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Narratives about the Macroeconomy

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Abstract

We provide evidence on narratives about the macroeconomy—the stories people tell to explain macroeconomic phenomena—in the context of a historic surge in inflation. We measure economic narratives in open-ended survey responses and represent them as Directed Acyclic Graphs. We apply this approach in surveys with more than 10,000 US households and 100 academic experts and document three main findings. First, households' narratives are strongly heterogeneous and coarser than experts' narratives, focus more on the supply side than on the demand side, and often feature politically loaded explanations. Second, households' narratives strongly shape their inflation expectations, which we demonstrate with descriptive survey data and a series of experiments. Third, an experiment varying news consumption shows that the media is an important source of narratives. Our findings demonstrate the relevance of narratives for understanding macroeconomic expectation formation.

Keywords: Narratives, Expectation Formation, Causal Reasoning, Inflation, Media, Attention.

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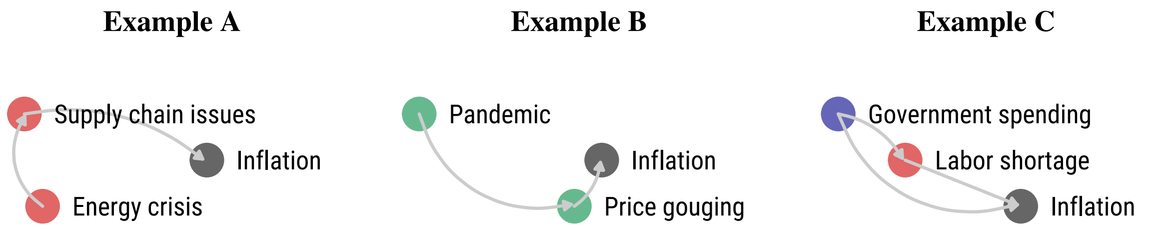
1 Introduction

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 to understand 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, Fuster and Zafar, 2018; Bachmann, Berg and Sims, 2015; Bailey, Dávila, Kuchler and Stroebel, 2018; Giglio, Maggiori, Stroebel and Utkus, 2021). Nonetheless, empirical evidence on economic narratives remains scarce.

In this paper, we consider economic narratives as causal accounts for why an economic event occurred and assess their nature, consequences, and origins in a high-stakes macroeconomic setting: the surge in US inflation experienced in late 2021 and 2022. Our 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 (Reis, 2021). We use this setting to examine three questions. First, what characterizes people's narratives about the historic surge in inflation? Second, what is the role of these narratives in shaping economic expectations? Finally, is the news media an important source of narratives about the macroeconomy?

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. To measure narratives, we ask 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 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. We employ this approach with more than 10,000 respondents. Specifically, we run several descriptive survey waves to characterize and compare households' and experts' inflation narratives and document the development of households' narratives over time. Moreover, we combine the measurement of narratives with experimental treatments that allow us to explore how narratives affect inflation expectations and study whether the news media shapes individuals'

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.

narratives.

We document three sets of results. First, we provide rich descriptive evidence on people's narratives about the rise in inflation, starting with a comparison of households' and experts' narratives. Households' narratives are simpler and more fragmented than those of experts. For example, experts often mention both demand 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 expert narratives, namely the idea that corporate greed and price gouging fueled inflation.

These aggregated results conceal substantial heterogeneity in households' narratives. Individuals differ in the complexity of their narratives (e.g., multi- versus mono-causal) and their selective focus on different parts of the economy (e.g., demand versus supply). This heterogeneity in turn 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 abruptly change over time. Households' narratives immediately adapt to the Russian invasion of Ukraine in our March 2022 survey, illustrating their high responsiveness to changes in the macroeconomic environment.

Our second set of 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 higher government spending 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. A machine learning model shows that the narrative data account for a substantial share of the total variation in inflation expectations.

To shed light on the causal effect of narratives on expectation formation, we conduct four experiments with US households that shift the narratives that are on top of respondents' minds. 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 uses a similar design to show that monetary policy narratives shape inflation expectations. We ran the experiment in June 2022 after a substantial tightening of monetary policy. 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 employs an alternative, complementary approach. It does not provide respondents with a new narrative but instead uses a contextual cue to exogenously draw respondents' attention to the role of government spending. Subsequently, respondents who were induced to think about government spending are more likely to mention the role of government spending in their narratives and—in line with the correlational results—expect higher inflation.

Our fourth experiment illustrates another channel through which narratives affect economic expectations: individuals interpret new information through the lens of their narratives. In a 2x2 factorial 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 over the past 12 months. 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 increase their inflation expectations in response to a higher government spending forecast.

Our final set of results provides support for a frequently-hypothesized source of narratives: the mass media. We conduct an experiment with endogenous news consumption, spread over three consecutive survey waves and a period of five days. In the first and third wave, we measure respondents' pre- and post-treatment inflation narratives. In the second wave, we provide a random subset of participants with monetary incentives to search for and read an article of their choice about US inflation. Respondents are exposed to a rich and diverse set of narratives when reading news about inflation. Moreover, the exogenous increase in news exposure generated by our intervention systematically affects which inflation narratives respondents subsequently invoke: treated respondents explain the rise of inflation with more complex narratives.

Taken together, our findings demonstrate that narratives shape the formation of economic expectations. In short, individuals use narratives about the past to forecast the future, and they interpret new information in light of these narratives. Therefore, narratives have important consequences for economic analysis and policy. For example, the heterogeneity of narratives helps to understand the widely documented disagreement in macroeconomic expectations (Coibion, Gorodnichenko and Kumar, 2018; Dovern, Fritsche and Slacalek, 2012; Giglio et al., 2021). Moreover, narratives provide new challenges and opportunities for policy communication and expectation management. In particular, central banks aiming to convince people that their measures are effective and sufficient to curb inflation could tailor their messages towards popular narratives or actively promote their own narratives.

Our study contributes to the literature on narratives in economics (Bénabou, Falk and Tirole, 2018; Eliaz and Spiegler, 2020; Schwartzstein and Sunderam, 2021; Shiller, 2017, 2020).[1] We provide a tractable empirical approach to measure and characterize economic narratives and provide evidence on their nature, consequences, and origins. Importantly, the DAG-based approach allows us to quantify the *causal structure* of economic narratives, which cannot be detected by existing techniques, such as topic modeling or simple word-counting techniques (e.g., Borup, Hansen, Liengaard and Schütte, 2021; Goetzmann, Kim and Shiller, 2022; Hansen, McMahon and Prat, 2018; Shiller, 2017, 2020).

Our findings contribute to a growing body of literature 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 (Goldfayn-Frank and Wohlfart, 2020; Malmendier and Nagel, 2016), cognitive abilities (D'Acunto, Hoang, Paloviita and Weber, 2019, 2021), exposure to grocery prices (Cavallo, Cruces and Perez-Truglia, 2017; Coibion, Gorodnichenko and Weber, 2022a; D'Acunto, Malmendier, Ospina and Weber, 2021), gas prices (Coibion and Gorodnichenko, 2015b), or monetary policy communication (Coibion, Gorodnichenko and Weber, 2022b; Roth, Wiederholt and Wohlfart, 2022). Our paper is also related to recent work by Andre, Pizzinelli, Roth and Wohlfart (2022) who document large disagreement about the perceived consequences of specific macroeconomic shocks for inflation and unemployment. Our paper contributes to this literature by providing large-scale experimental evidence on the consequences of economic narratives in the context of a high-stakes macroeconomic development—a significant surge in inflation. We show that narratives shape how people interpret the macroeconomic environment and forecast future economic developments.

We also contribute to research on the role of attention and memory in belief formation (Bordalo, Coffman, Gennaioli and Shleifer, 2016; Bordalo, Gennaioli and Shleifer, 2020;

[1]Other work has studied narratives in the moral and political domain (Ash, Gauthier and Widmer, 2021a; Ash, Mukand and Rodrik, 2021b; Bursztyn, Egorov, Haaland, Rao and Roth, 2022b; Levy, Razin and Young, 2022). See Morag and Loewenstein (2021) for an experiment on the role of narratives for the valuation of goods.

Gennaioli and Shleifer, 2010). We document which narratives are on top of people's minds, and our causal evidence highlights that contextual cues and attention shape people's reasoning about the economy and their macroeconomic expectations.

Finally, our evidence that media exposure shapes people's narratives about the macroeconomy relates to a growing body of literature on the role of mass media in spreading narratives (Bursztyn, Rao, Roth and Yanagizawa-Drott, 2022a; Bybee, Kelly, Manela and Xiu, 2021; Larsen and Thorsrud, 2021; Levy, 2021) and driving economic expectations and decisions (Chopra, 2021; Coibion et al., 2022b; Pedemonte, 2020). We contribute to this literature by providing direct experimental evidence on the role of mass media in shaping the narratives that people invoke to explain an economic phenomenon.

Our paper proceeds as follows: In Section 2, we provide a working definition of narratives. In Section 3, we present the data and the survey design. In Section 4, we present descriptive evidence on the prevalence and nature of narratives about the rise in inflation. In Section 5, we provide descriptive and causal evidence on the link between narratives and expectation formation. In Section 6, we shed light on the role of the media as a source of narratives. Finally, we conclude in Section 7.

2 Narratives: A Working Definition

This paper explores which narratives individuals invoke to explain a major macroeconomic event. This section introduces a 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 "sequence of causally linked events and their underlying sources." Similarly, psychologists have argued that causality is at the core of narratives (Pennington and Hastie, 1992; Sloman and Lagnado, 2015; Trabasso and van den Broek, 1985).

In this paper, we zoom in on this fundamental element of narratives and consider economic narratives as *causal accounts for past economic events*. Our focus is on backward-looking narratives. They offer the methodological and conceptual advantage that we can fix and clearly define the past event in which we are interested, allowing us to examine how individuals differ in their explanations of the same event.[2]

[2]By contrast, forward-looking narratives—i.e., explanations for expected future events—directly conflate people's narratives with their expectations. For instance, people who think inflation will be 10% in one year might invoke systematically different narratives than people who think inflation will be anchored at 2%, but these correlations might be driven by differences in the expected event that people explain rather than differences in how

Motivated by theoretical work on causal reasoning (Eliaz and Spiegler, 2020), we represent narratives 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] A central advantage of this DAG-based approach is that each narrative can be represented quantitatively by its graph, which in turn can be represented by a numeric adjacency matrix.

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 and the ensuing increased energy prices 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. This last narrative is indeed commonly invoked among our respondents.

As a theoretical tool to represent causality, DAGs are widely used in statistics, computer science, the social sciences, and philosophy (Hitchcock, 2020; Pearl, 2009; Sloman and Lagnado, 2015; Spiegler, 2020). DAGs also constitute a flexible and powerful empirical tool to document and study people's narratives. They can express simple, mono-causal accounts as well as complex, nuanced views of the world. And they allow us to capture the rich causal structure of economic narratives in a simple, quantitative, and comparable way.

3 Setting, Data, and Design

3.1 Setting

We study narratives about the macroeconomy in the context of rising inflationary pressures in late 2021 and early 2022. The topic of rising inflation received increased media attention from November 2021 onwards when the inflation rate surged 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 inflation up to 8.6% involved high stakes for many households, e.g., in the form of changes in real income or the

people interpret the same data. Our focus on backward-looking narratives thus increases interpersonal comparability. And, when studying the effect of narratives on expectations, the approach avoids the potentially confounding reverse effect of expectations on forward-looking narratives.

[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).

real value of assets and debt.[4] 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 on top of people's minds thus potentially affects expectation formation.

The increase in inflationary pressures 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 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.

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, Roth and Wohlfart, 2021). As shown in 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). 39% of our respondents have pre-tax annual income above $75,000, compared to 48% in the ACS. Our sample is also reasonably close to the population in terms of education: 42.3% 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 Table A.1 shows that the additional samples resemble the November 2021 sample in terms of demographic characteristics. 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 C of the Online Appendix for more details). Overall, 111 experts participated in our survey. Appendix Table A.2 shows summary statistics for the expert sample. 50.5% of the experts are based in the United States.[5]

[4] The level of 8.6% was reached in May, and the corresponding data were released in June.
[5] Responses of experts that are based outside the US are similar to those of experts based in the US.

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). 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 E.1 in the Online Appendix provides the core survey instructions.[6]

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.[7] 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 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 (Ferrario and Stantcheva, 2022). 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 on top of their minds (Bordalo et al., 2020; 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

[6]Detailed instructions are available on the following link: `https://osf.io/av48u/`.

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

open-ended questions is that they require more effort from respondents, which could introduce additional measurement error.

Inflation expectations We elicit probabilistic expectations about inflation over the next 12 months and five years from the survey. 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.

