# Narratives about the Macroeconomy*

Peter Andre Ingar Haaland Christopher Roth
Mirko Wiederholt Johannes Wohlfart

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**Abstract**

We study narratives about the macroeconomy—the stories people tell to explain macroeconomic phenomena—in the context of a historic surge in inflation. In our empirical analysis, we field surveys with more than 10,000 US households and 100 academic experts, measure economic narratives in open-ended questions, and represent them as Directed Acyclic Graphs. Households' narratives are strongly heterogeneous, coarser than experts' narratives, focus more on the supply than demand side, and often feature politically charged explanations. Moreover, narratives shape how households form inflation expectations and interpret new information, which we demonstrate in a series of experiments. Informed by these findings, our theoretical analysis incorporates narratives into an otherwise conventional New Keynesian model and demonstrates their importance for aggregate outcomes through their effect on agents' expectations.

**Keywords**: Narratives, Expectation Formation, Causal Reasoning, Inflation, Aggregate Consequences.

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*Peter Andre, Leibniz Institute for Financial Research SAFE and Goethe University Frankfurt, CESifo, IZA (e-mail: andre@safe-frankfurt.de); Ingar Haaland, NHH Norwegian School of Economics (e-mail: Ingar.Haaland@nhh.no); Christopher Roth, University of Cologne, NHH Norwegian School of Economics, and MPI for Research on Collective Goods Bonn (email: roth@wiso.uni-koeln.de); Mirko Wiederholt, LMU Munich and Sciences Po, CESifo, CEPR, email: Mirko.Wiederholt@gmail.com; Johannes Wohlfart, University of Cologne, ECONtribute, CESifo, MPI for Research on Collective Goods Bonn and CEBI, University of Copenhagen (e-mail: wohlfart@wiso.uni-koeln.de). We greatly thank all scholars who participated in the expert survey. We thank the editor and three anonymous referees for constructive suggestions that improved the paper considerably. Rüdiger Bachmann, Benjamin Born, Felix Chopra, Olivier Coibion, Armin Falk, Andreas Fuster, Andrej Gill, Yuriy Gorodnichenko, Christian Hellwig, Luca Henkel, Alistair Macaulay, Ulrike Malmendier and Andreas Stegmann for very helpful comments. Maximilian Fell, Astrid Fugleholm, Sophia Hornberger, Kanita Isaković, Apoorv Kanongo, Emir Kavukcu, Melisa Kurtis, Leonardo Arias Lievano, Luca Michels, Nico Röver, and Malin Siemers provided excellent research assistance. We also thank seminar and conference audiences at numerous places for helpful comments and discussions. The activities of the Center for Economic Behavior and Inequality (CEBI) are financed by the Danish National Research Foundation, Grant DNRF134. Funding by the Deutsche Forschungsgemeinschaft (DFG) through CRC TR 224 (Project A01) is gratefully acknowledged. Financial support from the Research Council of Norway through its Centre of Excellence Scheme (FAIR project No 262675) is gratefully acknowledged. Andre: Research support from the Leibniz Institute for Financial Research SAFE is gratefully acknowledged. Roth and Wohlfart: Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/1-390838866. IRB approval was obtained from the German Association for Experimental Economic Research (GfeW), the Ethics Committee of the University of Cologne, and the NHH Norwegian School of Economics.

## 1 Introduction

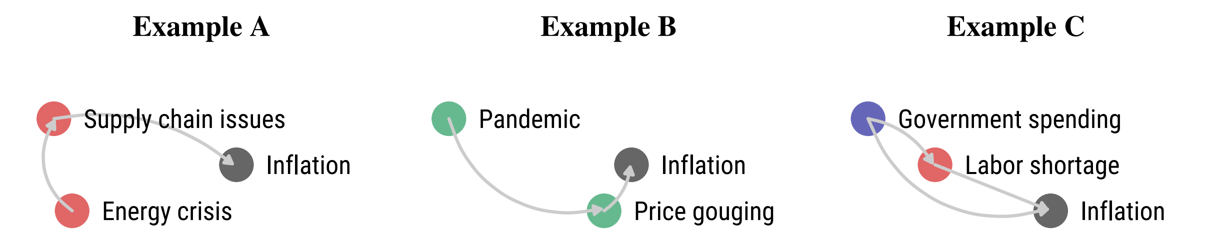
Narratives—the stories people tell to explain the world—provide a lens through which individuals can interpret data and forecast future developments. Psychologists have long acknowledged the importance of narratives, which they describe as "instruments of mind in the construction of reality" that are helpful to organize and explain the world (Bruner, 1991). More recently, economists have hypothesized that narratives also have important implications for the economy (Shiller, 2017, 2020). Narratives could be particularly relevant for understanding how people make sense of macroeconomic phenomena, which are often complex and consistent with different explanations. Narratives about the macroeconomy might thus shape individuals' macroeconomic expectations, which have been shown to affect important economic decisions (Armona et al., 2018; Bailey et al., 2018; Coibion et al., 2022; D'Acunto et al., 2021a, 2022; Giglio et al., 2021). Nonetheless, empirical evidence on economic narratives remains scarce and our formal understanding of their macroeconomic consequences limited.

In this paper, we consider economic narratives as causal accounts for why an economic event occurred and study their nature and consequences during the surge in US inflation experienced in late 2021 and 2022. This setting is ideal for the study of narratives. Various competing explanations for the rise in inflation circulated in the news, different trajectories of future inflation appeared likely through the lens of these narratives, and expectations about future inflation held central importance to policy-makers, who aimed to keep inflation expectations anchored. We use this setting to examine three related questions. Our first two questions are empirical in nature. First, what are people's narratives about the historic surge in inflation? Second, how do these narratives shape their economic expectations? Building on our empirical answers to these questions, we then turn to theory and incorporate narratives into an otherwise conventional New Keynesian model to explore our third question: whether narratives influence aggregate economic outcomes.

**What are people's narratives?** To empirically study people's narratives, we conduct a series of surveys with large, broadly representative samples of the US population and a sample of academic economists between November 2021 and June 2022. We measure narratives by asking respondents to explain in their own words why they think that inflation has increased. To quantitatively capture the rich causal structure of respondents' narratives, we represent each of these open-ended text responses as a Directed Acyclic Graph (DAG), which we manually identify using a tailored coding procedure. A causal DAG is a network of variables in which links between variables indicate causal relationships. Figure 1 displays three examples of the causal graphs of real narratives that respondents invoke, including, e.g., a narrative that attributes the rise of inflation to a disruption of global supply chains caused by higher energy prices.

This approach allows us to provide rich descriptive evidence on people's narratives about the rise in US inflation: our first set of empirical results. We start with a comparison of households'

Figure 1: Example narratives, represented by DAGs




*Notes:* Three example narratives for why inflation increased, represented by their DAGs. Blue nodes are demand-side factors, red nodes are supply-side factors, and green nodes are miscellaneous factors. The arrows indicate the direction of causality.

and experts' narratives. Households' narratives are simpler and more fragmented than those of experts. For example, experts often mention both demand-side and supply-side factors, whereas households tend to focus on either demand-side or supply-side factors. Households' and experts' narratives also differ in the factors that they invoke. Households frequently mention supply-side factors—such as supply chain disruptions, labor shortages, and the energy crisis—as important drivers of inflation, while neglecting demand-side factors, such as loose monetary policy. Experts' views are more balanced between the supply and the demand side. Moreover, households often invoke narratives that attribute inflation or its intermediary causes to incompetent policy-making by the government. Many households also refer to a channel that is completely absent among experts, namely the idea that corporate greed and price gouging fueled inflation.

The aggregated results conceal substantial heterogeneity in households' narratives. Individuals differ in the sophistication of their narratives (e.g., multi- versus mono-causal) and their selective focus on different aspects (e.g., demand versus supply). This heterogeneity is systematically related to individual background characteristics. For example, Republicans are substantially more likely than Democrats to attribute rising inflation to mismanagement by the government, underscoring the politicized nature of households' narratives. Moreover, exploiting repeated cross-sectional surveys, we document that the composition of narratives can change sharply over time.

**Do narratives shape economic expectations?** People's narratives provide a causal account of why inflation increased. Hence, narratives could also serve as a model through which people think about the future development of inflation. Indeed, our second set of empirical results shows that households' narratives systematically shape their expectations about future inflation. We start by providing correlational evidence based on our descriptive survey data. For instance, we show that respondents who attribute the rise in inflation to the energy crisis or fiscal stimulus predict significantly higher inflation over the next 12 months. By contrast, those who attribute the rise in inflation to temporary pent-up demand resulting from forced savings during the pandemic predict significantly lower inflation.

To shed light on the causal effect of narratives on expectation formation, we conduct three experiments with US households. In our first experiment, we provide respondents with one of two competing narratives about why the inflation rate has increased: a narrative that emphasizes pent-up demand and one that highlights the role of the energy crisis. The former narrative was commonly associated with a lower persistence of high inflation in the spring of 2022, when we ran the experiment. We find that respondents who are exposed to the pent-up demand narrative subsequently expect significantly lower inflation over the next 12 months compared to respondents exposed to the energy narrative. Our second experiment, run in June 2022 after a substantial tightening of monetary policy, uses a similar design to show that monetary policy narratives shape inflation expectations. In this context, exposure to a narrative that emphasizes that loose monetary policy had contributed to a surge in inflation significantly reduces households' expectations about future inflation compared to a narrative emphasizing the role of the energy crisis.

Our third experiment illustrates another channel through which narratives affect economic expectations: individuals interpret new information through the lens of their narratives. In a 2x2 design, the experiment exogenously induces respondents to hold narratives that highlight the role of either high government spending or the energy crisis in driving the increase in inflation. Subsequently, it exposes respondents to either a low or high forecast of the future growth in real government spending. Respondents react very differently to the government spending forecasts depending on which narrative they were exposed to before receiving the forecast. In fact, only respondents in the government spending narrative treatment significantly increase their inflation expectations in response to a higher government spending forecast.

**Do narratives matter for the macroeconomy?** If narratives affect agents' expectations, they could also be relevant for macroeconomic outcomes. To formalize how narratives can shape aggregate outcomes, we embed narratives into a New Keynesian macroeconomic model. The model has multiple factors with different persistence: productivity, government spending, and monetary policy. Informed by our empirical analysis, we formalize narratives about inflation as subjective causal models of inflation, i.e., beliefs about which factors have contributed to the current inflation rate (and by how much). Agents use these subjective models to form their expectations.

We show that the subjective causal models of inflation always affect equilibrium aggregate outcomes, as they shape agents' expectations about the future, consistent with our empirical evidence. A special case of the model is a rational expectations equilibrium: all agents hold the same belief and the correct belief about how each factor contributed to inflation. The equilibrium that emerges in this case is the textbook rational expectations equilibrium. However, our main proposition characterizes the mapping from narratives to equilibrium aggregate outcomes without imposing the restriction that agents' subjective causal models of inflation have to be the same for all agents and correct. We find that the effect of narratives on aggregate outcomes, such as inflation and aggregate output, can be sizable.

**Related Literature** Our study contributes to a growing literature on stories and narratives in economics, including theoretical (e.g., Aina, 2023; Bénabou et al., 2018; Eliaz and Spiegler, 2020; Flynn and Sastry, 2024; Schwartzstein and Sunderam, 2021, 2022) and empirical perspectives (e.g., Goetzmann et al., 2022; Han et al., 2024; Shiller, 2017, 2020) as well as research on behavioral mechanisms (e.g., Barron and Fries, 2024; Graeber et al., 2024b,c; Kendall and Charles, 2024).[1] We provide a tractable empirical approach to measure and characterize economic narratives and provide evidence on their nature and consequences. The DAG-based approach allows us to quantify the causal structure of economic narratives—the chain of events in people's explanations—which cannot be detected by topic modeling or simple word-counting techniques (e.g., Goetzmann et al., 2024; Hansen et al., 2018; Shiller, 2017, 2020). Moreover, our empirical findings demonstrate that narratives shape the formation of economic expectations. Individuals use narratives about the past to forecast the future, and they interpret new information in light of these narratives.

Therefore, we also contribute to an influential body of empirical work on the formation of macroeconomic expectations and, in particular, inflation expectations, which play a pivotal role in the context of rising inflation. This literature has focused on the role of experiences (Malmendier and Nagel, 2016), cognitive abilities (D'Acunto et al., 2019, 2021a), grocery prices (Cavallo et al., 2017; Coibion et al., 2023; D'Acunto et al., 2021c), gas prices (Coibion and Gorodnichenko, 2015b), monetary policy communication (Coibion et al., 2022; Roth et al., 2022) and people's subjective models of the economy (Andre et al., 2022). A key implication of our findings is that heterogeneity in narratives is an important driver of the widely documented disagreement in macroeconomic expectations (Coibion et al., 2018; Dovern et al., 2012; Giglio et al., 2021). In subsequent work, Binetti et al. (2024) study people's understanding of inflation—their perceived causes, consequences, trade-offs—and the policies they support to combat inflation. Their findings on the perceived causes of inflation confirm ours for later time periods.

Our theoretical model contributes to theoretical work on narratives and model misspecification in macroeconomics. Flynn and Sastry (2024) study beliefs about the economy that spread contagiously. Other papers examine model misspecification and learning in macroeconomic contexts (Marcet and Sargent, 1989a,b; Molavi, 2019). The key difference to Flynn and Sastry (2024) is that we model narratives as subjective causal models, and the key difference to the literature on learning and model misspecification is that we focus on characterizing the effects of those subjective causal models on aggregate equilibrium outcomes.[2]

[1] Other work has studied narratives in the moral and political domain (Ash et al., 2021, 2024; Bursztyn et al., 2023; Levy et al., 2022). Haaland et al. (2024) provide a review of studies of narratives using open-ended data.

[2] Work in financial economics has also studied market equilibria with agents who hold subjective models about how the markets works (e.g., Eyster and Piccione, 2013; Eyster et al., 2019; Bastianello and Fontanier, 2024).

## 2 Narratives: A Working Definition

We start by briefly discussing our working definition of narratives, aimed at making the concept quantifiable and measurable. We draw on an idea that is present in most definitions of narratives, namely that narratives provide a causal account of why a given event, episode, or phenomenon occurred. For example, the Oxford English Dictionary describes it as an "account of a series of events, facts, etc., given in order and with the establishing of connections between them." Akerlof and Snower (2016) describe a narrative as a "sequence of causally linked events and their underlying sources." Similarly, psychologists have argued that causality is at the core of narratives (Sloman and Lagnado, 2015; Trabasso and van den Broek, 1985). Therefore, this paper considers individuals' economic narratives as their *causal accounts for economic events* or, put differently, agents' assessments of cause-effect relationship across events.

To characterize narratives empirically, we represent them as causal Directed Acyclic Graphs (DAGs). A causal DAG is a network of variables in which links between variables indicate a causal relationship. The direction of links indicates the flow of causality, and the connection patterns are acyclic, meaning there is no causal path that connects an antecedent cause with itself.[3] DAGs are widely used to study causality in statistics, computer science, and the social sciences (Pearl, 2009; Sloman and Lagnado, 2015) and have also been used to study narratives in economic theory, which was an important inspiration for the empirical approach we take in this paper (Eliaz and Spiegler, 2020; Spiegler, 2016, 2020). The introductory Figure 1 presents three example narrative DAGs that provide different accounts for why inflation could have increased. Narrative A argues that the energy crisis led to supply chain issues—e.g., due to higher transportation costs—which boosted inflation. Narrative B puts forward that businesses engaged in price gouging to recoup losses suffered during the pandemic. Finally, Narrative C posits that increased government spending directly contributed to high inflation but also caused a labor shortage—e.g., because people preferred to cash in on generous unemployment benefits—which additionally fueled inflation.

From an empirical perspective, an advantage of DAGs is that they can express both simple, mono-causal accounts as well as sophisticated, nuanced views of the world. Moreover, each narrative can be represented quantitatively by its graph, which in turn can be represented by a numeric adjacency matrix, allowing us to capture the rich structure of economic narratives in a simple, quantitative, and comparable way. Therefore, we employ DAGs as a descriptive representation approach, but we remain open to the possibility that other strategies to represent narratives as causal accounts could prove fruitful in different contexts. In fact, our own formalization of narratives in Section 6 will take into account the technical demands of a New Keynesian macroeconomic environment.

[3]The restriction to acyclic graphs is of negligible importance in our context as we encountered virtually no lay narrative with a cycle. We allow our DAGs to be "signed": all causal connections present positive causal relationships (i.e., more A leads to more B).

## 3 Setting, Data, and Design

### 3.1 Setting

We study narratives about the macroeconomy in the context of surging US inflation in late 2021 and early 2022. The topic of rising inflation received increased media attention from November 2021 onwards when the US inflation rate rose to 6.2%. This is a good setting for studying narratives about the macroeconomy for several reasons. First, different narratives about the rise in inflation were widely discussed in the mass media, and there was substantial disagreement about the drivers of inflationary pressures. Second, the rise in US inflation up to 9.1% in June 2022 involved high stakes for many households, e.g., in the form of changes in real income or the real value of assets and debt. Indeed, Link et al. (2023a) show that inflation was the main factor on top of households' mind when thinking about their household's economic situation during the inflation surge. This suggests that we can study narratives about a decision-relevant event. Third, different narratives about what is driving the increase in inflation have vastly different implications for the persistence of higher inflation rates, and which narratives are top of people's minds thus potentially affects expectation formation.

At the time, the increase in inflation was often attributed to special conditions arising from the pandemic. On the supply side, the pandemic caused severe supply chain disruptions and labor shortages. These supply-side drivers were exacerbated by a global energy crisis and the associated strong increases in the prices of oil and natural gas. On the demand side, the fiscal stimulus aimed at lifting the economy out of the pandemic recession and loose monetary policy were central to many accounts of the increase in inflation. A further demand-side factor was related to forced savings during the pandemic and the pent-up demand that was unleashed after the reopening of the economy in the course of 2021.[4]

### 3.2 Samples

In this context, we study which narratives about the rise in inflation are prevalent among households and experts. Below, we describe how we recruit each sample.

**Households** We collect our first household sample between November 18 and November 21, 2021, with the survey company Lucid, which is commonly used in economic research (Haaland et al., 2023). As shown in Online Appendix Table A.1, the sample comprises 1,029 respondents and is broadly representative of the US population in terms of gender, age, region, and total household income. For example, 48.6% of our respondents are male, compared to 49% in the 2019 American Community Survey (ACS). The average age in our sample is 53.8 years, somewhat higher than the average age of 47.8 years in the ACS. 38.9% of our respondents have pre-tax annual income above $75,000, compared to 48% in the ACS. Our sample is also

[4]For example, the following two media articles from February 2022 highlight how different factors were held responsible for higher inflation: [1] for labor shortages, the energy crisis, supply chain issues and fiscal stimulus and [2] for labor shortages, supply chain issues, fiscal stimulus, pent-up demand and loose monetary policy.

reasonably close to the population in terms of education: 42.2% of the respondents in our sample have at least a bachelor's degree, compared to 31% in the ACS.

In addition to the November 2021 survey, we recruit samples of approximately 1,000 households in December 2021, January 2022, March 2022, and May 2022. We follow the same sampling approach as in our November survey, and the additional samples resemble the November 2021 sample in terms of demographic characteristics (Online Appendix Table A.1). Online Appendix Table A.5 provides an overview of the different data collections.

**Experts** Simultaneously with the data collection for the November 2021 household survey, we invite academic economists to participate in a separate expert survey. We invite experts who have published articles with the JEL code "E: Macroeconomics and Monetary Economics" in twenty top economics journals between 2015 and 2019 (see Section D of the Online Appendix for more details). Overall, 111 experts participated in our survey. 50.5% of the experts are based in the United States. Furthermore, 88.3% are male; on average they graduated with a PhD 18.6 years ago (at the time of the survey); they have on average 2.7 journal publications in one of the "top five" economics journals; and an average (median) Google Scholar h-index of 21.6 (16). They also have 5,534 citations on average according to Google Scholar as of December 2021/January 2022 (Online Appendix Table A.2). Thus, our expert sample consists of very experienced researchers with a high academic impact.

### 3.3 Survey

In what follows, we describe the main elements of the survey. Section G.1 in the Online Appendix provides the core survey instructions.

**Overview** For households, the survey starts with two attention checks, designed to screen out inattentive participants, and a few questions on background characteristics. We then provide respondents with a definition of inflation and elicit their baseline knowledge of inflation.[5] We next measure narratives about the rise in inflation with an open-ended question. Subsequently, we measure respondents' quantitative beliefs about future inflation. Inflation narratives and inflation expectations are the main objects of interest of the survey. Finally, we elicit a range of additional measures and background variables. Due to space constraints, the expert survey only includes questions on inflation narratives and expectations.

**Narratives** We measure the narratives that people provide to explain the rise in inflation using an open-ended question. To ensure that respondents explain the same event, we first inform them that the inflation rate in the US typically ranges between 1.5% and 2.5% and tell them about the recent rise in the inflation rate and its current level. For example, in the November 2021 survey, respondents are informed that the inflation rate has increased to 6.2%. Subsequently, we

[5] About 90% of our respondents are aware that inflation at the time of the survey is higher than a year earlier, and people's perceived inflation rate is on average very close to the actual rate (see Online Appendix Figure B.1).

ask them to tell us in an open-text box: “Which factors do you think caused the increase in the inflation rate? Please respond in full sentences.”

There are several important advantages of open-ended measurement of narratives compared to using structured question formats (Haaland et al., 2024). First, open-ended responses offer a lens into people’s spontaneous thoughts. While individuals have likely been exposed to many different narratives, what ultimately matters for their economic expectations and decisions is which narratives are top of mind (Gennaioli and Shleifer, 2010). Second, the open-ended response format leaves individuals’ answers unrestricted and does not prime them on any particular issue, e.g., through the available response options. Third, open-ended responses may be better suited to capture typical reasoning in real-world situations. Fourth, open-ended responses can also reveal misunderstanding or confusion and allow for qualitative insights that cannot be achieved with structured measures. A potential drawback of open-ended questions is that they require more cognitive effort from respondents, which could introduce additional measurement error. Reassuringly, there is only very limited attrition of 0.29% during the narrative elicitation and most respondents provide a plausible narrative (see next subsection).

**Inflation Expectations** We elicit probabilistic expectations about inflation over the next 12 months and five years from the survey, following the format of the New York Fed’s Survey of Consumer Expectations (SCE). Specifically, we ask our respondents to indicate the percent chances they attach to inflation falling into ten bins that are mutually exclusive and collectively exhaustive. The inflation expectations measured in our survey closely match the results from the SCE, both in terms of their level and in terms of their development over time (Online Appendix Figure B.2).

Eliciting the subjective distribution instead of a point forecast has the advantage that (i) we can derive the expected value of the distribution, which respondents do not reliably report in point forecasts, and (ii) we can also calculate respondents’ perceived uncertainty (Armantier et al., 2013; Manski, 2004). At the same time, this approach poses some potential concerns. Respondents may not be used to the probabilistic elicitation format and find it challenging. Reassuringly, we observe only limited attrition (less than 0.2%) at the relevant survey screens, and only 7.7% of respondents report distributions with arguably implausible features, such as a pronounced bimodality or “holes”. Moreover, the question uses the top bin “12% or higher”, which could conceal that some respondents hold very extreme inflation expectations. However, the average probability mass assigned to the highest bin is 12.6% in our November 2021 wave and 22.2% in our May 2022 wave, suggesting that this issue is of limited quantitative importance. When we calculate the expected value of a respondent’s subjective distribution, we use the midpoints of each bin and assign $-12\%$ and 12% to the extreme bins of “$-12\%$ or lower” and “12% or higher,” respectively. Our results are not sensitive to the exact values we assign to the extreme bins. Lastly, there could be framing effects, e.g., because respondents interpret the bins as a signal about likely inflation outcomes. Since we are mostly interested in understanding differences in inflation expectations across households, level biases such as those introduced by framing effects are less problematic in the context of our study.

### 3.4 Classifying Narratives

To quantitatively analyze the richness of the open-ended explanations for why inflation increased, we represent each of these responses as a DAG, which we manually identify using a tailored coding procedure.

We start by defining the set of "factors" that narratives can draw on. These factors constitute the nodes of the DAGs. They correspond to variables or events that are commonly associated with the rise in inflation. We cover most of the major drivers of inflation brought forward by the theoretical literature but also non-textbook drivers often invoked in the media or by households in pilot studies. Table 1 provides a complete overview of all factors together with examples. Among the demand-side drivers, we include higher government spending, loose monetary policy, pent-up demand (e.g., due to forced savings during the lockdowns), and a shift in demand (e.g., from services towards durables). We also allow for a residual demand factor that includes additional demand-side drivers that cannot be classified into any of the aforementioned demand-side factors. Among the supply-side drivers, we include supply chain disruptions, a shortage of workers leading to higher wage costs, the energy crisis with its associated higher energy costs, and a residual category for additional supply-side explanations. We also consider a set of miscellaneous factors, including the COVID-19 pandemic and government mismanagement, a factor that encompasses policy failure and mismanagement by policy-makers. Other miscellaneous factors include price gouging, high levels of government debt, and Russia's invasion of Ukraine.[6]

Then, the DAG of each narrative is identified by coding causal connections between the factors that are—explicitly or implicitly—mentioned. For example, a narrative that connects inflation with the factors "supply chain issues" and "labor shortage", both caused by the factor "pandemic", is coded as *pandemic* $\rightarrow$ *supply chain issues* $\rightarrow$ *inflation* and *pandemic* $\rightarrow$ *labor shortage* $\rightarrow$ *inflation*.

We instruct research assistants to apply this coding procedure to the text responses. All coders are blind to the objectives of the research project. We use human coding because it allows us to capture the full richness of our narrative data. Nevertheless, one important drawback of human coding is its subjectivity, in particular in light of the inherent ambiguities of language and the causal structures expressed in written texts. We address this issue in two steps: first, we train the coders extensively; and second, for our descriptive evidence, each response is independently coded by two research assistants, allowing us to cross-verify each classification.[7] Wherever a

[6] We added the "Russia-Ukraine war" code to the coding scheme in March 2022. Virtually none of the responses collected before March 2022 refers to Russia's aggression against Ukraine.

[7] Each coder has economics training and participates in a joint training session in which we introduce the coding scheme and discuss various examples. Afterward, each coder independently works on multiple test responses, which are then discussed, reviewed, and—if necessary—corrected in another joint training session. The training takes place together so that coders can later draw on the same set of instructions and experiences.

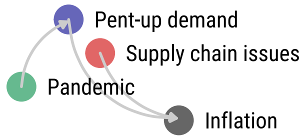
Table 1: Overview of factors on which the coding of narratives builds

| Category | Explanation | Example |
|---|---|---|
| **Demand** | | |
| Government spending | Increases in government spending (e.g., stimulus payments). | "[...] Stimulus checks were given to all middle income families; A second round of stimulus checks were also given to all families by the new administration [...]" |
| Monetary policy | Loose monetary policy by the Federal Reserve. | "[...] The Federal Reserve increasing the amount of money in the economy [...]" |
| Pent-up demand | Reopening of the economy and the associated higher incomes, new spending opportunities, and optimism about the future. | "[...] now that the lockdowns have ended, the demand is there and more people are trying to get their lives back to normal." |
| Demand shift | Shift of demand across sectors (particularly increases in durables). | "[...] Shifts in what people are buying due to the pandemic - more goods, especially durables, fewer services. [...]" (*taken from the expert sample*) |
| Demand (residual) | Increase in demand that cannot be attributed to the other demand channels. | "That people are buying a lot more products [...]" |
| **Supply** | | |
| Supply chain issues | Disruption of global supply chains. | "[...] containers sitting at docks waiting for pick up [...]" |
| Labor shortage | Shortage of workers, e.g., due to some workers dropping out of the labor force, and higher wage costs. | "[...] People are less motivated to work currently, causing businesses to hike up rates, and offer a higher wage to attract employees. [...]" |
| Energy crisis | The global energy crisis, leading to shortages of, e.g., oil and natural gas and higher energy prices. | "I think the rising cost of gas has caused the inflation rate to rise on other products. [...]" |
| Supply (residual) | Negative supply effects other than labor shortage, supply chain issues, energy crisis. | "[...] less production in goods [...]"<br>"[...] business shutdowns [...]" |
| **Miscellaneous** | | |
| Pandemic | The COVID-19 pandemic, the global pandemic recession, lockdowns, and other policy measures. | "The pandemic was the beginning factor, it caused the economy to shut down and thus caused the beginning of inflation. [...]" |
| Government mismanagement | Explicit reference to policy failure, mismanagement by policymakers, politicized negative judgment of policies. | "I think Joe Biden and the Democratic Party are at fault for the inflation increasing so rapidly. [...]" |
| Russia-Ukraine war | The Russian invasion of Ukraine, the international economic, political, and military response. | "[...] the war in Ukraine has a lot to do with the inflation rate as well because of the sanctions with Russia. [...]" (*taken from March 2022 household sample)* |
| Inflation expectations | Expectations about high inflation in the coming years, making firms preemptively increase prices and workers bargain for higher wages. | "[...] Producers may raise prices to cover the expected increase in wages for workers willing to meet the rising cost of living [...]" |
| Base effect | Mentions that inflation is high due to a base effect, i.e., a very low inflation rate during the pandemic, leading almost mechanically to high inflation rates now. | "The first reason inflation is as high as 6.2% at an annual rate is a base effect due to low levels of inflation during the COVID-19 crisis [...]" (*taken from the expert sample*) |
| Government debt | High level of government debt. | "[...] With the debt as high as it is, the only recourse is for inflation increase. [...]" |
| Tax increases | Tax increases, such as VAT hikes. | "[...] Our prices rise because of the tax increase." |
| Price-gouging | Greedy companies exploit opportunities to increase profits. Companies are trying to make up for the money they lost during the pandemic. | "I think that companies used the Covid pandemic to increase their profits so they could make up for lost profit during the shut down. [...]" |

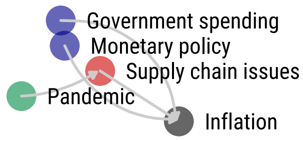
*Notes:* This table provides an overview of the different factors in our coding scheme, an explanation for each factor, and example extracts from open-text responses. If not otherwise indicated, example responses come from the November 2021 household sample.

Table 2: Example narratives

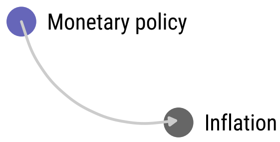
**Expert example 1**
*Supply chain issues is probably the most important factor. Pent up demand from the pandemic, combined with historically high household savings/wealth, which has made consumers less price-sensitive, is probably the second most important factor. [...]*



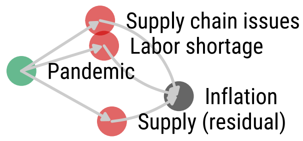

**Expert example 2**
*The rise in inflation is due to severely negative supply shocks and positive aggregate demand shocks. The aggregate demand shocks are driven by government fiscal spending, which was at a record high last year, as well as very low real rates of return, which encouraged consumption rather than savings. The negative supply shocks are due to supply-chain issues (pandemic-induced disruptions of manufacturing and transportation sectors).*



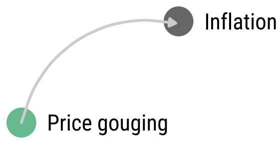

**Expert example 3**
*Money printing (cheap Fed rates and quantitative easing). Inflation is a monetary phenomenon and will always be so.*



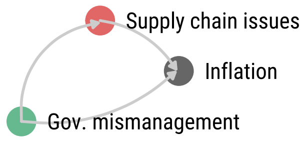

**Household example 1**
*I think the biggest factor in the large inflation rate over the last year or so is probably the pandemic. With labor shortages and business shutdowns because of the pandemic, certain goods are harder to get a hold of, and supply chains have been heavily impacted.*




**Household example 2**
*Manufacturers raising prices on goods and services, claiming the effect of the pandemic has forced them to do so. [...] [M]anufacturers have arbitrarily begun raising prices although not, in most cases, to cover their own costs, but rather to increase profits.*




**Household example 3**
*I fully believe that our President is responsible for this disaster of inflation. He is not leading as he should, and people are scared. Prices are rising because of this fear. Our President has not helped with the backflow of container ships sitting out in the harbors. [...]*




*Notes:* This table presents a series of example responses from experts and households, all taken from the November survey waves, as well as their DAG representation. Blue nodes are demand-side factors, red nodes are supply-side factors, and green nodes are miscellaneous factors. The arrows indicate the direction of causality.

conflict occurs, the case is revisited and a final decision is made.[8] This approach reduces the likelihood that any particular causal connection is overlooked and ensures that difficult cases are reviewed a third time. Given the high inter-rater reliability of the hand-coded text responses in our descriptive surveys (see below), we do not use any double-coding in the context of the experiments described in Sections 5 and Appendix 1. To illustrate the results of this coding procedure, Table 2 presents a series of example narratives from experts and households and their corresponding DAGs.

It is worth bearing in mind that respondents sometimes use different language and terms to refer to the same underlying factor. For example, when experts talk about "accommodative monetary policy" and households about "printing money," we map both responses to the monetary policy code. In other cases, the language and terminology that respondents use constrain the precision of their narrative. For example, when households blame policymakers but cannot articulate which economic factor is at fault, we can only assign their response to the government mismanagement code.

**Quality of Hand-Coded Data** We assess the quality of the resulting narrative data in several ways, using data from all survey waves. First, we detect a causal narrative for 91% of households' and 100% of experts' explanations.[9]

Second, we introduce an auxiliary code to mark responses that are nonsensical or clearly refuse to engage with the task. Only 3% of households' responses (0% among experts) are assigned to this category. The remaining 6% of households who do not express a causal narrative indicate that they do not know what drove the increase in inflation.

Third, we calculate how often two independent reviewers assign the same causal connection to a response. If one coder refers to a factor, there is an 88% chance that the other coder does so as well. If one coder assigns a causal connection between two specific factors, there is a 77% chance that the other coder does so as well. 95% of the assigned factors and 89% of the assigned connections make it to the final version. These numbers suggest that the open-ended responses are of high quality and that our coding scheme has a high degree of reliability. The hit rates produced by random coding would be very small due to the large number of possible combinations. Moreover, when coders disagree, they typically disagree about the finer details of the coding protocol, such that the aforementioned numbers can be interpreted as a lower bound for agreement. The coarser the resolution, the higher the agreement. For example, in 94% of the cases, the coders agree on whether to assign any demand-side factor to a response. The

[8]The conflict resolution was conducted by a member of the research team for the November wave. In later waves, research assistants took over the task.

[9]If not providing a narrative is systematically related to educational attainment, this could mean that our elicitation format is less suited to capture narratives among those with lower cognitive skills, who might find it difficult to articulate their views. Systematic patterns by education would also have implications for people's ability to understand monetary policy communication. However, in unreported regressions, we find that household respondents' education is unrelated to whether the response can be represented by a DAG or not. Instead, respondents in full-time work are less likely to provide a narrative, while those who read news frequently—perhaps unsurprisingly—are more likely to provide a narrative.

corresponding figure is 93% for supply-side mechanisms.

Fourth, we also examine the test–retest reliability of respondents' narratives. The test–retest reliability expresses the congruence between two successive measures for the same person, typically taken on different days. It captures the reliability of the measure (here: open-ended question, DAG coding) and the stability of the underlying object (here: inflation narratives). We measure the test–retest reliability in two consecutive waves of an auxiliary survey conducted in May 2022 using the survey platform Prolific. Of the 512 respondents who completed the first wave, 384 respondents (68%) completed the second wave three days later. Averaged across all factors, we estimate a correlation coefficient of 0.63 between the factors mentioned in wave 1 and those mentioned in wave 2 ($p < 0.01$). Given that our surveys were run in turbulent economic times, we view the test–retest correlation of 0.63 as an indicator of significant persistence. Indeed, the test–retest correlation is comparable to the persistence of economic preferences (0.71–0.86; Falk et al., 2022). These results point to a significant degree of stability in households' narratives.[10]

## 4 Descriptive Evidence on Narratives

In this section, we characterize the narratives that people put forward to explain the increase in inflation in late 2021 and early 2022. Using our main survey wave from November 2021, we start by describing and comparing the aggregated narratives of households and experts (Section 4.1). Next, we explore the heterogeneity of households' narratives. We identify common narrative "clusters" among households (Section 4.2) and study correlates of the narratives households invoke (Section 4.3). Then, we characterize the development of households' narratives over time, using the data from all descriptive survey waves (Section 4.4).

