

Household Perceived Sources of Business Cycle Fluctuations: a Tale of Supply and Demand*

Clodomiro Ferreira

Stefano Pica

Bank of Spain

Bank of Italy

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Abstract

We study the joint behavior of households' survey expectations for a wide range of macroeconomic and individual-level variables in the largest six euro area countries, both in the cross-section and time series. Although households disagree, their expectations are correlated in the cross-section. Two principal components explain a significant portion of the variance of all expectations. These components capture households' perceptions of the sources of macroeconomic dynamics, with the first capturing supply-side views and the second component reflecting demand-side views. This structure of perceptions and disagreement is stable across countries and time and does not vary with demographic or socioeconomic characteristics. We then use these insights to identify two common factors driving expectations over time. The factors co-move strongly with measures of supply and demand disturbances and align well with a narrative based on increasing perceived inflationary pressures coming from supply after the invasion of Ukraine in February 2022.

JEL: D1, D8, E2, E3

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*Contact: Clodomiro Ferreira, Bank of Spain, clodomiro.ferreira@bde.es. Stefano Pica, Bank of Italy, stpica@bu.edu. The views expressed in this manuscript are those of the authors and do not necessarily represent the views of the Bank of Spain, the Bank of Italy, or the Eurosystem. Manuel Amador, George-Marios Angeletos, Olivier Coibion, Gaetano Gaballo, Tullio Jappelli, Stefano Neri, Tommaso Oliviero, Gabriel Pérez-Quirós, Concetta Rondinelli, Tiziano Ropele, Saverio Simonelli, Giordano Zevi, and Roberta Zizza provided thoughtful discussions and comments. We also would like to thank seminar participants at the University of Naples Federico II, the Bank of Italy, the Bank of Spain, the G4 Monetary Policy Meetings and the Joint Conference of the Macroeconomics of Expectations for helpful suggestions. Iñaki Carril Zerpa and Juan Segura Buisán provided excellent research assistance.

1 Introduction

Household expectations are critical to macroeconomic theory and policy discussions as virtually every decision that households make, for example consumption and savings, depends on predicting future outcomes of relevant economic variables. While previous studies have primarily focused on household-level inflation and output expectations due to data limitations, we assert that studying a broader range of expectations that households hold is essential to comprehend their perceptions of the dynamics and types of shocks affecting the economy.

In this paper, we use expectations about macroeconomic and individual-level variables to identify and understand households' perceived sources of macroeconomic developments and dynamics. The potential for these perceptions to shape consumption and saving decisions has implications for policymakers on how they could adjust their policy and communication strategies to elicit the desired real outcomes from households.

Our analysis relies on the monthly Consumer Expectations Survey (CES) administered by the European Central Bank (ECB). This survey covers 6 major European economies, including Belgium, France, Germany, Italy, Spain, and the Netherlands, and comprises a representative panel of around 10,000 households. 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. The survey's limitation lies in its coverage, commencing in April 2020, encompassing only a three-year timeframe that includes both the pandemic era and the invasion in Ukraine.

We start by exposing 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, Coibion, and Gorodnichenko \(2020\)](#) 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, our investigation also reveals that 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.

The rest of the paper then explores 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.

We use 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 variation across household-level expectations (i.e., the disagreement) 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, explaining the highest fraction of variance in the data, captures what resembles a supply-side view of macroeconomic developments. Households anticipate a better economy while expecting lower inflation, suggesting either that they believe supply-side shocks, such as an oil shock, have impacted the economy or, more broadly, that people dislike inflation. 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. Running PCAs for different age and education groups reveals *barely any change* to our baseline results. This might strike as surprising, given the recent literature pointing towards an important role for experiences and sophistication in shaping expectations.¹ 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.

Our main cross-sectional results about perceptions are 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.

¹See, among others, [Malmendier and Nagel \(2015\)](#).

We then impose additional structure and estimate a static 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 April 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, Waggoner, and Zha \(2010\)](#) and [Altavilla et al. \(2019\)](#), we draw rotations and define as 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 with negative supply shocks hitting the euro area in this period (see, for example, [Ascari et al. \(2023\)](#)). 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 particularly appealing in our context because it is constructed from newspaper articles using text-analysis techniques, a dataset very different from the one we use in this paper. 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 both the supply and the demand factors react significantly to monetary policy surprises when we estimate the responses using standard local projection methods.

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. Along the way, we contribute to some strands of literature.

The paper is positioned within the broad literature that seeks to understand households’ expectations and the structure of their disagreement. [Candia, Coibion, and Gorodnichenko \(2020\)](#) 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. 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 add value to this recent literature by exploring a broader range of expectations across several different countries to show that, although households’ disagree, their expectations are correlated. The structure of this correlation indicates that households have both a supply-side and a demand-side view of the business cycle fluctuations. This sheds new lights on the way households behave and has natural policy-implications.

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 and French \(1993\)](#)), demand and supply determinants of inflation dynamics ([Stock and Watson \(2014\)](#), [Eickmeier and Hofmann \(2022\)](#)), as well as surprises to macroeconomic and financial variables (see for example [Altavilla et al. \(2019\)](#) and [Andrade and Ferroni \(2021\)](#)). In a recent important contribution, [Kučinskas and Peters \(2022\)](#) show that many expectation-formation theories can be mapped into a factor structure. [Juodis and Kučinskas \(2023\)](#) then use this insight to quantify the noise present in survey expectations, while [Herbst and 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 comoves across variables. We complement this literature by relying on insights on identification of factor models from [Rubio-Ramírez, Waggoner, and Zha \(2010\)](#), [Stock and 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 and demand, evolve along the business cycle.

Finally, a growing recent body of work examines the implications of expectations on the economy. Using firm-level expectations, [Rosolia \(2021\)](#) and [Coibion, Gorodnichenko, and Ropele \(2019\)](#) exploit a randomized information provision and estimate the causal impacts of inflation expectation based on a survey of firms in Italy. Our paper is instead part of a nascent set of projects that exploit the Consumer Expectations Survey (CES) in the euro area ([Bańkowska et al. \(2021\)](#)). The set of papers exploiting the CES is naturally small, given that the survey only became available in 2022. Notwithstanding its short time dimension, insights from the survey are now routinely being used in policy circles too. Three recent papers that complement ours, for example, were the first to exploit CES data in order to tackle different variants of the expectations-outcomes link

(Christelis et al. (2020), Coibion, D. Georgarakos, et al. (2021), and Diomitris Georgarakos and Kenny (2022)). They point to strong effects of financial concerns as well as economic uncertainty (mostly due to Covid-19) on spending, investment, marginal propensities to consume as well as precautionary savings. We contribute to this literature by showing how the perceived sources of business cycle fluctuations, summarized by a supply and a demand driver, separately relate to household decisions on real outcomes such as consumption and precautionary savings.

2 Data

2.1 Consumer Expectations Survey

We use data from the novel Consumer Expectations Survey (CES), which is administered by the European Central Bank (ECB). Our sample goes from April 2020 to April 2023.² The CES is a representative household-level online survey with a panel dimension, carried out in 6 major European economies (Belgium, France, Germany, Italy, Spain, and the Netherlands) and sampling 10,000 survey participants every month.³

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. See Christelis et al. (2020), Bańkowska et al. (2021), and Diomitris Georgarakos and Kenny (2022) for more information about the survey.

The CES survey is a comprehensive source of household expectations about economic variables, making it valuable for analyzing household perceptions of the business cycle. We next outline the variables we use in our statistical analysis and present some descriptive statistics.

2.2 Descriptive Statistics

In this paper we use information about household-level demographics, income, spending, and expectations.⁴ 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

²While 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).

³The sample contains approximately 2,000 participants from the four largest economies, and 1,000 from Belgium and the Netherlands.

⁴To correct for outliers, most quantitative variables are winsorised at the 10th and 90th percentiles of the weighted distribution in each month and country.

bracket.⁵ 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 a relatively high unemployment rate of 9.5%.

Turning to expectations, households feature a certain degree of disagreement about the expected future economic outlook. 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. In the first part of the sample, when the first wave of the pandemic was at its peak, the distribution of 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%. All in all, despite significant disagreement,

⁵Because it is asked in the background questionnaire, disposable income is only provided by each household once.

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

	Mean	p10	Median	p90	N
Age	50.68	26.00	42.00	80.00	470,999
Disposable Income	34,649.69	12,500.00	35,000.00	67,500.00	470,999
Nondurable Spending	17,552.33	7,440.00	17,040.00	28,476.00	162,848
Spent on Durables (0-1)	0.18	0.00	0.00	1.00	132,756
Precautionary Savings	7,194.76	500.00	4,400.00	19,600.00	146,352
E(Economic Growth)	-1.05	-8.00	0.00	5.00	470,999
E(Inflation Rate)	4.32	0.00	3.00	10.00	470,973
E(Inflation Rate 3Y)	3.39	0.00	2.00	10.00	465,827
E(House Price Growth)	2.45	0.00	1.10	10.00	470,999
E(Unemployment Rate)	11.87	5.00	9.50	22.80	470,999
E(Interest Rate on Mortgages)	3.57	1.00	3.00	7.00	422,077
E(Own Income Growth)	0.70	-4.00	0.00	5.00	470,999
E(Own Spending Growth)	2.64	0.00	0.00	10.00	398,970
E(Own Durable Spending)	0.29	0.00	0.00	1.00	469,952
E(Own Credit Access)	2.78	1.00	3.00	4.00	465,234
E(Own Financial Situation)	2.81	2.00	3.00	4.00	470,999