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. Our goal is to capture the broad range of causes that laypeople and experts talk about. The factors are designed to 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 in our coding scheme 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 (see Table 1 for the complete list).[8]

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*.

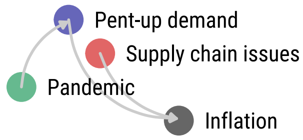
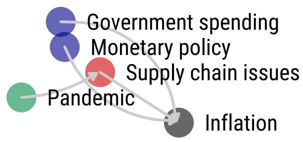
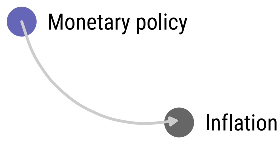
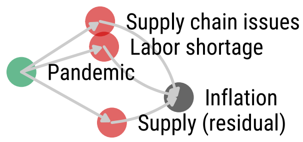
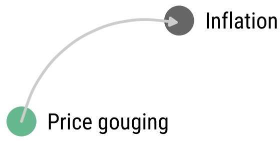
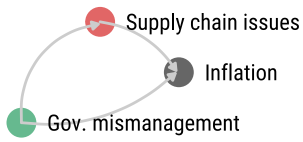
[8] We added the "Russia-Ukraine war" code to the coding scheme in March 2022. Virtually none of the responses collected before March 2022 refers to Russia's aggression against Ukraine.

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 [...]" "[...] 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	Policy failure, mismanagement by policymakers, policymakers are blamed.	"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.

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 artificial intelligence methods still have difficulties detecting the (often implicit) causal structure in human language, while this task is natural and intuitive for humans. Thus, human coding allows us to capture the full richness of our narrative data. Nevertheless, one drawback of human judgment is its subjectivity, in particular in light of the inherent ambiguities of language. 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.[9] Wherever a conflict occurs, the case is revisited and a final decision is made.[10] This approach reduces the likelihood that any particular causal connection is overlooked and ensures that difficult cases are reviewed a third time. To illustrate the results of this coding procedure, Table 2 above presents a series of example narratives from experts and households and their corresponding DAGs.

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. 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) were assigned to this category.

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 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 corresponding figure is 93% for supply-side mechanisms.

Fourth, we test whether respondents' narratives reflect the views about the drivers of past

[9] 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.

[10] The conflict resolution was conducted by a member of the research team for the November wave. In later descriptive waves, research assistants took over the task. 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 6.

inflation that they would express in a structured question format. In an auxiliary data collection in May 2022 with 485 respondents on Prolific, we elicit respondents' open-ended narratives and their beliefs about what drove the inflation increase using a structured survey question. 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 Appendix Figure B.9). This finding also highlights that narratives about the past shape people's models of the future development of inflation.

Fifth, 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 that we 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. We detect a high test-retest reliability. 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 ($p < 0.01$).[11]

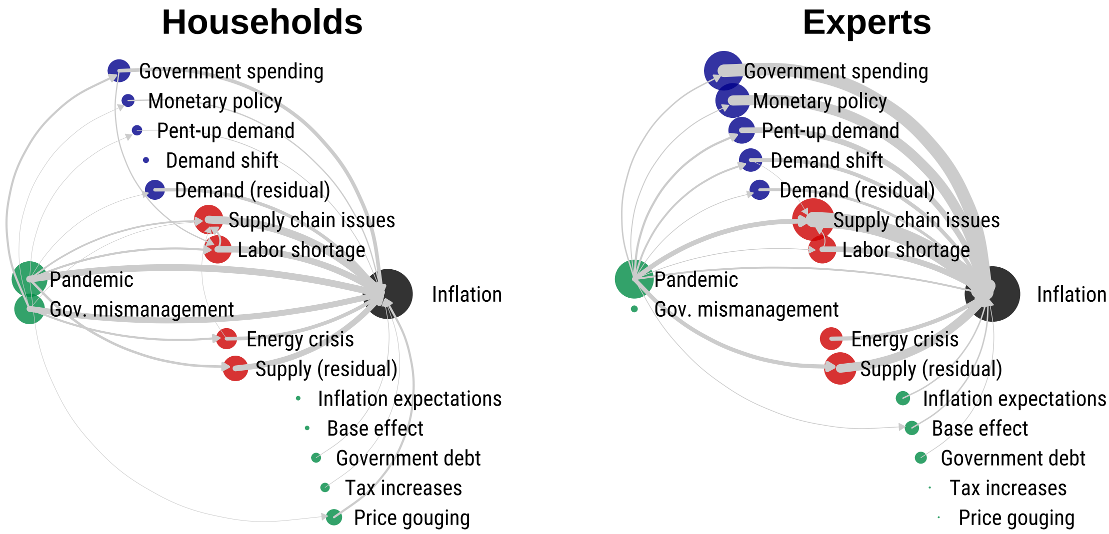
Finally, we use a LASSO procedure to examine how accurately the assignment of the different narrative factors can be predicted from the open-text data. The high accuracy of these predictions, usually around 90%, illustrates that the manual DAG coding is highly sensitive to and firmly grounded in the open-text data (see Appendix Table A.11). 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.

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

[11] This average correlation conceals small variations in the persistence of different factors in people's narratives (see Appendix Figure B.8).

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.

"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).

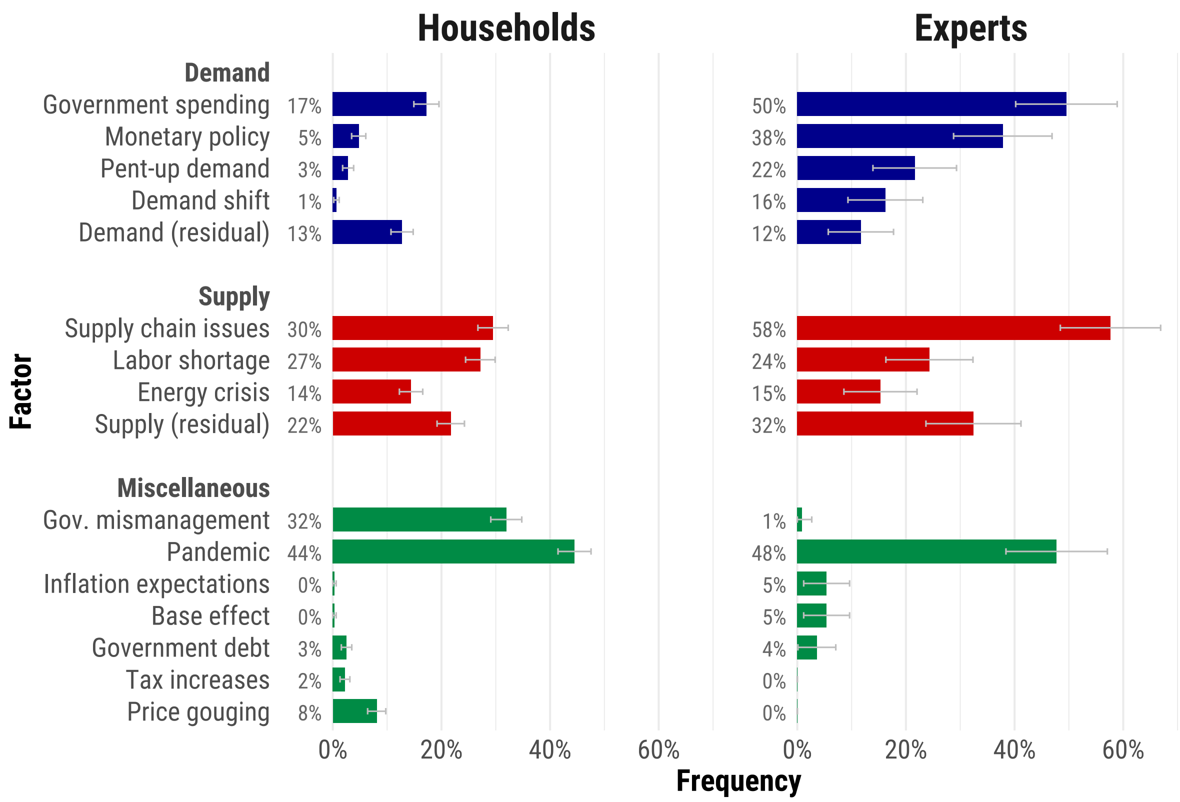
4.1 Comparison of Households' and Experts' Narratives

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 complex, and indicate a coarser understanding of the economy. Expert DAGs include on average 4.3 factors (including inflation) and 3.6 links, while household DAGs contain only 3.5 factors and 2.8 links (for both comparisons: $p < 0.01$).[12] For example, Figure 2 shows that households often attribute the rise in inflation

[12]The differences persist if we control for the response time and the number of words that respondents use in

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.

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 demand *and* a supply 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 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 (29%; 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

their open-ended explanation (see Appendix Table A.10). Hence, they do not simply reflect differences in effort and care by household and expert respondents but rather reflect differences in their understanding of the rise in inflation.

(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 for high inflation—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' narratives 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). Some of the most complex narrative structures among households emanate from "government mismanagement."

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.[13]

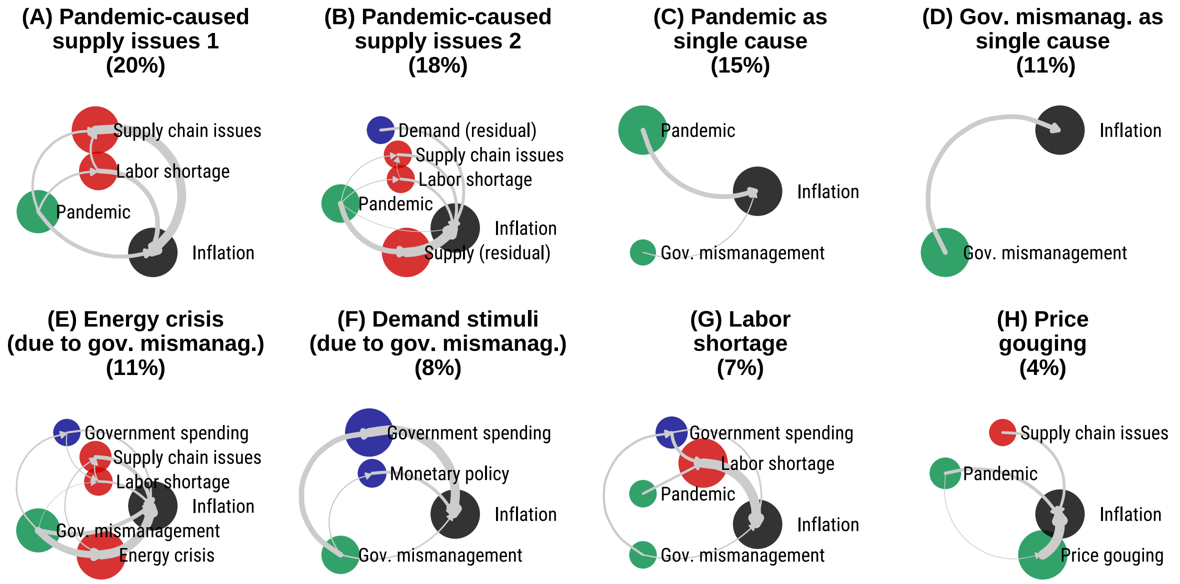
4.2 Heterogeneity and Narrative Clusters

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 narrative factor is 58% at the maximum (supply chain issues). These numbers already 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 similarity between two narratives i and j as the Jaccard difference $D(i, j)$ between the edge lists of their DAGs (E_i and E_j):

[13]Other explanations for the rise in inflation are much less common and are thus not included in our coding scheme. For example, the ideas that US border policies, immigration, or climate change are driving US inflation are only mentioned by very few respondents.

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 D). 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.

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

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 Appendix D, which also shows that we can replicate the results with an alternative cosine distance measure.[14]

Figure 4 presents the resulting clusters and their average DAGs. Four clusters (A, B, E,

[14]The most important technical details are: (i) we use the average linkage method (see Figure D.1 for the dendrogram); (ii) we use the Silhouette method to determine the optimal number of clusters, which turns out to be fifteen; (iii) we only display clusters with at least 30 observations (i.e., at least approximately 3% of the total sample) to focus on those that are unlikely to be the product of noise; and (iv) within each cluster, we drop factors that occur in less than 20% of narratives and connections that occur in less than 5% of narratives to highlight the most characteristic features of a cluster. Appendix D confirms the robustness of our results to these procedural details.

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 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.

The results reveal that households' narratives can be classified into distinct clusters that differ in both their complexity and in their focus on aspects of the overall economic situation. Thus, when households think about the rise in inflation, distinctly different explanations come to their minds.

