is asked at a quarterly frequency, it refers to spending on nondurable goods and services in the month preceding the interview, and it is annualized and PPP-adjusted. “Spent on Durables (0-1)” is asked at a quarterly frequency, and is a dummy variable capturing whether households have spent on durable goods in the month preceding the interview. “Precautionary Savings” is asked at a quarterly frequency, it refers to the amount households think they need to put aside in total savings to deal with unexpected events, and it is PPP-adjusted. All expectations are asked on a monthly basis and are based on a 12 months horizon except for “E(Inflation Rate 3Y)”, which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). The sample for all variables in the table covers the period from April 2020 to November 2023, except for the expectation concerning the interest rate, which starts in September 2020.

**Table A.4:** Results from the PCA using individual fixed-effect residuals

| | Component 1 | Component 2 |
|---|---|---|
| E(Economic Growth) | 0.27 | 0.31 |
| E(Inflation Rate) | -0.54 | 0.21 |
| E(Inflation Rate 3Y) | -0.51 | 0.31 |
| E(House Price Growth) | -0.29 | 0.38 |
| E(Unemployment Rate) | -0.27 | -0.06 |
| E(Interest Rate on Mortgages) | -0.14 | 0.03 |
| E(Own Income Growth) | 0.12 | 0.56 |
| E(Own Financial Situation) | 0.34 | 0.43 |
| E(Own Credit Access) | 0.25 | 0.30 |
| E(Own Durable Spending) | 0.01 | 0.12 |
| Observations | 517501 | 517501 |
| % Variance Explained | 17.1 | 13.7 |

*Note*: All expectations are residualized using regression (2) instead than regression (2). The analysis pools together data from all time periods and all countries, and the sample covers the period from September 2020 to November 2023. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). All expectations are residualized using regression (2).

**Table A.5:** Results from the PCA run in each country separately, pooling data across time

| | DE | | BE | | ES | | FR | | IT | | NL | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 |
| E(Economic Growth) | 0.34 | 0.16 | 0.33 | 0.03 | 0.23 | 0.33 | 0.34 | 0.16 | 0.27 | 0.25 | 0.30 | 0.10 |
| E(Inflation Rate) | -0.44 | 0.25 | -0.45 | 0.20 | -0.47 | 0.21 | -0.44 | 0.23 | -0.45 | 0.26 | -0.45 | 0.23 |
| E(Inflation Rate 3Y) | -0.42 | 0.32 | -0.44 | 0.22 | -0.46 | 0.26 | -0.44 | 0.31 | -0.44 | 0.29 | -0.45 | 0.29 |
| E(House Price Growth) | -0.28 | 0.37 | -0.29 | 0.36 | -0.28 | 0.33 | -0.24 | 0.44 | -0.12 | 0.40 | -0.27 | 0.36 |
| E(Unemployment Rate) | -0.32 | 0.14 | -0.30 | 0.18 | -0.36 | 0.13 | -0.30 | 0.19 | -0.36 | 0.21 | -0.33 | 0.16 |
| E(Interest Rate on Mortgages) | -0.21 | 0.10 | -0.25 | 0.19 | -0.28 | 0.13 | -0.21 | 0.14 | -0.30 | 0.21 | -0.25 | 0.14 |
| E(Own Income Growth) | 0.16 | 0.58 | 0.16 | 0.55 | 0.14 | 0.58 | 0.22 | 0.52 | 0.21 | 0.55 | 0.18 | 0.53 |
| E(Own Financial Situation) | 0.39 | 0.40 | 0.35 | 0.47 | 0.32 | 0.46 | 0.38 | 0.42 | 0.37 | 0.40 | 0.34 | 0.47 |
| E(Own Credit Access) | 0.33 | 0.32 | 0.32 | 0.38 | 0.30 | 0.29 | 0.34 | 0.31 | 0.33 | 0.26 | 0.33 | 0.34 |
| E(Own Durable Spending) | 0.02 | 0.20 | 0.05 | 0.22 | 0.07 | 0.10 | 0.01 | 0.19 | 0.10 | 0.13 | 0.07 | 0.23 |
| Observations | 111583 | 111583 | 41715 | 41715 | 115841 | 115841 | 116925 | 116925 | 120003 | 120003 | 40337 | 40337 |
| % Variance Explained | 25.8 | 14.5 | 28.0 | 14.0 | 25.9 | 16.7 | 26.0 | 14.9 | 25.8 | 15.8 | 25.9 | 15.1 |

*Note*: The analysis pools together data from all time periods and is performed in each country separately. The sample goes from September 2020 to November 2023. All expectations are asked on a monthly basis and are based on a 12 months horizon except for "E(Inflation Rate 3Y)", which instead refers to a 3 years horizon. All expectations are provided as numerical values, except for own durable spending (where a dummy variable indicates whether the household plans to buy durables), own credit access (measured on a 1 to 5 qualitative scale), and own financial situation (measured on a 1 to 5 qualitative scale). All expectations are residualized using regression (2).

