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Attention to the Macroeconomy*

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Abstract

We collect novel measures of households' and firms' attention to the economy using open-ended survey questions, fielded during a large shock to inflation, and test the predictions of theories of rational, goal-optimal attention allocation. We find support for several predictions of such theories: attention to the macroeconomy exhibits large and persistent cross-sectional heterogeneity, which is related to agents' degree of exposure to the economy and measures of information costs; attention to the macroeconomy responds strongly to shocks; more attentive respondents adjust their inflation expectations more frequently during the shock, are more confident in their beliefs, and hold smaller misperceptions about realized inflation. However, at odds with goal-optimality of attention, more attentive agents' expectations about future inflation deviate more strongly from expert benchmarks. To explain these patterns, we present a model of selective memory, in which attention can be "non-goal-optimal". In this model, prior experiences shape both attention allocation and belief formation, and attention to other variables can spill over to inflation expectations. We confirm these additional predictions in our data.

JEL Classification: D83, D84, E71.
Keywords: Attention, Expectation formation, Memory, Experiences, Inflation.

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1 Introduction

Economic agents' attention allocation is a key determinant of belief formation and decision-making (Bordalo, Gennaioli and Shleifer, 2020, 2022). In macroeconomic models, how much attention agents pay to aggregate developments in general and how much attention is allocated to specific variables – e.g., inflation, monetary policy, or GDP growth – is central to agents' expectation formation and thereby affects business cycle fluctuations and the transmission of policies (Maćkowiak and Wiederholt, 2009; Paciello and Wiederholt, 2014; Reis, 2006a). Macroeconomists traditionally model attention as "goal-optimal": paying attention allows agents to form more accurate beliefs and make better decisions, and these benefits are rationally traded-off against the cost of paying attention (Maćkowiak, Matějka and Wiederholt, 2023). By contrast, research in behavioral economics suggests that attention may not be goal-optimal. For instance, selective attention to specific aspects of a problem may be associated with suboptimal decisions (Bordalo, Conlon, Gennaioli, Kwon and Shleifer, 2023a; Bordalo, Gennaioli, Lanzani and Shleifer, 2025). Whether attention to the economy is well captured by models of goal-optimal attention is not well understood. One potential reason is that there exist limited direct individual-level data on attention allocation.

In this paper, we present new data on households' and firms' attention to the economy, with the goal of gaining a better understanding of the empirical properties of attention. We think of attention as the allocation of cognitive resources across different economic domains. To measure attention, we rely on open-ended text responses to a prompt that puts survey respondents into the mindset relevant for their economic decision-making. Specifically, we ask respondents what comes to their mind when thinking about their economic situation. Our measures of attention are dummy variables indicating whether a respondent refers to a specific topic – such as inflation, monetary policy, or household- or firm-level economic topics. Thus, our premise is that the topics that are top of respondents' minds reflect the allocation of cognitive resources at the time of the survey. Compared to a more structured question format, the key advantage of this open-ended measure is that it does not change participants' attention or restrict which topics are captured through the displayed response options. We validate our attention measure using measures of news consumption, Google Trends data, and a structured survey question.

We include these measures of attention in quarterly panel surveys of German households from a representative online panel and German firms participating in the ifo Business Survey. We fielded the surveys between December 2020 and March 2023, i.e., before and during the historic post-pandemic shock to inflation. Each wave comprises up to 5,000 households and up to 3,500 firms. Although our evidence is purely descriptive, it is based on a period characterized by a changing economic environment, large samples of households and firms, and naturally occurring variation in attention. As such, our data allow us to paint a unique and comprehensive picture of agents' real-world attention allocation to different aspects of their economic situation, as well as its potential drivers and consequences.

We start by presenting a simple model of rational attention choice, in which an agent facing an information constraint decides how much attention to pay to the economy. Despite its simplicity, the model makes several testable predictions. Crucially, attention is "goal-optimal": paying attention allows the agent to form more accurate beliefs. The stylized model shares characteristics and predictions with a wide class of theories of goal-optimal attention (Gabaix, 2019; Maćkowiak et al., 2023; Pfäuti, 2024b; Reis, 2006a; Sims, 2003; Woodford, 2003).

We test the model predictions in two steps. First, we explore the cross-sectional and time variation in attention to different aspects of the economy. Consistent with the model, there is substantial variation in attention to macroeconomic topics both across and within the household and the firm samples. On average, firms are more attentive to aggregate developments than households. Moreover, attention to aggregate variables is strongly persistent at the individual level, with individual fixed effects accounting for approximately 41% and 33% of the total variation in attention to macroeconomic variables in the household and the firm sample, respectively. The individual fixed effects in attention vary positively with measures of agents' exposure to the economy and negatively with a proxy for information costs, confirming core predictions of the model. Also the time variation in attention is systematic: amidst the post-pandemic shock to inflation, both households and firms increase their attention to inflation. In December 2020 – when inflation is close to zero – only 3% of households and 5% of firms are attentive to inflation. By 2022, when annual inflation reaches 10%, up to 38% of households and 43% of firms are attentive to inflation. The model suggests two potential drivers of the increase in attention to inflation: higher and more volatile inflation as well as a reduction of information costs through increased media coverage of inflation.

Second, we zoom in on inflation to examine the relationship between attention and belief formation. Several key predictions of the model are supported in our data: more attentive respondents are more likely to adjust their inflation expectations from one wave to the next – consistent with them being more likely to notice the rapidly changing inflation outlook over our sample period; attention is strongly positively associated with respondents' confidence in their expectations; and more attentive respondents hold smaller misperceptions about realized inflation. However, at odds with the model, attentive agents' expectations about future inflation deviate more strongly upward from the benchmark of professional forecasts than inattentive agents' expectations. This suggests that higher attention is not necessarily associated with more well-calibrated beliefs – i.e., attention may not be goal-optimal. Attentive agents also disagree more about forecasts than about nowcasts, at odds with another model prediction. Lastly, attentive firm managers are more likely to increase product prices, suggesting that the higher inflation expectations of these managers pass through to firm decisions.

Motivated by these empirical findings, we modify our model to allow for interference of selective memory, building on a recent literature on memory and belief formation (Bordalo, Conlon, Gennaioli, Kwon and Shleifer, 2023b; Bordalo et al., 2020, 2025; Kahana, 2012). In the belief formation stage, selective recall distorts how agents use their information when forming forecasts as agents overweight memories that are similar to the current context, as in Gennaioli, Leva, Schoenle and Shleifer (2024). Agents that pay attention to inflation and observe high current inflation recall memories of past inflationary episodes. Because the persistence of inflation is higher during such episodes (Benati, 2008), selective recall leads agents to overestimate future inflation. Hence, attentive agents are likely to deviate upward from the rational benchmark, rendering attention potentially non-goal-optimal. Moreover, as selective memory recall interferes with agents' perceived inflation persistence, disagreement in forecasts increases relative to disagreement in nowcasts. The modified model thus accounts for the two core empirical failures of the baseline model of goal-optimal attention. Selective memory also matters in the attention stage: in our model, higher perceived inflation persistence in inflationary environments due to selective recall increases attention to inflation. Alternatively, this effect could be modeled as operating through categorization of the current environment into an "inflation" category due to the similarity to past inflationary episodes (Bordalo et al., 2025).

The distortions of selective recall should be more pronounced for agents whose memory database contains past experiences of high inflation. We next test this additional prediction empirically. In our data, past experiences of high inflation such as having lived through the 1970s oil crises strongly predict respondents' attention to inflation, even after conditioning on a large set of controls for fundamental features of the decision environment. Moreover, respondents with past inflation experiences increase their attention and their inflation expectations more strongly in response to the inflation shock, leading to stronger upward deviations from expert benchmarks. We thus find support for core predictions of the modified model in our data. These findings also demonstrate that our earlier evidence is robust to exploiting variation in attention due to a shock to the environment interacting with predetermined individual characteristics.

Lastly, we turn to another prediction of the model of selective memory: interference of attention to other topics with agents' inflation expectations. Specifically, our model predicts that, if an agent is attentive to energy prices and observes high current energy prices, she recalls past periods of high energy prices – which tend to be periods of high inflation – and then overestimates future inflation. Our sample period includes a global energy crisis, which was aggravated following Russia's invasion of Ukraine. Consistent with our model, respondents that pay attention to energy prices expect higher inflation and deviate more strongly upwards from professional forecasts. We confirm these results using the interaction of firms' pre-crisis energy cost share and the current level of energy prices as an "attention shifter" to energy prices.

We build on and contribute to a growing empirical literature studying attention to the macroeconomy. Some recent work has used experiments to test predictions of models of goal-optimal attention, e.g., studying the role of perceived uncertainty (Mikosch, Roth, Sarferaz and Wohlfart, 2024) or perceived stake size (Fuster, Perez-Truglia, Wiederholt and Zafar, 2022;

Roth, Settele and Wohlfart, 2022). While these studies offer clean causal evidence on specific mechanisms operating in models of goal-optimal attention, they rely on stylized and relatively narrow measures of attention such as the willingness to pay for a professional forecast.

Other studies have examined the time variation in attention using measures constructed from observational data on beliefs (Bracha and Tang, 2024; Coibion and Gorodnichenko, 2015; Goldstein, 2023; Pfäuti, 2024a,b; Yotzov, Bloom, Bunn, Mizen and Thwaites, 2024), the strength of learning from exogenously provided information (Weber, Candia, Afrouzi, Ropele, Lluberas, Frache, Meyer, Kumar, Gorodnichenko, Georgarakos, Coibion and Kenny, 2025), or Twitter and internet searches (Korenok, Munro and Chen, 2023). These studies detect higher attention in more volatile environments, consistent with standard models of goal-optimal attention. Fewer studies have examined how attention is related to beliefs and decisions. Coibion, Gorodnichenko and Kumar (2018) show that firm managers who report tracking inflation exhibit smaller backcast and forecast errors. Flynn and Sastry (2024) employ textual data from firms' regulatory findings to show that higher firm attention is associated with smaller input-choice mistakes. Song and Stern (2024) use a similar approach to study the role of attention in shaping company performance. Our study differs from previous work in at least three ways: (i) we propose a novel direct measure of attention based on open-ended survey data, (ii) we include this measure in large-scale firm and households panels collected in an environment with a large shock, and (iii) we test theories of goal-optimal attention against an alternative model of selective memory.

While macroeconomists have mostly focused on goal-optimal attention, evidence from behavioral economics suggests that attention can be non-goal-optimal. For instance, Bordalo et al. (2023a) highlight that selective attention to particular aspects of a statistical problem can distort agents' predictions. Hartzmark, Hirshman and Imas (2021) demonstrate that ownership of a good channels attention to associated information, which in turn leads to over-reaction. Our paper provides direct evidence for non-goal-optimal attention in a macroeconomic context.

Finally, our paper contributes to a literature that examines how economic beliefs are shaped by personal experiences (D'Acunto, Malmendier, Ospina and Weber, 2021; Goldfayn-Frank and Wohlfart, 2020; Malmendier and Nagel, 2011) and memory (Afrouzi, Kwon, Landier, Ma and Thesmar, 2023; Bordalo, Burro, Coffman, Gennaioli and Shleifer, 2024; Bordalo et al., 2023a,b, 2020; Butera, Lian, Saccarola and Taubinsky, 2024; Cenzon, 2025; Charles and Sui, 2024; Enke, Schwerter and Zimmermann, 2024; Garcia-Lembergman, Hajdini, Leer, Pedemonte and Schoenle, 2024; Graeber, Zimmermann and Roth, 2024; Jiang, Liu, Peng and Yan, 2024; Salle, Gorodnichenko and Coibion, 2023). In seminal work, Malmendier and Nagel (2016) show that inflation experiences persistently affect households' inflation expectations. Gennaioli et al. (2024) demonstrate that a model of selective recall can quantitatively account for the post-pandemic increase in inflation expectations and reconcile differences between point and distributional beliefs. Bordalo et al. (2024) provide evidence that experiences affect belief formation through the process of mental simulation. Our study takes a joint view and highlights how similarity-based recall of prior experiences shapes both the allocation of attention and the way agents use information they attend to when forming macroeconomic expectations.

2 Data and setting

In this section, we describe the macroeconomic environment during our data collection, our samples, and our attention measure.

2.1 Macroeconomic environment

We collected data from December 2020 to March 2023, covering the time just before and during the post-pandemic inflation surge. The rise of inflation occurred amidst supply-chain disruptions and labor shortages as well as demand-side pressures from loose monetary policy and fiscal stimulus programs. As shown in Appendix Figure A.1, German CPI inflation was -0.3% at the start of our sample period. It started increasing in mid-2021 and accelerated further after Russia's invasion of Ukraine in early 2022, reaching levels of around 10% by the end of 2022 before reverting back. The figure highlights that the surge in inflation was unexpected by households, firms, and also professional forecasters. In response to the increase in inflation, the European Central Bank (ECB) started raising interest rates from the zero lower bound in mid-2022, reaching a level of 3.5% in March 2023. While inflation rose, the aggregate unemployment rate remained fairly stable at values between 5% and 6% from mid-2021.

2.2 Samples

Household panel We conducted quarterly surveys of German households between December 2020 and March 2023 in collaboration with the online panel provider Dynata, which is widely used in the social sciences (Haaland, Roth and Wohlfart, 2023). In each wave, we recontacted all respondents who participated in at least one of the previous waves. We then supplemented the data collection with new respondents to obtain an overall sample size of about 5,000 respondents for each wave. From March 2022 onward, the sample size was lower at around 2,500 respondents.[1] Panels A and B of Appendix Figure A.2 depict the composition of our sample by the wave a respondent entered the panel and by tenure. Attrition is typically highest between the first and the second waves of participation, and more limited thereafter. For instance, among respondents to wave 1, 51% participated in wave 2 and 49% participated in wave 3. Conditional on participating more than once, respondents participated on average 4.6 times.

Panel A of Appendix Table A.1 shows summary statistics of our household sample pooled

[1]We drop partial responses and duplicate responses to any given wave.

across all waves and a comparison with the 2020 wave of the German Socioeconomic Panel (GSOEP), a representative household survey. Our sample is roughly representative of the population in terms of gender, age, region, and household income. The main difference is higher average education in our sample, a common feature in online surveys (Haaland et al., 2023).

Firm panel In parallel to the household surveys, we conducted surveys containing mostly identical questions with firms participating in the ifo Business Survey (IBS), a large and representative monthly panel survey of German firms.[2] Respondents to the online portion of the regular IBS received a separate link to our module in the invitation email to the regular IBS of the last month in each quarter. Roughly half of the invited participants responded to our module, resulting in an overall sample size of approximately 3,000 firms per wave at the start and around 3,500 by the end of the sample period. Panels C and D of Appendix Figure A.2 display the composition of the firm samples for each wave by the first wave a firm participated and by tenure in the panel. Attrition rates are lower than for households. For instance, of those who responded to wave 1 of the firm survey, 73.2% also participated in wave 2 and 72.8% participated in wave 3. Conditional on participating more than once, respondents participated on average 7.0 times.

Panel B of Appendix Table A.1 shows summary statistics for the firms who completed our survey. 29% of the firms operate in manufacturing, 41% in services industries, and 8% in construction, and 22% are retailers or wholesalers. The median number of employees is 40 and the average share of exports in the firms' revenue is 15%. In wave 3, we asked respondents about their influence on the firm's decisions regarding investment, production, personnel, and price setting. 78% of managers report having "very high influence" in at least one of these areas. This is in line with Sauer et al. (2023), who document that the vast majority of respondents to the regular IBS are in an upper management position such as owner, CEO, or department head.

2.3 Measuring attention

Measurement We think of attention as the *allocation of cognitive resources across different domains* (Gabaix, 2019; Loewenstein and Wojtowicz, 2025). In macroeconomics, attention is often modeled as the frequency at which agents acquire information (Mankiw and Reis, 2002; Reis, 2006a,b) or as the amount of effort exerted when processing information (Maćkowiak and Wiederholt, 2009; Mankiw and Reis, 2002; Sims, 2003). Our definition is broad and agnostic about the exact margins through which attention matters. We focus on attention to *economic* topics, including aggregate topics such as inflation, economic growth, or monetary policy, but also household- or firm-level topics such as the personal job situation or investment projects.

[2]The IBS is the basis of the ifo Business Climate Index, the most recognized leading indicator of the German business cycle. See Sauer, Schasching and Wohlrabe (2023) for details on the IBS. The IBS micro data have been used extensively in previous research in economics (e.g., Bachmann, Born, Elstner and Grimme, 2019; Bachmann, Carstensen, Lautenbacher and Schneider, 2021; Bachmann, Elstner and Sims, 2013; Born, Enders, Menkhoff, Müller and Niemann, 2025; Buchheim, Dovern, Krolage and Link, 2022; Enders, Hünnekes and Müller, 2019).

A key challenge in designing an attention measure is that the measurement itself should ideally not change agents' attention allocation. For instance, the measurement should not prime individuals on a specific topic – say, inflation – and thereby change the allocation of respondents' cognitive resources. We address this challenge using an open-ended question format that allows survey participants to provide written responses – a method that has recently become more commonly used in economics (Andre, Haaland, Roth, Wiederholt and Wohlfart, 2025; Bordalo et al., 2023a; Stantcheva, 2021).[3] To elicit attention allocation across different *economic* topics, we require a prompt that puts survey respondents into the mindset relevant for their economic decision-making. Specifically, we ask our respondents the following question:

> *What topics come to mind when you think about the economic situation of your household/company?*

The written text responses to this question provide a unique snapshot of respondents' attention allocation in the sense of *which topics are top of mind*. Our premise is thus that the topics that are top of mind reflect the allocation of cognitive resources at the time of the survey. Depending on respondents' attention allocation, we would expect them to think of either aggregate or more household- or firm-specific economic topics when being confronted with the prompt.

Although our prompt may still influence respondents' attention allocation, it is broad, relatively neutral, and avoids priming on specific macroeconomic or household-/firm-level topics. Compared to a more structured format, our open-ended elicitation does not influence or restrict participants' responses through the displayed response options. Overall, our open-ended elicitation minimizes concerns that the measurement itself changes respondents' attention.

We count a survey response as being attentive to a specific topic if that topic is mentioned in the open-ended question. While responses are classified as attentive or inattentive to a given issue, it is important to keep in mind that the measures contain noise, e.g., due to differences in the interpretation of the prompt or in the extent to which a respondent is explicit about the topics that are top of mind (Haaland et al., 2024). Moreover, respondents may only write about the issues they pay most attention to while neglecting other issues they pay some attention to. Thus, while there will be a *difference in the average level of attention* between responses being classified as attentive or inattentive to a given topic according to our measure, it would be misleading to interpret this as *full attention* and *complete inattention*.

The surveys include additional questions, which we introduce when discussing the related exercises. Appendix E provides the original and translated instructions of key survey questions.

Coding scheme To analyze the unstructured text data, we devise a coding scheme that contains codes for a range of macroeconomic and household- or firm-level topics. Each response can receive multiple codes. Table 1 displays the main factors in our scheme along with example

[3] See Haaland, Roth, Stantcheva and Wohlfart (2024) for a methods review on open-ended survey data.

responses, while Appendix B provides the complete list of codes for macroeconomic, household-level, and firm-level topics along with the explanations contained in our original coding manual. Our main codes of interest capture four macroeconomic topics: the Covid-19 pandemic, inflation, interest rates or monetary policy, and economic growth. We also define variables that aggregate all macroeconomic or all household- or firm-level codes contained in our scheme ("Any macro topic", "Any household-level topic" and "Any firm-level topic", respectively).

We instruct research assistants to apply the coding scheme to the text responses. All coders are either Bachelor's or Master's students in economics. 85.5% of the open-text responses from the household survey and 97.3% of firm managers' responses can be assigned at least one code from our scheme. For a subset of the data (1,896 responses from waves 3 to 6 of the household survey and 1,540 responses from waves 1 to 5 of the firm survey), two research assistants code the responses independently of each other, and conflicts are resolved through discussion between the reviewers. We detect a high inter-rater reliability: when one coder assigns a given code to a household's response, there is a 79.0% chance that the other coder does so too. The corresponding number is 79.4% for the firm survey. The inter-rater reliability increases to 91.3% for households and to 87.9% for firms when calculating it based on the subset of topics that most of our analysis focuses on, namely Covid-19, inflation, monetary policy, and economic growth.

To further check the quality of the hand-coding, we conduct two additional exercises. First, Appendix Table A.2 shows for the case of inflation that our hand-coded data are strongly positively correlated with simple counts of inflation-related words, both in the pooled sample and within each wave. Second, we use a large language model to code a subset of the responses from the March 2023 household wave.[4] Appendix Figure A.3 compares the topic distribution between the hand-coded and the AI-coded data, while Appendix Table A.3 displays cross-sectional correlations between hand-coded and AI-coded measures for key topics. Both exercises demonstrate a high degree of agreement between the two methods. Overall, these patterns suggest that the hand-coded data capture the content of the open-ended responses well.

Validation 1: News consumption We validate the open-ended data in various ways. We start by correlating attention as measured in the open-ended question with measures of news consumption included in some survey waves. First, referring to inflation in the open-ended question is strongly positively related to the number of reports on inflation a respondent has read in the news, seen on TV, or heard on the radio over the last three months, among both households and firms (Appendix Figure A.4 Panels A and C). Second, it is strongly positively correlated with the number of minutes a household or firm manager has spent consuming news

[4]We use Scikit-LLM's zero-shot multi-label classifier with GPT-4 as the underlying AI-model (Pedregosa, Varoquaux, Gramfort, Michel, Thirion, Grisel, Blondel, Prettenhofer, Weiss, Dubourg et al., 2011) and focus on a random subsample ($n = 200$) from the March 2023 wave. The codes are reformulated into whole sentences, as recommended by the Scikit-LLM guidelines, using exclusively information provided in the coding scheme handed to the research assistants who initially hand-coded the responses. The codes assigned by the multi-label classifier (per default, no more than ten per response) are then compared to the codes assigned in the hand-coding.