4.3 Correlates of Narratives

The heterogeneity of households' narratives raises the question of whether narratives systematically differ across socio-demographic groups. 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"; Appendix Table A.6), (ii) dummies for whether a narrative that belongs to a specific cluster is expressed (e.g., the cluster "Pandemic as single cause"; Appendix Table A.7), and (iii) various measures of narrative complexity (Appendix Table A.8).

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 25 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 39 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 20 pp more often, $p < 0.01$) or high energy prices (mentioned 15 pp more often, $p < 0.01$).

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 have longer causal chains. All differences are highly statistically significant, hinting at the potential powerful role of media consumption in the formation of narratives.

Finally, men provide significantly less complex 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 complex narratives.

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 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 change quite abruptly in response to major economic and political events, and thus could play a particularly important role in driving short-term economic fluctuations.

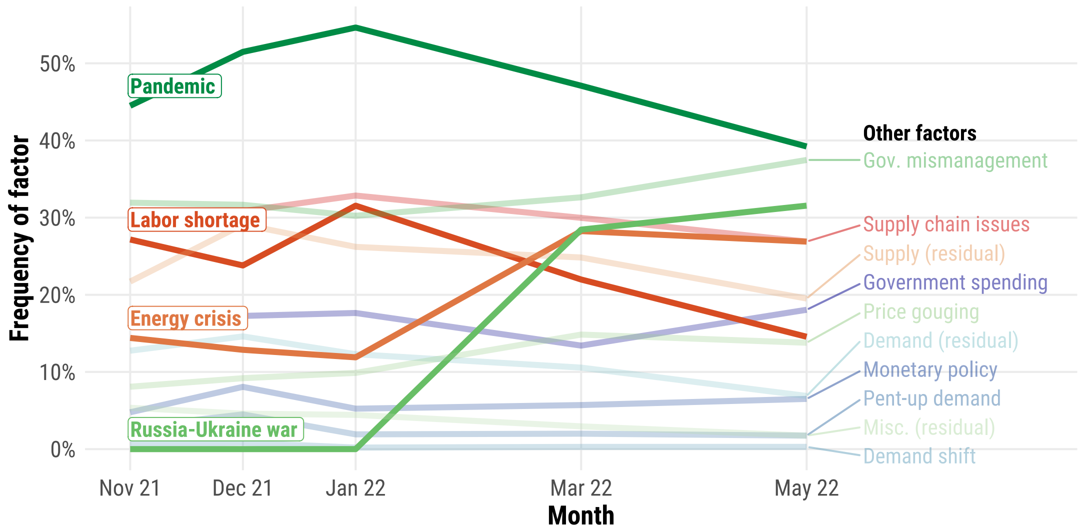
4.5 Summary of Descriptive Evidence

We summarize our first descriptive set of results as follows:

Result 1.

a) Households' narratives focus more on the supply than on the demand side. They are often politicized, and mention accounts that are absent in experts' narratives, such as the idea that price gouging fuels inflation. Households' narratives are simpler and more fragmented than those of experts.

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.

b) Households' narratives are highly heterogeneous and differ in their complexity and their selective focus on different aspects of the economy.

c) This heterogeneity is systematically related to individual characteristics, in particular political affiliation and news consumption.

d) Narratives can change abruptly in response to economic or political 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.[15] We start by providing correlational evidence, using our descriptive survey waves. Then, we present experiments that exogenously vary which narratives are on top of our respondents' minds. 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 calculate a respondent's expected inflation rate as the mean of the respondent's subjective probability distribution.[16] We proceed in three steps.

First, we ask which narrative factors are associated with higher and lower inflation expectations, respectively. Table 3 regresses respondents' 1-year-ahead and 5-year-ahead 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.[17] 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 0.180 pp lower inflation rate one year ahead ($p = 0.457$) and a 0.623 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 (0.740 pp; $p < 0.01$) and five years later (0.361 pp; $p = 0.222$), 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 (1.234 pp; $p < 0.01$) and five years later (0.821 pp; $p < 0.01$), as do households with narratives mentioning government spending,

[15]We focus on households because their expectations are central in macroeconomic models and because our expert sample is too small to provide meaningful evidence on the role of narratives in experts' inflation forecasts.

[16]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 (resulting to a change in our coding scheme with an own category for the Russia–Ukraine war). Results are similar if we also include the waves from March and May 2022. We calculate the means using the midpoints of the bins containing the different potential inflation realizations, assigning -12% and 12% to the extreme bins of "less than -12%" and "above 12%."

[17]Figure B.2 shows similar results without the inclusion of demographic controls.

consistent with a view that government intervention in the economy is a more chronic cause of high inflation rates.[18]

Next, we investigate which share of the variation in inflation expectations can be statistically explained by narratives. 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. To avoid overfitting, 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 R^2 for the test data.[19] We estimate that the narrative data account for approximately 10% of the variation in respondents' mean 1-year-ahead inflation expectation (Appendix Table A.12).[20] 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). 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 (Appendix Table A.13).

Finally, we 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 (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 of narratives captures the essence of information contained in the text data.

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 four experiments.

[18]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.9). For instance, individuals telling stories focused on higher government spending or mismanagement by the government are less uncertain about future inflation at both the one- and five-year horizon.

[19]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.

[20]We find similar results when employing support vector regressions instead of the LASSO procedure.

Table 3: Correlations between narratives and inflation expectations

	Expected inflation rate (in %)	
	(1) 1 year	(2) 5 years
Demand factors:		
Monetary policy	1.018***	0.422
	(0.269)	(0.315)
Government spending	0.624***	0.340
	(0.188)	(0.219)
Pent-up demand	-0.180	-0.623**
	(0.242)	(0.308)
Residual demand	-0.277	-0.229
	(0.191)	(0.205)
Supply factors:		
Supply chain issues	0.548***	0.068
	(0.145)	(0.157)
Labor shortage	0.355**	0.148
	(0.148)	(0.166)
Energy	0.740***	0.361
	(0.195)	(0.222)
Residual supply	0.160	-0.194
	(0.145)	(0.162)
Other factors:		
Pandemic	-0.081	0.070
	(0.147)	(0.161)
Government mismanagement	1.234***	0.821***
	(0.181)	(0.197)
Price gouging	0.763***	0.568**
	(0.231)	(0.248)
N	2,951	2,951
Controls	Yes	Yes
Survey FE	Yes	Yes
Mean	4.86	3.99

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' future 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 (Eyal, David, Andrew, Zak and Ekaterina, 2021). The experiment proceeds in two waves, namely a baseline survey in which respondents are assigned to different treatment groups and a follow-up survey 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 survey to the follow-up survey across the two narrative treatment arms described below (p = 0.527), yet there is somewhat lower attrition in the pure control group compared to the two narrative treatments (p = 0.030). 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.[21] 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. Appendix E.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 Appendix Figure B.3). 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.

[21] 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) Pent-up	(2) Energy	(3) Confidence	(4) Main	(5) 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.

We start by comparing respondents' narratives across the different treatment groups. For simplicity, we focus on the frequency with which respondents mention 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 2.8% among the control group respondents. Similarly, being exposed to the energy treatment increases the fraction of respondents mentioning the energy crisis when asked about the driver of higher inflation by 29 pp (column 2, $p < 0.01$), compared to 17.5% among control group respondents.[22] 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.[23] Moreover, column 3 shows that both the energy treatment ($p < 0.05$) and the pent-up demand treatment ($p < 0.01$) increase respondents' confidence in their understanding of why the inflation rate increased, consistent with the notion

[22]In addition, the pent-up demand treatment reduces the fraction mentioning the energy crisis by 7.9 pp. As highlighted in Appendix Figure B.4, we also observe small crowding-out effects on other narrative factors.

[23]The large "first stage" effect on narratives has the methodological advantage that it increases the statistical power of the experimental design. However, the result does not imply that narratives are commonly easy to shift. First, respondents' narratives primarily change in one explicitly targeted dimension (pent-up demand versus energy crisis) while many other factors and causal connections remain unaffected. Second, the increase in inflation was a relatively recent phenomenon so that people's narratives might be especially malleable.

that narratives help individuals to 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, $p = 0.911$). A potential reason for the muted effect of the energy crisis treatment is that inflationary worries among households were already elevated at the time of our survey, which may reduce the scope to shift inflation expectations further upward. 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.[24]

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. We hypothesize that the monetary policy narrative which argues that loose monetary policy was a key driver of the 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 data collection, we confirm that a majority of 61% of respondents are aware

[24]Here and below, we consider it very unlikely that the treatment effects are driven by experimenter demand effects (de Quidt, Haushofer and Roth, 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 survey 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.10), and the estimates are virtually identical if we restrict our main specification to respondents who do not correctly guess the hypothesis (results available upon request).

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 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 (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.

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 ($p < 0.01$). Because both treatment groups receive 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 ($p < 0.01$).[25]

Together, the two narrative provision experiments show that being exposed to different narratives about the past causally changes households' future inflation expectations.

5.3 The Causal Effect of Attention

Our next experiment uses an alternative approach to shift which narratives are on top of people's minds. It does not provide respondents with a new narrative but instead uses a contextual cue

[25] Only 6.1% of respondents correctly guess the hypothesis of the experiment (Panel B of Figure B.10). Results are virtually identical if we restrict our main specification to respondents that do not correctly guess the hypothesis (results available upon request).

Table 6: Attention experiment

	(1) Narrative: Gov. spending	(2) Expected 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.

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.[26] 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.

Sample We collect a sample of 1,126 Prolific respondents on December 10–12, 2021. Summary statistics are shown in 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 Appendix E.5 for the key survey questions).

Results Table 6 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 compared 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

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

higher than the control group mean of 6.6% (p = 0.019), an increase that corresponds to 14% of a standard deviation.[27]

These findings corroborate the positive relationship between government spending narratives and respondents' inflation expectations that we documented in Section 5.1 and further corroborate the idea that narratives shape households' expectations. Moreover, the fact that respondents' narratives strongly change in response to a simple contextual cue suggests that selective attention is central to which narratives are invoked by individuals, consistent with recent work on memory and belief formation (Bordalo et al., 2020).

5.4 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 also affect how people form their economic expectations in response to new information. We explore this in an additional experiment which, again, 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 government spending narrative will adjust their inflation expectations more strongly to forecasts about future government spending.

Sample We use Prolific to collect a sample of 997 respondents on April 27 and 28, 2022. Appendix Table A.3 provides summary statistics.

Design 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. 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 of our respondents are shown information about future changes in government spending. Specifically, we provide them with one of two forecasts from

[27] Only 3.2% of respondents correctly guess the hypothesis of the experiment (Panel C of Figure B.10). 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).

individual experts who participated in the first quarter of 2022 wave of the Survey of Professional Forecasters. Respondents in the "low government spending" group receive a forecast from an expert who predicts a decrease in real federal government spending by 4% over the next 12 months. By contrast, respondents in the "high government spending" group are shown an expert forecast predicting a 6% increase. The active control group 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., 2021).

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. Appendix E.6 provides the core survey instructions.

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 7 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 respondents 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 receive the energy narrative update their spending expectations slightly more than those who receive the spending narrative, although the difference between the two estimates is not statistically significant ($p = 0.134$).

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 difference in 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,

Table 7: 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.

the difference between these coefficients is highly statistically significant ($p < 0.01$).[28] This demonstrates that exposure to narratives can have a quantitatively important impact on how new information shapes expectation formation.

5.5 Summary

Taken together, the evidence presented in this section shows that narratives play an important role in households' expectation formation. We summarize our second main result as follows:

Result 2. Households' expectations about future inflation systematically correlate with the narratives they invoke to explain the recent inflation increase. Moreover, the provision of narratives and contextual cues causally affects the narratives individuals invoke and their subsequent inflation expectations. Finally, narratives influence how individuals interpret new information and adjust their expectations.

6 Narratives Are Shaped by News Media

What are the sources of the narratives that individuals endorse? One important candidate is the news media. The news media is the primary source of macroeconomic information for most 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 the effect of exposure to endogenously chosen news content.

6.1 Sample

We collect data for this experiment between February 8–12, 2022. As in the experiments described in the previous section, 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 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 ($p = 0.597$).

[28]Only 9.5% of respondents correctly guess the hypothesis of the experiment (Panel D of Figure B.10). Results are virtually identical if we restrict the main specification to respondents that do not correctly guess the hypothesis (results available upon request).

6.2 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.[29] Next, we randomly assign 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 to deal with potential differential attrition that could arise from people's unwillingness to complete the task of looking up and summarizing news articles. 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

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

our respondents how many online or offline newspaper articles they read about the latest-released inflation numbers. Appendix E.7 provides the core instructions of the media experiment.