**Table A.6:** Persistence in within-country ranking of household expectations: Belgium

| | Persistence $t$ to $t+1$ | | | | Persistence $t$ to $t+3$ | | | |
|---|---|---|---|---|---|---|---|---|
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.16 | 0.04 | $Low_{t+3}$ | 0.78 | 0.13 | 0.04 |
| E(Economic Gr.) | $Mid_{t+1}$ | 0.18 | 0.64 | 0.14 | $Mid_{t+3}$ | 0.16 | 0.64 | 0.14 |
| | $High_{t+1}$ | 0.05 | 0.2 | 0.83 | $High_{t+3}$ | 0.06 | 0.23 | 0.82 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.15 | 0.03 | $Low_{t+3}$ | 0.76 | 0.16 | 0.04 |
| E(Inflation 1yr) | $Mid_{t+1}$ | 0.16 | 0.66 | 0.13 | $Mid_{t+3}$ | 0.18 | 0.62 | 0.16 |
| | $High_{t+1}$ | 0.06 | 0.18 | 0.83 | $High_{t+3}$ | 0.06 | 0.22 | 0.8 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.84 | 0.14 | 0.04 | $Low_{t+3}$ | 0.81 | 0.14 | 0.05 |
| E(Inflation 3yr) | $Mid_{t+1}$ | 0.11 | 0.68 | 0.13 | $Mid_{t+3}$ | 0.13 | 0.63 | 0.15 |
| | $High_{t+1}$ | 0.05 | 0.19 | 0.83 | $High_{t+3}$ | 0.06 | 0.22 | 0.81 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.8 | 0.14 | 0.04 | $Low_{t+3}$ | 0.78 | 0.15 | 0.04 |
| E(House Price Gr.) | $Mid_{t+1}$ | 0.14 | 0.66 | 0.12 | $Mid_{t+3}$ | 0.16 | 0.64 | 0.12 |
| | $High_{t+1}$ | 0.05 | 0.2 | 0.84 | $High_{t+3}$ | 0.06 | 0.21 | 0.83 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.81 | 0.15 | 0.04 | $Low_{t+3}$ | 0.79 | 0.16 | 0.05 |
| E(Unemp. Rate) | $Mid_{t+1}$ | 0.14 | 0.64 | 0.15 | $Mid_{t+3}$ | 0.15 | 0.6 | 0.16 |
| | $High_{t+1}$ | 0.05 | 0.22 | 0.81 | $High_{t+3}$ | 0.06 | 0.24 | 0.79 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.8 | 0.15 | 0.04 | $Low_{t+3}$ | 0.78 | 0.17 | 0.05 |
| E(Own Income Gr.) | $Mid_{t+1}$ | 0.15 | 0.64 | 0.13 | $Mid_{t+3}$ | 0.16 | 0.6 | 0.15 |
| | $High_{t+1}$ | 0.06 | 0.21 | 0.83 | $High_{t+3}$ | 0.06 | 0.23 | 0.81 |

*Note*: the table presents non-parametric estimates of the probability $p^h_{ji}$ that a household's expectation transitions from tercile $i \in \{Low, Mid, High\}$ in the distribution of expectations within Belgium at $t$ to tercile $j \in \{Low, Mid, High\}$, in the distribution within her country at $t+1$ ($h = 1$, left column) and at $t+3$ ($h = 3$, right column). Each probability is estimated by counting frequencies of each possible transition at the household level in a given month $t$, and then averaging over time.

