Narratives about the Macroeconomy*

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Abstract

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

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

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1 Introduction

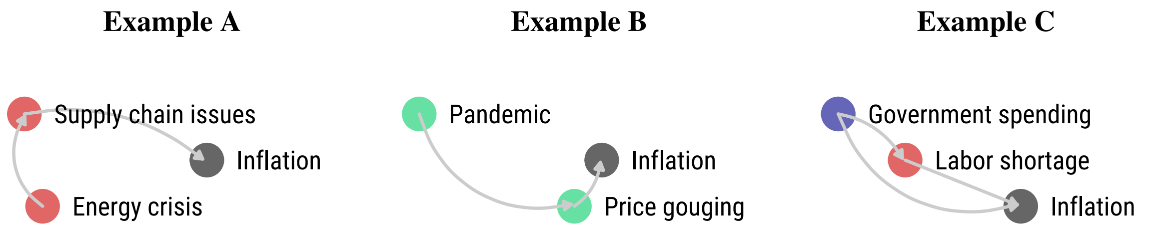
Narratives—the stories people tell to explain the world—provide a lens through which individuals can interpret data and forecast future developments. Psychologists have long acknowledged the importance of narratives, which they describe as "instruments of mind in the construction of reality" that are helpful to organize and explain the world (Bruner, 1991). More recently, economists have hypothesized that narratives also have important implications for the economy (Shiller, 2017, 2020). Narratives could be particularly relevant for understanding how people make sense of macroeconomic phenomena, which are often complex and consistent with different explanations. Narratives about the macroeconomy might thus shape individuals' macroeconomic expectations, which have been shown to affect important economic decisions (Armona et al., 2019; Bailey et al., 2019; Coibion et al., 2022; D'Acunto et al., 2022, 2023; Giglio et al., 2021). Nonetheless, empirical evidence on economic narratives remains scarce and our formal understanding of their macroeconomic consequences limited.

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

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

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

Figure 1: Example narratives, represented by DAGs



Notes: Three example narratives for why inflation increased, represented by their DAGs. Blue nodes are demand-side factors (gray when viewed in grayscale), red nodes are supply-side factors (gray), and green nodes are miscellaneous factors (light gray). The arrows indicate the direction of causality.

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

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

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

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

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

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

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

Related literature Our study contributes to a growing literature on stories and narratives in economics, including theoretical (e.g., Aina, 2025; Bénabou et al., 2018; Eliaz and Spiegler, 2020; Flynn and Sastry, 2024; Schwartzstein and Sunderam, 2021, 2022) and empirical perspectives (e.g., Goetzmann et al., 2023; Han et al., 2025; Shiller, 2017, 2020) as well as research on behavioral mechanisms (e.g., Barron and Fries, 2025; Charles and Kendall, 2024; Graeber et al., 2024b,c).[1] We provide a tractable empirical approach to measure and characterize economic narratives and provide evidence on their nature and consequences. The DAG-based approach allows us to quantify the causal structure of economic narratives—the chain of events in people's explanations—which cannot be detected by topic modeling or simple word-counting techniques (e.g., Goetzmann et al., 2024; Hansen et al., 2018; Shiller, 2017, 2020). Moreover, our empirical findings demonstrate that narratives shape the formation of economic expectations. Individuals use narratives about the past to forecast the future, and they interpret new information in light of these narratives.

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

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

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

[2] Work in financial economics has also studied market equilibria with agents who hold subjective models about how markets work (e.g., Eyster and Piccione, 2013; Eyster et al., 2019; Bastianello and Fontanier, 2025).

2 Narratives: A Working Definition

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

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

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

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

3 Setting, Data, and Design

3.1 Setting

We study narratives about the macroeconomy in the context of surging US inflation in late 2021 and early 2022. The topic of rising inflation received increased media attention from November 2021 onwards when the US inflation rate rose to 6.2%. This is a good setting for studying narratives about the macroeconomy for several reasons. First, different narratives about the rise in inflation were widely discussed in the mass media, and there was substantial disagreement about the drivers of inflationary pressures. Second, the rise in US inflation up to 9.1% in June 2022 involved high stakes for many households, e.g., in the form of changes in real income or the real value of assets and debt. Indeed, Link et al. (2026) show that inflation was the main factor on top of households' minds when thinking about their household's economic situation during the inflation surge. This suggests that we can study narratives about a decision-relevant event. Third, different narratives about what is driving the increase in inflation have vastly different implications for the persistence of higher inflation rates, and which narratives are top of people's minds thus potentially affects expectation formation.

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

3.2 Samples

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

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

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

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

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

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

3.3 Survey

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

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

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

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

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

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

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

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

3.4 Classifying Narratives

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

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

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

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

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

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

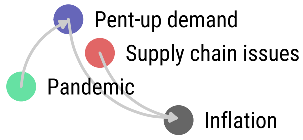
Table 1: Overview of factors on which the coding of narratives builds

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

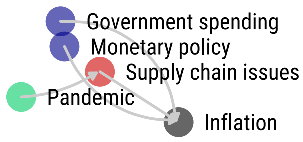
Notes: This table provides an overview of the different factors in our coding scheme, an explanation for each factor, and example extracts from open-text responses. If not otherwise indicated, example responses come from the November 2021 household sample.