6.3 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).[30]

The average news narrative (Appendix Figure B.6) is complex and features an 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:

$$\mathrm{y}_{i3} = \alpha_0 + \alpha_1 \mathrm{Treatment}_i + \alpha_2 \mathrm{y}_{i1} + \alpha_3 \mathbf{x}_i + \varepsilon_{i3} \tag{1}$$

[30]There is also substantial heterogeneity in the sources that our respondents consult (Appendix Figure B.5). 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.

where y_{i3} is the outcome variable for individual i from wave 3 such as whether an individual invokes any supply-side narrative; 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); 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 ε_{i3} is an individual-specific error term. We use robust standard errors in all specifications.

Table 8 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% ($p < 0.01$).[31] This increased exposure to inflation-related news translates into an increase in the complexity of people's causal 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 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 Appendix Figures Figure B.6 and Figure B.7). 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 ($p < 0.01$, Appendix Figure B.7). 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, Appendix Table A.14 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.

The results from our media experiment can be summarized as follows:

Result 3. 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. Thus, the mass media is an important source of households' narratives about the macroeconomy.

[31] 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 8: 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.

7 Conclusion

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 complex than those of experts. They also focus more on supply-side than on demand-side factors and often feature politically loaded 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 shifting the narratives that are on top of people's minds causally affects their inflation expectations and how they interpret new inflation-related information. A final experiment sheds light on the origins of narratives. Giving people incentives to read news articles about inflation affects their narratives, indicating that the mass media is an important source of households' narratives.

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) but 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, Peichl, Roth and Wohlfart, 2020; Mankiw, Reis and Wolfers, 2003).

Our evidence suggests that economic narratives also matter for policy communication. Economic agents forecast the future and interpret new information in light of their explanations of the past. Hence, policy communication could be tailored towards existing narratives. Policy-makers who aim to keep inflation expectations anchored should be aware that they communicate with people who hold very heterogeneous accounts for why inflation has increased. They could even engage in "narrative management" and actively promote new or correct misleading narratives. Indeed, we show experimentally that narratives about the role of monetary policy affect people's future inflation expectations.

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.

References

Akerlof, George A. and Dennis J. Snower, "Bread and Bullets," *Journal of Economic Behavior & Organization*, 6 2016, *126*, 58–71.

Andre, Peter, Carlo Pizzinelli, Christopher Roth, and Johannes Wohlfart, "Subjective Models of the Macroeconomy: Evidence from Experts and Representative Samples," *The Review of Economic Studies*, 2022.

Armona, Luis, Andreas Fuster, and Basit Zafar, "Home Price Expectations and Behaviour: Evidence from a Randomized Information Experiment," *The Review of Economic Studies*, 2018, *86* (4), 1371–1410.

Ash, Elliott, Germain Gauthier, and Philine Widmer, "RELATIO: Text Semantics Capture Political and Economic Narratives," *Working Paper*, 2021.

_ , Sharun Mukand, and Dani Rodrik, "Economic Interests, Worldviews, and Identities: Theory and Evidence on Ideational Politics," *Working Paper*, 2021.

Bachmann, Rüdiger, Tim O Berg, and Eric R Sims, "Inflation Expectations and Readiness to Spend: Cross-Sectional Evidence," *American Economic Journal: Economic Policy*, 2015, *7*, 1–35.

Bailey, Michael, Eduardo Dávila, Theresa Kuchler, and Johannes Stroebel, "House Price Beliefs And Mortgage Leverage Choice," *Review of Economic Studies*, 11 2018, *86* (6), 2403–2452.

Bénabou, Roland, Armin Falk, and Jean Tirole, "Narratives, Imperatives, and Moral Reasoning," *NBER Working Paper No. 24798*, July 2018.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer, "Stereotypes," *The Quarterly Journal Economics*, 2016, *131* (4), 1753–1794.

_ , Nicola Gennaioli, and Andrei Shleifer, "Memory, Attention, and Choice," *The Quarterly Journal of Economics*, 08 2020, *135* (3), 1399–1442.

Borup, Daniel, Jorge W. Hansen, Benjamin Liengaard, and Erik C. M. Schütte, "Quantifying Investor Narratives and Their Role During COVID-19," *Working Paper*, 2021.

Bruner, Jerome, "The Narrative Construction of Reality," *Critical Inquiry*, 10 1991, *18* (1), 1–21.

Bursztyn, Leonardo, Aakaash Rao, Christopher P. Roth, and David H. Yanagizawa-Drott, "Opinions as Facts," *The Review of Economic Studies*, 2022.

_ , Georgy Egorov, Ingar K. Haaland, Aakaash Rao, and Christopher Roth, "Justifying Dissent," *NBER Working Paper No. 27288*, May 2022.

Bybee, Leland, Bryan T. Kelly, Asaf Manela, and Dacheng Xiu, "Business News and Business Cycles," *Working Paper*, 2021.

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia, "Inflation Expectations, Learning, and Supermarket Prices: Evidence from Survey Experiments," *American Economic Journal: Macroeconomics*, 2017, *9* (3), 1–35.

Chopra, Felix, "Media Persuasion and Consumption: Evidence from the Dave Ramsey Show," *Available at SSRN*, 2021.

Coibion, Olivier and Yuriy Gorodnichenko, "What Can Survey Forecasts Tell us about Information Rigidities?," *Journal of Political Economy*, 2012, *120* (1), 116–159.

_ **and** _ , "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts," *American Economic Review*, 2015, *105* (8), 2644–2678.

_ **and** _ , "Is the Phillips Curve Alive and Well after All? Inflation Expectations and the Missing Disinflation," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 197–232.

_ **,** _ **, and Michael Weber**, "The Expected, Perceived, and Realized Inflation of U.S. Households Before and During the COVID19 Pandemic," *NBER Working Paper No. 29640*, 2022.

_ **,** _ **, and** _ , "Monetary Policy Communications and Their Effects on Household Inflation Expectations," *Journal of Political Economy*, 2022, *130* (6), 1537–1584.

_ **,** _ **, and Saten Kumar**, "How Do Firms Form Their Expectations? New Survey Evidence," *American Economic Review*, 2018, *108* (9), 2671–2713.

D'Acunto, Francesco, Daniel Hoang, Maritta Paloviita, and Michael Weber, "Cognitive Abilities and Inflation Expectations," *American Economic Review Papers and Proceedings*, 2019, *109* (01), 562–566.

_ **,** _ **,** _ **, and** _ , "IQ, Expectations, and Choice," *Review of Economic Studies*, 2021.

de Quidt, Jonathan, Johannes Haushofer, and Christopher Roth, "Measuring and Bounding Experimenter Demand," *American Economic Review*, 2018, *108* (11), 3266–3302.

Dovern, Jonas, Ulrich Fritsche, and Jiri Slacalek, "Disagreement Among Forecasters in G7 Countries," *The Review of Economics and Statistics*, 2012, *94* (4), 1081–1096.

D'Acunto, Francesco, Ulrike Malmendier, Juan Ospina, and Michael Weber, "Exposure to Grocery Prices and Inflation Expectations," *Journal of Political Economy*, 2021, *129* (5), 1615–1639.

Eliaz, Kfir and Ran Spiegler, "A Model of Competing Narratives," *American Economic Review*, 2020, *110* (12), 3786–3816.

Eyal, Peer, Rothschild David, Gordon Andrew, Evernden Zak, and Damer Ekaterina, "Data Quality of Platforms and Panels for Online Behavioral Research," *Behavior Research Methods*, 2021, pp. 1–20.

Ferrario, Beatrice and Stefanie Stantcheva, "Eliciting People's First-Order Concerns: Text Analysis of Open-Ended Survey Questions," *American Economic Association Papers & Proceedings*, 2022.

Gennaioli, Nicola and Andrei Shleifer, "What Comes to Mind," *The Quarterly Journal of Economics*, 2010, *125* (4), 1399–1433.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, "Five Facts about Beliefs and Portfolios," *American Economic Review*, 2021, *111* (5), 1481–1522.

Goetzmann, William N, Dasol Kim, and Robert J Shiller, *Crash Narratives* 2022.

Goldfayn-Frank, Olga and Johannes Wohlfart, "Expectation Formation in a New Environment: Evidence from the German Reunification," *Journal of Monetary Economics*, 2020, *115*, 301–320.

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart, "Designing Information Provision Experiments," *Journal of Economic Literature*, 2021.

Hansen, Stephen, Michael McMahon, and Andrea Prat, "Transparency and Deliberation within the FOMC: A Computational Linguistics Approach," *The Quarterly Journal of Economics*, 2018, *133* (2), 801–870.

Hitchcock, Christopher, "Causal Models," in "Stanford Encyclopedia of Philosophy," Zalta, Edward N., 2020.

Larsen, Vegard and Leif Anders Thorsrud, "Business Cycle Narratives," *Working Paper*, 2021.

Levy, Gilat, Ronny Razin, and Alwyn Young, "Misspecified Politics and the Recurrence of Populism," *American Economic Review*, 2022, *112* (03), 928–962.

Levy, Ro'ee, "Social Media, News Consumption, and Polarization: Evidence from a Field Experiment," *American Economic Review*, 2021, *111* (3), 831–70.

Link, Sebastian, Andreas Peichl, Christopher Roth, and Johannes Wohlfart, "Information Frictions Among Firms and Households," *Available at SSRN 3739940*, 2020.

Malmendier, Ulrike and Stefan Nagel, "Learning from Inflation Experiences," *The Quarterly Journal of Economics*, 2016, *131* (1), 53–88.

Mankiw, N. Gregory and Ricardo Reis, "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *The Quarterly Journal of Economics*, 2002, *117* (4), 1295–1328.

_, _, and Justin Wolfers, "Disagreement About Inflation Expectations," *NBER Macroeconomics Annual*, 2003, *18*, 209–248.

Morag, Dor and George F. Loewenstein, "Narratives and Valuations," *Available at SSRN 3919471*, 2021.

Pearl, Judea, *Causality: Models, Reasoning, and Inference*, 2 ed., Cambridge: Cambridge University Press, 2009.

Pedemonte, Mathieu, "Fireside Chats: Communication and Consumers' Expectations in the Great Depression," *FRB of Cleveland Working Paper No. 20-30*, 2020.

Pennington, Nancy and Reid Hastie, "Explaining the Evidence: Tests of the Story Model for Juror Decision Making," *Journal of Personality and Social Psychology*, 1992, *62* (2), 189–206.

Reis, Ricardo, "Inattentive Consumers," *Journal of Monetary Economics*, 2006, *53* (8), 1761–1800.

_, "Losing the inflation anchor," CEPR Discussion Papers 16664, C.E.P.R. Discussion Papers October 2021.

Roth, Christopher, Mirko Wiederholt, and Johannes Wohlfart, "The Effects of Monetary Policy: Theory with Measured Expectations," *ECONtribute Discussion Paper No. 126*, 2022.

Schwartzstein, Joshua and Adi Sunderam, "Using Models to Persuade," *American Economic Review*, 2021, *111* (1), 276–323.

Shiller, Robert J., "Narrative Economics," *American Economic Review*, 2017, *107* (4), 967–1004.

Shiller, Robert J, *Narrative Economics: How Stories Go Viral and Drive Major Economic Events*, Princeton University Press, 2020.

Sloman, Steven A. and David Lagnado, "Causality in Thought," *Annual Review of Psychology, Available at SSRN*, 2015, *66*, 223–247.

Spiegler, Ran, "Behavioral Implications of Causal Misperceptions," *Annual Review of Economics*, 2020, *12* (1), 81–106.

Trabasso, Tom and Paul van den Broek, "Causal Thinking and the Representation of Narrative Events," *Journal of Memory and Language*, 1985, *24* (5), 612–630.