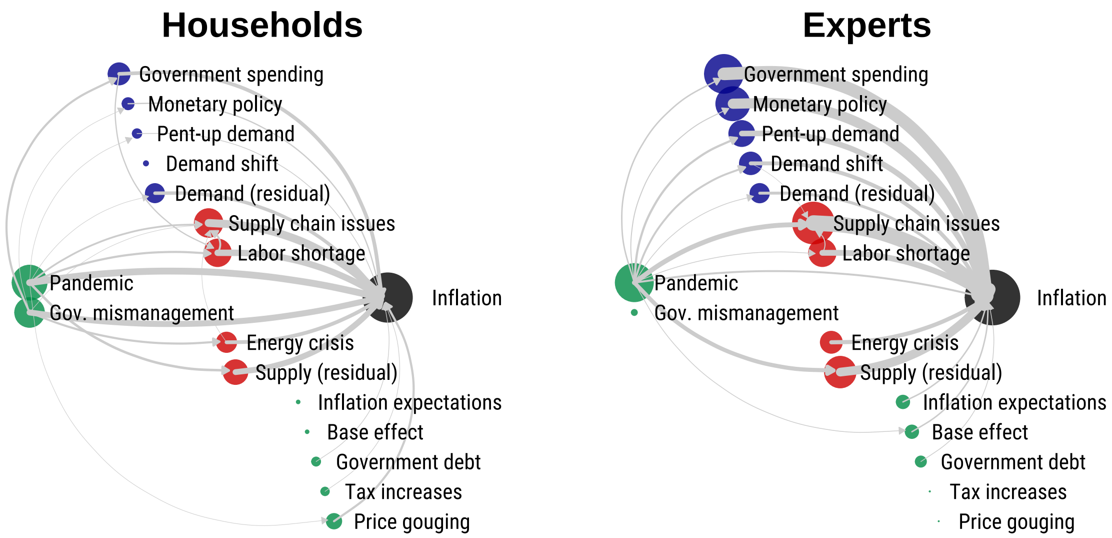
### 4.1 Comparison of Households' and Experts' Narratives

Figure 2 describes and contrasts the aggregated narratives of households and experts. It displays the "average DAG" of households' and experts' narratives in the main survey wave from November 2021. As in the DAGs presented earlier in the paper, each factor is presented as a circle and each causal connection as a line. However, factors that occur more often in respondents' narratives are now displayed as larger circles, and more common causal connections are displayed as thicker lines. The figure thus shows which factors and causal connections are most prevalent in households' and experts' narratives. In addition, the bar plots in Figure 3 display the exact shares of households and experts that mention a particular factor. Both figures reveal important features of and differences in the narratives of households and experts.

First, household narratives are shorter, less sophisticated, and indicate a coarser understanding of the economy. Expert DAGs include on average 4.3 factors (including inflation) and 3.6

[10]The average correlation conceals small variations in the persistence of different factors in people's narratives (see Online Appendix Figure B.3). We describe two additional checks demonstrating the high quality of the hand-coded data in Online Appendix C.1.

Figure 2: "Average" narratives among households and experts



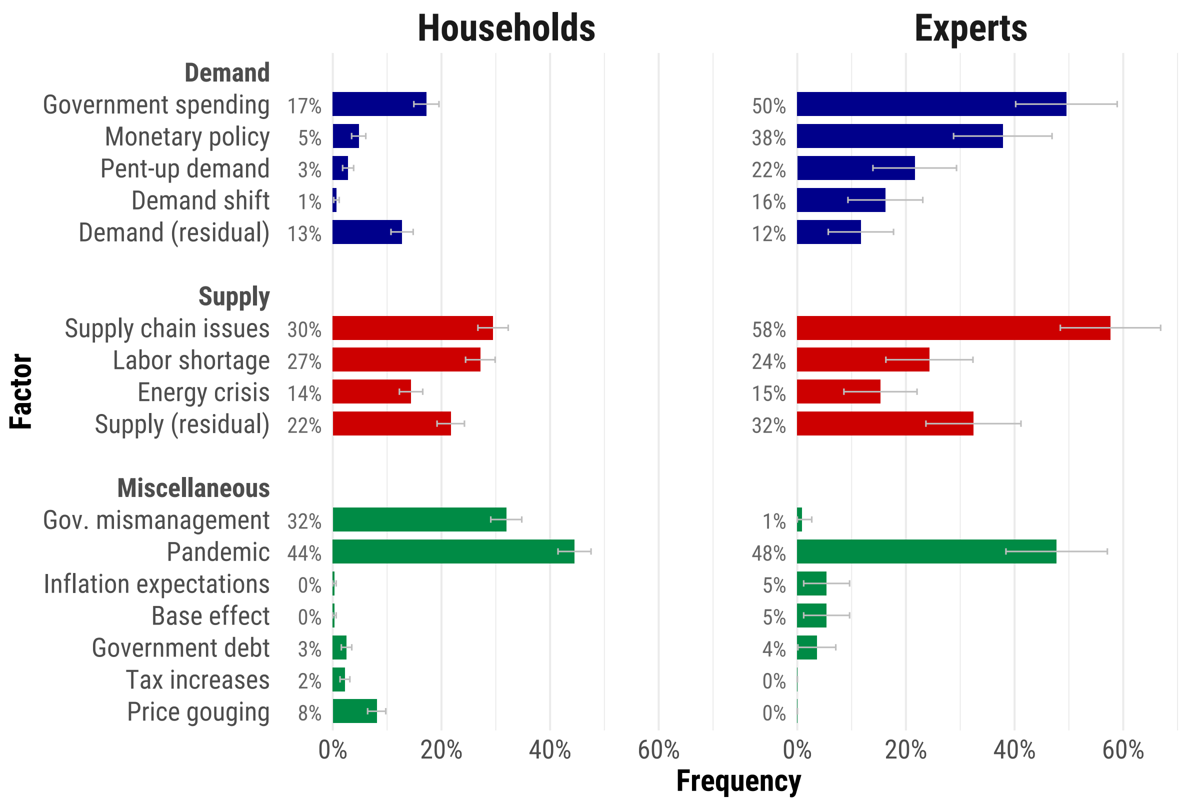

*Notes:* This figure shows the "average" narratives invoked by households (left panel) and experts (right panel), displayed as causal networks. The aggregated DAGs show which variables and causal links are most relevant in households' and experts' narratives. **Factor size**: The size of the factors is proportional to the share of narratives that refer to the factors. **Factor color**: Red indicates supply-side factors, blue indicates demand-side factors, green indicates miscellaneous factors, black is used for inflation. **Connection thickness**: The thickness of the connections is proportional to the share of narratives that refer to the causal connections (among households and experts, respectively). Edges with a relative frequency of less than 1% are not displayed.

links, while household DAGs contain only 3.5 factors and 2.8 links (for both comparisons: $p < 0.01$).[11] For example, Figure 2 shows that households often attribute the rise in inflation directly to the pandemic, while experts more often provide additional details and link the pandemic to subsequent causes of higher inflation, such as federal stimulus packages or supply chain disruptions. Moreover, many experts think about *both* supply- and demand-side factors. In particular, among all experts who mention at least one supply *or* one demand narrative, 77% mention both a supply *and* a demand narrative. The corresponding fraction among households is much smaller at 34%.

Second, households' narratives predominantly focus on the supply side, while experts' focus on both the demand and the supply side. 57% of households think about at least one supply-side channel, while only 32% think about a demand-side channel. The most common factors in households' narratives are supply chain disruptions (30%, see Figure 3), a shortage of workers (27%), and other supply-side factors (22%), while demand-side factors are mentioned much less frequently. The leading demand-side factor is government spending, but it is only part of 17% of household narratives. Moreover, very few household narratives refer to loose monetary policy as a cause of inflation (5%). Experts' narratives are more balanced between supply- and demand-side factors. 90% of experts refer to at least one supply-side factor, and 84% refer to at least one demand-side factor. In particular, experts assign a central role to government spending

[11] The differences persist if we control for the response time and the number of words that respondents use in their open-ended explanation (see Online Appendix Table A.6). Hence, they do not simply reflect differences in effort between households and experts but rather reflect differences in their understanding of the rise in inflation.

Figure 3: Frequency of factors




*Notes:* This figure shows how often different factors occur in the narratives of households (left panel) and experts (right panel). The gray bars indicate 95% confidence intervals.

(50%) and monetary policy (38%).

Third, narratives are highly politicized among households. The factor "government mismanagement"—which captures whether respondents blame low-quality decision-making by policy-makers—is common among households (32%) but virtually absent among experts (1%). The high prevalence of this narrative among households indicates that inflation is a politicized topic in the US. Not only do households blame government mismanagement directly for high inflation, but such mismanagement is also seen as a primary cause of high government spending, loose monetary policy, and the energy crisis (see Figure 2).

Finally, some household narratives revolve around explanations that are virtually absent among experts. Foremost, this concerns price gouging or profiteering, which is part of 8% of household narratives (but 0% among experts). Households posit that businesses seize the moment to increase their profits, either out of greed or to recoup the losses suffered during the lockdowns. To give another example, the idea that high government spending caused the labor shortage can be found in 5% of household DAGs but only in one expert DAG.

In additional analyses, we show that the differences between households' and experts' narratives remain largely unchanged when we control for gender, age, education, and location (Online Appendix Tables A.7 and A.9). This suggests that experts' knowledge or their higher attention to the economy account for the differences across the two samples rather than the fact that experts usually come from a different demographic group. While we do not know the exact causes of the inflation increase with certainty, the large discrepancy between household and expert narratives and the large heterogeneity of narratives among households (to which we turn next) suggests that many households hold a misspecified narrative.

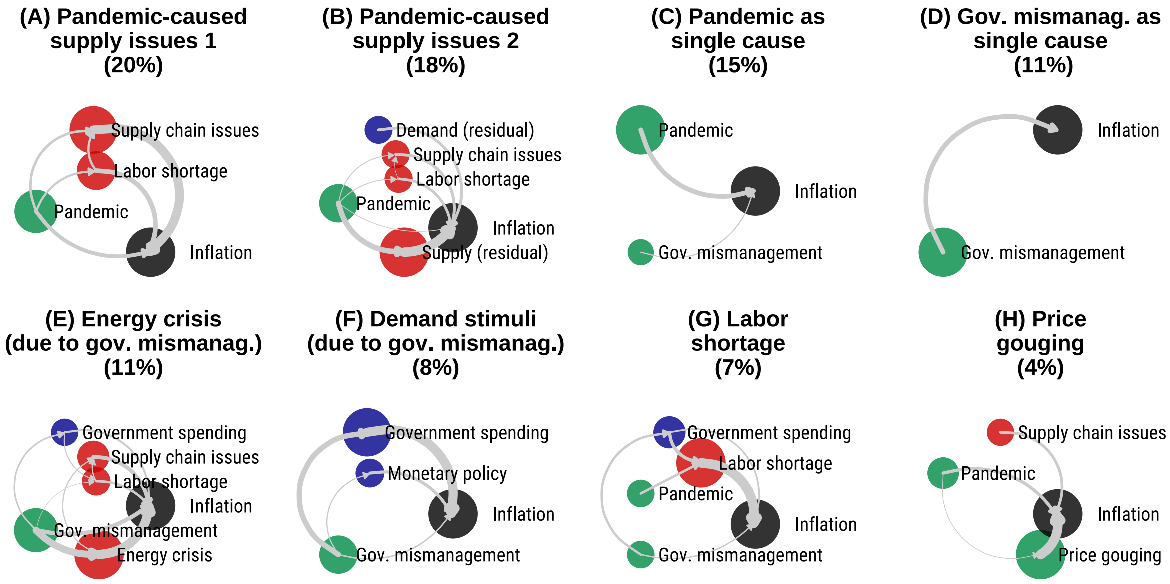
### 4.2 Heterogeneity and Narrative Clusters

The aggregated results, presented above, conceal substantial heterogeneity in respondents' narratives within each sample. As highlighted in Figure 3, the fraction of household respondents mentioning a given narrative factor is at most 44% ("Pandemic"). Among experts, the fraction of respondents mentioning a specific factor is 58% at the maximum (supply chain issues). These numbers point to major within-sample disagreement about the causes of the increase in inflation. To provide more systematic evidence on within-sample heterogeneity, we next investigate whether there are heterogeneous "narrative clusters," namely distinct clusters of factors and causal connections that are commonly mentioned together. We focus on household narratives since we need large samples to reliably distinguish between different narrative clusters.

We draw on an agglomerative hierarchical clustering procedure. This common unsupervised machine learning technique locates clusters of similar narratives in our data, while ensuring that the clusters themselves differ. It requires a distance metric that measures the dissimilarity between narratives. For this purpose, we represent narratives by their graphical "edge lists" $E$, i.e., their set of causal connections. Next, we define the dissimilarity between two narratives $i$ and $j$ as the Jaccard difference $D(i,j) = 1 - \frac{|E_i \cap E_j|}{|E_i \cup E_j|}$ between the edge lists of their DAGs ($E_i$ and $E_j$), where $|\cdot|$ denotes the number of elements in a set. The Jaccard difference is zero for identical narratives ($E_i = E_j$), one for completely distinct narratives ($|E_i \cap E_j| = 0$), and increases with the number of differing causal connections. Equipped with this distance measure, we apply the agglomerative clustering procedure. The procedure and all technical details are discussed in Online Appendix E, which also shows that we can replicate the results with an alternative cosine distance measure.

Figure 4 presents the resulting clusters and their average DAGs. Four clusters (A, B, E, G) revolve around supply-side factors. They deal with either pandemic-related supply chain disruptions (Cluster A, 20%), general, less specific supply-side causes (Cluster B, 18%), the role of the energy crisis, which in turn is often attributed to "government mismanagement" (Cluster E, 11%), or the issue of labor shortages, for which both the pandemic and government spending (often due to "government mismanagement") are held responsible (Cluster G, 7%). Together, they encompass 55% of all narratives, corroborating the earlier result that households' narratives are skewed towards the supply side. By contrast, the only clear demand-side cluster is Cluster F (8%). Here, government spending and loose monetary policy are both viewed as causal drivers of high inflation. The narratives in clusters C, D, and H represent less specific, often mono-causal

Figure 4: Popular narrative clusters among households




*Notes:* Cluster analysis of narratives from household survey (November wave). Only households who provide a causal narrative are considered. **Clustering**: An agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives is applied (described in detail in Appendix E). The Silhouette approach suggests an optimal number of cluster of $k = 15$ which we follow, but the figure only displays the eight clusters with at least 30 observations (thus, unlikely to be the product of noise). The figure displays the "average" narrative of each cluster. **Factor size**: The size of the factors is proportional to the share of narratives that refer to the factors. **Factor color**: Red indicates supply-side factors, blue indicates demand-side factors, green indicates miscellaneous factors, and black is used for inflation. **Connection thickness**: The thickness of the connections is proportional to the share of narratives that refer to the causal connections. Within each cluster, nodes with a share of less than 20% and connections with a share of less than 5% are not displayed to focus on the most characteristic features of a cluster.

narratives. Either the pandemic, government mismanagement, or price gouging are viewed as responsible for the hike in inflation. Their large population shares—15%, 11%, and 4%, respectively—indicate how prominent simple narratives are among households.

### 4.3 Correlates of Narratives

The heterogeneity in households' narratives raises the question of whether narratives systematically differ across sociodemographic groups. Such heterogeneity by demographic characteristics could be relevant to optimally target policy communication to different groups of households. We use multivariate regressions to explore which background characteristics are associated with different narratives and consider three sets of outcome variables: (i) dummies for whether a given factor is used (e.g., the factor "labor shortage"; Online Appendix Table A.7), (ii) dummies for whether a narrative that belongs to a specific cluster is expressed (e.g., the cluster "Pandemic as single cause"; Online Appendix Table A.8), and (iii) various measures of narrative sophistication (Online Appendix Table A.9).

The analyses reveal three findings. First, there are sizable differences in the narratives mentioned by groups with different partisan affiliations, indicating a substantial political polarization of economic narratives. For example, Democrat-leaning respondents are 26 percentage points (pp) more likely to view the pandemic as a root cause of the rise in inflation ($p < 0.01$). Consequently, they more frequently talk about pandemic-related supply issues and corporate greed. By contrast, Republican-leaning respondents are 38 pp more likely to blame government mismanagement ($p < 0.01$). Their narratives also favor factors that they view as consequences of government mismanagement, such as high government spending (mentioned 19 pp more often, $p < 0.01$) or high energy prices (mentioned 14 pp more often, $p < 0.01$). It is an open question to what extent the strong political heterogeneity in narratives generalizes to other countries that are less polarized than the US.

Second, we observe that respondents who report to regularly follow inflation-related news invoke narratives that contain more factors, more often talk about *both* demand and supply factors, and describe longer chains of events. All differences are highly statistically significant, hinting at the potential powerful role of media consumption in the formation of narratives. In Appendix 1, we present an experiment providing causal evidence on the effect of news consumption on households' narratives, suggesting that these correlations reflect an underlying causal relationship.

Finally, men provide significantly less sophisticated narratives with fewer factors and causal links. In particular, they are 11 pp ($p < 0.01$) less likely to talk about supply chain disruptions and 9 pp less likely to talk about labor shortages ($p < 0.01$), although their narratives more often refer to monetary policy (4 pp, $p < 0.01$). By contrast, older respondents and—to a lesser degree—individuals with a college degree invoke more sophisticated narratives. Full-time employees generally invoke less sophisticated narratives. They focus on fewer factors and are less likely to mention both demand and supply factors. The narratives of agents with different employment characteristics are of interest when thinking about households' wage bargaining and job search behavior (Pilossoph and Ryngaert, 2023).[12]

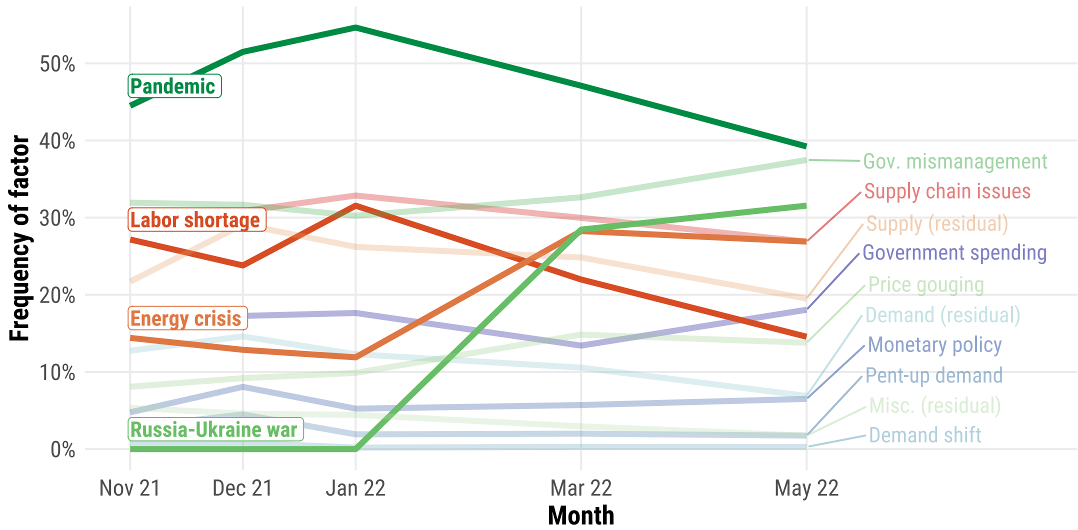
### 4.4 Development of Narratives over Time

Up to now, we have described people's narratives about the rise in inflation in November 2021. In this subsection, we draw on the follow-up surveys that we launched in December 2021, January, March, and May 2022—always shortly after the new inflation data were announced—to analyze the development of narratives over time.

Figure 5 documents the trends in narratives from November 2021 to May 2022. For each survey wave, it shows which fraction of narratives refer to a given factor. The figure highlights marked changes in the content of narratives, all of which likely constitute a direct response to the Russian invasion of Ukraine in late February. First, while virtually no narrative refers

[12] In unreported regressions, we applied a more fine-grained educational classification and found that the patterns are not driven by any specific educational group. We also applied a more fine-grained measure of employment status and found that the less sophisticated narratives among the full-time employed are not driven by any specific group outside full-time employment. These results are omitted for brevity.

Figure 5: Development of narratives over time




*Note:* This figure shows the development of narratives about the rise in inflation over time. It plots the shares of narratives that mention a given factor. To facilitate orientation, factors for which only small changes are detected are printed in higher transparency. The data come from our descriptive surveys in November 2021, December 2021, January 2022, March 2022, and May 2022.

to the already ongoing Russia-Ukraine conflict in November 2021 to January 2022, 28% do so in March 2022. Second, the rise of the Russia-Ukraine war narrative is accompanied by an increasing prominence of the energy crisis narrative. 28% of households mention energy shortages or high energy prices in March 2022, compared to only 12% in January 2022. Third, while the pandemic increasingly appears in the narratives from November 2021 (44%) to January 2022 (55%), its frequency declines to 47% in March 2022 and 39% in May 2022. Similarly, the frequency of references to labor shortages sharply declines from 32% in January 2022 to 15% in May 2022. Together, these results highlight that narratives can change quite abruptly in response to major economic and political events and could thereby contribute to how economic agents change their expectations around such events.

## 5 Narratives Shape Expectation Formation

Narratives about economic events could be central for understanding the formation of economic expectations. Narratives clarify which forces have been relevant in the past and thereby suggest which mechanisms are likely important for the future. For example, the causes of the rise in inflation that people mention are commonly associated with different degrees of persistence. Short-term factors such as pent-up demand will likely only have a transitory impact on inflation. Narratives that build on them would suggest that inflation will return to lower levels relatively soon. Other factors might be viewed as more persistent (e.g., energy shortage, government mismanagement) and potentially come with persistently higher inflation expectations. Moreover, the role that a narrative attributes to a specific factor could affect how people interpret new information about that factor.

In this section, we test these hypotheses and investigate whether and how households' narratives shape their inflation expectations. We start by providing correlational evidence, using our descriptive survey waves. Then, we present experiments that exogenously vary which narratives respondents are exposed to. Finally, we conduct an additional experiment to study whether narratives shape how individuals interpret new information.

### 5.1 Correlational Evidence

To gain a first impression of the potential role of narratives for expectation formation, we explore whether narratives about the rise in inflation are correlated with respondents' inflation expectations. We pool the data from the three household surveys conducted in November 2021, December 2021, and January 2022 and proceed in three steps.[13]

First, we ask which narrative factors are associated with higher and lower inflation expectations, respectively. Table 3 regresses the expected value of respondents' 1-year-ahead and 5-year-ahead probabilistic inflation expectations on dummy variables indicating whether a respondent's narrative mentions a specific factor. We include wave fixed effects and control for sociodemographic characteristics.[14] Table 3 presents the results of the multivariate regressions and shows that the narratives with which households explain the increase in inflation are strongly correlated with their expectations about the future development of inflation.

For example, households who attribute the rise in inflation to pent-up demand expect a 0.279 pp lower inflation rate one year ahead ($p = 0.258$) and a 0.640 pp lower inflation rate five years ahead ($p < 0.05$). These patterns are consistent with the notion that pent-up demand is a transitory driver of the inflation rate. By contrast, narratives featuring supply chain disruptions and labor shortages—both of which are often linked to the pandemic—are associated with higher inflation expectations over the next 12 months, but not in five years, in line with the idea that pandemic-induced supply-side disruptions only fade away in the medium-term. Households whose narratives revolve around energy shortages predict higher inflation both over the next 12 months (0.661 pp; $p < 0.01$) and five years later (0.330 pp; $p = 0.138$), consistent with the perception that energy shortages are going to prevail, e.g., due to a shift toward more climate-friendly energy sources. Respondents mentioning government mismanagement predict significantly higher inflation both over the next 12 months (1.155 pp; $p < 0.01$) and five years later (0.805 pp; $p < 0.01$), as do households with narratives mentioning government spending, consistent with a view that government intervention in the economy is a more chronic cause of

[13] We focus on the months from November 2021 to January 2022 because they share a relatively constant macroeconomic environment, which changed with the Russian invasion of Ukraine in late February 2022. Results are similar if we also include the waves from March and May 2022.

[14] Figure B.4 shows similar results without the inclusion of demographic controls.

high inflation rates.[15,16]

Next, we investigate which share of the variation in inflation expectations can be explained by narratives in out-of-sample predictions. Here, we turn to machine learning techniques, which efficiently handle the high-dimensional structure of the narrative data. We predict respondents' 1-year-ahead and 5-year-ahead inflation expectations with the help of a set of "factor dummies" for each of the 16 factors and a set of "connection dummies" for each possible causal connection between the factors. We employ a simple LASSO procedure and focus on out-of-sample predictions. Specifically, we randomly split the data in a training sample (70%) and a test sample (30%), estimate the LASSO model on the training data, and derive the out-of-sample predictions and the resulting out-of-sample $R^2$ for the test data.[17] We estimate that the narrative data account for approximately 10% of the variation in respondents' mean 1-year-ahead inflation expectation (Online Appendix Table A.12).The share of explained variation is considerable, given the low explanatory power typically found for other co-variates of macroeconomic expectations, such as demographics or experiences (Malmendier and Nagel, 2016). For instance, D'Acunto et al. (2021c) find a within-sample $R^2$ of 10% when relating inflation expectations to exposure to grocery prices, which they argue reflects that inflation expectations are likely shaped by a multitude of factors. Giglio et al. (2021) relate stock return expectations to a large set of investor characteristics and detect a within-sample $R^2$ of between 2% to 7%. They argue that the unexplained variation reflects "complex combinations of individual characteristics and experiences, some of which economic research has yet to discover." We find a lower $R^2$ when predicting respondents' 5-year-ahead expectations, reflecting that long-term inflation expectations were still relatively anchored in the winter 21/22 and viewed as less dependent on recent drivers of inflation (Online Appendix Table A.13).[18]

Together, these correlational results show that narratives about the past predict inflation expectations for the future and explain a significant share of variation in expectations. The results are consistent with the idea that narratives causally shape inflation expectations. However, our estimates could also reflect the influence of unobserved third factors. Therefore, we next provide complementary causal evidence based on three experiments.

[15] Online Appendix Table A.10 shows that the results are robust to excluding respondents reporting subjective distributions with implausible features such as a pronounced bimodality or "holes."

[16] The narratives that households use to explain the recent inflation hike are also correlated with their perceived uncertainty of future inflation (as shown in Appendix Table A.11).

[17] We repeat this procedure 100 times with different random sample splits, and, each time, LASSO's penalty parameter is calibrated with the help of five-fold cross-validation within the training data.

[18] We also examine whether the qualitative text data predict inflation expectations above and beyond their DAG representation. To test this, we feed the LASSO with additional dummies for used word stems and variables that measure text sentiment, length, and complexity. We find that models with DAG and text data perform only marginally better than models that use only the DAG data (Online Appendix Table A.12). For example, for 1-year-ahead mean inflation expectations, the model with DAG and text data delivers an $R^2$ of 0.11 compared to an $R^2$ of 0.10 for the DAG-exclusive model. Thus, in the context of predicting inflation expectations, the quantitative DAG representation captures the essence of information contained in the text data.

Table 3: Correlations between narratives and inflation expectations

| | Expected inflation rate (in %) | |
|---|---|---|
| | (1)<br>1 year | (2)<br>5 years |
| **Demand factors**: | | |
| Monetary policy | 1.005*** | 0.427 |
| | (0.269) | (0.317) |
| Government spending | 0.609*** | 0.343 |
| | (0.187) | (0.219) |
| Pent-up demand | -0.279 | -0.640** |
| | (0.246) | (0.312) |
| Residual demand | -0.262 | -0.232 |
| | (0.191) | (0.205) |
| **Supply factors**: | | |
| Supply chain issues | 0.477*** | 0.067 |
| | (0.146) | (0.160) |
| Labor shortage | 0.290* | 0.131 |
| | (0.148) | (0.167) |
| Energy | 0.661*** | 0.330 |
| | (0.194) | (0.222) |
| Residual supply | 0.133 | -0.199 |
| | (0.145) | (0.162) |
| **Other factors**: | | |
| Pandemic | -0.091 | 0.073 |
| | (0.146) | (0.161) |
| Government mismanagement | 1.155*** | 0.805*** |
| | (0.182) | (0.199) |
| Price gouging | 0.690*** | 0.550** |
| | (0.229) | (0.247) |
| N | 2,951 | 2,951 |
| Controls | Yes | Yes |
| Survey FE | Yes | Yes |
| Mean | 4.86 | 3.99 |
| R-squared | 0.18 | 0.068 |

*Note:* This table uses data from the Fall 2021 and early 2022 descriptive household survey waves (November 2021, December 2021, January 2022) and shows OLS regressions where the dependent variables are the mean of a respondent's subjective probability distribution over future inflation, constructed based on the midpoints of the different bins of potential inflation realizations. The explanatory variables are binary variables indicating which factors are included in the DAG constructed from the open-ended responses. Factors rarely mentioned are included in the regressions but not displayed in the table. All regressions include survey wave fixed effects as well as the following indicator variables as controls: gender, age, college education, economics in college, full-time work, income, and political views.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

### 5.2 The Causal Effect of Narratives

In this section, we present two experiments in which we provide households with narratives that are commonly associated with different degrees of persistence of high inflation rates. Households who invoke narratives that explain the rise in inflation with factors that appear less persistent should expect lower inflation going forward. We therefore study how the provision of different narratives about the rise of inflation causally affects respondents' inflation expectations.

#### 5.2.1 Narratives on Pent-Up Demand and the Energy Crisis

**Sample** We collect data for this experiment between April 6–10, 2022. We recruit respondents via Prolific, a survey provider commonly used in social science research (Peer et al., 2021).[19] The experiment proceeds in two waves: a baseline survey in which respondents are assigned to different treatment groups and a follow-up that elicits respondents' own narrative and their inflation expectations. 2,397 respondents completed the baseline survey, of whom 1,329 completed the follow-up. We do not observe any differential attrition from the main to the follow-up survey across the two narrative treatments described below ($p = 0.527$), yet there is somewhat lower attrition in the pure control group compared to the two treatments ($p = 0.030$). Online Appendix Table A.3 provides summary statistics.

**Design** Respondents are randomly assigned into one of two treatment groups or a control group. Respondents in the "pent-up demand" treatment receive an account that emphasizes the role of pent-up demand as a result of forced savings from the pandemic in driving the inflation increase, while the respondents in the "energy crisis" treatment receive an account that emphasizes the role of the energy crisis. Each treatment (truthfully) presents the narrative as an explanation used by experts and includes a few example quotes from our November 2021 expert survey. Respondents in the control group do not receive any narrative. Afterwards, we elicit all respondents' 1-year-ahead point forecasts of inflation.[20] In the follow-up survey—conducted one day after the main survey—respondents report their own narrative for the rise in inflation and their inflation expectations. Online Appendix G.3 provides the key survey questions.

Neither of the narrative treatments mentions the persistence of the factors nor their consequences for future inflation. Still, we know—based on data from the control group—that households view pent-up demand as a more temporary phenomenon than the energy crisis (as shown in Online Appendix Figure B.5). At the time of the experiment, the energy crisis had just been exacerbated by Russia's invasion of Ukraine. By contrast, pent-up demand resulting from the lockdowns was commonly viewed as becoming increasingly irrelevant.

[19] Compared to Lucid—the provider we work with in our descriptive collections—which offers advantages in terms of representativeness, Prolific allows re-interviewing respondents in follow-up surveys and provides access to participants that are on average more willing to take part in longer and potentially more taxing studies.

[20] We do not elicit subjective probability distributions in any of the experiments reported in this section to keep the surveys short.

Table 4: Narrative provision experiment: Pent-up demand and energy crisis

| | Narratives | | | Expected inflation rate (in %) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Pent-up | Energy | Confidence | Main | Follow-up |
| Energy (a) | 0.013 | 0.290*** | 0.148** | -0.016 | -0.058 |
| | (0.013) | (0.030) | (0.061) | (0.149) | (0.182) |
| Pent-up demand (b) | 0.378*** | -0.079*** | 0.303*** | -0.712*** | -0.630*** |
| | (0.024) | (0.023) | (0.059) | (0.144) | (0.171) |
| N | 1329 | 1329 | 1329 | 2397 | 1329 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Control mean | 0.028 | 0.175 | 0.000 | 8.263 | 8.127 |
| P-value: a = b | 0.000 | 0.000 | 0.006 | 0.000 | 0.002 |

*Note:* This table uses data from the narrative provision experiment with households. "Energy (a)" and "Pent-up demand (b)" are treatment indicators for whether respondents were randomly assigned to the energy or pent-up demand treatments, respectively. "Pent-up" and "Energy" are dummy variables equal to one for respondents for which pent-up demand or the energy crisis, respectively, are featured in their narratives as measured in the follow-up study. "Confidence" is a measure of confidence in one's own understanding of why inflation has increased (z-scored based on a 6-point Likert scale response in which higher values imply higher confidence). "Main" and "Follow-up" refer to 12-month inflation expectations measured in the main study and the follow-up study, respectively. The elicited point estimates are top and bottom coded at 20% and 0%, respectively. Controls include age in years, log income, and dummies for gender, college education, economics in college, full-time work, region, and voting indicators for the 2020 presidential election.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

**Results** We regress post-treatment narratives and inflation expectations on dummies for the two treatment arms and a set of control variables. The results are shown in Table 4.

To provide evidence on the first-stage effects, we start by comparing respondents' narratives across the different treatment groups. For simplicity, we focus on treatment effects on the fraction of respondents mentioning the pent-up demand and the energy crisis factor in their narratives. Respondents exposed to the pent-up demand treatment are 37.8 pp more likely to invoke a narrative about pent-up demand in the follow-up (column 1, $p < 0.01$), compared to a control group fraction of 2.8% mentioning this factor. Similarly, being exposed to the energy treatment increases the fraction of respondents mentioning the energy crisis by 29 pp (column 2, $p < 0.01$), compared to 17.5% among control group respondents. In addition, the pent-up demand treatment reduces the fraction mentioning the energy crisis by 7.9 pp (column 2, $p < 0.01$). As highlighted in Online Appendix Figure B.6, we also observe small crowding-out effects on other narrative factors. Thus, our treatments successfully generate variation in respondents' narratives about higher inflation, which also highlights that households' narratives are elastic to the provision of new information.[21] Moreover, column 3 shows that both the energy treatment ($p < 0.05$) and the

[21]The large "first-stage" effect on narratives has the methodological advantage that it increases the statistical power of the experimental design. The first-stage results also highlight how narratives are adopted, enabling them to spread through the economy (Bénabou et al., 2018; Eliaz and Spiegler, 2020; Flynn and Sastry, 2024; Schwartzstein and Sunderam, 2021, 2022). One potential concern is that the large size of the first-stage effects partly reflects social desirability bias, which pushes respondents to simply restate the provided information, although the fact that respondents' own narratives are only elicited in the follow-up survey should mitigate such concerns (de Quidt et al., 2018).

pent-up demand treatment ($p < 0.01$) increase respondents' confidence in their understanding of why the inflation rate increased, consistent with the notion that narratives help individuals make sense of the world.