Table 2: Example narratives

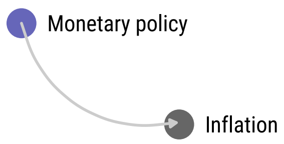
Expert example 1
Supply chain issues is probably the most important factor. Pent up demand from the pandemic, combined with historically high household savings/wealth, which has made consumers less price-sensitive, is probably the second most important factor. [...]



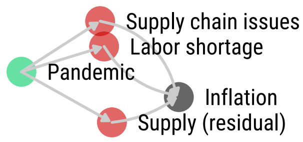
Expert example 2
The rise in inflation is due to severely negative supply shocks and positive aggregate demand shocks. The aggregate demand shocks are driven by government fiscal spending, which was at a record high last year, as well as very low real rates of return, which encouraged consumption rather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



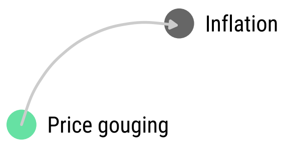
Expert example 3
Money printing (cheap Fed rates and quantitative easing). Inflation is a monetary phenomenon and will always be so.



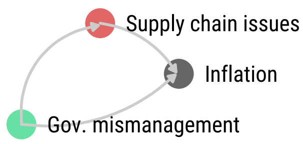
Household example 1
I think the biggest factor in the large inflation rate over the last year or so is probably the pandemic. With labor shortages and business shutdowns because of the pandemic, certain goods are harder to get a hold of, and supply chains have been heavily impacted.



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



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



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

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

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

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

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

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

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

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

corresponding figure is 93% for supply-side mechanisms.

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

4 Descriptive Evidence on Narratives

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

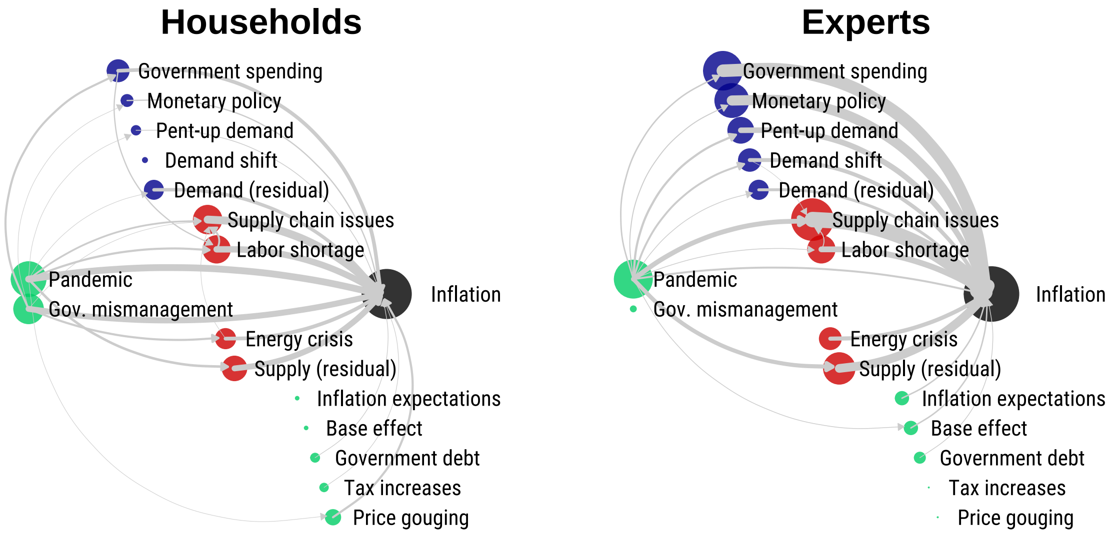
4.1 Comparison of Households' and Experts' Narratives