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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	0.486	0.471	0.450	0.470	0.498
Age (years)	47.78	53.792	48.985	51.815	51.234	56.145
Employed	0.620	0.499	0.555	0.508	0.500	0.429
College	0.31	0.422	0.487	0.414	0.431	0.298
High income	0.482	0.389	0.386	0.352	0.317	0.274
Northeast	0.17	0.200	0.197	0.223	0.185	0.211
Midwest	0.21	0.245	0.241	0.236	0.245	0.225
South	0.38	0.399	0.378	0.415	0.349	0.355
West	0.24	0.156	0.184	0.126	0.222	0.209
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) Attention Dec 2021	(2) Media Feb 2022	(3) Narrative provision April 2022	(4) Info interpretation April 2022	(5) Monetary policy June 2022
Male	0.419	0.477	0.424	0.347	0.471
Age (years)	35.455	39.894	37.354	38.162	33.045
Employed	0.702	0.718	0.679	0.662	0.664
College	0.582	0.636	0.592	0.562	0.500
High income	0.432	0.427	0.408	0.388	0.367
Northeast	0.189	0.182	0.211	0.203	0.180
Midwest	0.225	0.231	0.213	0.193	0.192
South	0.385	0.363	0.342	0.364	0.412
West	0.202	0.224	0.234	0.240	0.217
Observations	1,126	763	1,329	977	1,069

Note: This table displays the mean value of basic covariates from the attention experiment in December 2021 (column 1), the final wave of the media experiment in February 2022 (column 2), the first wave of the narrative provision experiment in April 2022 (column 3), the interpretation of information experiment in April 2022 (column 4), and the first wave of the monetary policy narrative provision experiment (column 5). "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 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) Structured May 2022	(2) Test–retake 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
Attention Experiment (December 2021)	Prolific (n = 1,126)	Government prime treatment versus control group	Inflation narratives and inflation expectations
Narratives and the Interpretation of New Information (April 2022)	Prolific (n = 977)	(Government spending narrative vs. energy shortage narrative) $\times$ (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: 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	0.038***	0.031	-0.027***	-0.052**	-0.112***	-0.092***	-0.017	-0.066**	0.054**	-0.117***
	(0.013)	(0.023)	(0.010)	(0.021)	(0.028)	(0.028)	(0.021)	(0.026)	(0.027)	(0.031)
High age	-0.021*	-0.003	0.002	-0.020	0.092***	0.000	0.004	0.018	0.015	0.034
	(0.011)	(0.016)	(0.005)	(0.018)	(0.021)	(0.020)	(0.013)	(0.022)	(0.021)	(0.027)
College degree	0.013	0.015	0.012	0.015	0.047	0.006	0.070**	-0.040	-0.028	0.040
	(0.020)	(0.030)	(0.014)	(0.030)	(0.039)	(0.037)	(0.028)	(0.034)	(0.033)	(0.039)
College-level econ	0.024	0.016	0.008	0.002	0.034	-0.009	0.001	0.010	-0.025	-0.009
	(0.015)	(0.027)	(0.011)	(0.025)	(0.034)	(0.033)	(0.025)	(0.031)	(0.031)	(0.035)
Full-time employee	-0.013	-0.059**	-0.034**	-0.040	-0.169***	-0.087***	-0.072***	-0.020	-0.058*	-0.030
	(0.015)	(0.028)	(0.014)	(0.024)	(0.034)	(0.034)	(0.024)	(0.031)	(0.031)	(0.036)
High income	0.029*	-0.010	0.017	0.013	0.045	-0.013	-0.020	0.079**	-0.012	-0.016
	(0.017)	(0.029)	(0.016)	(0.026)	(0.035)	(0.034)	(0.025)	(0.032)	(0.031)	(0.035)
Democrats	-0.031**	-0.196***	0.023*	0.091***	0.079***	0.013	-0.148***	0.069***	-0.392***	0.250***
	(0.013)	(0.025)	(0.012)	(0.020)	(0.029)	(0.029)	(0.023)	(0.027)	(0.028)	(0.031)
News consumption	0.040***	0.066***	0.025**	0.005	0.129***	0.129***	0.068***	-0.004	0.062**	0.051
	(0.012)	(0.023)	(0.011)	(0.021)	(0.028)	(0.028)	(0.022)	(0.027)	(0.027)	(0.031)
N	1,014	1,014	1,014	1,014	1,014	1,014	1,014	1,014	1,014	1,014
Base rate	0.048	0.17	0.028	0.13	0.30	0.27	0.14	0.22	0.32	0.44

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.

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

Table A.7: 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	-0.064**	-0.051**	0.026	0.064***	-0.026	0.050***	-0.005	0.038***
	(0.026)	(0.025)	(0.023)	(0.022)	(0.020)	(0.018)	(0.017)	(0.014)
High age	0.041*	-0.003	-0.014	0.006	-0.005	-0.000	-0.039**	0.017
	(0.021)	(0.025)	(0.026)	(0.018)	(0.013)	(0.013)	(0.016)	(0.012)
College degree	0.061*	-0.064**	0.059**	-0.075***	0.048*	0.018	-0.021	-0.021
	(0.035)	(0.031)	(0.028)	(0.023)	(0.026)	(0.021)	(0.019)	(0.015)
College-level econ	-0.004	0.021	-0.028	-0.011	0.004	0.012	-0.016	0.001
	(0.031)	(0.029)	(0.025)	(0.024)	(0.023)	(0.019)	(0.018)	(0.015)
Full-time employee	-0.076**	0.017	0.099***	0.057**	-0.058***	-0.027	0.014	-0.010
	(0.032)	(0.030)	(0.028)	(0.025)	(0.021)	(0.021)	(0.021)	(0.018)
High income	-0.037	0.079**	0.028	0.009	-0.025	-0.008	0.005	-0.034**
	(0.032)	(0.031)	(0.026)	(0.025)	(0.023)	(0.019)	(0.020)	(0.015)
Democrats	0.136***	0.104***	0.053**	-0.103***	-0.152***	-0.092***	-0.036**	0.056***
	(0.027)	(0.025)	(0.023)	(0.022)	(0.020)	(0.018)	(0.017)	(0.014)
News consumption	0.070***	-0.048*	-0.064***	-0.017	0.050**	0.024	0.002	-0.012
	(0.027)	(0.026)	(0.024)	(0.021)	(0.019)	(0.017)	(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 D.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.8: Correlates of different measures of DAG complexity

	(1) Number edges	(2) Longest ingoing path	(3) Demand and supply	(4) Number no-end links	(5) Longest path
Panel A: Demographics					
Male	-0.326***	-0.170**	-0.091***	-0.180***	-0.141***
	(0.106)	(0.067)	(0.026)	(0.061)	(0.042)
High age	0.194**	0.075	-0.018	0.122**	0.065**
	(0.086)	(0.058)	(0.019)	(0.048)	(0.033)
College degree	0.189	0.226***	0.050	-0.001	-0.030
	(0.144)	(0.084)	(0.035)	(0.084)	(0.054)
College-level econ	0.101	0.028	-0.019	0.083	0.076
	(0.128)	(0.076)	(0.030)	(0.075)	(0.050)
Full-time employee	-0.799***	-0.353***	-0.111***	-0.284***	-0.207***
	(0.127)	(0.078)	(0.031)	(0.071)	(0.046)
High income	-0.013	0.009	0.077**	0.023	-0.004
	(0.131)	(0.080)	(0.032)	(0.075)	(0.049)
Democrats	-0.367***	-0.098	-0.031	-0.233***	-0.155***
	(0.114)	(0.069)	(0.027)	(0.065)	(0.043)
News consumption	0.629***	0.272***	0.099***	0.245***	0.179***
	(0.109)	(0.067)	(0.026)	(0.063)	(0.042)
N	1,014	910	1,014	910	910
Base rate	2.49	2.05	0.23	0.72	1.53
Panel B: Households vs. experts					
Expert sample	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

Note: Panel A uses data from the household November sample and shows OLS regressions where the dependent variables are different measures of DAG complexity. "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. Panel B includes data from the expert sample. "Expert sample" takes the value one for experts and zero for households.

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

Table A.9: Correlations between narratives and perceived inflation uncertainty

	Perceived uncertainty of future inflation (in s.d.)	
	(1) 12 months	(2) 60 months
Demand factors:		
Monetary policy	-0.057	-0.033
	(0.178)	(0.179)
Government spending	-0.468***	-0.369***
	(0.114)	(0.121)
Pent-up demand	-0.360**	-0.366**
	(0.156)	(0.183)
Residual demand	0.195	0.183
	(0.130)	(0.138)
Supply factors:		
Supply chain issues	-0.505***	-0.458***
	(0.093)	(0.097)
Labor shortage	-0.055	-0.102
	(0.095)	(0.101)
Energy	-0.112	-0.119
	(0.123)	(0.134)
Residual supply	-0.081	-0.067
	(0.097)	(0.105)
Other factors:		
Pandemic	-0.059	-0.112
	(0.100)	(0.102)
Government mismanagement	-0.419***	-0.301**
	(0.120)	(0.122)
Price gouging	-0.465***	-0.407**
	(0.143)	(0.159)
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.10: DAG complexity: Experts vs. households

	Number of DAG codes		Number of edges	
	(1)	(2)	(3)	(4)
Expert	1.189***	0.939***	1.082***	0.774***
	(0.157)	(0.115)	(0.178)	(0.143)
N	1138	1138	1138	1138
Controls for response length and time	No	Yes	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 and 2) and the number of edges of the DAG (columns 3 and 4). The regressions in columns 2 and 4 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).

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

Table A.11: 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.

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

	Expected inflation rate (in %)		Perceived SD of future inflation	
	(1) DAG	(2) DAG and text	(1) DAG	(2) 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, complexity 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) DAG	(2) DAG and text	(1) DAG	(2) 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 after news exposure

	(1) Endline narrative
Newspaper narrative	0.066***
	(0.020)
Baseline narrative	0.443***
	(0.033)
Constant	0.121***
	(0.009)
N	6239

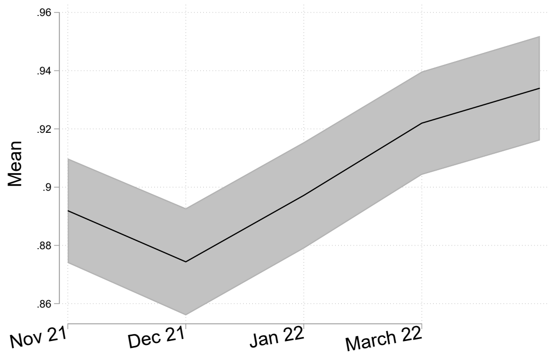
Note: This table uses data from all three waves of the media experiment, focusing on the 367 respondents in the treatment group that completed all three waves. The dataset is at the narrative factor-respondent level and contains 17 observations (number of narrative factors in our coding scheme) for each 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.

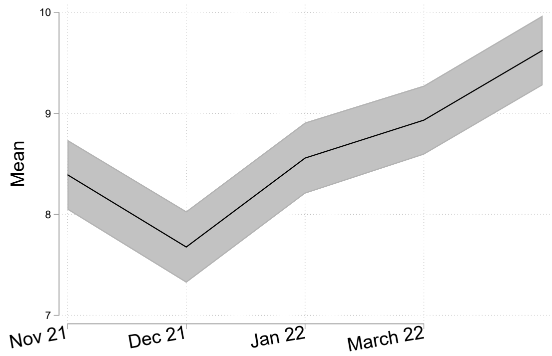
B Additional Figures

Figure B.1: Descriptives on beliefs about past inflation

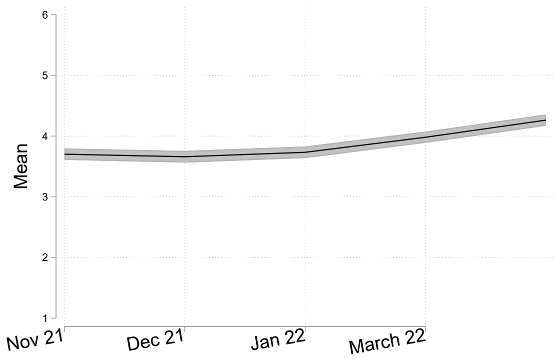
(a) Inflation: Higher today



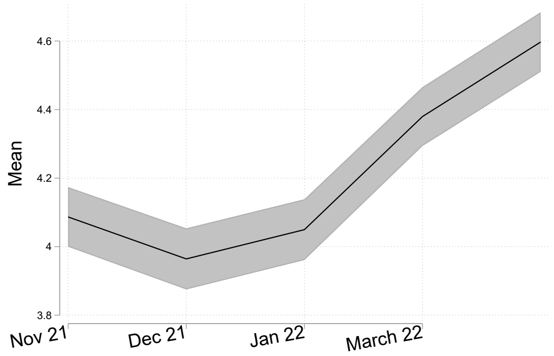
(b) Inflation last 12 months



(c) Frequency: Thinking about inflation

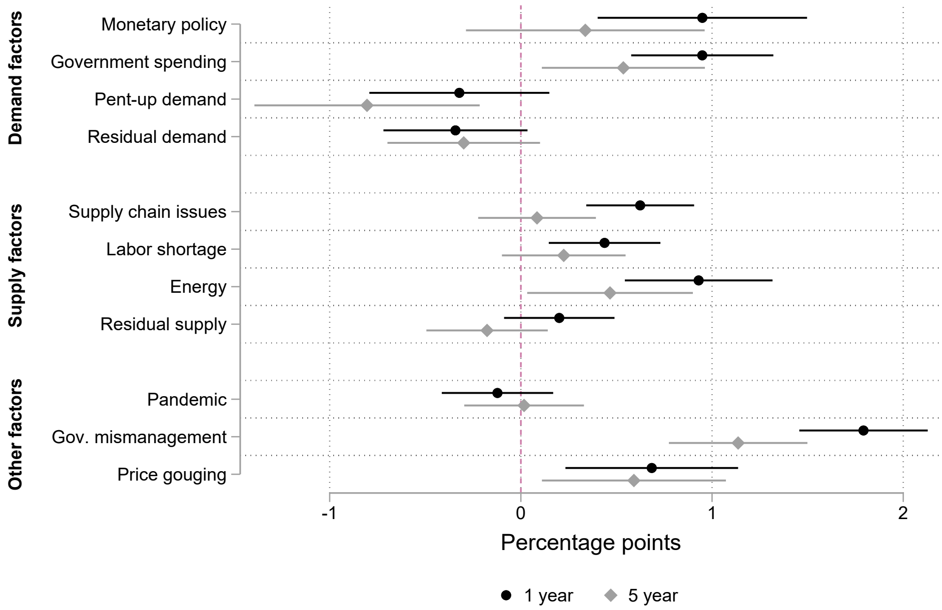


(d) Frequency: News consumption



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).