We next turn to the effects of our narrative intervention on respondents' inflation expectations. Being exposed to the pent-up demand treatment significantly reduces respondents' inflation expectations as measured in the main survey by 0.71 pp (column 4, $p < 0.01$), consistent with pent-up demand being viewed as a more temporary driver of inflation. This effect is both economically and statistically significant and corresponds to a 24% of a standard deviation change in inflation expectations. By contrast, the energy crisis treatment reduces respondents' inflation expectations insignificantly by 0.02 pp (column 4, $p = 0.911$). Potential reasons for the muted effect of the energy crisis treatment are that the energy crisis' implications for future inflation were already fairly salient at the time of our survey and that people perceived the energy crisis as equally persistent as the narratives "crowded out" by the treatment. Column 5 highlights that the treatment effects on inflation expectations persist at a similar size in the follow-up survey.

Importantly, the table also highlights that inflation expectations significantly differ between the pent-up demand and the energy crisis treatments ($p < 0.01$). Thus, our treatment effects do not simply capture the effect of being provided with *an* explanation versus no explanation. Instead, holding *different* narratives is reflected in differences in inflation expectations.[22]

### 5.2.2 Monetary Policy Narratives

**Sample** We conduct this experiment with Prolific between June 17–18, 2022. 1,069 respondents complete the baseline survey, out of which 736 respondents complete a follow-up survey one day later. There is no significant differential attrition in the follow-up survey across the two treatment arms ($p = 0.321$).

**Design** The design is similar to the previous experiment. Respondents are randomly assigned to one of two treatment groups. Respondents in the "monetary policy" treatment receive an account that emphasizes the role of monetary policy in driving the inflation increase. Respondents in the "energy crisis" treatment receive an account that emphasizes the role of the energy crisis, similar to the previous experiment, in which it did not affect inflation expectations compared to a pure control group.[23] We hypothesize that the monetary policy narrative, which argues that loose

[22]Here and below, we consider it very unlikely that the treatment effects are driven by experimenter demand effects (de Quidt et al., 2018). First, the provision of narratives is naturally embedded in our description of the current inflation situation. This shrouds the link to the subsequent elicitation of inflation expectations. Second, the follow-up further conceals this link. Third, only 10.7% of respondents correctly guess the hypothesis of the experiment at the end of the study (see Panel A of Figure B.7), and the estimates are virtually identical if we restrict our main specification to those who do not correctly guess the hypothesis (results available upon request).

[23]Here, we opt for an active control group design, in which all respondents receive a narrative, and against an additional pure control group for various reasons. First, our goal is to provide causal evidence on the effect of holding *different* narratives on expectations. Second, the active control group design creates fully exogenous variation in narratives in both experimental conditions, allowing us to interpret treatment effects without accounting for prior narratives. Third, the provision of narratives per se might have side-effects, such as changing uncertainty about drivers of inflation, igniting emotional responses, and increasing the length of the survey, all of which are more comparable in an active control group design. Finally, we observe in Section 5.2.1 that the energy crisis treatment

Table 5: Narrative provision experiment: Monetary policy and energy crisis

| | Narratives | | | Expected inflation rate | |
|---|---|---|---|---|---|
| | (1) Monetary policy | (2) Energy | (3) Confidence | (4) Main | (5) Follow-up |
| Treatment: Monetary policy | 0.386*** | -0.499*** | -0.065 | -0.402** | -0.617*** |
| | (0.031) | (0.030) | (0.073) | (0.202) | (0.219) |
| N | 736 | 736 | 736 | 1069 | 736 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Energy group mean | 0.103 | 0.621 | 0.000 | 9.400 | 9.286 |

*Note:* This table uses data from the monetary policy narrative provision experiment with households. "Treatment: Monetary policy" is a treatment dummy taking the value one for respondents assigned the monetary policy narrative and zero for respondents assigned the energy crisis narrative. "Monetary policy" and "Energy" are dummy variables equal to one for respondents for which monetary policy or the energy crisis, respectively, are featured in their narratives as measured in the follow-up study. "Confidence" is a measure of confidence in one's own understanding of why inflation has increased (z-scored based on a 6-point Likert scale response in which higher values imply higher confidence). "Main" and "Follow-up" refer to 12-month inflation expectations (in %) measured in the main study and the follow-up study, respectively. The elicited point estimates are top and bottom coded at 20% and 0%, respectively. Controls include age in years, log income, and dummies for gender, college education, economics in college, full-time work, region, and voting indicators for the 2020 presidential election.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

monetary policy was a key driver of inflation in the past, should lead to lower expected future inflation because monetary policy had been substantially tightened since early 2022. As before, we mention neither the departure from low interest rates nor the persistently high energy prices. But, in an auxiliary collection, we confirm that a majority of 61% of respondents are aware that the Fed had abandoned its low interest rate policy (June 20, 2022, $n = 100$, same subject pool).

**Results** Columns 1 and 2 of Table 5 show that the treatments successfully shape people's narratives. Compared to the energy crisis treatment, respondents in the monetary policy treatment are 39 pp more likely to invoke narratives regarding monetary policy ($p < 0.01$) and 50 pp less likely to invoke an energy crisis narrative ($p < 0.01$). Consistent with both treatment groups receiving a narrative, we do not find a differential effect on confidence in one's own understanding of the rise in inflation (column 3). We next turn to the effects on respondents' inflation expectations. In line with our hypothesis, column 4 shows that respondents in the monetary policy treatment arm have 0.40 pp lower ($p < 0.01$) inflation expectations. Furthermore, column 5 shows that these effects persist in the follow-up study one day later ($p < 0.01$).[24]

Together, the two narrative provision experiments show that being exposed to different narratives about the past causally changes households' future inflation expectations. In Appendix 2, we present a complementary experiment which demonstrates that drawing attention to government spending changes households' narratives and inflation expectations.

has no strong effect on inflation expectations, suggesting that we do not loose much information by not including a pure control group. See Haaland et al. (2023) for a discussion of active versus pure control group designs.

[24]Only 6.1% of respondents correctly guess the hypothesis of the experiment (Panel B of Figure B.7). Results are virtually identical if we exclude these respondents from our main specification (results available upon request).

### 5.3 Narratives and the Interpretation of New Information

Because narratives specify which factors have been important in the past, they provide a lens through which people could interpret new evidence. Therefore, we investigate whether narratives about the past also affect how people form their expectations about the future in response to new information. We explore this in an additional experiment which revolves around the government spending narrative. In the aftermath of the pandemic stimulus packages, future government spending growth remained uncertain, making it a good candidate to study how respondents update their expectations in response to new information. We hypothesize that respondents exposed to a narrative that government spending affected inflation in the past will adjust their future inflation expectations more strongly to forecasts about future government spending.

**Sample and design** We use Prolific to collect a sample of 997 respondents on April 27 and 28, 2022. Online Appendix Table A.3 provides summary statistics. Our experiment consists of a simple 2×2 factorial design, in which we vary (i) the narrative and (ii) subsequent information that respondents receive before they make their prediction of future inflation. In the first part of our experiment, we exogenously shift respondents' narratives about the past inflation increase.[25] Respondents in the "government spending" treatment receive an account emphasizing that government spending programs have been an important driver of the inflation increase. Respondents in a control "energy crisis" treatment receive an explanation emphasizing the role of the energy crisis. We use the energy narrative as an active control, holding constant the survey flow and the length of the instructions. This ensures that any effect on updating is not driven by the provision of *a* narrative but rather the provision of different narratives. Each treatment (truthfully) presents the narrative as an explanation used by experts and includes an example quote from our expert survey.

In the second part of the experiment, all respondents are shown information about future changes in government spending. Specifically, we provide them with one of two forecasts from individual experts participating in the first quarter of 2022 wave of the Survey of Professional Forecasters. Respondents in the "low government spending" arm receive a forecast from an expert who predicts a decrease in real federal government spending by 4% over the next 12 months. By contrast, those in the "high government spending" arm are shown an expert forecast predicting a 6% increase. The active control design, where all respondents are provided with information, allows us to cleanly vary beliefs while holding potential side-effects from providing information such as priming effects constant across treatment arms (Haaland et al., 2023).

After providing the government spending forecasts, we elicit respondents' 1-year-ahead point forecasts of inflation and the real growth of federal government spending over the next 12 months. Online Appendix G.6 provides the core survey instructions.

[25] As in Section 5.2.2, we use on an active control group design. See footnote 23 for a discussion.

Table 6: Narratives and the interpretation of new information

| | OLS | | IV |
|---|---|---|---|
| | (1) Expected government spending growth | (2) Expected inflation rate | (3) Expected inflation rate |
| **Panel A: Spending narrative** | | | |
| Treatment: High spending | 4.723*** | 1.786*** | |
| | (0.629) | (0.276) | |
| Expected government spending growth | | | 0.378*** |
| | | | (0.060) |
| N | 498 | 498 | 498 |
| Controls | Yes | Yes | Yes |
| **Panel B: Energy narrative** | | | |
| Treatment: High spending | 6.770*** | 0.344 | |
| | (1.236) | (0.271) | |
| Expected government spending growth | | | 0.051 |
| | | | (0.038) |
| N | 479 | 479 | 479 |
| Controls | Yes | Yes | Yes |
| *p*-value: Panel A = Panel B | 0.134 | 0.000 | 0.000 |

*Note:* The table shows OLS regression results (columns 1 and 2) and IV regression results (column 3) from the belief updating experiment. Panel A shows results for respondents who are exposed to a government spending narrative prior to receiving the forecast, while Panel B shows results for respondents who are instead exposed to a narrative about the energy crisis. "Treatment: High spending" is a binary variable taking the value of one for respondents assigned to the high government spending forecast (predicting a 6% increase in real federal government spending over the next 12 months) and value zero for respondents assigned to the low government spending forecast (predicting a 4% decrease). "Expected government spending growth" refers to point beliefs about changes in real government spending growth in percent. "Expected inflation rate" refers to 12-month point inflation expectations in percent. The elicited point forecasts are top and bottom coded at 20% and 0%, respectively. In the IV regression in column 3, the continuous variable for government spending expectations has been instrumented with the treatment indicator for receiving a high/low government spending forecast. Controls include age in years, log income, and dummies for gender, college education, economics in college, full-time work, region, and voting indicators for the 2020 presidential election.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

**Results** We regress respondents' post-treatment expectations about government spending and inflation on a dummy indicating whether the respondent has received the high spending forecast (instead of the low spending forecast) and a set of controls. We run these regressions separately for those who received the government spending narrative and those who received the energy crisis narrative before being provided with the forecast.

Column 1 of Table 6 shows that the "high spending" treatment successfully increases expectations of government spending growth by 4.7 pp among respondents who received the government spending narrative ($p < 0.01$) and by 6.8 pp among those who received the energy crisis narrative ($p < 0.01$), corresponding to 47% and 68% of the difference between the two expert forecasts (10 pp). Thus, respondents who previously have received the energy narrative update their spending expectations slightly more than those who have received the spending narrative, although the difference is not statistically significant ($p = 0.134$). One factor that could rationally explain a difference in the first stage is that prior knowledge about previous government spending might reduce the weight respondents assign to the expert forecast on future government spending.

Turning to the results on inflation expectations (column 2), we see a strong increase of 1.79 pp in inflation expectations in the "high spending" treatment among respondents who receive the government spending narrative ($p < 0.01$). By contrast, respondents who receive the energy crisis narrative do not react differentially to receiving the high or the low government spending forecast. Their inflation expectations only increase by a non-significant 0.34 pp ($p = 0.205$). In line with the hypothesis, the updating of inflation expectations is significantly different across the narrative treatment groups ($p < 0.01$).

Column 3 provides a quantitative interpretation of the effect size using an instrumental variable estimator. We study the effect of government spending expectations on inflation expectations, using the different forecasts about government spending as an instrument. Among respondents who received the government spending narrative, a 1 pp increase in government spending expectations leads to a 0.378 pp increase in inflation expectations ($p < 0.01$), compared to only 0.051 pp ($p = 0.184$) among respondents who received the energy narrative. Again, the difference between these coefficients is highly statistically significant ($p < 0.01$). This demonstrates that exposure to narratives about the past can have a quantitatively important impact on how new information shapes the formation of expectations about the future.

One potential concern is that the treatment manipulations are prone to experimenter demand effects. To assuage such concerns, we analyze respondents' beliefs about the experimental hypothesis, which we elicit at the end of the survey using the following open-ended question "Which hypothesis do you think the researchers try to test with this survey?" We hand-coded responses using a conservative coding scheme that errs on the side of coding a response as correctly guessing the experimental hypothesis (Appendix Figure B.7 provides details). As in the other experiments in the paper, only a small fraction—9.5%—of the respondents correctly guess the hypothesis of the experiment (Panel D of Online Appendix Figure B.7). Results are virtually identical if we restrict the main specification to respondents that do not correctly guess the hypothesis (as shown in Online Appendix Table A.14).[26]

## 6 The Effects of Narratives on the Macroeconomy

In the empirical analysis, we measure narratives and show that they affect inflation expectations. This raises the important question whether narratives could also shape aggregate outcomes through their effect on expectations. Yet, based on the survey alone, one cannot make claims about the effect of narratives on economy-wide outcomes. To study how narratives can affect

[26]The fact that our results are quantitatively unchanged even if exclude the 9.5% respondents who are most likely aware of our study hypothesis and hence potentially affected by conformity bias is reassuring. This means that, even if some participants understood our hypothesis but did not articulate it in the open-text question, they are very unlikely to affect our conclusion.

economy-wide outcomes, we therefore turn to a macroeconomic model.

We first formalize narratives in a way that is consistent with our empirical evidence. We then use this theory of narratives to study the effect of narratives on outcomes in an otherwise conventional New Keynesian model.

### 6.1 A formalization of the term "narrative"

In Section 2, we describe economic narratives as causal accounts for past economic events. Building on this idea, we now formalize narratives as *subjective causal models*, and we do so in a way that easily lends itself to macroeconomic modeling.

Each household $i \in [0,1]$ believes that inflation in period $t$, denoted $\pi_t$, has been caused by a set of factors, $z_{1,t},\ldots,z_{N,t}$. We assume that the individual perfectly observes inflation, the individual perfectly observes the $N$ factors that may have contributed to inflation, and the individual's explanation for inflation is linear in the factors:

$$\pi_t = \psi_1(i)\,z_{1,t} + \psi_2(i)\,z_{2,t} + \ldots + \psi_N(i)\,z_{N,t}. \tag{1}$$

The factors $z_{1,t},\ldots,z_{N,t}$ are the potential drivers of inflation, the coefficient $\psi_n(i)$ is individual $i$'s perceived marginal effect of factor $n$ on inflation in period $t$, and the term $\psi_n(i)\,z_{n,t}$ is the amount of inflation in period $t$ that the individual attributes to the current value of factor $n$. Equation (1) together with values for the coefficients $(\psi_1(i),\ldots,\psi_N(i)) \in \mathbb{R}^{\mathbb{N}}$ is individual $i$'s subjective causal model of inflation.

We place some restrictions on agents' perceived law of motion for the $N$ factors. We assume that individual $i$ believes in period $t$ that each factor $z_{n,t}$ follows a first-order autoregressive process with perceived persistence parameter $\rho_n(i)$ from period $t+1$ onwards:

$$\begin{pmatrix} z_{1,t+1} \\ \vdots \\ z_{N,t+1} \end{pmatrix} = \begin{bmatrix} \rho_1(i) & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \rho_N(i) \end{bmatrix} \begin{pmatrix} z_{1,t} \\ \vdots \\ z_{N,t} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t+1} \\ \vdots \\ \varepsilon_{N,t+1} \end{pmatrix}, \tag{2}$$

with $\begin{pmatrix} \varepsilon_{1,t+1} & \ldots & \varepsilon_{N,t+1} \end{pmatrix}' \sim i.i.d.(0,\Sigma(i))$. We place no restrictions on the perceived variance-covariance matrix of the innovations, $\sum(i)$. We also place no restrictions on what individual $i$ believes has caused the current values of the $N$ factors in period $t$. For example, the individual may believe that the current values of the $N$ factors have been caused by some common cause, the pandemic, which could also mean that the individual believes in a non-zero covariance structure between the factor innovations.

In the language of the learning literature, equations (1)–(2) characterize individual $i$'s perceived law of motion for inflation. Following Eliaz and Spiegler (2020), the causal model of inflation implied by equation (1) and some perceived underlying causes for the factors can be represented by a directed acyclical graph.

We interpret narratives as verbal summaries of such subjective causal models of inflation.

This formalization of narratives is informed by the empirical analysis in Sections 3–5. Equation (1) captures that: (i) an individual's subjective causal model of inflation may be focused on supply-side factors, focused on demand-side factors, or be balanced between supply- and demand-side factors, independent of what has actually caused inflation, (ii) an individual's subjective causal model of inflation may be richer with more factors or coarser with fewer factors, and (iii) the subjective causal model of inflation may differ across individuals, as indicated by the index $i$ on the coefficients. Furthermore, equations (1)–(2) imply that agents' narratives shape their inflation expectations. Formally, individual $i$'s expectation of future inflation is

$$E_t^i\left[\pi_{t+1}\right] = \psi_1(i)\,\rho_1(i)\,z_{1,t} + \psi_2(i)\,\rho_2(i)\,z_{2,t} + \ldots + \psi_N(i)\,\rho_N(i)\,z_{N,t}. \quad (3)$$

Agents with narratives that build on more persistent factors have higher inflation expectations, and if a group of agents puts more weight on a more persistent factor, then the average inflation expectation in that group increases. This captures the mechanism that underlies our narrative provision experiments (Tables 4–5).[27]

Before moving on it may be useful to illustrate equation (1) with an example. The $N$ factors may be supply chain disruptions leading to unusually low productivity ($z_{1,t}$), increased preference for leisure leading to higher wage costs ($z_{2,t}$), unusually high markups or energy costs ($z_{3,t}$), higher government spending ($z_{4,t}$), loose monetary policy ($z_{5,t}$), and pent-up demand ($z_{6,t}$); and the subjective causal model of one individual $i$ may have a focus on the supply side

$$\pi_t = \psi_1(i)\,z_{1,t} + \psi_2(i)\,z_{2,t} + \psi_3(i)\,z_{3,t},$$

while the subjective causal model of another individual $j$ may have a focus on the demand side

$$\pi_t = \psi_4(j)\,z_{4,t} + \psi_5(j)\,z_{5,t} + \psi_6(j)\,z_{6,t}.$$

In addition, some individuals may be experts with a rich subjective causal model (i.e., a vector $(\psi_1(i), \ldots, \psi_N(i))$ with few zeros), while other individuals may be non-experts with a coarse subjective model (i.e., a vector $(\psi_1(i), \ldots, \psi_N(i))$ with many zeros) or even a monocausal model.

Moreover, we note that we have moved from the qualitative cause-effect nature of narratives to a quantitative representation in the form of the coefficients $(\psi_1(i), \ldots, \psi_N(i)) \in \mathbb{R}^{\mathbb{N}}$ that can not only be zero or non-zero but that can also take larger or smaller non-zero values. Hence, agents are allowed to believe that a factor is more or less important. This assumption is made for generality and also implies that our formalization of narratives nests the rational expectations equilibrium of a standard macro model as a special case.

[27] We can also interpret the experiment that studies narratives' impact on the interpretation of new information (Table 6) through the lens of the model: the experiment cross-randomizes a shift in households' belief about the future realization of the factor government spending with a shift in participants' narratives.

### 6.2 A DSGE model with the model of narratives

We now turn to studying the effects of narratives on aggregate outcomes in a dynamic stochastic general equilibrium (DSGE) model. The model is a conventional New Keynesian model (see Online Appendix F.1) with one novel feature: agents form expectations about the future with a subjective causal model of inflation that may be misspecified by putting too much weight on some drivers of inflation and too little weight on other drivers of inflation.

The model setup is a completely standard for a New Keynesian model. The economy consists of households, firms, and a government. Households maximize the expected discounted sum of period utility, which is increasing in composite consumption and decreasing in labor supply. Composite consumption is a CES aggregator of differentiated consumption goods. These differentiated goods are produced by firms using labor as the only input. The market for these differentiated goods is monopolistically competitive. The labor market is perfectly competitive. There is price stickiness, as in Calvo (1983). The wage rate is perfectly flexible. The single asset is a nominal government bond. The central bank sets the nominal interest rate according to a rule. The government finances government spending by collecting lump-sum taxes or issuing nominal government bonds. All agents have complete information, i.e., they know the entire history of the factors and the endogenous variables up to and including the current period. We assume that there are three factors: productivity, government spending, and monetary policy, each following a first-order autoregressive process.[28]

We start by analyzing a version of the model where all households (and all firms) have the same subjective causal model of inflation. We then move to a version of the model that allows for heterogeneity in narratives among households.

#### 6.2.1 Model setup without heterogeneity

When all households in this simple New Keynesian model have the same subjective causal model of inflation, they all take the same consumption decision, which has to satisfy the consumption Euler equation:

$$c_t = -\frac{1}{\gamma}\left(r_t - E_t^H\left[\pi_{t+1}\right]\right) + E_t^H\left[c_{t+1}\right] \tag{4}$$

Here $c_t$ denotes consumption in period $t$, $r_t$ denotes the nominal interest rate in period $t$, and $E_t^H\left[\pi_{t+1}\right]$ and $E_t^H\left[c_{t+1}\right]$ denote the households' period-$t$ expectation of next period's inflation and consumption. The parameter $\gamma > 0$ is the inverse of the intertemporal elasticity of substitution. Furthermore, when all firms in this simple New Keynesian model have the same subjective causal model of inflation, inflation is given by the usual New Keynesian Phillips curve:

$$\pi_t = \kappa\left[(\gamma + \varsigma\alpha)\, c_t + \varsigma\,(1-\alpha)\, g_t - (1+\varsigma)\, a_t\right] + \beta E_t^F\left[\pi_{t+1}\right] \tag{5}$$

[28] In the notation of equation (1), this means $N = 3$. We chose a model with three factors as it illustrates that no result in this section depends on having only two factors, while maintaining readability of all the following equations.

Here, $\pi_t$ denotes inflation in period $t$, $g_t$ and $a_t$ are government spending and productivity in period $t$, and $E_t^F[\pi_{t+1}]$ denotes the firms' period-$t$ expectation of next period's inflation. The parameter $\beta \in (0,1)$ is the discount factor, the coefficient $\kappa > 0$ depends only on the degree of price stickiness and the discount factor, the parameter $\varsigma > 0$ controls the convexity of the disutility of labor in hours worked, and the coefficient $(1-\alpha)$ is the share of government spending in GDP in the non-stochastic steady state of the model. All variables are expressed in terms of log-deviations from this non-stochastic steady state. Finally, the central bank sets the interest rate according to the rule

$$r_t = \phi \pi_t + \nu_t \tag{6}$$

where $\phi > 1$ is a policy coefficient governing the responsiveness of the central bank to inflation, $\phi \pi_t$ is the systematic component of monetary policy, and $\nu_t$ is the period-$t$ deviation of the interest rate from the systematic component of monetary policy.

We assume, as in equation (1), that each agent's subjective causal model of inflation is linear in the factors. This is a natural assumption since also the rational expectations equilibrium is linear in the factors. Households' subjective causal model of inflation in period $t$ is that, $\forall s = t, t+1, \ldots$,

$$\pi_s = \psi_a^H a_s + \psi_g^H g_s + \psi_\nu^H \nu_s \tag{7}$$

Firms' subjective causal model of inflation is that, $\forall s = t, t+1, \ldots$,

$$\pi_s = \psi_a^F a_s + \psi_g^F g_s + \psi_\nu^F \nu_s \tag{8}$$

The coefficients in the households' subjective causal model of inflation, $(\psi_a^H, \psi_g^H, \psi_\nu^H)$, and the coefficients in the firms' subjective causal model of inflation, $(\psi_a^F, \psi_g^F, \psi_\nu^F)$, may be correct or incorrect. That is, subjective causal models of inflation may be correctly specified or misspecified by putting too much weight on some drivers of inflation and too little weight on other drivers of inflation.

The consumption Euler equation (4) also contains an expectation of future consumption. We therefore need to specify a third subjective causal model to solve the model. We assume that households' subjective causal model of income, denoted $\tilde{x}_s$, is that, $\forall s = t, t+1, \ldots$,

$$\tilde{x}_s = \varphi_a^H a_s + \varphi_g^H g_s + \varphi_\nu^H \nu_s \tag{9}$$

The subjective causal model of income may also be correctly specified or misspecified by giving too much importance to some drivers of income and too little importance to other other drivers of income.

Finally, as in equation (2), we assume that all agents believe in period $t$ that each factor follows a first-order autoregressive process from period $t+1$ onwards:

$$\begin{pmatrix} a_{t+1} \\ g_{t+1} \\ v_{t+1} \end{pmatrix} = \begin{bmatrix} \rho_a & 0 & 0 \\ 0 & \rho_g & 0 \\ 0 & 0 & \rho_v \end{bmatrix} \begin{pmatrix} a_t \\ g_t \\ v_t \end{pmatrix} + \begin{pmatrix} \varepsilon^a_{t+1} \\ \varepsilon^g_{t+1} \\ \varepsilon^v_{t+1} \end{pmatrix}, \tag{10}$$

with $\begin{pmatrix} \varepsilon^a_{t+1} & \varepsilon^g_{t+1} & \varepsilon^v_{t+1} \end{pmatrix}' \sim i.i.d.(0,\Sigma)$. Hence, equations (7)-(10) have the form of equations (1)–(2).

Equilibrium is defined as follows. Equations (4)–(6) are satisfied. Firms' expectation of future inflation, $E^F_t[\pi_{t+1}]$, is given by firms' perceived law of motion of inflation, consisting of equations (8) and (10). Households' expectations of future inflation and of future real income, $E^H_t[\pi_{t+1}]$ and $E^H_t[\tilde{x}_{t+1}]$, are given by households' perceived law of motion of inflation and income, consisting of equations (7), (9), and (10). Households understand that there exists the following relationship between aggregate consumption and aggregate income: $c_t = \tilde{x}_t$.

We first present the rational expectations equilibrium as a benchmark. If one imposes the restriction that households have the correct coefficients $\psi^H_a, \psi^H_g, \psi^H_v$ in their subjective causal model of inflation, households have the correct coefficients $\varphi^H_a, \varphi^H_g, \varphi^H_v$ in their subjective causal model of income, and firms have the correct coefficients $\psi^F_a, \psi^F_g, \psi^F_v$ in their subjective causal model of inflation, one obtains the rational expectations equilibrium.

**Proposition 1 ("rational expectations equilibrium")**: Under the restriction of rational expectations (i.e., under the restriction that agents' perceived law of motion of the economy given by equations (7)–(10) has to equal the actual law of motion of the economy), inflation and consumption in any period $t$ are given by:

$$\begin{aligned} \pi_t = \; & \frac{-\kappa(1+\varsigma)(1-\rho_a)}{(1-\rho_a)(1-\beta\rho_a)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}(\phi-\rho_a)} a_t \\ & + \frac{\kappa\varsigma(1-\alpha)\left(1-\rho_g\right)}{\left(1-\rho_g\right)\left(1-\beta\rho_g\right)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left(\phi-\rho_g\right)} g_t \\ & + \frac{-\frac{1}{\gamma}\kappa(\gamma+\varsigma\alpha)}{(1-\rho_v)(1-\beta\rho_v)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}(\phi-\rho_v)} v_t \end{aligned}$$

$$\begin{aligned} c_t = \; & \frac{\frac{1}{\gamma}(\phi-\rho_a)\kappa(1+\varsigma)}{(1-\rho_a)(1-\beta\rho_a)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}(\phi-\rho_a)} a_t \\ & + \frac{-\frac{1}{\gamma}\left(\phi-\rho_g\right)\kappa\varsigma(1-\alpha)}{\left(1-\rho_g\right)\left(1-\beta\rho_g\right)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left(\phi-\rho_g\right)} g_t \\ & + \frac{-\frac{1}{\gamma}(1-\beta\rho_v)}{(1-\rho_v)(1-\beta\rho_v)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}(\phi-\rho_v)} v_t \end{aligned}$$

**Proof:** See Online Appendix F.2.

This rational expectations equilibrium is the object that is usually presented in textbooks on the New Keynesian model. Note that the coefficients of the subjective causal models do not appear in the last two equations because they have been substituted out using the correctness requirement.

We now relax the correctness requirement of rational expectations in three steps. We will use the following notation. Let $\omega_z^H \equiv \frac{\psi_z^H z_t}{\pi_t}$ denote the percentage contribution of factor $z_t$ to current inflation, according to *households' current subjective causal model of inflation* (7). Let $\omega_z^F \equiv \frac{\psi_z^F z_t}{\pi_t}$ denote the percentage contribution of factor $z_t$ to current inflation, according to *firms' current subjective causal model of inflation* (8). Let $\varpi_z^H \equiv \frac{\varphi_z^H z_t}{\tilde{x}_t}$ denote the percentage contribution of factor $z_t$ to current income, according to *households' current subjective causal model of income (9).*

**Proposition 2:** First, if one relaxes the restriction that the coefficients in the households' subjective causal model of inflation have to be correct, the equilibrium becomes:

$$\pi_t = \begin{array}{l} \frac{-\kappa(1+\varsigma)(1-\rho_a)}{(1-\rho_a)(1-\beta\rho_a)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}a_t \\ +\frac{\kappa\varsigma(1-\alpha)\left(1-\rho_g\right)}{\left(1-\rho_g\right)\left(1-\beta\rho_g\right)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}g_t \\ +\frac{-\frac{1}{\gamma}\kappa(\gamma+\varsigma\alpha)}{(1-\rho_v)(1-\beta\rho_v)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}v_t \end{array} \tag{11}$$

$$c_t = \begin{array}{l} \frac{\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]\kappa(1+\varsigma)}{(1-\rho_a)(1-\beta\rho_a)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}a_t \\ +\frac{-\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]\kappa\varsigma(1-\alpha)}{\left(1-\rho_g\right)\left(1-\beta\rho_g\right)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}g_t \\ +\frac{-\frac{1}{\gamma}(1-\beta\rho_v)}{(1-\rho_v)(1-\beta\rho_v)+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}v_t \end{array} \tag{12}$$

Second, if one also relaxes the restriction that the coefficients in the firms' subjective causal model of inflation have to be correct, the equilibrium becomes:

$$\pi_t = \begin{array}{l} \frac{-\kappa(1+\varsigma)(1-\rho_a)}{(1-\rho_a)\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}a_t \\ +\frac{\kappa\varsigma(1-\alpha)\left(1-\rho_g\right)}{\left(1-\rho_g\right)\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}g_t \\ +\frac{-\frac{1}{\gamma}\kappa(\gamma+\varsigma\alpha)}{(1-\rho_v)\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}v_t \end{array} \tag{13}$$

$$c_t = \begin{array}{l} \frac{\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]\kappa(1+\varsigma)}{(1-\rho_a)\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}a_t \\ +\frac{-\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]\kappa\varsigma(1-\alpha)}{\left(1-\rho_g\right)\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}g_t \\ +\frac{-\frac{1}{\gamma}\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]}{(1-\rho_v)\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]}v_t \end{array} \tag{14}$$

Third, if one relaxes, in addition, the restriction that the coefficients in the households' subjective causal model of income have to be correct, the equilibrium becomes:

$$\pi_t = \frac{-[\kappa(1+\varsigma)a_t-\kappa\varsigma(1-\alpha)g_t]\left[1-\left(\sum_{z=a,g,v}\varpi_z^H\rho_z\right)\right]-\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}v_t}{\left[1-\left(\sum_{z=a,g,v}\varpi_z^H\rho_z\right)\right]\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]} \tag{15}$$

$$c_t = \frac{\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]\left[\kappa(1+\varsigma)a_t-\kappa\varsigma(1-\alpha)g_t\right]-\frac{1}{\gamma}\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]v_t}{\left[1-\left(\sum_{z=a,g,v}\varpi_z^H\rho_z\right)\right]\left[1-\beta\left(\sum_{z=a,g,v}\omega_z^F\rho_z\right)\right]+\kappa(\gamma+\varsigma\alpha)\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,v}\omega_z^H\rho_z\right)\right]} \tag{16}$$

**Proof:** See Online Appendix F.3.

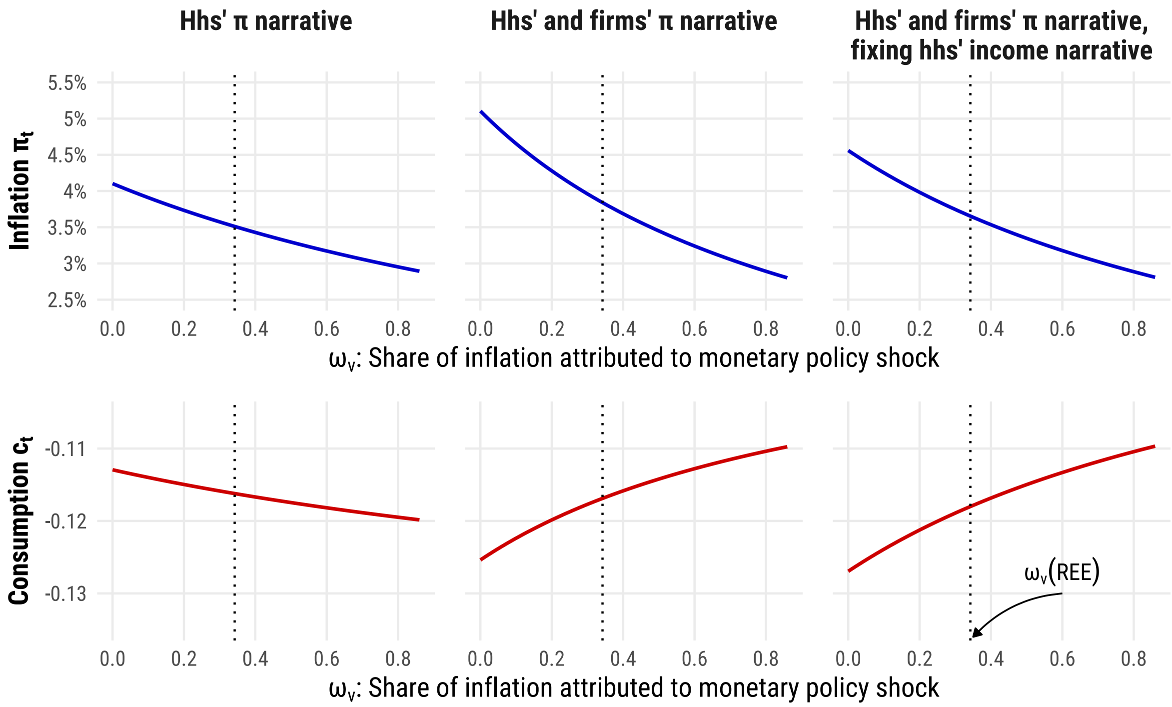
Equations (15)–(16) give inflation and consumption as a function of the structural parameters, the current levels of the three factors, and agents' subjective causal models of inflation and income, where the subjective causal models are summarized by the households' perceived inflation shares $\omega_a^H, \omega_g^H, \omega_v^H$, the firms' perceived inflation shares $\omega_a^F, \omega_g^F, \omega_v^F$, and the households' perceived income shares $\varpi_a^H, \varpi_g^H, \varpi_v^H$. The perceived shares $\left\{\omega_z^H, \omega_z^F, \varpi_z^H\right\}_{z=a,g,v}$ may vary with $t$ in an arbitrary way. We suppress the time subscript $t$ on those perceived shares for ease of exposition. Equations (15)–(16) are our main theoretical result and characterize the mapping from narratives to aggregate outcomes in a conventional New Keynesian model.