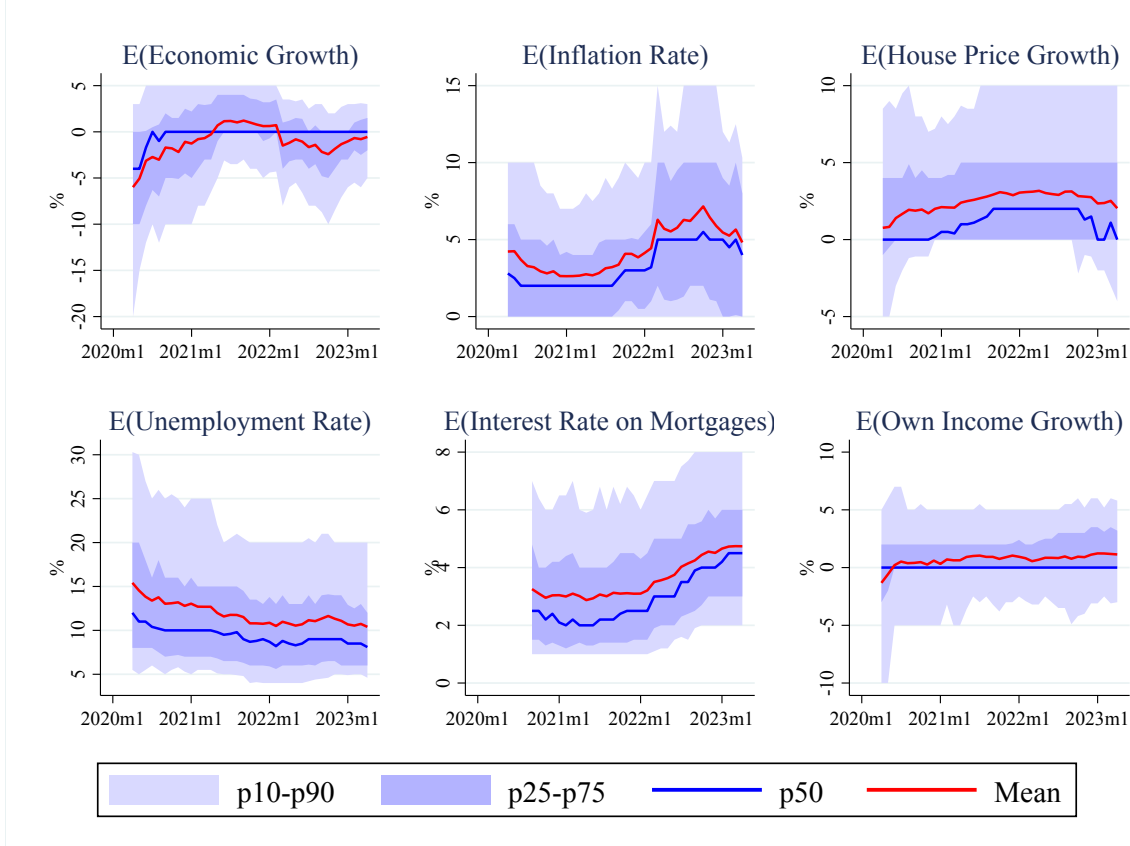
Note: “Age” is provided in four brackets ([18-34], [35-49], [50-64], 65+), and we assign the median value to each household. “Disposable Income” refers to the 12 months preceding the interview and it is PPP-adjusted. “Nondurable Spending” is asked at a quarterly frequency, it refers to spending on nondurable 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 April 2023, except for the expectation concerning the interest rate, which starts in September 2020.

households seem to correctly perceive business cycles, at least in this particular sample period.⁶

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

⁶As 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.6 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 April 2023, except for the expectation concerning the interest rate on mortgages, which starts in September 2020.

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.1-A.6 in Appendix A, are surprisingly similar.

3 Latent Drivers of Expectations in the Cross-Section

What are the households' perceived sources of macroeconomic dynamics? To shed light on this question, this section studies the joint behaviour of household-level expectations, and their *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, we will work not with the level of expectations,

but with the residuals from the following regression:

$$y_{h,c,t}^{\mathbb{E}} = \alpha_{c,t} + \epsilon_{h,c,t} \quad (1)$$

where $y_{h,c,t}^{\mathbb{E}}$ is 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 2 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 (1) so that in each month and country, (residualized) expectations have zero mean.

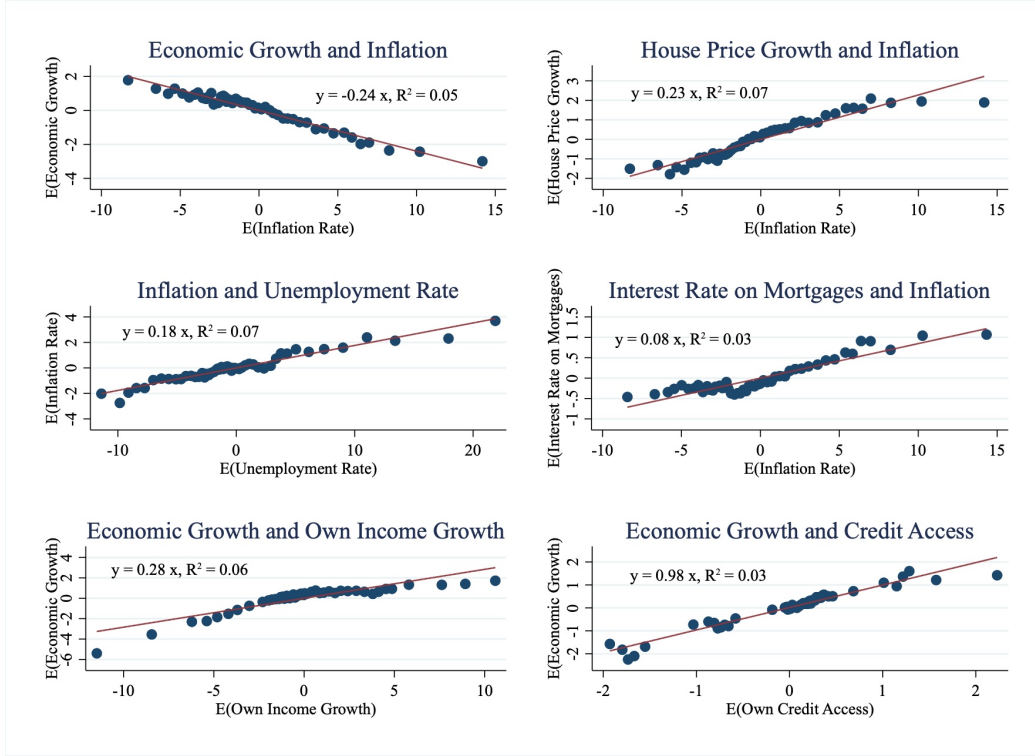
Two such correlations were already noticed in the literature. First, the top-left panel illustrates a negative correlation between expected output growth and expected inflation, a pattern Candia, Coibion, and Gorodnichenko (2020) show holds also in the US from 1978 to 2020 and that they have defined 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. Our first 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 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 0.28 percentage-point increase in expected output growth. Therefore, households expect their income to grow when they believe the economy will strengthen.⁷ Finally, the bottom-right panel shows that households expecting higher output growth also expect improved credit access conditions.

⁷Immordino, Jappelli, and Oliviero (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.

Figure 2: 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 April 2023, except for the expectation concerning the interest rate on mortgages, which starts in September 2020. All expectations are residualized using regression equation (1).

These results together indicate that household expectations about both aggregate-level and individual-level variables are correlated. As they stand, these correlation might emerge 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 \(1996\)](#).

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 4 where we estimate a factor model. In Section 3.5 we present a robustness exercise where we repeat our analysis in each month separately and show that the results are consistent over time.

3.1 PCA Baseline Results

We have established in Figure 2 above 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 April 2023.

Appendix B formalizes a standard way to decompose the raw data \mathbf{X} into principal component scores \mathbf{S} and loadings $\boldsymbol{\omega}$. Because our data \mathbf{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 weights 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 \mathbf{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 time dimension, which we will instead exploit in Section 4 where we estimate a factor model.

Table 2 presents the findings of our analysis on the first two principal components, which account for more than 40% of the total variance.⁸ The first takeaway is that the first principal component offers a supply-side perspective of macroeconomic developments. 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.⁹ 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.

⁸The third principal component only contributes with 11% of additional variance and for this reason we only focus on the first two components.

⁹What 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).

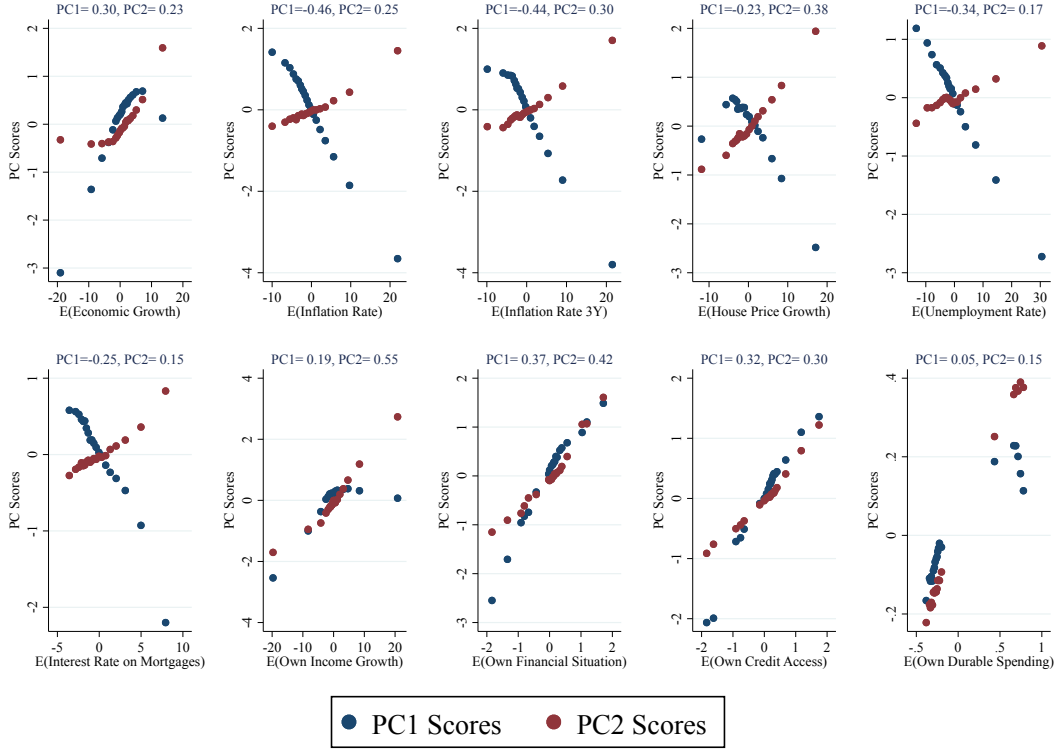
Table 2: Loadings from the PCA that pools data across time and countries

	Component 1	Component 2
E(Economic Growth)	0.31	0.22
E(Inflation Rate)	-0.46	0.26
E(Inflation Rate 3Y)	-0.44	0.31
E(House Price Growth)	-0.23	0.42
E(Unemployment Rate)	-0.31	0.10
E(Interest Rate on Mortgages)	-0.23	0.15
E(Own Income Growth)	0.19	0.56
E(Own Financial Situation)	0.38	0.39
E(Own Credit Access)	0.33	0.28
E(Own Durable Spending)	0.04	0.20
Observations	415857	415857
% Variance Explained	25.2	15.2

Note: The analysis pools together data from all time periods and all countries, and the sample covers the period from September 2020 to April 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 (1).