Table 1: Coding scheme and example responses for the open-ended data

Category	Explanation	Examples
Any macro	Covid-19, inflation, monetary policy, growth, labor market, stock market, housing market, fiscal policy, regulation, structural transformation, trade, pension system, health system, education system, inequality, migration, environment/climate change, uncertainty, other macro topics.	"Taxes"; "The labor market"; "Politics is increasingly burdening me through levies and taxes, and through regulations on the industry, which in the end also affect me again through rising consumer prices"; "The war in Ukraine and the inflation."; "Debt crisis, financial crisis, economic upswing."; "I am afraid of the effects of the war."; "Firstly, climate change and, as a result of it, the energy crisis, which of course is also extremely intensified due to the war in Ukraine. And of course, like everyone else, we are also affected by inflation."
Covid-19	Covid, corona, pandemic, lockdown.	"Due to Corona, I have been on short-time work for a year already. Therefore, my financial situation doesn't look too rosy. The government urgently needs to take action here."; "Tense due to Covid-19"; "Income has been halved since Corona"
Inflation	Inflation, rising prices, price level, price increase, purchasing power, gas prices, electricity prices.	"Rising food prices"; "Difficult times and skyrocketing prices"; "Inflation rate and the monetary value of one's own savings"; "Currently the very high inflation rate"; "Price increase in food, higher energy costs, saving not possible"; "Electricity has become very expensive."
Monetary policy	Interest rates, monetary policy, central bank, ECB, negative interest rate.	"Interest rates and investment"; "Low interest rates"; "No interest on assets, uncertainty in stock investment."; "Pension adjustments, interest rates, DAX."; "That credit interest rates are becoming increasingly expensive and prices are rising. Hopefully, there will be a salary increase soon."
Growth	Economic growth, GDP, general economic situation, aggregate economy, business cycle, upswing, downturn, insolvencies, company bankruptcies, aggregate demand, overall industrial production, economic crisis, recession.	"Recession, Economic Crisis"; "The faltering economy and rising inflation"; "One economic crisis after another is eroding my retirement savings, so that I will soon become a welfare case."; "The economic situation in Germany is stable, in my eyes."; "Economic crisis. High prices for food and energy."
Any household-level	Overall household situation, spending, income, job situation, saving, financial assets, housing costs, debt, health issues, insurance, uncertainty, other household-level topics.	"Concern about job loss in the future."; "We are doing well. No debt. A vacation is possible."; "Relatively secure, due to fixed income from pension"; "old-age poverty"; "I'm just barely making ends meet with my money."; "The economic situation is bad, with only one earner with a low pension among two adults."; "We are getting along well and don't have to cut back. In addition to everyday expenses, there is also enough money left over for vacation and leisure activities."
Any firm-level	Overall firm situation, costs, supply chain, demand, labor input, profits/profitability, liquidity/solvency, process organization, government aid programs, R&D, regulation, financing, short-time work, capacity utilization, rent/housing costs, uncertainty, other firm-level topics.	"Automation + process optimization"; "Sustainability, innovation, product life cycles"; "increasing material and energy costs, personnel costs, parts supply"; "Liquidity bottlenecks, difficult storage, dissatisfaction with the banks"; "How do I get specialized staff, especially mathematicians and computer scientists?"; "There is hardly any suitable skilled personnel, investment backlog and tough competition"; "Investment in digitization and expansion of our product portfolio."

Notes: This table provides an overview of the main topics in our coding scheme, an explanation for each code, and example extracts from open-text responses (translated into English). All example responses – except for the firm-level categories – draw on the household survey. For the codes "Covid-19", "Inflation", "Monetary policy", and "Growth", the explanations correspond to the instructions in the coding manual handed out to research assistants. For "Any macro", "Any household-level", and "Any firm-level", the explanations include all codes in the coding scheme that are subsumed under these aggregate categories. The complete coding scheme handed out to research assistants can be found in Appendix B.

about inflation over the last week (Panels B and D). These patterns validate the open-ended data and motivate their use to study the predictions of macroeconomic models in which attention and information acquisition are closely linked (Maćkowiak et al., 2023).

Validation 2: Google Trends We next turn to Google Trends data, which is commonly used in the social sciences to measure attention (Choi and Varian, 2012; Fetzer, Hensel, Hermle and Roth, 2021). Specifically, we compare the evolution of our survey measure of attention to different macro variables over time with the evolution of Google searches. We focus on inflation, growth, and monetary policy. We do not include Covid-19, as Google searches about this topic are likely primarily driven by health concerns rather than economic motives. Appendix Figure A.5 shows that the evolution of Google searches over our sample period and the distribution of searches across the different topics closely resemble the patterns for our survey measures.

Validation 3: Structured attention measure As a final validation, we compare our open-ended measurement with measurement based on a structured survey question included in an additional data collection with German households. The survey was conducted in September 2023 on the platform Prolific, which is widely used in the social sciences (Peer, Rothschild, Gordon, Evernden and Damer, 2021). Out of the 502 respondents who completed our survey, we drop 34 who fail to pass a simple screener question.

Participants first respond to our main open-ended question. On the next screen, they are again asked which topics come to their mind when thinking about the economic situation of their household. However, instead of writing their response into a text box, they now select all relevant topics from a list presented to them, where the order of the topics is randomized. Compared to the open-ended elicitation, the structured elicitation mitigates the concern that respondents may be hesitant or unable to articulate their thoughts. At the same time, the structured elicitation mechanically changes attention by exposing respondents to the included response options. Appendix F provides the instructions in German and translated to English.

As shown in Appendix Figure A.6, the baseline fractions of respondents indicating attention to different aggregate and household-level topics are higher in the structured measure across all topics, which is a common finding when comparing structured and open-ended elicitations (see, e.g., Andre, Pizzinelli, Roth and Wohlfart, 2022). This pattern may indicate a lower effort cost of indicating that a particular topic matters as well as mechanical increases in attention driven by the displayed response options. However, given these baseline differences, the variation of attention across topics appears very similar in the two elicitation modes. In the cross-section, attention as measured by the open-ended question is highly correlated with attention as measured by the structured question for most of the key topics analyzed below (Appendix Table A.4).

Survey participation and attention After the initial question on attention allocation, each wave of our panel survey includes several questions on macroeconomic issues. Recontacted respondents may recall the survey topic and therefore express more thoughts about macroeconomic topics in the question on attention allocation. To check whether this is the case, we regress dummy variables indicating attention to a given topic on a dummy variable indicating whether the response is from a recontacted participant, time fixed effects and individual fixed effects. As shown in Appendix Table A.5, repeated participation is not associated with a systematic increase in attention to aggregate topics, neither among households nor among firms.

3 A model of goal-optimal attention

We now present a simple theoretical framework of attention and belief formation. The model is a highly stylized and standard model of rational inattention and shares its predictions with a wide class of theories of goal-optimal attention (Gabaix, 2019; Maćkowiak and Wiederholt, 2015; Pfäuti, 2024a,b; Reis, 2006a; Sims, 2003; Woodford, 2003). We subsequently test these predictions in our data. Attention in the model is "goal-optimal" in the sense that higher attention allows the agent to form more accurate beliefs, and this benefit is rationally traded-off against the cost of paying attention. In Section 5, we present a model which introduces interference of selective memory recall, and highlight the potential distortions of "non-goal optimal" attention.

For exposition and because much of our empirical analysis focuses on inflation, we frame our model as one of inflation expectations, but it can be viewed and applied more broadly. For simplicity, we focus on the case in which the agent chooses her attention to a single variable, but the model can be easily extended to allow for multiple variables.

In our model, the agent chooses how attentive to inflation she wants to be. Inflation follows an AR(1) process such that inflation in the next period, π', depends on inflation today, π, as follows:

$$\pi' = \rho_\pi \pi + \nu, \tag{1}$$

where $\nu \sim i.i.N.(0, \sigma_\nu^2)$, and $\rho_\pi \in [0,1]$ is the persistence of inflation. Without loss of generality, we set the mean to 0 for notational simplicity.

Inflation in the current period is unobservable, so before forming an expectation about future inflation, the agent needs to form an expectation about today's inflation. Let us denote this nowcast by $\widetilde{\pi}$. Given the law of motion (1), the full-information forecast is given by $\pi^{e*} \equiv \rho_\pi \pi$. Deviations from π^{e*} are costly and the agent acquires information to minimize these deviations.

The loss from these deviations $L(.)$ is assumed to be quadratic:

$$L(\pi^e, \pi) = \frac{B}{2} \left(\rho_\pi \pi - \pi^e\right)^2,$$

where B captures the stakes of making a mistake – i.e., the agent's exposure to inflation – and π^e is the agent's inflation forecast. In particular, agents that are more exposed to inflation have a higher B as forecast errors are more costly for these agents. $L(\cdot)$ can be microfounded by taking a second-order approximation of the agent's utility function (or profit function, for firms) so that B depends on the underlying parameters (see, e.g., Maćkowiak and Wiederholt, 2009).

The agent wants to minimize $L(\cdot)$ but faces a cost of information acquisition and processing. As it is standard in the rational inattention literature, we assume that this cost function $C(f)$ is linear in mutual information $I(\pi;\pi^e)$, i.e., the expected reduction in entropy of π due to knowledge of π^e is

$$C(f) = \kappa I(\pi;\pi^e) = \kappa \left(H(\pi) - E\left[H(\pi|\pi^e)\right]\right),$$

where $H(x) = -\int f(x) log(f(x))dx$ is the entropy of x and κ is the cost of information. The agent's prior $g(\pi)$ is Gaussian; $\pi \sim N\left(\widehat{\pi}, \sigma_\pi^2\right)$. For simplicity, we assume the prior mean $\widehat{\pi}$ to be 0. We think of the cost parameter κ as capturing the agent's cognitive capacity as well as other factors shaping the cost of information acquisition and processing, such as news coverage. If news coverage of inflation is high, κ may be lower as it requires less effort to acquire (and process) information about inflation.

The agent chooses the form of the signal s she receives about current inflation in order to minimize $L(\cdot)$ subject to the cognitive cost.[5] In this setup, Gaussian signals are optimal (Matějka and McKay, 2015) and take the form

$$s = \pi + \varepsilon,$$

with $\varepsilon \sim i.i.N.(0, \sigma_\varepsilon^2)$. Using this in the agent's optimization problem, the attention choice follows from

$$\max_{\sigma_{\pi|s}^2 \leq \sigma_\pi^2} E_\pi \left[E_s \left[-\frac{B}{2} \rho_\pi^2 \left(\pi - E[\pi|s]\right)^2 \right] \right] - \kappa I(\pi;\pi^e) = \max_{\sigma_{\pi|s}^2 \leq \sigma_\pi^2} \left(-\frac{B}{2} \rho_\pi^2 \sigma_{\pi|s}^2 - \frac{\kappa}{2} \log \frac{\sigma_\pi^2}{\sigma_{\pi|s}^2} \right). \quad (2)$$

The optimal nowcast is given by

$$\widetilde{\pi} = E\left[\pi|s\right] = \gamma_\pi \cdot s \quad (3)$$

where $\gamma_\pi = 1 - \frac{\sigma_{\pi|s}^2}{\sigma_\pi^2} \in [0,1]$ is the agent's attention to inflation. Bayesian updating implies that a rationally inattentive agent's forecast is given by $\mathbb{E}[\pi'|s] = \rho_\pi \gamma_\pi s$. When the agent is inattentive, she obtains relatively noisy signals and, thus, puts little weight on these signals in her nowcasts and forecasts, reflected in a small γ_π. If the agent is completely inattentive, $\gamma_\pi = 0$, she does not update her beliefs at all as new information arrives. Hence, attentive agents update their beliefs more strongly and/or more frequently in an environment of new signals, such as our study period. Everything else equal, a more attentive agent should be better at predicting current and future inflation – i.e., attention is goal-optimal. Of course, there could always be unexpected shocks that move inflation and induce forecast errors ex-post. In our empirical exercise we therefore focus on an ex-ante benchmark when assessing forecast accuracy.

[5] Since acquiring information is costly, it cannot be optimal to acquire multiple signals that lead to an identical forecast. Due to this one-to-one relation of signal and forecast, we can directly work with the joint distribution of π^e and π, $f(\pi^e, \pi)$, instead of working with the signal.

Solving for the optimal level of attention yields

$$\gamma_\pi = max\left\{0, 1 - \frac{\kappa}{B\rho_\pi^2\sigma_\pi^2}\right\}. \tag{4}$$

Hence, there is systematic heterogeneity in attention: agents with higher exposure to inflation B should be more attentive to inflation; by contrast, agents facing a higher cost of information acquisition and processing κ should pay less attention. The model further predicts that agents are more attentive in times of volatile inflation, reflected in a higher prior uncertainty σ_π.

The model also makes predictions about agents' confidence as captured by their posterior uncertainty about inflation. Posterior uncertainty is given by $Var(\pi'|s) = \rho_\pi^2 Var(\pi|s) + \sigma_v^2$, where $Var(\pi|s) = \frac{\kappa}{B\rho_\pi^2}$. So posterior uncertainty for attentive agents (denoted by superscript A) is lower than for inattentive agents (denoted by IA) if

$$\begin{aligned} &\rho_\pi^2 Var^A(\pi|s) < \rho_\pi^2 Var^{IA}(\pi|s) \\ \Leftrightarrow \quad &1 < \frac{\kappa^{IA}}{\kappa^A} \cdot \frac{B^A}{B^{IA}}. \end{aligned} \tag{5}$$

Inequality (5) illustrates that attentive agents exhibit less posterior uncertainty, i.e., they are more confident in their forecasts, if their cost of information relative to the stakes $\frac{\kappa^A}{B^A}$ is lower than that of inattentive agents. This condition is usually fulfilled if agents are more attentive, unless they are more attentive solely due to higher prior uncertainty.

The final model prediction concerns disagreement across agents. While there is no clear prediction whether attentive or inattentive agents disagree more, the model predicts that, among attentive agents, i.e., $\gamma_\pi > 0$, disagreement about nowcasts should be weakly larger than disagreement about forecasts. To illustrate this, consider two agents with nowcasts at the 25th and the 75th percentile, respectively. Their disagreement, measured as the absolute distance between the two, about nowcasts is given by $|\gamma_{\pi,1}s_1 - \gamma_{\pi,2}s_2|$, which is weakly larger than their disagreement about forecasts, $|\rho_\pi||\gamma_{\pi,1}s_1 - \gamma_{\pi,2}s_2| \leq |\gamma_{\pi,1}s_1 - \gamma_{\pi,2}s_2|$, simply because $|\rho_\pi| \leq 1$.[6] The same is true for other measures of disagreement, such as the standard deviation of beliefs.

Taken together, the model makes the following testable predictions:

1. **Variation in attention:** There is systematic heterogeneity in attention, with agents being more attentive (i) if they perceive a higher degree of exposure to the variable in question, (ii) if they face lower information costs (e.g., due to higher news coverage), or (iii) if the variable to be forecast is more volatile.

[6]While this clear-cut result arises because inflation is assumed to follow an AR(1) process – which is a standard assumption in the literature and supported by empirical evidence (Canova, 2007; Faust and Wright, 2013) – the result captures a more general idea. Namely, agents acquire information about the current state of the economy and use that information to formulate their forecasts. Hence, they put less weight on that information in their forecasts than in their nowcasts, leading to less disagreement about the future than about the present.

2. **Attention and beliefs:** Attentive agents are more likely to adjust their expectations when there are changes in the environment, are more confident in their beliefs, and make more accurate nowcasts and (ex-ante) more accurate forecasts. Attentive agents disagree (weakly) more about nowcasts than about forecasts.

4 Testing theories of goal-optimal attention

In this section, we describe the cross-sectional and time variation in attention and the relation between attention and beliefs in our data. Throughout, we test the predictions of theories of goal-optimal attention as outlined in Section 3.

4.1 Cross-sectional and time variation in attention

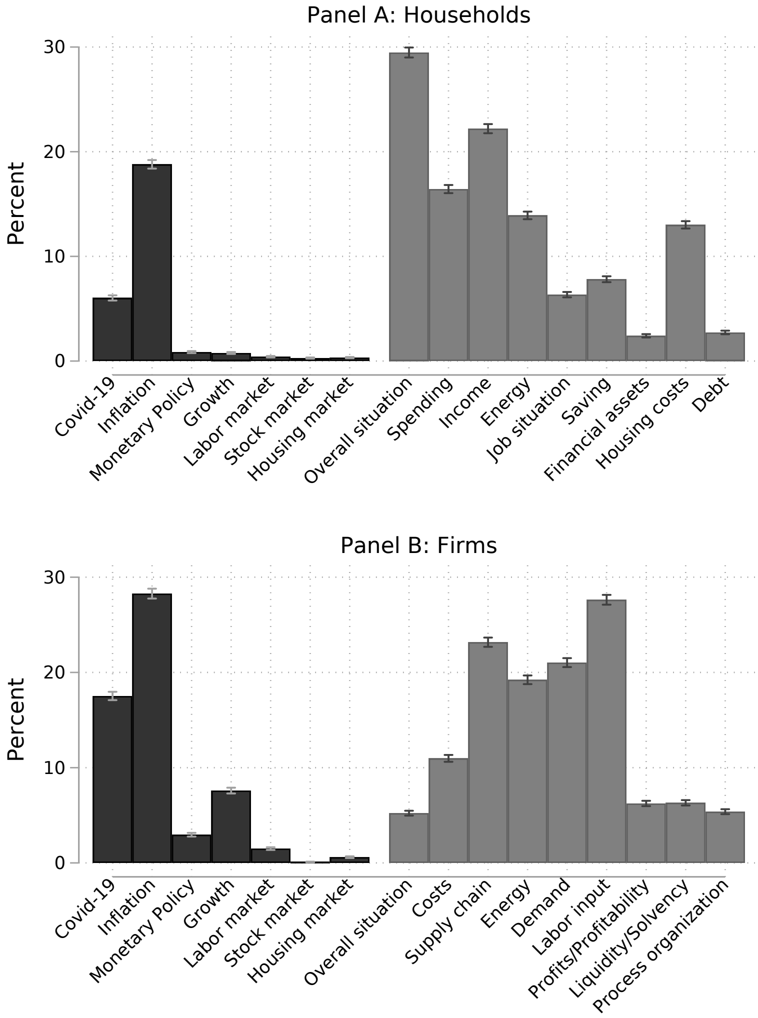
Attention allocation across topics and types of agents We start by describing how the attention of households and firms varies across different topics, pooling all our survey waves. 75% of households pay attention to at least one household-level topic, while 28% are attentive to at least one macroeconomic topic. Panel A of Figure 1 shows that inflation is the macroeconomic topic that is most frequently attended to by households (19%), followed by Covid-19 (6%). Households' attention to growth and monetary policy is very low at 1% for each. Within household-level topics, the household's overall economic situation (30%), income (22%), consumption/spending (16%), energy (14%) and housing costs (13%) are most important.

Among firm managers, 80% mention at least one firm-specific topic. A similarly high fraction (67%) pay attention to at least one macroeconomic topic. Panel B of Figure 1 shows that, within macro topics, firms pay most attention to inflation (28%), followed by Covid-19 (17%), growth (8%), and monetary policy (3%). The overall higher levels of attention to macroeconomic topics among firms than among households are consistent with recent evidence on differences in information frictions across the two types of agents (Link, Peichl, Roth and Wohlfart, 2023). Through the lens of the model in Section 3, this difference could reflect a greater exposure to macroeconomic fluctuations or lower information costs among firms. Within firm-specific topics, issues regarding labor input (28%), supply chains (23%), and demand for a firm's own product/service (21%) are the most frequently mentioned topics.

Variance decomposition Theories of goal-optimal attention predict systematic heterogeneity in attention across agents and over time. How much of the empirical variation in attention is explained by persistent individual-level heterogeneity and how much by changes in the macroeconomic environment?[7] To see this, we regress our main measures of attention on

[7] We use the term "individual" for both households and firms, abstracting from the fact that different waves of the firm survey can potentially be answered by different persons working at the same firm. In practice, the

Figure 1: Attention allocation across topics



Notes: This figure presents the distribution of attention to different macroeconomic topics (black) and household-/firm-level topics (gray) pooled across all waves from December 2020 to March 2023. The bars indicate the fractions of respondents paying attention to a given topic. The measure of attention is based on people's responses to our main open-ended question: *"What topics come to mind when you think about the economic situation of your company/household?"* Panel A shows results for households. Panel B displays results for firms.

(i) individual fixed effects only, (ii) time fixed effects only, and (iii) both sets of fixed effects jointly, and compare the R-squared of these regressions (see Giglio, Maggiori, Stroebel and Utkus, 2021, for such a decomposition in the context of stock return expectations). We focus on dummy variables indicating attention to specific macroeconomic topics and dummy variables for paying attention to at least one macro or to at least one household- or firm-level topic.

The results are shown in Table 2. Panel A is based on the samples of respondents that appear at least twice in our data, i.e., the largest possible samples for this exercise. Individual fixed effects are an important source of variation in attention in the household sample. Across topics, the individual fixed effects by themselves explain between 25% and 44% of the variation in

questionnaires are usually filled out by the same person and churn rates are very low (Sauer et al., 2023).

