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Narratives About the Macroeconomy

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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 8,000 US households and 100 academic experts. We document three main findings. First, compared to experts, households' narratives are coarser, focus less on the demand side, and are more likely to 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. (*JEL*: D83, D84, E31, E52, E71)

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

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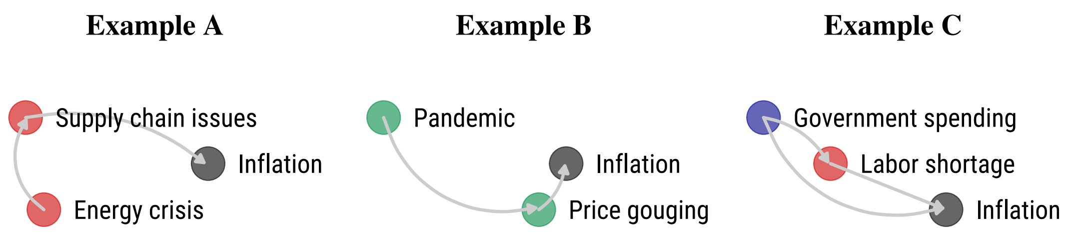
1 Introduction

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 portray 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 play an important role in shaping economic expectations and macroeconomic outcomes (Shiller, 2017, 2020). Nonetheless, empirical evidence on economic narratives remains scarce.

In this paper, we assess the nature, consequences, and origins of economic narratives 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 narratives about the rise in inflation circulated in the news; different trajectories of future inflation appeared likely through the lens of these narratives; and expectations about future inflation held central importance to policy-makers who aimed to keep inflation expectations anchored. We use this setting to examine three 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 April 2022. In our surveys, we elicit open-ended text responses in which respondents explain which factors they think caused the recent increase in inflation. To quantitatively capture the rich causal structure of respondents' narratives, we represent each of the open-text responses by its 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. We employ this approach with more than 8,000 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 tailored experimental treatments that allow us to explore how narratives affect inflation expectations and study whether the news media

Figure 1: Example narratives, represented by DAGs



Notes: Three example narratives for why inflation increases, 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.

shapes individuals' narratives.

We document three sets of results. We first 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. While both groups often mention supply-side factors as important drivers of inflation—such as supply chain disruptions, labor shortages, and the energy crisis—households are much less likely than experts to mention demand-side factors, such as loose monetary policy. Instead, households are more likely to invoke politicized narratives and often attribute inflation or its 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. A cluster analysis reveals that 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 Democratic government, consistent with the politicized nature of households' narratives. Moreover, exploiting repeated cross-sectional surveys, we document that the composition of narratives can abruptly change. Indeed, households' narratives immediately adapt to the Russian invasion of Ukraine in our March 2022 survey, illustrating their high elasticity to new economic or political events.

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 associated with the reopening of the economy predict significantly lower inflation.

To shed light on the causal effect of narratives on expectation formation, we conduct three 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 resulting from forced savings during the pandemic, and one that highlights the role of the energy crisis. The former narrative is commonly associated with a lower persistence of high inflation in the future. Indeed, 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 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 their pre-existing beliefs about 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—report higher inflation expectations.

Our third experiment illustrates that individuals interpret new information in light 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 prior to 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.

These correlational and experimental findings suggest that economic narratives are central to households' macroeconomic expectation formation. Individuals use narratives about the past to forecast the future, and they interpret new information and update their beliefs through the lens of these narratives. Different narratives induce people to draw different conclusions from the same evidence.

Our final set of results provides support to 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. The endogenous choice of information source embeds naturalistic news consumption in a controlled environment. We show that 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. These results suggest that the mass media is an important source of households' narratives.

Taken together, our findings demonstrate that narratives shape people's economic outlook and play a central role in their reasoning about the macroeconomy. The heterogeneity of narratives helps to understand the widely-documented disagreement in macroeconomic expectations (Coibion and Gorodnichenko, 2012; Coibion et al., 2018; Dovern et al., 2012; Giglio et al., 2021). Furthermore, the pronounced differences between expert and household narratives could point to new opportunities for managing economic expectation. For example, central bank communicators who aim 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 builds on and contributes to the literature on narratives in economics (Bénabou et al., 2018; Eliaz and Spiegler, 2020; Shiller, 2017, 2020).[1] We provide a tractable empirical approach to measure and characterize economic narratives. Building on the theoretical work of Eliaz and Spiegler (2020), we consider narratives as causal accounts of why a specific event occurred and represent such narratives as causal graphs.

[1]Other work has studied narratives in the moral and political domain (Ash et al., 2021a,b; Barron et al., 2021; Bursztyn et al., 2022b,c). See Morag and Loewenstein (2021) for an experiment on the role of narratives for the valuation of goods.

This approach is in line with a broad theoretical literature on causality and causal inference (Ellis and Thysen, 2021; Olea et al., 2021; Pearl, 2009; Spiegler, 2020a,b, 2021).

In our empirical analyses, we provide novel evidence on the nature of laypeople's economic narratives. In particular, the comparison of household and expert narratives allows us to identify unique features of household narratives, such as their fragmented and politicized nature. Importantly, our DAG-based approach allows us to quantify the causal structure of economic narratives, which cannot be detected by common existing techniques such as topic modeling or simple word-counting techniques (e.g., Borup et al., 2021; Hansen et al., 2018; Müller et al., 2022; Shiller, 2017, 2020). However, the causal structure that individuals perceive behind past events is crucial when it comes to forecasting future economic outcomes or interpreting new information.

Our finding that narratives shape economic expectations contributes 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 the rise in inflation. This literature has focused on the role of experiences (Goldfayn-Frank and Wohlfart, 2020; Malmendier and Nagel, 2016), cognitive abilities (D'Acunto et al., 2019, 2021), exposure to grocery prices (Cavallo et al., 2017; Coibion et al., 2022; D'Acunto et al., 2021), gas prices (Coibion and Gorodnichenko, 2015b), or monetary policy communication (Coibion et al., 2019; Roth et al., 2021). Our paper is also related to recent work by Andre et al. (2022) who document large disagreement about the perceived consequences of specific macroeconomic shocks for inflation and unemployment. By contrast, our paper focuses on the stories that people tell to explain a real-world, real-time, high-stakes macroeconomic development—a significant surge in inflation—and explores how holding different narratives affects expectation formation. By doing so, we provide an empirical test of the idea that narratives provide a model through which people interpret the world (Eliaz and Spiegler, 2020).

We also contribute to research on the role of attention and memory in belief formation (Bordalo et al., 2016, 2020; Enke et al., 2020; Gabaix, 2019; 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 et al., 2022a; Bybee et al., 2021; Larsen and Thorsrud, 2021; Levy, 2021) and driving economic expectations and decisions (Chen and Yang, 2019; Chopra, 2021; Coibion et al., 2019; Link et al., 2022; 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 evidence on the prevalence and nature of narratives about the rise in inflation. In Section 5, we provide evidence on the link between narratives and inflation expectations. 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 and make sense of a major macroeconomic event. This section introduces a working definition of narratives, aiming to make 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, Shiller (2017) describes a narrative as a "simple story or easily expressed explanation." 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 why a specific economic event occurred*. Our focus is thus on backward-looking narratives, which offers the advantage that we can fix and define the event in which we are interested. 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. A central advantage of our 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. This allows us to analyze our narrative data in a simple and quantitatively precise way.[2]

Examples of economic narratives abound. For instance, the introductory Figure 1 presents three narratives as 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 respondents to our household surveys. Of course, narratives have also been brought forward in the context of various other historical economic events, such as the 2007 financial crisis or the dot-com bubble burst of 2000 (Shiller, 2017).

In our empirical application, we are interested in the narratives that *come to people's minds* when they think about an economic phenomenon. These narratives reflect how people make sense of economic events. While individuals have likely been exposed to many different narratives, what may ultimately matter for their economic expectations and decisions is which narratives they retrieve from their memory database, i.e., which narratives are on top of their minds (Bordalo et al., 2020; Gennaioli and Shleifer, 2010).

[2]DAGs are widely used in the literature on causal models, bridging statistics, computer science, the social sciences, and philosophy (Hitchcock, 2020; Pearl, 2009; Sloman, 2005; Sloman and Lagnado, 2015; Spiegler, 2016). The restriction to acyclic graphs is of negligible importance in our context as we encountered virtually no lay narrative with a causal cycle. We allow our DAGs to be "signed": all causal connections present positive causal relationships (i.e., more A leads to more B).

3 Setting, Data, and Design

3.1 Setting

We study narratives about the macroeconomy in the context of rising inflationary pressures in late 2021 and early 2022. This is an important 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 8.5% involved high stakes for many households, e.g., in the form of changes in real income or the real value of assets and debt.[3] 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 invoked thus potentially affects expectation formation.

We fielded our main descriptive survey between November 18 and 21, 2021, around one week after the release of inflation statistics uncovered a surge in inflation to 6.2% in October 2021, a rate that had last been experienced in 1990. The increase in the inflation rate was widely covered by the media. An increasing number of economists and policy-makers raised concerns that the rise in inflation might prove to be persistent. The subsequent increases in the inflation rate up to 8.5% in March 2022 further sparked wide media coverage and discussions about potentially permanently higher inflation.

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, e.g., due to workers who were worried about health risks dropping out of the labor force. 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. Finally, a special feature of the pandemic was a shift away from service-based towards durable consumption, which resulted in particularly strong excess demand for a subset of products, such as cars.

[3]The level of 8.5% was reached in March, and the corresponding data were released in April.