**Table A.7:** Persistence in within-country ranking of household expectations: France

| | | **Persistence $t$ to $t+1$** | | | | **Persistence $t$ to $t+3$** | | |
|---|---|---|---|---|---|---|---|---|
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| E(Economic Gr.) | $Low_{t+1}$ | 0.61 | 0.03 | 0.01 | $Low_{t+3}$ | 0.58 | 0.03 | 0.01 |
| | $Mid_{t+1}$ | 0.32 | 0.78 | 0.21 | $Mid_{t+3}$ | 0.34 | 0.77 | 0.22 |
| | $High_{t+1}$ | 0.07 | 0.18 | 0.78 | $High_{t+3}$ | 0.09 | 0.19 | 0.77 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| E(Inflation 1yr) | $Low_{t+1}$ | 0.54 | 0.03 | 0.01 | $Low_{t+3}$ | 0.52 | 0.03 | 0.01 |
| | $Mid_{t+1}$ | 0.37 | 0.77 | 0.22 | $Mid_{t+3}$ | 0.39 | 0.76 | 0.23 |
| | $High_{t+1}$ | 0.08 | 0.2 | 0.77 | $High_{t+3}$ | 0.09 | 0.21 | 0.76 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| E(Inflation 3yr) | $Low_{t+1}$ | 0.48 | 0.03 | 0.01 | $Low_{t+3}$ | 0.45 | 0.03 | 0.01 |
| | $Mid_{t+1}$ | 0.44 | 0.77 | 0.22 | $Mid_{t+3}$ | 0.47 | 0.76 | 0.23 |
| | $High_{t+1}$ | 0.08 | 0.19 | 0.77 | $High_{t+3}$ | 0.09 | 0.2 | 0.76 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| E(House Price Gr.) | $Low_{t+1}$ | 0.74 | 0.12 | 0.06 | $Low_{t+3}$ | 0.71 | 0.16 | 0.07 |
| | $Mid_{t+1}$ | 0.17 | 0.68 | 0.15 | $Mid_{t+3}$ | 0.19 | 0.62 | 0.17 |
| | $High_{t+1}$ | 0.09 | 0.2 | 0.79 | $High_{t+3}$ | 0.1 | 0.22 | 0.76 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| E(Unemp. Rate) | $Low_{t+1}$ | 0.79 | 0.12 | 0.04 | $Low_{t+3}$ | 0.76 | 0.15 | 0.05 |
| | $Mid_{t+1}$ | 0.15 | 0.71 | 0.14 | $Mid_{t+3}$ | 0.16 | 0.66 | 0.16 |
| | $High_{t+1}$ | 0.06 | 0.17 | 0.82 | $High_{t+3}$ | 0.07 | 0.2 | 0.8 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| E(Own Income Gr.) | $Low_{t+1}$ | 0.75 | 0.11 | 0.04 | $Low_{t+3}$ | 0.71 | 0.14 | 0.04 |
| | $Mid_{t+1}$ | 0.17 | 0.71 | 0.14 | $Mid_{t+3}$ | 0.21 | 0.66 | 0.15 |
| | $High_{t+1}$ | 0.07 | 0.18 | 0.82 | $High_{t+3}$ | 0.08 | 0.21 | 0.81 |

*Note*: the table presents non-parametric estimates of the probability $p^h_{ji}$ that a household's expectation transitions from tercile $i \in \{Low, Mid, High\}$ in the distribution of expectations within France at $t$ to tercile $j \in \{Low, Mid, High\}$, in the distribution within her country at $t+1$ ($h = 1$, left column) and at $t+3$ ($h = 3$, right column). Each probability is estimated by counting frequencies of each possible transition at the household level in a given month $t$, and then averaging over time.

**Table A.8:** Persistence in within-country ranking of household expectations: Germany

| | | Persistence $t$ to $t+1$ | | | | Persistence $t$ to $t+3$ | | |
|---|---|---|---|---|---|---|---|---|
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.51 | 0.12 | 0.05 | $Low_{t+3}$ | 0.47 | 0.11 | 0.05 |
| E(Economic Gr.) | $Mid_{t+1}$ | 0.36 | 0.65 | 0.21 | $Mid_{t+3}$ | 0.41 | 0.64 | 0.22 |
| | $High_{t+1}$ | 0.13 | 0.23 | 0.75 | $High_{t+3}$ | 0.13 | 0.24 | 0.73 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.5 | 0.1 | 0.04 | $Low_{t+3}$ | 0.45 | 0.12 | 0.04 |
| E(Inflation 1yr) | $Mid_{t+1}$ | 0.38 | 0.68 | 0.19 | $Mid_{t+3}$ | 0.42 | 0.66 | 0.19 |
| | $High_{t+1}$ | 0.12 | 0.21 | 0.77 | $High_{t+3}$ | 0.12 | 0.22 | 0.77 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.61 | 0.1 | 0.05 | $Low_{t+3}$ | 0.55 | 0.1 | 0.05 |
| E(Inflation 3yr) | $Mid_{t+1}$ | 0.28 | 0.69 | 0.18 | $Mid_{t+3}$ | 0.32 | 0.67 | 0.19 |
| | $High_{t+1}$ | 0.12 | 0.21 | 0.77 | $High_{t+3}$ | 0.13 | 0.23 | 0.76 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.68 | 0.14 | 0.06 | $Low_{t+3}$ | 0.62 | 0.14 | 0.06 |
| E(House Price Gr.) | $Mid_{t+1}$ | 0.22 | 0.66 | 0.15 | $Mid_{t+3}$ | 0.27 | 0.62 | 0.18 |
| | $High_{t+1}$ | 0.1 | 0.2 | 0.79 | $High_{t+3}$ | 0.11 | 0.23 | 0.76 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.8 | 0.15 | 0.05 | $Low_{t+3}$ | 0.77 | 0.18 | 0.06 |
| E(Unemp. Rate) | $Mid_{t+1}$ | 0.14 | 0.69 | 0.12 | $Mid_{t+3}$ | 0.16 | 0.64 | 0.14 |
| | $High_{t+1}$ | 0.06 | 0.16 | 0.84 | $High_{t+3}$ | 0.07 | 0.18 | 0.8 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.16 | 0.05 | $Low_{t+3}$ | 0.76 | 0.17 | 0.06 |
| E(Own Income Gr.) | $Mid_{t+1}$ | 0.15 | 0.68 | 0.11 | $Mid_{t+3}$ | 0.16 | 0.64 | 0.14 |
| | $High_{t+1}$ | 0.07 | 0.16 | 0.83 | $High_{t+3}$ | 0.08 | 0.19 | 0.8 |