Table 2: Variance decomposition of attention allocation

	Households R^2 (%) of panel regression				Firms R^2 (%) of panel regression			
	(1) Indiv. FE	(2) Time FE	(3) Time FE + Indiv. FE	(4) Obs.	(5) Indiv. FE	(6) Time FE	(7) Time FE + Indiv. FE	(8) Obs.
Panel A: At least two non-missing observations								
Any macro topic	41.1	3.2	43.3	31,347	33.0	0.7	33.6	27,548
Inflation	38.1	10.1	44.8	31,347	31.8	8.0	38.7	27,548
Monetary policy	27.9	0.0	28.0	31,347	34.3	0.7	35.0	27,548
Growth	25.2	0.1	25.3	31,347	27.4	0.5	27.8	27,548
Covid-19	37.9	2.7	39.6	31,347	32.2	10.5	41.1	27,548
Any household-/firm-level topic	44.1	0.7	44.6	31,347	29.7	0.7	30.3	27,548
Panel B: At least four non-missing observations								
Any macro topic	37.1	3.3	39.7	24,076	30.2	0.8	31.0	23,833
Inflation	34.0	9.8	41.6	24,076	29.0	8.2	36.5	23,833
Monetary policy	24.2	0.1	24.3	24,076	31.7	0.6	32.4	23,833
Growth	20.3	0.1	20.4	24,076	24.1	0.5	24.5	23,833
Covid-19	31.2	2.7	33.2	24,076	28.8	10.4	38.4	23,833
Any household-/firm-level topic	39.4	0.8	40.0	24,076	26.1	0.6	26.6	23,833
Panel C: At least six non-missing observations								
Any macro topic	34.6	3.6	37.8	15,303	28.6	0.8	29.4	19,079
Inflation	30.9	9.9	39.7	15,303	26.5	8.9	35.0	19,079
Monetary policy	21.6	0.1	21.7	15,303	30.7	0.7	31.4	19,079
Growth	16.2	0.1	16.3	15,303	21.1	0.5	21.5	19,079
Covid-19	27.6	2.9	30.1	15,303	27.0	10.5	37.1	19,079
Any household-/firm-level topic	36.5	0.8	37.2	15,303	24.1	0.6	24.7	19,079

Notes: This table displays the R-squared from regressing dummies for mentioning different topics in the response to the open-ended question on individual fixed effects (Columns 1 and 5), time fixed effects (Columns 2 and 6), and both time and individual fixed effects (Columns 3 and 7). Columns 4 and 8 display the number of observations. For each variable, only respondents with at least two (Panel A), four (Panel B), and six non-missing observations (Panel C) for the corresponding variable are included, respectively.

attention (Column 1), while time fixed effects by themselves account for at most 10% of the variation in attention to a given topic (Column 2). Systematic time variation is most important for attention to inflation. Including individual and time fixed effects together leaves between 55% and 75% of the variation in attention to a given topic unexplained (Column 3). This variation reflects idiosyncratic time variation at the household level. Similarly to the patterns for households, individual fixed effects are a central source of variation in attention among firms (Column 5). The importance of time fixed effects among firms mirrors that among households, the only difference being stronger systematic time variation in attention to Covid-19 (Column 6). Between 59% and 72% of the variation in attention is idiosyncratic time-variation at the firm-level (Column 7). Panels B and C restrict the samples to households or firms that appear at least four or six times in our panels, leaving the results very similar. We next explore the systematic cross-sectional and time variation in attention to the macroeconomy in more detail.

Cross-sectional variation in attention Is the variation of attention to the economy across agents consistent with the predictions of theories of goal-optimal attention? We explore this by studying the covariates of the individual fixed effects in attention to different topics.

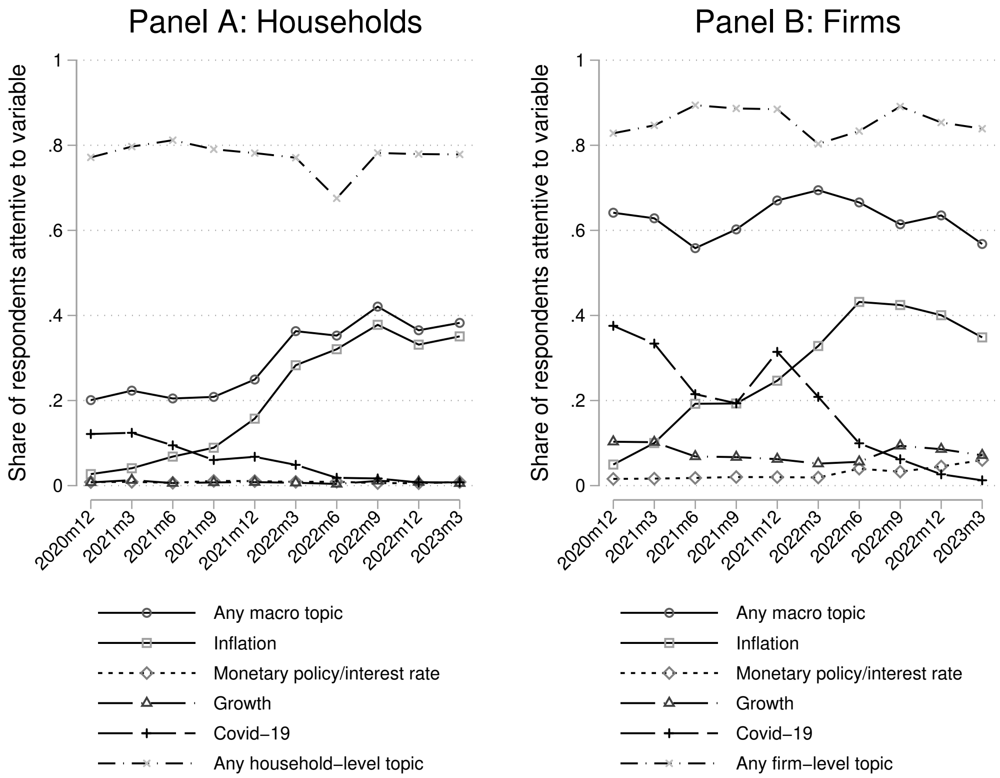
To proxy economic exposure to different variables, we employ structured survey questions that ask respondents to rate on five-point scales how much their household's (or their firm's) economic situation, in general, depends on the development of a given variable, such as inflation or economic growth. To account for potential time-variation in average exposure, we first purge these measures of survey wave fixed effects. Then, we calculate the respondent-specific average response across all waves in which the respondent participates and this question is included, and define dummies indicating above-average exposure. For households, we also use a measure of information acquisition costs: in the September 2021 wave, respondents indicate on a five-point categorical scale their perceived difficulty of obtaining macroeconomic information, which we recode into a dummy indicating below-average perceived difficulty.

We regress the individual fixed effects in attention to a given variable obtained from the variance decomposition on these measures of perceived exposure and information costs as well as a set of demographics. The results for the household sample are shown in Appendix Table A.6. As highlighted in Column 1, high perceived exposure to inflation increases the likelihood that a household respondent attends to inflation by 9.8 p.p ($p < 0.01$), while facing low information acquisition costs increases attention to inflation by 3.0 p.p. ($p < 0.01$). These effects appear sizable given an overall fraction of 19% attending to inflation. Columns 2–4 highlight that the associations of perceived exposure and information acquisition costs with attention extend to monetary policy, growth, as well as macroeconomic topics more broadly. Among the background variables, older and more educated respondents are more likely to pay attention to macroeconomic topics, while the patterns by employment status and income are less systematic. Appendix Table A.7 shows the results for the firm sample. We find similar patterns for economic exposure as for households.[8] Among the background variables, firm size is positively associated with attention to macroeconomic topics. Moreover, attention to inflation is more pronounced in the manufacturing sector than in the services and retail/wholesale sectors. Overall, the variation of attention with perceived exposure and information costs is consistent with theories of goal-optimal attention such as the model described in Section 3, and in line with studies using more stylized attention measures (Mikosch et al., 2024; Roth et al., 2022).

Time variation in attention We next turn to how attention evolves over time. According to Panel A of Figure 2, households' attention to Covid-19 decreases almost monotonically throughout the sample period. Meanwhile, the fraction of households paying attention to inflation rises from close to 0% in December 2020 to 38% in September 2022, and then remains at this elevated level. Panel B of Figure 2 shows broadly similar changes in attention over time for firms and households: while attention to Covid-19 declines, attention to inflation steadily increases from close to 0% in December 2020 to a maximum of 43% in June 2022. Subsequently, attention to inflation slightly declines until the end of the sample period. Monetary policy receives little attention from both firms and households throughout the period.

[8]We have no measures of information acquisition costs for the firm sample.

Figure 2: Attention to different topics over time



Notes: This figure displays the evolution of the fractions of respondents that raise different topics in the open-ended survey question among households (Panel A) and firms (Panel B) across survey waves. The "Any macro topic" and "Any household-/firm-level topic" summarize all household-/firm-level topics and all topics related to the macroeconomy, respectively. The remaining lines refer to specific macroeconomic topics, i.e., inflation, monetary policy/interest rates, growth, and Covid-19.

These changes in attention mirror the business cycle movements in Germany shown in Appendix Figure A.1: while the economy recovered from the coronavirus recession, it experienced increasing inflationary pressures starting in mid-2021, which were aggravated by Russia's invasion of Ukraine in February 2022 and the associated energy shortages. Through the lens of theories of goal-optimal attention, the increase in attention to inflation over our sample period could reflect both higher inflation volatility and increased news coverage of inflation, effectively reducing information costs. Remarkably, the ECB's sharp rate hikes from 0% to 3.5% were not associated with strong increases in households' or firms' attention to monetary policy.

Summary Taken together, our first empirical result can be summarized as follows:

Result 1.

(a) Households' and firms' attention varies strongly across topics, with attention being highest for household- and firm-level topics. Attention to macroeconomic topics is dominated by attention to Covid-19 and inflation and is higher among firms than among households.

(b) Attention varies systematically across agents and over time in a way that is consistent with theories of goal-optimal attention: (i) it increases in economic exposure, (ii) it decreases in information costs, and (iii) it is higher when the variable to be forecast is more volatile and covered more extensively in the news.

In Appendix D.1 we present additional evidence on the joint variation of attention across topics, including attentional crowding-out.

4.2 Attention and beliefs

We next turn to the relationship between attention and beliefs. We focus on inflation, for which there is a major shift in the environment during our sample period and for which we observe strong cross-sectional and time variation in attention. Moreover, expected inflation is key to both households' and firms' decision-making in canonical macro models. While our exercise is purely correlational, it allows us to study whether the basic predictions of theories of goal-optimal attention, as highlighted in Section 3, are consistent with the data.

Belief data The analyses in this section heavily use data on respondents' beliefs. In each survey wave, we elicit respondents' expectations about the inflation rate over the next 12 months, as well as their confidence in these expectations on a five-point categorical scale. We winsorize inflation expectations at 30% to reduce the impact of outliers.[9] None of our findings are sensitive to the exact choice of the cutoff or to whether we set to missing extreme observations instead. Median inflation expectations in our firm and household samples closely track median inflation expectations from representative firm and household surveys conducted by the Bundesbank (Appendix Figure A.7), suggesting that our expectations data are of high quality.

Updating, confidence and deviations from benchmarks We first analyze differences in beliefs between attentive and inattentive households. In particular, we regress different measures of the respondents' beliefs about inflation on a dummy variable for being attentive to inflation as well as a set of control variables and time fixed effects.[10]

Models of goal-optimal attention posit that more attentive agents adjust their expectations more quickly when signals change. During our sample period, which covers an unexpected surge in inflation, attentive households are indeed 2.1 p.p. more likely to change their expectations about 12-month-ahead inflation from one survey wave to the next by at least 0.5 p.p., compared to an overall fraction of 79% reporting such changes in beliefs (Table 3 Panel A Column 1, $p < 0.01$). Another prediction of these models is that higher attention is associated with reduced

[9]Our data contain no negative outliers for expected inflation.

[10]Specifically, we control for gender, age, education, employment status, income, homeownership, and stock ownership in the household sample, which are mostly elicited in the first wave a household participates in the panel. In the firm sample, we control for firms' number of employees (in logs) and export share, dummies for broad industry group, and a dummy taking value one if the respondent reports having "very high" influence on the firm's decisions regarding investment, production, personnel, or price setting, which is elicited in survey wave 3.

Table 3: Attention and beliefs: Cross-sectional correlations

	Absolute change in expectation ≥ 0.5 p.p.	Confidence (z)	Expected inflation	Absolute deviation from expert forecast	Perceived current inflation	Absolute deviation from current level
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Households						
Attention to inflation	0.021***	0.167***	0.171**	0.104	-0.111	-0.502***
	(0.007)	(0.016)	(0.087)	(0.085)	(0.072)	(0.061)
Distinct respondents	6,716	10,755	10,755	10,755	8,328	8,328
Observations	20,983	34,976	34,976	34,976	24,404	24,404
R-squared	0.02	0.12	0.16	0.10	0.14	0.07
Mean dep. var.	0.79	0.04	7.08	4.88	6.32	2.67
SD dep. var.	0.41	0.99	6.50	6.17	5.26	4.26
Panel B: Firms						
Attention to inflation	0.013**	0.044**	0.212***	0.200***		
	(0.006)	(0.017)	(0.046)	(0.046)		
Distinct respondents	4,402	6,193	6,235	6,235		
Observations	18,423	27,121	28,107	28,107		
R-squared	0.02	0.02	0.49	0.23		
Mean dep. var.	0.80	0.04	5.47	3.00		
SD dep. var.	0.40	1.02	3.44	2.72		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays regressions of households' (Panel A) and firms' (Panel B) beliefs on attention to inflation – i.e., an indicator taking value one if inflation is mentioned in response to the open-ended survey question. The dependent variables are an indicator that is one if the respondent changed 12-month ahead inflation expectations by at least 0.5 p.p. between the previous and the current survey wave (Column 1), a respondent's confidence in his/her own inflation forecast (z-scored, Column 2), expected inflation over the next twelve months (Column 3), the absolute deviation of expected inflation from the mean professional forecast from FocusEconomics (Column 4), a respondent's perception of the current inflation rate over the last 12 months (Column 5), and the absolute deviation of this perception from the actually realized current inflation rate (Column 6). Besides survey wave fixed effects, all regressions control for the individual's gender, age, education, employment status, household income, homeownership, and stock ownership, and the respondent's influence on decisions in the firm, the firm's number of employees (in logs) and export share, as well as dummies for four broad industry groups, respectively. For a version with individual fixed effects, see Appendix Table A.9. Standard errors clustered at the individual/firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

subjective uncertainty about future inflation. Consistent with this prediction, attentive households are 0.17 standard deviations more confident in their expectations (Column 2, $p < 0.01$).

The core prediction of goal-optimal attention is that more attentive agents' beliefs are better calibrated, i.e., their beliefs are closer to benchmarks. In the household survey, we elicit perceptions of realized inflation over the previous 12 months, i.e., the current inflation rate at the time of the survey. Attentive households, on average, exhibit 0.1 p.p. lower inflation perceptions over the combined pre-shock and shock period (Column 5, $p = 0.12$), resulting in a 0.5 p.p. smaller absolute misperception about realized inflation (Column 6, $p < 0.01$). The choice of benchmark is more complicated for expectations about future inflation. Using the actual realization of inflation as an ex-post benchmark is not meaningful, as our short sample period is characterized by an extreme unexpected shock to inflation. Thus, respondents with lower forecast errors were not necessarily better calibrated from an ex-ante perspective. We instead rely on professional forecasts of German CPI inflation from FocusEconomics as an ex-ante benchmark.[11] Although professional forecasts themselves may be biased, they are typically much less dispersed than household or firm expectations (Andre et al., 2022; Candia, Coibion and Gorodnichenko, 2024) and exhibit much smaller average forecast errors over long sample periods (Carroll, 2003). Attentive households expect 0.17 p.p. higher inflation than inattentive households on average over our sample period (Column 3, $p < 0.05$). However, higher attention is not associated with a smaller absolute deviation of respondents' expectations from the average professional forecast. In fact, the inflation expectations of attentive households differ more strongly from expert forecasts than the expectations of inattentive households, albeit not significantly so (Column 4, $p = 0.22$). Appendix Table A.8 confirms the robustness of this finding to using the ifo Institute's forecast for German CPI inflation or the mean forecast of HICP inflation in the euro zone from the ECB Survey of Professional Forecasters as an alternative benchmark. Overall, the prediction of smaller deviations from benchmarks among attentive households is borne out for beliefs about current but not for expectations about future inflation.

In the firm sample, we find similar patterns for the frequency of updating, confidence, levels of expectations, and deviations from professional forecasts as among households, as shown in Columns 1–4 of Panel B. Appendix Table A.9 shows a version of Table 3 that includes individual fixed effects and therefore only exploits variation in attention and beliefs within the same household or firm over time. The estimates mostly have the same sign as the OLS estimates, although they differ in size and statistical significance. One exception is that the association between attention and a household's absolute misperception about realized inflation is no longer significantly negative but close to zero and insignificant. Most importantly, our key finding that attentive households' expectations are not closer to expert forecasts is even more pronounced in the fixed effects specifications. Given that the inclusion of fixed effects shuts down most of the available variation – particularly in the household sample, where some respondents only participate a few times – we view these results as supporting the robustness of our findings. In Section 5.2, we confirm our findings on the link between attention and beliefs exploiting variation in attention due to the interaction of an unexpected shock with agent characteristics that are predetermined with respect to the shock.

Disagreement Our model of goal-optimal attention in Section 3 predicts that agents that pay at least some attention disagree (weakly) more about current than about future inflation.[12]

[11] FocusEconomics provides economic analyses and forecasts for almost all countries in the world. Their forecasts are based on the consensus of a diverse range of reputable sources including investment banks, economic think tanks, and international organizations.

[12] The reason is that inflation is less than fully persistent, and agents all use the same (here, the true) persistence parameter to go from nowcasts to forecasts.

Table 4: Disagreement about current and future inflation

	Households			Firms		
	(1) SD	(2) IQR	(3) p90-p10	(4) SD	(5) IQR	(6) p90-p10
Expected inflation						
Attentive to inflation (a)	4.86	3.08	8.00	2.71	2.42	5.12
Inattentive to inflation (b)	5.97	2.98	8.80	2.60	2.17	4.77
p-value: (a)=(b)	0.00	0.19	0.01	0.00	0.00	0.05
Perceived current inflation						
Attentive to inflation (c)	4.06	2.66	5.16			
Inattentive to inflation (d)	5.25	2.80	6.82			
p-value: (c)=(d)	0.00	0.07	0.00			
p-value: (a)=(c)	0.00	0.00	0.00			

Notes: This table displays the standard deviation, the interquartile range, and the range between the 90th and 10th percentile of expected inflation and perceived current inflation separately for respondents who pay attention to inflation according to our text-based measure and those who do not. Before calculating the dispersion measures, the data of each sample are purged of survey wave fixed effects. The displayed p-values refer to tests of the equality of standard deviations (Columns 1 and 4, Levene's test) and tests of the equality of the interquartile range and the range between the 90th and 10th percentile (remaining columns, bootstrapped) between respondents that are attentive ((a) and (c)) and respondents that are inattentive ((b) and (d)) to inflation according to the open-ended measure as well as between expected and perceived current inflation of attentive households. The sample is restricted to waves from September 2021 onward (start date of the question on perceived current inflation). The distributional parameters of expected inflation are very similar when calculated based on the full sample.

Table 4 presents different measures of belief dispersion separately for attentive and for inattentive respondents. To only capture within-wave disagreement, the inflation expectations are purged of wave fixed effects before calculating dispersion. For households, the table displays dispersion in both nowcasts and forecasts, while for firms, only forecasts are available. Contrary to the model predictions, attentive households disagree *less* about current than about future inflation. For instance, the difference between the 90th and the 10th percentile of attentive households' beliefs is 8.0 p.p. for forecasts and only 5.2 p.p. for nowcasts (Column 3, $p < 0.01$).

The model's predictions regarding the link between attention and belief dispersion are ambiguous. We nevertheless briefly discuss how expectation dispersion varies between attentive and inattentive agents. Among households, disagreement in nowcasts is lower among attentive than among inattentive respondents. The same is true for households' forecasts, except when disagreement is measured by the interquartile range, in which case there are no strong differences. For firms, the differences in expectation dispersion between attentive and inattentive respondents are smaller and less systematic. If anything, dispersion appears somewhat higher among attentive firms than among inattentive firms.

Attention and pricing decisions Are changes in attention reflected in agents' decision-making? We explore this issue using qualitative questions on realized price changes over the last month and planned price changes over the next three months that are part of the regular IBS. As illustrated in Appendix Table A.10, firms that are attentive to inflation are significantly more likely to plan or to have implemented price increases. Conversely, they are less likely to have reduced or to be planning to reduce their prices. These patterns hold both in the cross-section and conditional on individual fixed effects. They suggest that the higher inflation expectations of attentive firms pass-through to firms' economic decisions.

Summary Taken together, our second empirical result is the following:

Result 2. Consistent with theories of goal-optimal attention, attentive respondents update their beliefs more frequently when signals change, are more confident in their beliefs, and perceive realized inflation more accurately. At odds with goal-optimality, attentive respondents' inflation expectations deviate more strongly from expert benchmarks and their disagreement in forecasts exceeds their disagreement in nowcasts. Finally, attention is reflected in firms' pricing decisions.

5 Selective memory and non-goal-optimal attention

The previous section illustrates that the predictions of theories of goal-optimal attention – as presented in Section 3 – regarding the determinants of attention, and the link between attention and the accuracy of nowcasts are confirmed in our data. However, contrary to the model predictions, attention does not appear to move forecasts closer to benchmarks, and disagreement in forecasts exceeds disagreement in nowcasts. In this section, we build on a recent literature on the role of selective memory in shaping mental representations and belief formation (Bordalo et al., 2023b, 2020, 2025; Gennaioli et al., 2024; Kahana, 2012) and present a theory of non-goal-optimal attention that can explain the empirical patterns. The modified model makes additional predictions, which we then test in our data.

5.1 A model of selective memory

We proceed in two steps. First, we discuss the belief formation stage and describe how attention affects inflation forecasts when there is interference of selective memory recall. This is a natural starting point, as both failures of the baseline model concern the link between attention and beliefs. The key mechanism is that the current context – in our case, reflected in the agent's information when making an inflation forecast – cues the agent to think of similar past episodes in her memory database, leading to overweighting of these episodes when forming an expectation about the future (Bordalo et al., 2024, 2023b; Gennaioli et al., 2024). We focus on the simplest case in which only observations of current inflation cue the agent to recall memories of past inflation, and later present an extension in which paying attention to other variables may interfere with the agent's inflation forecast. Second, we go back to the attention stage and illustrate how the agent's memory shapes the allocation of attention (Bordalo et al., 2025). A key feature of the modified model is that agents' experiences become an important, state-dependent determinant of agents' attention and expectations.