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-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 2): 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 (Candia, Coibion, and Gorodnichenko (2020)). 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.

Figure 3: 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 (1)). The analysis pools together data from all time periods and all countries, and the sample covers the period from September 2020 to April 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).

3.2 Interpreting the Principal Component Scores

The principal component scores are summary measures of household expectations.¹⁰ 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 3 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 ω 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

¹⁰See Equation (B.1) in Appendix B for a basic derivation.

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. Therefore, the first principal component scores can be considered as a supply-side force (e.g., an oil shock) hitting the economy over the following 12 months.

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,¹¹ 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. Therefore, the second principal component score can be considered a demand-side source of business cycle fluctuations, possibly resulting from factors such as monetary policy shocks.

An important feature of the principal component scores is that they are orthogonal to each other by construction. Figure A.7 in Appendix A plots the first principal component scores against the second. Although the regression line coincides with the horizontal axis (again because the two principal component scores are orthogonal), it is interesting to note that there exist observations that span all four quadrants of the graph. Examining the relationship between scores and expected inflation and expected economic growth, we can classify each quadrant into high and low values of each expectation. Therefore, household-level principal component scores reflect the significance they attach to the various sources of future business cycle dynamics, and the combination of scores provides us with joint values of expectations for each household.

3.3 The Role of Household 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 about inflation and house price changes, among other variables, tend to be influenced by experience and sophistication; see for example Malmendier and Nagel (2015). Table 3 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.

¹¹Intuitively, 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.

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)	0.29	0.23	0.33	0.22	0.30	0.27	0.32	0.17
E(Inflation Rate)	-0.47	0.24	-0.46	0.29	-0.47	0.25	-0.46	0.27
E(Inflation Rate 3Y)	-0.46	0.28	-0.43	0.34	-0.44	0.31	-0.44	0.31
E(House Price Growth)	-0.26	0.39	-0.20	0.47	-0.23	0.43	-0.23	0.41
E(Unemployment Rate)	-0.32	0.10	-0.31	0.06	-0.31	0.09	-0.30	0.10
E(Interest Rate on Mortgages)	-0.23	0.15	-0.23	0.12	-0.23	0.13	-0.21	0.16
E(Own Income Growth)	0.14	0.56	0.21	0.55	0.16	0.56	0.20	0.55
E(Own Financial Situation)	0.36	0.42	0.39	0.35	0.38	0.37	0.38	0.40
E(Own Credit Access)	0.33	0.31	0.33	0.25	0.34	0.27	0.33	0.30
E(Own Durable Spending)	0.02	0.21	0.04	0.18	0.04	0.19	0.03	0.21
Observations	237952	237952	177905	177905	188417	188417	227440	227440
% Variance Explained	24.8	16.2	25.5	14.2	24.9	15.2	25.3	15.2

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 April 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 (1).

To confirm and generalize this result further, we repeat the baseline PCA after controlling for individual fixed-effects. In particular, instead of residualizing the expectations using equation (1) we use the residuals from the following individual fixed-effect regression:

$$y_{h,t}^{\mathbb{E}} = \alpha_h + \alpha_t + \epsilon_{h,t} \quad (2)$$

where $y_{h,t}^{\mathbb{E}}$ is the value of the expectation about a variable y for household h in month t , α_h is an household fixed effect, and α_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 (2). 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 32%. 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.

3.4 Perceptions, Consumption, and Saving Behavior

We also investigate how the perceived sources of business cycle fluctuations identified through the PCA relate to household decisions on real outcomes such as consumption and

savings. In Appendix C, we estimate a series of fixed-effect regressions and find strong correlations between the two principal component scores and different measures of realized and planned spending, as well as precautionary savings.

Because in the data households tend to spend more when expecting higher inflation, our findings from the fixed-effect regressions point to the importance of expected inflation in explaining spending. This is the reason why in Table C.1 the association between spending and the first score is negative while the association with the second score is positive.¹² That is, regardless of whether future economic growth and inflation are driven by supply or demand, households tend to spend more when they expect higher inflation.

Turning to precautionary savings, our analysis in Table C.2 shows that precautionary savings are only associated with the first principal component score, pointing to the fact that supply forces are more important than demand ones when it comes to saving for precautionary reasons. Specifically, households tend to precautionary save more in periods of higher expected growth of the economy and lower expected inflation.

3.5 Robustness

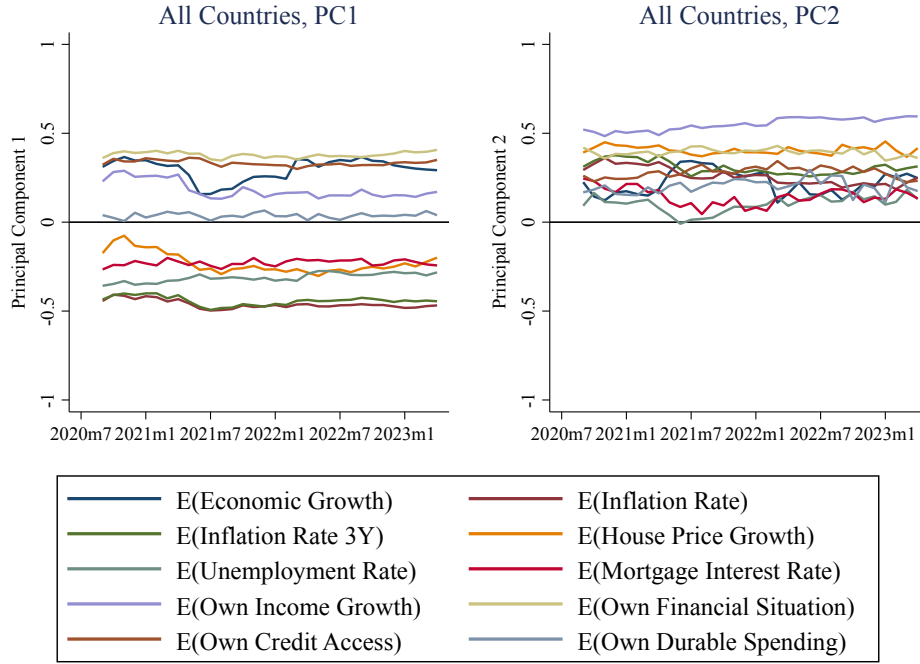
Results Month-by-Month. To assess the robustness of our baseline PCA findings where we analyzed all the months in our data together, we examine whether the results remain consistent when we conduct our analysis on each month separately.

Figure 4 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 than 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 weights have the same sign in the whole sample, some weights experience small fluctuations. For instance, when examining the first principal component (left panel), we observe a decline in the weight assigned to expected economic growth during the latter half of 2021, while the weight assigned to expected house price growth has been increasing in magnitude over time. Nonetheless, the majority of weights remain quantitatively similar across the entire sample period.

¹²Recall that the first principal component score decreases with expected inflation while the second score increases with expected inflation. This is highlighted in the second subplot of Figure 3 and in the loadings of the Table 2

Figure 4: 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 April 2023.

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 3.1 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 27.9% in Belgium for the supply-side factor, and from 13.7% in Belgium to 17% 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.

Table 4: PCA run on a reduced set of expectations pooling data across time and countries

	Component 1	Component 2
E(Economic Growth)	0.58	0.57
E(Inflation Rate)	-0.64	-0.13
E(Interest Rate on Mortgages)	-0.51	0.81
Observations	422051	422051
% Variance Explained	45.0	29.7

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 April 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 (1).

Results by Country-Month. We finally run the PCA for each month and country separately, and Figure A.8 plots the loadings on expected economic growth and expected inflation separately. 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 4 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.

4 Common Latent Perceptions Over Time

In Section 3 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 3, we identify and estimate two common factors, and relate them to different measures of supply and demand forces.

4.1 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 $y_{h,t}^{\mathbb{E}}$ about all variables E of all households H as columns of \mathbf{X}_t , and define the following factor structure:

$$x_{i,t} = \lambda_i' F_t + e_{i,t} \quad i = 1, \dots, E \times H \quad (3)$$

where F_t is a 2×1 vector of common factors, λ_i is a 2×1 vector of household-and-expectation specific loadings, and $e_{i,t}$ is the idiosyncratic component. Specification (3) 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 and Peters (2022) show that, under mild regularity conditions, many expectation-formation theories can be mapped into a factor structure.¹³

Some additional features deserve a brief discussion. First, although a dynamic factor structure can be cast into the static specification (3), 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 (3) assumes that households observe the same common sources of fluctuations (the F_t 's), but might a priori interpret their impact differently; i.e. the λ 's are household and expectation specific.¹⁴ We next turn to our identification strategy.

4.2 Identification and Estimation

When trying to extract the factors in Equation (3), 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:

¹³Juodis and Kučinskas (2023) uses their insights to quantify the noise present in survey expectations.

¹⁴An 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 and Winkler (2021) study a factor structure for heterogeneous expectations under this alternative specification.

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

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

Our identification strategy relies on the results of Section 3: We identify rotations that imply loadings which satisfy a set of sign restrictions consistent with the cross-sectional PCA results. Following the insights from Rubio-Ramírez, Waggoner, and Zha (2010), we proceed in multiple steps. First, factors in (3) are estimated as the first two principal components of \mathbf{X}_t . Second, a finite number of rotations $\{\tilde{F}_t\}$ of the estimated factors is obtained using orthonormal matrices $\{Q\}$ that results from a QR decomposition. Third, we run an OLS estimations of $x_{i,t} = \lambda'_i \tilde{F}_t + v_{i,t}$, and we keep the rotations which imply estimated loadings $\{\hat{\lambda}_i^{OLS}\}_{i=1}^{ExH}$ that satisfy the set of sign restrictions. Fourth and finally, among all the valid rotations, we select one that minimizes a standard distance criteria.

Identification of static and dynamic factor models by sign restrictions has been used in the literature that uncovers, for example, supply and demand drivers of inflation and business cycles. A recent paper which carries out such an exercise is Eickmeier and Hofmann (2022). Their approach imposes restrictions on loadings which are consistent with standard theoretical mechanisms in a supply and demand framework. Our innovation here is to use granular cross-sectional variation in expectations in order to motivate the sign restrictions and identify common unobserved drivers over time. 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.