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 main household sample between November 18 and November 21, 2021, with the survey company Lucid, which is commonly used in economic research (Haaland et al., 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.[4]

In addition to the November 2021 survey, we recruit three samples of household respondents in December 2021, January 2022, and March 2022. Each wave encompasses roughly 1,000 respondents. We follow the same sampling approach as in our November survey, and Table A.1 shows that the new samples closely resemble the November 2021 sample in terms of their underlying demographic characteristics. Table A.4 provides an overview of the different descriptive data collections.

Experts Simultaneously with the data collection for our main 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.3 shows summary statistics for the expert sample. 50.5% of the experts are based in the United States.[5] 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

[4]The representativeness in terms of education is thus comparable to the New York Fed's Survey of Consumer Expectations, a leading US survey measuring households' inflation expectations (Armantier et al., 2013).

[5]Responses of experts that are based outside the US are similar to those of experts based in the US.

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). Overall, it is thus clear that our expert sample is a set 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. A more detailed version can be found under https://osf.io/av48u/.

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.[6] We next measure narratives about the rise in inflation with an open-ended question. Subsequently, we measure respondents' quantitative beliefs about future inflation. The inflation narratives and the beliefs about future inflation 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 focuses on the measurement of inflation narratives and expectations.

Narratives We measure the narratives that people provide to explain the rise in inflation using an open-ended question. We first inform all respondents 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." The information provision about the current inflation rate before the elicitation of narratives ensures that all respondents explain the same event in their open-text responses.

There are several important advantages of open-ended measurement of narratives

[6] 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).

compared to using more structured questions. First, open-ended responses offer a lens into people's spontaneous thoughts without priming them on any particular issue, e.g., through the available response options. Second, open-ended responses are more natural to respondents and may be better suited to capture typical reasoning in real-world situations. Third, open-ended responses may reveal misunderstanding or confusion on the part of participants and allow for qualitative insights that cannot be achieved with structured measures.

Inflation expectations We elicit probabilistic expectations about inflation over the next 12 months and in five years from the survey, closely following the question format used in the New York Fed's Survey of Consumer Expectations (Armantier et al., 2017). 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-text explanations for why inflation increased, we develop a tailored coding scheme to manually identify the narrative of each response.

We start by defining the set of "factors" that narratives can draw on. These factors constitute the building blocks of narratives. They correspond to variables or events that are commonly associated with the rise in inflation. Our goal was 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 by the media or households in pilot studies.

Table 1 provides a complete overview of all factors in our coding scheme together with illustrative 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 close-contact services towards durables). We also allow for a residual demand factor that includes additional demand-side drivers that cannot be classified under one of the other 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 negative 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 expectations of high inflation in the coming years and the associated preemptive price and wage adjustments, price gouging, high levels of government debt, and the Russia-Ukraine conflict (see Table 1 for the complete list).[7]

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

We instruct research assistants to apply this coding procedure to the text responses. All coders are blind to the objectives of the research project. We use human coding because 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 narrative classification.[8] Wherever a conflict occurs, the case is revisited and a final decision is made.[9] 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 presents a series of example

[7]We added the "Russia-Ukraine war" code to the coding scheme in March 2022. We reviewed responses that were collected and coded before March 2022. Virtually none of them refers to the Russia-Ukraine conflict.

[8]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.

[9]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.

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

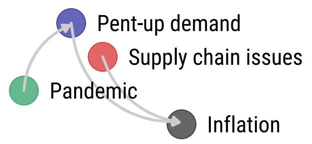
Category	Explanation	Example
Demand		
Government spending	Increases in government spending (e.g., stimulus payments).	"[...] Stimulus checks were given to all middle income families; A second round of stimulus checks were also given to all families by the new administration [...]"
Monetary policy	Loose 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 war against 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

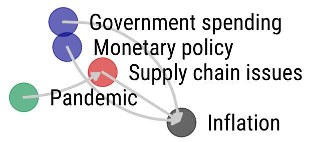
Expert example 1

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. [...]



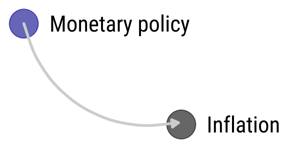
Expert example 2

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).



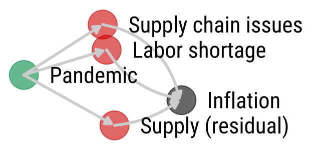
Expert example 3

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



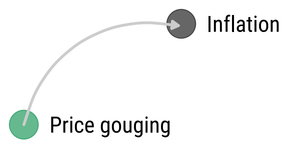
Household example 1

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.



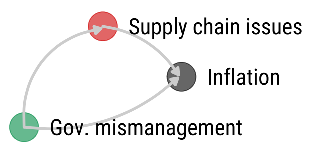
Household example 2

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.

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 90% of households' and 100% of experts' explanations. Both fractions are sizable given the degree of measurement error typically contained in open-text data.

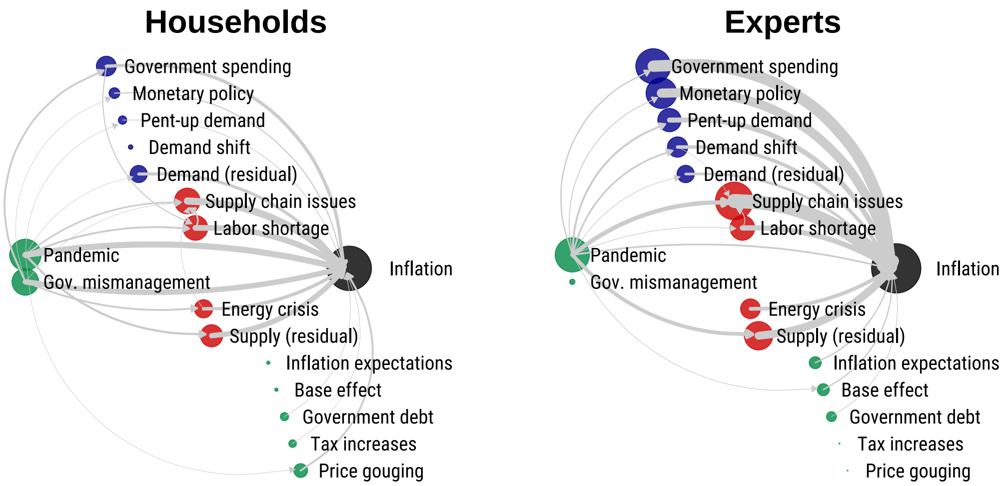
Second, we introduce an auxiliary code to mark responses that are nonsensical or clearly refuse to engage with the task. Only 3% of households' responses (0% among experts) were assigned to this category.

Third, we derive how often two independent reviewers assign the same causal connection to a response. If one coder refers to a factor, there is a 87% chance that the other coder also does so. If one coder assigns a causal connection between two specific factors, there is a 75% chance that the other coder also does so. 94% of the assigned factors and 88% of the assigned connections make it to the final version. These numbers suggest that the open-text 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 or not to assign any demand-side factor to a response. The corresponding figure is 93% for supply-side mechanisms.

4 Descriptive Evidence on Narratives

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

Figure 2: "Average" narratives among households and experts



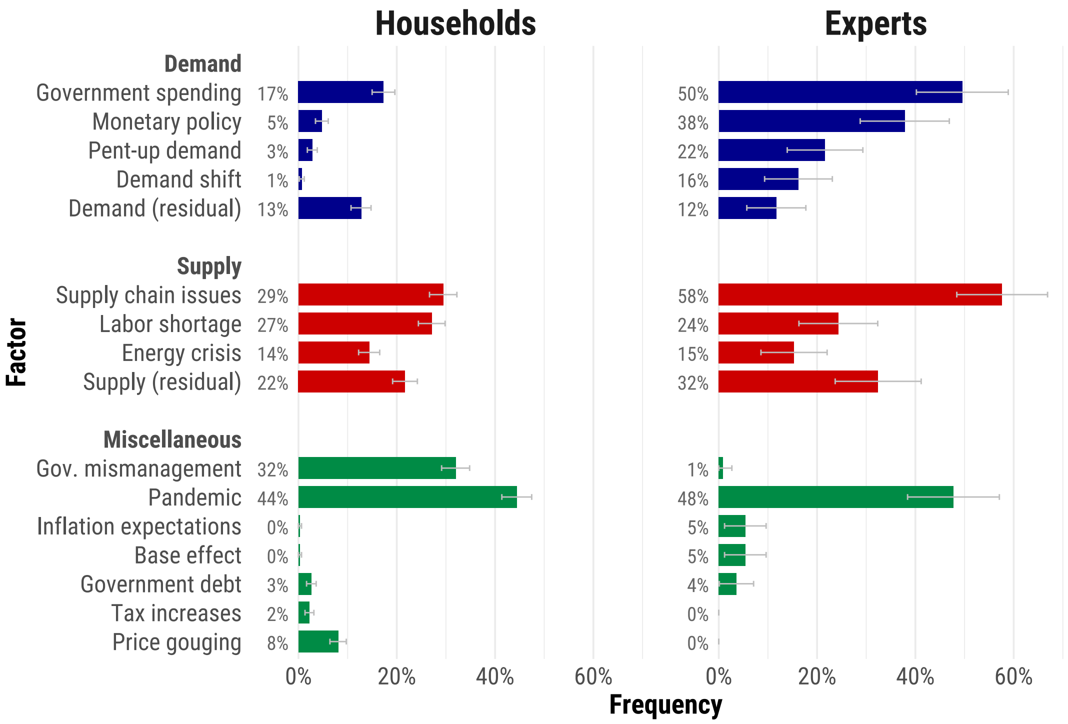
Notes: This figure shows the "average" narratives invoked by households (left panel) and experts (right panel), displayed as causal networks. The aggregated DAGs show which variables and causal links are most relevant in households' and experts' narratives. **Factor size**: The size of the factors is 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.