Belief formation stage We start with the step in which the agent has made her attention choice, and has received the signal about current inflation. The agent now makes a forecast of future inflation. When forming her inflation forecast – i.e., when going from signals about the current environment to the future – the agent retrieves memories of how inflation evolved in the past after an episode similar to the current one. To keep the simplicity of our model in Section 3, we model this selective recall as affecting the perceived persistence of inflation:

$$\hat{\rho}_\pi = \rho_\pi(1+\theta), \tag{6}$$

where $\theta \neq 0$ captures the influence of selective memory. We focus on the perceived persistence as this is the only parameter in our stylized model that captures how agents extrapolate from information about the current environment to the future. We follow the literature on memory to model how selective recall of certain memories affects an agent's $\hat{\rho}_\pi$. The framework closest to ours is Gennaioli et al. (2024). Our key innovation is to take into account that agents systematically differ in their attention choice, as outlined in Section 3, and consequently differ in their perceptions of current inflation, whereas in Gennaioli et al. (2024) all agents observe the current inflation rate.[13] If an agent pays attention to inflation and sees that inflation is currently high, this cues her to retrieve memories of past episodes of high inflation. Given that periods of high inflation tend to be characterized by high persistence (Benati, 2008; Fuhrer, 2010; Gallegos, 2023), a selective focus on these episodes implies $\theta > 0$, and hence, $\hat{\rho}_\pi > \rho_\pi$, so the agent will deviate upwards from the rational forecast. Put differently, the agent over-extrapolates from her information about the current environment to the future because of selective memory recall.[14]

To formalize this intuition, let $\mathscr{I}_t$ denote the information the agent acquires in the current period t, and let D_t denote the agent's database in period t, i.e., all the information, knowledge and experiences the agent has acquired in the past. The agent recalls past experiences based on their similarity to $\mathscr{I}_t$:

$$\theta \propto S(\rho_{\pi_{t-s}}, \mathscr{I}_t, D_t),$$

where $S(\cdot)$ denotes a similarity function that is higher when the current context $\mathscr{I}_t$ is similar to episodes s periods ago – included in D_t – in which the persistence of inflation $\rho_{\pi_{t-s}}$ was high.

Given our data, we are mainly interested in qualitative statements rather than the exact

[13]We do, however, abstract from other channels that are present in Gennaioli et al. (2024). For instance, we do not model how agents form probabilistic inflation forecasts.

[14]To some extent, perceived a higher ρ_π in times of high inflation may be rational since actual inflation persistence is higher during such episodes. However, our empirical benchmark in Section 4 are the expectations of professional forecasters, who likely account for such changes in inflation persistence. Thus, if ρ_π is indeed time-varying, the best way to think of θ is as deviation from this time-varying ρ_π due to selective retrieval of past episodes of high inflation and consequent underweighting of relevant information from other episodes.

functional form of θ. We therefore model how selective recall affects θ by focusing on covariances between past ρ_π and the similarity of the current context to the past context. Formally, θ depends negatively on $cov(\rho_{\pi_{t-s}}, (\pi_{t-s} - \widetilde{\pi})^2)$:

$$\frac{\partial \theta}{\partial cov(\rho_{\pi_{t-s}}, (\pi_{t-s} - \widetilde{\pi})^2)} < 0, \tag{7}$$

where $(\pi_{t-s} - \widetilde{\pi})^2$ is the squared distance of the agent's current perception of inflation $\widetilde{\pi}$ and inflation s periods ago. Given that $\rho_{\pi_{t-s}}$ is usually high in periods of high inflation π_{t-s}, the covariance term is negative when current inflation is high, and hence, $\theta > 0$. For example, the linear functional form

$$\theta \propto -\chi_\pi \cdot cov(\rho_{\pi_{t-s}}, (\pi_{t-s} - \widetilde{\pi})^2) \tag{8}$$

satisfies these assumptions. Gennaioli et al. (2024) show how such a linear functional form can be obtained by a linear approximation of a similarity function that decreases exponentially with a quadratic distance function.

The agent's inflation forecast is given by

$$\pi^e = (1+\theta)\rho_\pi \gamma_\pi s, \tag{9}$$

and hence, the agent will deviate upwards from the rational forecast due to $\theta > 0$ in times of high inflation if she pays attention to inflation, as documented empirically. Attentive agents perceive lower persistence when inflation is low, as in this case the covariance terms are positive. Thus, the model offers a microfoundation for state-dependent perceived inflation persistence, in a way that is consistent with empirical findings (Pfäuti, 2024b). Crucially, the distortion occurs at the stage where agents go from nowcasts to forecasts. The model is thus consistent with the empirical pattern that attentive agents perceive current inflation more accurately but deviate more strongly upwards from benchmarks in their forecasts. It thus overcomes a key failure of the model of goal-optimal attention from Section 3.

To understand the role of attention for this result, it is instructive to consider corner cases. A fully attentive agent is likely to overpredict future inflation compared to the rational benchmark in times of high inflation due to the mechanism outlined above. An agent that is completely inattentive will not receive any information about inflation – in particular, that current inflation is high. Thus, the agent will not recall memories of high inflation, and hence, will not overshoot compared to the rational forecast given her level of attention. In fact, fully inattentive agents will underpredict future inflation during times of high inflation because they do not realize that inflation is currently high. In theory, there exists an intermediate level of attention and interference of selective recall such that an agent's inflation forecast is equal to the full-information rational forecast, though for the wrong reasons.[15] In general, however, during times of high inflation,

[15]To see this, consider the following example. Assume current inflation is $\pi = 4\%$ and the true persistence

more attentive agents are more likely to overshoot professional forecasts than inattentive agents. Selective memory recall can thus render attention non-goal-optimal.

In our data, attentive agents disagree more about future than about current inflation, in contrast to what the model of goal-optimal attention from Section 3 predicts. The model with selective memory can account for this finding. To see this, consider again the case of two agents, 1 and 2. In the rational updating model of Section 3, their disagreement about nowcasts is given by $|\gamma_{\pi,1}s_1 - \gamma_{\pi,2}s_2|$ which is weakly larger than their disagreement about forecasts: $|\rho_\pi||\gamma_{\pi,1}s_1 - \gamma_{\pi,2}s_2| \leq |\gamma_{\pi,1}s_1 - \gamma_{\pi,2}s_2|$ because $|\rho_\pi| \leq 1$. With selective memory, however, disagreement in forecasts is given by $|\hat{\rho}_{\pi,1}\gamma_{\pi,1}s_1 - \hat{\rho}_{\pi,2}\gamma_{\pi,2}s_2|$, which can be larger than $|\gamma_{\pi,1}s_1 - \gamma_{\pi,2}s_2|$ because agents differ in their $\hat{\rho}_\pi$ due to individual-specific memory.[16]

Attention allocation stage So far, we have assumed that agents choose their attention as outlined in Section 3 without taking into account that the obtained signals cue them to retrieve certain experiences, which in turn change their perceived inflation persistence. In practice, however, the agent is likely to receive some free signal before choosing her attention – e.g., through grocery shopping or incidental news consumption – which will cue the agent to think of past episodes similar to the current one. Hence, in times of high inflation the agent will already perceive a higher ρ_π in the attention stage, and hence, pay more attention to inflation. To see this, recall that the agent's attention choice in Section 3 was given by

$$\gamma_\pi = max\left\{0, 1 - \frac{\kappa}{B\rho_\pi^2\sigma_\pi^2}\right\},$$

with ρ_π being the actual persistence. However, if the agent chooses attention after receiving some free information but before receiving the signal s, she will instead apply $\tilde{\rho}_\pi > \rho_\pi$, and pay more attention. This mechanism thus offers an alternative explanation for the increase in attention to inflation in response to the inflation shock (see Figure 2). Higher attention to inflation may suboptimally crowd out attention to other variables if the overall attention budget is limited. Selective memory thus generates deviations in the allocation of attention from what a fully rational agent would choose.

Selective recall predicts a key role for agents' prior experiences in shaping attention and beliefs. In particular, selective recall of past inflationary episodes cued by high current inflation should be stronger for agents whose memory database contains more such episodes. Hetero-

is $\rho_\pi = 0.5$. The rational forecast in this case is $\pi^{e*} = \rho_\pi \cdot \pi = 2\%$. A completely inattentive agent (IA) would undershoot this optimal forecast since her forecast would be $\pi^{e,IA} = 0$ because $\gamma_\pi^{IA} = 0$. A fully attentive (A) agent with $\gamma_\pi^A = 1$ would overshoot the rational forecast, $\pi^{e,A} = (1+\theta^A)\cdot\rho_\pi\cdot\pi > \pi^{e*}$, due to memory interference $\theta^A > 0$. An agent that is attentive, but not fully, $\gamma_\pi \in (0,1)$, could perfectly align with the rational forecast in the knife-edge case where $\pi^e = (1+\theta)\rho_\pi\gamma_\pi s = \pi^{e*}$.

[16] Consider the following example: agents 1 and 2 are equally attentive with $\gamma_\pi = 0.5$, but agent 1 receives a relatively high signal of $s_1 = 5\%$ and agent 2 a relatively low signal of $s_2 = 2\%$. Disagreement about nowcasts is $0.5\cdot|5-2| = 1.5\%$. Now, due to selective recall, agent 1 retrieves memories of high past inflation, and hence, has a relatively high $\hat{\rho}_\pi$, e.g., $\hat{\rho}_{\pi,1} = 0.9$, whereas agent 2 has a relatively low $\hat{\rho}_\pi$, e.g., $\hat{\rho}_{\pi,2} = 0.1$. Disagreement about forecasts is then $0.5\cdot|5\cdot0.9 - 2\cdot0.1| = 2.15\%$ – higher than disagreement about nowcasts.

geneity in memory databases thus generates differences in attention – even among agents who share the same B, σ_π^2 and κ – and dispersion in beliefs. Prior experiences shape the strength of the distortion in both the attention allocation and the belief formation stage.

An alternative approach to modeling the attention stage is provided by Bordalo et al. (2025). In their approach, the experience database shapes which features of a problem individuals attend to. Having more experience with a specific "category" – in our case, the "inflation" category, which features attention to inflation – implies that the category is used more often, even when the fundamental aspects of the decision problem are otherwise equal. Moreover, greater similarity of the current context to past experiences where a specific category was used makes agents more likely to rely on that category. Unless a category is dominant, familiarity and similarity of the context are complements in driving use of that category. In our case, agents with prior experiences of high inflation would then become disproportionately more likely to apply the inflation category when inflation increases.

Summary A model of selective memory overcomes the empirical failures of theories of goal-optimal attention regarding forecasting accuracy and disagreement. The modified model makes the additional prediction that past experiences are a key determinant of attention and beliefs, which we test in the next section. In Appendix C, we show that the extended model can still account for those predictions of the baseline model that are supported by our data.

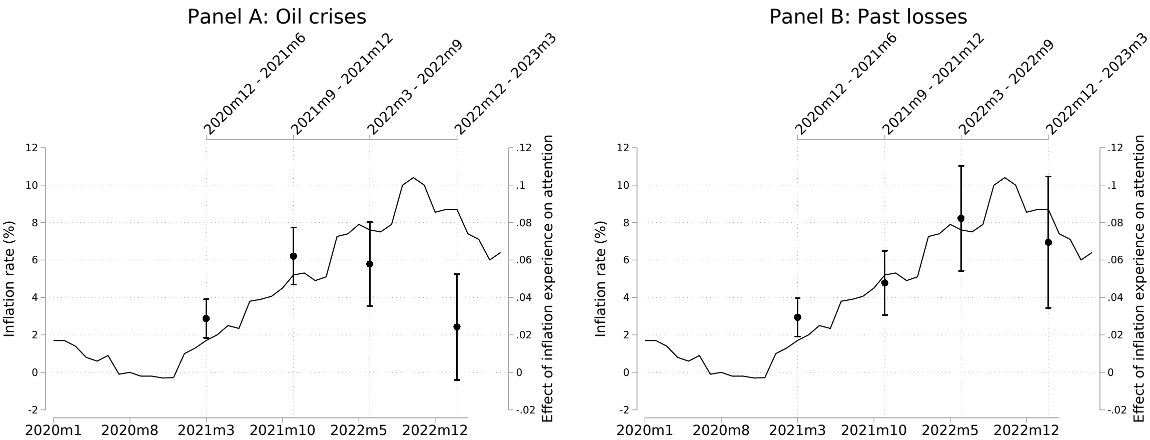
5.2 Empirical evidence on experiences, attention and beliefs

Theories of selective memory – as presented in Section 5.1 – predict that prior experiences are a key driver of attention and beliefs, even after conditioning on fundamental aspects of the decision problem. We now test this prediction in our data, focusing on households, for which we have rich measures of prior experiences with inflation.

Experience measures We consider two different types of experiences. First, we focus on the collective experience of having lived through the oil crises of the 1970s, when inflation reached historically high levels. In particular, we follow Binder and Makridis (2022) and construct a dummy variable for cohorts that were at least teenagers by the late 1970s.[17] Second, we use survey measures of personal experiences, which also vary within cohorts. Specifically, in March and June 2021, i.e., prior to the inflation surge, we elicited whether respondents ever incurred substantial real income drops or real wealth losses due to increases in inflation. These measures capture both across-cohort variation from differences in experienced aggregate inflation rates as well as within-cohort variation from (i) differential co-movement of one's income or wealth

[17] We elicited age using a question with six brackets and thus cannot precisely pin down respondents' birth years. We classify those aged 55 or older as having experienced the oil crises. This captures cohorts born 1965 or earlier for respondents who entered the panel in 2020 and cohorts born 1968 or earlier for those who entered in 2023.

Figure 3: Experiences and responses of attention to the shock: Households



Notes: This figure displays the coefficients of regressions of attention to inflation as measured in the open-ended data on measures of prior inflation experiences interacted with different time periods displayed at the top with the measures of pre-shock experiences with inflation. In Panel A, the experience measure is an indicator for cohorts aged 55 or older at the time of the survey, i.e., those who were at least teenagers during the oil crises of the 1970s. In Panel B, the experience measure is based on whether the respondent had ever experienced a real income loss or a real wealth loss due to inflation in the past, as elicited in the pre-shock period in March or June 2021 (based on the first wave this is elicited for a given respondent). Both specifications include survey wave fixed effects and control for the individual's gender, education, employment status, household income, homeownership, and stock ownership. In Panel B, we also control for respondents' age. Confidence bands are based on standard errors clustered at the household level and refer to the 95%-level. For contextualization, the solid time series display the inflation rate reported by the German Federal Statistical Office in the respective month indicated on the axis at the bottom.

with inflation, (ii) differences in experienced household-level inflation rates, or (iii) differential encoding or recall of inflation experiences.

Experiences and attention For each subperiod of our dataset, we regress a dummy variable for paying attention to inflation on one of our experience measures. We include a large set of controls, including demographics as well as respondents' perceived exposure to inflation and information costs, aiming to capture fundamental aspects of the decision environment. Figure 3 plots the estimated coefficients. As shown in Panel A, individuals who lived through the oil crises are 2.9 p.p. ($p < 0.01$) more likely to pay attention to inflation in the pre-shock period. This is consistent with the idea that differences in memory databases are associated with mental representations that guide attention to different aspects of a problem (Bordalo et al., 2025). The correlation increases to 6.2 p.p. ($p < 0.01$) when the inflation shock hits the economy in mid-2021 and remains at an elevated level of 5.9 p.p. ($p < 0.01$) following Russia's invasion of Ukraine, before reverting back to 2.4 p.p. ($p < 0.1$) in the period of decreasing inflation. Panel B displays similar patterns for experiences of past real income or wealth losses due to inflation. These state-dependent effects are in line with the prediction of selective memory that attention is jointly shaped by the context and agents' experiences depending on the degree of similarity.

Experiences and beliefs We next examine whether the stronger increases in attention to inflation in response to the shock among those with prior inflation experiences are reflected in stronger increases in inflation expectations. We estimate specifications of the following type on our full study period from December 2020 to March 2023:

$$
\begin{aligned}
\mathrm{Y}_{it} = {} & \alpha_1 \text{ Prior inflation experience}_i \times 1(\mathrm{t} \in \{21\mathrm{m}9,\, 21\mathrm{m}12\}) \\
& + \alpha_2 \text{ Prior inflation experience}_i \times 1(\mathrm{t} \in \{22\mathrm{m}3,\, 22\mathrm{m}6,\, 22\mathrm{m}9\}) \\
& + \alpha_3 \text{ Prior inflation experience}_i \times 1(\mathrm{t} \in \{22\mathrm{m}12,\, 23\mathrm{m}3\}) \\
& + \phi_t + \phi_i + \varepsilon_{it},
\end{aligned} \tag{10}
$$

where the experience measure is interacted with dummy variables for three subperiods of the inflationary episode. The time before the inflation shock, December 2020 until June 2021, is the base period. ϕ_t and ϕ_i are time and individual fixed effects, respectively. The coefficients α_1, α_2 and α_3 thus capture the differential response among those with prior inflationary experiences.

The results are shown in Table 5. Columns 1 and 2 confirm the differential attention responses to the inflation shock among those with prior inflation experiences from Figure 3 exploiting only within-individual variation. As shown in Column 3, respondents who lived through the oil crises exhibit a 0.6 p.p. stronger increase in inflation expectations when the inflation shock first hits in the second half of 2021 (Column 3, $p < 0.01$). The effect increases to 1 p.p. in the period following Russia's invasion of Ukraine in 2022 ($p < 0.01$). Column 4 displays similar patterns using past real income or wealth losses due to inflation as a measure of inflation experiences. Columns 5 and 6 show that the stronger increases in inflation expectations among households with prior experiences lead to stronger deviations from professional forecasts. These patterns are consistent with the idea that the distortions of selective memory are more pronounced when the memory database contains more experiences of past inflationary episodes.

The above findings highlight the robustness of the evidence presented in Section 4.2 to relying on variation in attention due to the interaction of a shock to the environment with predetermined individual characteristics. Our finding of a stronger updating of inflation expectations in response to the shock among those with prior inflation experiences is consistent with recent evidence from the U.S. (Gennaioli et al., 2024).

Robustness Instead of prior experiences interacting with the similarity of the current context, our results could reflect interactions of the changing environment with other agent characteristics. For instance, agents who permanently consume more inflation-related news could be more exposed to the increasing supply of inflation-related news over the study period. Similarly, high economic exposure to inflation and a changing volatility of inflation could differentially shift agents' attention and beliefs. We address these possibilities by controlling for interactions of the shock periods with various other predetermined agent characteristics. As shown in Appendix Table A.11, the differential effects of experiences are almost unaffected by the inclusion of these additional controls.

Table 5: Experiences and responses of attention and beliefs to the shock: Households

	Attention to inflation		Expected inflation next 12 months		Absolute deviation from expert forecast	
	(1)	(2)	(3)	(4)	(5)	(6)
Inflation experience						
$\times$ 1(t $\in$ {21m9, 21m12})	0.036***	0.026***	0.565***	0.185	0.556***	0.200
	(0.009)	(0.009)	(0.130)	(0.136)	(0.127)	(0.133)
$\times$ 1(t $\in$ {22m3, 22m6, 22m9})	0.030**	0.054***	1.029***	0.591***	0.946***	0.563***
	(0.013)	(0.014)	(0.162)	(0.175)	(0.157)	(0.171)
$\times$ 1(t $\in$ {22m12, 23m3})	0.004	0.051***	1.042***	0.565***	0.934***	0.491**
	(0.016)	(0.018)	(0.188)	(0.207)	(0.181)	(0.200)
Experience measure	Oil crises	Past losses	Oil crises	Past losses	Oil crises	Past losses
Distinct respondents	7,126	4,913	7,925	5,404	7,925	5,404
Observations	31,347	23,820	36,451	27,913	36,451	27,913
R-squared	0.45	0.43	0.67	0.65	0.65	0.63
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays regressions of attention and beliefs on measures of prior inflation experiences interacted with the shock period. In Columns 1 and 2, the dependent variables are dummy variables indicating whether a household pays attention to inflation as measured in the open-ended data. In Columns 3–6, the dependent variables are the household's expected inflation over the next 12 months or the absolute deviation of the household's expected inflation from the mean professional forecast reported to FocusEconomics, respectively. The interaction terms interact dummies for time periods with the measures of pre-shock experiences with inflation, i.e., they estimate a differential effect relative to the base period (December 2020-June 2021). In Columns 1, 3 and 5, the experience measure is an indicator for cohorts aged 55 or older at the time of the survey, i.e., those who were at least teenagers during the oil crises of the 1970s. In Columns 2, 4, and 6, the experience measure is based on whether the respondent had ever experienced a real income loss or a real wealth loss due to inflation in the past, as elicited in the pre-shock period in March or June 2021 (based on the first wave this is elicited for a given respondent). All specifications include individual fixed effects and survey wave fixed effects, and thus drop singleton observations. Standard errors are clustered at the household level. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Summary Taken together, our third empirical result is the following:

Result 3. Past inflation experiences are associated with respondents' attention and beliefs in a way that is consistent with theories of selective memory: those with prior experiences of high inflation (i) pay more attention to inflation before the shock, (ii) increase their attention to inflation more strongly once the shock hits, and (iii) increase their inflation expectations more strongly in response to high inflation, which shifts their forecasts away from benchmarks.

5.3 Interference of attention to other variables

Model extension So far, we focused on the case where selective memory recall is cued only by the agent's observation of current inflation. In principle, however, also attention to other variables may interfere with the agent's inflation forecast (Bordalo et al., 2025). Consider, for example, an agent that pays attention to energy costs. If this agent observes that her energy bill is high, she recalls memories of past episodes of high energy prices. When the agent is now asked to forecast inflation, she thinks of periods in which energy prices were high and recalls whether inflation was high in these periods or not. Since inflation has historically been higher in times of high energy prices, she would expect relatively high inflation.

Formally, interference of paying attention to energy prices affects agents' inflation forecasts through θ as follows:

$$\frac{\partial \theta}{\partial cov(\rho_{\pi_{t-s}}, (x_{t-s} - \widetilde{x}_t)^2)} < 0, \tag{11}$$

where x here captures energy prices. In principle, there could be many variables – idiosyncratic variables or aggregate ones other than inflation – interfering with the agent's inflation forecast. Denoting those other variables by x_i, the simple linear function

$$\theta \propto -\chi_\pi \cdot cov(\rho_{\pi_{t-s}}, (\pi_{t-s} - \widetilde{\pi})^2) - \sum_i \chi_i \cdot cov(\rho_{\pi_{t-s}}, (x_{i,t-s} - x_{i,t|t})^2), \tag{12}$$

would satisfy our assumption (11).

Empirical evidence We now return to our data to test whether attention to other variables can interfere with agents' inflation forecasts. We stick to the example of the cost of energy – a highly relevant one in the context of our study period: Germany was hit particularly strongly by the post-pandemic energy crisis, which was aggravated by Russia's invasion of Ukraine in 2022. The energy component of the producer price index tripled between late 2020 and September 2022 (see Panel C of Appendix Figure A.1).