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

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

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

Figure 2: "Average" narratives among households and experts



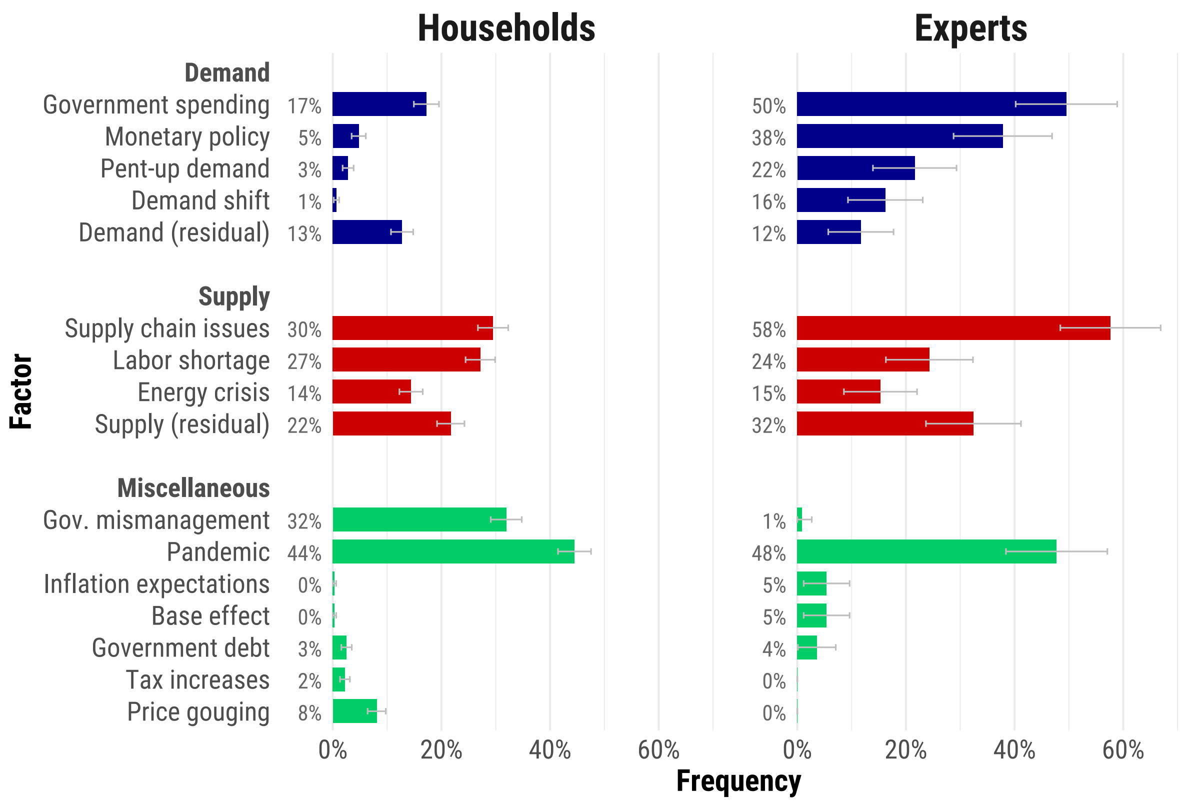
Notes: This figure shows the "average" narratives invoked by households (left panel) and experts (right panel), displayed as causal networks. The aggregated DAGs show which variables and causal links are most relevant in households' and experts' narratives. **Factor size**: The size of the factors is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

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

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

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

Figure 3: Frequency of factors



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

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 policymakers—is common among households (32%) but virtually absent among experts (1%). The high prevalence of this narrative among households indicates that inflation is a politicized topic in the US. Not only do households blame government mismanagement directly for high inflation, but such mismanagement is also seen as a primary cause of high government spending, loose monetary policy, and the energy crisis (see Figure 2).

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

In additional analyses, we show that the differences between households' and experts' narratives remain largely unchanged when we control for gender, age, education, and location

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

4.2 Heterogeneity and Narrative Clusters

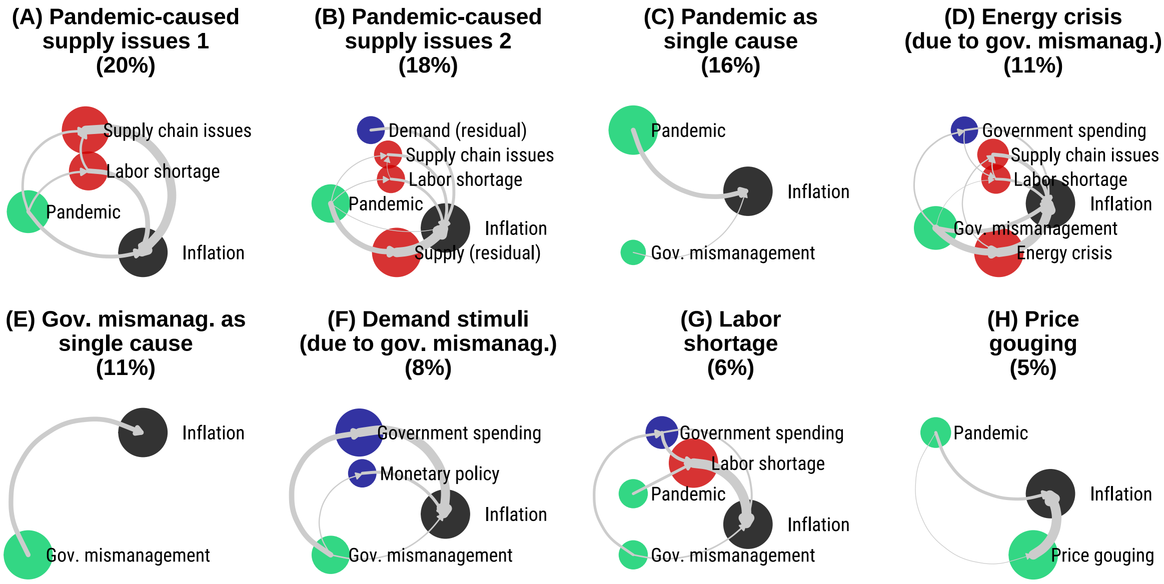
The aggregated results, presented above, conceal substantial heterogeneity in respondents' narratives within each sample. As highlighted in Figure 3, the fraction of household respondents mentioning a given narrative factor is at most 44% ("Pandemic"). Among experts, the fraction of respondents mentioning a specific factor is 58% at the maximum (supply chain issues). These numbers point to major within-sample disagreement about the causes of the increase in inflation.