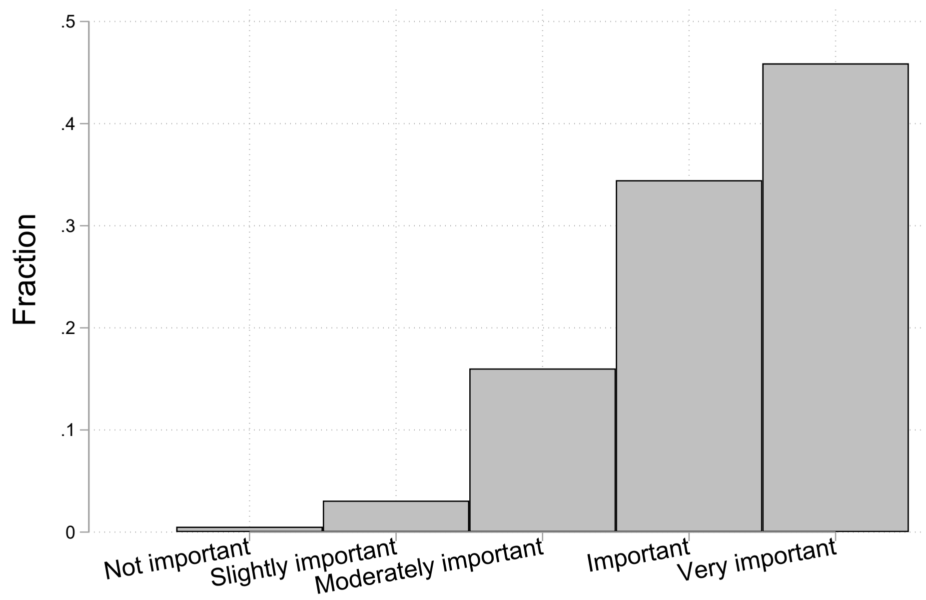
Figure B.2: Correlations between inflation expectations and inflation narratives



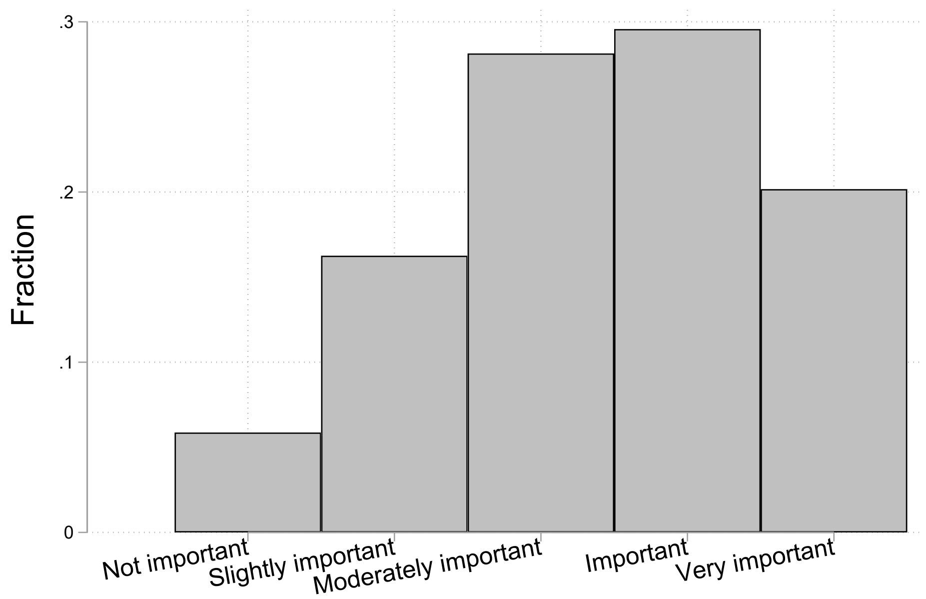
Note: The circles (diamonds) show estimated regression coefficients from a regression of one-year (five-year) inflation expectations on a set of dummy variables indicating which factors are included in the inflation narratives. Lines indicate 95% confidence intervals. Factors with few responses are included 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.3: Descriptives on beliefs about persistence

(a) Importance of energy crisis

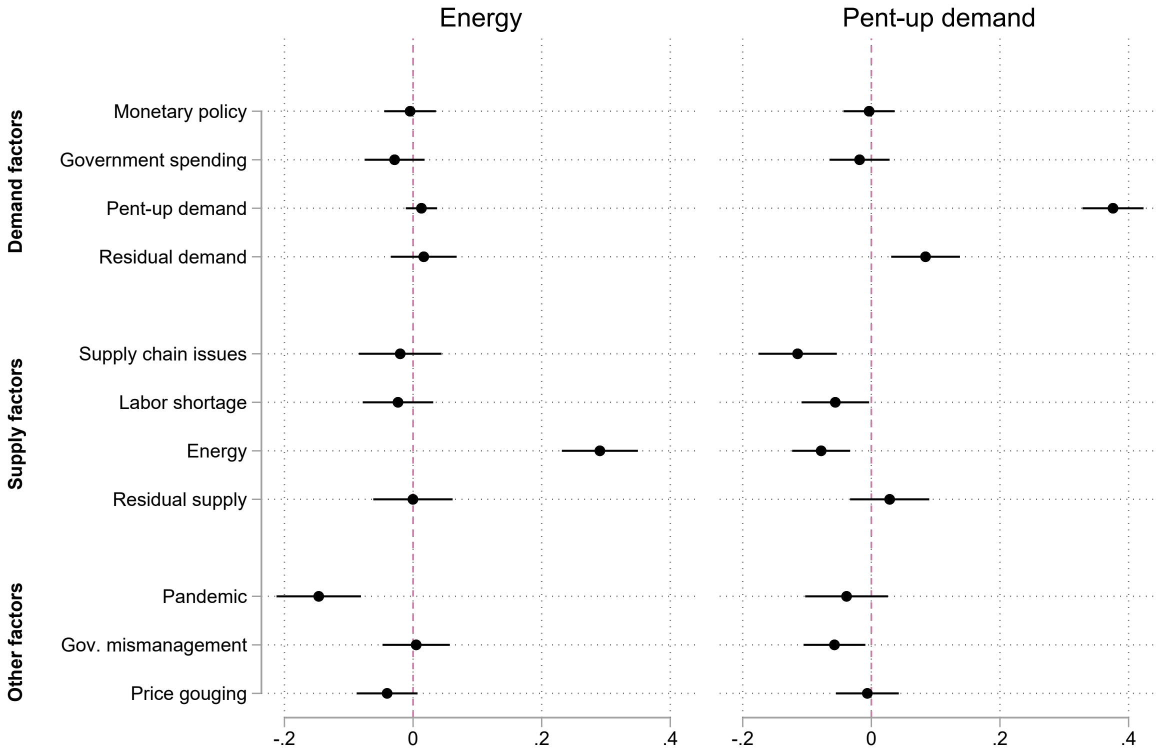


(b) Importance of pent-up demand



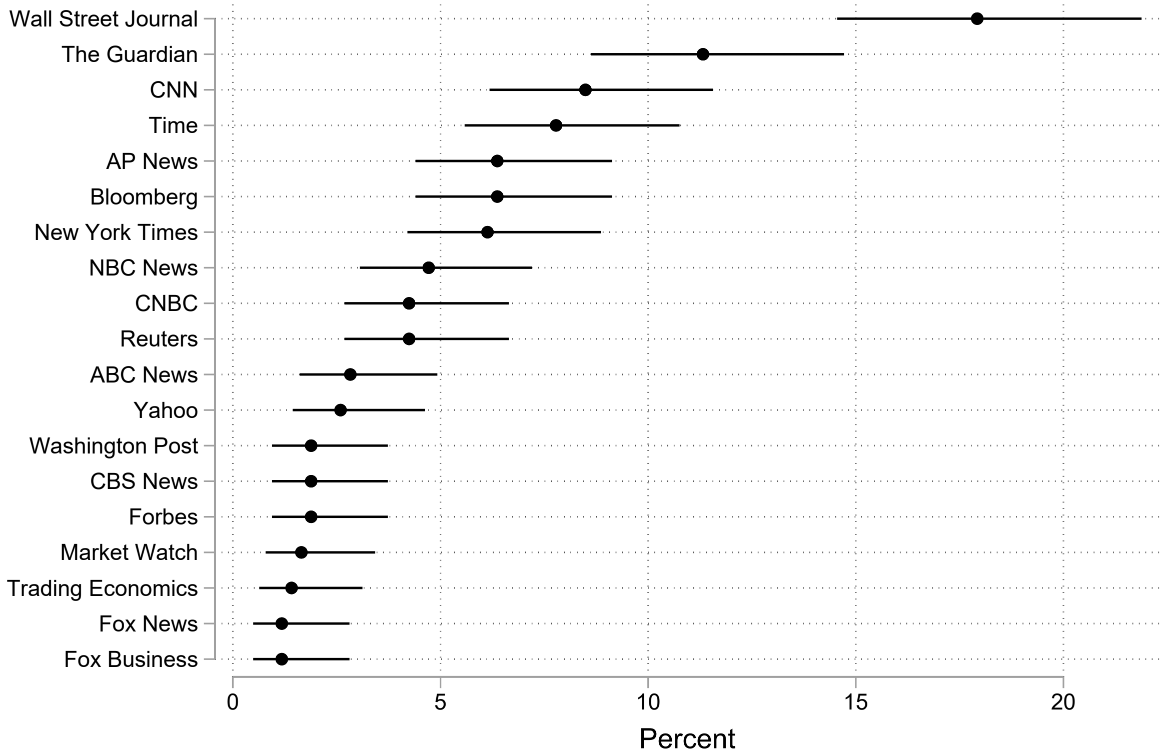
Note: This figure uses control group respondents from the narrative provision experiment and shows the distribution of responses to the following questions: “How important do you think that the global energy crisis will be for inflation over the next 12 months?” (Panel A) and “How important do you think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

Figure B.4: 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.

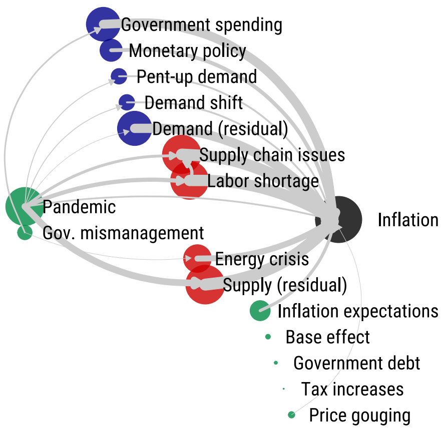
Figure B.5: Top 20 outlets for news about inflation



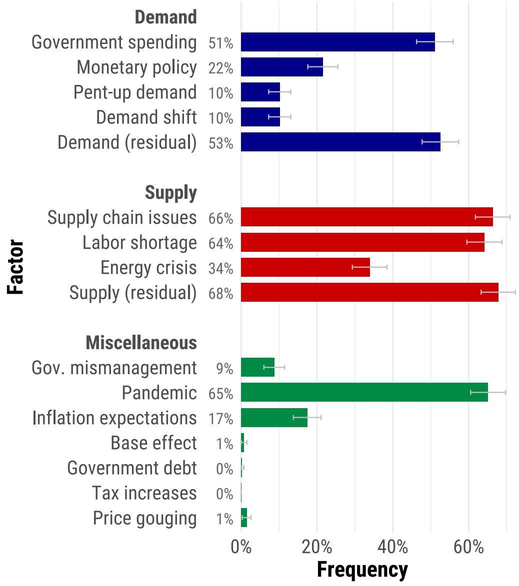
Note: This figure shows the top 20 outlets consulted by treated respondents in wave 2 of the media experiment when looking up a news article about inflation.