Our measure of attention to energy is a dummy variable taking value one for every respondent who raises this topic in response to the open-ended question. We regress the respondents' beliefs on this dummy, time fixed effects and individual fixed effects. Table 6 shows the results for firms. Consistent with the extended model, paying attention to energy increases firm managers' inflation expectations by 0.2 p.p. (Column 1, $p < 0.01$), which fully translates into a stronger deviation from professional forecasts (Column 3, $p < 0.01$). Columns 2 and 4 highlight that attention to energy and attention to inflation shape inflation expectations also conditional on one another. This is in line with a core feature of the extended model: in a period of both high inflation and high energy prices, agents hold particularly high inflation expectations if they pay attention to both topics. Appendix Table A.12 shows that also households increase their inflation expectations and deviate more strongly from expert forecasts when becoming attentive to energy, although the effect decreases when controlling for attention to inflation.

For firms, we also exploit shifts in attention to energy due to the interaction of (pre-determined) exposure to energy and fluctuations in energy prices. Firms' exposure to energy prices is captured by the ratio of energy costs to revenues prior to Russia's invasion of Ukraine as elicited in the regular IBS. Managers of firms with a higher exposure to energy costs increase their attention more strongly when energy prices increase (Column 5, $p < 0.01$). This shift

Table 6: Attention to energy costs and inflation forecasts: Firms

	Expected inflation next 12 months		Absolute deviation from expert forecast		Attention to energy	Expected inflation next 12 months	Absolute deviation from expert forecast
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Attention to energy	0.204***	0.182***	0.203***	0.183***			
	(0.048)	(0.048)	(0.047)	(0.047)			
Attention to inflation		0.152***		0.147***			
		(0.033)		(0.032)			
Energy exposure × PPI energy					0.511***	2.389***	2.355***
					(0.115)	(0.760)	(0.743)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distinct respondents	4,891	4,891	4,891	4,891	3,228	3,376	3,376
Observations	26,763	26,763	26,763	26,763	20,090	21,902	21,902
R-squared	0.75	0.75	0.62	0.62	0.45	0.73	0.61
Mean dep. var.	5.46	5.46	2.99	2.99	0.20	5.46	3.00
SD dep. var.	3.41	3.41	2.69	2.69	0.40	3.44	2.75

Notes: This table investigates the relationship between firms' attention/exposure to energy costs and inflation forecasts. The dependent variables are expected inflation over the next twelve months (Columns 1, 2, and 6), the absolute deviation of expected inflation from the mean professional forecast from FocusEconomics (Columns 3, 4, and 7), and attention to energy costs – i.e., an indicator taking value one if topics related to energy are mentioned in response to the open-ended survey question (Column 5). The independent variables include attention to energy (Columns 1–4), attention to inflation (Columns 2 and 4), or the interaction between the energy component of the producer price index (published by the German Federal Statistical Office in the month of the survey) and firms' exposure to energy costs given by the ratio of energy costs to revenues prior to the Russian invasion of Ukraine elicited in the April 2022 wave of the regular IBS (Columns 5–7). All regressions control for survey wave fixed effects and firm fixed effects. Standard errors clustered at the firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

in attention to energy is reflected in a stronger increase in inflation expectations (Column 6, $p < 0.01$), shifting expectations away from expert benchmarks (Column 7, $p < 0.01$). These patterns are in line with evidence that individuals overextrapolate from idiosyncratic or local events when forming macroeconomic expectations (Andrade, Coibion, Gautier and Gorodnichenko, 2022; Butera et al., 2024; D'Acunto et al., 2021; Kuchler and Zafar, 2019). Relative to previous studies, we provide direct evidence on how attention mediates the effect of a firm-level event – being hit particularly hard by high energy costs due to energy-intensive production – on expectations about aggregate outcomes.

Taken together, our fourth and final empirical result is the following:

Result 4. Attention to high energy costs is associated with higher and less well-calibrated inflation expectations. This is consistent with the idea that attention to other variables can interfere with inflation forecasts, as suggested by theories of selective memory.

6 Conclusion

Attention to the economy is a central element in macroeconomic models that depart from the full-information rational expectations assumption, but its empirical properties are not well understood. To fill this gap, we collect new panel data on households' and firms' attention to the economy based on open-ended survey questions. We use these data to test key predictions of theories of goal-optimal attention, such as theories of rational inattention (Maćkowiak et al., 2023). We confirm several of these predictions in our data: attention increases in exposure to and volatility of the variable of interest, and decreases in information costs; attentive agents update their inflation expectations more frequently during the post-pandemic inflation shock, are more confident in these expectations, and hold smaller misperceptions about realized inflation. Yet, at odds with goal-optimal attention, attentive agents' expectations about future inflation deviate more strongly upward from expert benchmarks. We show that a model of selective memory (Bordalo et al., 2025; Gennaioli et al., 2024), in which attention can be non-goal-optimal, can account for the empirical patterns. The modified model makes additional predictions about the role of past experiences in shaping attention and beliefs and about interference of attention to other variables with agents' inflation forecasts, which we confirm in our data.

Bordalo et al. (2023a) call for evidence from naturalistic settings on how attention and memory interact in shaping economic beliefs and decisions. We provide such evidence from a macroeconomic context. While macroeconomics has been dominated by rational, goal-optimal approaches to attention and belief formation, our findings support an alternative approach centered around similarity-based retrieval of experiences depending on the context, which shapes attention, mental representations, and how information agents attend to is used to form beliefs (Bordalo et al., 2023b, 2020, 2025). Our results align with previous evidence on the role of attention in statistical reasoning (Bordalo et al., 2023a) and on selective memory in mental simulation (Bordalo et al., 2024). Gennaioli et al. (2024) provide theory and evidence on how selective recall shapes point and distributional inflation expectations. In our paper, we take a joint view and provide direct evidence on how attention to the economy is shaped by selective recall and mediates its effect on inflation forecasts.

Our findings point to promising directions for macroeconomic modeling. We highlight that selective memory recall can explain many empirical patterns in agents' attention to the economy and macroeconomic expectations. Although beyond the scope of this paper, it would be interesting to incorporate this mechanism into a macroeconomic model and explore implications for business cycle dynamics and the transmission of policies.

From a methodological perspective, the rich and detailed picture of agents' attention allocation obtained using our measure points to the promise of using open-ended survey data to measure attention in economic contexts more generally. Such measures could be included in existing panel surveys of households and firms, and be routinely analyzed using human or AI-based coding. These data could help policymakers make more informed decisions and provide new empirical insights that inform future theoretical work.

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Online Appendix: Attention to the Macroeconomy

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Summary of the Online Appendix

Section A contains supplementary figures and tables.

Section B presents the full list of codes in our scheme for the open-ended data.

Section C provides additional theoretical results.

Section D contains additional empirical results.

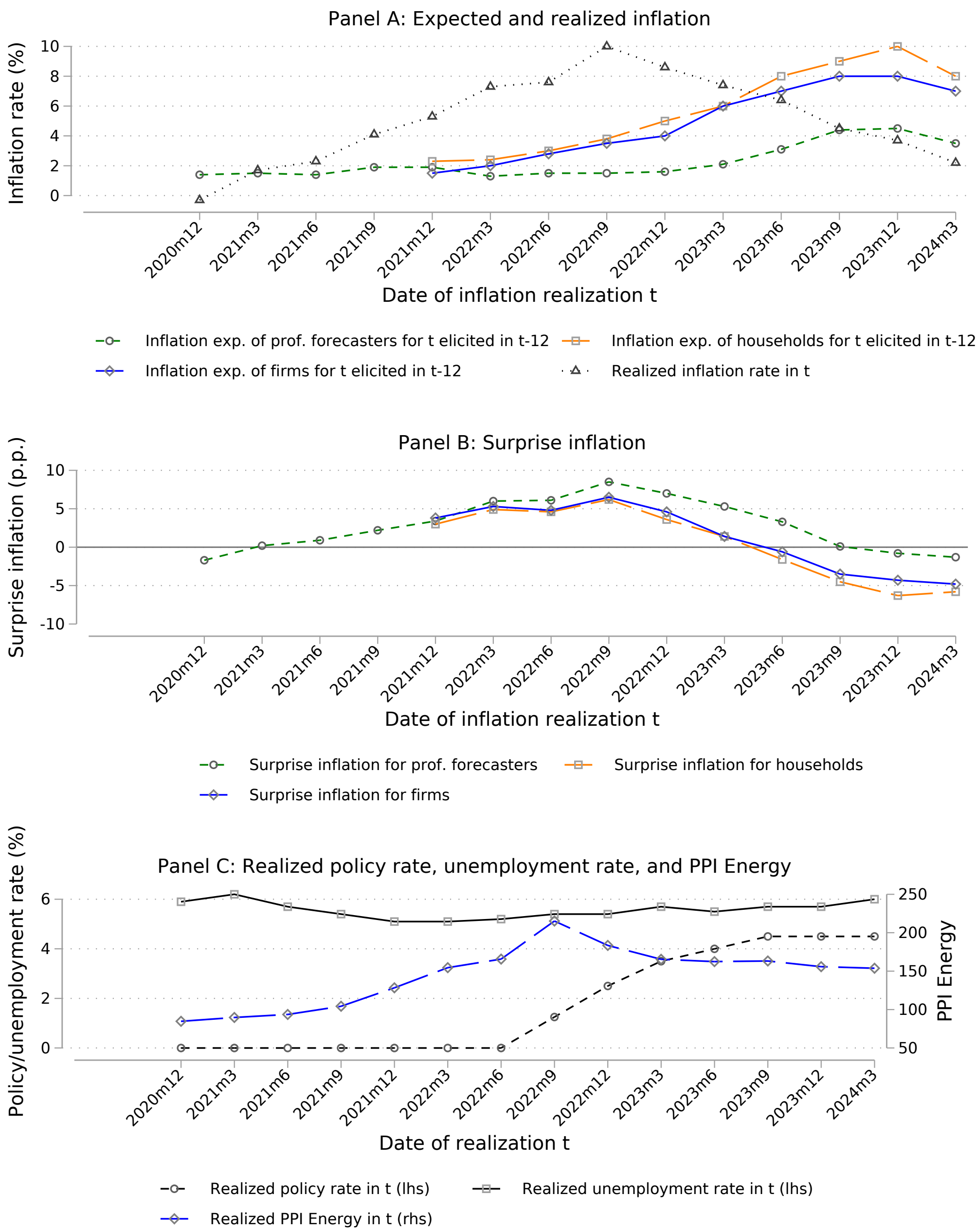
Section E provides the key survey questions from our household and firm panels.

Section F provides the key survey questions from our September 2023 validation survey.

A Supplementary exhibits

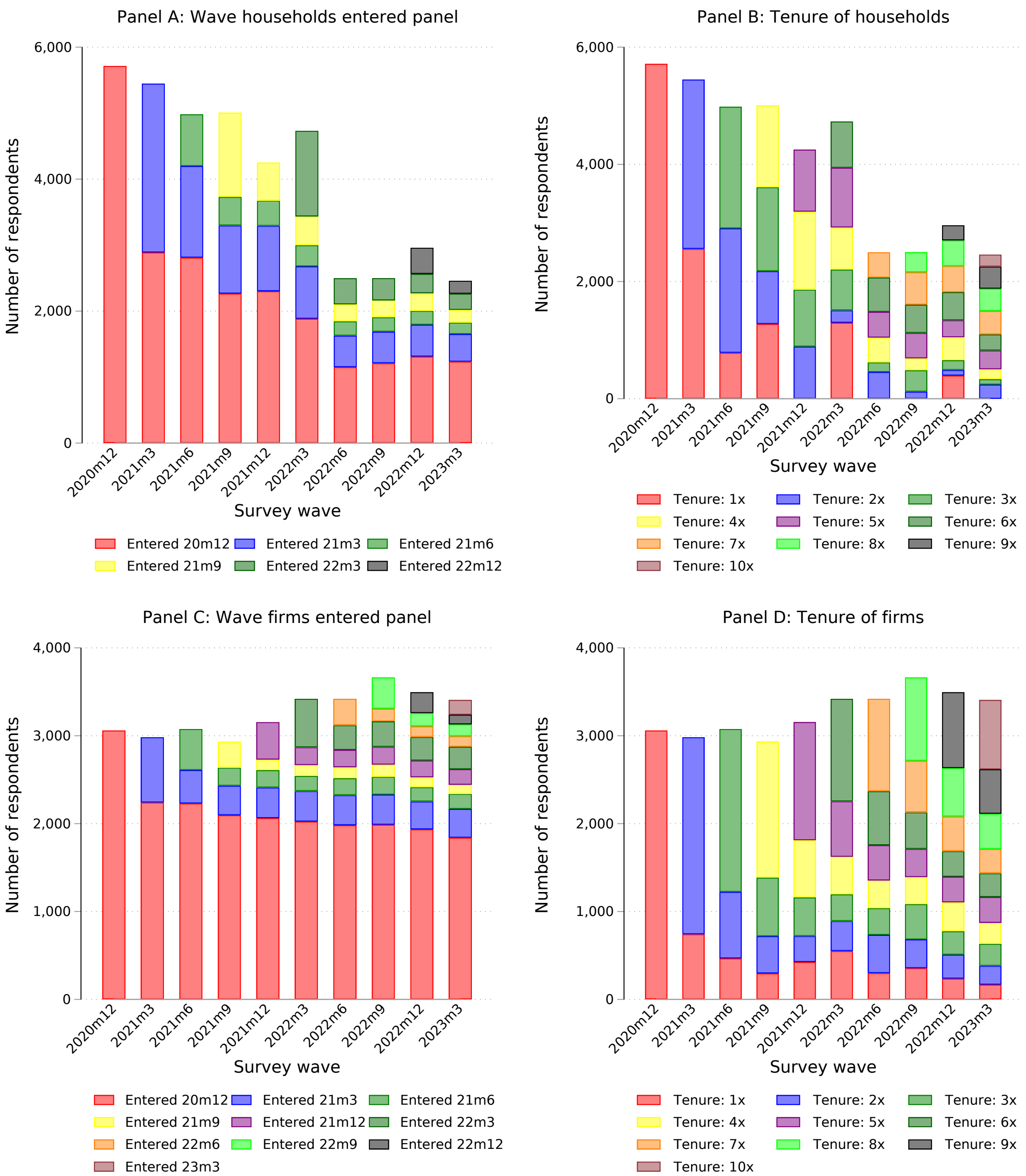
A.1 Additional figures

Figure A.1: Setting: Unexpected shock to inflation



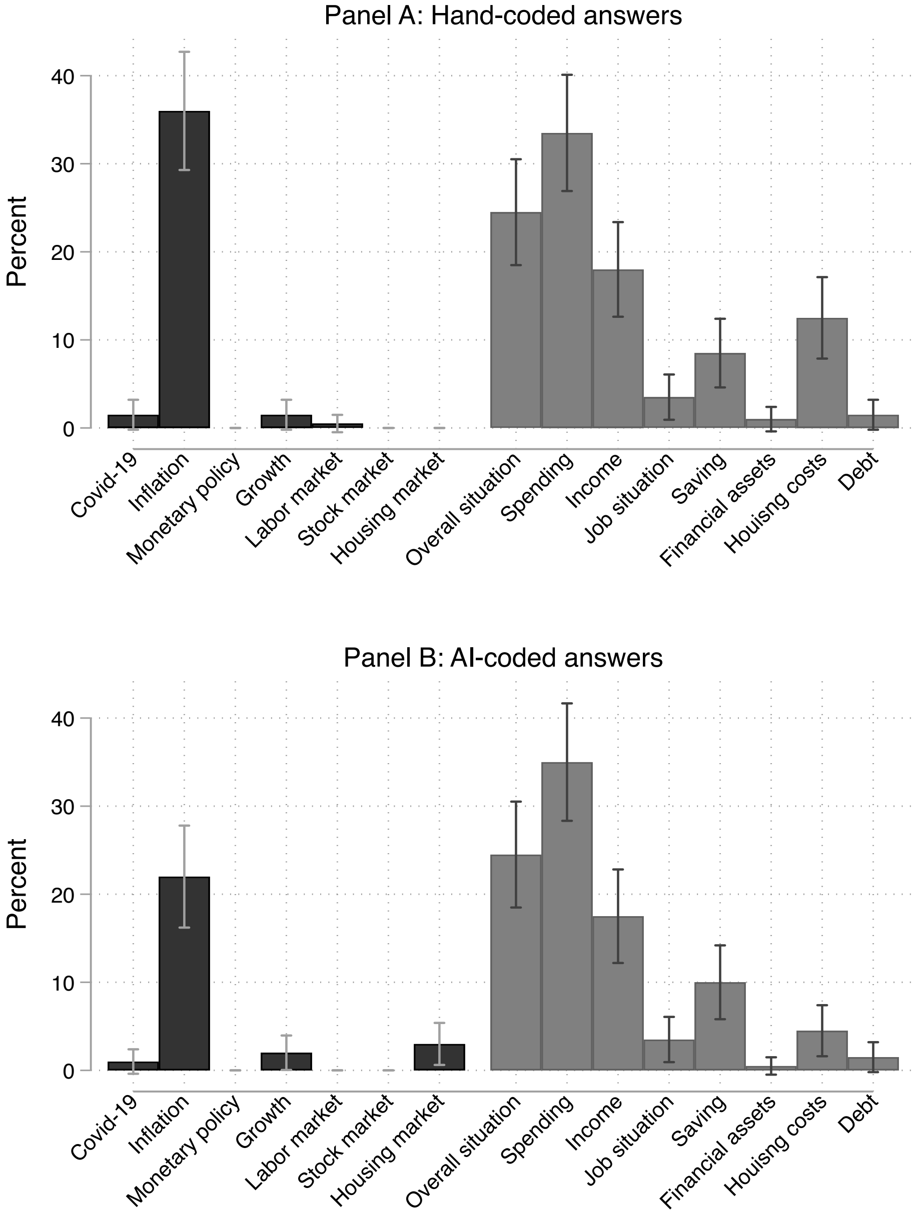
Notes: Panel A displays the median expected inflation rate over the next 12 months among households and firms along with the average professional forecast from FocusEconomics and the ex-post realized inflation rate in Germany. Expectations are shifted by 12 months such that the dates depicted on the x-axis refer to the date of the inflation realization, i.e., the date the expectations refer to. Panel B displays the "surprise inflation", i.e., the difference between forecasts and ex-post realized inflation rates in percentage points. Panel C shows the development of the ECB policy rate and of the unemployment rate in Germany on the left-hand axis, and the energy component of the producer price index (2021=100) on the right-hand axis.

Figure A.2: Survey participation across waves



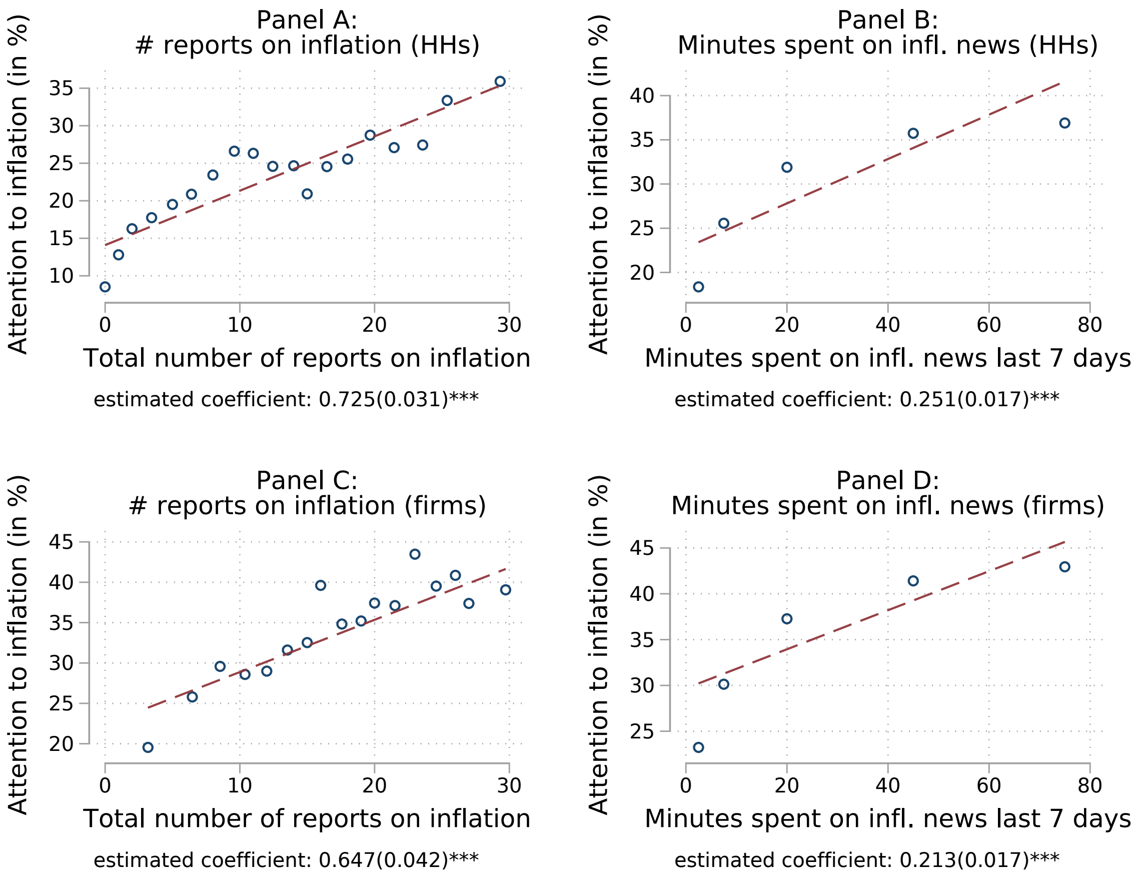
Notes: This figure displays the composition of the different survey waves in terms of the wave responding households and firms entered the panel (Panels A and C) and in terms of their tenure in the panel (Panels B and D).