To provide more systematic evidence on within-sample heterogeneity, we next investigate whether there are heterogeneous "narrative clusters," namely distinct clusters of factors and causal connections that are commonly mentioned together. We focus on household narratives since we need large samples to reliably distinguish between different narrative clusters.

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

Figure 4 presents the resulting clusters and their average DAGs. Four clusters (A, B, D, 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 D, 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, 6%). 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

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 Online Appendix E). The Silhouette approach suggests an optimal number of clusters of $k = 14$, 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 (gray when viewed in grayscale), blue indicates demand-side factors (dark gray), green indicates miscellaneous factors (light gray), 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.

of high inflation. The narratives in clusters C, E, and H represent less specific, often mono-causal narratives. Either the pandemic, government mismanagement, or price gouging are viewed as responsible for the hike in inflation. Their large population shares—16%, 11%, and 5%, respectively—indicate how prominent simple narratives are among households.

4.3 Correlates of Narratives

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

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

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

Finally, men provide significantly less sophisticated narratives with fewer factors and causal links. In particular, they are 11 pp ($p < 0.01$) less likely to talk about supply chain disruptions and 9 pp less likely to talk about labor shortages ($p < 0.01$), although their narratives more often refer to monetary policy (4 pp, $p < 0.01$). By contrast, older respondents and—to a lesser degree—individuals with a college degree invoke more sophisticated narratives. Full-time employees generally invoke less sophisticated narratives. They focus on fewer factors and are less likely to mention both demand and supply factors. The narratives of agents with different employment characteristics are of interest when thinking about households' wage bargaining and job search behavior (Pilossoph and Ryngaert, 2024).[12]

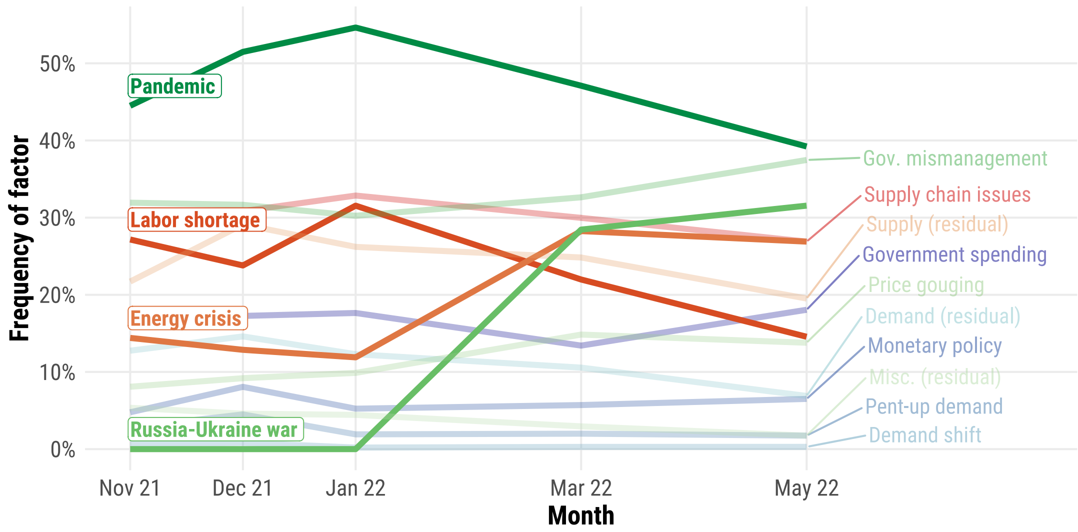
4.4 Development of Narratives over Time

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

Figure 5 documents the trends in narratives from November 2021 to May 2022. For each survey wave, it shows which fraction of narratives refer to a given factor. The figure highlights marked changes in the content of narratives, all of which likely constitute a direct response

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

Figure 5: Development of narratives over time



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

to the Russian invasion of Ukraine in late February. First, while virtually no narrative refers to the already ongoing Russia-Ukraine conflict in November 2021 to January 2022, 28% do so in March 2022. Second, the rise of the Russia-Ukraine war narrative is accompanied by an increasing prominence of the energy crisis narrative. 28% of households mention energy shortages or high energy prices in March 2022, compared to only 12% in January 2022. Third, while the pandemic increasingly appears in the narratives from November 2021 (44%) to January 2022 (55%), its frequency declines to 47% in March 2022 and 39% in May 2022. Similarly, the frequency of references to labor shortages sharply declines from 32% in January 2022 to 15% in May 2022. Together, these results highlight that narratives can change quite abruptly in response to major economic and political events and could thereby contribute to how economic agents change their expectations around such events.