*Note*: the table presents non-parametric estimates of the probability $p^h_{ji}$ that a household's expectation transitions from tercile $i \in \{Low, Mid, High\}$ in the distribution of expectations within Germany at $t$ to tercile $j \in \{Low, Mid, High\}$, in the distribution within her country at $t+1$ ($h = 1$, left column) and at $t+3$ ($h = 3$, right column). Each probability is estimated by counting frequencies of each possible transition at the household level in a given month $t$, and then averaging over time.

**Table A.9:** Persistence in within-country ranking of household expectations: Italy

| | | **Persistence $t$ to $t+1$** | | | | **Persistence $t$ to $t+3$** | | |
|---|---|---|---|---|---|---|---|---|
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.72 | 0.13 | 0.07 | $Low_{t+3}$ | 0.71 | 0.12 | 0.08 |
| E(Economic Gr.) | $Mid_{t+1}$ | 0.18 | 0.74 | 0.12 | $Mid_{t+3}$ | 0.17 | 0.75 | 0.14 |
| | $High_{t+1}$ | 0.1 | 0.13 | 0.81 | $High_{t+3}$ | 0.11 | 0.14 | 0.79 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.75 | 0.11 | 0.07 | $Low_{t+3}$ | 0.71 | 0.13 | 0.07 |
| E(Inflation 1yr) | $Mid_{t+1}$ | 0.15 | 0.76 | 0.12 | $Mid_{t+3}$ | 0.18 | 0.73 | 0.14 |
| | $High_{t+1}$ | 0.1 | 0.13 | 0.82 | $High_{t+3}$ | 0.11 | 0.15 | 0.79 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.81 | 0.1 | 0.07 | $Low_{t+3}$ | 0.79 | 0.11 | 0.08 |
| E(Inflation 3yr) | $Mid_{t+1}$ | 0.1 | 0.77 | 0.1 | $Mid_{t+3}$ | 0.11 | 0.75 | 0.12 |
| | $High_{t+1}$ | 0.09 | 0.12 | 0.83 | $High_{t+3}$ | 0.1 | 0.13 | 0.8 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.73 | 0.1 | 0.06 | $Low_{t+3}$ | 0.67 | 0.12 | 0.07 |
| E(House Price Gr.) | $Mid_{t+1}$ | 0.17 | 0.77 | 0.14 | $Mid_{t+3}$ | 0.22 | 0.74 | 0.17 |
| | $High_{t+1}$ | 0.1 | 0.13 | 0.8 | $High_{t+3}$ | 0.11 | 0.14 | 0.76 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.11 | 0.09 | $Low_{t+3}$ | 0.76 | 0.14 | 0.11 |
| E(Unemp. Rate) | $Mid_{t+1}$ | 0.12 | 0.76 | 0.13 | $Mid_{t+3}$ | 0.13 | 0.72 | 0.16 |
| | $High_{t+1}$ | 0.1 | 0.13 | 0.77 | $High_{t+3}$ | 0.11 | 0.14 | 0.73 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.1 | 0.08 | $Low_{t+3}$ | 0.75 | 0.12 | 0.09 |
| E(Own Income Gr.) | $Mid_{t+1}$ | 0.13 | 0.75 | 0.13 | $Mid_{t+3}$ | 0.15 | 0.72 | 0.15 |
| | $High_{t+1}$ | 0.09 | 0.14 | 0.79 | $High_{t+3}$ | 0.1 | 0.16 | 0.76 |

*Note*: the table presents non-parametric estimates of the probability $p^h_{ji}$ that a household's expectation transitions from tercile $i \in \{Low, Mid, High\}$ in the distribution of expectations within Italy at $t$ to tercile $j \in \{Low, Mid, High\}$, in the distribution within her country at $t+1$ ($h = 1$, left column) and at $t+3$ ($h = 3$, right column). Each probability is estimated by counting frequencies of each possible transition at the household level in a given month $t$, and then averaging over time.