Figure A.3: Attention allocation across topics in the open-ended data as classified using human coding and as classified using AI-coding



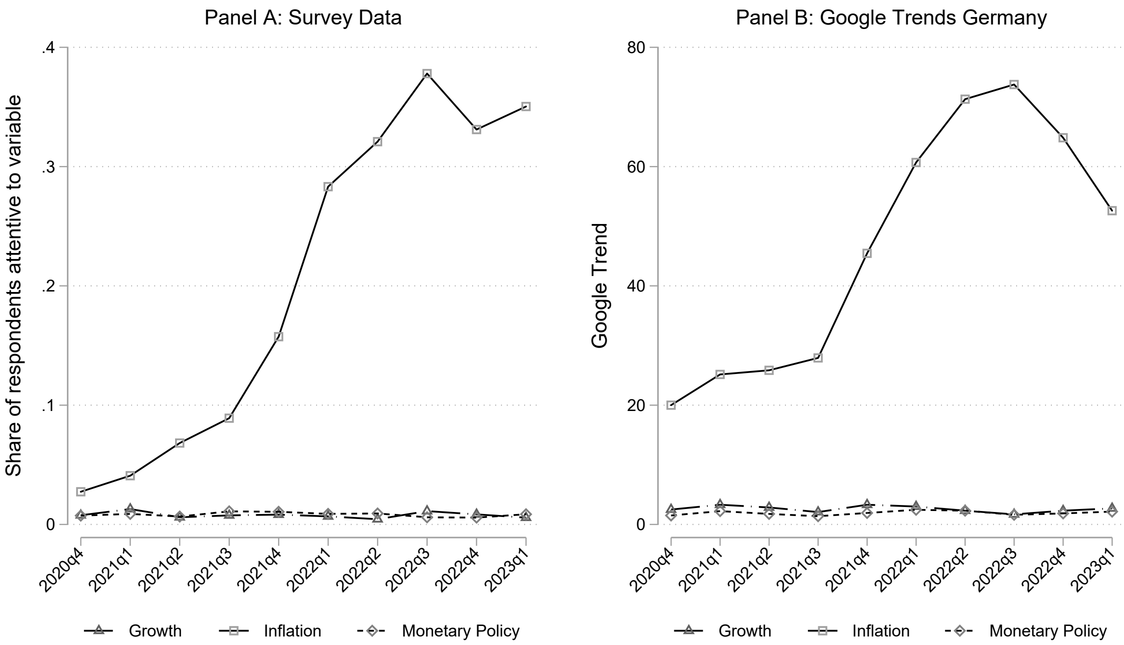
Notes: This figure presents a validation exercise for the hand-coding of the open-ended data based on a subsample from the household survey wave in March 2023, which was both hand-coded and AI-coded using GPT-4. It shows the distribution of attention to different macroeconomic topics (black) and household-level topics (gray). The bars indicate the fractions of respondents paying attention to a given topic. The measure of attention is based on people's responses to our main open-ended question: "What topics come to mind when you think about the economic situation of your household?" Panel A shows results from the hand-coding. Panel B displays results from the AI-coding.

Figure A.4: Attention as measured in the open-ended question and news consumption



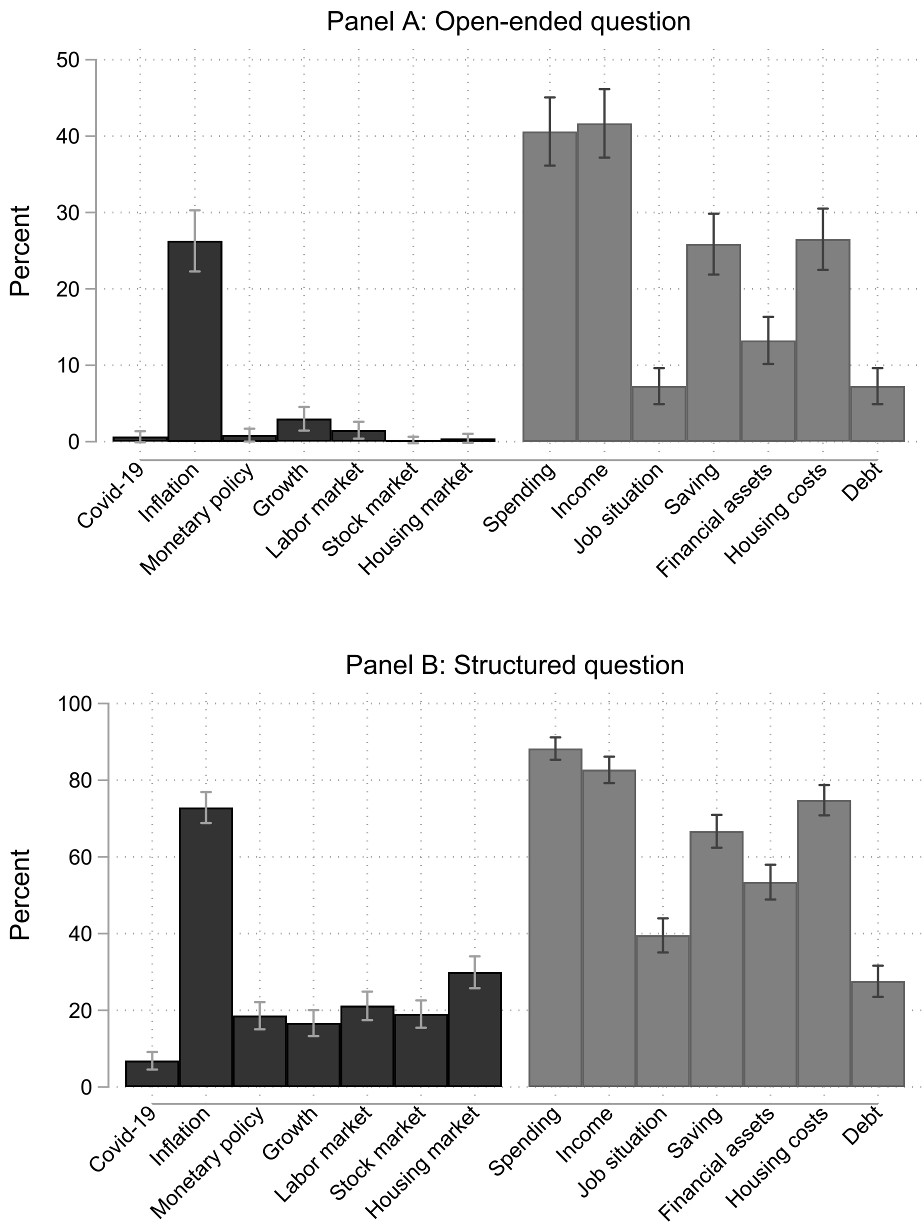
Notes: This figure displays binned scatter plots regressing attention to inflation – i.e., an indicator taking value one (expressed as 100% for expositional reasons) if inflation is mentioned in response to the open-ended survey question – on different measures of news consumption regarding inflation. Panels A and C regress attention on the total number of reports on inflation a respondent reports to have read in the news, to have seen on TV, or to have heard in the radio over the last three months. Panels B and D regress attention on the number of minutes a household or firm manager reports to have spent consuming news about inflation over the last week. Panels A and B focus on households, while Panels C and D focus on firms. Standard errors clustered at the household/firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Figure A.5: Attention as measured in the open-ended question and Google Trends data



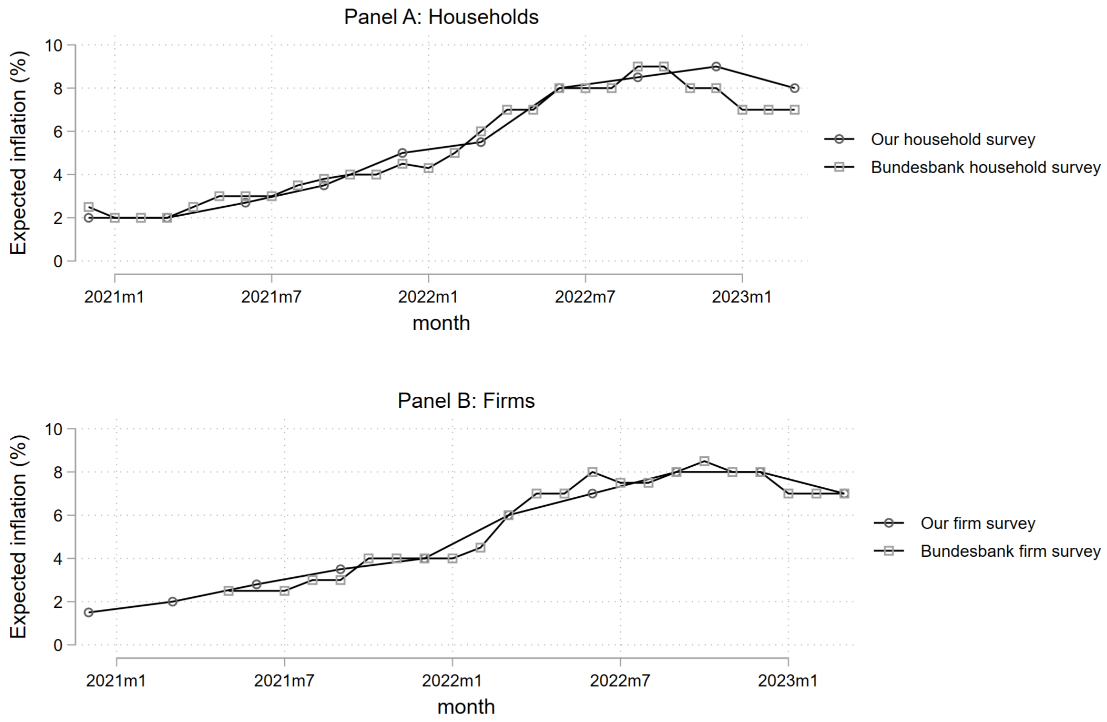
Notes: This figure displays the evolution of the fractions of household respondents that raise different topics in the open-ended survey question across survey waves (Panel A) and weekly Google Trends data for Germany (Panel B). The lines refer to specific macroeconomic topics: inflation, monetary policy, and growth. Google Trends offers a platform to explore search data, delivering a search intensity metric for each query that ranges from 0 to 100. A score of 100 indicates the peak popularity of the terms queried within a specific area and period. Users can formulate queries using single search terms or broader topics that include multiple related terms. We follow the latter approach. To make the searches comparable in relative terms, we select the three topics at the same time. We aggregate the respective topics to quarterly frequency for comparability to the survey data. Note that due to the quarterly aggregation, the peak searches within our period (in our case, inflation) are below 100, as the peak refers to the weekly data.

Figure A.6: Attention allocation across topics as measured in the open-ended and as measured in a structured survey question



Notes: This figure presents a validation exercise of our hand-coded attention data based on an additional German household survey run with Prolific in September 2023. It shows the fractions of respondents paying attention to different topics according to the open-ended question (Panel A) and according to a structured question included later in the survey (Panel B), including error bands. Aggregate topics are displayed in black, while household-level topics are displayed in gray.

Figure A.7: Median inflation expectations in our surveys compared to Bundesbank surveys



Notes: This figure compares the development of the median inflation expectations in our household and firm surveys over time to the development of median expectations in the Bundesbank Online Panels of Firms and of Households (BOP-HH and BOP-F, respectively), which aim to be representative of the underlying populations.

A.2 Additional tables

Table A.1: Summary statistics

	GSOEP	Survey samples					
	(1) Mean	(2) Mean	(3) p25	(4) Median	(5) p75	(6) SD	(7) N
Panel A: Households							
Female	0.51	0.45	0.00	0.00	1.00	0.50	40,552
Age	51.19	52.53	40.00	50.00	60.00	13.85	40,552
East	0.17	0.17	0.00	0.00	0.00	0.38	40,552
Log(HH net income)	7.96	7.78	7.60	8.01	8.36	0.69	40,552
At least highschool	0.39	0.50	0.00	1.00	1.00	0.50	40,552
Employed	0.64	0.59	0.00	1.00	1.00	0.49	38,421
Homeowner	0.49	0.48	0.00	0.00	1.00	0.50	40,552
Stockowner	0.26	0.42	0.00	0.00	1.00	0.49	40,552
Panel B: Firms							
Employees		326.00	14.00	40.00	125.00	2336.81	32,539
Export share		0.15	0.00	0.01	0.24	0.24	17,101
Manufacturing firm		0.29	0.00	0.00	1.00	0.45	32,612
Services firm		0.41	0.00	0.00	1.00	0.49	32,612
Construction firm		0.08	0.00	0.00	0.00	0.27	32,612
Retail/wholesale firm		0.22	0.00	0.00	0.00	0.41	32,612
High influence on decisions in firm		0.78	1.00	1.00	1.00	0.42	20,417

Notes: This table provides summary statistics for the household sample (Panel A) and the firm sample (Panel B). Column 1 shows population benchmarks from the 2020 wave of the German Socioeconomic Panel, which is representative of the German population. Column 7 indicates for how many observations in our panel dataset a particular variable is available, counting repeat respondents multiple times.

Table A.2: Relationship b/w hand-coded data and word count: Attention to inflation

	Hand-coded	Automated word count					Correl-ation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Inflation	Price	Cost	Expen-sive	Joint word count	hand-coded vs. joint word count
Panel A: Households							
Wave 1: 2020m12	0.03	0.01	0.02	0.01	0.03	0.05	0.60
Wave 2: 2021m3	0.04	0.01	0.02	0.01	0.03	0.06	0.75
Wave 3: 2021m6	0.07	0.02	0.04	0.02	0.04	0.10	0.81
Wave 4: 2021m9	0.09	0.04	0.05	0.02	0.05	0.13	0.78
Wave 5: 2021m12	0.16	0.07	0.07	0.02	0.04	0.17	0.88
Wave 6: 2022m3	0.28	0.09	0.14	0.04	0.06	0.27	0.88
Wave 7: 2022m6	0.32	0.21	0.17	0.05	0.06	0.39	0.82
Wave 8: 2022m9	0.38	0.20	0.20	0.08	0.06	0.43	0.86
Wave 9: 2022m12	0.33	0.23	0.19	0.06	0.07	0.42	0.80
Wave 10: 2023m3	0.35	0.23	0.18	0.06	0.08	0.44	0.82
Total (Waves 1-10)	0.19	0.09	0.09	0.03	0.05	0.22	0.84
Panel B: Firms							
Wave 1: 2020m12	0.05	0.01	0.04	0.01	0.03	0.09	0.69
Wave 2: 2021m3	0.10	0.01	0.07	0.01	0.04	0.14	0.79
Wave 3: 2021m6	0.19	0.02	0.15	0.03	0.03	0.23	0.87
Wave 4: 2021m9	0.19	0.03	0.14	0.04	0.06	0.28	0.78
Wave 5: 2021m12	0.25	0.07	0.16	0.04	0.02	0.28	0.89
Wave 6: 2022m3	0.33	0.09	0.24	0.07	0.02	0.39	0.76
Wave 7: 2022m6	0.43	0.19	0.24	0.07	0.03	0.48	0.82
Wave 8: 2022m9	0.42	0.19	0.28	0.10	0.02	0.52	0.75
Wave 9: 2022m12	0.40	0.20	0.22	0.09	0.02	0.46	0.76
Wave 10: 2023m3	0.35	0.20	0.16	0.06	0.02	0.41	0.79
Total (Waves 1-10)	0.28	0.11	0.16	0.06	0.03	0.34	0.81

Notes: Column 1 indicates the fraction of respondents mentioning inflation in response to the open-ended survey question based on manual coding by RAs. Columns 2 – 5 show the fractions of respondents mentioning specific words based on automated counts of the following words "inflation" (Column 2), "preis" (Column 3), "koste" (Column 4) + at least one out of the following: "steig", "stieg", "erhöh", "anheb", or "hoch"; "teuer" or "teurer" (Column 5). Column 6 shows the fraction of respondents for which at least one of the words and word combinations from Columns 2–5 is mentioned. Column 7 depicts the correlation coefficient between hand-coded data (Column 1) and automated word count (Column 6). Panel A focuses on households, while Panel B focuses on firms.

Table A.3: Correlation between hand-coded and AI-coded open-ended data on attention

	AI-coded				
	(1) Covid-19	(2) Inflation	(3) Growth	(4) Any macro topic	(5) Any household-level topic
AI-coded: Covid-19	0.997***	-0.079	-0.004		
	(0.004)	(0.070)	(0.007)		
AI-coded: Inflation	-0.006	0.808***	0.015		
	(0.006)	(0.032)	(0.013)		
AI-coded: Growth	-0.003	0.421**	0.746***		
	(0.004)	(0.205)	(0.219)		
AI-coded: Any macro topic				0.657***	-0.080*
				(0.057)	(0.044)
AI-coded: Any household-level topic				0.095*	0.767***
				(0.054)	(0.059)
Observations	200	200	200	200	200
R-squared	0.66	0.52	0.75	0.38	0.65

Notes: This table presents a validation exercise for the hand-coding of the open-ended data based on a subsample from the household survey wave in March 2023, which was both hand-coded and AI-coded using GPT-4. It regresses dummy variables indicating whether a respondent pays attention to a given topic according to the AI-coding on dummy variables indicating whether a respondent pays attention to a given topic according to the hand-coding. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.4: Correlation between attention as measured in open-ended and as measured in structured survey question

	Open-ended					
	(1)	(2)	(3)	(4)	(5)	(6)
	Covid-19	Inflation	Monetary policy	Growth	Any macro topic	Any household-level topic
Structured: Covid-19	0.098*	-0.032	-0.012*	0.012		
	(0.053)	(0.086)	(0.007)	(0.040)		
Structured: Inflation	0.008*	0.159***	0.008*	0.002		
	(0.005)	(0.041)	(0.004)	(0.014)		
Structured: Monetary policy	-0.008	0.040	0.032	0.039*		
	(0.005)	(0.059)	(0.024)	(0.023)		
Structured: Growth	-0.018*	0.089	-0.006	0.072**		
	(0.010)	(0.062)	(0.020)	(0.029)		
Structured: Any macro topic					0.151***	-0.032
					(0.049)	(0.050)
Structured: Any household-level topic					-0.072	0.469**
					(0.203)	(0.192)
Observations	468	468	468	468	468	468
R-squared	0.10	0.04	0.02	0.04	0.01	0.02
Mean dep. var.	0.01	0.26	0.01	0.03	0.29	0.79

Notes: This table presents a validation exercise of our hand-coded attention data based on an additional German household survey run with Prolific in September 2023. It regresses dummy variables indicating whether a respondent pays attention to a given topic according to the open-ended data on dummy variables indicating whether a respondent pays attention to a given topic according to a structured survey question included later in the survey. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.5: Attention: New vs. recontacted respondents

	Attention to					
	(1)	(2)	(3)	(4)	(5)	(6)
	Covid-19	Inflation	Monetary policy	Growth	Any macro topic	Any household- or firm-level topic
Panel A: Households						
Recontact	-0.003	0.008	-0.001	-0.002	-0.010	0.001
	(0.006)	(0.008)	(0.002)	(0.002)	(0.010)	(0.009)
Distinct respondents	10,755	10,755	10,755	10,755	10,755	10,755
Observations	34,976	34,976	34,976	34,976	34,976	34,976
R-squared	0.03	0.11	0.00	0.00	0.04	0.01
Mean dep. var.	0.06	0.19	0.01	0.01	0.29	0.78
SD dep. var.	0.24	0.39	0.09	0.09	0.45	0.42
Panel B: Firms						
Recontact	-0.000	-0.015	0.002	-0.007	-0.024*	-0.008
	(0.010)	(0.011)	(0.004)	(0.007)	(0.013)	(0.009)
Distinct respondents	6,283	6,283	6,283	6,283	6,283	6,283
Observations	28,880	28,880	28,880	28,880	28,880	28,880
R-squared	0.13	0.10	0.01	0.01	0.01	0.01
Mean dep. var.	0.18	0.28	0.03	0.08	0.63	0.86
SD dep. var.	0.38	0.45	0.17	0.26	0.48	0.35
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual/Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays regressions of a household's (Panel A) or firm's (Panel B) attention to a given topic (indicated at the top) as measured in the open-ended data on a dummy taking value zero for respondents that participate in the panel for the first time and one for those being recontacted in a later wave. All regressions control for survey wave fixed effects as well as household or firm fixed effects. Standard errors clustered at the household/firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.6: Determinants of fixed effects in attention: Households

	Attention			
	(1) Inflation	(2) Monetary policy	(3) Growth	(4) Any macro topic
Low information acquisition costs	0.030***	0.003*	-0.001	0.046***
	(0.007)	(0.002)	(0.002)	(0.009)
High perceived exposure to variable	0.098***	0.005***	0.007***	0.126***
	(0.005)	(0.001)	(0.001)	(0.007)
Female	0.005	-0.003***	-0.003*	0.005
	(0.005)	(0.001)	(0.001)	(0.007)
Age	0.002***	0.000***	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
At least high school	0.004	0.004***	0.001	0.037***
	(0.005)	(0.001)	(0.001)	(0.007)
Employed	-0.000	-0.000	0.002	-0.002
	(0.006)	(0.001)	(0.002)	(0.009)
Log(Income)	-0.001	0.000	0.000	-0.012**
	(0.004)	(0.001)	(0.001)	(0.006)
Home owner	-0.009	0.003**	-0.001	-0.012
	(0.006)	(0.001)	(0.001)	(0.008)
Stock owner	-0.011*	0.003**	0.002	-0.015*
	(0.006)	(0.001)	(0.002)	(0.008)
Observations	10,755	10,755	10,755	10,755
R-squared	0.05	0.01	0.00	0.05

Notes: This table displays regressions of fixed effects in households' attention to a given topic (indicated at the top) as measured in the open-ended data on potential determinants of attention as well as a set of background characteristics. The fixed effects are obtained from regressions of attention to the topic of interest on individual and time fixed effects. "High exposure" is a dummy indicating whether the respondent reports that the respective variable is relevant for the economic situation of the household (at least four on the five-digit scale) in one of the waves between December 2020 and June 2021 (based on the participant's average response for those who are asked multiple times). For "any macro topic" (Column 4), this variable is defined as the respondent's household's mean exposure across inflation, monetary policy, and growth. "Low information acquisition costs" is a dummy that is one if a household states a perceived difficulty of finding relevant information about the development of the economy of at most two on a categorical five-point scale. We further control for gender, age, education, employment status, household income, home ownership, and stock ownership. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.7: Determinants of fixed effects in attention: Firms

	Attention			
	(1) Inflation	(2) Monetary policy	(3) Growth	(4) Any macro topic
High perceived general exposure	0.101***	0.034***	0.026***	0.081***
	(0.007)	(0.003)	(0.005)	(0.009)
High influence on decisions in firm	-0.035***	-0.002	-0.007	0.001
	(0.013)	(0.005)	(0.007)	(0.014)
Log(Employees)	0.007**	0.002*	0.003**	0.015***
	(0.003)	(0.001)	(0.002)	(0.003)
Export share	-0.050**	-0.009	0.027*	0.013
	(0.024)	(0.007)	(0.015)	(0.028)
Services firm	-0.122***	0.027***	-0.002	-0.014
	(0.010)	(0.004)	(0.006)	(0.012)
Construction firm	-0.005	0.059***	0.001	-0.001
	(0.017)	(0.010)	(0.010)	(0.018)
Retail/Wholesale firm	-0.051***	0.020***	-0.014**	0.002
	(0.012)	(0.004)	(0.007)	(0.013)
Observations	6,051	6,047	6,047	6,028
R-squared	0.08	0.04	0.01	0.02