Equations (11)–(14) present intermediate stages where households' income expectations and/or firms' inflation expectations are still formed rationally. Relaxing the assumption of rational expectations in three steps, as we do in Proposition 2, allows us to illustrate the channels through which narratives affect aggregate outcomes.[29]

We illustrate the main prediction of the model—the effects of inflation narratives on economy-wide outcomes—with Figure 6. We take the preference, price stickiness, and monetary policy parameters from a standard textbook on the New Keynesian model (Galí, 2015, chapter 3, page 67): $\beta = 0.99$ (quarterly model), $\gamma = 1$ (log utility), $\varsigma = 5$ (Frisch elasticity of labor supply equal to 0.2), $\lambda = 3/4$ (an average price duration of four quarters), and $\phi = 1.5$. We take the ratio of government spending to output in the non-stochastic steady state from Christiano et al. (2011): $1-\alpha = 0.2$. Finally, we set the persistence of the monetary policy shock to $\rho_v = 0.5$ and the persistence of the productivity shock to $\rho_a = 0.9$, following again Galí (2015); and we set the persistence of the government spending shock to $\rho_g = 0.8$, following again Christiano et al. (2011). We consider the following combination of shocks: a ten percent reduction in productivity ($a_t = -0.1$), a simultaneous ten percent increase in government spending ($g_t = 0.1$), and a policy rate that is two percentage points below the one recommended by the Taylor rule ($v_t = -0.02$). For these parameter values and shocks the rational expectations equilibrium from Proposition 1 is: $\pi_t = 1.92\% + 0.50\% + 1.26\% = 3.68\%$ and $c_t = -11.51\% - 1.76\% + 1.48\% = -11.79\%$. Hence, the period-$t$ rational expectations inflation omegas are $\omega_a^{RE} = 0.52$, $\omega_g^{RE} = 0.14$ and $\omega_v^{RE} = 0.34$, and the period-$t$ rational expectations income omegas are $\varpi_a^{RE} = 0.98$, $\varpi_g^{RE} = 0.15$ and $\varpi_v^{RE} = -0.13$. If one substitutes those rational expectations omegas into equations (15)–(16), those equations reduce to the equations given in Proposition 1 and one receives the rational

[29] There is one subtle complication. In the two intermediate stages (equations (11)–(12) and equations (13)–(14)), some expectations are still formed rationally. To compute the rational expectations in these two intermediate stages, one has to make some assumption about how narratives evolve over time because future narratives affect future outcomes. We assume in equations (11)–(14) that households adjust their subjective causal model of inflation over time so as to keep the perceived shares $\omega_a^H, \omega_g^H, \omega_v^H$ constant over time. See Online Appendix F.3.

Figure 6: The effect of narratives on aggregate outcomes in a DSGE model




*Notes*: This figure illustrates the quantitative effects of inflation narratives on aggregate inflation (row 1) and aggregate consumption (row 2). We hold $\omega_g$ fixed at 0.14 and vary $(\omega_v,\ \omega_a)$ linearly from (0, 0.86) to (0.86, 0), i.e., we increase the perceived importance of monetary policy, while decreasing the perceived importance of productivity. The left column corresponds to the first case of Proposition 2: households have a subjective inflation narrative, but firms' inflation expectations and households' income expectations are still rational. The middle column considers the second case of Proposition 2: households and firms have a subjective inflation narrative (which we additionally assume to be identical), but households' income expectations are still rational. The right column corresponds to the third case of Proposition 2: households have a subjective inflation narrative, firms have a subjective inflation narrative, and households have a subjective income narrative. The households' and firms' inflation narratives are assumed to be identical, and the households' income narrative is set equal to the values in the rational expectations equilibrium of the model. The text describes how we parameterize the model.

expectations equilibrium. However, if agents misperceive the current inflation and income shares, the equilibrium will no longer equal the rational expectations equilibrium and it will still be given by equations (15)–(16).

The right panel of Figure 6 plots equations (15)–(16). In the point $\omega_v = 0.34$, we set all the omegas to the values in the rational expectations equilibrium, and for this reason, consumption and inflation equal the rational expectations equilibrium. As one moves to the right, we increase the perceived importance of monetary policy for inflation, $\omega_v^H$, and we decrease the perceived importance of productivity for inflation, $\omega_a^H$, by the same amount, while $\omega_g^H$ is held constant. For ease of exposition, we set the firms' omegas equal to the households' omegas, and we hold constant the households' income omegas at the values $\varpi_a^{RE} = 0.98$, $\varpi_g^{RE} = 0.15$, $\varpi_v^{RE} = -0.13$. The main result is the following. As households and firms give more importance to monetary policy and less importance to productivity in their inflation narrative, consumption increases and inflation falls, holding constant parameter values and shocks.

To illustrate the channels at work, we turn to the other panels of Figure 6. The left panel of

Figure 6 plots equations (11)–(12), i.e., households may have an incorrect subjective causal model of inflation, but to isolate channels, firms are assumed to have rational inflation expectations and households are assumed to have rational income expectations. As one moves to the right, we again increase $\omega_v^H$, and we decrease $\omega_a^H$, while $\omega_g^H$ is held constant. As households give more importance to monetary policy in their narrative about inflation, consumption and inflation fall. The reason is simple. As households give more importance to a less persistent factor in their explanation of inflation, their inflation expectation falls. Causal evidence on this channel was presented in Section 5.2 (see Table 5). As a result, the ex-ante real interest rate increases, which reduces consumption and inflation.[30]

The middle panel of Figure 6 plots equations (13)–(14), i.e., households and firms may have an incorrect subjective causal model of inflation, but to isolate channels, households are assumed to have rational income expectations.[31] As households and firms give more importance to monetary policy in their inflation narrative, consumption increases and inflation falls. The reason is that, as firms give more importance to a less persistent factor in their inflation narrative, their inflation expectation falls. Hence, inflation falls, which causes a fall in the nominal interest rate and an increase in consumption.[32] This effect on consumption dominates the effect on consumption illustrated in the left panel of Figure 6.

In sum, as households and firms give more importance to monetary policy in their narrative about inflation, inflation expectations fall, inflation falls, and consumption increases. Four additional points are worth mentioning. First, the fall in inflation and the increase in consumption are an unambiguously preferred outcome from the view of the central bank, so long as inflation is above target and consumption is below the first-best consumption level. Second, the implications of an increase in $\omega_v^H$ for inflation and consumption are qualitatively the same to the left and to the right of the rational expectations equilibrium, which implies that, for the comparative statics, it is irrelevant whether or not the central bank knows the location of the rational expectations equilibrium. Third, the downward-sloping lines in Figure 6 are not that convex and the upward-sloping lines in Figure 6 are not that concave, implying that the size of the effect of changing $\omega_v^H$ does not vary that much with $\omega_v^H$. Fourth, turning to magnitudes, raising $\omega_v^H$ from 0.1 to 0.2 reduces equilibrium inflation by 27 basis points and increases equilibrium consumption by 27 basis points (right panel of Figure 6). In an environment with a less reactive central bank (e.g., $\phi = 1.25$ in equation (6)), this modest change in narratives reduces equilibrium inflation by 62 basis points and raises equilibrium consumption by 30 basis points.

Central banks routinely provide narratives of current inflation. If households or firms adjust their subjective causal model of inflation in response to the central bank's provision of a narrative,

[30]That the ex-ante real interest rate affects consumption of some households (and thus inflation) is a central feature of any New Keynesian model.

[31]For ease of exposition, households and firms have the same subjective causal model of inflation. As one moves to the right, $\omega_v^H = \omega_v^F$ increases, $\omega_a^H = \omega_a^F$ decreases, and $\omega_g^H = \omega_g^F$ is held constant.

[32]That firm inflation expectations affect inflation is another central feature of any New Keynesian model.

then the model presented above makes the following prediction: The central bank's provision of a narrative changes economy-wide outcomes. Furthermore, the measurement of household narratives is important, because the central bank needs to know whether it moves households to the right or to the left in Figure 6 through the provision of its own narrative.

### 6.2.2 Model setup with heterogeneity

Now, we turn to the effects of heterogeneity in narratives among households on aggregate outcomes. We consider a simple example. Suppose that all households have the same beginning-of-period financial wealth in period $t$. Furthermore, suppose that all households believe in period $t$ that the other households have the same narrative of inflation and income as them in periods $t$ and $t+1$.[33] These two assumptions imply that all households believe in period $t$ that their own consumption level in period $t+1$ equals the aggregate consumption level in period $t+1$. Then, the consumption Euler equation of household $i$ reads:

$$c_t(i) = -\frac{1}{\gamma}\left(r_t - E_t^i[\pi_{t+1}]\right) + E_t^i[c_{t+1}(i)] = -\frac{1}{\gamma}\left(r_t - E_t^i[\pi_{t+1}]\right) + E_t^i[c_{t+1}] \tag{17}$$

Household $i$'s perceived law of motion of inflation (equations (1)–(2)) implies

$$E_t^i[\pi_{t+1}] = \psi_a(i)\rho_a(i)a_t + \psi_g(i)\rho_g(i)g_t + \psi_\nu(i)\rho_\nu(i)\nu_t \tag{18}$$

Household $i$'s perceived law of motion of aggregate income (equations (9)–(10) with household-specific importance of the factors and household-specific perceived persistence of the factors) implies

$$E_t^i[\tilde{x}_{t+1}] = \varphi_a(i)\rho_a(i)a_t + \varphi_g(i)\rho_g(i)g_t + \varphi_\nu(i)\rho_\nu(i)\nu_t \tag{19}$$

Households still understand that there exists the following relationship between *aggregate* consumption and *aggregate* income: $c_t = \tilde{x}_t$. Integrating equation (17) with equations (18)–(19) across $i$ and using the definitions $\omega_z(i) \equiv \frac{\psi_z(i)z_t}{\pi_t}$ and $\varpi_z(i) \equiv \frac{\varphi_z(i)z_t}{\tilde{x}_t}$ yields

$$c_t = -\frac{1}{\gamma}\left(r_t - \left(\sum_{z=a,g,\nu}\int \rho_z(i)\,\omega_z(i)\,di\right)\pi_t\right) + \left(\sum_{z=a,g,\nu}\int \rho_z(i)\,\varpi_z(i)\,di\right)c_t \tag{20}$$

For comparison, in Section 6.2.1, the aggregate consumption Euler equation reads

$$c_t = -\frac{1}{\gamma}\left(r_t - \left(\rho_a\omega_a^H + \rho_g\omega_g^H + \rho_\nu\omega_\nu^H\right)\pi_t\right) + \left(\rho_a\varpi_a^H + \rho_g\varpi_g^H + \rho_\nu\varpi_\nu^H\right)c_t \tag{21}$$

Hence, in this model setup with heterogeneity in narratives, one obtains equations (15)–(16), but with $\rho_z\omega_z^H$ replaced by $\int \rho_z(i)\,\omega_z(i)\,di$ and $\rho_z\varpi_z^H$ replaced by $\int \rho_z(i)\,\varpi_z(i)\,di$. See Online Appendix F.4.

[33] That is, households falsely believe that other households are like them. This is an assumption about higher-order beliefs (what agents believe that other agents believe). In a companion, pure theory paper, we study the effects of heterogeneity in narratives among households on aggregate outcomes in more detail and we relax this assumption. Note that this assumption is trivially satisfied in Section 6.2.1.

This has two implications. First, in the model setup with heterogeneity in narratives among households, aggregate outcomes depend on the joint distribution of a factor's perceived persistence, $\rho_z(i)$, and the factor's perceived importance, $\omega_z(i)$, in the population.[34] Second, in the model setup with heterogeneity in narratives among households, this heterogeneity causes consumption heterogeneity (equations (17)–(19)). By contrast, the efficient allocation in this New Keynesian model has the property that all households consume the same amount (Galí, 2015, chapter 4.1).

## 7 Concluding remarks

We study narratives about the macroeconomy in the context of a historic surge in inflation. Drawing on representative samples of the US population, our analysis reveals several stylized facts about people's narratives for why inflation increased. Households' narratives are highly heterogeneous. They are coarser and less sophisticated than those of experts. They also focus more on supply-side than on demand-side factors and often feature politically charged explanations, such as government mismanagement or price gouging by greedy corporations. We furthermore provide systematic evidence on the relationship between household narratives and inflation expectations. We first establish that households' narratives are correlated with their inflation expectations. Next, we document experimentally that narratives causally affect the formation of inflation expectations and the interpretation of new inflation-related information.

To examine the importance of narratives for aggregate outcomes, we formalize narratives as subjective causal models in a conventional New Keynesian model and study their effects on equilibrium aggregate outcomes. In contrast to the rational expectations equilibrium of the conventional New Keynesian model, which is a special case of our model, we do not impose the restriction that agents' subjective causal models of inflation have to be identical and correct for all agents. We show that the subjective causal models always affect equilibrium aggregate outcomes as long as the different driving factors of inflation have different perceived persistence. The key mechanism is that the subjective causal models of inflation affect inflation expectations, consistent with our empirical evidence.

The large extent of heterogeneity and fragmentation in households' narratives has important consequences for the formation of economic expectations. Households are not only imperfectly informed about the current state of the economy (Coibion and Gorodnichenko, 2012; Mankiw and Reis, 2002; Reis, 2006), they also systematically disagree about why the current state has been reached. Heterogeneity in narratives thus contributes to the widely-documented disagreement in macroeconomic expectations (Coibion and Gorodnichenko, 2015a; Dovern et al., 2012; Giglio et al., 2021; Link et al., 2023b; Mankiw et al., 2003). One important question for future research

[34]For example, if $\rho_z(i) = \rho_z + a(i-0.5)$ and $\omega_z(i) = \omega_z^H + b(i-0.5)$, $\int \rho_z(i)\,\omega_z(i)\,di = \rho_z\omega_z^H + ab\int(i-0.5)^2\,di$. The integral $\int \rho_z(i)\,\omega_z(i)\,di$ is larger than the product of the average perceived persistence of the factor, $\rho_z$, and the average perceived importance of the factor, $\omega_z^H$, if households who attribute a high importance to the factor also have a high perceived persistence of the factor (i.e., the coefficients $a$ and $b$ have the same sign).

is to better understand the origins of the substantial heterogeneity in household narratives. While differential media exposure is likely to drive some of the heterogeneity, our experiment with exogenous variation in media exposure suggests (as discussed in Appendix 1) that traditional news media is only part of the story. A related open question revolves around the social processes that make some narratives go viral (Graeber et al., 2024a; Shiller, 2017). For instance, narratives involving corporate greed and price gouging are common among households but are neither endorsed by experts nor prominently featured in the media, suggesting that social interactions are important. We view it as an important question for future research to understand which features determine the virality of narratives and to better understand the role of social interactions.

Related to recent work on the importance of tailoring policy communication to heterogeneous groups of economic agents (Coibion et al., 2020a; D'Acunto et al., 2020, 2021b), our analysis suggests that economic narratives may also be a relevant margin for tailored policy communication. Specifically, policy-makers who aim to keep inflation expectations anchored should be aware that they communicate with people who hold very heterogeneous accounts for past movements of inflation, and these accounts influence how economic agents forecast the future and interpret new information. Hence, policy communication could be tailored towards the various existing narratives held by different groups of economic agents. Policy-makers could also engage in "narrative management" and actively promote new narratives or correct existing misleading narratives. Correcting misleading narratives might be particularly important to keep expectations anchored when these narratives are associated with a high degree of persistence.

While our paper focuses on the role of narratives in expectation formation, one important open empirical question is the extent to which these narratives influence everyday economic decisions. In our model, narratives affect households' behavior through inflation expectations. By changing inflation expectations, narratives affect expected real income and real interest rates, which shape households' consumption-savings decisions. Empirically, however, the precise link between inflation expectations and consumption-savings decisions remains a subject of active inquiry (Coibion and Gorodnichenko, 2024; Jiang et al., 2024). A better understanding of how narratives and inflation expectations affect firm decision-making is also important (Coibion et al., 2018, 2020b). It also seems likely that narratives matter through channels that our simple model does not capture. For example, via their effect on inflation expectations, narratives could also shape the timing of durable purchases (D'Acunto et al., 2022) and pass-through to stock investment decisions (Schnorpfeil et al., 2024). Moreover, narratives could play a major role in the political economy by affecting voting decisions. Indeed, narratives attributing high inflation to government mismanagement may have influenced the recent 2024 presidential election in the US, where high inflation was a key issue.[35] When thinking about the role of narratives in shaping everyday economic decisions, it is also important to explore how context-specific the narratives are that come to households' minds. For example, how closely do the narratives

[35] See, e.g., https://www.wsj.com/economy/economy-election-trump-voters-c4c2e9a3.

measured in a survey align with those considered in relevant decision environments (Bordalo et al., 2023a)? Some of our findings—such as the persistence of narratives when measured in subsequent surveys—suggest a significant degree of stability of households' narratives.

Our approach to measure narratives with open-ended questions and to represent them as DAGs provides a versatile tool to quantify people's rich causal reasoning about the economy, opening fruitful avenues for future research. For example, researchers could investigate economic narratives in other countries or contexts such as booms and busts in the housing or stock market. The approach is applicable in many other domains, can be applied to many sources of text data, including survey responses, speeches, or newspaper articles, and the quantification of the text data facilitates comparability between respondents and across studies.

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## Appendix

We discuss two additional experiments that explore the role of news media and attention.

### Appendix 1: Households Construct Narratives from News Media

The news media is the primary source of macroeconomic information for many individuals and could thus play a key role in the dissemination and propagation of economic narratives. This section presents an additional experiment that provides participants with incentives to search for and read news about inflation. The experiment allows us to (i) shed light on the narratives that people encounter in the news and (ii) study whether agents adopt narratives they encounter in endogenously chosen news content.

### Sample

We collect data for this experiment between February 8–12, 2022. We recruit respondents via the survey platform Prolific. The experiment has three waves: a baseline survey (wave 1), a second survey in which the treatment is administered (wave 2), and a final survey (wave 3).

1,558 respondents completed wave 1 of our survey. Out of those respondents, 848 respondents completed wave 2, of whom 763 completed wave 3. Our main analysis focuses on the 763 respondents who completed all three waves (see Online Appendix Table A.3 for summary statistics). The treatment, which is randomly assigned in the second wave, is uncorrelated with the likelihood of completing the third wave ($p = 0.597$).

### Experimental Design

**Wave 1** In the first wave, which was conducted on February 8 and 9, 2022, we elicit respondents' baseline narratives for the recent surge in inflation and their confidence in their narrative.

**Wave 2** The second wave took place on February 10, 2022, the day the inflation numbers for January 2022 were published. The announced inflation rate of 7.5% was the largest 12-month increase since February 1982 and was very saliently featured in all major news outlets at the launch of the second wave.

At the beginning of the second survey, all respondents are told that they will be assigned to a topic and asked to spend around five minutes to find a relevant article on the topic and carefully read the article. We furthermore inform respondents that they would be asked to provide a link to the article and a short summary in their own words. The summary aims to ensure that respondents actually engage with the content of the article. To further ensure that respondents comply with their task, we inform respondents that everyone who provides a short summary of the article in their own words would receive a bonus of 50 cents.[36] Next, we randomly assign

[36] Virtually all summaries were of high quality and based on the respondents' own words.

respondents into a treatment and a control group. Respondents in the treatment group are asked to read a newspaper article about "US inflation", while respondents in the control group are asked to read an article about a topic unrelated to inflation, namely "tourist attractions in Miami." Respondents in both conditions are asked to choose a source that they would normally consult to read about the topic.

This active control group design, where respondents in both conditions are asked to read and summarize an article, allows us to provide identical monetary incentives to respondents in the treatment and control group. This helps us deal with potential differential attrition that could arise from people's unwillingness to complete the task of looking up and summarizing news articles. At the same time, reading an article about tourist attractions in Miami—a topic unrelated to inflation—should not affect respondents' narratives about inflation and as such control for naturally occurring changes in narratives between waves 1 and 3. By asking our respondents to provide us with the link, while at the same time allowing them to freely search the internet, we obtain precise information on people's endogenous information acquisition.

**Wave 3** On the day after a respondent completed the second wave, the respondent receives an invitation to take part in the third wave. To avoid that the respondents merely restate their answers from the wave 1 survey and to provide a natural justification for asking the same questions again, we tell them to "keep in mind that the questions today refer to the latest inflation numbers released yesterday." We then elicit respondents' narratives for the increase in inflation to 7.5% using an otherwise identical wording as in the first wave (in which respondents were asked to explain the increase in inflation to 7.2% based on the inflation rate in December 2021). Finally, to quantify the first stage generated by the treatment on inflation-related news consumption, we ask our respondents how many online or offline newspaper articles they read about the latest-released inflation numbers. Online Appendix G.7 provides the core instructions of the media experiment.

### Results

We start by describing the narratives to which respondents are exposed when they are incentivized to search for and read an inflation-related article. We apply our coding scheme to identify the inflation narratives in each of the newspaper articles that respondents in the treatment group read in the second wave of our experiment. Indeed, the large majority of articles (97%) contain a narrative, confirming that online news media are a rich source of narratives about the economy. However, there is substantial variation in narratives across news outlets. While some factors (e.g., supply chain disruptions or labor shortages) are mentioned in two thirds of the articles, others are only contained in one quarter or less of the articles (e.g., monetary policy or pent-up demand).[37]

The average news narrative (Online Appendix Figure B.9) is sophisticated and features an

[37] There is also substantial heterogeneity in the sources that our respondents consult (Online Appendix Figure B.8). The most common source is *The Wall Street Journal* (which was consulted by 18% of treated respondents), followed by *The Guardian* (11%), *CNN* (8.5%), *Time* (7.8%), and *AP News* (6.4%). In total, our respondents relied on 110 unique newspaper articles from 46 different news outlets.

average of 5.9 factors (compared to 4.3 among experts and 3.5 among households, as described in Section 4.1) and 5.4 links (compared to 3.6 among experts and 2.8 among households). News narratives commonly feature both demand and supply factors. Out of all articles mentioning at least one demand or supply factor, 76% mention both a demand and a supply factor. Moreover, narratives that appear in the news are less politicized than households' narratives, with only 9% of the articles endorsing government mismanagement as a cause of rising inflation, and hardly any news narrative blames price gouging for the rise in inflation, contrary to the popularity of this narrative among households. These patterns highlight that individuals are exposed to a rich and diverse set of narratives when they read about inflation in the news. The news narratives also appear closer to the average expert narrative than to the average household narrative. Of course, the news sources that people consult to read up on economic facts may differ from the news they consume in general. Still, this suggests that some of the distinctive features of households' narratives, such as the prominence of price gouging, do not originate from a disproportionate coverage of those aspects in the news outlets that our respondents consult when they explicitly seek to inform themselves about inflation.

Next, we use our experimental intervention to examine how an exogenous increase in media exposure affects individuals' narratives. To analyze the effects of the treatment, we estimate the following empirical specification with OLS:

$$\mathrm{y}_{i3} = \alpha_0 + \alpha_1 \mathrm{Treatment}_i + \alpha_2 \mathrm{y}_{i1} + \alpha_3 \mathbf{x}_i + \varepsilon_{i3}$$

where $\mathrm{y}_{i3}$ is the outcome variable for individual $i$ from wave 3 such as whether an individual invokes any supply-side narrative; $\mathrm{y}_{i1}$ is the same outcome for individual $i$ from the wave 1 survey (only included if the outcome was elicited in the baseline survey); $\mathrm{Treatment}_i$ is a binary variable taking the value of one (zero) for respondents who were incentivized to search for and read an article about inflation (tourist attractions in Miami); $\mathbf{x}_i$ is a vector of basic control variables; and $\varepsilon_{i3}$ is an individual-specific error term. We use robust standard errors in all specifications.

Table 7 presents the estimated treatment effects. Column 1 shows that our treatment successfully increases exposure to inflation-related news. Treated respondents are 35.8 pp more likely to have read an article about the latest inflation numbers, compared to a control group fraction of 48.8% ($p < 0.01$). The fact that almost half of the control group respondents have read about the latest release of inflation statistics suggests that the news media is a source of narratives that respondents are frequently exposed to at the time of our surveys.[38] The increased exposure to inflation-related news generated by our treatment translates into an increase in the sophistication of people's reasoning about the drivers of inflation. The treatment increases the total number of factors mentioned by our respondents by 0.29 on average, a 10% increase compared to the baseline mean of 2.9 factors (column 2; $p < 0.01$). The treatment also significantly increases

[38]The fact that not all respondents in the treatment group say that they read an article about the latest inflation number likely reflects measurement error or confusion about what "latest" means.

Table 7: The causal effect of media exposure on narratives

| | News | Narratives | | | | Confidence |
|---|---|---|---|---|---|---|
| | (1) Read news | (2) Number of factors | (3) Contains supply factor | (4) Contains demand factor | (5) Contains other factors | (6) Confidence in narrative |
| Treatment | 0.358*** | 0.287*** | 0.096*** | 0.073** | 0.039 | 0.104* |
| | (0.031) | (0.091) | (0.026) | (0.031) | (0.027) | (0.053) |
| N | 747 | 747 | 747 | 747 | 747 | 747 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline control | No | Yes | Yes | Yes | Yes | Yes |
| Baseline mean | 0.488 | 2.886 | 0.751 | 0.452 | 0.835 | -0.000 |

*Note:* The table shows OLS regression results from the media experiment. All of the outcomes are elicited in wave 3 (post-treatment). "Treatment" is a binary variable taking the value one for respondents who were assigned to read an article about inflation. "Read news" is a binary variable for whether the respondent had read any news about the latest inflation numbers released in the week of the experiment. "Number of factors" refers to the number of factors (excluding inflation) in the DAG constructed from the open-ended responses to the question "Which factors do you think caused the increase in the inflation rate?" "Contains supply factor" and "Contains demand factor" are binary variables for whether the DAG respectively features any supply- or demand-side explanations. "Contains other factors" is a binary variable for whether the DAG features any explanations that cannot be categorized into demand or supply. "Confidence in narrative" is a measure of confidence in one's own understanding of why inflation has increased (z-scored based on a 6-point Likert scale response in which higher values imply higher confidence). All regressions include basic control variables (age in years and log income and dummies for party affiliation, Trump voting, gender, college education, region, and full-time work). Furthermore, the regressions in columns 2–6 also include the same outcome elicited in wave 1 (pre-treatment) as a control variable.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

the fraction of respondents who mention at least one supply-side factor by 9.6 pp (column 3; $p < 0.01$) and the fraction invoking at least one demand-side factor by 7.3 pp (column 4; $p = 0.018$). Disaggregated across the different narrative factors, we observe the largest increases for the "residual" (unspecific) supply and demand factors, which are very common in the news narratives (see Online Appendix Figures Figure B.9 and Figure B.10). We also observe an insignificant 3.9 pp increase in the fraction of respondents who invoke narratives unrelated to demand or supply (column 5; $p = 0.148$), mostly driven by a 10 pp increase in the pandemic narrative ($p < 0.01$, Online Appendix Figure B.10). Finally, column 6 shows that media exposure not only changes people's narratives but also makes them 10.4% of a standard deviation more confident in their understanding of why inflation has increased ($p = 0.050$).

Consistent with this causal evidence, Online Appendix Table A.15 shows that respondents who read about a specific narrative factor in their endogenously chosen news article are 7 pp more likely to invoke this factor in their wave 3 narrative. At first glance, the effect might appear relatively small compared to the strong updating effects of 30 to 40 pp that we observed in the narrative provision experiment in Section 5.2. However, the effect is sizable if one takes into account that the newspaper articles often contain several narrative factors and mention some of them only in passing.

Taken together, the results from our media experiment show that individuals are exposed to a rich and diverse set of narratives when they read news about inflation. An exogenous increase in news exposure shapes which narratives individuals subsequently invoke. While our experiment highlights that news content people are exposed to is used to construct narratives, it cannot directly speak to the quantitative importance of news media in shaping the narratives economic agents hold in the real world. Future research should aim to better understand the quantitative role of news media relative to other factors—such as exposure to social media or word-of-mouth information transmission (see, e.g., Graeber et al. (2024a))—in shaping the narratives invoked by economic agents. Indeed, our finding that the narratives households encounter in the news media are close to experts' narratives suggests that the differences between households' and experts' narratives have other sources than traditional media.

**Appendix 2: The Causal Effect of Attention**

We present an experiment using an alternative approach to shift which narratives are top of respondents' minds, which complements the experiments presented in Sections 5.2.1 and 5.2.2. It does not provide respondents with a new narrative but instead uses a contextual cue to direct respondents' attention to one specific factor—recent government spending programs—which was widely discussed in the media when we ran this experiment in December 2021. Thus, the experiment aims to shift which narratives come to participants' minds, while holding their information set constant. Based on our correlational evidence, we hypothesize that an increased tendency to think of government spending as an explanation for the rise in inflation should be reflected in higher inflation expectations.[39]

**Sample** We collect a sample of 1,126 Prolific respondents on December 10–12, 2021. Summary statistics are shown in Online Appendix Table A.3.

**Design** We randomize respondents into a treatment and a control group. At the start of the survey, we prompt respondents in the treatment group to think about recent government spending programs by asking them: "What comes to your mind when you think about recent government spending programs? Please write 3-4 sentences." Then, we elicit respondents' inflation narratives and their inflation expectations. Respondents in the control group directly proceed to these main outcomes (see Online Appendix G.5 for the key survey questions).

**Results** Table 8 presents the treatment effects from the experiment. First, we discuss the effect of the attention manipulation on the narratives that come to respondents' minds. As shown in column 1, treated respondents are 9.6 pp more likely to mention the government spending channel in their narratives. This effect is large and corresponds to a 60% increase relative to the 16% of control group respondents that mention government spending ($p < 0.01$). Next, column 2 shows that this exogenous shift in attention to government spending also leads to higher inflation expectations. Treated respondents expect 1-year-ahead inflation to be 0.40 pp

[39] One potential drawback is that the attention manipulation might not exclusively operate through changes in narratives.

Table 8: Attention experiment

| | (1)<br>Narrative:<br>Gov. spending | (2)<br>Expected<br>inflation rate (in %) |
|---|---|---|
| Attention treatment | 0.096*** | 0.399** |
| | (0.024) | (0.169) |
| N | 1,101 | 1,101 |
| Controls | Yes | Yes |
| Control group mean | 0.160 | 6.654 |

*Note:* This table uses data from the priming experiment with households. "Attention treatment" is a binary variable taking the value one for respondents assigned to the treatment group. "Narrative: Gov. spending" is a dummy equal to one for respondents whose narratives feature government spending. "Inflation expectations" are 12-month inflation expectations in percent. The elicited point estimates are top and bottom coded at 20% and 0%, respectively. Controls include age in years, log income, and dummies for gender, college education, economics in college, full-time work, region, and party affiliation.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

higher than the control group mean of 6.6% ($p = 0.019$), an increase that corresponds to 14% of a standard deviation.[40] Given the subtle nature of the cue and the size of the first-stage effect on respondents' own narratives, we view this effect size as moderate but meaningful. The sizes of the first-stage and downstream effects are consistent with other priming interventions in the context of macroeconomic expectations (Andre et al., 2022).

These findings provide causal evidence that narratives of loose government spending increase households' inflation expectations, corroborating the correlational evidence presented in Section 5.1. Moreover, the fact that households' narratives respond to a simple contextual cue suggests that selective memory is central to which narratives are invoked by individuals. When contextual features draw respondents' attention to government spending programs, they may retrieve memories of specific news content on fiscal stimulus programs they were exposed to, which in turn changes how they rationalize the increase in the inflation rate. Thus, households may use different narratives to explain the same event when asked in a different context. These findings are in line with recent work on associative memory and belief formation (Bordalo et al., 2023a,b; Enke et al., 2024).

[40] Only 3.2% of respondents correctly guess the hypothesis of the experiment (Panel C of Figure B.7). Moreover, the results are almost identical if we restrict our main specification to respondents that do not correctly guess the hypothesis (results available upon request).

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# Narratives about the Macroeconomy

Peter Andre, Ingar Haaland, Christopher Roth, Mirko Wiederholt, and Johannes Wohlfart

## A Additional Tables

Table A.1: Summary statistics: Descriptive surveys

| | (1) ACS | (2) Nov 21 | (3) Dec 21 | (4) Jan 22 | (5) March 22 | (6) May 22 |
|---|---|---|---|---|---|---|
| Male | 0.49 | 0.49 | 0.47 | 0.45 | 0.47 | 0.50 |
| Age (years) | 47.78 | 53.79 | 48.98 | 51.82 | 51.23 | 56.14 |
| Employed | 0.62 | 0.50 | 0.55 | 0.51 | 0.50 | 0.43 |
| College | 0.31 | 0.42 | 0.49 | 0.41 | 0.43 | 0.30 |
| High income | 0.48 | 0.39 | 0.39 | 0.35 | 0.32 | 0.27 |
| Northeast | 0.17 | 0.20 | 0.20 | 0.22 | 0.18 | 0.21 |
| Midwest | 0.21 | 0.25 | 0.24 | 0.24 | 0.24 | 0.23 |
| South | 0.38 | 0.40 | 0.38 | 0.42 | 0.35 | 0.36 |
| West | 0.24 | 0.16 | 0.18 | 0.13 | 0.22 | 0.21 |
| Observations | | 1,027 | 979 | 992 | 1,051 | 1,030 |

*Note:* This table displays the mean value of basic covariates from the 2019 American Community Survey (column 1) and our descriptive households waves in November 2021 (column 2), December 2021 (column 3), January 2022 (column 4), March 2022 (column 5), and May 2022 (column 6). "Male" is a binary variable with value one for male respondents. "Age (years)" is the age of the respondent (in column 4, we use the midpoint of the selected age bracket). "Employed" is a dummy variable taking value one if the respondent is employed full-time, part-time, or self-employed. "High income" is a binary variable taking value one if the respondent has a household pre-tax annual income above USD 75,000. "College degree" is a binary variable taking value one if the respondent has at least a bachelor's degree. "Northeast", "Midwest", "West", and "South" are binary variables with value one if the respondent lives in the respective region.

Table A.2: Summary statistics: Expert sample

| | Mean | Standard deviation | Median | Observations |
|---|---|---|---|---|
| **Personal characteristics**: | | | | |
| Years since PhD | 18.648 | 11.246 | 14 | 105 |
| Male | 0.883 | 0.323 | 1 | 111 |
| **Academic output**: | | | | |
| Number of top 5 publications | 2.664 | 4.400 | 1 | 110 |
| H-index | 21.602 | 18.889 | 16 | 103 |
| Citations | 5534.757 | 9282.612 | 1888 | 103 |
| **Location of institution**: | | | | |
| United States | 0.505 | 0.502 | 1 | 111 |
| Asia | 0.054 | 0.227 | 0 | 111 |
| Australia | 0.018 | 0.134 | 0 | 111 |
| Europe | 0.351 | 0.480 | 0 | 111 |
| North America | 0.559 | 0.499 | 1 | 111 |
| South America | 0.018 | 0.134 | 0 | 111 |

*Note:* This table displays the basic background characteristics of the participants in the expert survey conducted in November 2021. These data are not matched with individual responses and are externally collected (i.e., not self-reported). "Male" is a binary variable taking the value one for males and zero otherwise. 'Years since PhD" is the number of years between 2022 and the year the experts obtained their PhD. "Number of top 5 publications" is the number of publications in five highly cited general-interest economics journals (the American Economic Review, the Quarterly Journal of Economics, the Journal of Political Economy, Econometrica, and the Review of Economic Studies). "H-index" and 'Citations" are, respectively, their H-index and their total number of citations taken from their Google Scholar profile (as of December 2021/January 2022). "United States" is a binary variable taking the value one if the expert is based at an institution in the United States. "Asia", "Australia", "Europe", "North America", and "South America" are regional indicators taking the value one if the institution the expert works for is based in the region.