5 Narratives Shape Expectation Formation

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

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

5.1 Correlational Evidence

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

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

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

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

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

high inflation rates.[15,16]

Next, we investigate which share of the variation in inflation expectations can be explained by narratives in out-of-sample predictions. Here, we turn to machine learning techniques, which efficiently handle the high-dimensional structure of the narrative data. We predict respondents' 1-year-ahead and 5-year-ahead inflation expectations with the help of a set of "factor dummies" for each of the 16 factors and a set of "connection dummies" for each possible causal connection between the factors. We employ a simple LASSO procedure and focus on out-of-sample predictions. Specifically, we randomly split the data in a training sample (70%) and a test sample (30%), estimate the LASSO model on the training data, and derive the out-of-sample predictions and the resulting out-of-sample R^2 for the test data.[17] We estimate that the narrative data account for approximately 10% of the variation in respondents' mean 1-year-ahead inflation expectation (Online Appendix Table A.12).

The share of explained variation is considerable, given the low explanatory power typically found for other covariates of macroeconomic expectations, such as demographics or experiences (Malmendier and Nagel, 2016). For instance, D'Acunto et al. (2021c) find a within-sample R^2 of 10% when relating inflation expectations to exposure to grocery prices, which they argue reflects that inflation expectations are likely shaped by a multitude of factors. Giglio et al. (2021) relate stock return expectations to a large set of investor characteristics and detect a within-sample R^2 of between 2% and 7%. They argue that the unexplained variation reflects "complex combinations of individual characteristics and experiences, some of which economic research has yet to discover." We find a lower R^2 when predicting respondents' 5-year-ahead expectations, reflecting that long-term inflation expectations were still relatively anchored in the winter 21/22 and viewed as less dependent on recent drivers of inflation (Online Appendix Table A.13).[18]

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

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

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

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

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

Table 3: Correlations between narratives and inflation expectations

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

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

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

5.2 The Causal Effect of Narratives

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

5.2.1 Narratives on Pent-Up Demand and the Energy Crisis

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

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

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

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

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

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

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

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

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

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

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

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

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

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

[22]Here and below, we consider it very unlikely that the treatment effects are driven by experimenter demand

5.2.2 Monetary Policy Narratives

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

Design The design is similar to the previous experiment. Respondents are randomly assigned to one of two treatment groups. Respondents in the "monetary policy" treatment receive an account that emphasizes the role of monetary policy in driving the inflation increase. Respondents in the "energy crisis" treatment receive an account that emphasizes the role of the energy crisis, similar to the previous experiment, in which it did not affect inflation expectations compared to a pure control group.[23] We hypothesize that the monetary policy narrative, which argues that loose monetary policy was a key driver of inflation in the past, should lead to lower expected future inflation because monetary policy had been substantially tightened since early 2022. As before, we mention neither the departure from low interest rates nor the persistently high energy prices. But, in an auxiliary collection, we confirm that a majority of 61% of respondents are aware that the Fed had abandoned its low interest rate policy (June 20, 2022, $n = 100$, same subject pool).

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

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

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

[23] Here, we opt for an active control group design, in which all respondents receive a narrative, and against an additional pure control group for various reasons. First, our goal is to provide causal evidence on the effect of holding *different* narratives on expectations. Second, the active control group design creates fully exogenous variation in narratives in both experimental conditions, allowing us to interpret treatment effects without accounting for prior narratives. Third, the provision of narratives per se might have side-effects, such as changing uncertainty about drivers of inflation, igniting emotional responses, and increasing the length of the survey, all of which are more comparable in an active control group design. Finally, we observe in Section 5.2.1 that the energy crisis treatment has no strong effect on inflation expectations, suggesting that we do not lose much information by not including a pure control group. See Haaland et al. (2023) for a discussion of active versus pure control group designs.

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

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

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

Notes: This table uses data from the monetary policy narrative provision experiment with households. "Treatment: Monetary policy" is a treatment dummy taking the value one for respondents assigned the monetary policy narrative and zero for respondents assigned the energy crisis narrative. "Monetary policy" and "Energy" are dummy variables equal to one for respondents for which monetary policy or the energy crisis, respectively, are featured in their narratives as measured in the follow-up study. "Confidence" is a measure of confidence in one's own understanding of why inflation has increased (z-scored based on a 6-point Likert scale response in which higher values imply higher confidence). "Main" and "Follow-up" refer to 12-month inflation expectations (in percent) 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.

to government spending changes households' narratives and inflation expectations.