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 the signs estimated in the PCA results presented in Table 2. As a benchmark, we impose restrictions on each *individual* pair of loadings.¹⁵ We then keep a given rotation matrix if the share of satisfied restrictions is above a threshold.¹⁶

¹⁵Note that we have approximately $E \times H \approx 10 \times 10,000 = 100,000$ pairs.

¹⁶We also consider two alternative ways to identify the rotations: (i) include *average* expectation within each country as additional variables in X and impose sign restrictions on these, keeping a rotation for which *all* (i.e. 100%) of the restrictions are satisfied, and (ii) impose restrictions on the *average loading* across households. Results don't change under these alternative ways of identifying the rotations.

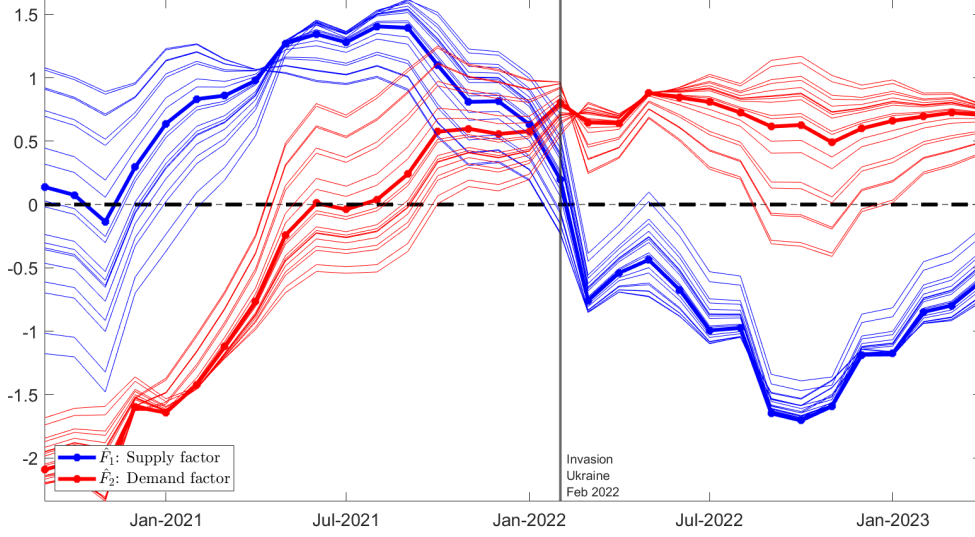
4.3 Interpreting the Rotated Factors

The two extracted (rotated) common factors from our benchmark identification strategy are presented in Figure 5. The two dark thick lines represent the *optimal* factors as defined by using a standard euclidean metric. The thinner lines represent other (nearby) 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; 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 a vertical solid line on the date of the Russian invasion of Ukraine (February 2022).

Some features are worth mentioning. First, note that the thinner lines capture *model* uncertainty, not estimation (sampling) uncertainty. Second, the two factors capture perceptions that are in line with a narrative post-Ukraine invasion based on increasing importance of supply 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. In particular, starting at the end of 2020, the supply factor captures the perceptions that supply-side disruptions were diminishing, implying increasing downward pressure on inflation and upward pressure on economic growth. On the other hand, 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. These trends shifted abruptly with the invasion of Ukraine. Since then, and at least until the end of 2022, households seemed to be perceiving strong inflationary pressures and negative growth perspectives emerging from supply, while mildly inflationary pressures from demand. Third, we also estimate the factor model for each country separately, and Figure A.9 in Appendix A shows that the dynamics of the extracted factors are very similar across all countries. This means that the results

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 and Hofmann \(2022\)](#) estimate a static factor model 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

Figure 5: Evolution of identified factors over the sample period



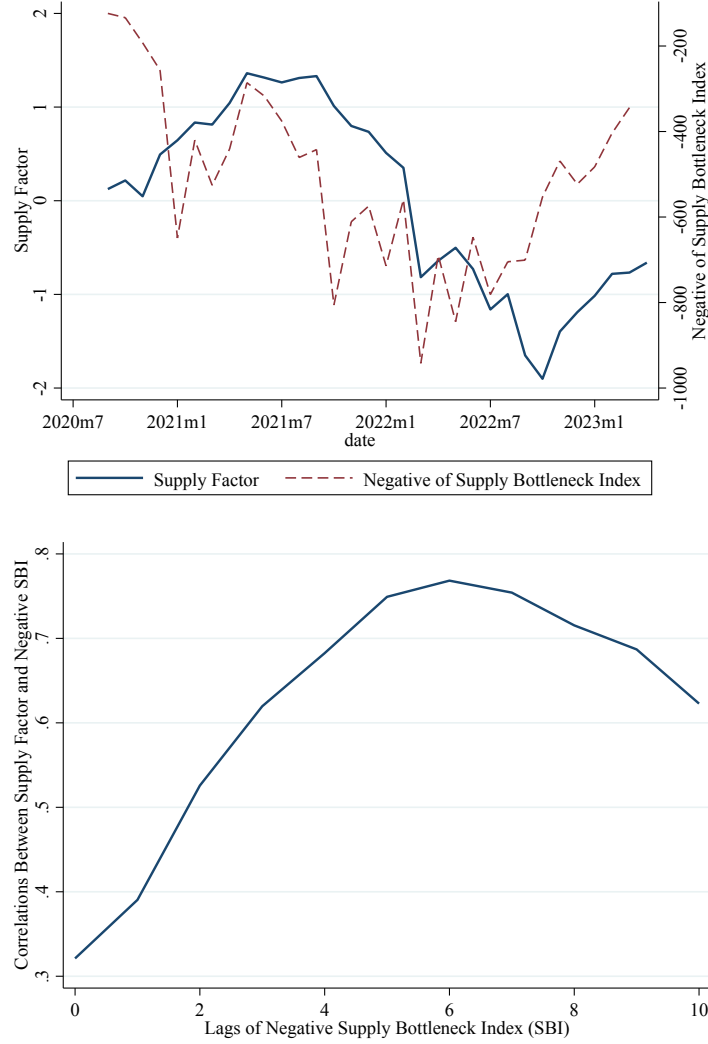
Note: The figure plots valid (i.e. that satisfy the sign restriction criteria defined in the main text) rotated factors as estimated from (3). The two dark thick lines represent the *optimal* factors as defined using a standard euclidean metric. The thinner lines represent other (nearby) valid rotations. 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 a vertical solid line on the date of the Russian invasion of Ukraine (February 24th, 2022).

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 and Hofmann (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 different measures of supply disruptions and demand forces that have recently been identified in the literature.

Co-movement of factors with measures of supply disruptions. 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,

Figure 6: Supply factor and Supply Bottleneck Index from Burriel et al. (2023)



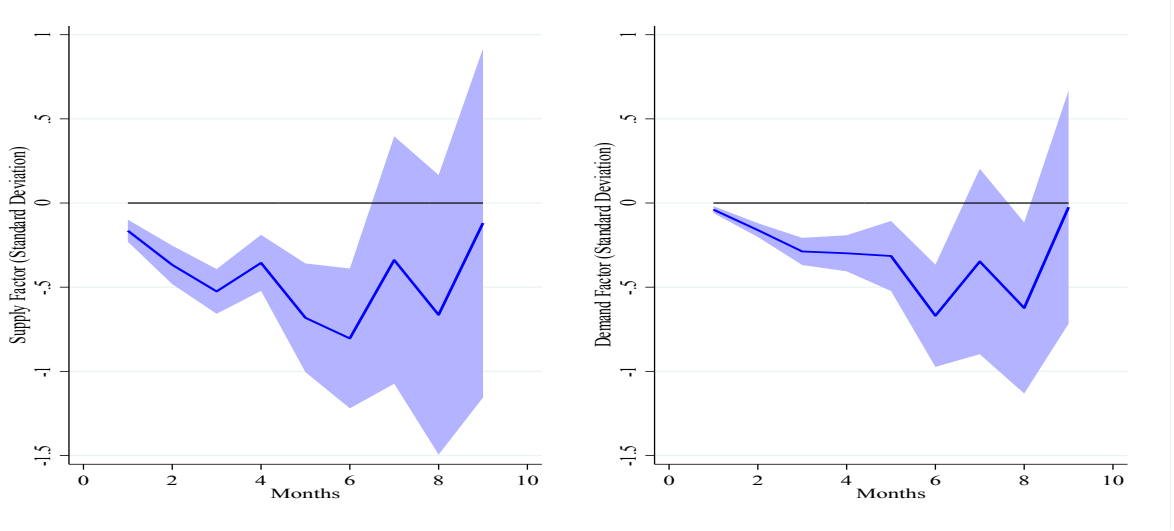
Note: The figure compares the first factor identified from the model (3) with the newspaper-based Supply Bottleneck Index (SBI) as constructed by Burriel et al. (2023). The top panel plots the supply-type factor against the (negative of) the SBI for the sample period for which we have expectations data. The bottom panel plots the correlation structure of the supply-type factor with different lags of the SBI; i.e. $\text{Corr}(\hat{F}_{1,t}, SBI_{t-j})$ for $j = 1, \dots, 10$, where the number of lags (in months) are represented in the x-axis.

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 recently¹⁷, this SBI is particularly useful in our set-up because it covers the four largest countries (out of six) in our sample.

Figure 6 compares our supply factor with the (negative of the) SBI in the top panel, while the bottom panel plots the correlation of the first factor with different lags of the SBI; i.e. $\text{Corr}(\hat{F}_{1,t}, SBI_{t-j})$ for $j = 1, \dots, 10$. Interestingly enough, the pattern of

¹⁷See for example Shapiro et al. (2022), Ascari et al. (2023), and De Santis and Stoevsky (2023).

Figure 7: The response of a contractionary monetary policy shock on identified factors



Note: The figure plots the IRFs to a 1 standard deviation surprise in the 1-year OIS rate of the supply-type (left panel) and demand-type (right panel) factors identified from (3). IRFs are estimated from the local projection specification (4).

correlations 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 and adjust their expectations with some delays.

$$F_{t+h,i} - F_{t-1,i} = \alpha^{h,i} + \beta^{h,i} \epsilon_t^{MP} + \sum_{k=1}^2 \gamma_k^{h,i} \epsilon_{t-k}^{MP} + u_t^{h,i} \quad (4)$$

where $\forall h = 0, \dots, 9$ months, and $i \in \{supply, demand\}$.