**Table A.10:** Persistence in within-country ranking of household expectations: Netherlands

| | Persistence $t$ to $t+1$ | | | | Persistence $t$ to $t+3$ | | | |
|---|---|---|---|---|---|---|---|---|
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.16 | 0.05 | $Low_{t+3}$ | 0.77 | 0.16 | 0.06 |
| E(Economic Gr.) | $Mid_{t+1}$ | 0.16 | 0.61 | 0.14 | $Mid_{t+3}$ | 0.14 | 0.55 | 0.16 |
| | $High_{t+1}$ | 0.07 | 0.23 | 0.82 | $High_{t+3}$ | 0.09 | 0.29 | 0.78 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.8 | 0.15 | 0.04 | $Low_{t+3}$ | 0.77 | 0.17 | 0.05 |
| E(Inflation 1yr) | $Mid_{t+1}$ | 0.14 | 0.65 | 0.14 | $Mid_{t+3}$ | 0.16 | 0.61 | 0.15 |
| | $High_{t+1}$ | 0.06 | 0.21 | 0.82 | $High_{t+3}$ | 0.08 | 0.22 | 0.8 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.81 | 0.16 | 0.05 | $Low_{t+3}$ | 0.78 | 0.18 | 0.06 |
| E(Inflation 3yr) | $Mid_{t+1}$ | 0.12 | 0.62 | 0.15 | $Mid_{t+3}$ | 0.13 | 0.57 | 0.17 |
| | $High_{t+1}$ | 0.07 | 0.23 | 0.8 | $High_{t+3}$ | 0.09 | 0.25 | 0.77 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.81 | 0.15 | 0.04 | $Low_{t+3}$ | 0.78 | 0.17 | 0.05 |
| E(House Price Gr.) | $Mid_{t+1}$ | 0.13 | 0.62 | 0.15 | $Mid_{t+3}$ | 0.14 | 0.56 | 0.18 |
| | $High_{t+1}$ | 0.06 | 0.23 | 0.81 | $High_{t+3}$ | 0.08 | 0.27 | 0.77 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.79 | 0.18 | 0.05 | $Low_{t+3}$ | 0.77 | 0.18 | 0.06 |
| E(Unemp. Rate) | $Mid_{t+1}$ | 0.14 | 0.57 | 0.15 | $Mid_{t+3}$ | 0.15 | 0.53 | 0.16 |
| | $High_{t+1}$ | 0.06 | 0.25 | 0.8 | $High_{t+3}$ | 0.08 | 0.29 | 0.77 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.79 | 0.16 | 0.06 | $Low_{t+3}$ | 0.76 | 0.19 | 0.08 |
| E(Own Income Gr.) | $Mid_{t+1}$ | 0.14 | 0.56 | 0.16 | $Mid_{t+3}$ | 0.15 | 0.5 | 0.19 |
| | $High_{t+1}$ | 0.07 | 0.28 | 0.78 | $High_{t+3}$ | 0.09 | 0.31 | 0.73 |

*Note*: the table presents non-parametric estimates of the probability $p^h_{ji}$ that a household's expectation transitions from tercile $i \in \{Low, Mid, High\}$ in the distribution of expectations within Netherlands at $t$ to tercile $j \in \{Low, Mid, High\}$, in the distribution within her country at $t+1$ ($h=1$, left column) and at $t+3$ ($h=3$, right column). Each probability is estimated by counting frequencies of each possible transition at the household level in a given month $t$, and then averaging over time.

**Table A.11:** Persistence in within-country ranking of household expectations: Spain

| | | **Persistence $t$ to $t+1$** | | | | **Persistence $t$ to $t+3$** | | |
|---|---|---|---|---|---|---|---|---|
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.75 | 0.14 | 0.1 | $Low_{t+3}$ | 0.73 | 0.15 | 0.1 |
| E(Economic Gr.) | $Mid_{t+1}$ | 0.13 | 0.69 | 0.14 | $Mid_{t+3}$ | 0.14 | 0.67 | 0.15 |
| | $High_{t+1}$ | 0.12 | 0.17 | 0.77 | $High_{t+3}$ | 0.13 | 0.18 | 0.75 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.73 | 0.14 | 0.1 | $Low_{t+3}$ | 0.72 | 0.15 | 0.11 |
| E(Inflation 1yr) | $Mid_{t+1}$ | 0.14 | 0.68 | 0.15 | $Mid_{t+3}$ | 0.13 | 0.65 | 0.16 |
| | $High_{t+1}$ | 0.13 | 0.19 | 0.75 | $High_{t+3}$ | 0.14 | 0.2 | 0.73 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.13 | 0.07 | $Low_{t+3}$ | 0.76 | 0.13 | 0.08 |
| E(Inflation 3yr) | $Mid_{t+1}$ | 0.13 | 0.72 | 0.13 | $Mid_{t+3}$ | 0.13 | 0.71 | 0.15 |
| | $High_{t+1}$ | 0.09 | 0.15 | 0.8 | $High_{t+3}$ | 0.11 | 0.16 | 0.77 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.75 | 0.14 | 0.09 | $Low_{t+3}$ | 0.74 | 0.15 | 0.1 |
| E(House Price Gr.) | $Mid_{t+1}$ | 0.14 | 0.7 | 0.14 | $Mid_{t+3}$ | 0.15 | 0.69 | 0.16 |
| | $High_{t+1}$ | 0.1 | 0.16 | 0.77 | $High_{t+3}$ | 0.11 | 0.16 | 0.74 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.14 | 0.07 | $Low_{t+3}$ | 0.75 | 0.16 | 0.08 |
| E(Unemp. Rate) | $Mid_{t+1}$ | 0.13 | 0.71 | 0.13 | $Mid_{t+3}$ | 0.15 | 0.69 | 0.14 |
| | $High_{t+1}$ | 0.09 | 0.15 | 0.8 | $High_{t+3}$ | 0.1 | 0.15 | 0.78 |
| | | $Low_t$ | $Mid_t$ | $High_t$ | | $Low_t$ | $Mid_t$ | $High_t$ |
| | $Low_{t+1}$ | 0.78 | 0.15 | 0.06 | $Low_{t+3}$ | 0.77 | 0.16 | 0.07 |
| E(Own Income Gr.) | $Mid_{t+1}$ | 0.13 | 0.71 | 0.13 | $Mid_{t+3}$ | 0.14 | 0.68 | 0.15 |
| | $High_{t+1}$ | 0.08 | 0.15 | 0.81 | $High_{t+3}$ | 0.09 | 0.16 | 0.77 |