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 who mention a particular factor. Both figures reveal important differences in the narratives of households and experts.

First, the narratives on households' minds 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: $p < 0.001$). For example, Figure 2 shows that

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.

households often attribute the rise in inflation directly to the pandemic, while experts more often provide additional details and link the pandemic to subsequent causes of higher inflation, such as federal stimulus packages or supply chain disruptions. Moreover, many experts think about *both* supply- and demand-side factors. In particular, among all experts who mention at least one supply *or* one demand narrative, 77% mention both a 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 (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). Moreover, the idea that high government spending caused the labor shortage can be found in 5% of household DAGs (but only in one expert DAG). Some of the most complex narrative structures among households emanate from "government mismanagement."[10]

Finally, some household narratives revolve around explanations that are completely 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.[11]

4.2 Narrative Clusters

The aggregated results presented above could conceal substantial heterogeneity in households' narratives. Next, we thus 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.

[10]For instance, three household respondents argue that government mismanagement has led to high government spending and benefits, enticing people to stay at home and remain unemployed, which has created the labor shortages that interrupted the supply chain, thereby causing high inflation. Many households endorse smaller parts of this narrative.

[11]Other explanations for the rise in inflation are 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 a few respondents.

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):

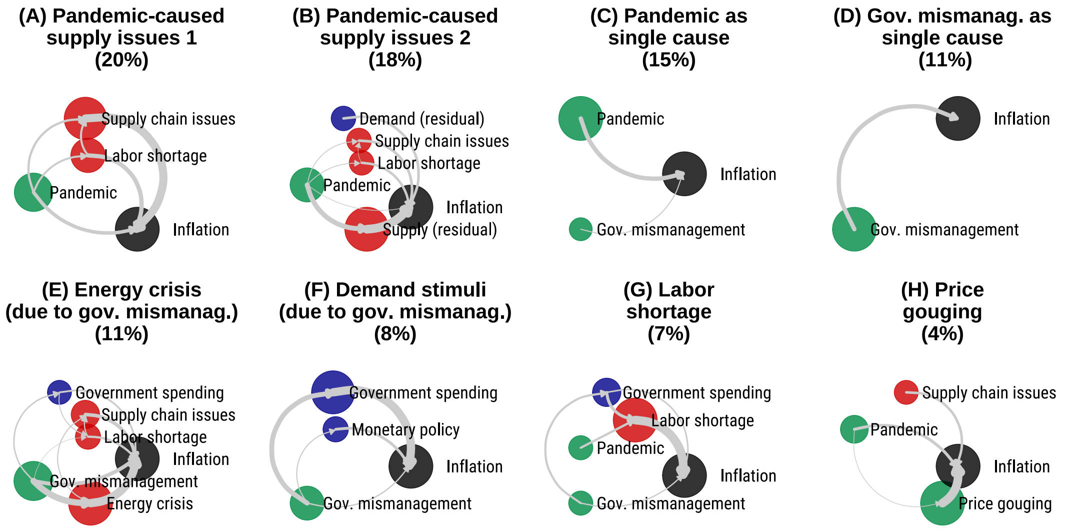
$$D(i, j) = 1 - \frac{| E_i \cap E_j |}{| E_i \cup E_j |}$$

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.[12]

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

[12]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.

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.

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 partial 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 substantial 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., labor shortage; Appendix Table A.5), (ii) dummies for whether a narrative that belongs to a specific cluster is expressed (e.g., the "Pandemic as single cause" cluster; Appendix Table A.6), and (iii) various measures of narrative complexity (Appendix Table A.7).

The analyses reveal three consistent patterns. 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, $p < 0.01$).

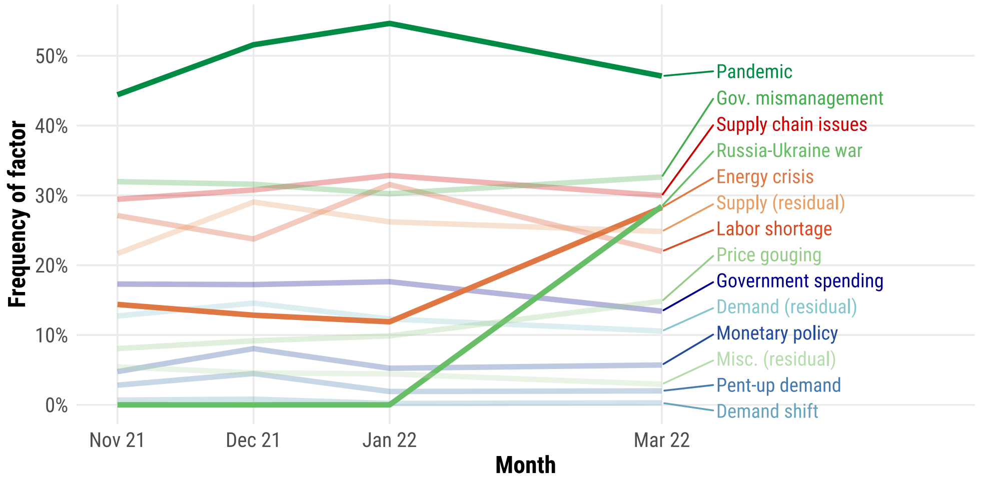
Second, we observe that respondents who report regularly following inflation-related news have richer narratives that contain more factors, more often talk about *both* demand and supply factors, and have longer causal chains. All differences are highly statistically significant, hinting at the potential 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 show 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 and March 2022—shortly after the new inflation data were announced—to analyze the development of narratives over time. The dynamic proper-

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 historic changes are detected are printed in higher transparency. The data come from our descriptive surveys in November 2021, December 2021, January 2022, and March 2022.

ties of economic narratives matter. For example, narratives could play a particularly important role in short-term economic fluctuations if they themselves fluctuate and are elastic to new events. This raises the question of whether narratives adapt slowly or quickly to new economic or political developments.

Our setting is well suited to shed light on this descriptive question. Inflation has continued to be a central concern in the US since November 2021. Some causes of the surge in inflation have dissipated over time (e.g., the pandemic), while others have worsened (e.g., energy prices). Moreover, the Russian invasion of Ukraine, which started in late February 2022, marked a global turning point with severe economic repercussions, one of which—the rise in global energy prices—was immediately felt by US households.

Figure 5 documents the trends in narratives from November 2021 to March 2022. For each survey wave, it shows which fraction of narratives refer to a given factor. The figure highlights three abrupt changes in narratives in March 2022, all of which likely constitute a direct response to the Russia-Ukraine war. First, while virtually no narrative in November 2021 to January 2022 refers to the already ongoing Russia-

Ukraine conflict, 28% do so in March 2022, after Russia started its invasion. 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 featured in the narratives from November 2021 (44%) to January 2022 (55%), its frequency declines to 47% in March 2022. For most other factors, households' narratives have largely been stable over the period from November 2021 to March 2022.

4.5 Summary of Descriptive Evidence

We summarize our first descriptive set of results as follows:

Result 1.

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

b) Households' narratives are highly heterogeneous. They 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 over time and adapt to new economic or political events.

5 Narratives Affect Expectation Formation

People's narratives about economic events could shape their expectations about the future. Narratives emphasize which forces have been relevant in the past and thereby suggest which mechanisms are likely to operate going forward. Narratives could thus be central to understanding expectation formation.

Our setting is ideal to study the role of narratives in expectation formation. First, the causes of the rise in inflation that people endorse in their narratives are 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) or even "chronic" (e.g., government mismanagement) and potentially cause persistently high inflation. Second, the role that a narrative attributes to a specific factor (e.g., government spending) could affect how people interpret new information about the factor (e.g., changes in government spending growth).

In this section, we therefore investigate whether people's narratives shape their inflation expectations. We start by providing correlational evidence, using our descriptive survey waves. Then, we provide experimental evidence based on two manipulations that shift 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 calculate a respondent's expected inflation rate as the mean of the respondent's subjective probability distribution.[13] Table 3 displays coefficient estimates from a multivariate regression of respondents' 1-year-ahead and 5-year-ahead inflation expectations on dummy variables indicating whether a respondent's narrative mentions a specific factor. We pool data from the three household surveys conducted in November 2021, December 2021, and January 2022 to maximize statistical power, and include wave fixed effects and additional controls.[14]

As shown in Table 3, the narratives that households use to explain the increase in inflation are strongly correlated with their expectations about the future development of

[13] 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%."

[14] We found similar patterns across waves when studying these correlations separately for each survey round. Figure B.2 shows similar results without the inclusion of demographic controls.

inflation. For example, households who attribute the rise in inflation to pent-up demand expect a 0.161 pp lower inflation rate one year ahead ($p = 0.508$) and a 0.606 pp lower inflation rate five years ahead ($p < 0.01$). 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 (0.73 pp; $p < 0.01$) and five years later (0.351 pp; $p = 0.110$), consistent with the perception that energy shortages are going to prevail, e.g., due to a shift toward more climate-friendly energy sources.

Finally, respondents mentioning government mismanagement predict significantly higher inflation both over the next 12 months (1.207 pp; $p < 0.01$) and five years later (0.838 pp; $p < 0.01$), as do households with narratives mentioning government spending, consistent with a view that government intervention in the economy is a more chronic cause of high inflation rates.[15]

While these correlational results are consistent with the idea that narratives shape inflation expectations, our estimates could also reflect unobserved third factors. Therefore, we next provide complementary evidence based on three experimental interventions that shift the narratives that are on top of respondents' minds before they make they make their inflation prediction.