Notes: This table displays regressions of fixed effects in firms' attention to a given topic (indicated at the top) as measured in the open-ended data on a set of covariates. The fixed effects are obtained from regressions of attention to the topic of interest on individual and time fixed effects. "High exposure" is a dummy indicating whether the respondent reports that the respective variable is relevant for the economic situation of the firm (at least four on the five-digit scale) in one of the waves between December 2020 and June 2021 (based on the participant's average response for those who are asked multiple times). For "any macro topic" (Column 4), this variable is defined as the respondent's firm's mean exposure across inflation, monetary policy, and growth. We further control for the respondent's influence on decisions in the firm, the firm's number of employees (in logs) and export share, as well as dummies for four broad industry groups. Robust standard errors are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.8: Attention and deviation from expert benchmarks: Robustness to alternative expert benchmarks

	Absolute deviation from expert forecast (FocusEconomics)		Absolute deviation from expert forecast (ifo Institute)		Absolute deviation from expert forecast (ECB SPF Euro Area Inflation)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Households						
Attention to inflation	0.104	0.414***	0.022	0.400***	0.098	0.409***
	(0.085)	(0.070)	(0.083)	(0.068)	(0.085)	(0.070)
Distinct respondents	10,755	7,126	10,755	7,126	10,755	7,126
Observations	34,976	31,347	34,976	31,347	34,976	31,347
R-squared	0.10	0.66	0.11	0.66	0.10	0.66
Mean dep. var.	4.88	4.67	4.43	4.21	4.84	4.63
SD dep. var.	6.17	5.74	6.09	5.67	6.18	5.76
Panel B: Firms						
Attention to inflation	0.200***	0.164***	0.169***	0.131***	0.204***	0.169***
	(0.046)	(0.032)	(0.043)	(0.032)	(0.046)	(0.032)
Distinct respondents	6,235	4,891	6,235	4,891	6,235	4,891
Observations	28,107	26,763	28,107	26,763	28,107	26,763
R-squared	0.23	0.62	0.24	0.59	0.23	0.62
Mean dep. var.	3.00	2.99	2.60	2.59	2.96	2.95
SD dep. var.	2.72	2.69	2.59	2.57	2.72	2.69
Controls	Yes	No	Yes	No	Yes	No
Individual/Firm FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table demonstrates the robustness of the regressions of the absolute deviation of expected inflation from expert benchmarks on attention to inflation – i.e., an indicator taking value one if inflation is mentioned in response to the open-ended survey question – to using alternative benchmarks, among the samples of households (Panel A) and firms (Panel B). Columns 1 and 2 replicate the baseline results using the mean professional forecast from FocusEconomics presented in Column 4 of Tables 3 and A.9, respectively. In Columns 3 and 4, the benchmark is the 12 month-ahead inflation expectation underlying the Economic Forecasts of the ifo Institute, which publishes YoY-forecasts for CPI inflation in Germany at a quarterly frequency. Columns 5 and 6 use the mean forecast of HICP inflation in the euro zone from the ECB Survey of Professional Forecasters as benchmark. All regressions control for survey wave fixed effects. In Columns 1, 3, and 5, regressions further control for the individual's gender, age, education, employment status, household income, homeownership, and stock ownership, and the respondent's influence on decisions in the firm, the firm's number of employees (in logs) and export share, as well as dummies for four broad industry groups, respectively. Columns 2, 4, and 6 include individual/firm fixed effects. Standard errors clustered at the individual/firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.9: Attention and beliefs: Within-individual patterns

	Absolute change in expectation ≥ 0.5 p.p.	Confidence (z)	Expected inflation	Absolute deviation from expert forecast	Perceived current inflation	Absolute deviation from current level
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Households						
Attention to inflation	0.014	0.022*	0.438***	0.414***	0.114*	0.011
	(0.009)	(0.013)	(0.071)	(0.070)	(0.068)	(0.057)
Distinct respondents	4,720	7,126	7,126	7,126	5,568	5,568
Observations	18,987	31,347	31,347	31,347	21,644	21,644
R-squared	0.28	0.66	0.68	0.66	0.65	0.61
Mean dep. var.	0.79	0.06	6.93	4.67	6.30	2.53
SD dep. var.	0.41	0.98	6.12	5.74	4.97	3.93
Panel B: Firms						
Attention to inflation	0.005	0.024*	0.169***	0.164***		
	(0.008)	(0.013)	(0.033)	(0.032)		
Distinct respondents	3,483	4,819	4,891	4,891		
Observations	17,504	25,747	26,763	26,763		
R-squared	0.22	0.55	0.75	0.62		
Mean dep. var.	0.80	0.04	5.46	2.99		
SD dep. var.	0.40	1.02	3.41	2.69		
Controls	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual/Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays regressions of households' (Panel A) and firms' (Panel B) beliefs on attention to inflation – i.e., an indicator taking value one if inflation is mentioned in response to the open-ended survey question. The dependent variables are an indicator that is one if the respondent changed 12-month ahead inflation expectations by at least 0.5 p.p. between the previous and the current survey wave (Column 1), a respondent's confidence in his/her own inflation forecast (z-scored, Column 2), expected inflation over the next twelve months (Column 3), the absolute deviation of expected inflation from the mean professional forecast from FocusEconomics (Column 4), a respondent's perception of the current inflation rate over the last 12 months (Column 5), and the absolute deviation of this perception from the actually realized current inflation rate (Column 6). Besides survey wave fixed effects, all regressions control for household or firm fixed effects, and thus drop singleton observations. For a version without fixed effects, see Table 3. Standard errors clustered at the household/firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.10: Attention and planned and realized changes in own sales prices: Firms

	Planned price change (trichotomous)		Planned price increase (dummy)		Planned price decrease (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Planned price changes next three months						
Attention to inflation	0.101***	0.086***	0.095***	0.078***	-0.007**	-0.008***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.003)	(0.003)
Distinct respondents	6,178	4,873	6,178	4,873	6,178	4,873
Observations	28,198	26,893	28,198	26,893	28,198	26,893
R-squared	0.10	0.44	0.12	0.45	0.03	0.37
Mean dep. var.	0.42	0.42	0.46	0.46	0.04	0.04
	Realized price change (trichotomous)		Realized price increase (dummy)		Realized price decrease (dummy)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Realized price changes last month						
Attention to inflation	0.063***	0.059***	0.057***	0.055***	-0.006**	-0.005
	(0.008)	(0.008)	(0.007)	(0.007)	(0.003)	(0.003)
Distinct respondents	6,184	4,878	6,184	4,878	6,184	4,878
Observations	28,366	27,060	28,366	27,060	28,366	27,060
R-squared	0.10	0.43	0.13	0.45	0.03	0.41
Mean dep. var.	0.25	0.25	0.29	0.29	0.04	0.04
Controls	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays regressions of firms' pricing plans for the next three months (Panel A) or realized price changes in the last month (Panel B) on attention to inflation. In Columns 1 and 2, the dependent variables are measured on a trichotomous scale: [-1] decrease; [0] stay the same; [1] increase. Regressions in Columns 3 and 4 use dummies indicating planned/realized price increases and Columns 5 and 6 dummies for price decreases. Odd-numbered columns control for the respondent's influence on decisions in the firm, the firm's number of employees (in logs) and export share, as well as dummies for four broad industry groups, respectively. Even-numbered columns control for firm fixed effects and thus drop singleton observations. All specifications control for survey wave fixed effects. Standard errors clustered at the firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.11: Experiences and responses of attention and beliefs to the shock controlling for additional interaction terms: Households

	Attention to inflation		Expected inflation next 12 months		Absolute deviation from expert forecast	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Controlling for inflation exposure						
Inflation experience						
× 1(t ∈ {21m9, 21m12})	0.038***	0.020**	0.610***	0.112	0.603***	0.123
	(0.009)	(0.009)	(0.129)	(0.140)	(0.126)	(0.137)
× 1(t ∈ {22m3, 22m6, 22m9})	0.026*	0.039***	0.995***	0.477***	0.909***	0.455***
	(0.013)	(0.014)	(0.165)	(0.178)	(0.161)	(0.174)
× 1(t ∈ {22m12, 23m3})	0.006	0.041**	0.958***	0.398*	0.851***	0.340*
	(0.017)	(0.018)	(0.195)	(0.210)	(0.188)	(0.204)
Perceived inflation exposure (pre-shock)						
× 1(t ∈ {21m9, 21m12})	0.038***	0.034***	0.496***	0.474***	0.514***	0.496***
	(0.009)	(0.009)	(0.129)	(0.140)	(0.126)	(0.137)
× 1(t ∈ {22m3, 22m6, 22m9})	0.099***	0.091***	0.845***	0.716***	0.805***	0.685***
	(0.013)	(0.014)	(0.165)	(0.178)	(0.161)	(0.174)
× 1(t ∈ {22m12, 23m3})	0.075***	0.059***	1.073***	1.060***	0.953***	0.958***
	(0.017)	(0.018)	(0.193)	(0.211)	(0.187)	(0.204)
Experience measure	Oil crises	Past losses	Oil crises	Past losses	Oil crises	Past losses
Distinct respondents	5,662	4,913	6,460	5,404	6,460	5,404
Observations	26,432	23,820	31,533	27,913	31,533	27,913
R-squared	0.44	0.43	0.66	0.65	0.64	0.63
Panel B: Controlling for changing news supply						
Inflation experience						
× 1(t ∈ {21m9, 21m12})	0.038***	0.026***	0.617***	0.188	0.609***	0.201
	(0.009)	(0.009)	(0.129)	(0.136)	(0.127)	(0.133)
× 1(t ∈ {22m3, 22m6, 22m9})	0.026*	0.053***	1.000***	0.595***	0.914***	0.566***
	(0.013)	(0.014)	(0.166)	(0.175)	(0.162)	(0.171)
× 1(t ∈ {22m12, 23m3})	0.007	0.051***	0.973***	0.586***	0.867***	0.514**
	(0.017)	(0.018)	(0.196)	(0.207)	(0.189)	(0.200)
High news consumption on inflation (pre-shock)						
× 1(t ∈ {21m9, 21m12})	0.002	-0.005	0.004	-0.053	0.022	-0.028
	(0.009)	(0.009)	(0.129)	(0.136)	(0.127)	(0.133)
× 1(t ∈ {22m3, 22m6, 22m9})	0.016	0.010	-0.032	-0.059	-0.025	-0.044
	(0.013)	(0.014)	(0.166)	(0.175)	(0.161)	(0.170)
× 1(t ∈ {22m12, 23m3})	-0.000	-0.006	-0.313	-0.314	-0.363*	-0.353*
	(0.017)	(0.018)	(0.194)	(0.207)	(0.187)	(0.200)
Exposure/experience measure	Oil crises	Past losses	Oil crises	Past losses	Oil crises	Past losses
Distinct respondents	5,662	4,913	6,460	5,404	6,460	5,404
Observations	26,432	23,820	31,533	27,913	31,533	27,913
R-squared	0.44	0.43	0.66	0.65	0.64	0.63
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays regressions of attention and beliefs on measures of prior inflation experiences interacted with the shock period, controlling for perceived economic exposure to inflation or exposure to changing news supply. In Columns 1 and 2, the dependent variables are dummy variables indicating whether a household pays attention to inflation as measured in the open-ended data. In Columns 3–6, the dependent variables are the household's expected inflation over the next 12 months or the absolute deviation of the household's expected inflation from the mean professional forecast reported to FocusEconomics, respectively. The interaction terms interact dummies for time periods with the measures of pre-shock experiences with inflation, i.e., they estimate a differential effect relative to the base period (December 2020-June 2021). In Columns 1, 3 and 5, the experience measure is an indicator for cohorts aged 55 or older at the time of the survey, i.e., those who were at least teenagers during the oil crises of the 1970s. In Columns 2, 4 and 6, the experience measures is based on whether the respondent had ever experienced a real income loss or a real wealth loss due to inflation in the past, as elicited in the pre-shock period in March or June 2021 (based on the first wave this is elicited for a given respondent). In Panel A, we control for additional interactions of the shock periods with a measure of households' perceived exposure to inflation that is one if the respondent reports that the respective variable is relevant for the economic situation of the household (at least four on the five-digit scale) in the waves between December 2020 and June 2021 (based on the participant's average response for those who are asked multiple times). In Panel B, we control for additional interactions of the shock periods with a dummy indicating whether the respondent reports to have informed herself more often about inflation than the median respondent in the waves between December 2020 and June 2021. All specifications include individual fixed effects and survey wave fixed effects, and thus drop singleton observations. Standard errors are clustered at the household level. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table A.12: Attention to energy costs and beliefs about inflation: Households

	Expected inflation next 12 months		Absolute deviation from expert forecast	
	(1)	(2)	(3)	(4)
Attention to energy	0.163**	0.064	0.127*	0.033
	(0.077)	(0.079)	(0.075)	(0.077)
Attention to inflation		0.426***		0.407***
		(0.073)		(0.072)
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Distinct respondents	7,126	7,126	7,126	7,126
Observations	31,347	31,347	31,347	31,347
R-squared	0.68	0.68	0.66	0.66
Mean dep. var.	6.93	6.93	4.67	4.67
SD dep. var.	6.12	6.12	5.74	5.74

Notes: This table investigates the relationship between households' attention to energy costs and beliefs about inflation. The dependent variables are expected inflation over the next twelve months (Columns 1 and 2) and the absolute deviation of expected inflation from the mean professional forecast from FocusEconomics (Columns 3 and 4). The independent variables are dummy variables indicating whether a respondent pays attention to energy (all columns) or inflation (even-numbered columns) as measured in the open-ended data. All regressions control for survey waves fixed effects and individual fixed effects. Standard errors clustered at the household level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

B Full list of codes for classification of open-ended data

In this appendix, we present the full list of codes and explanations that we initially handed out to research assistants to code the open-ended responses to the question: *What topics come to mind when you think about the economic situation of your household/company?* Each response could receive multiple codes. Some topics appear both as a macro and as a household- or firm-level code, which were meant to be used depending on the context. Research assistants were instructed to err on the side of using the household- or firm-level instead of the macro code in unclear or ambiguous cases.

Table B.1: List of codes for classification of open-ended data: Macroeconomic topics

Category	Explanation
Covid-19	Everything related to the pandemic (also if personal consequences of the pandemic for the respondents' household are mentioned – in that case indicate "corona" under "macro topic" and the specific personal consequences under the respective "personal topic"), Covid, corona, pandemic, lockdown.
Inflation	Inflation, rising prices, price level, price increase, purchasing power, gas prices, electricity prices.
Monetary policy	Interest rates, monetary policy, central bank, ECB, negative interest rate.
Growth	Economic growth, GDP, general economic situation, aggregate economy, business cycle, upswing, downturn, insolvencies, company bankruptcies, aggregate demand, overall industrial production, economic crisis, recession.
Labor market	Short-time work, employment, labor market, unemployment rate.
Stock market	DAX, stock exchange, stock market.
Housing market	Housing/residential market, real estate prices, rents
Fiscal policy	tax policy; general generosity of welfare system, government debt: overall financial situation of the government/state, deficit, public debt, public budget (deficit/surplus), value-added tax (reduction).
Regulation	Regulation, minimum wage, subsidies (R&D grants/funding).
Structural transformation	Long-term trends in the economy, digitalization, structural change, structural problems.
Trade	Imports, exports, outsourcing, foreign countries (e.g., "US elections", "Brexit"), globalization, etc.
Pension system	Pension system, old-age poverty.
Health system	Healthcare system, nursing care, shortage of nurses.
Education	Education system, vocational training, universities, schools, research, development.
Inequality	Inequality, income distribution, wealth distribution, social gap, poverty, social equity, gender inequality.
Migration	(Im-)migration, asylum seekers, refugees.
Environment/ Climate change	Environment, pollution, climate, climate crisis.
Uncertainty	Uncertainty about macroeconomic development.
Other	Residual code for macro topics.

Notes: This table lists all macroeconomic topics in our coding scheme and provides an explanation for each topic.

Table B.2: List of codes for classification of open-ended data: Household-level topics

Category	Explanation
Overall situation	General financial and economic situation of the household.
Spending	Expenditure/spending, consumption.
Income	Income, liquidity, money troubles, shortage/lack of money, insufficient financial security, etc.
Job situation	Job loss, job security, job search, short-time work.
Saving	Capital accumulation, retirement provision, old-age provision, building up reserves.
Financial assets	Shares, other financial investments, investment decisions.
Housing costs	Rental costs, house prices, ancillary leasing costs.
Energy	Energy, oil, gas, gasoline/Diesel, electricity, heating, heat pump, carbon tax.
Debt	Debt, loans, amortisation payments, interest payments on existing debt, etc.
Health issues	Health risks, medical expenses.
Insurance	Insurance, protection, provision.
Uncertainty	Uncertainty about the financial and economic future of the household/the individual.
Other	Residual code for household-level topics.

Notes: This table lists all household-level topics in our coding scheme and provides an explanation for each topic.

Table B.3: List of codes for classification of open-ended data: Firm-level topics

Category	Explanation
Overall situation	Overall situation of firm.
Costs	Material costs, purchase prices, prices of intermediate inputs, labor costs, freight costs.
Energy	Energy, oil, gas, gasoline/Diesel, electricity, heating, heat pump, carbon tax.
Supply chain	Problems with supply chain, bottlenecks in primary products/raw materials, logistics problems, suppliers.
Demand	Sales, demand, customers, orders/order situation/order backlog, competitive pressure.
Labor input	Labor shortage, shortage of skilled workers, vacancies, layoffs, personnel development, (vocational) training.
Profits/ Profitability	profits, margin, EBIT, profitability.
Liquidity/ Solvency	Liquidity, reserves, equity, insolvency.
Process organization	Work processes, digitalization, work-from-home, restructuring, process optimization.
Government aid programs	KfW loans (Investment Bank of German Government), financial aid and governmental crisis response programs (e.g., in response to Covid crisis) (all if related to own firm, only).
R&D	Innovation, quality improvement, product development.
Regulation	Approval processes/authorization procedures, bureaucracy/relation to public/tax authorities, public tender offers, taxation system/tax burden, environmental requirements (all if related to own firm, only).
Financing	Financing conditions, lending, debt.
Short time work	Employees put to short-time work, short-time work announced by the firm to the Federal Employment Agency.
Capacity utilization	Utilization of production capacities.
Rent and housing costs	Rent, housing costs.
Investment	Investment.
Uncertainty	Uncertainty regarding future development of firm.
Other	Residual code for firm-level topics.

Notes: This table lists all firm-level topics in our coding scheme and provides an explanation for each topic.

C Model appendix

C.1 Other predictions of attention with selective memory recall

The model of selective memory recall in Section 5 can account for the two core empirical failures of theories of goal-optimal attention such as the model of Section 3. We now demonstrate that those predictions of the baseline model of Section 3 that are confirmed in the data still hold in the modified model of Section 5.

First, the determinants of attention remain the same, except that experiences may also affect agents' attention allocation. Hence, the model still predicts that agents that are more exposed to a variable or face lower information costs pay – ceteris paribus – more attention to it. Second, selective recall affects agents' nowcasts only in the sense that it makes agents more or less attentive. Conditional on the attention choice, however, nowcasts are unaffected. Hence, the model still predicts that attentive agents should hold smaller misperceptions about realized inflation. Third, attentive agents still update their expectations more frequently in an environment of changing signals. Fourth, in Section 4 we show that agents that are attentive to inflation are more confident in their inflation forecasts. To see that the model of Section 5 can still account for this fact, recall that posterior uncertainty is given by $Var(\pi'|s) = \rho_\pi^2 Var(\pi|s) + \sigma_v^2$, where $Var(\pi|s) = \frac{\kappa}{B\rho_\pi^2}$. We assume that the posterior uncertainty agents report in the survey already accounts for the updated $\hat{\rho}_\pi$, so $Var(\pi'|s) = \hat{\rho}_\pi^2 Var(\pi|s) + \sigma_v^2$. So posterior uncertainty for attentive agents (denoted by superscript A) is lower than for inattentive agents (denoted by IA) if

$$\begin{aligned}(\hat{\rho}_\pi^A)^2 Var^A(\pi|s) &< (\hat{\rho}_\pi^{IA})^2 Var^{IA}(\pi|s) \\ \frac{(1+\theta^A)^2}{(1+\theta^{IA})^2} &< \frac{\kappa^{IA}}{\kappa^A} \cdot \frac{B^A}{B^{IA}}. \end{aligned} \tag{13}$$

Inequality (13) illustrates that attentive agents exhibit less posterior uncertainty if the influence of their selective memory recall when formulating their forecasts does not distort their beliefs too strongly relative to inattentive agents.

D Additional empirical results

D.1 Joint variation of attention to different topics

For simplicity, in our models in Sections 3 and 5 agents attend to and form beliefs about only one variable. In models featuring both a cost of attention and multiple variables, paying more attention to a given topic can reduce attention to other topics. In this appendix, we study the joint variation of attention to different topics. We estimate specifications of the following type:

$$\text{Attention topic A}_{it} = \beta_0 + \beta_1 \text{Attention topic B}_{it} + X_{it}'\Pi + \phi_t + \varepsilon_{it}, \tag{14}$$

where the attention variables are dummy variables indicating attention to topic A or to topic B, respectively. X_{it} includes our standard set of controls, which in some specifications is replaced by individual fixed effects. In addition, all specifications include survey wave fixed effects, ϕ_t. Throughout the paper, standard errors are clustered at the respondent level.

Panel A of Table D.1 shows the results for households. Attention to inflation and attention to monetary policy are strongly positively correlated. Specifically, being attentive to monetary policy increases the likelihood of being attentive to inflation by 30.1 p.p. according to our pooled OLS estimates (Column 3, $p < 0.01$) and by 13.0 p.p. conditional on individual fixed effects (Column 4, $p < 0.01$). Attention to economic growth is weakly positively related to attention to inflation or monetary policy (Columns 1, 2, 5, and 6). Lastly, attention to household-level topics is strongly negatively associated with attention to macroeconomic topics: paying attention to at least one household-level topic reduces the likelihood of paying attention to at least one aggregate topic by 14.1 p.p. and 25.0 p.p. according to pooled OLS and individual fixed effects estimates, respectively (Columns 7 and 8, $p < 0.01$). Panel B of Table D.1 shows broadly similar results for firms. Figure D.1 displays pairwise correlation coefficients for attention to a broader set of macroeconomic and household- or firm-level topics.