*Note*: the table presents non-parametric estimates of the probability $p^h_{ji}$ that a household's expectation transitions from tercile $i \in \{Low, Mid, High\}$ in the distribution of expectations within Spain at $t$ to tercile $j \in \{Low, Mid, High\}$, in the distribution within her country at $t+1$ ($h=1$, left column) and at $t+3$ ($h=3$, right column). Each probability is estimated by counting frequencies of each possible transition at the household level in a given month $t$, and then averaging over time.

# Appendix B Mathematical Background of the PCA

The PCA is a statistical technique for reducing the dimensionality of a dataset. This is accomplished by linearly transforming the data so as to retain fewer dimensions of the initial data while preserving most of its variation.

Consider an $H \times E$ data matrix $\boldsymbol{X}$, where $H$ is the number of households and $E$ is the number of expectations. An observation about household $h$ is an $1 \times E$ vector $\boldsymbol{x}_h = \{x_{h,1}, \ldots, x_{h,E}\}$, which provides the collection of household $h$ expectations.

The PCA consists of extracting through an optimization problem a set of size $K$ of $E$-dimensional vectors of loadings $\boldsymbol{\omega}_k = \{w_{1,k}, \ldots, w_{E,k}\}$ mapping the data matrix $\boldsymbol{X}$ to a data matrix $\boldsymbol{S}$ of dimension $H \times K$, where $K$ is chosen to be smaller than $E$ in order to reduce dimensionality. The vectors $\boldsymbol{\omega}_k$ are the principal components or loadings. The new data matrix $\boldsymbol{S}$ is made of principal component scores $\boldsymbol{s}_h = \{s_{h,1}, \ldots, s_{h,K}\}$ given by:

$$s_{h,k} = \boldsymbol{x}_h \cdot \boldsymbol{\omega}_k \qquad h = 1, \ldots, H;\;\; k = 1, \ldots, K \tag{B.1}$$

The principal component scores inherit the maximum possible variance from the data $\boldsymbol{X}$, and each one of them is orthogonal to the others.

**A simple example:** Consider $H$ households and $E = 3$ expectations about inflation ($\pi$), output growth ($Y$), and unemployment rate ($U$). If we perform a PCA and decide to retain $K = 2$ principal components, then we obtain two sets of loadings $\boldsymbol{\omega}_1$ and $\boldsymbol{\omega}_2$ (each one $3 \times 1$) so that the principal components scores for household $h$ are defined as:

$$s_{h,1} = x_h^{\pi} \cdot w_1^{\pi} + x_h^{Y} \cdot w_1^{Y} + x_h^{U} \cdot w_1^{U}$$

$$s_{h,2} = x_h^{\pi} \cdot w_2^{\pi} + x_h^{Y} \cdot w_2^{Y} + x_h^{U} \cdot w_2^{U}$$

where $x_h^{\pi}$ is household h expectation about inflation, $x_h^{Y}$ is household h expectation about output growth, and $x_h^{U}$ is household h expectation about the unemployment rate.

As a consequence, we have reduced the dimension of our data from $\boldsymbol{X}$ with dimension $H \times 3$ to $\boldsymbol{S}$ with dimension $H \times 2$ while retaining most of the original variation.

# Appendix C Expectations, Consumption and Savings

In this section, our aim is to explore the relationship between household expectations, as represented by the principal component scores identified in Section 4, and their consumption expenditures and savings decisions. These scores, which capture the perceived sources of macroeconomic dynamics, are orthogonal to one another, providing independent variations in household spending and savings decisions. As a result, our analysis sheds light on how these perceived sources of fluctations relate to household decisions and, in turn, to the macroeconomy.