5.3 Narratives and the Interpretation of New Information

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

Sample and design We use Prolific to collect a sample of 997 respondents on April 27 and 28, 2022. Online Appendix Table A.3 provides summary statistics. Our experiment consists of a simple 2×2 factorial design, in which we vary (i) the narrative and (ii) subsequent information that respondents receive before they make their prediction of future inflation. In the first part of our experiment, we exogenously shift respondents' narratives about the past inflation increase.[25] Respondents in the "government spending" treatment receive an account emphasizing that government spending programs have been an important driver of the inflation increase. Respondents in a control "energy crisis" treatment receive an explanation emphasizing

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

the role of the energy crisis. We use the energy narrative as an active control, holding constant the survey flow and the length of the instructions. This ensures that any effect on updating is not driven by the provision of *a* narrative but rather the provision of different narratives. Each treatment (truthfully) presents the narrative as an explanation used by experts and includes an example quote from our expert survey.

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

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

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

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

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

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

Notes: The table reports OLS estimates (columns 1 and 2) and IV estimates (column 3) from the belief-updating experiment. Panel A shows results for respondents exposed to a government spending narrative prior to receiving the forecast, while Panel B shows results for respondents exposed to a narrative about the energy crisis. "Treatment: High spending" is an indicator equal to 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 zero for respondents assigned to the low government spending forecast (predicting a 4% decrease). "Expected government spending growth" refers to respondents' point beliefs about changes in real government spending over the next 12 months, in percent. "Expected inflation rate" refers to respondents' 12-month point inflation expectations, in percent.
In the IV specification in column 3, expected government spending growth is instrumented with the treatment indicator. All specifications include controls for age (in years), log income, and indicators for gender, college education, having studied economics in college, full-time employment, region, and voting behavior in the 2020 U.S. presidential election. The final row reports p-values from tests of equality of coefficients across Panels A and B. Elicited point forecasts are top- and bottom-coded at 20% and 0%, respectively. Standard errors are reported in parentheses.

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

line with the hypothesis, the updating of inflation expectations is significantly different across the narrative treatment groups ($p < 0.01$).

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

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

6 The Effects of Narratives on the Macroeconomy

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

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

6.1 A formalization of the term "narrative"

In Section 2, we describe economic narratives as causal accounts for past economic events. Building on this idea, we now formalize narratives as *subjective causal models*, and we do so in

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

a way that easily lends itself to macroeconomic modeling.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

6.2 A DSGE model with the model of narratives

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

The model setup is completely standard for a New Keynesian model. The economy consists

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

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

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

6.2.1 Model setup without heterogeneity

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

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

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

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

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

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

rate according to the rule

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

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

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

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

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

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

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

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

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

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

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

$$\begin{pmatrix} a_{t+1} \\ g_{t+1} \\ \nu_{t+1} \end{pmatrix} = \begin{bmatrix} \rho_a & 0 & 0 \\ 0 & \rho_g & 0 \\ 0 & 0 & \rho_\nu \end{bmatrix} \begin{pmatrix} a_t \\ g_t \\ \nu_t \end{pmatrix} + \begin{pmatrix} \varepsilon_{t+1}^a \\ \varepsilon_{t+1}^g \\ \varepsilon_{t+1}^\nu \end{pmatrix}, \tag{10}$$

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

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

We first present the rational expectations equilibrium as a benchmark. If one imposes the restriction that households have the correct coefficients $\psi_a^H, \psi_g^H, \psi_v^H$ in their subjective causal model of inflation, households have the correct coefficients $\varphi_a^H, \varphi_g^H, \varphi_v^H$ in their subjective causal model of income, and firms have the correct coefficients $\psi_a^F, \psi_g^F, \psi_v^F$ in their subjective causal model of inflation, one obtains the rational expectations equilibrium.

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

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

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

Proof: See Online Appendix F.2.

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

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

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

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

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

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

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

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

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

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

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

Proof: See Online Appendix F.3.

Equations (15)–(16) give inflation and consumption as a function of the structural parameters, the current levels of the three factors, and agents' subjective causal models of inflation and income, where the subjective causal models are summarized by the households' perceived inflation shares

$\omega_a^H, \omega_g^H, \omega_v^H$, the firms' perceived inflation shares $\omega_a^F, \omega_g^F, \omega_v^F$, and the households' perceived income shares $\varpi_a^H, \varpi_g^H, \varpi_v^H$. The perceived shares $\{\omega_z^H, \omega_z^F, \varpi_z^H\}_{z=a,g,v}$ may vary with t in an arbitrary way. We suppress the time subscript t on those perceived shares for ease of exposition. Equations (15)–(16) are our main theoretical result and characterize the mapping from narratives to aggregate outcomes in a conventional New Keynesian model.