5.2 The Causal Effect of Providing Narratives

In our first experiment, we exogenously provide households with narratives that suggest either a low or high degree of persistence of high inflation rates, namely narratives of pent-up demand and the energy crisis. Households who invoke narratives that explain the rise in inflation with factors that appear less persistent should hold lower inflation expectations. We therefore study how the provision of different narratives causally

[15]We also find that the narratives that households use to explain the recent inflation hike are correlated with their perceived uncertainty of future inflation (as shown in Appendix Table A.8). 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.

Table 3: Correlations between narratives and inflation expectations

	Inflation expectations (in %)	
	(1) 12 months	(2) 60 months
Demand factors:		
Monetary policy	0.972***	0.334
	(0.271)	(0.321)
Government spending	0.621***	0.403*
	(0.189)	(0.220)
Pent-up demand	-0.161	-0.606**
	(0.243)	(0.308)
Residual demand	-0.254	-0.144
	(0.191)	(0.203)
Supply factors:		
Supply chain issues	0.522***	0.085
	(0.145)	(0.157)
Labor shortage	0.369**	0.166
	(0.148)	(0.165)
Energy	0.730***	0.351
	(0.193)	(0.219)
Residual supply	0.175	-0.141
	(0.144)	(0.160)
Other factors:		
Pandemic	-0.064	0.092
	(0.146)	(0.159)
Government mismanagement	1.207***	0.838***
	(0.178)	(0.195)
Price gouging	0.733***	0.647***
	(0.229)	(0.244)
N	2,953	2,953
Controls	Yes	Yes
Survey FE	Yes	Yes
Mean	4.85	3.99

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 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 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 include our basic set of controls as well as survey wave fixed effects.

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

affects respondents' inflation expectations.

Sample We collect data for this experiment between April 6–10, 2022. We recruit respondents using Prolific, a survey provider commonly used in social science research (Eyal et al., 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 two narrative treatment arms described below ($p = 0.527$), yet there is somewhat lower attrition in the pure control group compared to the two treatments ($p = 0.030$). Appendix Table A.2 provides summary statistics.

Design In line with our descriptive household surveys, our baseline survey starts with two attention screeners, basic demographic questions, a definition of inflation, questions about past inflation, as well as information about the recent inflation increase. Subsequently, 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 in driving the rise in inflation. Each treatment presents the narrative as an explanation endorsed 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' one-year-ahead point forecasts of inflation.[16] 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.2 provides the key survey questions.[17]

Our goal is to study how the provision of narratives that are implicitly associated

[16]We do not elicit subjective probability distributions in any of the experiments reported in this section in the interest of keeping the surveys relatively short.

[17]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 and alleviates concerns about experimenter demand effects (de Quidt et al., 2018). The follow-up survey further mitigates such concerns.

Table 4: Narrative provision experiment

	Narratives			Inflation expectations (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 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 and the energy crisis, respectively, are featured in their narratives. "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.

with different degrees of persistence affects households' inflation expectations. At the time of our survey, the energy crisis had just been exacerbated by Russia's invasion of Ukraine. By contrast, pent-up demand associated with the end of lockdown was commonly viewed as a temporary and increasingly irrelevant phenomenon. While our treatments do not explicitly mention the persistence of these factors, we elicit beliefs about their persistence at the end of the follow-up survey. Based on data from the control group, we find that households indeed view pent-up demand as a more temporary driver of inflation than the energy crisis (as shown in Appendix Figure B.3).

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. Compared to respondents in the control group, those 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.[18] Thus, our treatments successfully generate variation in respondents' narratives about higher inflation. These findings also highlight that households' narratives are elastic to the provision of new information. 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 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 available variation to shift inflation expectations further upward. Importantly, the table also highlights that inflation expectations significantly differ between the pent-up demand and the energy crisis treatments ($p < 0.01$). This highlights that holding *different* narratives is reflected in differences in inflation expectations. Thus, our treatment effects do not simply capture the effect of being provided with *an* explanation (vs. no explanation). Column 5 highlights that the treatment effects on inflation expectations persist at a similar size in the follow-up survey. To summarize, being exposed to different narratives causally changes households' beliefs about the persistence of higher inflation rates.

[18] 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 some crowding out of other narrative factors, such as the pandemic for the energy treatment, and supply chain issues, labor shortages, and government mismanagement for the pent-up demand treatment. However, the treatment effects on these other factors are all substantially smaller than the effects on the narrative factor presented to respondents in the treatment.

5.3 The Causal Effect of Attention

Our second 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 to direct respondents' attention to their pre-existing beliefs about one specific factor—recent government spending programs—which was widely discussed in the media when we ran this experiment in December 2021. Thus, the experiment aims to shift which narratives come to participants' minds, while holding their information set constant. Based on our correlational evidence, we hypothesize that an increased tendency to think of government spending as an explanation for the rise in inflation should be reflected in higher inflation expectations. In addition, our experiment sheds light on the role of selective attention in shaping which narratives people endorse.

Sample We collect a sample of 1,126 respondents using Prolific. The survey was fielded between December 10–12, 2021. Summary statistics are shown in Appendix Table A.2.

Design The first part of the survey is virtually identical to our main descriptive household survey and includes attention screeners, questions on demographics, a definition of inflation, and questions about recent inflation. We then randomize respondents into a treatment and a control group. Respondents in the treatment group are prompted to think about recent government spending programs before the main outcomes (inflation narratives and inflation expectations), while the control group respondents proceed directly to the main outcomes. Specifically, right before we elicit our main outcomes, treated respondents receive the following prompt:

> What comes to your mind when you think about recent government spending programs? Please write 3-4 sentences.

We then elicit respondents' inflation narratives using similar instructions as in our descriptive household surveys. Subsequently, respondents report their point forecasts of the inflation rate over the next 12 months (see Appendix E.3 for the key survey questions).[19]

[19] Asking an additional open-ended question with no explicit connection to the later questions on inflation is a relatively subtle way of changing the contextual cues to which our respondents are exposed, which mitigates concerns about experimenter demand effects.

Table 5: Attention experiment

	(1) Narrative: Gov. spending	(2) Inflation expectations (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.

Results Table 5 shows the treatment effects from the experiment. We first discuss the effect of the attention manipulation on the narratives that come to respondents' mind. As shown in column 1, treated respondents are 9.6 pp more likely to mention the government spending channel in their narratives, as measured by the DAGs derived from the open-ended data. This effect is large and corresponds to a 60% increase compared to the 16% of control group respondents that mention government spending ($p < 0.01$). 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 the assumptions in Bordalo et al. (2020). When respondents' attention is drawn to government spending programs, they may retrieve memories of specific news content to which they were exposed, which in turn changes the narrative on top of their minds. This suggests that the narrative that an individual uses to explain the same phenomenon vary across contexts.

Column 2 shows that this exogenous shift in attention to government spending also leads to higher inflation expectations. Treated respondents expect 12-month-ahead inflation to be 0.40 pp higher than the control group mean of 6.6% ($p = 0.019$), an increase that corresponds to 14% of a standard deviation. This finding replicates the positive relationship between government spending narratives and respondents' inflation expectations that we documented in Section 5.1 and further corroborates the idea that narratives shape households' expectations.[20]

5.4 Narratives and the Interpretation of New Information

Recent theoretical work suggests that narratives change the lens through which people interpret new evidence and thus how they form economic expectations (Eliaz and Spiegler, 2020; Spiegler, 2016). We therefore conduct an additional experiment to examine whether an exogenous shift in narratives also affects how people update their economic expectations in response to new information. Again, we focus on 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.

Sample We use Prolific to collect a sample of 997 respondents on April 27 and 28, 2022. Appendix Table A.2 provides summary statistics.

Design Our experiment consist 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 stage of our experiment, we exogenously shift respondents' narratives. 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 the control "energy crisis" treatment receive an account 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 presents the narrative as an explanation endorsed by experts and includes an example quote from our November 2021 expert survey.

In the second stage of the experiment, all of our respondents are shown information about future changes in government spending. Specifically, we provide them with a forecast from one of two experts who participated in the first quarter of the 2022

[20] We view this exercise as another piece of evidence consistent with the idea that narratives shape households' expectations. However, it is conceivable that the treatment effects on inflation expectations do not exclusively operate through changes in narratives.

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 (differential) information, allows us to cleanly vary beliefs while holding other 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 all respondents' one-year-ahead point forecasts of inflation and the real growth of federal government spending over the next 12 months. Appendix E.4 provides the core survey instructions.

Our goal is to examine how the provision of narratives affects the interpretation of new information. Information about whether government spending will increase or decrease could plausibly affect households' inflation expectations if they think that government spending has been relevant for inflation in the past. Thus, we hypothesize that respondents who have been exposed to the government spending narrative will adjust their inflation expectations more strongly in response to information about future government spending compared to respondents who instead received the energy crisis narrative.

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) as well as a set of controls. We run these regressions separately for those who received the government spending narrative and those who received the energy crisis narrative before being provided with the forecast.

Column 1 of Table 6 shows that the "high spending" treatment successfully increases expectations of government spending growth by 4.7 pp among respondents who received the government spending narrative ($p < 0.01$) and by 6.8 pp among respondents who received the energy crisis narrative ($p < 0.01$), corresponding to 47% and 68% of the difference between the two signals (10 pp). It seems that 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 the forecasts. Their inflation expectations only increase by a non-significant 0.34 pp ($p = 0.205$). The difference in treatment effects on inflation expectations is highly statistically significant ($p < 0.01$).