Table A.3: Summary statistics: Experiments

| | (1)<br>Media<br>Feb 2022 | (2)<br>Narrative provision<br>April 2022 | (3)<br>Info interpretation<br>April 2022 | (4)<br>Monetary policy<br>June 2022 |
|---|---|---|---|---|
| Male | 0.477 | 0.424 | 0.347 | 0.471 |
| Age (years) | 39.894 | 37.354 | 38.162 | 33.045 |
| Employed | 0.718 | 0.679 | 0.662 | 0.664 |
| College | 0.636 | 0.592 | 0.562 | 0.500 |
| High income | 0.427 | 0.408 | 0.388 | 0.367 |
| Northeast | 0.182 | 0.211 | 0.203 | 0.180 |
| Midwest | 0.231 | 0.213 | 0.193 | 0.192 |
| South | 0.363 | 0.342 | 0.364 | 0.412 |
| West | 0.224 | 0.234 | 0.240 | 0.217 |
| Observations | 763 | 1,329 | 977 | 1,069 |

*Note:* This table displays the mean value of basic covariates from the final wave of the media experiment in February 2022 (column 1), the first wave of the narrative provision experiment in April 2022 (column 2), the interpretation of information experiment in April 2022 (column 3), and the first wave of the monetary policy narrative provision experiment (column 4). "Male" is a binary variable with value one for male respondents. "Age (years)" is the age of the respondent (in column 3, we use the midpoint of the selected age bracket). "Employed" is a dummy variable taking value one if the respondent is employed full-time, part-time, or self-employed. "High income" is a binary variable taking value one if the respondent reports a pre-tax annual household income above USD 75,000. "College degree" is a binary variable taking value one if the respondent has at least a bachelor's degree. "Northeast", "Midwest", "West" and "South" are binary variables with value one if the respondent lives in the respective region.

Table A.4: Summary statistics: Robustness

| | (1)<br>Structured<br>May 2022 | (2)<br>Test–retake<br>May 2022 |
|---|---|---|
| Male | 0.489 | 0.374 |
| Age (years) | 37.329 | 40.441 |
| Employed | 0.676 | 0.741 |
| College | 0.548 | 0.624 |
| High income | 0.427 | 0.391 |
| Northeast | 0.200 | 0.236 |
| Midwest | 0.223 | 0.230 |
| South | 0.394 | 0.408 |
| West | 0.184 | 0.126 |
| Observations | 485 | 348 |

*Note:* This table displays the mean value of basic covariates from robustness experiments conducted in May 2022 with Prolific. “Male” is a binary variable with value one for male respondents. “Age (years)” is the age of the respondent (using the midpoint of the selected age bracket). “Employed” is a dummy variable taking value one if the respondent is employed full-time, part-time, or self-employed. “High income” is a binary variable taking value one if the respondent reports a pre-tax annual household income above USD 75,000. “College degree” is a binary variable taking value one if the respondent has at least a bachelor’s degree. “Northeast”, “Midwest”, “West” and “South” are binary variables with value one if the respondent lives in the respective region.

Table A.5: Overview of data collections

| Data collection | Sample | Treatments arms | Main outcomes |
|---|---|---|---|
| Descriptive Wave 1 (November 2021) | Lucid ($n$ = 1,029) | None | Inflation narratives and inflation expectations |
| Descriptive Wave 2 (December 2021) | Lucid ($n$ = 981) | None | Inflation narratives and inflation expectations |
| Descriptive Wave 3 (January 2022) | Lucid ($n$ = 992) | None | Inflation narratives and inflation expectations |
| Descriptive Wave 4 (March 2022) | Lucid ($n$ = 1,051) | None | Inflation narratives and inflation expectations |
| Descriptive Wave 5 (May 2022) | Lucid ($n$ = 1,030) | None | Inflation narratives and inflation expectations |
| Validation Experiment (May 2022) | Prolific ($n$ = 485) | None | Inflation narratives and structured measures of perceived importance of drivers of inflation |
| Test–Retest validation (May 2022) | Prolific: Wave 1 ($n$ = 512); Wave 2 ($n$ = 384) | None | Inflation narratives |
| Narrative Provision Experiment Wave 1 (April 2022) | Prolific ($n$ = 2,397) | Pent-up demand treatment, energy crisis treatment, and pure control | Inflation expectations |
| Narrative Provision Experiment Wave 2 (April 2022) | Prolific ($n$ = 1,329) | None | Inflation narratives and inflation expectations |
| Monetary Policy Narrative Experiment Wave 1 (June 2022) | Prolific ($n$ = 1,069) | Monetary policy treatment, energy crisis treatment | Inflation expectations |
| Monetary Policy Narrative Experiment Wave 2 (June 2022) | Prolific ($n$ = 736) | None | Inflation narratives and inflation expectations |
| Narratives and the Interpretation of New Information (April 2022) | Prolific ($n$ = 977) | (Government spending narrative vs. energy shortage narrative) × (high government spending forecast vs. low government spending forecast) | Inflation expectations and government spending expectations |
| Media Experiment Wave 1 (February 2022) | Prolific ($n$ = 1,558) | None | Inflation narratives and inflation expectations |
| Media Experiment Wave 2 (February 2022) | Prolific ($n$ = 848) | Treatment group receives incentives to read an article about inflation; Control group receives incentives to read an article about touristic attractions in Miami | None |
| Media Experiment Wave 3 (February 2022) | Prolific ($n$ = 763) | None | Inflation narratives and inflation expectations |

Table A.6: DAG sophistication: Experts vs. households

| | Number of DAG codes | | | Number of edges | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Expert | 1.189*** | 0.939*** | 1.215*** | 1.082*** | 0.774*** | 1.008*** |
| | (0.157) | (0.115) | (0.176) | (0.178) | (0.143) | (0.219) |
| N | 1138 | 1138 | 1138 | 1138 | 1138 | 1138 |
| Controls for response length and time | No | Yes | Yes | No | Yes | Yes |
| Demographic controls | No | No | Yes | No | No | Yes |

*Note:* This table uses data from expert and household samples from November 2021 and shows OLS regressions where the dependent variables are the number of factors included in the DAG constructed from the open-ended responses (columns 1–3) and the number of edges of the DAG (columns 4–6). The regressions in columns 2 and 5 include controls for response time (log of the number of seconds spent on the open-ended response page) as well as flexible controls for response length (including second- and third-order polynomials). The regressions in columns 3 and 6 furthermore include controls for gender, age (imputed for experts based on years since Ph.D.), location (dummy for the US), and dummies for college education, having taken economics in college, high income, and full-time work (all assumed taking the value one for experts who were all employed at the top economics institutions).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.7: Correlations between narratives and different background variables

| | (1) Monetary policy | (2) Government spending | (3) Pent-up demand | (4) Residual demand | (5) Supply chain | (6) Labor shortage | (7) Energy crisis | (8) Residual supply | (9) Government mismanagement | (10) Covid-19 pandemic |
|---|---|---|---|---|---|---|---|---|---|---|
| Male | 0.042*** | 0.034 | -0.026** | -0.052** | -0.106*** | -0.088*** | -0.012 | -0.066*** | 0.061** | -0.116*** |
| | (0.013) | (0.023) | (0.010) | (0.021) | (0.027) | (0.027) | (0.021) | (0.025) | (0.027) | (0.030) |
| High age | -0.023 | 0.063** | 0.030*** | -0.026 | 0.225*** | 0.129*** | 0.094*** | 0.085** | 0.141*** | 0.083** |
| | (0.017) | (0.029) | (0.011) | (0.029) | (0.034) | (0.035) | (0.024) | (0.034) | (0.033) | (0.040) |
| College degree | 0.009 | 0.015 | 0.013 | 0.013 | 0.059 | 0.010 | 0.074*** | -0.033 | -0.024 | 0.044 |
| | (0.020) | (0.030) | (0.015) | (0.030) | (0.038) | (0.037) | (0.028) | (0.033) | (0.033) | (0.039) |
| College-level econ | 0.023 | 0.019 | 0.009 | 0.001 | 0.042 | -0.002 | 0.006 | 0.015 | -0.018 | -0.005 |
| | (0.015) | (0.027) | (0.011) | (0.025) | (0.034) | (0.032) | (0.025) | (0.031) | (0.031) | (0.035) |
| Full-time employee | -0.018 | -0.031 | -0.021 | -0.049* | -0.084** | -0.030 | -0.035 | 0.008 | 0.000 | -0.000 |
| | (0.017) | (0.030) | (0.014) | (0.027) | (0.036) | (0.037) | (0.026) | (0.034) | (0.034) | (0.040) |
| High income | 0.034** | -0.003 | 0.018 | 0.015 | 0.042 | -0.007 | -0.017 | 0.078** | -0.003 | -0.015 |
| | (0.017) | (0.028) | (0.016) | (0.026) | (0.035) | (0.034) | (0.025) | (0.032) | (0.031) | (0.035) |
| Democrats | -0.031** | -0.188*** | 0.026** | 0.090*** | 0.096*** | 0.029 | -0.136*** | 0.078*** | -0.377*** | 0.256*** |
| | (0.013) | (0.024) | (0.012) | (0.021) | (0.029) | (0.029) | (0.022) | (0.026) | (0.028) | (0.031) |
| News consumption | 0.046*** | 0.053** | 0.018* | 0.009 | 0.090*** | 0.099*** | 0.049** | -0.026 | 0.030 | 0.032 |
| | (0.013) | (0.024) | (0.011) | (0.022) | (0.029) | (0.029) | (0.022) | (0.028) | (0.028) | (0.032) |
| N | 1,025 | 1,025 | 1,025 | 1,025 | 1,025 | 1,025 | 1,025 | 1,025 | 1,025 | 1,025 |
| Base rate | 0.080 | 0.20 | 0.047 | 0.13 | 0.32 | 0.27 | 0.14 | 0.23 | 0.29 | 0.45 |
| **Panel B: Households vs. experts** | | | | | | | | | | |
| Expert sample (a) | 0.331*** | 0.323*** | 0.188*** | -0.010 | 0.282*** | -0.028 | 0.009 | 0.107** | -0.310*** | 0.032 |
| | (0.047) | (0.049) | (0.039) | (0.032) | (0.049) | (0.043) | (0.036) | (0.046) | (0.017) | (0.050) |
| N | 1,138 | 1,138 | 1,138 | 1,138 | 1,138 | 1,138 | 1,138 | 1,138 | 1,138 | 1,138 |
| Controls | No | No | No | No | No | No | No | No | No | No |
| **Panel C: Households vs. experts** | | | | | | | | | | |
| Expert sample (b) | 0.290*** | 0.360*** | 0.196*** | 0.001 | 0.370*** | 0.076 | 0.050 | 0.112** | -0.216*** | 0.060 |
| | (0.049) | (0.052) | (0.040) | (0.037) | (0.054) | (0.047) | (0.040) | (0.052) | (0.028) | (0.057) |
| N | 1,136 | 1,136 | 1,136 | 1,136 | 1,136 | 1,136 | 1,136 | 1,136 | 1,136 | 1,136 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $p$-value: a = b | 0.001 | 0.055 | 0.272 | 0.554 | 0.000 | 0.000 | 0.039 | 0.838 | 0.000 | 0.325 |

*Note:* This table uses the household data (November wave) and shows OLS regressions where the dependent variables are the factors included in the DAG constructed from the open-ended responses (taking the value one for respondents who feature the factor in their DAG and zero otherwise), and the independent variables are dummy variables for different demographics. "Male" is a binary variable with value one for male respondents. "High age" is a binary variable with value one for respondents with age above 45 years. "College degree" is a dummy variable taking value one if the respondent has at least a bachelor's degree. "College-level econ" is a dummy variable taking the value one if the respondent took any course in economics, finance, or business in college or grad school. "Full-time employee" is a dummy variable taking value one if the respondent is working full-time. "High income" is a binary variable with value one for respondents with annual household income above $75,000. "Democrats" is a binary variable with value one for respondents who lean towards the Democratic Party. "News consumption" is a binary variable with value one for respondents who consume inflation-related news multiple times per week. "Base rate" shows the fraction of respondents that mention a given factor in the household sample. Panels B and C include data from the expert sample. "Expert sample" takes the value one for experts and zero for households. In Panel C, we include controls for gender, a high age dummy (imputed for experts based on years since Ph.D.), location (dummy for the US), and dummies for college education, having taken economics in college, high income, and full-time work (all assumed taking the value one for experts who were all employed at the top economics institutions).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.8: Correlations between background variables and different narrative clusters

| | (1) Pandemic supply I | (2) Pandemic supply II | (3) Pandemic single | (4) Gov. mis. single | (5) Mismanaged energy | (6) Mismanaged demand | (7) Labor shortage | (8) Price gouging |
|---|---|---|---|---|---|---|---|---|
| Male | -0.060** | -0.050** | 0.021 | 0.065*** | -0.023 | 0.051*** | -0.005 | 0.038*** |
| | (0.026) | (0.025) | (0.023) | (0.022) | (0.020) | (0.018) | (0.017) | (0.014) |
| High age | 0.114*** | 0.010 | -0.107*** | 0.033 | 0.039* | 0.010 | -0.049** | 0.010 |
| | (0.035) | (0.034) | (0.031) | (0.027) | (0.022) | (0.021) | (0.022) | (0.019) |
| College degree | 0.066* | -0.064** | 0.055** | -0.074*** | 0.049* | 0.018 | -0.024 | -0.021 |
| | (0.035) | (0.031) | (0.027) | (0.023) | (0.026) | (0.022) | (0.019) | (0.014) |
| College-level econ | -0.002 | 0.022 | -0.031 | -0.010 | 0.006 | 0.012 | -0.016 | 0.000 |
| | (0.031) | (0.029) | (0.025) | (0.024) | (0.023) | (0.020) | (0.018) | (0.015) |
| Full-time employee | -0.034 | 0.021 | 0.057* | 0.070** | -0.041* | -0.023 | -0.003 | -0.007 |
| | (0.035) | (0.033) | (0.030) | (0.027) | (0.023) | (0.021) | (0.022) | (0.019) |
| High income | -0.036 | 0.080** | 0.024 | 0.010 | -0.022 | -0.008 | 0.007 | -0.036** |
| | (0.032) | (0.031) | (0.026) | (0.024) | (0.023) | (0.020) | (0.019) | (0.015) |
| Democrats | 0.146*** | 0.106*** | 0.040* | -0.100*** | -0.146*** | -0.091*** | -0.037** | 0.055*** |
| | (0.027) | (0.026) | (0.023) | (0.022) | (0.020) | (0.018) | (0.017) | (0.014) |
| News consumption | 0.050* | -0.050* | -0.044* | -0.023 | 0.041** | 0.022 | 0.009 | -0.013 |
| | (0.028) | (0.027) | (0.024) | (0.022) | (0.020) | (0.018) | (0.017) | (0.014) |
| N | 910 | 910 | 910 | 910 | 910 | 910 | 910 | 910 |
| Base rate | 0.20 | 0.18 | 0.15 | 0.11 | 0.11 | 0.076 | 0.066 | 0.041 |

*Note:* This table uses the household data (November wave) and shows OLS regressions where the dependent variables are dummies indicating different narrative clusters (see Figure E.5 for details). "Male" is a binary variable with value one for male respondents. "High age" is a binary variable with value one for respondents with age above 45 years. "College degree" is a dummy variable taking value one if the respondent has at least a bachelor's degree. "College-level econ" is a dummy variable taking the value one if the respondent took any course in economics, finance, or business in college or grad school. "Full-time employee" is a dummy variable taking value one if the respondent is working full-time. "High income" is a binary variable with value one for respondents with annual household income above $75,000. "Democrats" is a binary variable with value one for respondents who lean towards the Democratic Party. "News consumption" is a binary variable with value one for respondents who consume inflation-related news multiple times per week. "Base rate" shows the fraction of respondents that mention a given factor in the household sample.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.9: Correlates of different measures of DAG sophistication

| | (1) Number edges | (2) Longest ingoing path | (3) Demand and supply | (4) Number no-end links | (5) Longest path |
|---|---|---|---|---|---|
| **Panel A: Demographics** | | | | | |
| Male | -0.287*** | -0.160** | -0.087*** | -0.171*** | -0.135*** |
| | (0.103) | (0.065) | (0.026) | (0.060) | (0.041) |
| High age | 1.022*** | 0.414*** | 0.083** | 0.401*** | 0.256*** |
| | (0.131) | (0.083) | (0.033) | (0.073) | (0.051) |
| College degree | 0.224 | 0.243*** | 0.052 | 0.011 | -0.023 |
| | (0.140) | (0.083) | (0.035) | (0.082) | (0.053) |
| College-level econ | 0.149 | 0.042 | -0.013 | 0.092 | 0.082* |
| | (0.125) | (0.075) | (0.030) | (0.074) | (0.049) |
| Full-time employee | -0.380*** | -0.191** | -0.075** | -0.126* | -0.105** |
| | (0.135) | (0.085) | (0.034) | (0.075) | (0.049) |
| High income | 0.023 | 0.019 | 0.084*** | 0.037 | 0.007 |
| | (0.127) | (0.078) | (0.032) | (0.074) | (0.048) |
| Democrats | -0.265** | -0.054 | -0.019 | -0.197*** | -0.130*** |
| | (0.110) | (0.068) | (0.027) | (0.064) | (0.043) |
| News consumption | 0.416*** | 0.186*** | 0.079*** | 0.170*** | 0.132*** |
| | (0.110) | (0.068) | (0.027) | (0.065) | (0.043) |
| N | 1,025 | 921 | 1,025 | 921 | 921 |
| Base rate | 2.49 | 2.05 | 0.23 | 0.72 | 1.53 |
| **Panel B: Households vs. experts** | | | | | |
| Expert sample (a) | 1.082*** | 0.732*** | 0.531*** | 0.069 | -0.012 |
| | (0.174) | (0.117) | (0.043) | (0.103) | (0.055) |
| N | 1,138 | 1,034 | 1,138 | 1,034 | 1,034 |
| Controls | No | No | No | No | No |
| **Panel C: Households vs. experts** | | | | | |
| Expert sample (b) | 1.717*** | 0.972*** | 0.624*** | 0.382** | 0.231*** |
| | (0.256) | (0.173) | (0.057) | (0.154) | (0.082) |
| N | 1,136 | 1,032 | 1,136 | 1,032 | 1,032 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| $p$-value: a = b | 0.001 | 0.062 | 0.044 | 0.006 | 0.000 |

*Note:* Panel A uses data from the household November sample and shows OLS regressions where the dependent variables are different measures of DAG sophistication. "Number of edges" refers to the number of edges a DAG contains. "Longest ingoing patch" refers to the longest path to inflation in a DAG. "Demand and supply" is a dummy equal to one if the DAG contains both demand and supply factors. "Number no end links" refers to the number of links that do not end at the factor inflation. "Longest path" refers to the longest path in the DAG. "Male" is a binary variable with value one for male respondents. "High age" is a binary variable with value one for respondents with age above 45 years. "College degree" is a dummy variable taking value one if the respondent has at least a bachelor's degree. "College-level econ" is a dummy variable taking the value one if the respondent took any course in economics, finance, or business in college or grad school. "Full-time employee" is a dummy variable taking value one if the respondent is working full-time. "High income" is a binary variable with value one for respondents with annual household income above $75,000. "Democrats" is a binary variable with value one for respondents who lean towards the Democratic Party. "News consumption" is a binary variable with value one for respondents who consume inflation-related news multiple times per week. "Base rate" shows the fraction of respondents that mention a given factor in the household sample. Panels B and C include data from the expert sample. "Expert sample" takes the value one for experts and zero for households. In Panel C, we include controls for gender, a high age dummy (imputed for experts based on years since Ph.D.), location (dummy for the US), and dummies for college education, having taken economics in college, high income, and full-time work (all assumed taking the value one for experts who were all employed at the top economics institutions).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.10: Correlations between narratives and inflation expectations: Robustness

| | Expected inflation rate (in %) | |
|---|---|---|
| | (1) 1 year | (2) 5 years |
| **Demand factors**: | | |
| Monetary policy | 0.997*** | 0.384 |
| | (0.260) | (0.319) |
| Government spending | 0.553*** | 0.315 |
| | (0.187) | (0.222) |
| Pent-up demand | -0.256 | -0.690** |
| | (0.235) | (0.310) |
| Residual demand | -0.325 | -0.238 |
| | (0.197) | (0.212) |
| **Supply factors**: | | |
| Supply chain issues | 0.445*** | 0.006 |
| | (0.145) | (0.159) |
| Labor shortage | 0.263* | 0.113 |
| | (0.148) | (0.166) |
| Energy | 0.820*** | 0.408* |
| | (0.189) | (0.225) |
| Residual supply | 0.119 | -0.138 |
| | (0.146) | (0.165) |
| **Other factors**: | | |
| Pandemic | -0.153 | -0.033 |
| | (0.149) | (0.164) |
| Government mismanagement | 1.166*** | 0.862*** |
| | (0.180) | (0.200) |
| Price gouging | 0.752*** | 0.615** |
| | (0.233) | (0.255) |
| N | 2,726 | 2,726 |
| Controls | Yes | Yes |
| Survey FE | Yes | Yes |
| Mean | 5.14 | 4.16 |
| R-squared | 0.18 | 0.072 |

*Note:* This table uses data from the Fall 2021 and early 2022 descriptive household survey waves (November 2021, December 2021, January 2022) and shows OLS regressions where the dependent variables are the mean of a respondent's subjective probability distribution over future inflation, constructed based on the midpoints of the different bins of potential inflation realizations. The explanatory variables are binary variables indicating which factors are included in the DAG constructed from the open-ended responses. Factors rarely mentioned are included in the regressions but not displayed in the table. For robustness reasons, this table excludes the 226 respondents who answered the probabilistic belief question on 1-year inflation expectations in a bimodal way or provided a distribution with clear holes. We classify bimodal distributions as those with higher probability mass on both high inflation (>4% inflation) and high deflation (>4% deflation) inflation categories than on the middle categories (between 4% inflation and 4% deflation). Furthermore, we classify distribution with "holes" as those where a given probability (from the second to the ninth bin) is at least ten percentage points lower than the probabilities assigned to both its neighboring bins. All regressions include survey wave fixed effects as well as the following indicator variables as controls: gender, age, college education, economics in college, full-time work, income, and political views.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.11: Correlations between narratives and perceived inflation uncertainty

| | Perceived uncertainty of future inflation (in s.d.) | |
|---|---|---|
| | (1)<br>12 months | (2)<br>60 months |
| **Demand factors**: | | |
| Monetary policy | -0.038 | -0.015 |
| | (0.178) | (0.179) |
| Government spending | -0.447*** | -0.349*** |
| | (0.113) | (0.120) |
| Pent-up demand | -0.241 | -0.248 |
| | (0.154) | (0.180) |
| Residual demand | 0.175 | 0.163 |
| | (0.128) | (0.135) |
| **Supply factors**: | | |
| Supply chain issues | -0.416*** | -0.369*** |
| | (0.094) | (0.097) |
| Labor shortage | 0.020 | -0.026 |
| | (0.095) | (0.100) |
| Energy | -0.025 | -0.030 |
| | (0.122) | (0.133) |
| Residual supply | -0.049 | -0.035 |
| | (0.096) | (0.104) |
| **Other factors**: | | |
| Pandemic | -0.044 | -0.097 |
| | (0.099) | (0.102) |
| Government mismanagement | -0.325*** | -0.207* |
| | (0.120) | (0.122) |
| Price gouging | -0.380*** | -0.322** |
| | (0.141) | (0.156) |
| N | 2,951 | 2,951 |
| Controls | Yes | Yes |
| Survey FE | Yes | Yes |
| Mean | 3.14 | 3.02 |

*Note:* This table uses data from the household samples (November 2021, December 2021, and January 2022) and shows OLS regressions where the dependent variables are the standard deviation of a respondent's subjective probability distribution over inflation over the next 12 months and over 12-month inflation five years into the future, constructed based on the midpoints of the different bins of potential inflation realizations. The explanatory variables are indicator variables about which factors are included in the DAG constructed from the open-ended stories. Factors rarely mentioned are included in the regressions but not displayed in the table. All regressions control for age in years, log income, dummies for gender, college education, economics in college, full-time work, region, and voting indicators for the 2020 presidential election, as well as survey wave fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.12: DAG data explain variation in **1-year-ahead** inflation expectation

| | Expected inflation rate (in %) | | Perceived SD of future inflation | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| | DAG | DAG and text | DAG | DAG and text |
| $R^2$ | 0.101 | 0.112 | 0.031 | 0.032 |
| $N$ | 2,683 | 2,683 | 2,683 | 2,683 |

*Note:* Results from LASSO regressions, using the descriptive household survey waves from November, and December 2021, and January 2022. The outcome variables are the mean 1-year-ahead inflation expectation (columns 1–2) and the standard deviation of expectations (columns 3–4). The LASSO uses either DAG data (dummies for whether a factor or connection are part of a narrative) or DAG data *and* text data (dummies for words, stemmed, lemmatized, stop words excluded; measures of text sentiment, sophistication and length). All models include wave fixed effects. The table presents the out-of-sample $R^2$, i.e., the share of explained variation. To avoid overfitting, the data are randomly split in a training sample (70%) and a test sample (30%). We estimate the LASSO model on the training data and derive the out-of-sample predictions and the resulting $R^2$ for the test data. We repeat this procedure 100 times with different random sample splits, and, each time, LASSO's penalty parameter is calibrated with the help of five-fold cross-validation within the training data.

Table A.13: DAG data explain variation in **5-year-ahead** inflation expectation

| | Expected inflation rate (in %) | | Perceived SD of future inflation | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| | DAG | DAG and text | DAG | DAG and text |
| $R^2$ | 0.022 | 0.026 | 0.019 | 0.017 |
| $N$ | 2,678 | 2,678 | 2,678 | 2,678 |

*Note:* This table repeats the analysis of in Table A.12 with 5-year-ahead inflation expectations as outcome variable. See the notes for Table A.12.

Table A.14: Narratives and the interpretation of new information: Robustness

| | OLS | | IV |
|---|---|---|---|
| | (1) Expected government spending growth | (2) Expected inflation rate | (3) Expected inflation rate |
| **Panel A: Spending narrative** | | | |
| Treatment: High spending | 4.807*** | 1.889*** | |
| | (0.668) | (0.294) | |
| Expected government spending growth | | | 0.393*** |
| | | | (0.063) |
| N | 448 | 448 | 448 |
| Controls | Yes | Yes | Yes |
| **Panel B: Energy narrative** | | | |
| Treatment: High spending | 6.598*** | 0.468* | |
| | (1.352) | (0.283) | |
| Expected government spending growth | | | 0.071* |
| | | | (0.041) |
| N | 432 | 432 | 432 |
| Controls | Yes | Yes | Yes |
| *p*-value: Panel A = Panel B | 0.228 | 0.000 | 0.000 |

*Note:* The table shows OLS regression results (columns 1 and 2) and IV regression results (column 3) from the belief updating experiment in which we exclude all respondents who correctly guessed the study purpose (9.5%). Panel A shows results for respondents who are exposed to a government spending narrative prior to receiving the forecast, while Panel B shows results for respondents who are instead exposed to a narrative about the energy crisis. "Treatment: High spending" is a binary variable taking the value of one for respondents assigned to the high government spending forecast (predicting a 6% increase in real federal government spending over the next 12 months) and value zero for respondents assigned to the low government spending forecast (predicting a 4% decrease). "Expected government spending growth" refers to point beliefs about changes in real government spending growth in percent. "Expected inflation rate" refers to 12-month point inflation expectations in percent. The elicited point forecasts are top and bottom coded at 20% and 0%, respectively. In the IV regression in column 3, the continuous variable for government spending expectations has been instrumented with the treatment indicator for receiving a high/low government spending forecast. Controls include age in years, log income, and dummies for gender, college education, economics in college, full-time work, region, and voting indicators for the 2020 presidential election.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.15: Narratives after news exposure

| | (1)<br>Endline narrative |
|---|---|
| Newspaper narrative | 0.066*** |
| | (0.020) |
| Baseline narrative | 0.443*** |
| | (0.033) |
| Constant | 0.121*** |
| | (0.009) |
| N | 6239 |

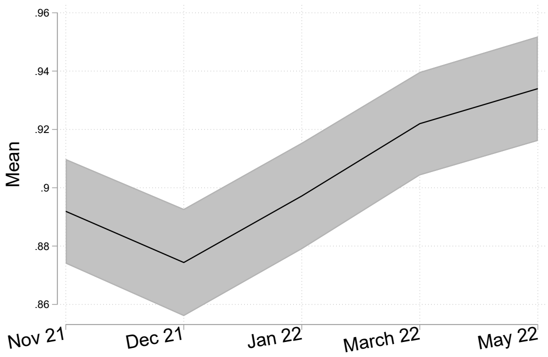
*Note:* This table uses data from all three waves of the media experiment, focusing on the 367 respondents in the treatment group that completed all three waves. The dataset is at the narrative factor-respondent level and contains 17 observations (number of narrative factors in our coding scheme) for each respondent. The dependent variable, "Endline narrative", takes the value one if a narrative is mentioned in the open-ended responses in wave 3 of the study. "Newspaper narrative" takes the value one if the same narrative is mentioned in the news article read by the respondent. "Baseline narrative" takes the value one if the same narrative is mentioned in the open-ended response in wave 1 of the study. We include individual and narrative fixed effects in all regressions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

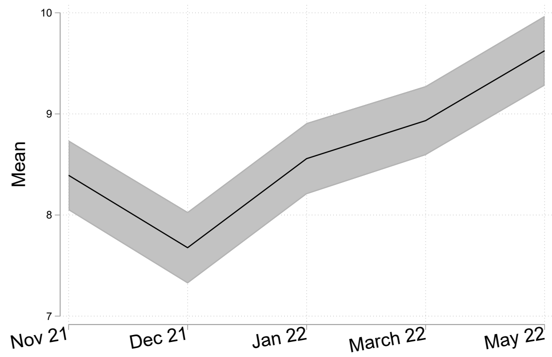
## B Additional Figures

Figure B.1: Descriptives on beliefs about past inflation

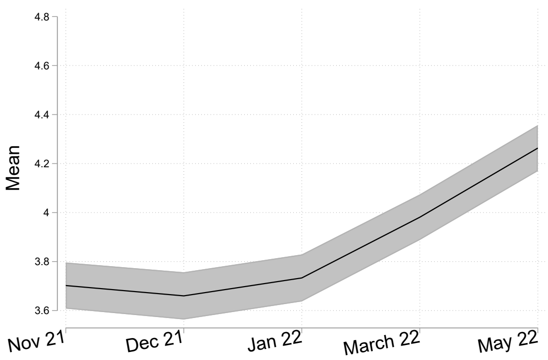
(a) Inflation: Higher today



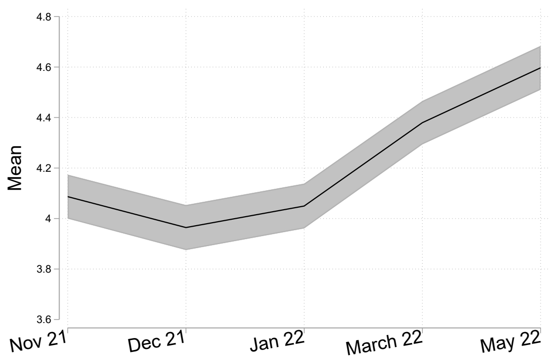

(b) Inflation last 12 months




(c) Frequency: Thinking about inflation

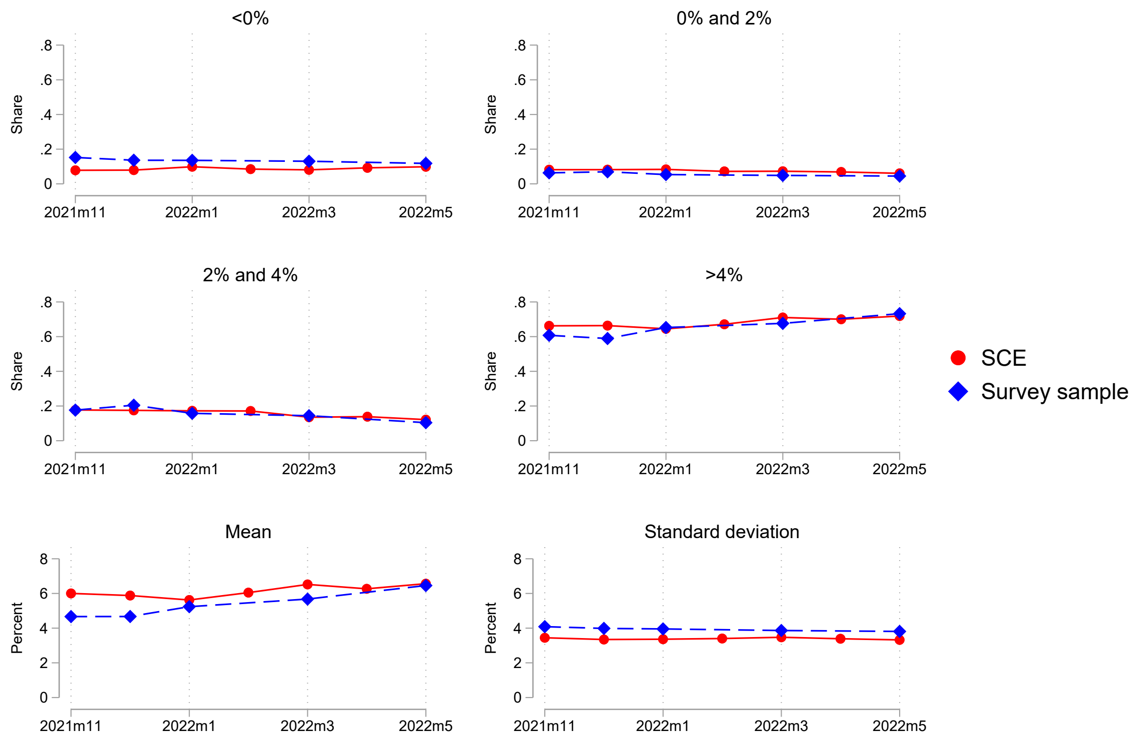



(d) Frequency: News consumption



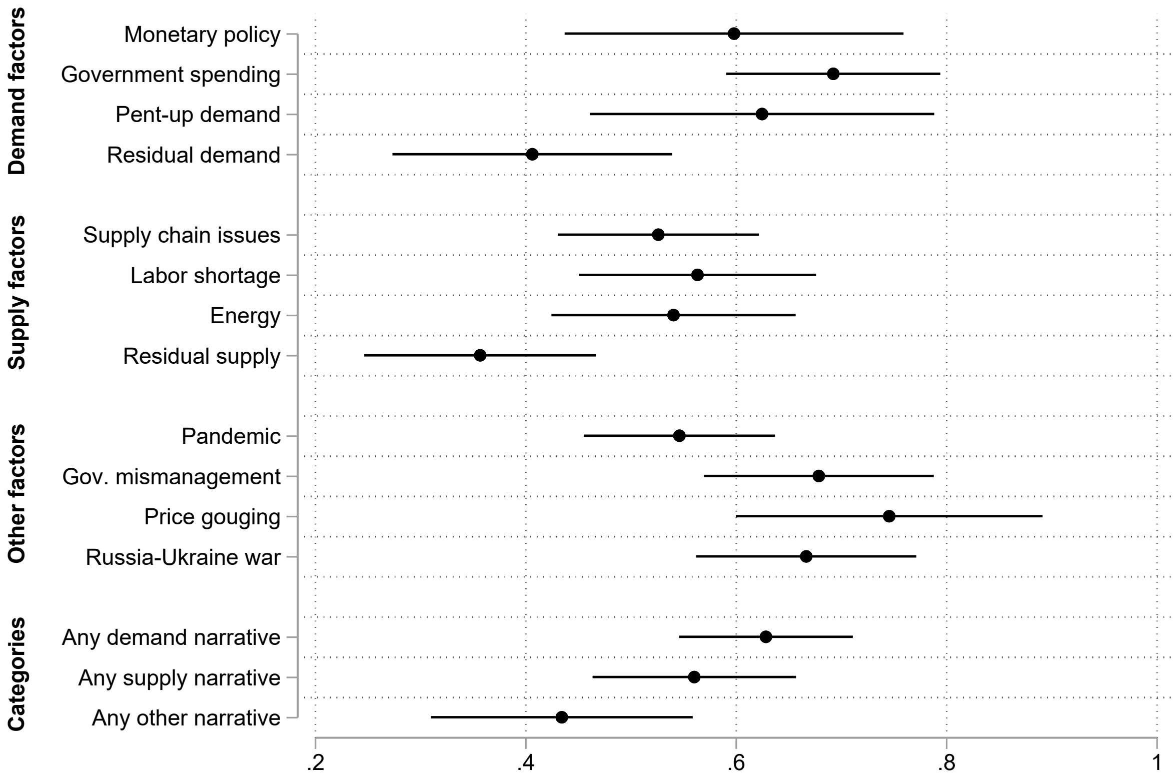

*Note:* This figure uses data from our descriptive waves. All questions are elicited before we inform people about the current inflation rate. Panel (a) shows the fraction of people who believe that inflation is higher at the time of the survey than one year earlier. Panel (b) shows average beliefs about the inflation rate over the last 12 months (top and bottom coded at 20% and 0%, respectively). Panel (c) shows the average frequency of thinking about inflation in the last three months (elicited on a 6-point scale from 1: Never to 6: Daily). Panel (d) shows the average frequency of reading about inflation in the last three months (elicited on a 6-point scale from 1: Never to 6: Daily).