Estimated IRFs to a contractionary 1-standard deviation surprise from specification (4) are presented in Figure 7. Some interesting features are worth commenting. First, even considering the short sample being used in the estimation (monthly data from September 2020 to April 2023), point estimates are significantly different from zero. Second, the contractionary surprise seems to have a negative effect on economics growth perceptions through both factors. Perceptions about the impact on future inflation are opposite, though, given the way the factors were identified. More specifically, the contractionary monetary shock increases inflation expectation through the supply factor but decreases inflation expectation through the demand factor. Therefore, while the impact on inflation expectation is ambiguous, the impact on economic growth expectation is negative.

4.4 Discussion

Although the analysis in this paper is purely positive, we here draw some policy implications of our results.

In Section 3.4 we have discussed the strong associations between supply and demand components with household-level economic decisions such as consumption and precautionary savings. The potential for these perceptions to shape consumption and saving decisions has implications for policymakers on how they could adjust their policy and communication strategies to elicit the desired real outcomes from households. This is particularly relevant in times of rapid changes in the contribution of perceived supply and demand in shaping expected output and inflation, such as the increasing importance of supply observed in Figure 5 to explain the rise in expected inflation at the start of 2022. The advantage of our analysis is that we can track at a monthly frequency the evolution of supply and demand perceptions as new data comes out, so that policy-makers can adjust their policy in a timely fashion.

5 Conclusions

Household expectations about a wide range of aggregate and individual level variables are correlated. Identifying the drivers behind them – and the ways households perceive the sources of macroeconomic dynamics – is crucial to inform policy and the communication to the public.

In this paper we have exploited a very rich set 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 that, although households disagree, they do so with an interesting 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 developments, whereby households associate higher growth of the economy with lower inflation. The second components, instead, reflects a demand-side view, leading households to forecast an improve of the economy together with an increase in inflation. These results are surprisingly robust to different cuts of the data, including analysis done within each country, each month and age and education groups.

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.

Our methodology timely tracks at a monthly frequency the evolution of supply and demand perceptions, and this can help policy-makers to adjust their policy as the structure of expectations changes across the business cycle.

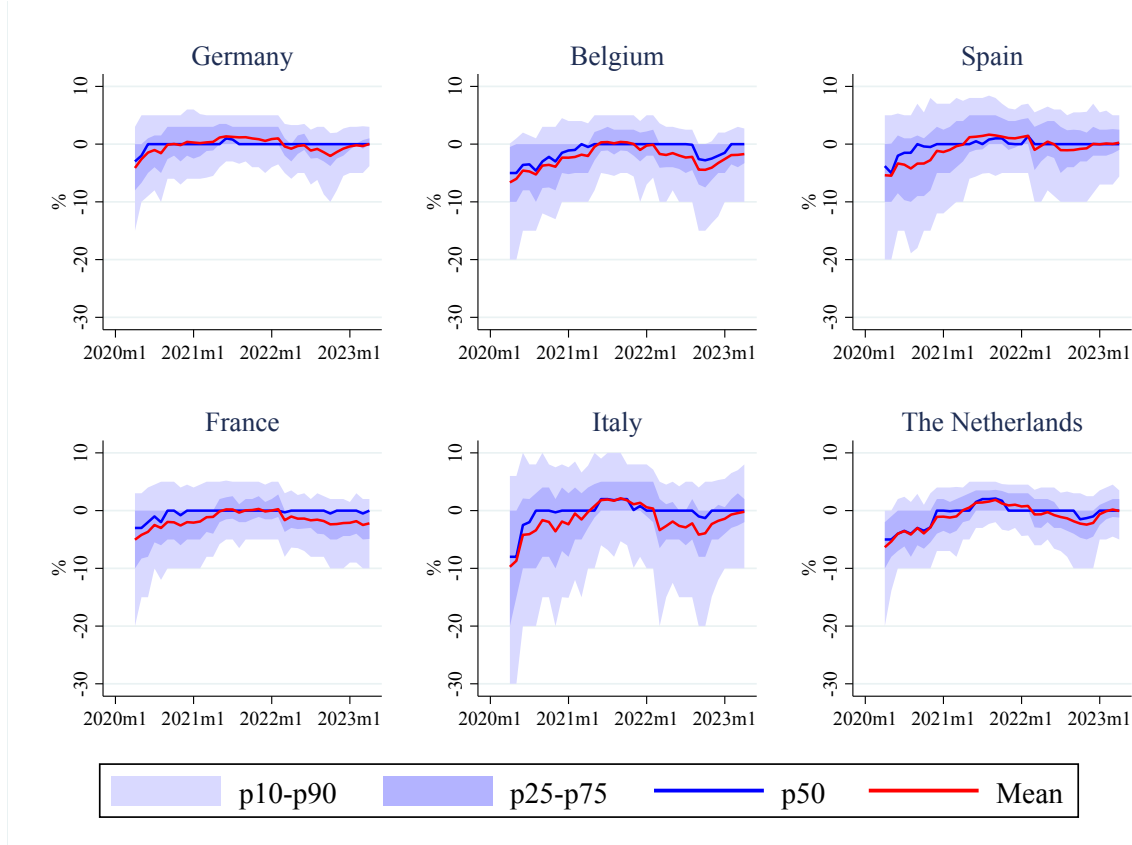
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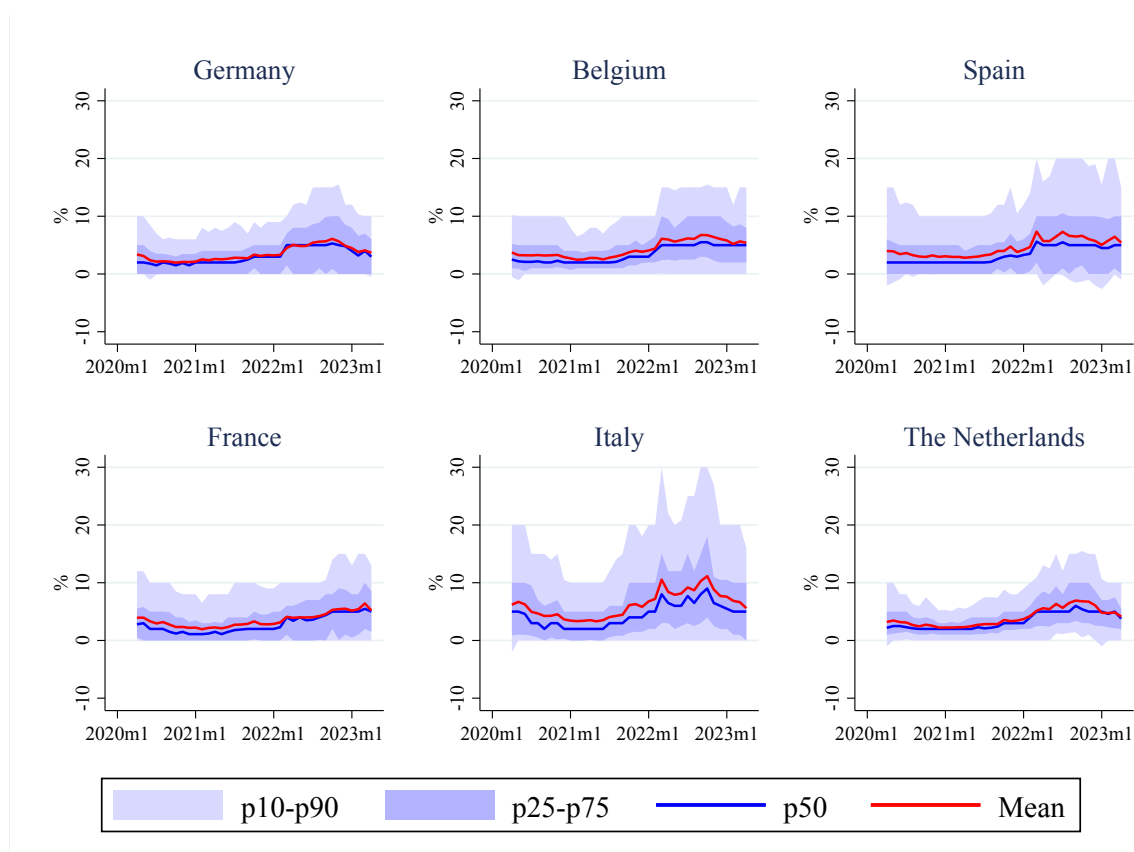
Appendix A Additional Figures and Tables

Figure A.1: Evolution of household-level expectations over time, country-by-country: $E(\text{Economic Growth})$



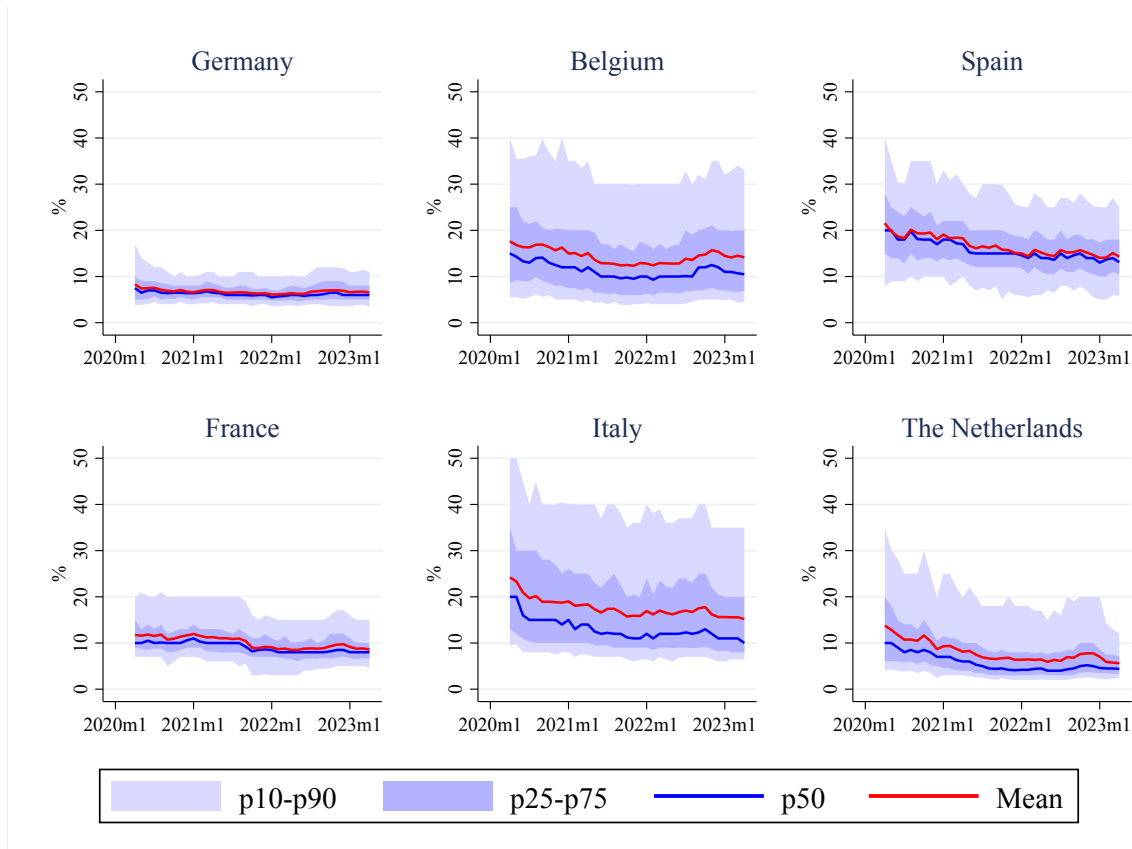
Note: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about economic growth in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April 2020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