One concern is that the open-response format might mechanically produce negative relationships between attention to different topics, as respondents may only provide a response of a certain length. Given that attention is strongly *positively* correlated across some topics (e.g., inflation and monetary policy), this concern appears less severe. Moreover, the length of responses could reflect limits to respondents' actual "attention budget" rather than additional filtering through the response format. A related concern is that respondents may interpret the prompt differently, leading them to refer either to aggregate or to local topics. However, (i) the interpretation of the prompt will at least partly reflect respondents' attention allocation, and (ii) more stable differences in response behavior are shut down by individual fixed effects.

Table D.2 shows that the negative relationship between attention to macro and attention to more local topics is robust to various checks. Columns 1 and 2 display the baseline specifications

Table D.1: Co-movement of attention to different topics

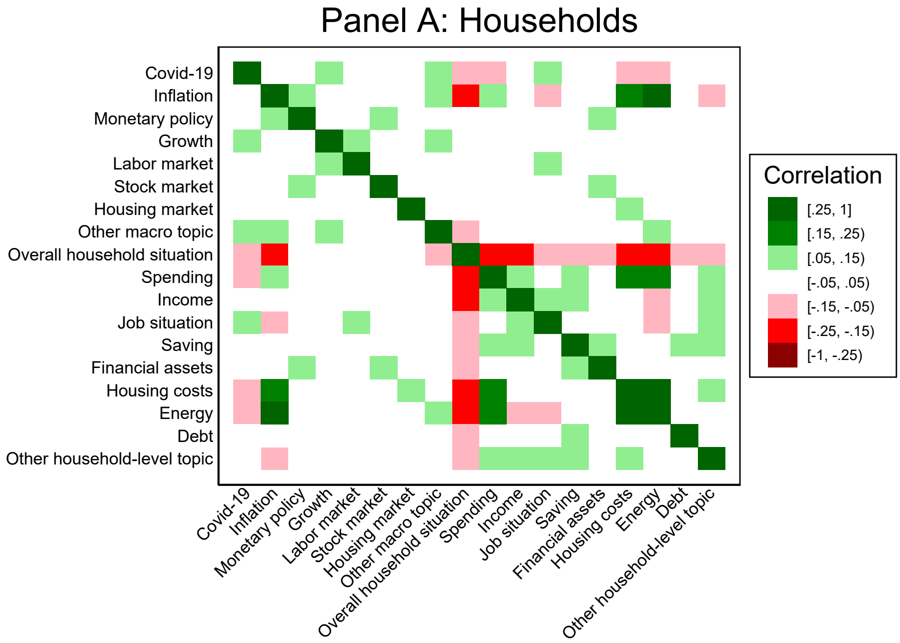
	Attention to inflation				Attention to monetary policy		Attention to any macro topic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Households								
Attention to growth	0.140***	0.057*			0.013	0.012		
	(0.027)	(0.031)			(0.009)	(0.008)		
Attention to monetary policy			0.301***	0.130***				
			(0.030)	(0.031)				
Attention to any household-level topic							-0.141***	-0.250***
							(0.008)	(0.008)
Distinct respondents	10,755	7,126	10,755	7,126	10,755	7,126	10,755	7,126
Observations	34,976	31,347	34,976	31,347	34,976	31,347	34,976	31,347
R-squared	0.11	0.45	0.12	0.45	0.01	0.28	0.05	0.46
Panel B: Firms								
Attention to growth	0.030***	-0.004			0.030***	0.010**		
	(0.011)	(0.011)			(0.005)	(0.005)		
Attention to monetary policy			0.210***	0.112***				
			(0.019)	(0.020)				
Attention to any firm-level topic							-0.312***	-0.294***
							(0.007)	(0.008)
Distinct respondents	6,283	4,951	6,283	4,951	6,283	4,951	6,283	4,951
Observations	28,880	27,548	28,880	27,548	28,880	27,548	28,880	27,548
R-squared	0.10	0.39	0.11	0.39	0.02	0.35	0.06	0.37
Controls	Yes	No	Yes	No	Yes	No	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual/Firm FE	No	Yes	No	Yes	No	Yes	No	Yes

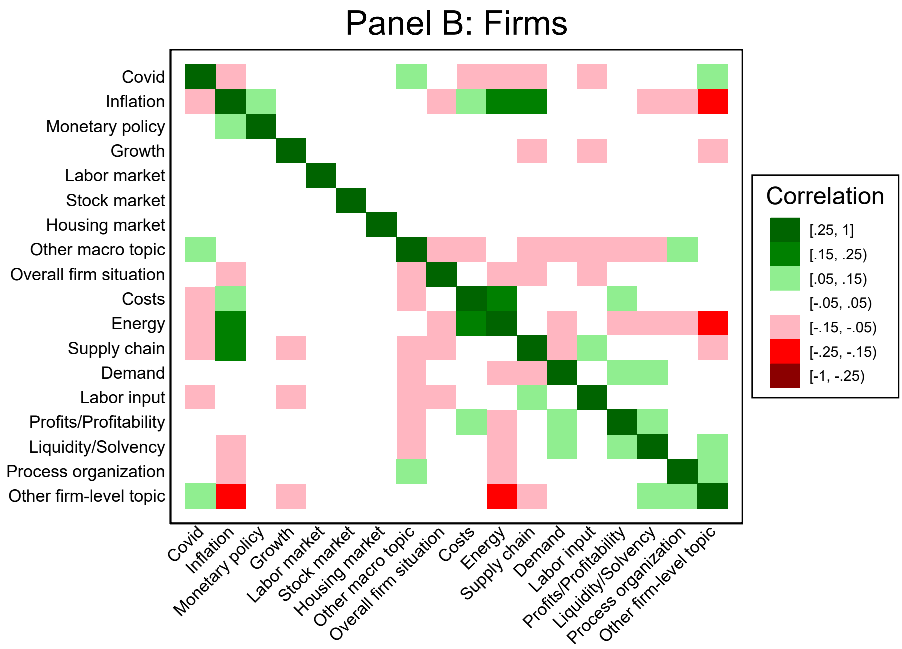
Notes: This table displays regressions of dummy variables indicating households' (Panel A) and firms' (Panel B) attention to a given topic – i.e., an indicator taking value one if the topic is mentioned in response to the open-ended survey question – on dummy variables indicating attention to another topic. Attention to macroeconomic topics in general (Columns 7 and 8) includes all macro topics. Attention to household-level or firm-level topics covers all local-level topics. Columns 1, 3, 5, and 7 control for the individual's gender, age, education, employment status, household income, homeownership, and stock ownership, and the respondent's influence on decisions in the firm, the firm's number of employees (in logs) and export share, as well as dummies for four broad industry groups, respectively. Columns 2, 4, 6 and 8 instead control for individual and firm fixed effects, respectively, and thus drop singleton observations. All specifications control for survey wave fixed effects. Standard errors clustered at the household/firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

using dummy variables for attending to at least one macro-, household- or firm-level topic. Columns 3 and 4 instead use continuous variables for the number of topics from a given family. Columns 5 and 6 exclude topics from the macro-, household-, and firm-level variables for which the classification into macro vs household-/firm-level may at times not be clear-cut.[1] Lastly,

[1]Specifically, we exclude "housing market", "regulation", "uncertainty", "labor market", and "monetary policy" from the macro topics, "housing costs", "energy", "uncertainty", "job situation", and "debt" from the household-level topics, and "costs", "rent/housing costs", "energy", "uncertainty", "labor input", "regulation", "government aid programs", "short-time work", and "financing" from the firm-level topics. Hence, only 14 out of 19 macro topics, 8 out of 13 household-level topics, and 10 out of 19 firm-level topics listed in Appendix Tables B.1–B.3 are still included.

Figure D.1: Attention: Correlations across topics





Notes: This figure presents correlation coefficients between attention to different topics as measured in the open-ended data. Positive correlation coefficients within specific ranges are presented in varying shades of green, while negative correlation coefficients are presented in varying shades of red. Panel A focuses on households, while Panel B focuses on firms. The categories "Other macro topic", "Other household-level topic", and "Other firm-level topic" subsume all macro, household-level, and firm-level topics in our coding scheme that are not displayed in their own columns/rows in the figure (i.e., the categories in the figure are broader than the original "other" categories in our coding scheme displayed in Appendix Tables B.1, B.2, and B.3).

Columns 7 and 8 show that the negative relationships between attention to aggregate and attention to household-/firm-level topics are robust to excluding Covid-19 from the macroeconomic topics,

Table D.2: Co-movement of attention to different topics: Robustness

	Attention to any macro topic (baseline)		Number of macro topics		Attention to any macro topic (narrow definition)		Attention to any macro topic excl. Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Households								
Attention to any household-level topic	-0.141***	-0.250***					-0.110***	-0.207***
	(0.008)	(0.008)					(0.007)	(0.008)
Number of household-level topics			-0.011***	-0.096***				
			(0.004)	(0.005)				
Attention to any household-level topic (narrow definition)					-0.201***	-0.244***		
					(0.006)	(0.007)		
Distinct respondents	10,755	7,126	10,755	7,126	10,755	7,126	10,755	7,126
Observations	34,976	31,347	34,976	31,347	34,976	31,347	34,976	31,347
R-squared	0.05	0.46	0.03	0.44	0.08	0.47	0.09	0.46
Panel B: Firms								
Attention to any firm-level topic	-0.312***	-0.294***					-0.276***	-0.268***
	(0.007)	(0.008)					(0.008)	(0.009)
Number of firm-level topics			-0.115***	-0.189***				
			(0.006)	(0.006)				
Attention to any firm-level topic (narrow definition)					-0.127***	-0.138***		
					(0.007)	(0.007)		
Distinct respondents	6,283	4,951	6,283	4,951	6,283	4,951	6,283	4,951
Observations	28,880	27,548	28,880	27,548	28,880	27,548	28,880	27,548
R-squared	0.06	0.37	0.03	0.41	0.03	0.35	0.07	0.37
Controls	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	No	No	No	Yes	No	No

Notes: This table displays regressions of dummy variables indicating households' (Panel A) and firms' (Panel B) attention to macroeconomic topics – i.e., an indicator taking value one if any macroeconomic topic is mentioned in response to the open-ended survey question – on dummy variables indicating attention to household-level or firm-level topics, respectively. Columns 1 and 2 replicate the baseline results displayed in Columns 7 and 8 of Table D.1. Columns 3 and 4 use continuous variables for the number of topics from a given family. Columns 5 and 6 exclude topics for which the classification into macro vs household-/firm level may at times not be clear-cut (see Footnote 1 for details). In Columns 7 and 8, Covid-19 is dropped from the macroeconomic topics (and also not coded as a household- or firm-level topic). Odd-numbered columns control for the individual's gender, age, education, employment status, household income, homeownership, and stock ownership, and the respondent's influence on decisions in the firm, the firm's number of employees (in logs) and export share, as well as dummies for four broad industry groups, respectively. Even-numbered columns instead control for household and firm fixed effects, respectively, and thus drop singleton observations. All specifications control for survey wave fixed effects. Standard errors clustered at the household/firm level are in parentheses. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

suggesting that the patterns are not driven by the specific circumstances of the pandemic at the beginning of our sample period.

Our results are consistent with attentional crowding-out between different variables, as predicted by theories featuring limited cognitive resources (Bordalo et al., 2025; Gabaix, 2014; Maćkowiak et al., 2023). Our data suggest that this crowding-out operates between aggregate and household- or firm-level topics, in line with the assumption in Maćkowiak and Wiederholt

(2009). Our findings are less supportive of sticky information models (Mankiw and Reis, 2002; Reis, 2006a), in which agents acquire information about all (economic) topics jointly. By contrast, crowding-out does not seem to occur between different aggregate topics. Instead, the positive correlation of attention across different macro topics, in particular between inflation and monetary policy, points to a role for attentional spillovers, e.g., due to joint news coverage. Our results on attentional crowding-out in a field setting complement recent evidence from online experiments showing that attention to one feature of a statistical problem can crowd out attention to another feature (Bordalo et al., 2023a).

E Instructions of panel surveys

This Appendix provides an overview of the translated and original survey instructions of the key questions in the household and firm surveys. We provide an overview of the main questions (asked in all waves) as well as additional questions only asked in subsets of the waves. In principle, the survey is identical for the household and firm panels. However, some questions are only asked in the household panel due to space constraints in the firm survey. Moreover, the wording of some questions is slightly tailored to better fit the respective situation of households and firms. Section E.1 provides instructions translated to English, while Section E.2 provides the original instructions in German.

E.1 English translation

E.1.1 Core instructions included in all waves

Attention:

What topics come to mind when you think about the economic situation of your company/household?

____

Expected inflation:

What do you think, what will the inflation rate (measured by the consumer price index) likely be in Germany over the next 12 months (i.e., until XXX)? __%

Confidence in forecast:

How certain are you about your previous estimate?
very uncertain ☐ ☐ ☐ ☐ ☐ very certain

E.1.2 Additional instructions included in subsets of the waves

Perceived current inflation (households only, starting 2021m9):

What do you think was the inflation rate in Germany over the last 12 months (i.e., from XXX to XXX)? __%

Experienced income loss (households only, 2021m3 & 2021m6):

Has your household income ever increased significantly less than the general price level?
☐ Yes ☐ No

Experienced wealth loss (households only, 2021m3 & 2021m6):

Has your wealth ever lost significant value due to inflation?
☐ Yes ☐ No

Minutes spent on inflation news (households: 2021m12-2022m12; firms: 2021m12-2022m9):

What do you think, how much time have you spent consuming news on inflation from various media (TV, newspaper, news websites, radio etc.) in the past 7 days?
☐ Less than 5 minutes
☐ Between 5 minutes and 10 minutes
☐ Between 10 minutes and 30 minutes
☐ Between 30 minutes and 60 minutes
☐ More than 60 minutes

Consumed reports on inflation (2021m9-2022m12):

How many reports on inflation in Germany do you estimate you have seen or heard in the last 3 months in the following media?

- Television
  none ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ 10 or more
- Newspapers/News websites
  none ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ 10 or more
- Radio
  none ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ 10 or more

Information acquisition about inflation:

What do you think: How frequently did you gather information about each of the following topics in the last 3 months before taking this survey?

- Development of inflation in Germany
  0 times ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ 10 times or more
- ...

Information acquisition costs (households only, 2021m9):
Imagine that you wanted to inform yourself about the development of the economy (e.g., inflation) in Germany. How difficult would it be for you to find relevant information about the development of the economy?
very easy ☐ ☐ ☐ ☐ ☐ very difficult

Self-reported exposure (Households: all waves, firms: 2020m12; 2021m9-2023m3):
To what extent do you agree with the following statements?

- Inflation in Germany is important for the economic situation of my firm/household.
  strongly disagree ☐ ☐ ☐ ☐ ☐ strongly agree
- Monetary policy of the ECB (e.g., interest rate policy) is important for the economic situation of my firm/household.
  strongly disagree ☐ ☐ ☐ ☐ ☐ strongly agree
- Economic growth in Germany is important for the economic situation of my firm/household.
  strongly disagree ☐ ☐ ☐ ☐ ☐ strongly agree

- (Household survey only:) The development of labor market conditions in my occupation are important for the economic situation of my household.
  strongly disagree ☐ ☐ ☐ ☐ ☐ strongly agree
- (Household survey only:) The costs of living in our location are important for the economic situation of my household.
  strongly disagree ☐ ☐ ☐ ☐ ☐ strongly agree

E.2 Original instructions in German

E.2.1 Core instructions included in all waves

Attention:

Welche Themen kommen Ihnen in den Sinn, wenn Sie an die wirtschaftliche Situation Ihres Unternehmens/Haushalts denken? _______________

Expected inflation:

Was denken Sie, wie hoch wird die Inflationsrate (gemessen am Verbraucherpreisindex) über die nächsten 12 Monate (also bis zum XXX) in Deutschland wahrscheinlich sein? __%

Confidence in forecast:

Wie sicher sind Sie sich bei dieser Einschätzung?
sehr unsicher ☐ ☐ ☐ ☐ ☐ sehr sicher

E.2.2 Additional instructions included in subsets of the waves

Perceived current inflation (households only, starting 2021m9):

Was denken Sie, wie hoch war die Inflationsrate in Deutschland über die letzten 12 Monate (also über den Zeitraum von XXX bis XXX)? __%

Experienced income loss (households only, 2021m3 & 2021m6):

Ist Ihr Haushaltseinkommen schon einmal deutlich weniger stark gestiegen als das allgemeine Preisniveau?
☐ Ja ☐ Nein

Experienced wealth loss (households only, 2021m3 & 2021m6):

Hat Ihr Vermögen schon einmal aufgrund von Inflation stark an Wert verloren?
☐ Ja ☐ Nein

Minutes spent on inflation news (households: 2021m12-2022m12; firms: 2021m12-2022m9):

Was schätzen Sie, wieviel Zeit haben Sie in den letzten 7 Tagen insgesamt damit verbracht, Nachrichten zur Inflation in verschiedenen Medien (Fernsehen, Zeitung, Nachrichten-Websites, Radio, etc.) zu konsumieren?

☐ Weniger als 5 Minuten
☐ Zwischen 5 Minuten und 10 Minuten
☐ Zwischen 10 Minuten und 30 Minuten
☐ Zwischen 30 Minuten und 60 Minuten
☐ Mehr als 60 Minuten

Consumed reports on inflation (2021m9-2022m12):

Was schätzen Sie, wie viele Berichte zur Inflation in Deutschland haben Sie in den letzten 3 Monaten in den folgenden Medien gesehen bzw. gehört?

- Fernsehen
  keine ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ 10 und mehr

- Zeitungen/Nachrichten-Websites
  keine ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ 10 und mehr

- Radio
  keine ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ 10 und mehr

Information acquisition about inflation:

Was schätzen Sie, wie oft haben Sie sich in den letzten 3 Monaten zu den folgenden Themen informiert?

- Entwicklung der Inflation in Deutschland
  gar nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ 10 mal und öfter

- . . .

Information acquisition costs (households only, 2021m9):
Stellen Sie sich vor, Sie wollen sich über die Entwicklung der Wirtschaft (wie z.B. der Inflation) in Deutschland informieren. Wie schwierig wäre es für Sie, relevante Informationen über die Entwicklung der Wirtschaft zu finden?
sehr leicht ☐ ☐ ☐ ☐ ☐ sehr schwierig

Self-reported exposure (Households: all waves, firms: 2020m12; 2021m9-2023m3):
Inwiefern stimmen Sie den folgenden Aussagen zu?

- Die Inflation in Deutschland ist wichtig für die derzeitige wirtschaftliche Situation unseres Unternehmens/meines Haushalts.
  stimme nicht zu ☐ ☐ ☐ ☐ ☐ stimme voll zu

- Die Geldpolitik der EZB (z.B. Zinspolitik) ist wichtig für die derzeitige wirtschaftliche Situation unseres Unternehmens/meines Haushalts.
  stimme nicht zu ☐ ☐ ☐ ☐ ☐ stimme voll zu

- Das Wirtschaftswachstum in Deutschland ist wichtig für die derzeitige wirtschaftliche Situation unseres Unternehmens/meines Haushalts.
  stimme nicht zu ☐ ☐ ☐ ☐ ☐ stimme voll zu

- (Household survey only:) Die Entwicklung des Arbeitsmarkts für meine Berufsgruppe ist wichtig für die derzeitige wirtschaftliche Situation meines Haushalts.
  stimme nicht zu ☐ ☐ ☐ ☐ ☐ stimme voll zu
- (Household survey only:) Die Entwicklung der Lebenshaltungskosten in meiner Wohngegend ist wichtig für die derzeitige wirtschaftliche Situation meines Haushalts.
  stimme nicht zu ☐ ☐ ☐ ☐ ☐ stimme voll zu

F Instructions of validation survey

This Appendix provides an overview of the translated and original survey instructions of the key questions in the validation survey that we conducted with a sample of German households in September 2023 on the platform Prolific. Section F.1 provides instructions translated to English, while Section F.2 provides the original instructions in German.

F.1 English translation

Attention: open-ended:

What topics come to mind when you think about the economic situation of your household? ________________

Attention: structured (randomized order of response options, except last):

Now please think again about the economic situation of your household. Which of the following topics come to mind? Please check all that apply.
☐ Covid-19 pandemic
☐ Inflation in Germany
☐ Interest rates and monetary policy of the European Central Bank (ECB)
☐ Economic growth in Germany
☐ The German labor market
☐ The German stock market
☐ The German real estate market
☐ Consumption spending of your household
☐ Your household income
☐ Job situation of the household members
☐ Savings behavior of your household
☐ Financial assets of your household
☐ Your expenditure on rent and housing
☐ Your household's cost of living
☐ Your household's debt
☐ None of the topics mentioned

F.2 Original instructions in German

Attention: open-ended:

Welche Themen kommen Ihnen in den Sinn, wenn Sie an die wirtschaftliche Situation Ihres Haushalts denken? ________________

Attention: structured (randomized order of response options, except last):

Denken Sie nun bitte nochmals an die wirtschaftliche Situation Ihres Haushalts. Welche der folgenden Themen kommen Ihnen dabei in den Sinn? Bitte kreuzen Sie alle zutreffenden Themen an.
☐ Covid-19 Pandemie

☐ Inflation in Deutschland
☐ Zinsen und Geldpolitik der Europäischen Zentralbank (EZB)
☐ Wirtschaftswachstum in Deutschland
☐ Der deutsche Arbeitsmarkt
☐ Der deutsche Aktienmarkt
☐ Der deutsche Immobilienmarkt
☐ Konsumverhalten Ihres Haushalts
☐ Ihr Haushaltseinkommen
☐ Arbeitsplatzsituation der Haushaltsmitglieder
☐ Sparverhalten Ihres Haushalts
☐ Finanzanlagen Ihres Haushalts
☐ Ihre Ausgaben für Miete und Wohnen
☐ Lebenshaltungskosten Ihres Haushalts
☐ Schulden Ihres Haushalts
☐ Keines der genannten Themen