Figure B.2: Comparison of beliefs about inflation: Survey sample vs. SCE



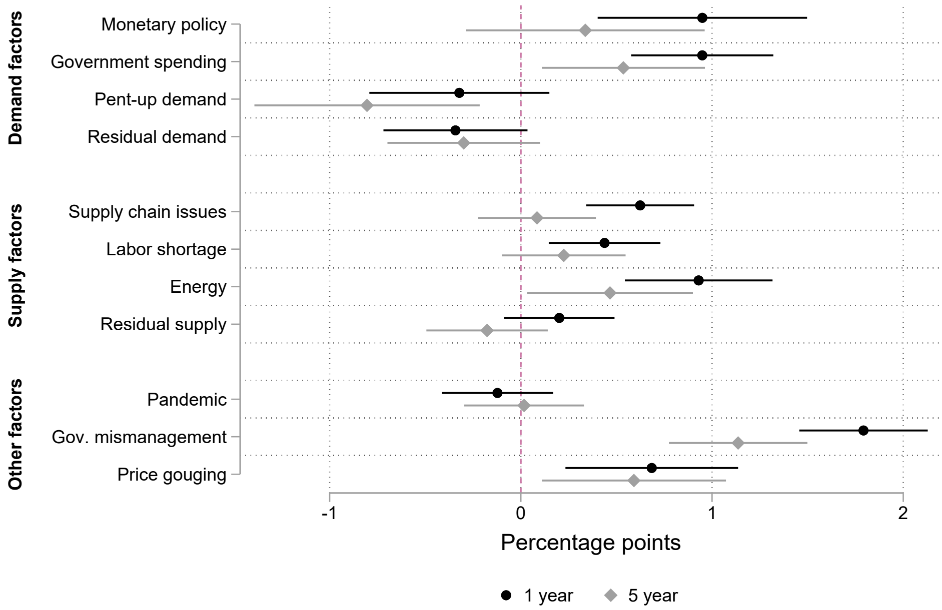

*Note:* This figure shows mean beliefs about the probability of different 1-year inflation outcomes (less than 0%; between 0% and 2%; between 2% and 4%, and above 4%) over time (November 2021, December 2021, January 2022, March 2022, and May 2022), comparing the Survey of Consumer Expectations (SCE) with our descriptive household surveys. The figure also indicates the mean and standard deviation of 1-year inflation expectations. The SCE is a nationally representative, Internet-based survey of a rotating panel of approximately 1,300 household heads; the data was downloaded from `https://www.newyorkfed.org/medialibrary/Interactives/sce/sce/downloads/data/FRBNY-SCE-Data.xlsx?sc_lang=en` on August 20, 2023.

Figure B.3: Persistence of narratives




*Note:* This figure uses data from wave 1 and wave 2 of the test–retest experiment. The circles show correlation coefficients between having a factor included in the DAG constructed from the open-ended responses in wave 1 and wave 2 of the surveys. Lines indicate 95% confidence intervals. See Table 1 for how the factors are classified.

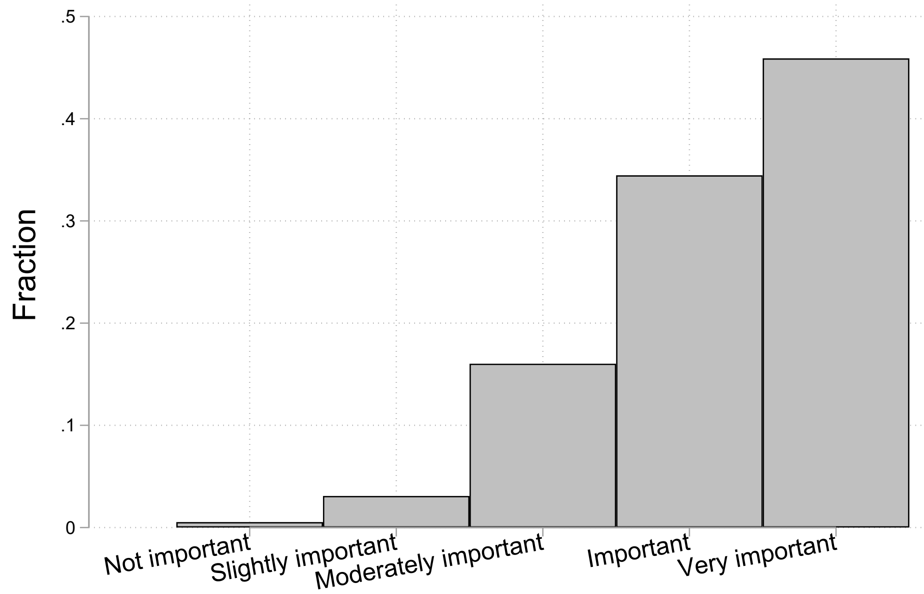
Figure B.4: Correlations between inflation expectations and inflation narratives



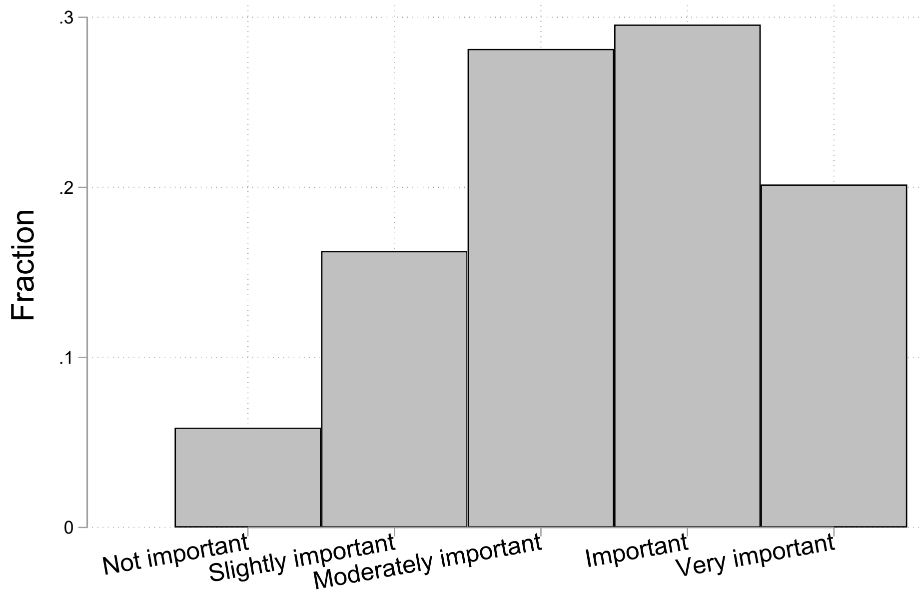

*Note:* The circles (diamonds) show estimated regression coefficients from a regression of one-year (five-year) inflation expectations on a set of dummy variables indicating which factors are included in the inflation narratives. Lines indicate 95% confidence intervals. Factors with few responses are included in the regression but not shown in the figure. Inflation expectations are measured as the means of respondent-level subjective probability distributions over different potential inflation realizations, where midpoints are assigned to the different bins.

Figure B.5: Descriptives on beliefs about persistence

(a) Importance of energy crisis

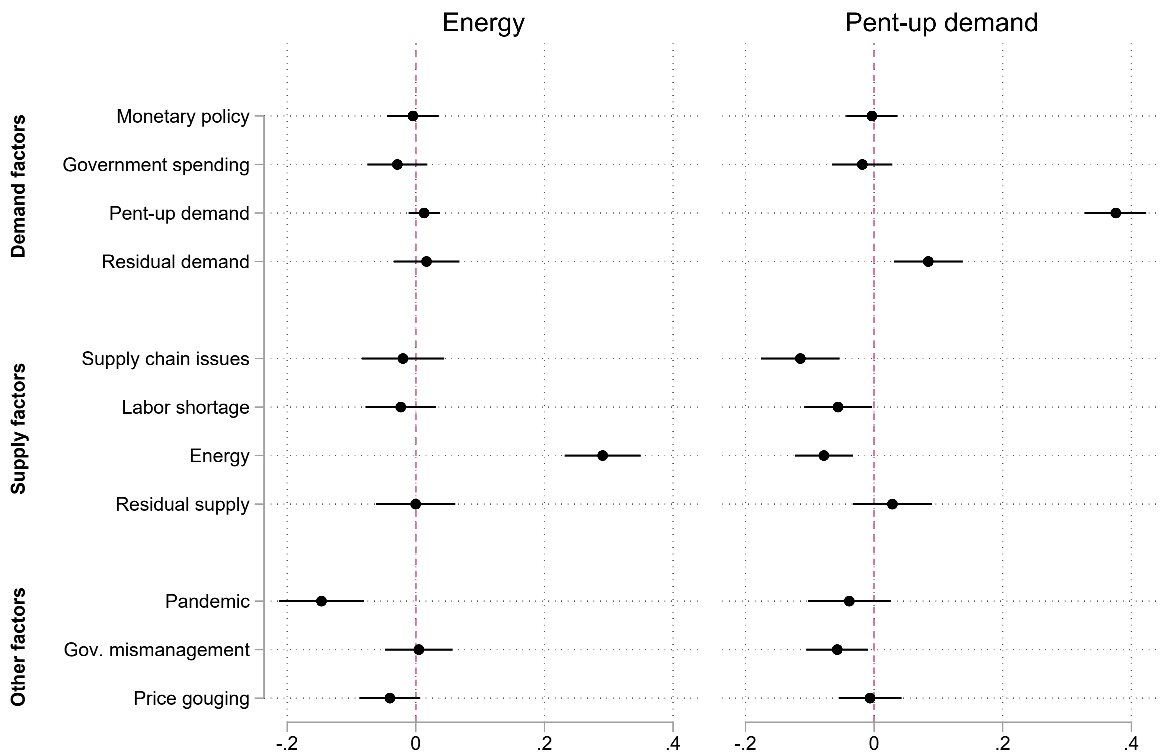



(b) Importance of pent-up demand




*Note:* This figure uses control group respondents from the narrative provision experiment and shows the distribution of responses to the following questions: "How important do you think that the global energy crisis will be for inflation over the next 12 months?" (Panel A) and "How important do you think that pent-up demand will be for inflation over the next 12 months?" (Panel B).

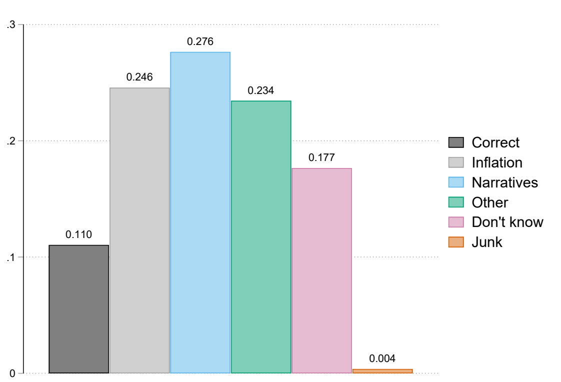
Figure B.6: Treatment effects on individual narratives: Narrative provision experiments



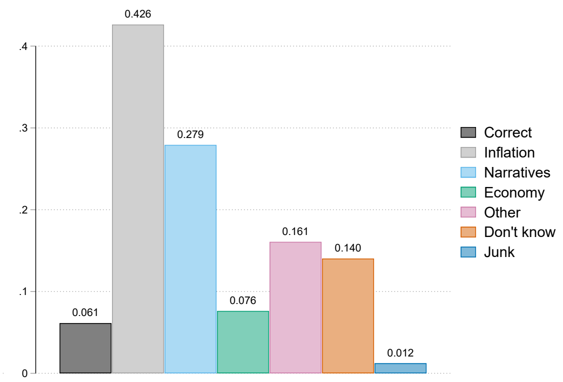

*Note:* The circles show estimated regression coefficients from regressions where the dependent variables are dummies indicating whether a factor is included in the DAG constructed from the open-ended responses about reasons for the recent increase in inflation and the independent variable is a treatment indicator. We run separate regressions for the energy treatment (left panel) and pent-up demand treatment (right panel). Lines indicate 95% confidence intervals. See Table 1 for how the factors are classified.

Figure B.7: Beliefs about researcher hypothesis: Main experiments

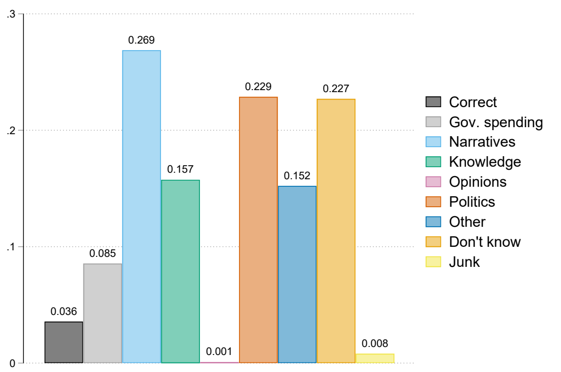
(a) Narrative provision: Pent-up demand & energy



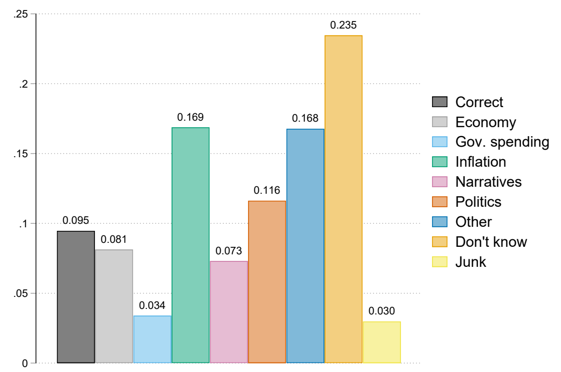

(b) Narrative provision: Monetary policy & energy




(c) Attention: Government spending

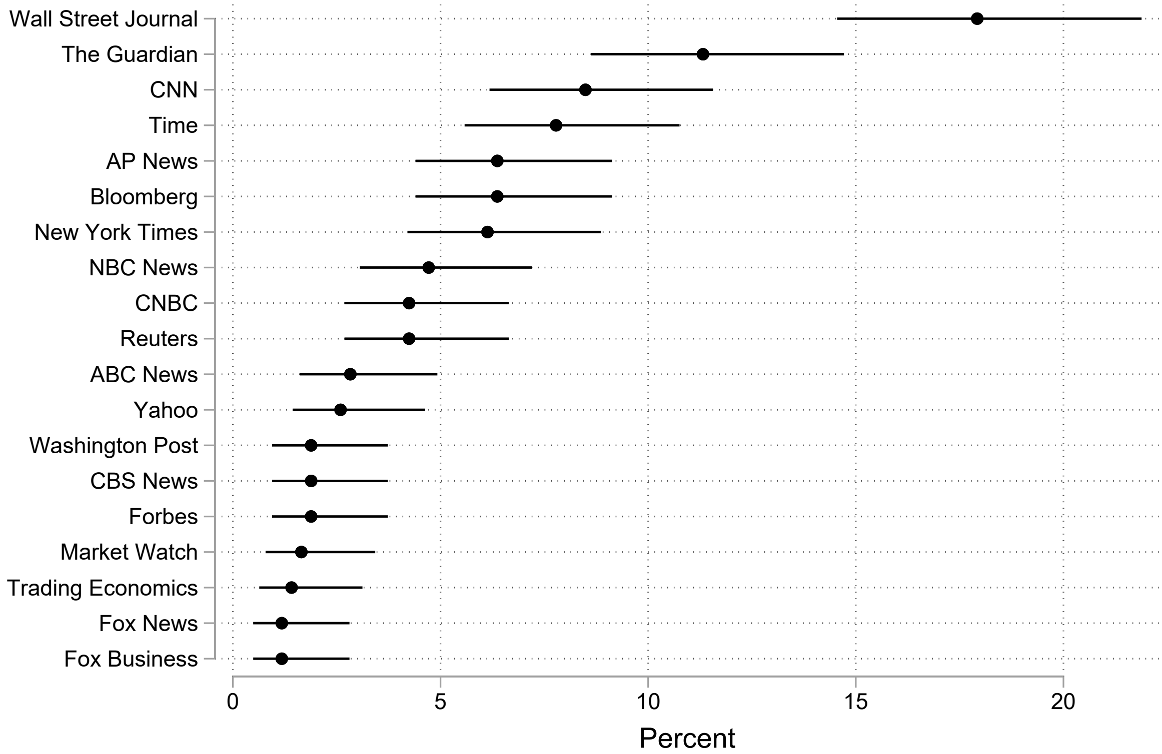



(d) Interpretation of new information




*Note:* This figure shows the distribution of the perceived study purpose across our main experiments. Specifically, at the end of the main experiments, respondents were asked the following open-ended question: "Which hypothesis do you think the researchers try to test with this survey?" A team of research assistants hand-coded the responses based on the categories indicated in the figure. Panel (a) shows evidence from the experiment providing narratives about pent-up demand and the energy crisis from April 2022 (see Section 5.2.1). Panel (b) shows evidence from the experiment providing narratives about monetary policy and the energy crisis from June 2022 (see Section 5.2.2). Panel (c) shows evidence from the experiment drawing attention to government spending from December 2021 (see Section Section 7). Panel (d) provides evidence from the experiment on the interpretation of new information from April 2022 (see Section 5.3). "Correct" takes value one if respondents correctly guess the hypothesis of interest. "Inflation" takes value one if respondents give generic responses indicating that the study purpose is related to inflation. "Narratives" takes value one if respondents give generic responses indicating that the study purpose is related to understanding what people think about the causes of inflation. "Economy" takes value one if respondents give generic responses indicating that the study purpose is related to the economy. "Gov. spending" takes value one if respondents give generic responses indicating that the study purpose is related to perceptions of government spending. "Politics" takes value one if respondents give generic responses indicating that the study purpose is related to how politics affects inflation. "Knowledge" takes value one if respondents give generic responses indicating that the study purpose is related to knowledge about the economy. "Opinion" takes value one if respondents give generic responses indicating that the study purpose is related to opinions. "Don't know" takes value one for respondents indicating that they don't know the study purpose. "Junk" takes value one for non-sensical responses.

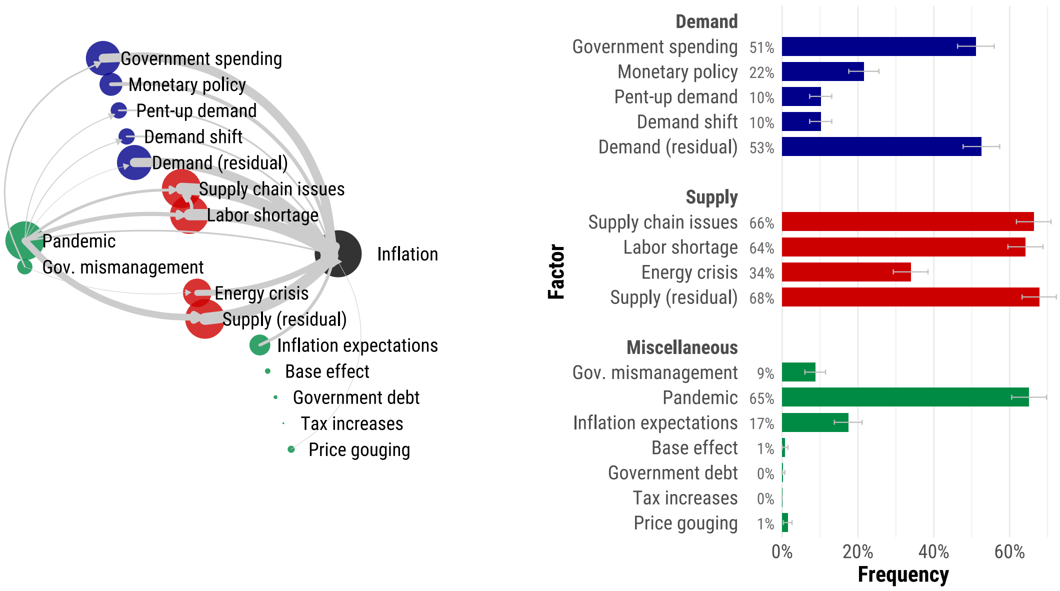
Figure B.8: Top 20 outlets for news about inflation




*Note:* This figure shows the top 20 outlets consulted by treated respondents in wave 2 of the media experiment when looking up a news article about inflation.

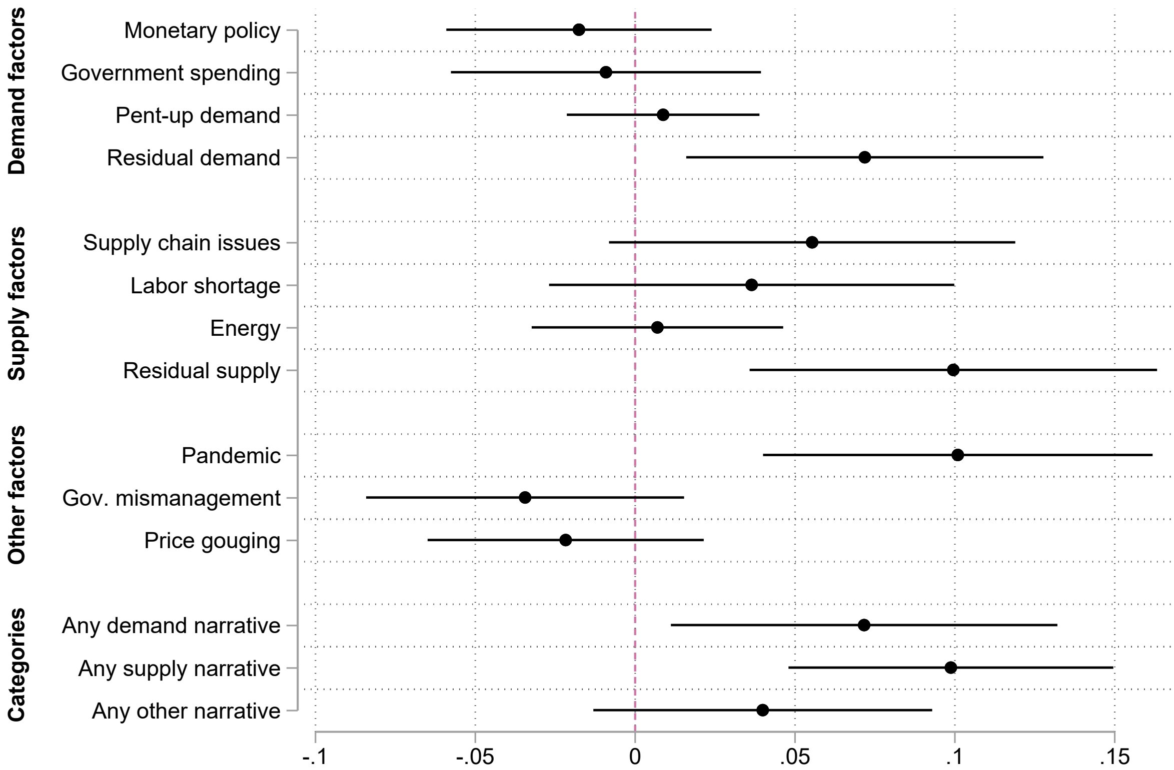
Figure B.9: Narratives in the news

(a) **Average DAG** (b) **Frequency of factors**




*Note:* **Panel (a)**: The "average" narratives mentioned in news articles (weighted by the frequency with which a given article is read), displayed as causal networks. The aggregated DAGs show which variables and causal links are most relevant in households' and experts' narratives. See the notes of main Figure 2 for a detailed description. **Panel (b)**: This panel presents how often different factors occur in the narratives of media articles (weighted by their population shares). The gray bars indicate 95% confidence intervals. Standard errors are derived at the respondent level.

Figure B.10: Treatment effects on individual narratives: Media experiment




*Note:* The circles show estimated regression coefficients from regressions where the dependent variables are dummies indicating whether a factor is included in the DAG constructed from the open-ended responses about reasons for the recent increase in inflation as measured in wave 3 and the independent variable is a treatment indicator (taking the value one for respondents who were instructed to read inflation-related news). All regressions include a dummy for whether the given narrative factor is mentioned by the respondent in wave 1. Lines indicate 95% confidence intervals. See Table 1 for how the factors are classified.

# C Additional analyses

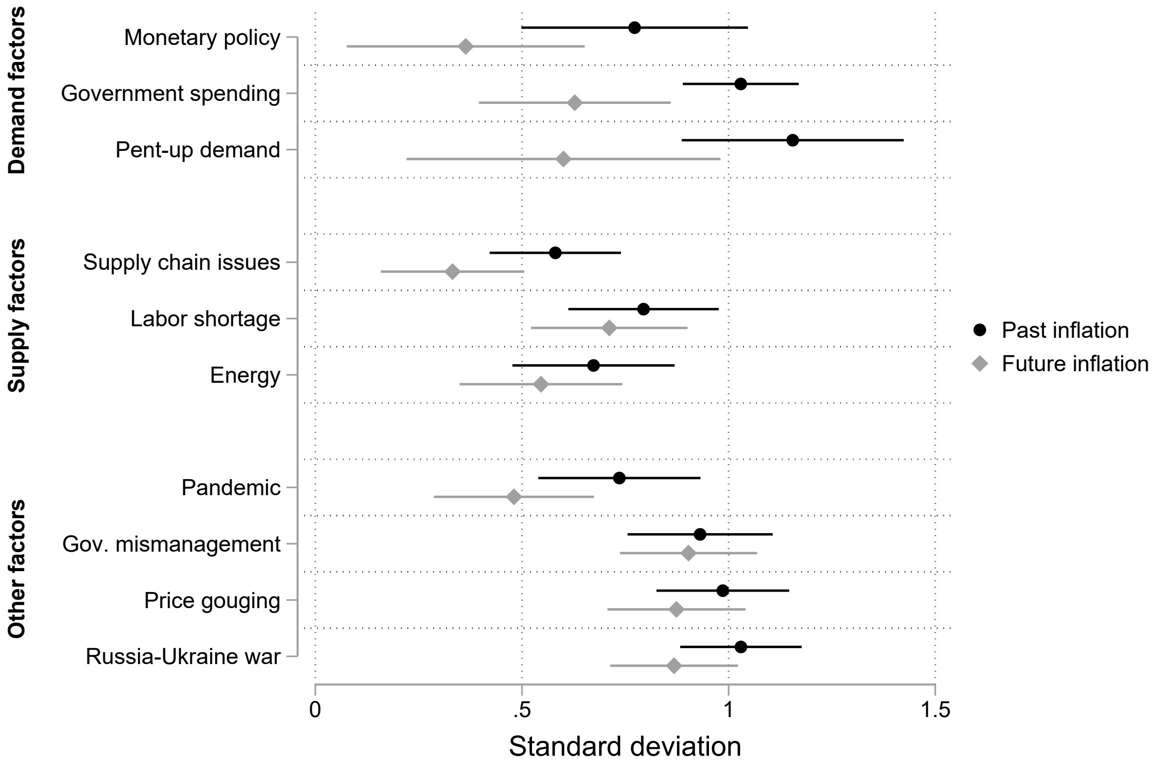
## C.1 Quality of hand-coded data

This Online Appendix section provides two additional checks on the quality of the hand-coded data on narratives.

First, we test whether respondents' narratives reflect the views about the drivers of past inflation that they would express in a structured question format. In an auxiliary data collection in May 2022 with 485 respondents on Prolific, we first elicit respondents' open-ended narratives about the inflation increase. Subsequently, we measure their beliefs about what drove the inflation increase using a structured survey question. We ask the open-ended question first to make sure that participants are not primed on the response options in the structured question when writing down their open-text responses. We ask our respondents to rate how important they think each of the factors in our coding scheme has been for the rise of inflation over the last 12 months on a 5-point scale ranging from "(1) Not at all important" to "(5) Extremely important". Afterwards, respondents also rate the expected importance of the factors for the development of inflation over the next twelve months. Reassuringly, we find that the factors mentioned in respondents' open-ended narratives are strongly positively correlated with their structured responses: having a factor included in the DAG constructed from the open-ended responses is associated with 83% and 65% of a standard deviation higher assigned importance to that factor in driving past and future inflation, respectively (both $p < 0.01$; see also Online Appendix Figure C.1). This finding also highlights that narratives about the past shape people's models of the future development of inflation.

Second, we use a LASSO procedure to examine how accurately the assignment of the different narrative factors can be predicted from the open-text data. The high accuracy of these predictions, usually around 90%, illustrates that the manual DAG coding is highly sensitive to and firmly grounded in the open-text data (see Online Appendix Table C.1). Moreover, the words that are predictive of a DAG factor align closely with its content, indicating a high degree of plausibility of our coding scheme.

Figure C.1: Validation with structured questions




*Note:* This figure uses data from the robustness experiments with structured outcomes. The circles (diamonds) show estimated regression coefficients from regressions where the dependent variables are structured measures of the importance of the factor in driving past (future) inflation and the independent variables are dummies indicating whether the factor is included in the DAG constructed from the open-ended responses. Lines indicate 95% confidence intervals. See Table 1 for how the factors are classified.

Table C.1: Hand-coded DAG factors are systematically related to the text data

| DAG factor | Accuracy | Precision | Examples of predictive words selected |
|---|---|---|---|
| Government spending | 0.930 | 0.841 | stimulu(+) spend(+) handout(+) give(+) check(+) |
| Monetary policy | 0.976 | 0.876 | print(+) interest(+) money(+) reserv(+) monetari(+) |
| Pent-up demand | 0.973 | 0.552 | pent(+) demand(+) save(+) spend(+) reopen(+) |
| Demand (residual) | 0.912 | 0.676 | demand(+) hoard(+) onlin(+) pent(−) panic(+) |
| Supply chain issues | 0.924 | 0.919 | chain(+) ship(+) transport(+) deliv(+) port(+) |
| Labor shortage | 0.921 | 0.869 | labor(+) worker(+) wage(+) workforc(+) employe(+) |
| Energy crisis | 0.972 | 0.941 | ga(+) oil(+) energi(+) pipelin(+) fuel(+) |
| Supply (residual) | 0.812 | 0.684 | chain(−) suppli(+) close(+) busi(+) shut(+) |
| Pandemic | 0.939 | 0.934 | covid(+) viru(+) use(−) close(+) excus(−) |
| Gov. mismanagement | 0.903 | 0.893 | polit(+) presid(+) biden(+) democrat(+) govern(+) |
| Russia-Ukraine war | 0.978 | 0.938 | russia(+) war(+) ukrain(+) russian(+) putin(+) |
| Price gouging | 0.958 | 0.888 | greed(+) greedi(+) goug(+) profit(+) advantag(+) |

*Note:* This table reports results from penalized logistic regressions that predict whether or not a DAG factor was manually assigned to a response based on the text data. The text data is represented by binary indicators for stemmed, lemmatized, non-stop words such as “stimulu” for “stimulus” or “spend” for “spending”. “Accuracy” measures how many predictions of the model are correct. “Precision” measures how many predictions are correct among all positive predictions. The sample is split into a training sample (70%) on which the model is trained and a test sample (30%) on which predictions are made. The penalty parameter is determined via cross-validation. A few examples for predictive word stems (and their directional effect) are provided for each DAG factor. We use data from all descriptive household survey waves (November and December 2021, January, March, and May 2022) and from the expert sample.

## D Details on Expert Sample

Starting from the EconLit publication database, we manually identified the email addresses of all economists who published in 20 top economics journals on JEL code "E: Macroeconomics and Monetary Economics" in the years 2015-2019.

We consider the following journals:

- Journal of Political Economy
- Quarterly Journal of Economics
- Econometrica
- Review of Economic Studies
- American Economic Review
- Journal of Economic Literature
- Journal of Economic Perspectives
- Journal of the European Economic Association
- Journal of Financial Economics
- Review of Financial Studies
- Journal of Finance
- Review of Economics and Statistics
- International Economic Review
- Journal of Monetary Economics
- Review of Economic Dynamics
- Economic Journal
- American Economic Journal: Macroeconomics
- American Economic Journal: Applied Economics
- Journal of Economic Growth
- Brookings Papers an Economic Activity.

We sent a link to our study to all of these economists by email. We did not send any reminders. In total, we contacted 1,925 economists. 111 economists responded to our survey, corresponding to a response rate of 5.8%.

## E Details on the Cluster Analysis of Narratives

This Online Appendix provides additional details on the clustering procedure we apply, and it presents multiple sensitivity analyses.

### E.1 Clustering Procedure

A cluster analysis attempts to assign objects into groups such that objects within a group are similar to each other while objects in different groups are not. We cluster narratives as follows.

**1. A measure of distance between narratives**. Each narrative is fully represented by the "edge list" of its DAG. The edge list $E$ is the set of causal connections of a narrative. As a working example, consider narrative $i$ with $E_i = \{A \to B,\ B \to C\}$ and narrative $j$ with $E_j = \{A \to C,\ B \to C\}$. The distance between the two narratives $i$ and $j$ is derived as the *Jaccard distance* between their edge lists, that is, one minus the number of common elements divided by the total number of unique elements:

$$D(i,j) = 1 - \frac{\mid E_i \cap E_j \mid}{\mid E_i \cup E_j \mid}$$

The Jaccard distance takes value 0 (1) if and only if two narratives are identical (share no common edge). It increases in the number of different elements relative to the total number of elements in two narratives. For example, the distance of the two example narratives is $D(i,j) = 1 - \frac{1}{3} = \frac{2}{3}$.

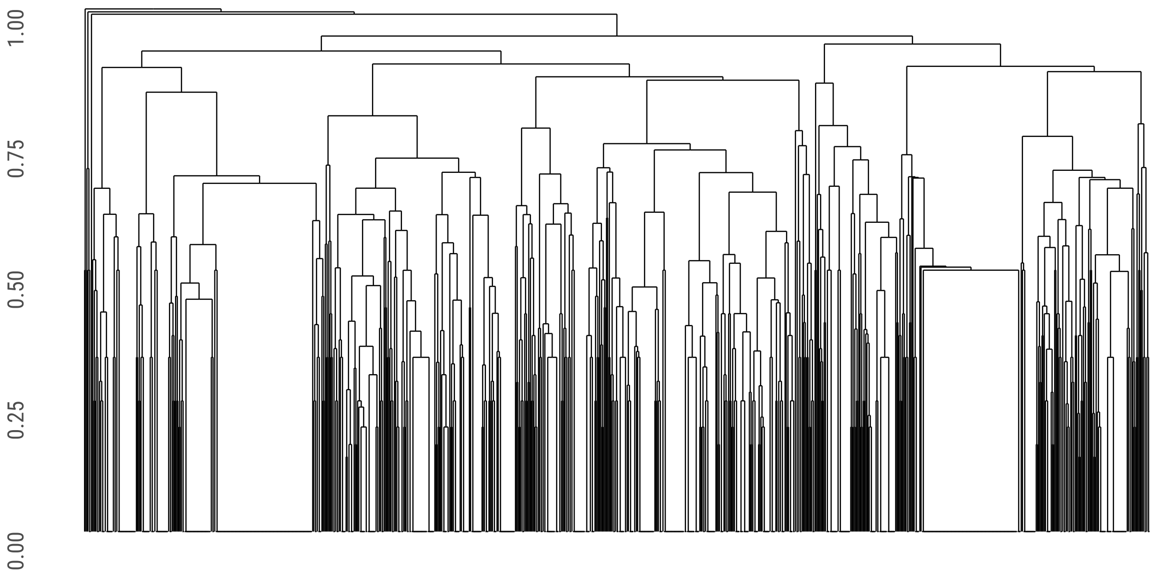
**2. Pairwise distances**. We derive the pairwise distances between all narratives.