Figure A.2: Evolution of household-level expectations over time, country-by-country: $E(\text{Inflation Rate})$



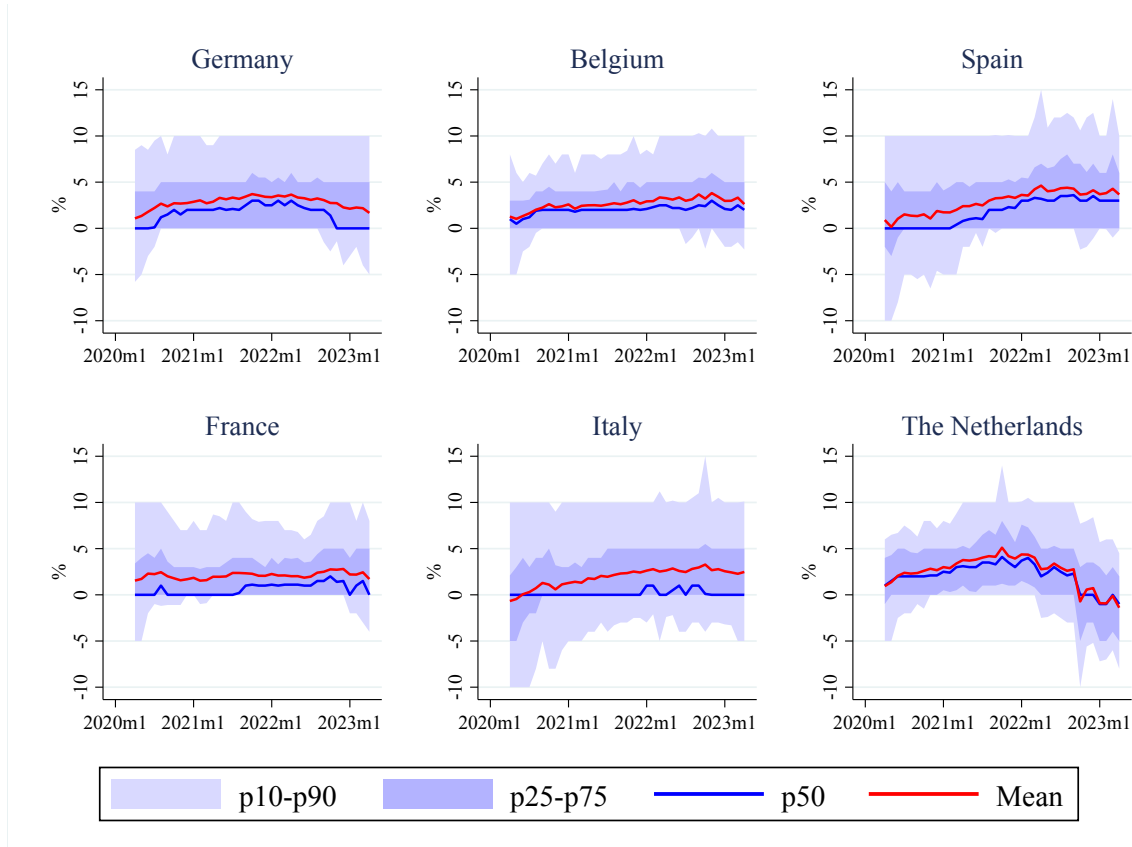
Note: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about the inflation rate in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April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

Figure A.3: Evolution of household-level expectations over time, country-by-country: $E(\text{Unemployment Rate})$



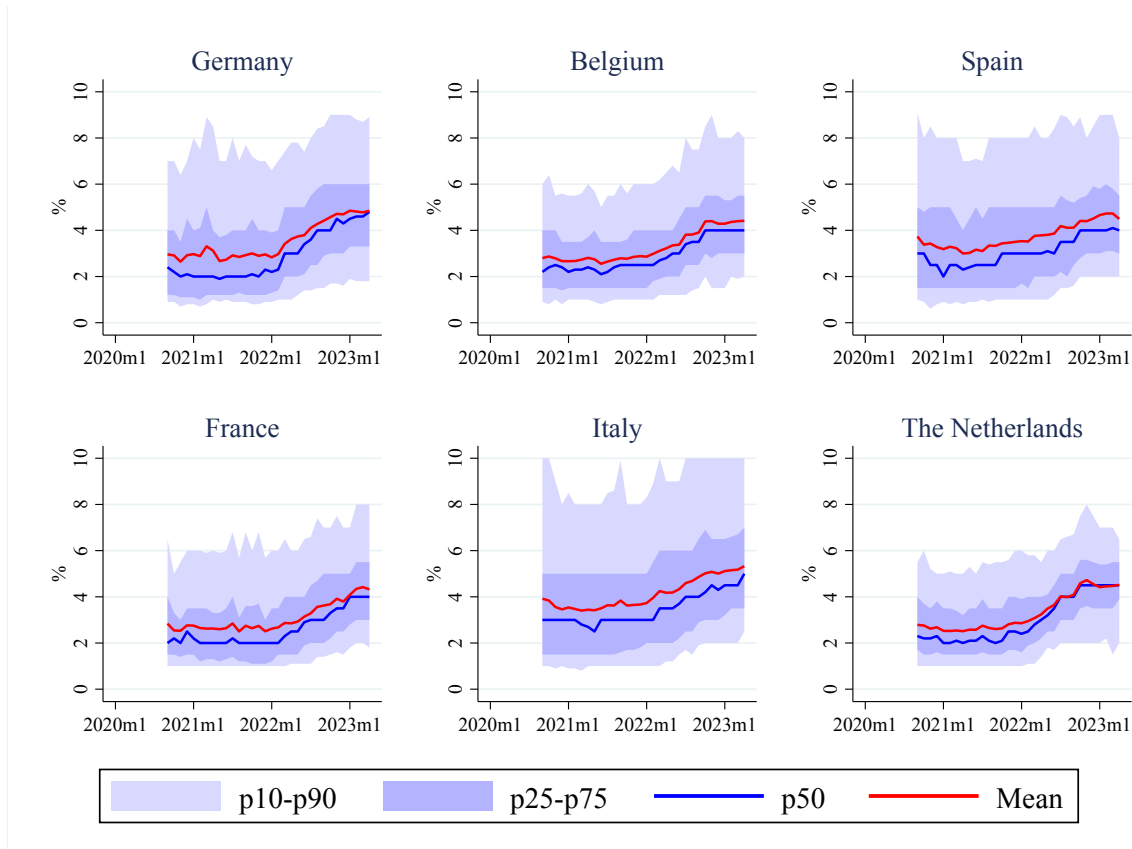
Note: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about the unemployment rate in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April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

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



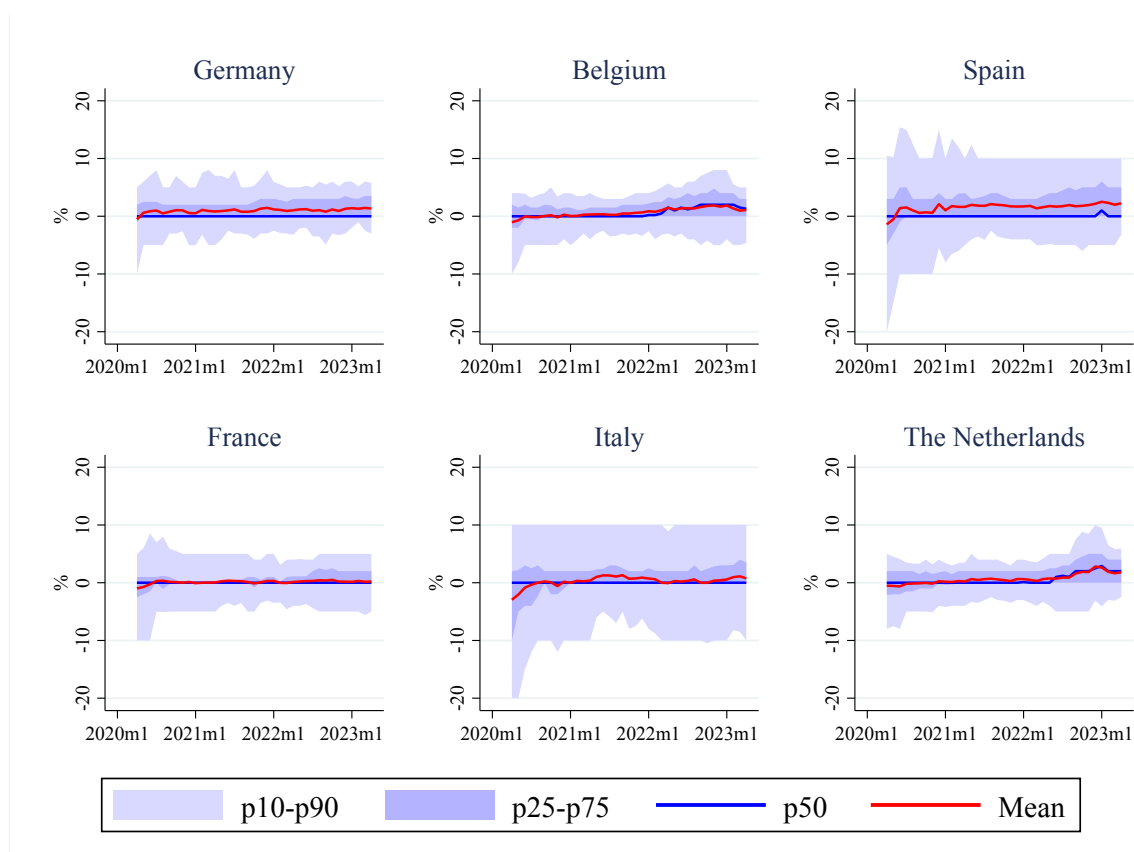
Note: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about house price growth in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April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