Column 3 provides a quantitative interpretation of the effect size using an instrumental variable estimator. In particular, we study the effect of government spending expectations on inflation expectations, using the different forecasts about government spending as an instrument. Assuming that the exclusion restriction holds (which is not unreasonable given our active control design that only varies the number included in the forecast), these regressions allow us to estimate the elasticity of inflation expectations to beliefs about changes in government spending separately for respondents exposed to the two different narratives. Among respondents who received the government spending narrative, a 1 pp increase in government spending expectations leads to a 0.378 percentage point increase in inflation expectations ($p < 0.01$). By comparison, the corresponding elasticity for respondents who received the energy narrative is only 0.051 ($p = 0.184$). The difference between these two estimated elasticities is highly statistically significant ($p < 0.01$). This demonstrates that exposure to narratives can have a quantitatively important impact on how new information shapes expectations.

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 third 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 affect the narratives individuals endorse and their subsequent inflation expectations. Finally, narratives affect how individuals update their expectations in response to new information.

Table 6: Narratives and the interpretation of new information

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

Note: The table shows OLS regression results (columns 1 and 2) and IV regression results (column 3) from the belief updating experiment. Panel A shows results for respondents who are exposed to a government spending narrative prior to receiving the forecast, while Panel B shows results for respondents who are instead exposed to a narrative about the energy crisis. "Treatment: High spending" is a binary variable taking the value of one for respondents assigned to the high government spending forecast (predicting a 6% increase in real federal government spending over the next 12 months) and value zero for respondents assigned to the low government spending forecast (predicting a 4% decrease). "Expected government spending growth" refers to 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 estimates 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.

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

6 Narratives Are Shaped by News Media

What are the sources of the narratives that individuals endorse? One key candidate is the news media. The news media is the primary source of macroeconomic information for most individuals and could thus play an important role in the dissemination and propagation of economic narratives.

In our previous analyses, we have shown that when people are exogenously provided with economic narratives, they incorporate them into their own narratives (Section 5.2), suggesting that narratives in the news media could have a similar effect. However, two important questions remain unaddressed. First, which narratives are people exposed to when informing themselves about the macroeconomy through endogenously-selected news? Second, do the narratives that people hold change in response to exposure to these self-selected narratives?

To answer these questions, 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 a natural news environment 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 to measure treatment effects (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. The treatment, which is randomly assigned in the second wave, is uncorrelated with the likelihood of completing the third wave ($p = 0.597$). Appendix Table A.2 presents summary statistics for the full sample.

6.2 Experimental Design

Wave 1 In the first wave, which was conducted on February 8 and 9, 2022, we first elicit basic background characteristics as well as respondents' knowledge about inflation. We then measure their open-ended explanations for the recent surge in inflation and their confidence in their explanation.

Wave 2 The second wave took place on February 10, 2022, the day the inflation numbers for January 2022 were published. The 7.5% increase in prices 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 wave, 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.[21]

We next 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 groups. 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.

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

Wave 3 On the day after a respondent completed the second wave, the respondent receives an invitation to take part in the third wave. To avoid that the respondents merely restate their answers from the wave 1 survey, and to provide a natural justification for asking the same questions again, we tell them to "keep in mind that the questions today refer to the latest inflation numbers released yesterday." We then elicit respondents' narratives for the increase in inflation to 7.5% using an otherwise identical wording as in the first wave (in which respondents were asked to explain the increase in inflation to 7.2% based on the inflation rate in December 2021). Finally, to quantify the first stage generated by the treatment on inflation-related news consumption, we ask our respondents how many online or offline newspaper articles they read about the latest-released inflation numbers. Appendix E.5 provides the core instructions of the media experiment.

6.3 Descriptive Evidence on Narratives in Online News Media

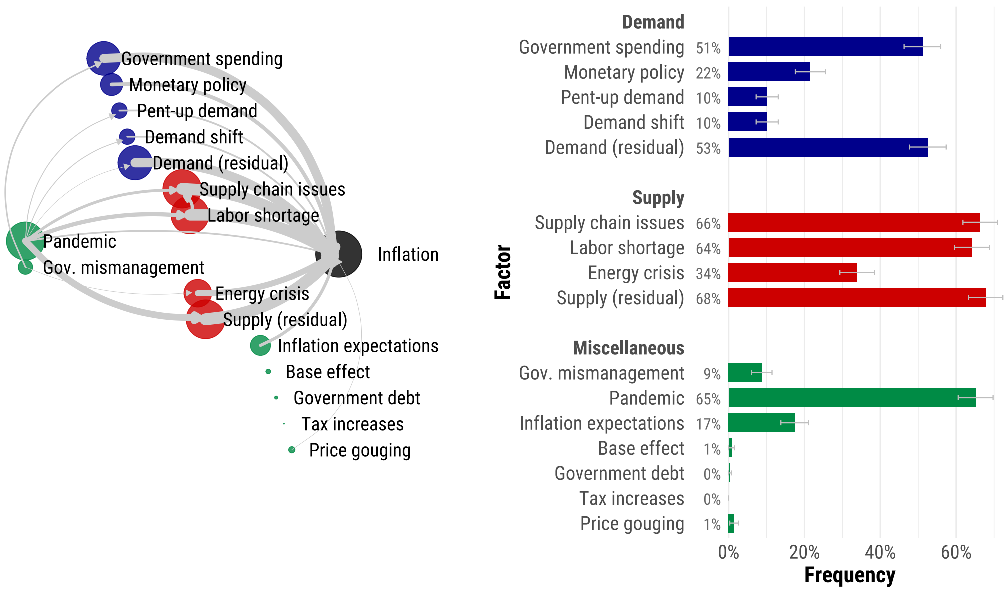
We first provide descriptive evidence on the narratives to which respondents are exposed when they are incentivized to search for and read an inflation-related article. We apply our coding scheme to identify the inflation narratives in each of the newspaper articles that respondents in the treatment group read in the second wave of our experiment.[22] Panel (a) of Figure 6 displays the average DAG of the newspaper narratives, while Panel (b) displays the frequency with which the different narrative factors are mentioned in the articles. All analyses are weighted by the frequency with which a given article is read, so that all estimates below reflect the properties of the "average article" read by respondents.

The large majority of articles, namely 97%, contain a narrative, confirming that online news media are indeed a rich source of narratives about the economy. However, there is substantial variation in which narratives are endorsed 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

[22] To ensure comparability with the household data, we rely on the same research assistants to hand-code both the newspaper articles and the open-ended household responses in the experiment. As shown in Figure B.5, there is substantial heterogeneity in the sources that our respondents consult. 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.

Figure 6: Narratives in the news

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



Note: **Panel (a)**: The "average" narratives mentioned in news articles (weighted by their population shares), 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.

(e.g., monetary policy or pent-up demand).

The average news narrative largely appears to be closer to the average expert narrative than to the average household narrative (as measured in our November 2021 wave).[23] First, the narratives provided by the media are complex, featuring an average of 5.9 factors (compared to 4.3 among experts and 3.5 among households) and 5.4 links (compared to 3.6 among experts and 2.8 among households). Similarly, they 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 (compared to 77% among experts and 34% among households). Second, narratives endorsed in the news are less politicized than households' narratives, with only 9% of articles endorsing government mismanagement as a cause of rising inflation (compared to 1% among experts and 32% among households). Third, the narratives endorsed in the news are fairly balanced between the demand and supply side, with 75% of articles mentioning at least one demand-side driver and 95% of articles mentioning at least one supply-side driver. Fourth, hardly any news narrative blames price gouging for the rise in inflation, contrary to the popularity of this narrative among households.

Taken together, these patterns highlight that individuals are exposed to a rich and diverse set of narratives when they read about inflation in the news. However, they also suggest 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 informing themselves about inflation.

6.4 The Causal Effects of Media Exposure

Next, we exploit 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:

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

[23] We use the November descriptive wave because it provides us with benchmarks for both households and experts. We obtain the same conclusions if we instead use the January descriptive wave or wave 1 of the media experiment as the household benchmark.

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 7 presents the estimated treatment effects. Column 1 shows that our treatment successfully increases exposure to inflation-related news. Treated respondents are 35.8 pp more likely to have read an article about the latest inflation numbers, compared to a control group fraction of 48.8% ($p < 0.01$).[24] 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 narrative 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 narratives factors, we observe the largest increases for the "residual" (unspecific) supply and demand factors, which are very common in the news narratives (see Figure 6 and Appendix Figure B.6). 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.6). 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.9 shows that respondents who read about a narrative factor in their endogenously chosen news article are 7 pp more likely to invoke it 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

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

Table 7: Media Experiment: 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, 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.

and mention some of them only in passing.

Taken together, 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. These points suggest that the mass media is an important source of households' narratives about the macroeconomy.

7 Conclusion

We provide evidence on narratives about the macroeconomy in the context of the 2021/22 surge in inflation. Drawing on representative samples of the US population and experts, we document substantial heterogeneity in causal accounts of the drivers of higher inflation rates. We measure the narratives using open-ended questions and represent them as Directed Acyclic Graphs (DAGs). Our analysis reveals fundamental differences between the narratives invoked by experts and households. Experts' narratives are more complex and focus on demand-side factors, such as fiscal and monetary policy, as well as disruptions on the supply side of the economy. Households' narratives are simpler, relatively less focused on the demand side, and more likely to feature politically-loaded explanations, such as government mismanagement or price gouging by greedy corporations. We show that households' narratives are predictive of their inflation expectations. Moreover, interventions that shift the narratives that are on top of people's minds causally affect inflation expectations and the way in which individuals interpret new inflation-related information. Finally, using an experiment giving people incentives to read news articles about inflation, we show that the mass media is a key source of the narratives that households endorse.

Our evidence suggests that narratives play a central role in people's reasoning about the macroeconomy. These narratives are highly heterogeneous, often differ from expert knowledge, and provide only fragmented accounts of the economy. Households are thus 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 a given economic state has been reached. Thereby, heterogeneity in narratives is likely to contribute to the widely-documented disagreement in macroeconomic expectations (Coibion and Gorodnichenko, 2015a; Dovern et al., 2012; Giglio et al., 2021; Link et al., 2020; Mankiw et al., 2003).