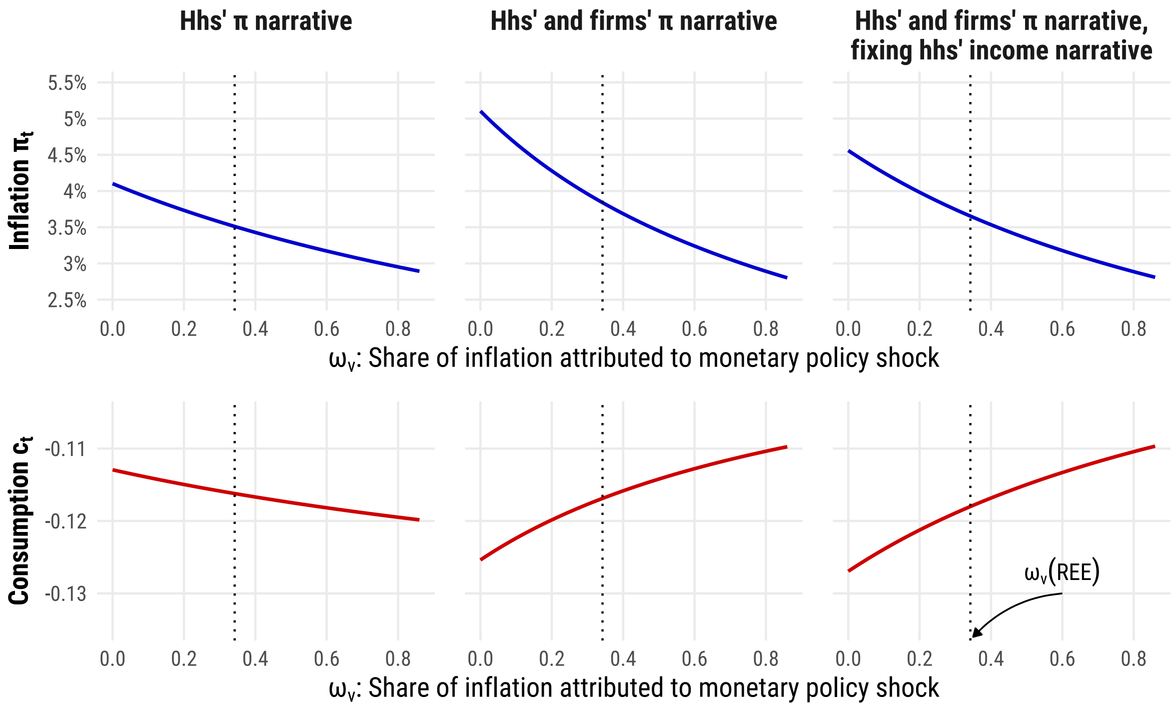
Equations (11)–(14) present intermediate stages where households' income expectations and/or firms' inflation expectations are still formed rationally. Relaxing the assumption of rational expectations in three steps, as we do in Proposition 2, allows us to illustrate the channels through which narratives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

We illustrate the main prediction of the model—the effects of inflation narratives on economy-wide outcomes—with Figure 6. We take the preference, price stickiness, and monetary policy parameters from a standard textbook on the New Keynesian model (Galí, 2015, chapter 3, page 67): $\beta = 0.99$ (quarterly model), $\gamma = 1$ (log utility), $\varsigma = 5$ (Frisch elasticity of labor supply equal to 0.2), $\lambda = 3/4$ (an average price duration of four quarters), and $\phi = 1.5$. We take the ratio of government spending to output in the non-stochastic steady state from Christiano et al. (2011): $1-\alpha = 0.2$. Finally, we set the persistence of the monetary policy shock to $\rho_v = 0.5$ and the persistence of the productivity shock to $\rho_a = 0.9$, following again Galí (2015); and we set the persistence of the government spending shock to $\rho_g = 0.8$, following again Christiano et al. (2011). We consider the following combination of shocks: a ten percent reduction in productivity ($a_t = -0.1$), a simultaneous ten percent increase in government spending ($g_t = 0.1$), and a policy rate that is two percentage points below the one recommended by the Taylor rule ($v_t = -0.02$). For these parameter values and shocks the rational expectations equilibrium from Proposition 1 is: $\pi_t = 1.92\% + 0.50\% + 1.26\% = 3.68\%$ and $c_t = -11.51\% - 1.76\% + 1.48\% = -11.79\%$. Hence, the period-$t$ rational expectations inflation omegas are $\omega_a^{RE} = 0.52$, $\omega_g^{RE} = 0.14$ and $\omega_v^{RE} = 0.34$, and the period-t rational expectations income omegas are $\varpi_a^{RE} = 0.98$, $\varpi_g^{RE} = 0.15$ and $\varpi_v^{RE} = -0.13$. If one substitutes those rational expectations omegas into equations (15)–(16), those equations reduce to the equations given in Proposition 1 and one receives the rational expectations equilibrium. However, if agents misperceive the current inflation and income shares, the equilibrium will no longer equal the rational expectations equilibrium and it will still be given by equations (15)–(16).

The right panel of Figure 6 plots equations (15)–(16). At the point $\omega_v = 0.34$, we set all the omegas to the values in the rational expectations equilibrium, and for this reason, consumption and inflation equal the rational expectations equilibrium. As one moves to the right, we increase the perceived importance of monetary policy for inflation, ω_v^H and decrease the perceived importance of productivity for inflation, ω_a^H, by the same amount, while ω_g^H is held constant.