Figure B.6: Narratives in the news

(a) **Average DAG**

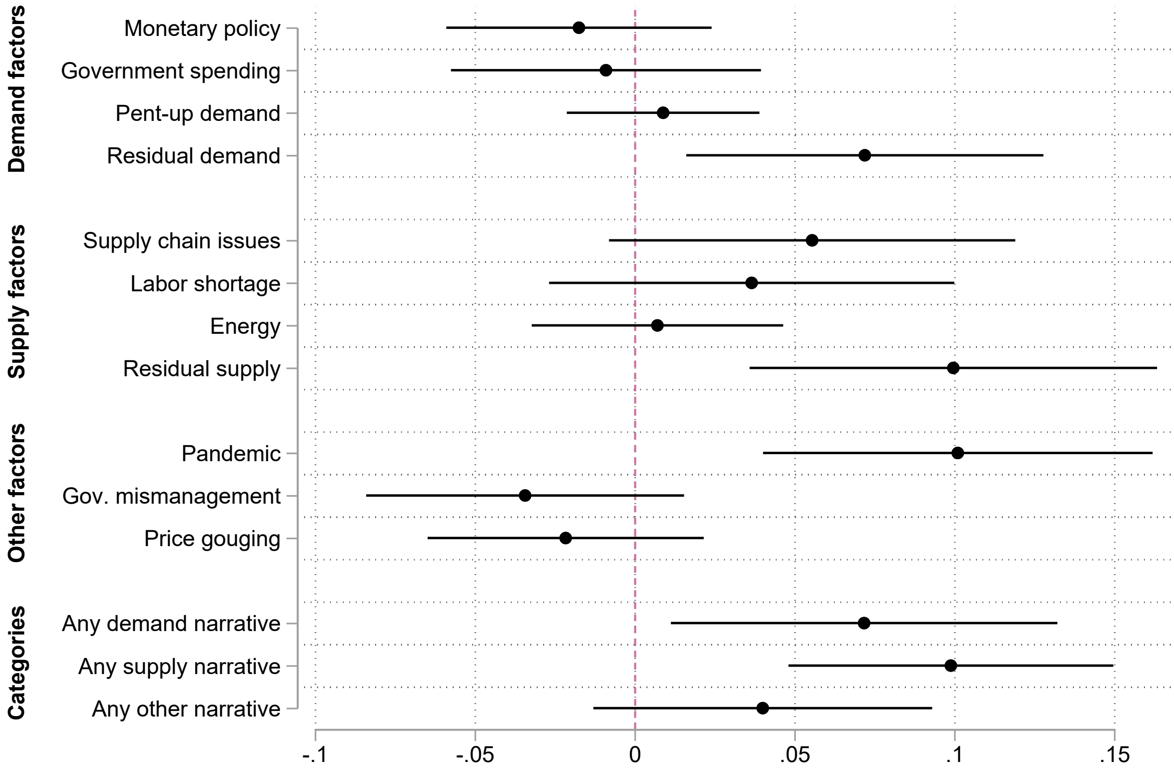


(b) **Frequency of factors**



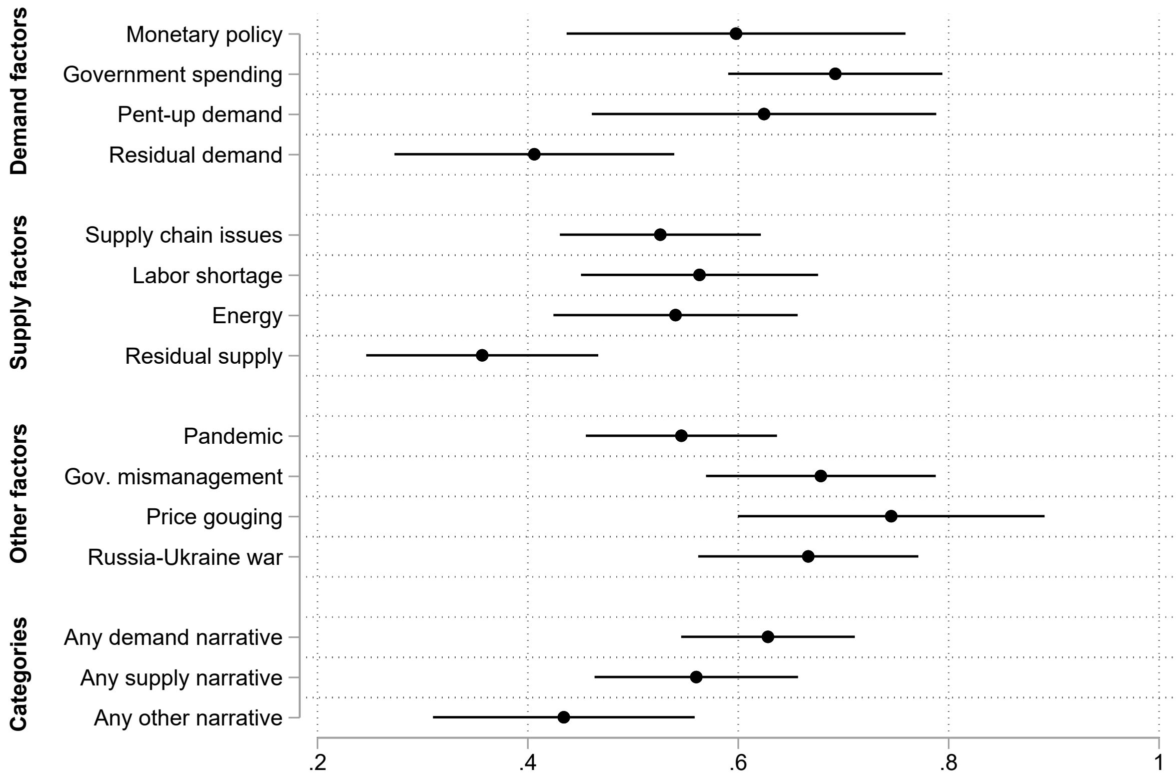
Note: **Panel (a)**: The "average" narratives mentioned in news articles (weighted by the frequency with which a given article is read), displayed as causal networks. The aggregated DAGs show which variables and causal links are most relevant in households' and experts' narratives. See the notes of main 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.7: Treatment effects on individual narratives: Media experiment



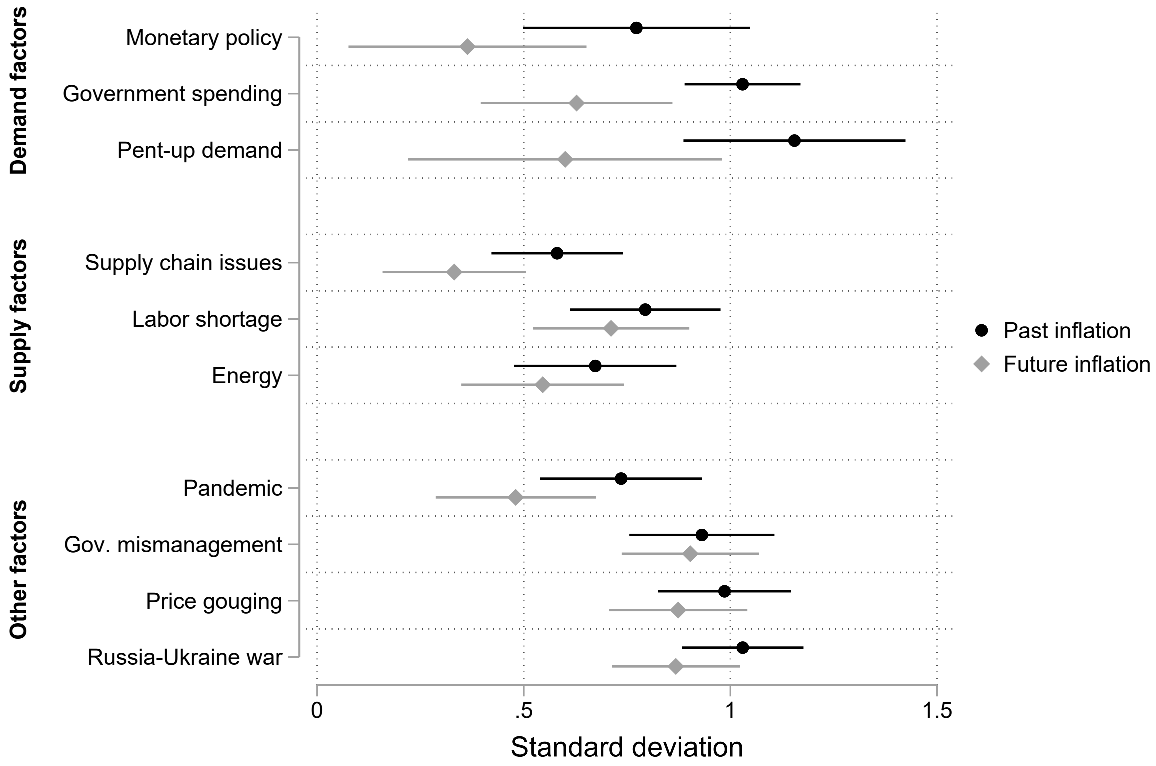
Note: The circles show estimated regression coefficients from regressions where the dependent variables are dummies indicating whether a factor is included in the DAG constructed from the open-ended responses about reasons for the recent increase in inflation as measured in wave 3 and the independent 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.

Figure B.8: 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.

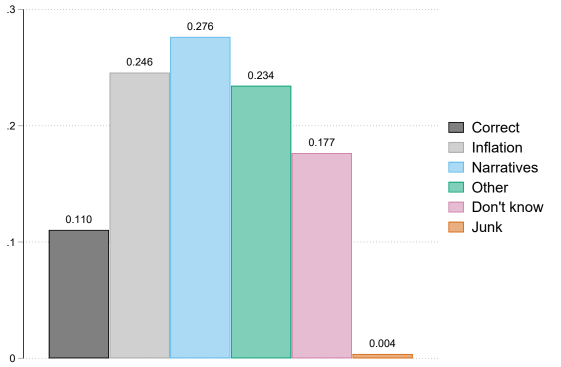
Figure B.9: Validation with structured questions



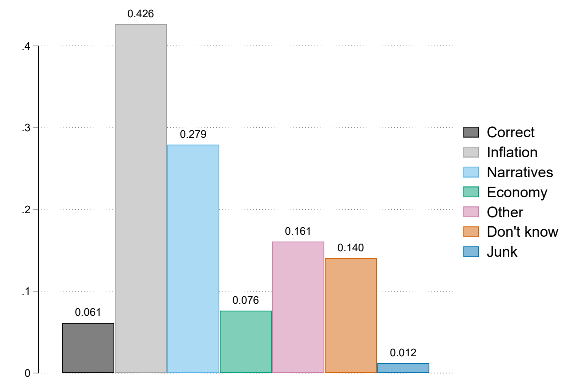
Note: This figure uses data from the robustness experiments with structured outcomes. The circles (diamonds) show estimated regression coefficients from regressions where the dependent variables are structured measures of the importance of the factor in driving past (future) inflation and the independent 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.

Figure B.10: Beliefs about researcher hypothesis: Main experiments

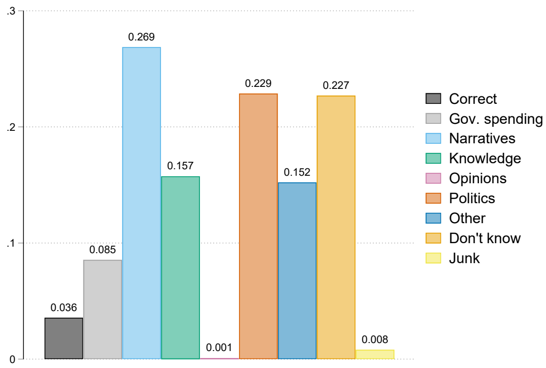
(a) Narrative provision: Pent-up demand & energy



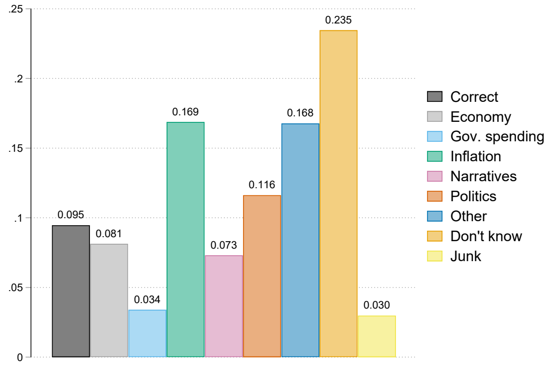
(b) Narrative provision: Monetary policy & energy



(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 5.3). Panel (d) provides evidence from the experiment on the interpretation of new information from April 2022 (see Section 5.4). "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.