The politicized nature of inflation narratives highlights how polarized the perception of economic reality is in the US, which could have important economic and political costs (Levy et al., 2022) and may complicate central bank communication. Policymakers who aim to keep inflation expectations anchored should be aware that they communicate with people who hold substantially heterogeneous views on why inflation has increased.

Our approach of representing narratives as DAGs provides a versatile tool to capture people's rich causal reasoning about the economy, opening fruitful avenues for future research. For example, researchers could investigate economic narratives in other contexts and countries, study which features make narratives popular and persuasive, or explore how heterogeneous narratives feed back into macroeconomic outcomes.

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Narratives about the Macroeconomy

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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
Male	0.49	0.486	0.470	0.450	0.470
Age (years)	47.78	53.792	48.936	51.815	51.234
Employed	0.620	0.498	0.556	0.508	0.500
College	0.31	0.423	0.486	0.414	0.431
High income	0.482	0.390	0.385	0.352	0.317
Northeast	0.17	0.199	0.197	0.223	0.185
Midwest	0.21	0.246	0.241	0.236	0.245
South	0.38	0.398	0.379	0.415	0.349
West	0.24	0.156	0.183	0.126	0.222
Observations		1,029	981	992	1,051

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), and March 2022 (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 has 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: Experiments

	(1) Attention Dec 2021	(2) Media Feb 2022	(3) Narrative provision April 2022	(4) Info interpretation April 2022
Male	0.419	0.477	0.424	0.347
Age (years)	35.455	39.894	37.354	38.162
Employed	0.702	0.718	0.679	0.662
College	0.582	0.636	0.592	0.562
High income	0.432	0.427	0.408	0.388
Northeast	0.189	0.182	0.211	0.203
Midwest	0.225	0.231	0.213	0.193
South	0.385	0.363	0.342	0.364
West	0.202	0.224	0.234	0.240
Observations	1,126	763	1,329	977

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 narratives provision experiment in April 2022 (column 3), and the interpretation of information experiment in April 2022 (column 4). "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 pre-tax annual income 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.3: Summary statistics: Expert sample

	Mean	Standard deviation	Median	Observations
Personal characteristics:				
Male	0.883	0.323	1	111
Years since PhD	18.648	11.246	14	105
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.4: Overview of data collections

Data collection	Sample	Treatments arms	Main outcomes
Descriptive Wave 1 (November 2021)	Online panel in collaboration with Lucid (n = 1,029)	None	Inflation narratives and inflation expectations
Descriptive Wave 2 (December 2021)	Online panel in collaboration with Lucid (n = 981)	None	Inflation narratives and inflation expectations
Descriptive Wave 3 (January 2022)	Online panel in collaboration with Lucid (n = 992)	None	Inflation narratives and inflation expectations
Descriptive Wave 4 (March 2022)	Online panel in collaboration with Lucid (n = 1,051)	None	Inflation narratives and inflation expectations
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
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 receive 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.5: 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	0.29	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 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 or more. “Base rate” shows how often each factor is mentioned overall in the household samples.

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

Table A.6: 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	0.077	0.066	0.041

Note: This table uses data from the household samples and shows OLS regressions where the dependent variables are 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 or more. "Base rate" shows how often each factor is mentioned overall in the household samples.

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

Table A.7: 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	1.083***	0.733***	0.531***	0.070	-0.012
	(0.174)	(0.117)	(0.043)	(0.103)	(0.055)
N	1,140	1,036	1,140	1,036	1,036

Note: Panel A uses data from the household November sample and shows OLS regressions where the dependent variables are different measures of DAG complexity. "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 or more. "Base rate" shows how often each factor is mentioned overall in the household samples. 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.8: Correlations between narratives and uncertainty of inflation expectations

	Inflation expectations (in s.d.)	
	(1)	(2)
	12 months	60 months
Demand factors:		
Monetary policy	-0.598	-0.953
	(1.513)	(1.407)
Government spending	-4.693***	-3.998***
	(0.891)	(0.936)
Pent-up demand	-5.293***	-4.701***
	(1.100)	(1.305)
Residual demand	1.107	1.091
	(1.114)	(1.177)
Supply factors:		
Supply chain issues	-5.411***	-5.305***
	(0.784)	(0.803)
Labor shortage	-1.740**	-1.901**
	(0.800)	(0.840)
Energy	-1.548	-0.925
	(1.072)	(1.165)
Residual supply	-1.497*	-1.309
	(0.825)	(0.892)
Other factors:		
Pandemic	-2.263***	-2.264***
	(0.868)	(0.862)
Government mismanagement	-3.120***	-2.186**
	(1.017)	(1.033)
Price gouging	-4.270***	-3.018**
	(1.141)	(1.316)
N	2,953	2,953
Controls	Yes	Yes
Survey FE	Yes	Yes
Mean	16.1	15.7

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 devitation 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 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 include our basic set of controls as well as survey wave fixed effects.

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

Table A.9: Narratives after news exposure

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

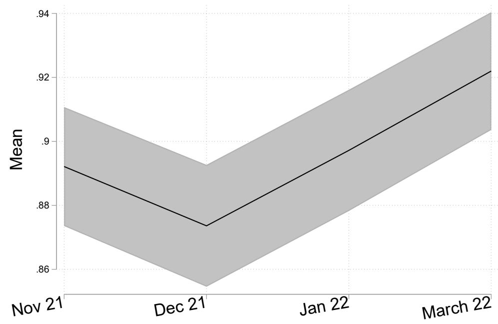
Note: This table uses data from all three waves of the media experiment, focusing on the 367 respondents in the treatment group that completed all three waves. The dataset is at the narrative factor-respondent level and contains 17 observations (number of narrative factors in our coding scheme) for each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

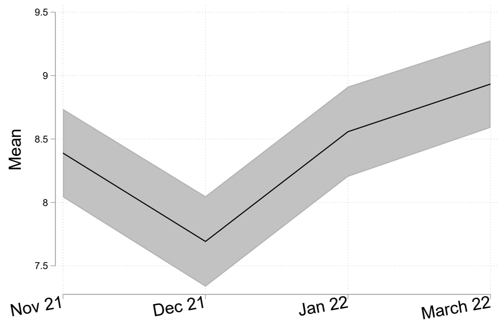
B Additional Figures

Figure B.1: Descriptives on beliefs about past inflation

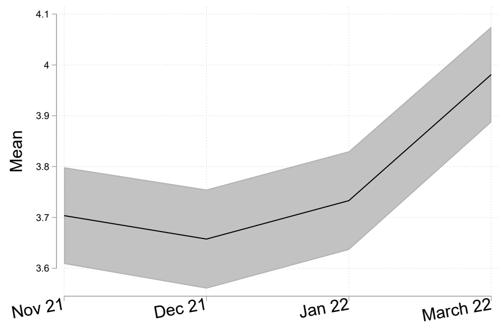
(a) Inflation: Higher today



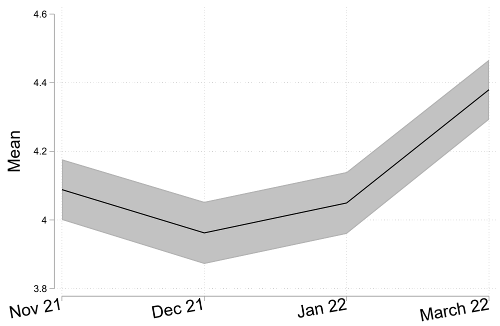
(b) Inflation last 12 months



(c) Frequency: Thinking about inflation

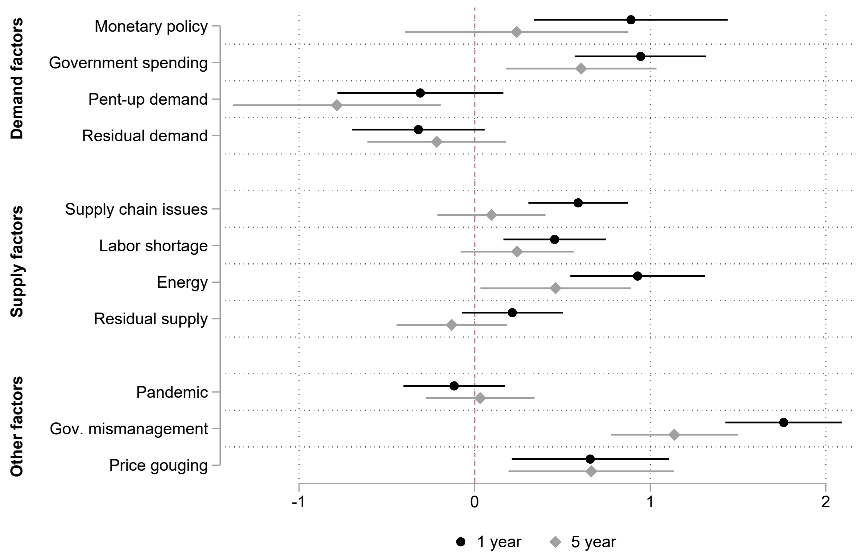


(d) Frequency: News consumption



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 ago. 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