Figure A.5: Evolution of household-level expectations over time, country-by-country: $E(\text{Interest Rate on Mortgages})$



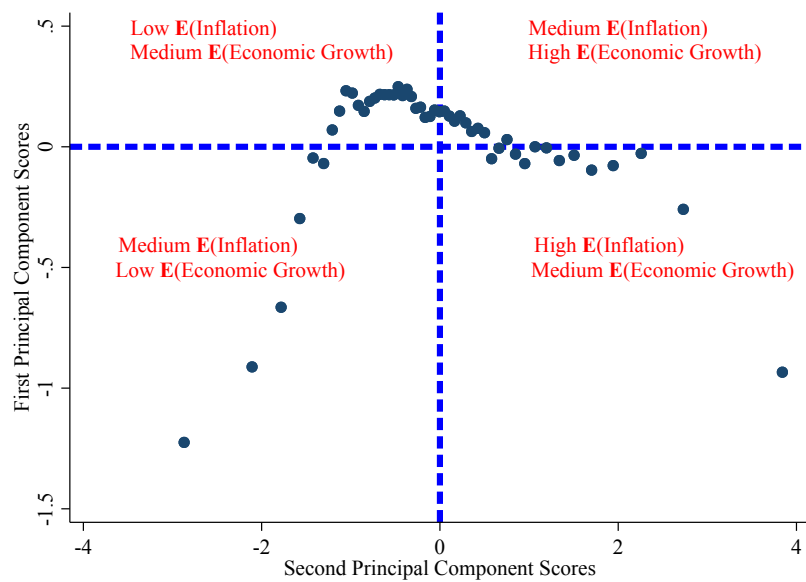
Note: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about the interate rate on mortgages in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period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

Figure A.6: Evolution of household-level expectations over time, country-by-country: **E(Own Income Growth)**



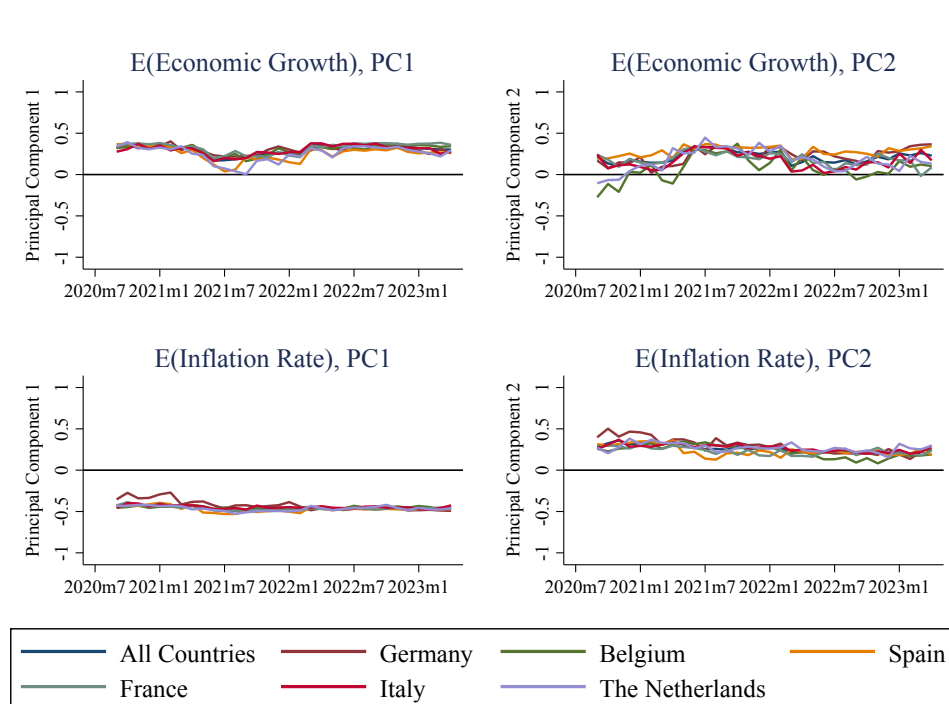
Note: The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of the expectation about own income growth in each month of the sample. The expectation is measured monthly, with a 12-month horizon, and reported as numerical values. The sample covers the period from April 2020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

Figure A.7: Diagram of PC scores and relation to expected inflation and economic growth



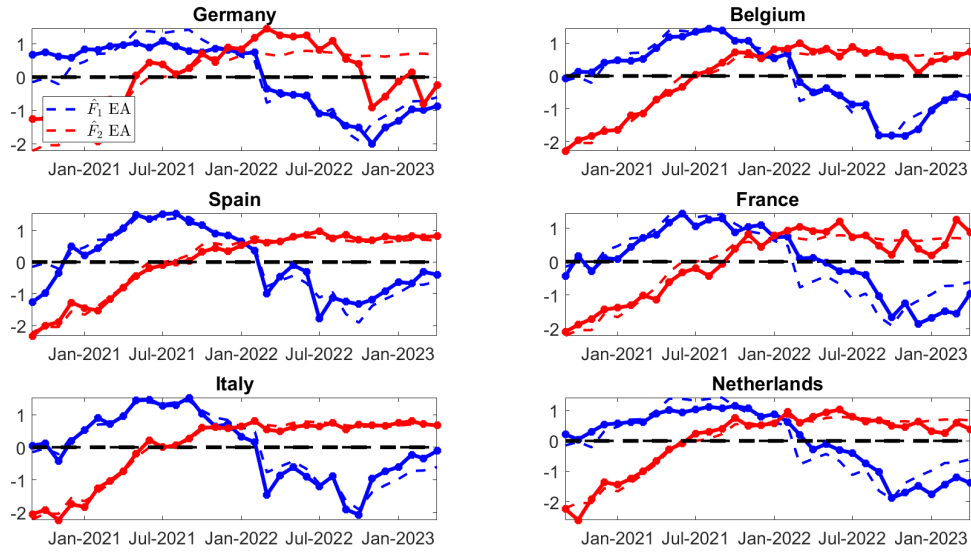
Note: The blue circles show the mean of the y-axis variables (first principal component score) for 50 bins of the x-axis variable (second principal component score). The scores divide the graph into four quadrants, which relates to the joint distribution of expectations. By “High” we mean higher than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

Figure A.8: 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 April 2023.

Figure A.9: 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 (3) 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.

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

	Mean	p10	Median	p90	N
<i>Belgium</i>					
Age	49.81	26.00	42.00	80.00	38,434
Disposable Income	37,041.82	17,500.00	35,000.00	67,500.00	38,434
Nondurable Spending	17,306.18	6,360.00	17,256.00	27,816.00	13,379
Spent on Durables (0-1)	0.17	0.00	0.00	1.00	10,232
Precautionary Savings	7,983.15	400.00	5,200.00	20,000.00	12,239
E(Economic Growth)	-2.30	-10.00	-0.20	3.00	38,434
E(Inflation Rate)	4.28	0.00	3.00	10.00	38,428
E(Inflation Rate 3Y)	3.37	0.00	2.30	10.00	37,922
E(House Price Growth)	2.68	0.00	2.00	8.00	38,434
E(Unemployment Rate)	14.40	5.00	11.00	30.00	38,434
E(Interest Rate on Mortgages)	3.28	1.20	3.00	6.00	33,186
E(Own Income Growth)	0.65	-3.00	0.00	4.00	38,434
E(Own Spending Growth)	3.45	0.00	2.00	10.00	30,961
E(Own Durable Spending)	0.24	0.00	0.00	1.00	38,323
E(Own Credit Access)	2.55	1.00	3.00	3.00	37,256
E(Own Financial Situation)	2.64	1.00	3.00	4.00	38,434
<i>France</i>					
Age	50.34	26.00	42.00	80.00	98,829
Disposable Income	35,670.57	17,500.00	35,000.00	55,000.00	98,829
Nondurable Spending	18,137.53	7,800.00	17,700.00	29,280.00	33,880
Spent on Durables (0-1)	0.16	0.00	0.00	1.00	28,039
Precautionary Savings	7,589.47	500.00	5,000.00	20,000.00	29,391
E(Economic Growth)	-1.58	-8.00	0.00	3.00	98,829
E(Inflation Rate)	3.53	0.00	2.40	10.00	98,826
E(Inflation Rate 3Y)	2.84	0.00	2.00	8.50	97,800
E(House Price Growth)	2.10	0.00	0.20	7.00	98,829
E(Unemployment Rate)	10.09	6.00	9.00	15.00	98,829
E(Interest Rate on Mortgages)	3.09	1.10	2.50	6.00	89,318
E(Own Income Growth)	0.12	-4.00	0.00	4.40	98,829
E(Own Spending Growth)	2.13	0.00	0.00	8.90	80,950
E(Own Durable Spending)	0.24	0.00	0.00	1.00	98,581
E(Own Credit Access)	2.71	1.00	3.00	4.00	97,718
E(Own Financial Situation)	2.73	2.00	3.00	4.00	98,829