**3. Clustering**. We implement a standard agglomerative hierarchical clustering procedure (`hclust` in `R`). The procedure follows a bottom-up approach. In the first iteration, each narrative forms a distinct cluster. Then, the narratives that are closest to each other are merged into a cluster. In many successive steps, the clusters closest to each other continue to be merged. The distance between two clusters is derived as the mean pairwise distance between the individual members of the two clusters (the unweighted pair group method with arithmetic mean). The procedure stops when all narratives have been merged to a single, all-encompassing cluster. Figure E.1, a so-called dendrogram, showcases how the narrative clusters (indicated by lines) are sequentially merged at an increasing distance (y-axis).

**4. The number of clusters**. We assign the narratives into distinct clusters by "stopping" the procedure when $k > 1$ clusters remain. We use the Silhouette method to determine the optimal number of clusters, which turns out to be $k^* = 15$.

**5. Visualization of clusters**. We only display clusters with at least 30 observations (approximately 3% of the total sample) to focus on those that are unlikely to be the product of noise (empirical relevance criterion). We plot the "average" DAGs of each such cluster. "Average" means that the displayed factor size is proportional to the within-cluster share of

Figure E.1: Dendrogram




*Note:* Dendrogram of the cluster analysis described in this section. It illustrates the bottom-down approach of the agglomerative hierarchical clustering procedure. At the bottom each individual narrative is indicated by a dot ($n = 925$). Then, narratives are sequentially merged into growing clusters. The lines indicate which narrative clusters are merged at which distance (height, y-axis).

narratives that mention a factor. The connection thickness is proportional to the within-cluster share of narratives that mention a connection. To focus on the most characteristic features of a cluster, we drop nodes that occur in less than 20% of narratives within a cluster and connections that occur in less than 5% of narratives within a cluster.

## E.2 Robustness

Figure E.2 reproduces the main results. To illustrate that the results are insensitive to the most important "degrees of freedom" in our clustering procedure, we derive the following alternative results.

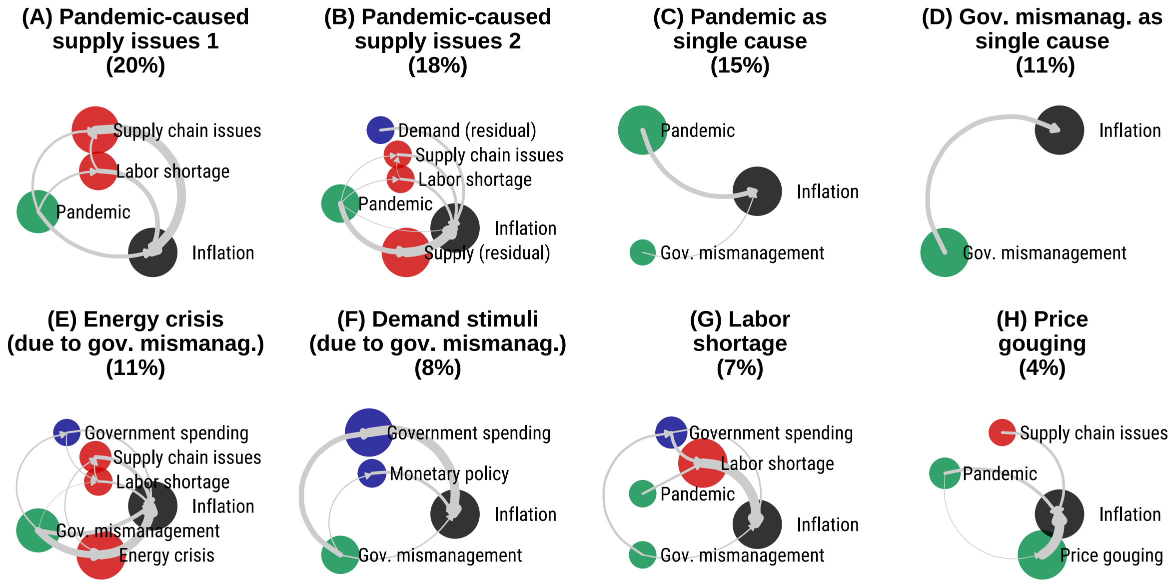
**1. Cosine distance as distance metric.** Instead of using *Jaccard distance*, we use the *Cosine distance* between edge lists to derive the dissimilarity of two narratives. Figure E.3 shows that this procedure yields very similar results. There is a corresponding cluster for every cluster from the main analysis (though the estimated frequencies differ marginally) with only one exception. The exception is the price gouging narrative which is relegated to position 9 (not displayed) because the "Pandemic-caused supply issues 2" cluster is split into two different narrative clusters (one named identically, the other named "Demand and supply factors").

**2. Use a higher number of clusters.** We derive results with $k = 20$ clusters to check whether clustering with a higher number of clusters reveals important additional clusters. Figure E.4 shows that this is not the case. The results are virtually identical. Clustering with a larger number of clusters basically produces additional clusters which have very few members and fail to pass our empirical relevance criterion.

**3. Display resulting average narratives with higher "resolution".** Figure E.5 displays the results from our main cluster analysis but only discards factors that are mentioned by less than 10% (instead of 20%) of narratives within a cluster. The results confirm that the main figure presents the patterns that are most characteristic for each narrative cluster.

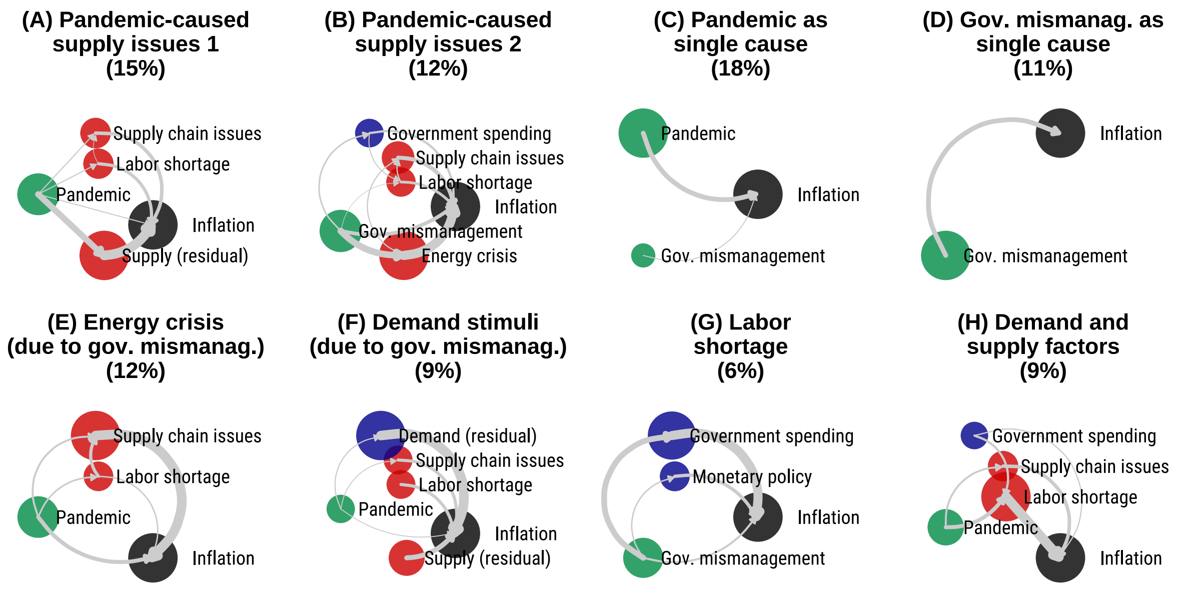
A final note on the linkage method: We do not derive results with different linkage methods (see step 3 in the previous subsection). Ward-type methods have been designed for application in Euclidean spaces, while our data are categorical. "Single linkage" successively adds narratives to one increasingly dominating cluster and thereby fails to reliably distinguish between different groups of narratives. And, with "complete linkage", outlier narratives within each cluster dominate and skew the linkage process. By contrast, the "average" method is applicable, intuitive in our context, and commonly applied in practice.

Figure E.2: Cluster analysis: main results (reproduced)



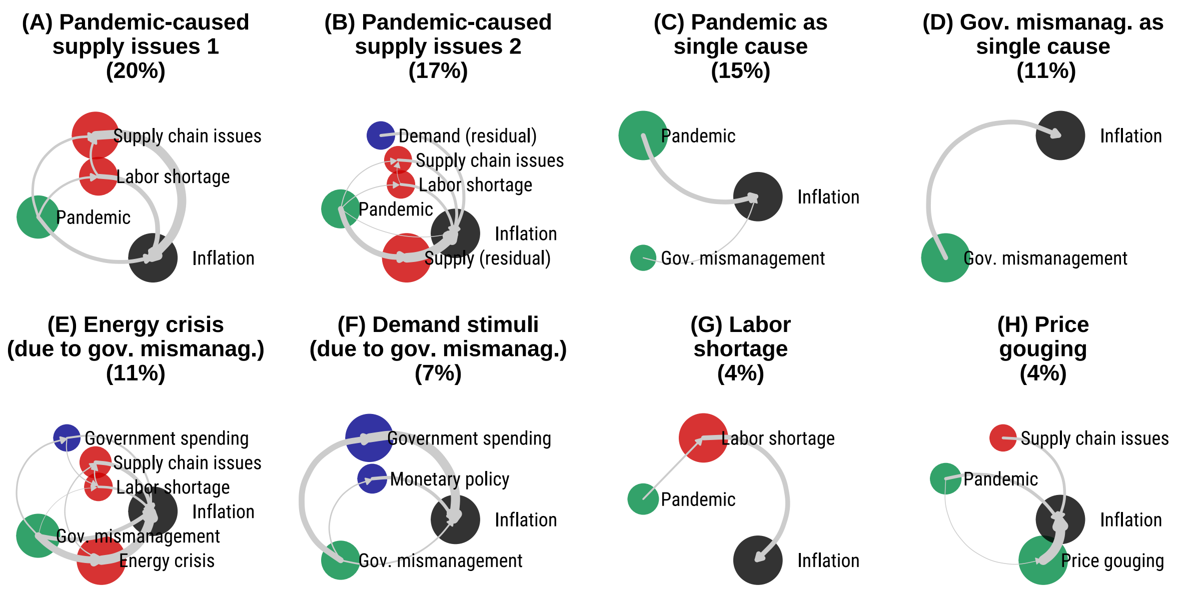

*Note:* Cluster analysis of narratives from household survey (November wave). Only households who provide a causal narrative are considered. **Clustering**: An agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives is applied (described in detail in Online Appendix E). The Silhouette approach suggests an optimal number of clusters of $k = 15$ which we follow, but the figure only displays the eight clusters with at least 30 observations (thus, unlikely to be the product of noise). The figure displays the "average" narrative of each cluster. **Factor size**: The size of the factors is proportional to the share of narratives that refer to the factors. **Factor color**: Red indicates supply-side factors, blue indicates demand-side factors, green indicates miscellaneous factors, and black is used for inflation. **Connection thickness**: The thickness of the connections is proportional to the share of narratives that refer to the causal connections. Within each cluster, nodes with a share of less than 20% and connections with a share of less than 5% are not displayed to focus on the most characteristic features of a cluster.

Figure E.3: Cluster analysis with Cosine distance



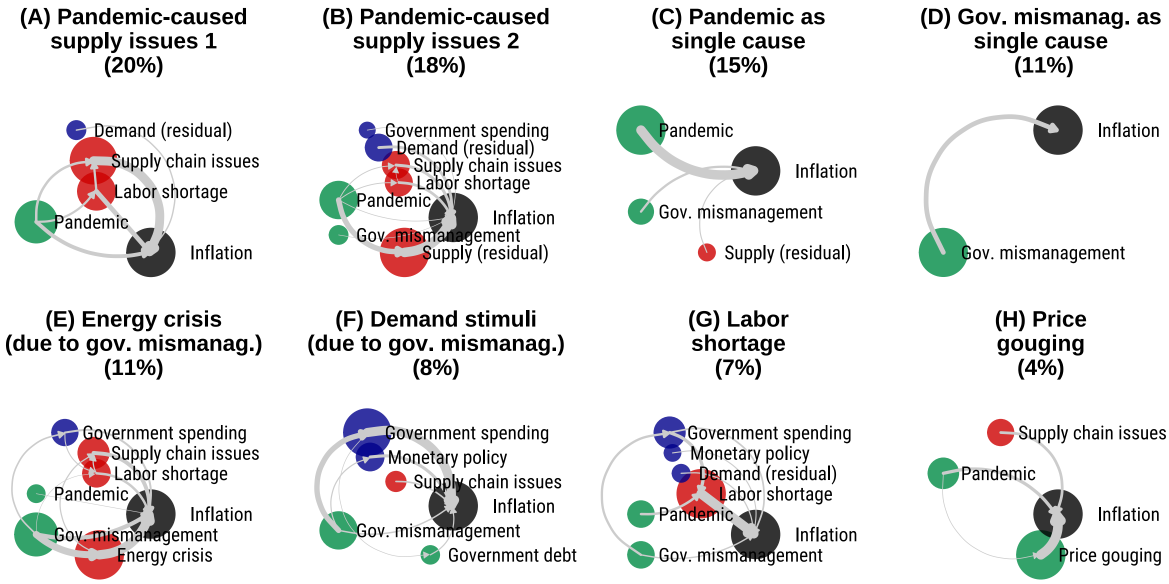

*Note:* Cluster analysis of narratives from household survey (November wave), based on Cosine distance. The eight largest clusters are displayed. In addition, see notes of Figure E.2.

Figure E.4: Cluster analysis with 20 total clusters




*Note:* Cluster analysis of narratives from household survey (November wave) with a total number of clusters $k = 20$, though the figure only displays the eight clusters with at least 30 observations (thus, unlikely to be the product of noise). In addition, see notes of Figure E.2.

Figure E.5: Cluster analysis: displaying clusters at higher "resolution"




*Note:* Cluster analysis of narratives from household survey (November wave). Within each cluster, nodes with a share of less than 10% (rather than 20%) and connections with a share of less than 5% are not displayed. In addition, see notes of Figure E.2.

## F Theory Appendix

### F.1 A Conventional New Keynesian model

The assumptions about preferences, technology, market structure, asset structure, price stickiness, and monetary and fiscal policy equal the assumptions in a conventional New Keynesian model.

There is a continuum of households of mass one, indexed by $i \in [0,1]$. In period t, each household chooses $\{C_s(i,j), L_s(i), B_s(i)\}_{s=t}^{\infty}$ so as to maximize $E_t^i\left[\sum_{s=t}^{\infty}\beta^{s-t}\left(\frac{C_s(i)^{1-\gamma}-1}{1-\gamma}-\frac{L_s(i)^{1+\varsigma}}{1+\varsigma}\right)\right]$ with $C_s(i) = \left(\int_0^1 C_s(i,j)^{\frac{\theta-1}{\theta}}dj\right)^{\frac{\theta}{\theta-1}}$, subject to the flow budget constraint $\int_0^1 P_t(j)C_t(i,j)\,dj + B_t(i) = R_{t-1}B_{t-1}(i) + W_tL_t(i) + D_t - T_t$, an initial condition for bond holdings, and a no-Ponzi scheme condition. Household $i$'s first-order condition for optimal bond holdings in period t reads $C_t(i)^{-\gamma} = E_t^i\left[\beta\frac{R_t}{\Pi_{t+1}}C_{t+1}(i)^{-\gamma}\right]$, where $\Pi_t = \frac{P_t}{P_{t-1}}$ with $P_t = \left(\int_0^1 P_t(j)^{1-\theta}dj\right)^{\frac{1}{1-\theta}}$ is inflation. Log-linearizing the first-order condition around the non-stochastic steady state of the model yields

$$c_t(i) = -\frac{1}{\gamma}\left(r_t - E_t^i[\pi_{t+1}]\right) + E_t^i[c_{t+1}(i)]$$

In the model setup without household heterogeneity, all households have the same initial bond holdings and the same beliefs, and for this reason, the same consumption level.

Firm $j$ supplies good $j$, which is produced with the technology $Y_t(j) = A_tN_t(j)$. There is price stickiness, as in Calvo (1983). Let $\lambda$ denote the probability that a firm cannot adjust its price. The usual derivation of the New Keynesian Phillips curve, when all firms know the current real marginal cost and all firms have the same beliefs about the future, yields

$$\pi_t = \kappa\tilde{mc}_t + \beta E_t^F[\pi_{t+1}]$$

where $\pi_t$ is the inflation rate, $\kappa = \frac{(1-\lambda)(1-\lambda\beta)}{\lambda}$, and $\tilde{mc}_t$ denotes real marginal cost.

The central bank follows the policy rule $R_t = \frac{1}{\beta}\Pi_t^{\phi}e^{\nu_t}$, which expressed in terms of log-deviations from the non-stochastic steady state of the model becomes equation (6). The government can finance maturing government debt and government expenditure by collecting lump-sum taxes or issuing new government debt, $T_t + B_t = R_{t-1}B_{t-1} + P_tG_t$. Combining the definition of aggregate consumption, $C_t = \int_0^1 C_t(i)\,di$, the individual flow budget constraints, the equation for aggregate dividends, $D_t = \int_0^1 P_t(j)Y_t(j)\,dj - W_t\int_0^1 L_t(i)\,di$, the government flow budget constraint, and the fact that $\int_0^1 P_t(j)C_t(i,j)\,dj = P_tC_t(i)$ yields $C_t = \int_0^1 \frac{P_t(j)Y_t(j)}{P_t}dj - G_t$. We denote the right-hand side of the last equation by $\tilde{X}_t$. In terms of log-deviations from the non-stochastic steady state, the last equation reads $c_t = \tilde{x}_t$. For simplicity of language, we assume that the government always runs a balanced budget ($T_t = P_tG_t$). Then one can refer to $\tilde{X}_t$ as aggregate (net real) income.

### F.2 Proof of Proposition 1

The New Keynesian Phillips curve (5) and firms' perceived law of motion for inflation, consisting of equations (8) and (10), imply

$$\pi_t = \kappa\left[(\gamma+\varsigma\alpha)\,c_t + \varsigma\,(1-\alpha)\,g_t - (1+\varsigma)\,a_t\right] + \beta\left(\psi_a^F\rho_a a_t + \psi_g^F\rho_g g_t + \psi_v^F\rho_v v_t\right) \tag{22}$$

The consumption Euler equation (4), the monetary policy rule (6), households' knowledge that $c_{t+1} = \tilde{x}_{t+1}$, and households' perceived law of motion for inflation and income, consisting of equations (7), (9) and (10), imply

$$c_t = -\frac{1}{\gamma}\left(\phi\pi_t + v_t - \left(\psi_a^H\rho_a a_t + \psi_g^H\rho_g g_t + \psi_v^H\rho_v v_t\right)\right) + \left(\varphi_a^H\rho_a a_t + \varphi_g^H\rho_g g_t + \varphi_v^H\rho_v v_t\right) \tag{23}$$

Next, solving this system of two equations for inflation and consumption yields two equations that determine inflation and consumption in period $t$ as a function of: (i) the structural parameters, (ii) the three factors $(a_t, g_t, v_t)$, and (iii) the nine coefficients in the subjective causal models of inflation and income. Importantly, each of these two equations is linear in $a_t$, $g_t$, and $v_t$.

Finally, we solve for the rational expectations equilibrium using the method of undetermined coefficients. Substituting the linearity of the solution, $\pi_t = \psi_a a_t + \psi_g g_t + \psi_v v_t$ and $c_t = \tilde{x}_t = (\varphi_a a_t + \varphi_g g_t + \varphi_v v_t)$, into equations (22)-(23), imposing the restriction that all the coefficients in the subjective causal models of inflation and income have to be correct ($\psi_a^H = \psi_a^F = \psi_a$, $\psi_g^H = \psi_g^F = \psi_g$, $\psi_v^H = \psi_v^F = \psi_v$, $\varphi_a^H = \varphi_a$, $\varphi_g^H = \varphi_g$, $\varphi_v^H = \varphi_v$), and recognizing that the resulting two equations have to hold for any values of the three factors, yields the following six restrictions:

$$\psi_a = \frac{1}{1-\beta\rho_a}\left[\kappa\,(\gamma+\varsigma\alpha)\,\varphi_a - \kappa\,(1+\varsigma)\right] \tag{24}$$

$$\psi_g = \frac{1}{1-\beta\rho_g}\left[\kappa\,(\gamma+\varsigma\alpha)\,\varphi_g + \kappa\varsigma\,(1-\alpha)\right] \tag{25}$$

$$\psi_v = \frac{1}{1-\beta\rho_v}\kappa\,(\gamma+\varsigma\alpha)\,\varphi_v \tag{26}$$

$$\varphi_a = -\frac{1}{1-\rho_a}\frac{1}{\gamma}\left(\phi-\rho_a\right)\psi_a \tag{27}$$

$$\varphi_g = -\frac{1}{1-\rho_g}\frac{1}{\gamma}\left(\phi-\rho_g\right)\psi_g \tag{28}$$

$$\varphi_v = -\frac{1}{1-\rho_v}\frac{1}{\gamma}\left(\phi-\rho_v\right)\psi_v - \frac{1}{1-\rho_v}\frac{1}{\gamma} \tag{29}$$

Solving this system of six equations for the coefficients $\psi_a, \psi_g, \psi_v, \varphi_a, \varphi_g, \varphi_v$ yields Proposition 1.

### F.3 Proof of Proposition 2

Households' subjective causal model of inflation is given by equation (7). Households believe that

$$\forall s = t, t+1, t+2, \ldots : \pi_s = \psi_a^H a_s + \psi_g^H g_s + \psi_\nu^H \nu_s$$

Firms' subjective causal model of inflation is given by equation (8). Firms believe that

$$\forall s = t, t+1, t+2, \ldots : \pi_s = \psi_a^F a_s + \psi_g^F g_s + \psi_\nu^F \nu_s$$

Households' subjective causal model of income is given by equation (9). Households believe that

$$\forall s = t, t+1, t+2, \ldots : \tilde{x}_s = \varphi_a^H a_s + \varphi_g^H g_s + \varphi_\nu^H \nu_s$$

In a rational expectations equilibrium, agents' subjective causal models have to be correct. More formally, agents' perceived law of motion of the economy, consisting of equations (7)–(10), has to imply an actual law of motion of the economy of the form:

$$\forall s = t, t+1, t+2, \ldots : \pi_s = \psi_a a_s + \psi_g g_s + \psi_\nu \nu_s \tag{30}$$

and

$$\forall s = t, t+1, t+2, \ldots : \tilde{x}_s = \varphi_a a_s + \varphi_g g_s + \varphi_\nu \nu_s \tag{31}$$

In addition, the following restrictions have to be satisfied:

$$\psi_a^H = \psi_a \quad \psi_g^H = \psi_g \quad \psi_\nu^H = \psi_\nu \tag{32}$$

$$\psi_a^F = \psi_a \quad \psi_g^F = \psi_g \quad \psi_\nu^F = \psi_\nu \tag{33}$$

$$\varphi_a^H = \varphi_a \quad \varphi_g^H = \varphi_g \quad \varphi_\nu^H = \varphi_\nu \tag{34}$$

This rational expectations equilibrium is presented in Proposition 1.

We now allow for the possibility that the subjective causal models are incorrect by relaxing restrictions (32)-(34). We proceed in three steps. We first relax restriction (32) and compute equilibrium outcomes; we then relax restriction (33) and recompute equilibrium outcomes; and we thereafter relax restriction (34) and recompute equilibrium outcomes. This procedure will allow us to cleanly identify the effect of each step on equilibrium outcomes.

The New Keynesian Phillips curve (5) and firms' perceived law of motion for inflation, consisting of equations (8) and (10), imply

$$\pi_t = \kappa\left[(\gamma + \varsigma\alpha) c_t + \varsigma(1-\alpha) g_t - (1+\varsigma) a_t\right] + \beta\left(\psi_a^F \rho_a a_t + \psi_g^F \rho_g g_t + \psi_\nu^F \rho_\nu \nu_t\right) \tag{35}$$

Households' consumption Euler equation (4), the monetary policy rule (6), households' knowledge that $c_{t+1} = \tilde{x}_{t+1}$, and households' perceived law of motion for inflation and income, consisting of equations (7), (9) and (10), imply

$$c_t = -\frac{1}{\gamma}\left(\phi\pi_t + \nu_t - \left(\psi_a^H \rho_a a_t + \psi_g^H \rho_g g_t + \psi_\nu^H \rho_\nu \nu_t\right)\right) + \left(\varphi_a^H \rho_a a_t + \varphi_g^H \rho_g g_t + \varphi_\nu^H \rho_\nu \nu_t\right) \quad (36)$$

We now define a new variable. Let $\omega_z^H \equiv \frac{\psi_z^H z_t}{\pi_t}$ with $z \in \{a, g, \nu\}$ denote the contribution of factor $z_t$ to the current inflation rate, *according to the households' current subjective causal model of inflation*. That is, according to the households' current subjective causal model of inflation, a fraction $\omega_a^H$ of current inflation is caused by low productivity, a fraction $\omega_g^H$ of current inflation is caused by high government spending, and a fraction $\omega_\nu^H$ of current inflation is caused by loose monetary policy. Since we place no restrictions on the coefficients $\psi_a^H, \psi_g^H, \psi_\nu^H$, the only restriction on $\omega_a^H, \omega_g^H, \omega_\nu^H$ is that $\omega_a^H + \omega_g^H + \omega_\nu^H = 1$. With this definition, the last equation can be written as

$$c_t = -\frac{1}{\gamma}\left(\phi\pi_t + \nu_t - \left(\rho_a\omega_a^H + \rho_g\omega_g^H + \rho_\nu\omega_\nu^H\right)\pi_t\right) + \left(\varphi_a^H \rho_a a_t + \varphi_g^H \rho_g g_t + \varphi_\nu^H \rho_\nu \nu_t\right) \quad (37)$$

The last two equations are mathematically equivalent.

Next, solving the system of equations consisting of equations (35) and (37) for inflation and consumption yields two equations that determine inflation and consumption in period $t$ as a function of: (i) the structural parameters, (ii) the three factors $(a_t, g_t, \nu_t)$, (iii) the six coefficients $\psi_a^F, \psi_g^F, \psi_\nu^F, \varphi_a^H, \varphi_g^H, \varphi_\nu^H$, and (iv) the three fractions $\omega_a^H, \omega_g^H, \omega_\nu^H$:

$$\pi_t = \begin{array}{c} \frac{1}{1+\frac{1}{\gamma}\kappa(\gamma+\varsigma\alpha)\left(\phi-\sum_{z=a,g,\nu}\rho_z\omega_z^H\right)}\left[\kappa\left[\varsigma(1-\alpha)g_t-(1+\varsigma)a_t\right]+\beta\left(\sum_{z=a,g,\nu}\psi_z^F\rho_z z_t\right)\right] \\ +\frac{\kappa(\gamma+\varsigma\alpha)}{1+\frac{1}{\gamma}\kappa(\gamma+\varsigma\alpha)\left(\phi-\sum_{z=a,g,\nu}\rho_z\omega_z^H\right)}\left[-\frac{1}{\gamma}\nu_t+\left(\sum_{z=a,g,\nu}\varphi_z^H\rho_z z_t\right)\right] \end{array} \quad (38)$$

and

$$c_t = \begin{array}{c} \frac{-\frac{1}{\gamma}\left(\phi-\sum_{z=a,g,\nu}\rho_z\omega_z^H\right)}{1+\frac{1}{\gamma}\kappa(\gamma+\varsigma\alpha)\left(\phi-\sum_{z=a,g,\nu}\rho_z\omega_z^H\right)}\left[\kappa\left[\varsigma(1-\alpha)g_t-(1+\varsigma)a_t\right]+\beta\left(\sum_{z=a,g,\nu}\psi_z^F\rho_z z_t\right)\right] \\ +\frac{1}{1+\frac{1}{\gamma}\kappa(\gamma+\varsigma\alpha)\left(\phi-\sum_{z=a,g,\nu}\rho_z\omega_z^H\right)}\left[-\frac{1}{\gamma}\nu_t+\left(\sum_{z=a,g,\nu}\varphi_z^H\rho_z z_t\right)\right] \end{array} \quad (39)$$

Importantly, each of these two equations is linear in $a_t$, $g_t$, and $\nu_t$.

Finally, we compute inflation and consumption in period $t$ under the restriction that the firms' subjective causal model of inflation is correct and the households' subjective causal model of income is correct. For this purpose, we use the method of undetermined coefficients. Substituting the linearity of the solution, $\pi_t = \psi_a a_t + \psi_g g_t + \psi_\nu \nu_t$ and $c_t = \tilde{x}_t = (\varphi_a a_t + \varphi_g g_t + \varphi_\nu \nu_t)$, into equations (35) and (37), imposing the restriction that two subjective causal models are correct ($\psi_a^F = \psi_a$, $\psi_g^F = \psi_g$, $\psi_\nu^F = \psi_\nu$, $\varphi_a^H = \varphi_a$, $\varphi_g^H = \varphi_g$ and $\varphi_\nu^H = \varphi_\nu$), and recognizing that the resulting two equations have to hold for any values of the three factors, yields the following six restrictions:

$$(1-\beta\rho_a)\,\psi_a = \kappa(\gamma+\varsigma\alpha)\,\varphi_a - \kappa(1+\varsigma) \tag{40}$$

$$(1-\beta\rho_g)\,\psi_g = \kappa(\gamma+\varsigma\alpha)\,\varphi_g + \kappa\varsigma(1-\alpha) \tag{41}$$

$$(1-\beta\rho_\nu)\,\psi_\nu = \kappa(\gamma+\varsigma\alpha)\,\varphi_\nu \tag{42}$$

$$(1-\rho_a)\,\varphi_a = -\frac{1}{\gamma}\left[\phi - \left(\sum_{z=a,g,\nu}\omega_z^H\rho_z\right)\right]\psi_a \tag{43}$$

$$(1-\rho_g)\,\varphi_g = -\frac{1}{\gamma}\left[\phi - \left(\sum_{z=a,g,\nu}\omega_z^H\rho_z\right)\right]\psi_g \tag{44}$$

$$(1-\rho_\nu)\,\varphi_\nu = -\frac{1}{\gamma}\left[\phi - \left(\sum_{z=a,g,\nu}\omega_z^H\rho_z\right)\right]\psi_\nu - \frac{1}{\gamma} \tag{45}$$

Solving this system of six equations for the six coefficients $\psi_a$, $\psi_g$, $\psi_\nu$, $\varphi_a$, $\varphi_g$ and $\varphi_\nu$ yields equations (11)-(12) in Proposition 2.

Moreover, if households' subjective causal model of inflation is incorrect in period t (i.e., restriction (32) is violated) and persistence differs across the three factors (it is not true that $\rho_a = \rho_g = \rho_\nu$), then households will have to adjust their subjective causal model of inflation in period t+1 to explain all of inflation in period t+1. We assume that households adjust their subjective causal model of inflation in future periods so as to keep the perceived shares $\omega_a^H, \omega_g^H, \omega_\nu^H$ constant over time. Then, equations (11)-(12) also give the equilibrium outcomes in future periods $t+1, t+2, \ldots$. Under this assumption, firms are right about the fact that inflation is given by an equation of the form (30) with *time-invariant* coefficients and households are right about the fact that income is given by an equation of the form (31) with *time-invariant* coefficients. Since $\psi_a^F = \psi_a, \psi_g^F = \psi_g, \psi_\nu^F = \psi_\nu$ and $\varphi_a^H = \varphi_a, \varphi_g^H = \varphi_g, \varphi_\nu^H = \varphi_\nu$, firms have rational inflation expectations and households have rational income expectations.

Next, we also drop the assumption that firms' subjective causal model of inflation has to be correct (i.e., restriction (32) and restriction (33) may be violated). Let $\omega_z^H \equiv \frac{\psi_z^H z_t}{\pi_t}$ with $z \in \{a, g, \nu\}$ denote the contribution of factor $z_t$ to the current inflation rate, according to the *households*' current subjective causal model of inflation (equation (7)). Let $\omega_z^F \equiv \frac{\psi_z^F z_t}{\pi_t}$ with $z \in \{a, g, \nu\}$ denote the contribution of factor $z_t$ to the current inflation rate, according to the *firms*' current subjective causal model of inflation (equation (8)). With this definition, the New Keynesian Phillips curve (35) and the consumption Euler equation (36) can be written as

$$\pi_t = \kappa\left[(\gamma+\varsigma\alpha)\,c_t + \varsigma(1-\alpha)\,g_t - (1+\varsigma)\,a_t\right] + \beta\left(\rho_a\omega_a^F + \rho_g\omega_g^F + \rho_\nu\omega_\nu^F\right)\pi_t \tag{46}$$

and

$$c_t = -\frac{1}{\gamma}\left(\phi\pi_t + \nu_t - \left(\rho_a\omega_a^H + \rho_g\omega_g^H + \rho_\nu\omega_\nu^H\right)\pi_t\right) + \left(\varphi_a^H\rho_a a_t + \varphi_g^H\rho_g g_t + \varphi_\nu^H\rho_\nu\nu_t\right) \tag{47}$$

The last two equations are mathematically equivalent to equations (35)-(36).

Solving equations (46)-(47) for inflation and consumption yields two equations that determine inflation and consumption in period $t$ as a function of: (i) the structural parameters, (ii) the three factors $(a_t, g_t, \nu_t)$, (iii) the six fractions $\omega_a^H, \omega_g^H, \omega_\nu^H, \omega_a^F, \omega_g^F, \omega_\nu^F$, and (iv) the three coefficients $\varphi_a^H, \varphi_g^H, \varphi_\nu^H$. Each of these two equations is linear in $a_t$, $g_t$, and $\nu_t$.

Finally, we compute inflation and consumption in period $t$ under the restriction that the households' subjective causal model of income is correct (i.e., the coefficients $\varphi_a^H, \varphi_g^H, \varphi_\nu^H$ satisfy restriction (34)). For this purpose, we use the method of undetermined coefficients. Substituting the linearity of the solution, $\pi_t = \psi_a a_t + \psi_g g_t + \psi_\nu \nu_t$ and $c_t = \tilde{x}_t = (\varphi_a a_t + \varphi_g g_t + \varphi_\nu \nu_t)$, into equations (46)-(47), imposing the restriction that one subjective causal model is correct ($\varphi_a^H = \varphi_a$, $\varphi_g^H = \varphi_g$, $\varphi_\nu^H = \varphi_\nu$), and recognizing that the resulting two equations have to hold for any values of the three factors, yields the following six restrictions:

$$\left[1-\beta\left(\sum_{z=a,g,\nu}\rho_z\omega_z^F\right)\right]\psi_a = \kappa(\gamma+\varsigma\alpha)\varphi_a - \kappa(1+\varsigma) \tag{48}$$

$$\left[1-\beta\left(\sum_{z=a,g,\nu}\rho_z\omega_z^F\right)\right]\psi_g = \kappa(\gamma+\varsigma\alpha)\varphi_g + \kappa\varsigma(1-\alpha) \tag{49}$$

$$\left[1-\beta\left(\sum_{z=a,g,\nu}\rho_z\omega_z^F\right)\right]\psi_\nu = \kappa(\gamma+\varsigma\alpha)\varphi_\nu \tag{50}$$

$$(1-\rho_a)\varphi_a = -\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,\nu}\rho_z\omega_z\right)\right]\psi_a \tag{51}$$

$$(1-\rho_g)\varphi_g = -\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,\nu}\rho_z\omega_z\right)\right]\psi_g \tag{52}$$

$$(1-\rho_\nu)\varphi_\nu = -\frac{1}{\gamma}\left[\phi-\left(\sum_{z=a,g,\nu}\rho_z\omega_z\right)\right]\psi_\nu - \frac{1}{\gamma} \tag{53}$$

Solving this system of six equations for the six coefficients $\psi_a$, $\psi_g$, $\psi_\nu$, $\varphi_a$, $\varphi_g$ and $\varphi_\nu$ yields equations (13)-(14) in Proposition 2.