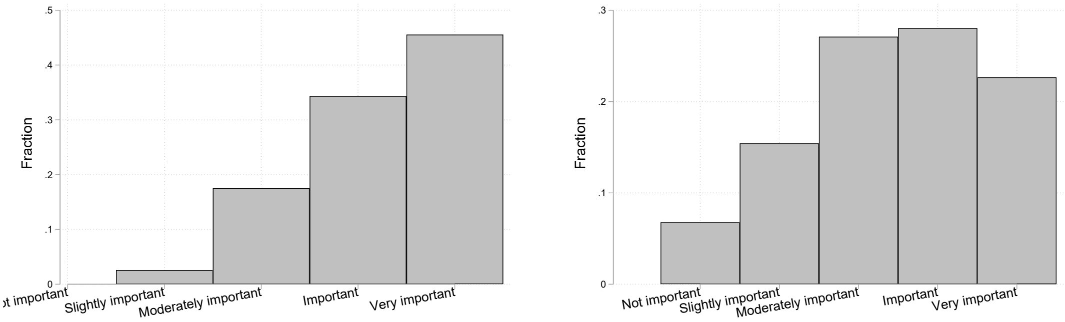


Note: The circles (diamonds) show estimated regression coefficients from a regression of one-year (five-year) inflation expectations on a set of dummy variables indicating which factors are included in the inflation narratives. Lines indicate 95% confidence intervals. Factors with few responses are included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

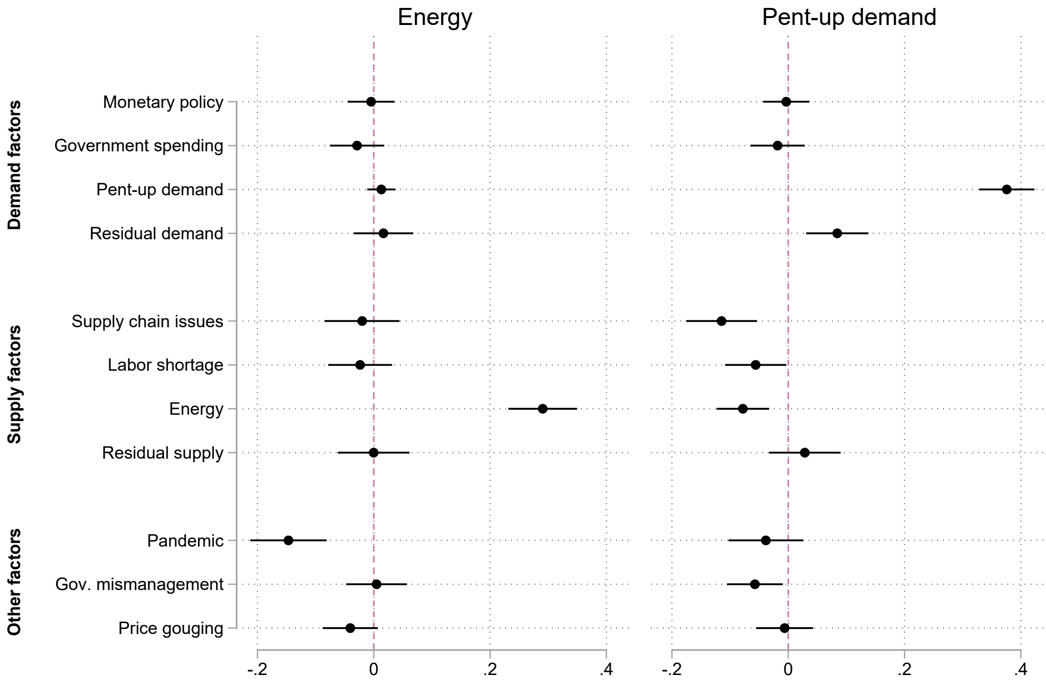
(a) Importance of energy crisis

(b) Importance of pent-up demand



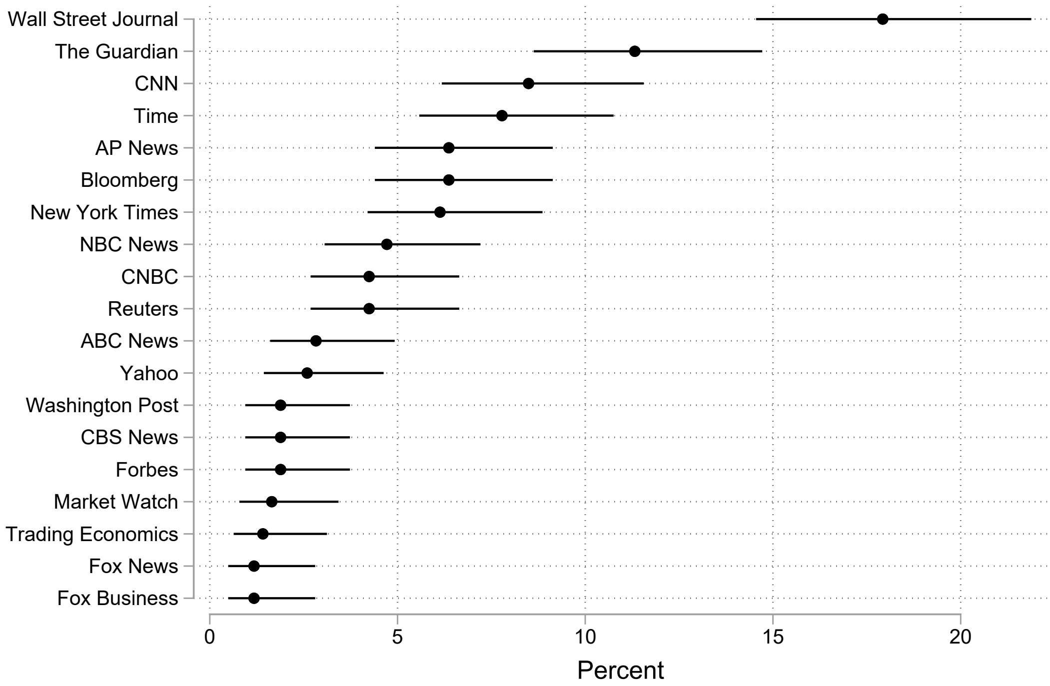
Note: This figure uses control group respondents from the narrative provision experiment and shows the distribution of responses to the following questions: "How important do you think that the global energy crisis will be for inflation over the next 12 months?" (Panel A) and "How important do you think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

Figure B.4: Treatment effects on individual narratives: DAG information provision experiments



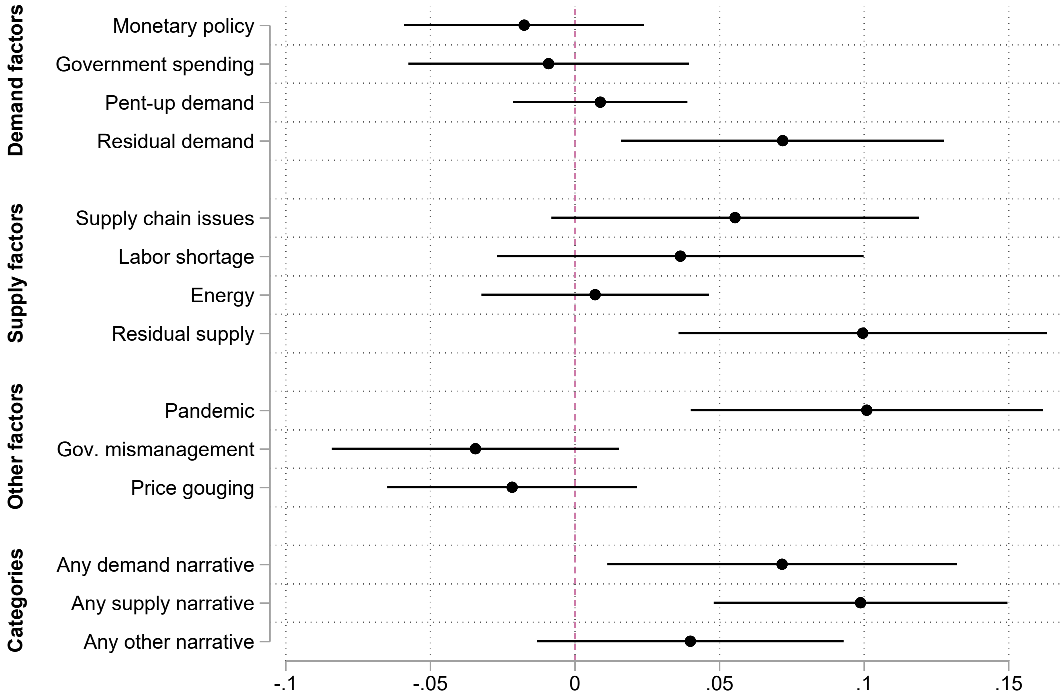
Note: The circles show estimated regression coefficients from regressions where the dependent variables are dummies indicating whether a factor is included in the DAG constructed from the open-ended responses about reasons for the recent increase in inflation and the independent variable is a treatment 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 among treated respondents in wave 2 of the media experiment.

Figure B.6: Treatment effects on individual narratives: Media experiment



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

C 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:

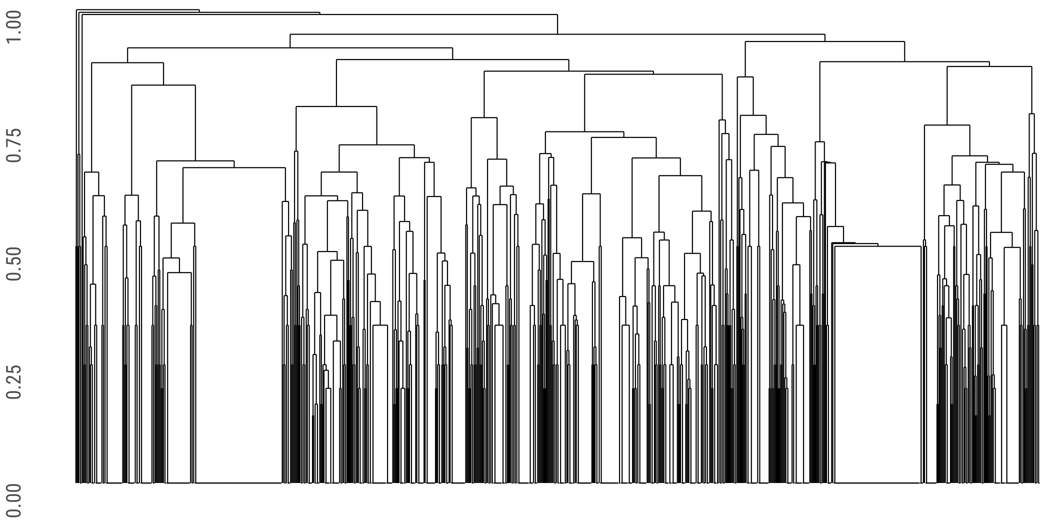
$$D(i,j) = 1 - \frac{\mid E_i \cap E_j \mid}{\mid E_i \cup E_j \mid}$$

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

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).

so-called dendrogram, showcases how the narrative clusters (indicated by lines) are sequentially merged at an increasing distance (y-axis).