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 April 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
<i>Germany</i>					
Age	50.68	26.00	57.00	80.00	95,248
Disposable Income	38,800.09	12,500.00	35,000.00	67,500.00	95,248
Nondurable Spending	19,395.25	9,000.00	19,080.00	30,600.00	32,906
Spent on Durables (0-1)	0.19	0.00	0.00	1.00	26,999
Precautionary Savings	7,400.24	500.00	4,400.00	20,000.00	29,009
E(Economic Growth)	-0.25	-5.00	0.00	4.00	95,248
E(Inflation Rate)	3.50	0.00	2.60	9.00	95,247
E(Inflation Rate 3Y)	2.61	0.00	2.00	7.00	94,171
E(House Price Growth)	2.82	0.00	2.00	10.00	95,248
E(Unemployment Rate)	6.76	4.00	6.20	10.00	95,248
E(Interest Rate on Mortgages)	3.53	1.00	3.00	7.00	85,875
E(Own Income Growth)	0.97	-2.50	0.00	5.00	95,248
E(Own Spending Growth)	2.74	0.00	0.00	8.10	81,721
E(Own Durable Spending)	0.29	0.00	0.00	1.00	95,068
E(Own Credit Access)	2.96	2.00	3.00	4.00	94,172
E(Own Financial Situation)	2.89	2.00	3.00	4.00	95,248
<i>Italy</i>					
Age	51.81	26.00	57.00	80.00	103,137
Disposable Income	30,658.46	12,500.00	27,500.00	55,000.00	103,137
Nondurable Spending	15,764.34	6,108.00	15,396.00	25,524.00	35,689
Spent on Durables (0-1)	0.20	0.00	0.00	1.00	29,538
Precautionary Savings	8,173.75	460.00	5,000.00	22,000.00	32,575
E(Economic Growth)	-1.64	-10.00	0.00	6.00	103,137
E(Inflation Rate)	6.17	0.00	4.60	15.00	103,133
E(Inflation Rate 3Y)	4.75	0.00	3.00	15.00	102,069
E(House Price Growth)	1.89	-3.00	0.00	10.00	103,137
E(Unemployment Rate)	17.65	7.50	13.00	36.00	103,137
E(Interest Rate on Mortgages)	4.13	1.10	3.50	8.00	92,933
E(Own Income Growth)	0.26	-8.20	0.00	10.00	103,137
E(Own Spending Growth)	2.90	-0.50	0.00	10.00	89,091
E(Own Durable Spending)	0.34	0.00	0.00	1.00	102,965
E(Own Credit Access)	2.73	1.00	3.00	3.00	102,210
E(Own Financial Situation)	2.74	2.00	3.00	4.00	103,137

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 April 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
<i>Spain</i>					
Age	50.27	26.00	42.00	80.00	98,772
Disposable Income	29,269.87	12,500.00	22,500.00	55,000.00	98,772
Nondurable Spending	15,698.91	6,960.00	15,060.00	25,440.00	34,104
Spent on Durables (0-1)	0.18	0.00	0.00	1.00	28,060
Precautionary Savings	5,417.89	360.00	3,400.00	15,000.00	31,300
E(Economic Growth)	-0.73	-9.00	0.00	5.50	98,772
E(Inflation Rate)	4.52	0.00	3.00	12.00	98,767
E(Inflation Rate 3Y)	3.90	0.00	2.50	10.00	97,714
E(House Price Growth)	2.89	-0.50	2.00	10.00	98,772
E(Unemployment Rate)	16.65	8.90	15.00	26.50	98,772
E(Interest Rate on Mortgages)	3.74	1.00	3.00	8.00	89,148
E(Own Income Growth)	1.55	-4.10	0.00	10.00	98,772
E(Own Spending Growth)	2.51	0.00	0.00	10.00	84,896
E(Own Durable Spending)	0.31	0.00	0.00	1.00	98,568
E(Own Credit Access)	2.76	1.00	3.00	4.00	98,255
E(Own Financial Situation)	2.92	2.00	3.00	4.00	98,772
<i>Netherlands</i>					
Age	49.50	26.00	42.00	80.00	36,579
Disposable Income	38,066.10	17,500.00	35,000.00	67,500.00	36,579
Nondurable Spending	18,010.95	7,860.00	17,664.00	28,500.00	12,890
Spent on Durables (0-1)	0.20	0.00	0.00	1.00	9,888
Precautionary Savings	5,685.55	220.00	3,600.00	15,000.00	11,838
E(Economic Growth)	-1.07	-6.10	0.00	3.50	36,579
E(Inflation Rate)	3.97	0.00	3.00	8.90	36,572
E(Inflation Rate 3Y)	2.96	0.00	2.50	6.80	36,151
E(House Price Growth)	2.51	-2.00	2.10	8.00	36,579
E(Unemployment Rate)	8.02	2.80	5.60	18.00	36,579
E(Interest Rate on Mortgages)	3.30	1.20	3.00	5.50	31,617
E(Own Income Growth)	0.67	-3.10	0.00	4.00	36,579
E(Own Spending Growth)	2.85	0.00	2.00	8.00	31,351
E(Own Durable Spending)	0.30	0.00	0.00	1.00	36,447
E(Own Credit Access)	2.63	1.00	3.00	3.00	35,623
E(Own Financial Situation)	2.72	2.00	3.00	4.00	36,579

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 April 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)	0.26	0.33
E(Inflation Rate)	-0.55	0.22
E(Inflation Rate 3Y)	-0.52	0.30
E(House Price Growth)	-0.31	0.37
E(Unemployment Rate)	-0.27	-0.08
E(Interest Rate on Mortgages)	-0.14	0.04
E(Own Income Growth)	0.13	0.55
E(Own Financial Situation)	0.33	0.44
E(Own Credit Access)	0.24	0.31
E(Own Durable Spending)	0.02	0.13
% Variance Explained	17.25	14.10

Note: All expectations are residualized using regression (1) instead than regression (1). The analysis pools together data from all time periods and all countries, and the sample covers the period from September 2020 to April 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 (1).

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)	0.31	0.24	0.31	0.04	0.27	0.28	0.32	0.20	0.32	0.14	0.29	0.18
E(Inflation Rate)	-0.46	0.28	-0.45	0.23	-0.47	0.26	-0.46	0.24	-0.44	0.28	-0.45	0.33
E(Inflation Rate 3Y)	-0.42	0.32	-0.45	0.23	-0.45	0.31	-0.45	0.30	-0.43	0.32	-0.44	0.37
E(House Price Growth)	-0.31	0.40	-0.30	0.39	-0.25	0.40	-0.29	0.45	-0.12	0.44	-0.26	0.45
E(Unemployment Rate)	-0.27	-0.04	-0.29	0.10	-0.35	0.03	-0.25	0.09	-0.34	0.18	-0.30	-0.00
E(Interest Rate on Mortgages)	-0.19	0.10	-0.23	0.11	-0.25	0.11	-0.16	0.11	-0.27	0.20	-0.20	-0.05
E(Own Income Growth)	0.14	0.56	0.13	0.59	0.15	0.57	0.19	0.54	0.25	0.53	0.22	0.48
E(Own Financial Situation)	0.42	0.33	0.36	0.43	0.35	0.42	0.39	0.40	0.38	0.39	0.38	0.38
E(Own Credit Access)	0.34	0.29	0.34	0.36	0.33	0.25	0.35	0.30	0.33	0.26	0.36	0.27
E(Own Durable Spending)	0.00	0.27	0.05	0.25	0.06	0.13	-0.03	0.23	0.08	0.17	0.07	0.26
% Variance Explained	24.90	15.08	27.89	13.71	25.25	16.98	25.57	15.34	26.43	15.45	24.58	15.23

Note: The analysis pools together data from all time periods and is performed in each country separately. The sample goes from September 2020 to April 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 (1).

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 \mathbf{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 $\mathbf{x}_h = \{x_{h,1}, \dots, x_{h,E}\}$, 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 weights $\boldsymbol{\omega}_k = \{w_{1,k}, \dots, w_{E,k}\}$ mapping the data matrix \mathbf{X} to a data matrix \mathbf{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 \mathbf{S} is made of principal component scores $\mathbf{s}_h = \{s_{h,1}, \dots, s_{h,K}\}$ given by:

$$s_{h,k} = \mathbf{x}_h \cdot \boldsymbol{\omega}_k \quad h = 1, \dots, H; \quad k = 1, \dots, K \quad (\text{B.1})$$

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

A simple example: Consider H households and $E = 3$ expectations about inflation (π), 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 weights $\boldsymbol{\omega}_1$ and $\boldsymbol{\omega}_2$ (each one 3×1) 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^π 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 \mathbf{X} with dimension $H \times 3$ to \mathbf{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 3, 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 fluctuations relate to household decisions and, in turn, to the macroeconomy.

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

$$y_{h,c,t} = \alpha_h + \alpha_t + \alpha_{c,t} + \beta_1 s_{1,h,c,t} + \beta_2 s_{2,h,c,t} + \gamma \mathbf{x}_{h,c,t} + \epsilon_{h,c,t} \quad (\text{C.1})$$

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, $\mathbf{x}_{h,c,t}$ is a set of household-level controls, α_i is the household FE, α_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 3.5, 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 $\mathbf{x}_{h,c,t}$ 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.¹⁸

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 3.1, 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 $\mathbf{x}_{h,c,t}$ 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

¹⁸The 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 _{<i>t-1</i>}		Spent on Durables _{<i>t-1</i>} (0-1)	
	Pooled	FE	Pooled	FE
PC1 Scores _{<i>t-2</i>}	-0.0226*** (0.0012)	-0.0045** (0.0020)	-0.0024*** (0.0008)	0.0020 (0.0014)
PC2 Scores _{<i>t-2</i>}	0.0263*** (0.0021)	0.0053** (0.0024)	0.0191*** (0.0013)	0.0056*** (0.0019)
Has Liquidity _{<i>t-2</i>}	0.0399*** (0.0086)	0.0068 (0.0093)	0.0211*** (0.0048)	-0.0033 (0.0063)
Has Liquidity _{<i>t-1</i>}	0.0531*** (0.0086)	0.0077 (0.0100)	0.0312*** (0.0047)	0.0132** (0.0060)
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	104,832	104,823	105,053	105,044
<i>R</i> ²	0.1908	0.0121	0.0283	0.0119

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 3.1. In the fixed-effect specifications, the scores are identified from the PCA run separately in each month of Section 3.5. “Has Liquidity” measures whether the household has enough liquidity to pay for an unexpected event equal to 1 month of her income.

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 other major items. Further information on these variables are provided in Section 2.2, 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 3 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 2.2 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

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

	Precautionary Savings		$\mathbb{E}(\text{Spending Growth})$	
	Pooled	FE	Pooled	FE
PC1 Scores _t	-0.0130*** (0.0023)	0.0067* (0.0035)	-0.6614*** (0.0055)	-0.3754*** (0.0125)
PC2 Scores _t	0.0369*** (0.0041)	0.0047 (0.0048)	0.6285*** (0.0094)	0.4081*** (0.0162)
Has Liquidity _t	0.6966*** (0.0118)	0.2503*** (0.0218)	0.4575*** (0.0214)	0.2768*** (0.0351)
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	134,797	134,786	351,198	351,184
R^2	0.1547	0.0339	0.2104	0.0846

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 3.1. In the fixed-effect specifications, the scores are identified from the PCA run separately in each month of Section 3.5. “Has Liquidity” measures whether the household has enough liquidity to pay for an unexpected event equal to 1 month of her income.

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 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.