Our preferred specification is the following fixed-effect (FE) regression:

$$y_{h,c,t} = \alpha_h + \alpha_t + \alpha_{c,t} + \beta_1 s_{1,h,c,t} + \beta_2 s_{2,h,c,t} + \boldsymbol{\gamma x}_{h,c,t} + \epsilon_{h,c,t} \tag{C.1}$$

where $y_{h,c,t}$ is the outcome of interest for household $h$ in country $c$ and month $t$ (consumption and precautionary savings), $s_{1,h,c,t}$ and $s_{2,h,c,t}$ are the two principal component scores, $\boldsymbol{x}_{h,c,t}$ is a set of household-level controls, $\alpha_i$ is the household FE, $\alpha_t$ is the month FE, and $\alpha_{c,t}$ are the country-month FEs. The scores $s_{1,h,c,t}$ and $s_{2,h,c,t}$ in equation (C.1) are computed from the PCA by month of Section 4.3, and are rescaled so that a unit increase in each score is associated with a 1 percentage point increase in expected economic growth. The household-level controls $\boldsymbol{x}_{h,c,t}$ contain a measure of liquidity, with or without lags depending on the timing of the dependent variable, measuring whether the household has enough liquidity to pay for an unexpected event equal to 1 month of her income.[24]

Together with the FE specification of equation (C.1), we also estimate its pooled counterpart. This involves utilizing the scores $s_{1,h,c,t}$ and $s_{2,h,c,t}$ generated from the baseline PCA outlined in Section 4.1, where households from all months of the sample are combined, and we again normalize the scores so that a unit increase in each of them is associated with a 1 percentage point increase in expected output growth. By employing this specification, we have the ability to explicitly control in $\boldsymbol{x}_{h,c,t}$ for household characteristics that remain constant over time, such as disposable income, age, gender, education, homeownership status, employment status, household size, and region of residence.

**Results on Realized Spending** We now discuss the connection between the principal component scores and spending on nondurable goods and services as well as past decisions to purchase durable goods. Nondurable spending is surveyed quarterly and includes spending on nondurable goods and services in the month preceding the interview. To make spending comparable across different countries, a purchasing power parity adjustment is performed, and logarithmic transformation is used. Spending on durables is surveyed quarterly since the start of 2021 using a dummy variable that captures whether households spent on durable goods in the month prior to the interview. The variable includes spending on cars, home appliances, and luxury items but excludes house purchases, holidays, and

[24]The monthly survey question is the following: "*Please think about your available financial resources, including access to credit, savings, loans from relatives or friends, etc. Suppose that you had to make an unexpected payment equal to one month of your household income. Would you have sufficient financial resources to pay for the entire amount?*".

**Table C.1:** OLS and FE Regression Estimates for Realized Spending

| | Nondurable Spending$_{t-1}$ | | Spent on Durables$_{t-1}$ (0-1) | |
|---|---|---|---|---|
| | Pooled | FE | Pooled | FE |
| PC1 Scores$_{t-2}$ | -0.0252*** | -0.0037* | -0.0023*** | 0.0018 |
| | (0.0011) | (0.0019) | (0.0007) | (0.0014) |
| PC2 Scores$_{t-2}$ | 0.0274*** | 0.0053** | 0.0182*** | 0.0055*** |
| | (0.0020) | (0.0024) | (0.0013) | (0.0018) |
| Has Liquidity$_{t-2}$ | 0.0329*** | 0.0043 | 0.0205*** | -0.0020 |
| | (0.0083) | (0.0091) | (0.0045) | (0.0057) |
| Has Liquidity$_{t-1}$ | 0.0573*** | 0.0172 | 0.0336*** | 0.0165*** |
| | (0.0084) | (0.0107) | (0.0044) | (0.0055) |
| Demographic Controls | Yes | No | Yes | No |
| Household FE | No | Yes | No | Yes |
| Wave FE | Yes | Yes | Yes | Yes |
| Country x Wave FE | Yes | Yes | Yes | Yes |
| Observations | 124,397 | 124,387 | 124,618 | 124,718 |
| $R^2$ | 0.1877 | 0.0149 | 0.0263 | 0.0111 |

*Note*: The table presents results from estimating equation (C.1) and the OLS pooled counterpart. The first dependent variable measures the log of spending on nondurable goods and services undergone in the previous month; the second dependent variable measures whether the household bought any durable goods in the previous month. "PC1 Scores" and "PC2 Scores" refer to first and second principal component scores; we normalize them so that in each different specification (each column of the table), a unit increase in them is associated with a 1 percentage point increase in expected output growth. In the pooled specifications, the scores are identified from the baseline PCA of Section 4.1. In the fixed-effect specifications, the scores are identified from the PCA run separately in each month of Section 4.3. "Has Liquidity" measures whether the household has enough liquidity to pay for an unexpected event equal to 1 month of her income.

other major items. Further information on these variables are provided in Section 2, and Table 1 provides descriptive statistics.