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

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

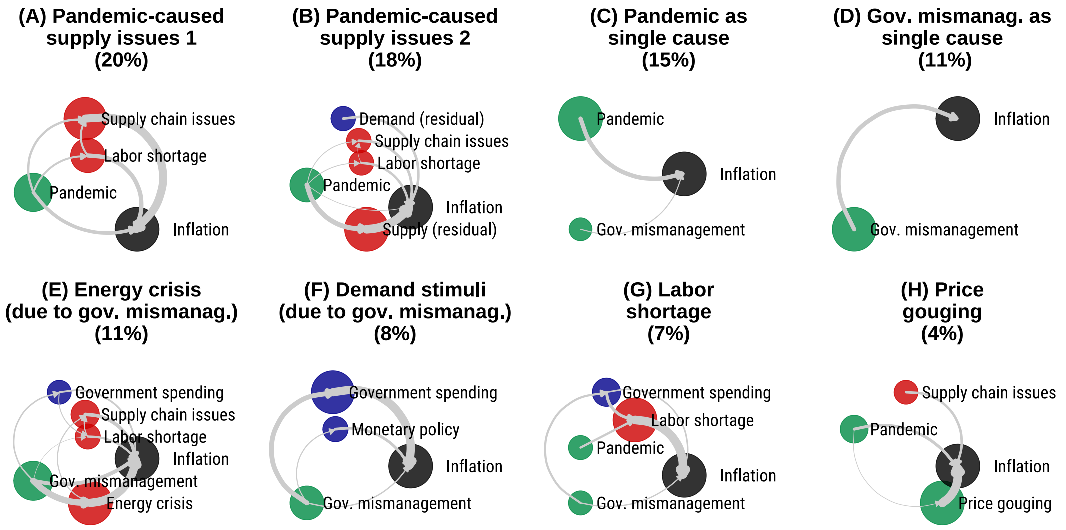
1. Cosine distance as distance metric. Instead of using *Jaccard distance*, we use the *Cosine distance* between edge lists to derive the dissimilarity of two narratives. Figure D.3 shows that this procedure yields very similar results. There is a corresponding cluster for every cluster from the main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

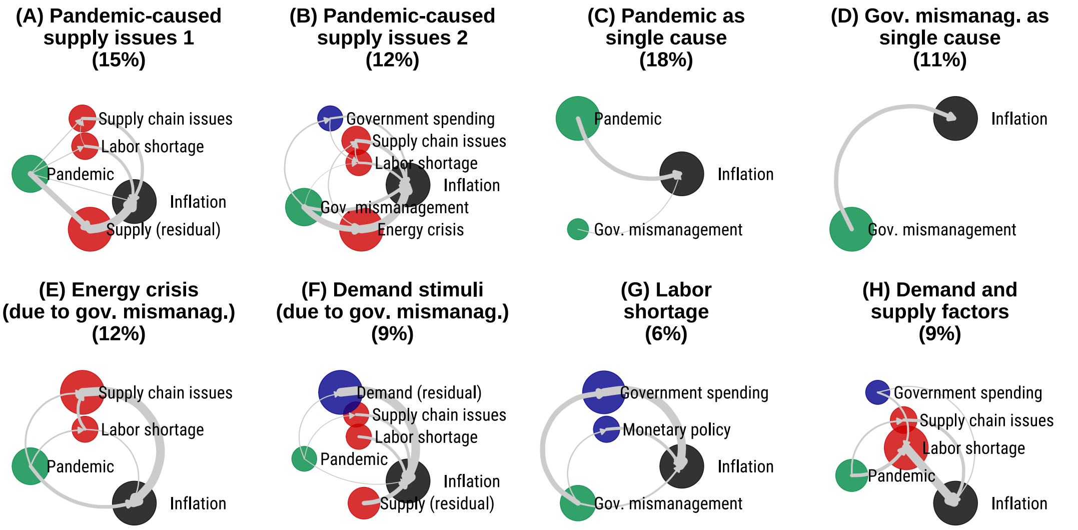
A final note on the linkage method: We do not derive results with different linkage methods (see step 3 in the previous subsection). Ward-type methods have been designed for application in Euclidean spaces, while our data are categorical. "Single linkage" successively adds narratives to one increasingly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



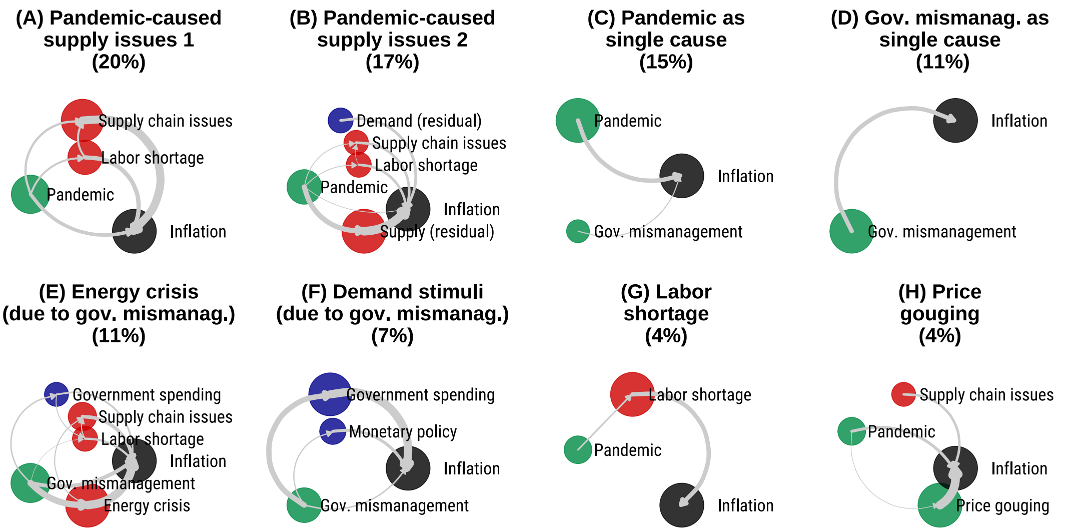
Note: Cluster analysis of narratives from household survey (November wave). Only households who provide a causal narrative are considered. **Clustering**: An agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives is applied (described in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



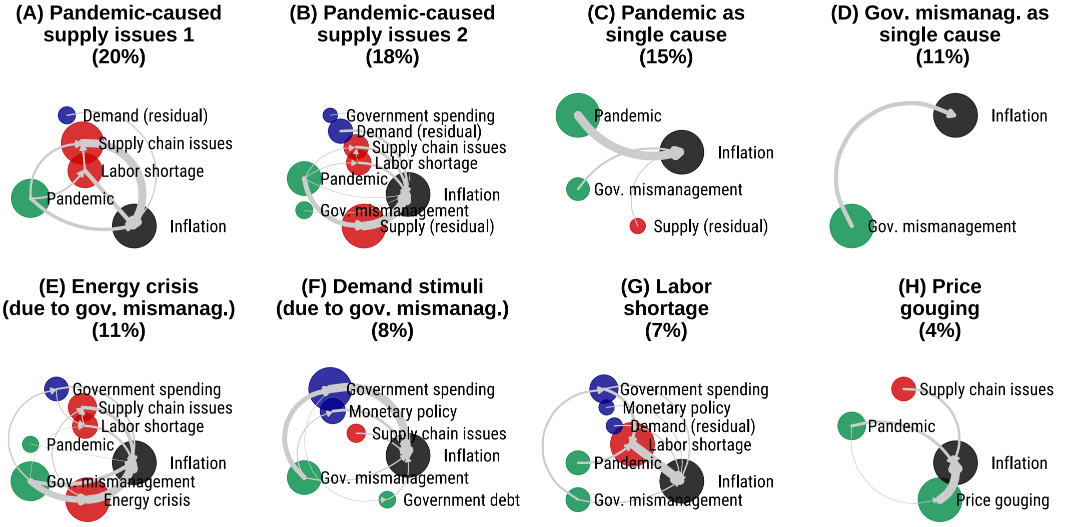
Note: Cluster analysis of narratives from household survey (November wave), based on Cosine distance. The eight largest clusters are displayed. In addition, see notes of Figure D.2.

Figure D.4: Cluster analysis with 20 total clusters



Note: Cluster analysis of narratives from household survey (November wave) with a total of 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, and March 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: 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.3 Household Survey: Priming Experiment (December 2021)

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

Priming treatment (treated respondents only)

US government spending

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

Please write 3-4 sentences.

→

Post-treatment outcomes

Why has the inflation rate increased?

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

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

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

→

Your forecast for the future

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

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

______ %

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

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

→

E.4 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.

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E.5 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

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

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

→

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

→

Miami treatment

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

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

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

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

04 55

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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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