C 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%.

D Details on the Cluster Analysis of Narratives

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

D.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 $D(i,j) = 1 - \frac{1}{3} = \frac{2}{3}$.

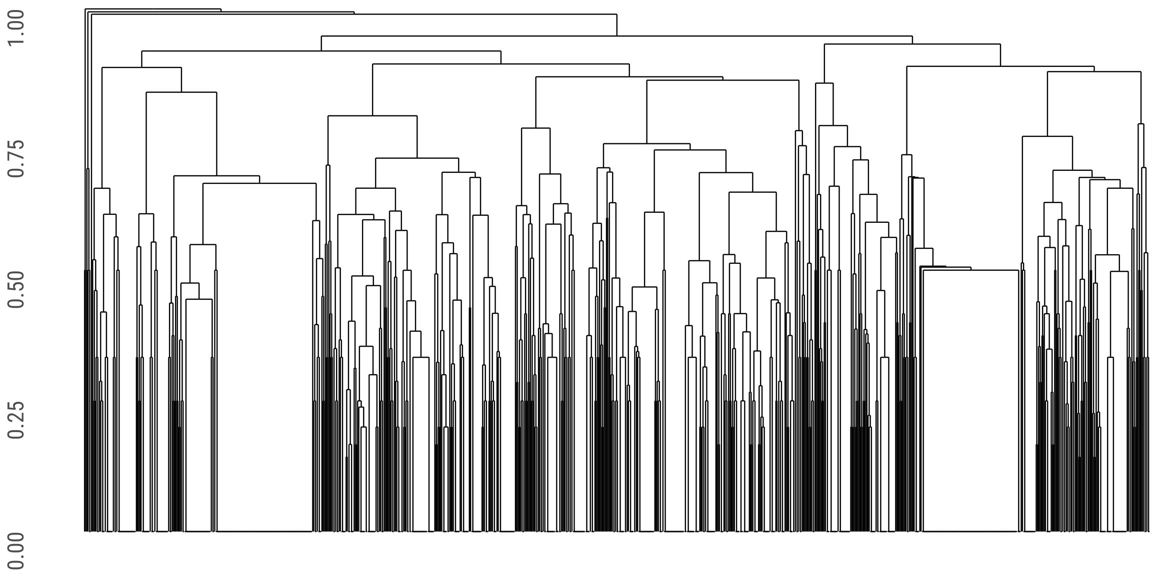
2. Pairwise distances. We derive the pairwise distances between all narratives.

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 D.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

Figure D.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).

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 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.

D.2 Robustness

Figure D.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.

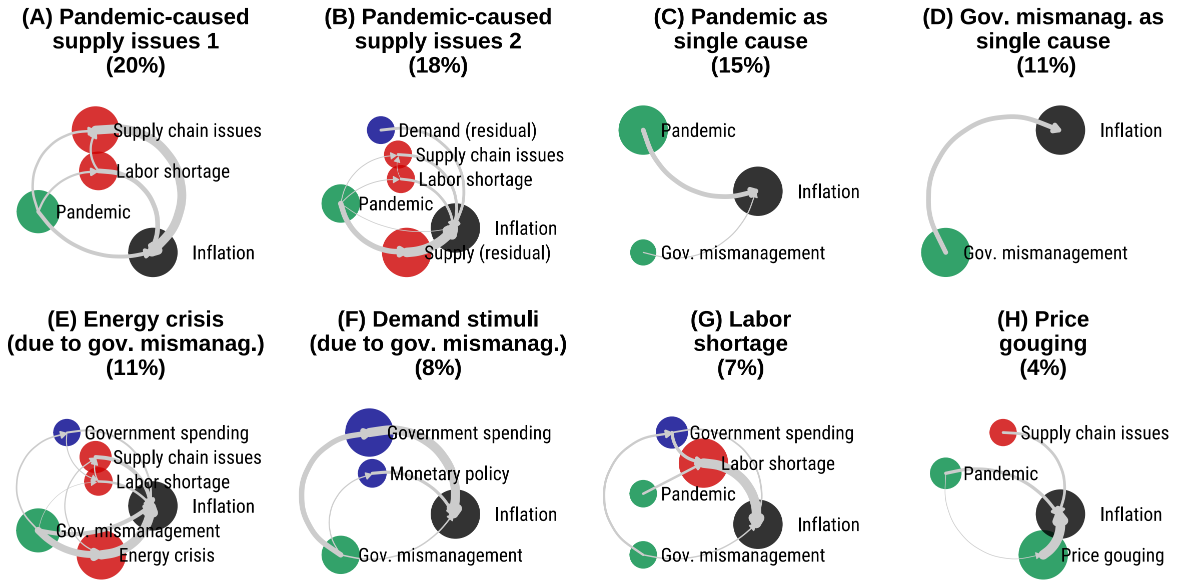
1. Cosine distance as distance metric. Instead of using *Jaccard distance*, we use the *Cosine distance* between edge lists to derive the dissimilarity of two narratives. Figure D.3 shows that this procedure yields very similar results. There is a corresponding cluster for every cluster from the main 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 D.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 D.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.

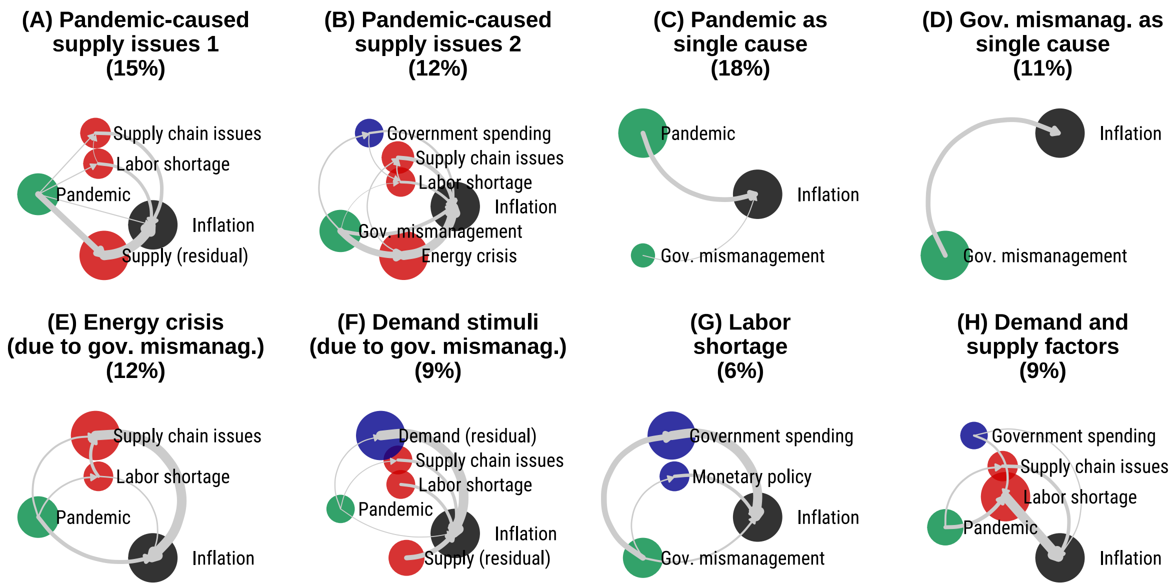
A final note on the linkage method: We do not derive results with different linkage methods (see step 3 in the previous subsection). Ward-type methods have been designed for application in Euclidean spaces, while our data are categorical. "Single linkage" successively adds narratives to one increasingly 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 D.2: Cluster analysis: main results (reproduced)



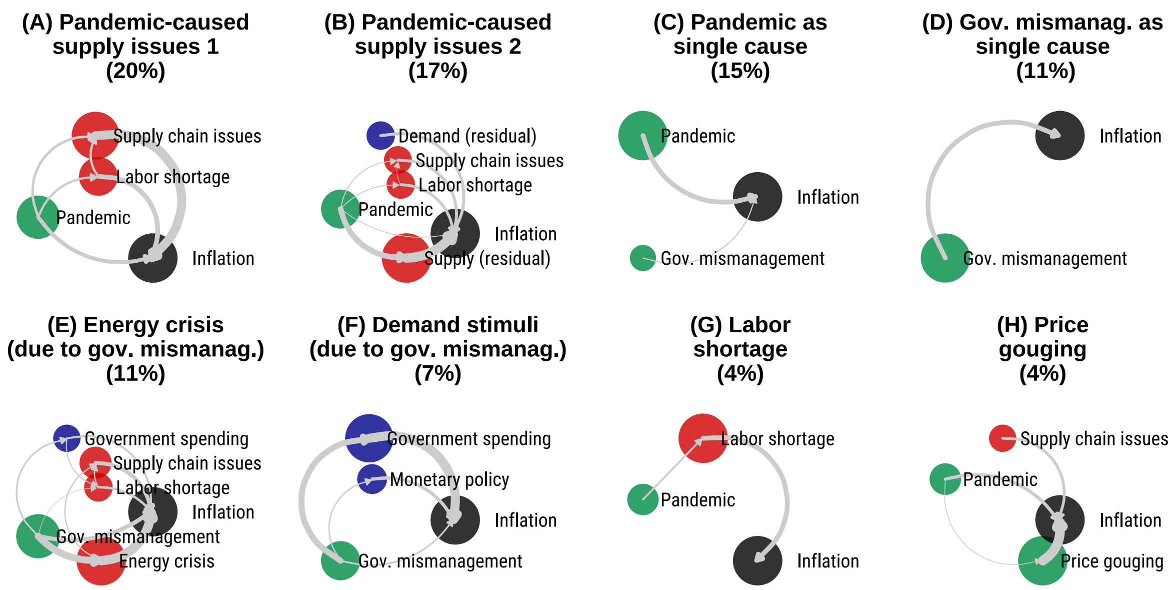
Note: Cluster analysis of narratives from household survey (November wave). Only households who provide a causal narrative are considered. **Clustering**: An agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives is applied (described in detail in Appendix D). 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 D.3: Cluster analysis with Cosine distance



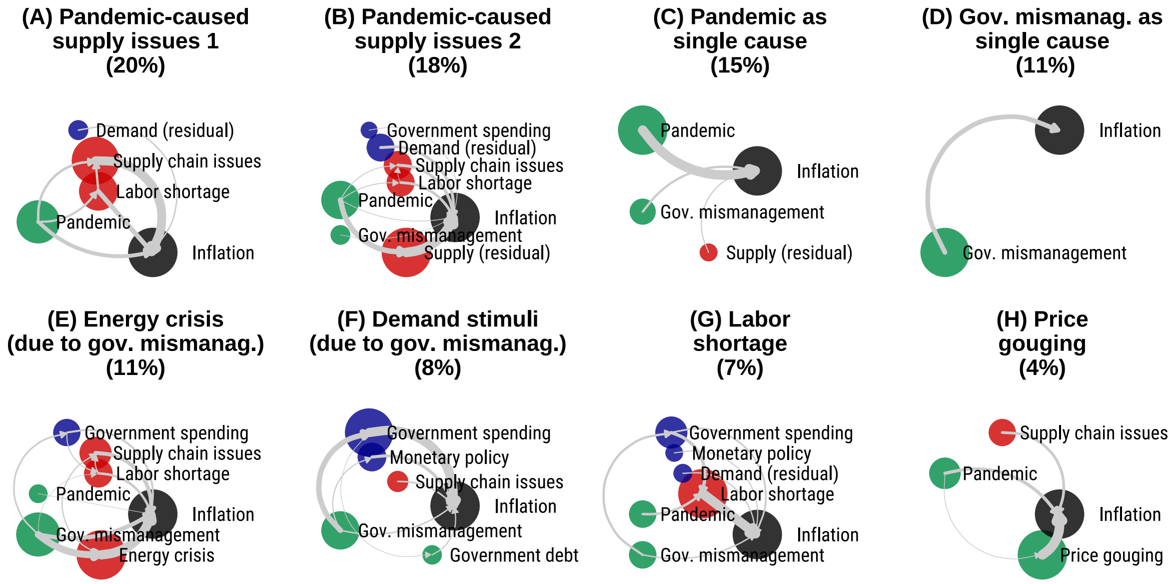
Note: Cluster analysis of narratives from household survey (November wave), based on Cosine distance. The eight largest clusters are displayed. In addition, see notes of Figure D.2.

Figure D.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 D.2.

Figure D.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 D.2.

E 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/.

E.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 %

→

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

→

E.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.

→

E.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.

→

E.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					Very confident
1	2	3	4	5	6
○	○	○	○	○	○

→

E.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.

→

E.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.

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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.

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