Moreover, if some agents' subjective causal model of inflation is incorrect in period t (i.e., restriction (32) or (33) is violated) and persistence differs across the three factors (it is not true that $\rho_a = \rho_g = \rho_\nu$), then some agents will have to adjust their subjective causal model of inflation in period t+1 to explain all of inflation in period t+1. We assume that households and firms adjust their subjective causal model of inflation in future periods so as to keep the perceived shares $\omega_a^H, \omega_g^H, \omega_\nu^H$ and $\omega_a^F, \omega_g^F, \omega_\nu^F$ constant over time. Then, equations (13)-(14) also give the equilibrium outcomes in future periods $t+1, t+2, \ldots$. Under this assumption, households are right about the fact that income is given by an equation of the form (31) with *time-invariant* coefficients. Since $\varphi_a^H = \varphi_a, \varphi_g^H = \varphi_g, \varphi_v^H = \varphi_v$, households have rational income expectations.

Finally, we also drop the assumption that households' subjective causal model of income has to be correct (i.e., restriction (32), restriction (33), and restriction (34) may be violated). Let $\omega_z^H \equiv \frac{\psi_z^H z_t}{\pi_t}$ denote the contribution of factor $z_t$ to the current inflation rate, according to the households' current subjective causal model of inflation (equation (7)), let $\omega_z^F \equiv \frac{\psi_z^F z_t}{\pi_t}$ denote the contribution of factor $z_t$ to the current inflation rate, according to the firms' current subjective causal model of inflation (equation (8)), and let $\varpi_z^H \equiv \frac{\varphi_z^H z_t}{\tilde{x}_t}$ denote the contribution of factor $z_t$ to current income, according to the households' current subjective causal model of income (equation (9)). With these definitions, households' inflation expectation in period t can be written as

$$E_t^H[\pi_{t+1}] = \psi_a^H \rho_a a_t + \psi_g^H \rho_g g_t + \psi_v^H \rho_v v_t = \left(\rho_a \omega_a^H + \rho_g \omega_g^H + \rho_v \omega_v^H\right) \pi_t \tag{54}$$

firms' inflation expectation in period t can be written as

$$E_t^F[\pi_{t+1}] = \psi_a^F \rho_a a_t + \psi_g^F \rho_g g_t + \psi_v^F \rho_v v_t = \left(\rho_a \omega_a^F + \rho_g \omega_g^F + \rho_v \omega_v^F\right) \pi_t \tag{55}$$

and households' income expectation in period t can be written as

$$E_t^H[\tilde{x}_{t+1}] = \varphi_a^H \rho_a a_t + \varphi_g^H \rho_g g_t + \varphi_v^H \rho_v v_t = \left(\rho_a \varpi_a^H + \rho_g \varpi_g^H + \rho_v \varpi_v^H\right) \tilde{x}_t \tag{56}$$

Hence, the New Keynesian Phillips curve (35) and the consumption Euler equation (36) can be written as

$$\pi_t = \kappa\left[(\gamma + \varsigma\alpha) c_t + \varsigma(1-\alpha) g_t - (1+\varsigma) a_t\right] + \beta\left(\rho_a \omega_a^F + \rho_g \omega_g^F + \rho_v \omega_v^F\right) \pi_t \tag{57}$$

$$c_t = -\frac{1}{\gamma}\left(\phi\pi_t + v_t - \left(\rho_a \omega_a^H + \rho_g \omega_g^H + \rho_v \omega_v^H\right) \pi_t\right) + \left(\rho_a \varpi_a^H + \rho_g \varpi_g^H + \rho_v \varpi_v^H\right) c_t \tag{58}$$

The last two equations are mathematically equivalent to equations (35)-(36).

Solving equations (57)-(58) for inflation and consumption yields equations (15)-(16) in Proposition 2.

### F.4 Aggregate outcomes with heterogeneity in narratives among households and between firms and households

Substituting the interest rate rule (6) into the aggregate consumption Euler equation (20) yields

$$c_t = -\frac{1}{\gamma}\left(\phi\pi_t + v_t - \left(\sum_{z=a,g,v} \int \rho_z(i)\, \omega_z(i)\, di\right) \pi_t\right) + \left(\sum_{z=a,g,v} \int \rho_z(i)\, \varpi_z(i)\, di\right) c_t \tag{59}$$

Solving the New Keynesian Phillips curve (57) and equation (59) for inflation and aggregate consumption yields

$$\pi_t = \frac{-\left[\kappa\left(1+\varsigma\right)a_t - \kappa\varsigma\left(1-\alpha\right)g_t\right]\left(1-B\right) - \kappa\left(\gamma+\varsigma\alpha\right)\frac{1}{\gamma}\nu_t}{\left(1-B\right)\left[1-\beta\left(\sum_{z=a,g,\nu}\rho_z\omega_z^F\right)\right] + \kappa\left(\gamma+\varsigma\alpha\right)\frac{1}{\gamma}\left[\phi - A\right]} \tag{60}$$

$$c_t = \frac{\frac{1}{\gamma}\left[\phi - A\right]\left[\kappa\left(1+\varsigma\right)a_t - \kappa\varsigma\left(1-\alpha\right)g_t\right] - \frac{1}{\gamma}\left[1-\beta\left(\sum_{z=a,g,\nu}\rho_z\omega_z^F\right)\right]\nu_t}{\left(1-B\right)\left[1-\beta\left(\sum_{z=a,g,\nu}\rho_z\omega_z^F\right)\right] + \kappa\left(\gamma+\varsigma\alpha\right)\frac{1}{\gamma}\left[\phi - A\right]} \tag{61}$$

with

$$A \equiv \textstyle\sum_{z=a,g,\nu}\int\rho_z\left(i\right)\omega_z\left(i\right)di \qquad B \equiv \sum_{z=a,g,\nu}\int\rho_z\left(i\right)\varpi_z\left(i\right)di$$

The last two equations are identical to equations (15)-(16) apart from the fact that $\rho_z\omega_z^H$ and $\rho_z\varpi_z^H$ have been replaced by $\int\rho_z\left(i\right)\omega_z\left(i\right)di$ and $\int\rho_z\left(i\right)\varpi_z\left(i\right)di$, respectively.

## G Survey Instructions

Below, we post the key survey questions from the different waves. A more detailed description of the survey instructions can be found under https://osf.io/av48u/.

### G.1 Household and Expert Surveys: Descriptive Waves

We conducted descriptive surveys with representative household samples in November 2021, December 2021, January 2022, March 2022, and May 2022 and with an expert sample in November 2021. The exact instructions vary slightly across the different waves of the household survey, but the key questions (posted below for the November 2021 household survey) are identical (with the exceptions of dates and inflation numbers). The expert survey does not include the explanation screen and the questions about past inflation.

#### What is the inflation rate?

On this page, we briefly explain in more detail what we mean when we refer to the inflation rate. Please read the definition carefully.

**The inflation rate measures how much prices in the economy rise from year to year.** It is defined as the **yearly growth of the general price level of goods and services** (Consumer Price Index).

For instance, an inflation rate of 2% means that, on average, prices for goods and services rise by 2% over 12 months. That is, a typical bundle of goods and services that costs $1,000 at the beginning of a year costs $1,020 at the end of that year.

If the inflation rate is negative, it is referred to as **deflation**. This means that goods and services become less expensive from one year to the next.

## A few opening questions

What do you think was the rate of inflation in the US over the last 12 months? Please respond in %.

[          ] %

Do you think that the inflation rate over the last 12 months is higher, lower, or about the same as inflation one year ago (from 24 months to 12 months ago)?

- Higher today
- About the same
- Lower today

Which response option describes best **how frequently you thought about inflation** in the last three months?

- Never
- Once a month
- Once every other week
- Once a week
- Multiple times a week
- Daily

Which response option describes best **how frequently you saw/read/heard news about inflation** in the last three months?

- Never
- Once a month
- Once every other week
- Once a week
- Multiple times a week
- Daily

→

## Why has the inflation rate increased?

**In previous years, the US inflation rate has mostly varied between 1.5% and 2.5%.** At this rate, a bundle of goods and services that costs $1,000 in one year, would cost between $1,015 and $1,025 in the next year.

**Recently, however, the inflation rate has increased. It is now at 6.2%.** At this rate, a bundle of goods and services that costs $1,000 in one year, would cost $1,062 in the next year.

**Which factors do you think caused the increase in the inflation rate?** Please respond in full sentences.

→

## Your forecasts for the future

Recall that, in previous years, the US inflation rate has mostly varied between 1.5% and 2.5%. Recently, however, the inflation rate has increased. It is now at 6.2%.

Next, we would like you to think about the different things that may happen to inflation **over the next 12 months**. We realize that this question may take a little more time. **In your view, what would you say is the percent chance that, over the next 12 months...**

(Please note: The numbers need to add up to 100%.)

| | | |
|---|---|---|
| The rate of inflation will be 12% or higher. | 0 | % |
| The rate of inflation will be between 8% and 12%. | 0 | % |
| The rate of inflation will be between 4% and 8%. | 0 | % |
| The rate of inflation will be between 2% and 4%. | 0 | % |
| The rate of inflation will be between 0% and 2%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be between 0% and 2%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be between 2% and 4%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be between 4% and 8%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be between 8% and 12%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be 12% or higher. | 0 | % |
| Total | 0 | % |

→

## Your forecasts for the future

Recall that, in previous years, the US inflation rate has mostly varied between 1.5% and 2.5%. Recently, however, the inflation rate has increased. It is now at 6.2%.

Now, we would like you to think about the different things that may happen to inflation over the time between **four and five years from now** (that is, between 49 and 60 months from now). **In your view, what is the percent chance that, over the time between 49 and 60 months from now…**

(Please note: The numbers need to add up to 100%.)

| | | |
|---|---|---|
| The rate of inflation will be 12% or higher. | 0 | % |
| The rate of inflation will be between 8% and 12%. | 0 | % |
| The rate of inflation will be between 4% and 8%. | 0 | % |
| The rate of inflation will be between 2% and 4%. | 0 | % |
| The rate of inflation will be between 0% and 2%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be between 0% and 2%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be between 2% and 4%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be between 4% and 8%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be between 8% and 12%. | 0 | % |
| The rate of deflation (the opposite of inflation) will be 12% or higher. | 0 | % |
| Total | 0 | % |

→

### G.2 Household Survey: Robustness with structured measures (May 2022)

In May 2022, we conducted an experiment with a household sample. We first ask our standard questions about demographics and knowledge of past inflation. We next elicit narratives with open-ended questions, confidence in their understanding of why inflation has increased, as well as structured questions about the importance of different factors for past and future inflation. We include the key screenshots below.

#### Why has the inflation rate increased?

**In previous years, the US inflation rate has mostly varied between 1.5% and 2.5%.** At this rate, a bundle of goods and services that costs $1,000 in one year, would cost between $1,015 and $1,025 in the next year.

**Recently, however, the inflation rate has increased. It is now at 8.5%.** At this rate, a bundle of goods and services that costs $1,000 in one year, would cost $1,085 in the next year.

**Which factors do you think caused the increase in the inflation rate?** Please respond in full sentences.

→

## What contributed to the past rise of inflation?

Below, we show you a list of different economic or political factors. What do you think? **Which of these factors have contributed to the rise of US inflation to 8.5% over the last twelve months?**

**Please rate how important you think each of these factors has been for the rise of inflation to 8.5% over the last twelve months.**

| | Not at all important | Slightly important | Moderately important | Very important | Extremely important |
|---|---|---|---|---|---|
| High levels of government debt. | ○ | ○ | ○ | ○ | ○ |
| Expectations about high inflation in the coming years and pre-emptive price and wage increases. | ○ | ○ | ○ | ○ | ○ |
| Businesses tried to increase their profits. | ○ | ○ | ○ | ○ | ○ |
| The global energy crisis: high energy prices and shortages of oil and natural gas. | ○ | ○ | ○ | ○ | ○ |
| A shortage of workers. | ○ | ○ | ○ | ○ | ○ |
| | Not at all important | Slightly important | Moderately important | Very important | Extremely important |
| Shifts in what people bought, especially a shift from services to durables. | ○ | ○ | ○ | ○ | ○ |
| Tax increases. | ○ | ○ | ○ | ○ | ○ |
| Disruptions of global supply chains. | ○ | ○ | ○ | ○ | ○ |
| Base effect: a low inflation rate during the pandemic. | ○ | ○ | ○ | ○ | ○ |
| The COVID-19 pandemic, the lockdowns, and other policy measures taken to contain the pandemic. | ○ | ○ | ○ | ○ | ○ |
| | Not at all important | Slightly important | Moderately important | Very important | Extremely important |
| The Russian war against Ukraine and the international economic, political, and military response. | ○ | ○ | ○ | ○ | ○ |
| Government mismanagement and bad political decisions by the government. | ○ | ○ | ○ | ○ | ○ |
| After the lockdowns were lifted, people spent more money (e.g. due to pent-up savings from the pandemic and new spending opportunities). | ○ | ○ | ○ | ○ | ○ |
| The Federal Reserve kept interest rates near zero. | ○ | ○ | ○ | ○ | ○ |
| Increases in government spending, e.g. the stimulus payments. | ○ | ○ | ○ | ○ | ○ |

→

## What will contribute to the future development of inflation?

Below, we show you a similar list of economic and political factors. The factors are presented in a different order. Now, your task is to think about the future. What do you think? **Which of these factors will contribute to the development of US inflation over the next twelve months?**

**Please rate how important you think each of these factors will be for the development of inflation over the next twelve months.**

| | Not at all important | Slightly important | Moderately important | Very important | Extremely important |
|---|---|---|---|---|---|
| After the lockdowns are lifted, people spend more money (e.g. due to pent-up savings from the pandemic and new spending opportunities). | ○ | ○ | ○ | ○ | ○ |
| Government spending, e.g. stimulus payments. | ○ | ○ | ○ | ○ | ○ |
| The Russian war against Ukraine and the international economic, political, and military response. | ○ | ○ | ○ | ○ | ○ |
| The COVID-19 pandemic, the lockdowns, and other policy measures taken to contain the pandemic. | ○ | ○ | ○ | ○ | ○ |
| Tax increases. | ○ | ○ | ○ | ○ | ○ |
| | Not at all important | Slightly important | Moderately important | Very important | Extremely important |
| Shifts in what people buy, especially a shift from services to durables. | ○ | ○ | ○ | ○ | ○ |
| Disruptions of global supply chains. | ○ | ○ | ○ | ○ | ○ |
| A shortage of workers. | ○ | ○ | ○ | ○ | ○ |
| The global energy crisis: high energy prices and shortages of oil and natural gas. | ○ | ○ | ○ | ○ | ○ |
| High levels of government debt. | ○ | ○ | ○ | ○ | ○ |
| | Not at all important | Slightly important | Moderately important | Very important | Extremely important |
| Low interest rates of the Federal Reserve. | ○ | ○ | ○ | ○ | ○ |
| Base effect: a low inflation rate during the pandemic. | ○ | ○ | ○ | ○ | ○ |
| Expectations about high inflation in the coming years and pre-emptive price and wage increases. | ○ | ○ | ○ | ○ | ○ |
| Government mismanagement and bad political decisions by the government. | ○ | ○ | ○ | ○ | ○ |
| Businesses trying to increase their profits. | ○ | ○ | ○ | ○ | ○ |

→

### G.3 Household Survey: Pent-up Demand and Energy Narrative Provision Experiment (April 2022)

In April 2022, we conducted an experiment with a household sample in which respondents are randomly assigned to receive a narrative blaming the energy crisis for higher inflation, receive a narrative blaming pent-up demand due to forced savings during the pandemic, or receive no narrative. Below we post the survey screens providing respondents with different narratives. Subsequently, we elicit respondents' own point forecasts of inflation over the next 12 months (not shown). We also conduct a follow-up survey in which we elicit respondents' narratives and re-elicit their inflation expectations (not shown).

**Treatment: Pent-up demand narrative**

**Why has inflation increased?**

*Please read the following information carefully. On the next page, we will ask you a question about the text below, so please read everything carefully.*

We recently surveyed economic experts who study inflation in the United States. These experts emphasized that **pent-up demand resulting from the pandemic** was an important cause for the rise of inflation.

According to this explanation, households were forced to save money during the pandemic because there were less opportunities to spend money. As the economy reopened and restrictions were lifted, people quickly started traveling again and going to restaurants. They were buying more, spending some of the money they couldn't spend during the lockdowns. **In short, people were flush with cash and eager to spend their lockdown savings**. This resulted in a high demand for goods and services, which led to increased prices.

Here are some example explanations from our expert survey:

> *During the 2 years of lockdown, demand has dropped because people postponed or could not visit shops. Now after the lockdowns, there is a catch up in demand, suddenly demand is high, but firms have not anticipated such a strong demand.*
>
> *Covid resulted in higher savings rates, so consumers had more money to spend.*
>
> *As a result of the lockdown, spending has been restrained. But now that we are returning to normality, consumers are eager to return to the usual spending.*

→

As you just read on the last page, experts emphasize that pent-up demand resulting from the pandemic was an important cause for the rise of inflation.

**Please describe in your own words how pent-up demand resulting from the pandemic caused the rise of inflation.**

→

## Treatment: Energy crisis narrative

**Why has inflation increased?**

*Please read the following information carefully. On the next page, we will ask you a question about the text below, so please read everything carefully.*

We recently surveyed economic experts who study inflation in the United States. These experts emphasized that the **global energy crisis** was an important cause for the rise of inflation.

According to this explanation, shortages of oil and natural gas led to climbing energy prices. There are many reasons for the energy crisis, including new environmental regulations, reduced investments in fossil fuels, closure of nuclear plants, global political insecurities, reduction in gas supplies from Russia, as well as disruptions to global supply chains.

Energy is an important input for many firms and expenditures for energy account for a substantial share of production costs. Companies responded by passing along those higher costs in the form of higher prices to consumers, contributing to high inflation. In addition, many households rely on natural gas for heating and on gasoline produced from oil for driving. Therefore, price increases of oil and natural gas substantially increased the inflation rate.

**In sum, the global energy crisis has led to higher electricity and gasoline bills for consumers as well as higher costs for firms, making them increase prices to cover the costs.**

Here are some typical explanations from our expert survey:

> *The price of energy has increased, with a knock-on effect on the cost of manufacture.*
>
> *Inflation is particularly high because of a spike in retail gasoline (petrol) prices.*
>
> *Energy inflation is due in part to reduced investment in fossil fuels capacity.*

→

As you just read on the last page, experts emphasize that the global energy crisis was an important cause for the rise of inflation.

**Please describe in your own words how the global energy crisis caused the rise of inflation.**

→

## G.4 Household Survey: Monetary Policy Narrative Provision Experiment (June 2022)

In June 2022, we conducted an experiment with a household sample in which respondents are randomly assigned to receive a narrative emphasizing that the energy crisis contributed to the rise in inflation or receive a narrative emphasizing the role of loose monetary policy in driving higher inflation. Below we post the survey screens providing respondents with different narratives. Subsequently, we elicit respondents' own point forecasts of inflation over the next 12 months (not shown). We also conduct a follow-up survey in which we elicit respondents' narratives and re-elicit their inflation expectations (not shown).

**Treatment: Monetary policy narrative**

> ### Why has inflation increased?
>
> *Please read the following information carefully. On the next page, we will ask you a question about the text below, so please read everything carefully.*
>
> We recently surveyed economic experts who study inflation in the United States. These experts emphasized that the **very low interest rates pursued by the Federal Reserve (Fed)**, which led to a massive injection of money into the economy, were an important cause for the rise of inflation.
>
> The Federal Reserve is the central bank of the US economy. It influences economy-wide interest rates by adjusting the federal funds rate, which is the most important interest rate in the economy. During the pandemic, the Federal Reserve reduced interest rates to historically low levels.
>
> The low interest rates led to a massive injection of money into the economy. Because of low interest rates, consumer credits, mortgages, and business investments became extremely cheap. At the same time, low interest rates made it unattractive to save money. This bolstered demand for big purchases, from houses and cars to business investments like machinery and computers.
>
> The high demand for goods and services created a mismatch: Strong demand exceeded the available supply, leading to economy-wide pressure on prices. Goods and services became more expensive. The result: a rise of inflation.
>
> **In sum, the Federal Reserve's low interest rate policy has led to too many dollars chasing the available goods and services, leading to a surge in inflation.**
>
> Here is one example explanation from our expert survey:
>
> > *"The Fed pumped far too much money into the economy in a short period of time during the COVID crisis."*

As you just read on the last page, experts emphasize that low interest rates pursued by the Federal Reserve were an important cause for the rise of inflation.

**Please describe in your own words how low interest rates pursued by the Federal Reserve caused the rise of inflation.**

→

**Treatment: Energy crisis narrative**

**Why has inflation increased?**

*Please read the following information carefully. On the next page, we will ask you a question about the text below, so please read everything carefully.*

We recently surveyed economic experts who study inflation in the United States. These experts emphasized that the **global energy crisis** was an important cause for the rise of inflation.

According to this explanation, shortages of oil and natural gas led to climbing energy prices. There are many reasons for the energy crisis, including new environmental regulations, reduced investments in fossil fuels, closure of nuclear plants, global political insecurities, reduction in gas supplies from Russia, as well as disruptions to global supply chains.

Energy is an important input for many firms and expenditures for energy account for a substantial share of production costs. Companies responded by passing along those higher costs in the form of higher prices to consumers, contributing to high inflation. In addition, many households rely on natural gas for heating and on gasoline produced from oil for driving. Therefore, price increases of oil and natural gas substantially increased the inflation rate.

**In sum, the global energy crisis has led to higher electricity and gasoline bills for consumers as well as higher costs for firms, making them increase prices to cover the costs.**

Here is one example explanation from our expert survey:

> *The price of energy has increased, with a knock-on effect on the cost of manufacture.*

As you just read on the last page, experts emphasize that the global energy crisis was an important cause for the rise of inflation.

**Please describe in your own words how the global energy crisis caused the rise of inflation.**

→

### G.5 Household Survey: Priming Experiment (December 2021)

In December 2021, we conducted an experiment with a household sample in which we exogenously draw respondents' attention to government spending. Below, we post the key questions of this experiment.

**Priming treatment (treated respondents only)**


US government spending

**What comes to your mind when you think about recent government spending programs?**

Please write 3-4 sentences.

**Post-treatment outcomes**

## Why has the inflation rate increased?

**In previous years, the US inflation rate has mostly varied between 1.5% and 2.5%.** At this rate, a bundle of goods and services that costs $1,000 in one year, would cost between $1,015 and $1,025 in the next year.

**Recently, however, the inflation rate has increased. It is now at 6.8%.** At this rate, a bundle of goods and services that costs $1,000 in one year, would cost $1,068 in the next year.

**Which factors do you think caused the increase in the inflation rate?** Please respond in full sentences.

→

## Your forecast for the future

Recall that, in previous years, the US inflation rate has mostly varied between 1.5% and 2.5%. Recently, however, the inflation rate has increased. It is now at 6.8%.

**What do you think the US inflation rate (in %) will be over the next 12 months?**

__________ %

---

**How confident are you in the above prediction?**
Please answer on a scale from 1 (Not confident at all) to 6 (Very confident).

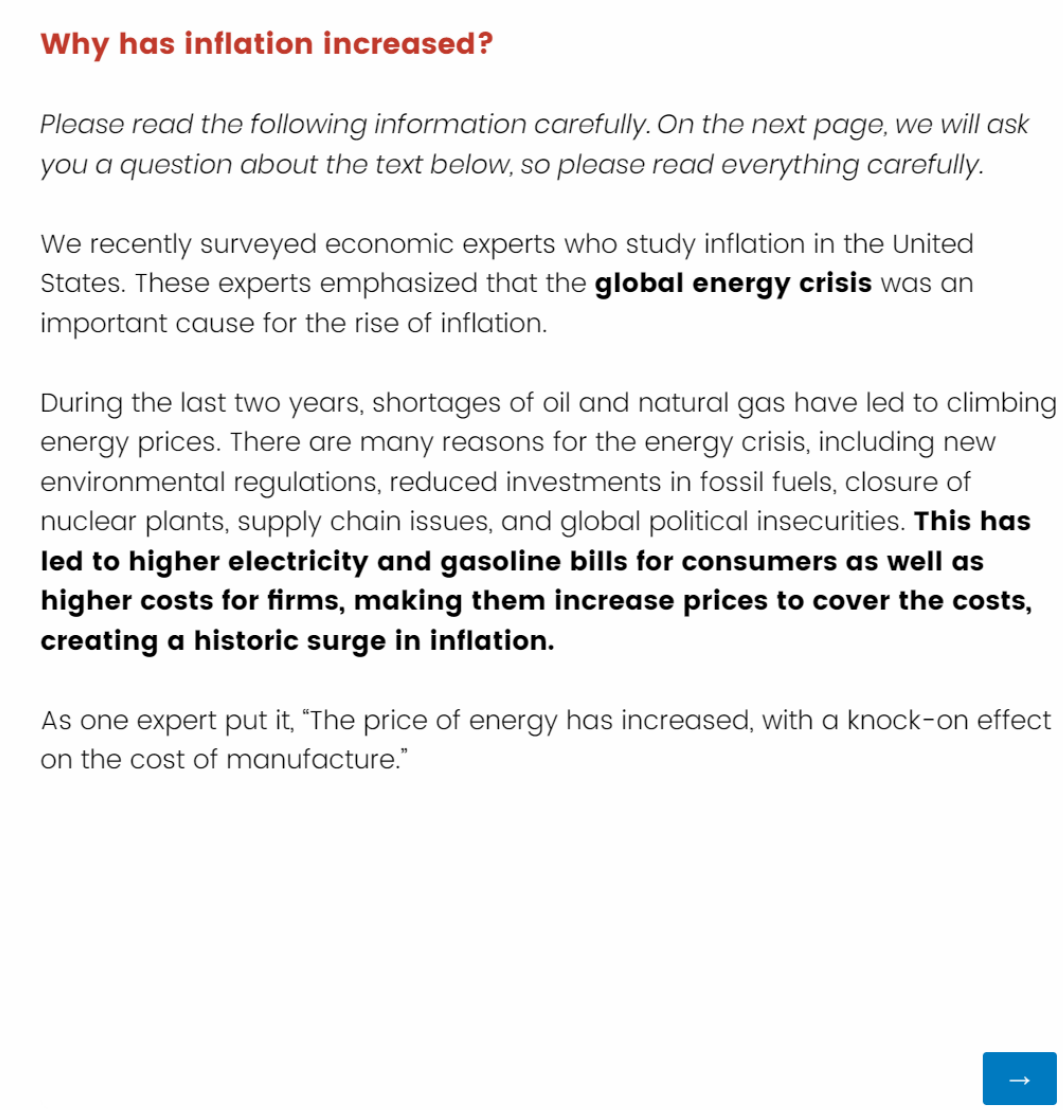
| Not confident at all 1 | 2 | 3 | 4 | 5 | Very confident 6 |
|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ |

→

### G.6 Household Survey: Experiment on Narratives and the Interpretation of Information (April 2022)

In April 2022, we conducted an experiment with a household sample. In a 2x2 design, respondents are first randomly assigned to either receive a narrative blaming the energy crisis for the increase in inflation or receive a narrative emphasizing the role of high government spending. Subsequently, they are randomly assigned to receive one of two different expert forecasts about future government spending. Below, we post the key treatment screens. After the treatments, we elicit respondents' point forecasts of real government spending growth and inflation over the next 12 months (survey screens not shown).

**Treatment: Energy crisis narrative**



**Why has inflation increased?**

*Please read the following information carefully. On the next page, we will ask you a question about the text below, so please read everything carefully.*

We recently surveyed economic experts who study inflation in the United States. These experts emphasized that the **global energy crisis** was an important cause for the rise of inflation.

During the last two years, shortages of oil and natural gas have led to climbing energy prices. There are many reasons for the energy crisis, including new environmental regulations, reduced investments in fossil fuels, closure of nuclear plants, supply chain issues, and global political insecurities. **This has led to higher electricity and gasoline bills for consumers as well as higher costs for firms, making them increase prices to cover the costs, creating a historic surge in inflation.**

As one expert put it, "The price of energy has increased, with a knock-on effect on the cost of manufacture."

→

## Why has inflation increased?

As you just read on the last page, experts emphasize that the global energy crisis was an important cause for the rise of inflation.

**Please describe in your own words how the "global energy crisis" caused the rise of inflation.**

→

**Treatment: Government spending narrative**

## Why has inflation increased?

*Please read the following information carefully. On the next page, we will ask you a question about the text below, so please read everything carefully.*

We recently surveyed economic experts who study inflation in the United States. These experts emphasized that **high demand caused by massive government spending** was an important cause for the rise of inflation.

During the last two years, Congress has unleashed a torrent of federal money to support the economy, approving roughly $6 trillion in relief measures, including the $1.9 trillion American Rescue Plan featuring $1,400 checks to most households.

The massive injection of money into the economy led to an extremely high demand for goods and services. **This resulted in too much money chasing too few goods, creating a historic surge in inflation.**

As one expert put it, “The increase in government spending has boosted aggregate demand, and hence inflation.”

→

## Why has inflation increased?

As you just read on the last page, experts emphasize that high demand caused by massive government spending was an important cause for the rise of inflation.

**Please describe in your own words how "high demand caused by massive government spending" caused the rise of inflation.**

→

**Treatment: Government spending increase**

### Expert forecast: Higher government spending ahead

The Survey of Professional Forecasters is a quarterly survey in which leading experts provide macroeconomic forecasts for the economy of the United States.

One of the key forecasts in the survey relates to changes in real federal government spending (that is, changes in federal government spending after adjusting for changes in the overall price level of goods and services).

According to a recent forecast by an expert from the Survey of Professional Forecasters, **real federal government spending will increase by six percentage points** over the next 12 months.

→

**Treatment: Government spending decrease**

**Expert forecast: Lower government spending ahead**

The Survey of Professional Forecasters is a quarterly survey in which leading experts provide macroeconomic forecasts for the economy of the United States.

One of the key forecasts in the survey relates to changes in real government spending (that is, changes in government spending after adjusting for changes in the overall price level of goods and services).

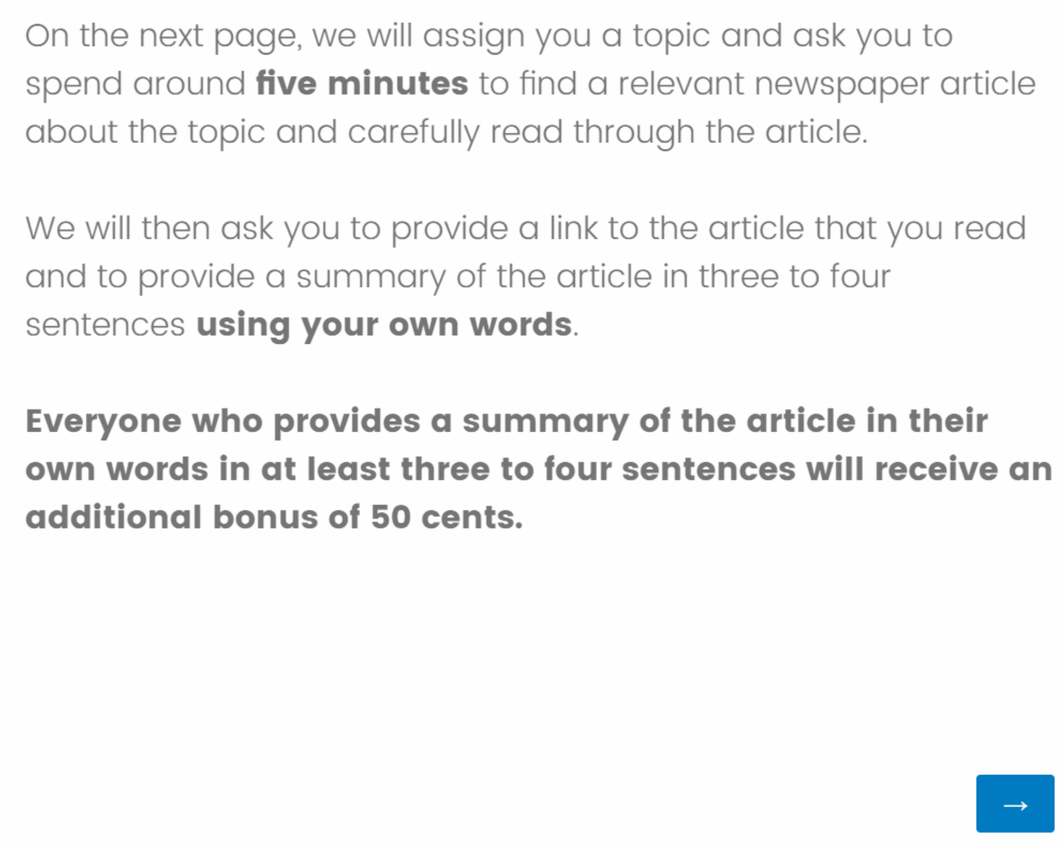
According to a recent forecast by an expert from the Survey of Professional Forecasters, **real federal government spending will decrease by four percentage points** over the next 12 months.

→

## G.7 Household Survey: Media Experiment (February 2022)

In February 2022, we conducted an experiment with a household sample in which we give respondents incentives to search for and read a news article about inflation. Wave 1 and wave 3 elicit households' inflation narratives using the same question format as in our other surveys, and ask some supplementary questions. Below, we post the key survey screens of wave 2, which exogenously assigns respondents to search for and read news articles either about inflation or about tourist attractions in Miami.

**Inflation treatment**


On the next page, we will assign you a topic and ask you to spend around **five minutes** to find a relevant newspaper article about the topic and carefully read through the article.

We will then ask you to provide a link to the article that you read and to provide a summary of the article in three to four sentences **using your own words**.

**Everyone who provides a summary of the article in their own words in at least three to four sentences will receive an additional bonus of 50 cents.**

→

The topic assigned to you is **US inflation**.

Please now spend around **five minutes** to find and read a relevant newspaper article about US inflation.

You can choose to read any newspaper article you want about US inflation. Choose a source that you would normally consult if you wanted to read up on US inflation.

This page will auto-advance after five minutes, but you can submit the page before if you manage to read through the article in less than five minutes.

04 58

→

Please copy the link to the article you read about US inflation in the text box below.

Please write a summary of the article you read about US inflation. Use your own words and respond in three to four sentences.

→

If there are any remarks that you would like to make or clarifications that you would like to obtain, please do let us know by writing them into the field below.

→

**Miami treatment**

The topic assigned to you is **tourist attractions in Miami**.

Please now spend around **five minutes** to find and read a relevant article about tourist attractions in Miami.

You can choose to read any article you want about tourist attractions in Miami. Choose a source that you would normally consult if you wanted to read up on tourist attractions in Miami.

This page will auto-advance after five minutes, but you can submit the page before if you manage to read through the article in less than five minutes.

04 55

→

Please copy the link to the article you read about tourist attractions in Miami in the text box below.

Please write a summary of the article you read about tourist attractions in Miami. Use your own words and respond in three to four sentences.

→