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

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



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

For ease of exposition, we set the firms' omegas equal to the households' omegas, and we hold constant the households' income omegas at the values $\varpi_a^{RE} = 0.98$, $\varpi_g^{RE} = 0.15$, $\varpi_v^{RE} = -0.13$. The main result is the following. As households and firms give more importance to monetary policy and less importance to productivity in their inflation narrative, consumption increases and inflation falls, holding constant parameter values and shocks.

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

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

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

Central banks routinely provide narratives of current inflation. If households or firms adjust their subjective causal model of inflation in response to the central bank's provision of a narrative, then the model presented above makes the following prediction: The central bank's provision of a narrative changes economy-wide outcomes. Furthermore, the measurement of household narratives is important, because the central bank needs to know whether it moves households to the right or to the left in Figure 6 through the provision of its own narrative.

6.2.2 Model setup with heterogeneity

Now, we turn to the effects of heterogeneity in narratives among households on aggregate outcomes. We consider a simple example. Suppose that all households have the same beginning-

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

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

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

of-period financial wealth in period t. Furthermore, suppose that all households believe in period t that the other households have the same narrative of inflation and income as them in periods t and $t+1$.[33] These two assumptions imply that all households believe in period t that their own consumption level in period $t+1$ equals the aggregate consumption level in period $t+1$. Then, the consumption Euler equation of household i reads:

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

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

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

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

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

Households still understand that there exists the following relationship between *aggregate* consumption and *aggregate* income: $c_{t+1} = \tilde{x}_{t+1}$. Integrating equation (17) with equations (18)–(19) across i and using the definitions $\omega_z(i) \equiv \frac{\psi_z(i)z_t}{\pi_t}$ and $\varpi_z(i) \equiv \frac{\varphi_z(i)z_t}{\tilde{x}_t}$ yields

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

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

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

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

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

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

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

New Keynesian model has the property that all households consume the same amount (Galí, 2015, chapter 4.1).

7 Concluding remarks

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

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

The large extent of heterogeneity and fragmentation in households' narratives has important consequences for the formation of economic expectations. Households are not only imperfectly informed about the current state of the economy (Coibion and Gorodnichenko, 2012; Mankiw and Reis, 2002; Reis, 2006), they also systematically disagree about why the current state has been reached. Heterogeneity in narratives thus contributes to the widely-documented disagreement in macroeconomic expectations (Coibion and Gorodnichenko, 2015a; Dovern et al., 2012; Giglio et al., 2021; Link et al., 2023; Mankiw et al., 2003). One important question for future research is to better understand the origins of the substantial heterogeneity in households' narratives. While differential media exposure is likely to drive some of the heterogeneity, our experiment with exogenous variation in media exposure suggests (as discussed in Appendix 1) that traditional news media is only part of the story. A related open question revolves around the social processes that make some narratives go viral (Graeber et al., 2024a; Shiller, 2017). For instance, narratives involving corporate greed and price gouging are common among households but are neither endorsed by experts nor prominently featured in the media, suggesting that social interactions are important. We view it as an important question for future research to understand which features determine the virality of narratives and to better understand the role of social interactions.

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

While our paper focuses on the role of narratives in expectation formation, one important open empirical question is the extent to which these narratives influence everyday economic decisions. In our model, narratives affect households' behavior through inflation expectations. By changing inflation expectations, narratives affect expected real income and real interest rates, which shape households' consumption-savings decisions. Empirically, however, the precise link between inflation expectations and consumption-savings decisions remains a subject of active inquiry (Coibion and Gorodnichenko, 2024; Jiang et al., 2024). A better understanding of how narratives and inflation expectations affect firm decision-making is also important (Coibion et al., 2018, 2020b). It also seems likely that narratives matter through channels that our simple model does not capture. For example, via their effect on inflation expectations, narratives could also shape the timing of durable purchases (D'Acunto et al., 2022) and pass-through to stock investment decisions (Schnorpfeil et al., 2025). Moreover, narratives could play a major role in the political economy by affecting voting decisions. Indeed, narratives attributing high inflation to government mismanagement may have influenced the recent 2024 presidential election in the US, where high inflation was a key issue.[35] When thinking about the role of narratives in shaping everyday economic decisions, it is also important to explore how context-specific the narratives are that come to households' minds. For example, how closely do the narratives measured in a survey align with those considered in relevant decision environments (Bordalo et al., 2023)? Some of our findings—such as the persistence of narratives when measured in subsequent surveys—suggest a significant degree of stability in households' narratives.

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

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

including survey responses, speeches, or newspaper articles, and the quantification of the text data facilitates comparability between respondents and across studies.

Data availability statement: The data and code underlying this research are available on Zenodo at `https://doi.org/10.5281/zenodo.15311300` (Andre et al., 2026).

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