To ensure the principal component scores precede spending in time, they are lagged twice along with the liquidity variable. The regression results in Table C.1 show that the two principal component scores, capturing perceptions about supply and demand forces, have opposite effects on nondurable spending. In the fixed effects specification, a unit increase in the first score decreases spending by 0.45%. On the contrary, a unit increase in the second score increases spending by 0.73%. Recall that the first and second principal component scores are comparable because they are both normalized to a 1 percentage point increase in economic growth. Therefore, supply and demand shocks have opposite effects on nondurable spending, which must be explained by the way households forecast inflation, along with house price growth and interest rates (recall from Table 2 that the loadings of the first and second principal components imply opposite correlation between quantities and prices). Households that forecast lower growth of prices in the economy tend to spend less on nondurables and services (as indicated by the negative coefficient on the first score), whereby households that forecast higher growth of prices tend to spend more (as indicated by the positive coefficient on the second score).

Regarding durable consumption, the fixed effects specification does not show any significant result for the first score, but it does so for the second score. Combining the results for realized spending, we conclude that an increase in the supply-side view of macroeconomic dynamics (associated with an increase in expected output growth) tend to decrease nondurable spending. In contrast, an increase in the demand-side view of macroeconomic dynamics (associated with an increase in expected output growth) tend to increase both nondurable spending and the likelihood of spending on durables.

**Results on Planned Spending and Savings** We now examine how expectations relate to planned spending and savings. To construct precautionary savings, we use a quarterly survey question that asks households how much they think they need to save in order to deal with unexpected events. To make euro values comparable across countries, we adjust for purchasing power parity and take the logarithmic transformation. To construct expected spending growth, we use a monthly survey question that asks households about their expected change in total spending over the next 12 months. We do not include this last expectation in our PCA of Section 4 because a significant number of households do not answer this question each month, but still we find it informative to use it as a dependent variable in this regression analysis. Section 2 provides further information on these variables and Table 1 provides descriptive statistics.

The regression results in Table C.2 indicate that the principal component scores are associated with planned spending and savings. Again in each specification, the first and second principal component scores are normalized so that a unit increase in either of them is associated with a 1 percentage point increase in expected economic growth. Under the FE specification, a unit increase in the first score is associated with a 1.5% increase in precautionary savings and a decrease in expected spending growth of 0.35 percentage points. Conversely, a unit increase in the second score is not associated with precautionary savings but is related to an increase in expected spending growth of 0.41 percentage points.

These results on expected spending are consistent with those on realized spending of Table C.1: They tend to be related to inflation (as well as house price growth and interest rate) expectations. Households who expect higher inflation (and therefore have a lower first score) tend to increase their nondurable spending and their expected total spending. However, only supply-side shocks – as summarized by the first principal component score – are associated with precautionary savings. Taken together, the results from Tables C.1-C.2 show that the joint distribution of expectations, as summarized by the principal component scores, move with consumption and precautionary savings. On one hand, an increase in the supply-side shock (that is, a higher first principal component score) tend to decrease realized nondurable spending and planned total spending while increasing precautionary

**Table C.2:** OLS and FE Regression Estimates for Planned Spending and Savings

| | Precautionary Savings | | $\mathbb{E}$(Spending Growth) | |
|---|---|---|---|---|
| | Pooled | FE | Pooled | FE |
| PC1 Scores$_t$ | -0.0149*** | 0.0077** | -0.7263*** | -0.4034*** |
| | (0.0022) | (0.0033) | (0.0052) | (0.0117) |
| PC2 Scores$_t$ | 0.0447*** | 0.0125*** | 0.6529*** | 0.4386*** |
| | (0.0039) | (0.0047) | (0.0091) | (0.0156) |
| Has Liquidity$_t$ | 0.6860*** | 0.2762*** | 0.3973*** | 0.2414*** |
| | (0.0109) | (0.0201) | (0.0194) | (0.0310) |
| Demographic Controls | Yes | No | Yes | No |
| Household FE | No | Yes | No | Yes |
| Wave FE | Yes | Yes | Yes | Yes |
| Country x Wave FE | Yes | Yes | Yes | Yes |
| Observations | 162,257 | 162,244 | 438,804 | 438,788 |
| $R^2$ | 0.1553 | 0.0333 | 0.2088 | 0.0829 |

*Note*: The table presents results from estimating equation (C.1) and the OLS pooled counterpart. The first dependent variable measures how much households think they need to put aside in total savings to deal with unexpected events, it is PPP-adjusted and transformed in logs. The second dependent variable measures the growth in expected spending within the following 12 months. “PC1 Scores” and “PC2 Scores” refer to first and second principal component scores; we normalize them so that in each different specification (each column of the table), a unit increase in them is associated with a 1 percentage point increase in expected output growth. In the pooled specifications, the scores are identified from the baseline PCA of Section 4.1. In the fixed-effect specifications, the scores are identified from the PCA run separately in each month of Section 4.3. “Has Liquidity” measures whether the household has enough liquidity to pay for an unexpected event equal to 1 month of her income.

savings. On the other hand, an increase in the demand-side shock (that is, a higher second principal component score) tend to increase realized and planned spending, but is not associated with precautionary savings. These results point to the importance that inflation expectations (through their opposite effects on the principal components) have on household-level real outcomes.

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