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Samuel Drößler

Ulrich Fritsche

Junbo Huang

Max Weinig

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THE CENTER FOR ECONOMIC RESEARCH
Department of Economics
Columbian College of Arts & Sciences
The George Washington University
Washington, DC 20052
https://cer.columbian.gwu.edu/

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The Stories People Tell: Households' Inflation Narratives and the Media

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This paper investigates how households conceptualize inflation and how these qualitative narratives correlate with inflation expectations and policy preferences. Using a representative survey of over 4,000 German households, we elicit open-ended narratives regarding the 2022–2023 inflation surge and represent them as directed acyclic graphs (DAGs) via fine-tuned large language models. We find that German households overwhelmingly interpret the inflation episode through supply-side channels and the war in Ukraine, while demand-side explanations remain comparatively rare. Beyond these aggregate patterns, inflation narratives systematically vary by financial literacy, personal economic experience, and institutional trust. Narrative structure and content correlate with inflation beliefs: supply-side narratives are associated with lower inflation expectations, whereas narratives emphasizing government action or corporate price gouging correspond to higher expectations and lower target inflation rates. A preregistered randomized information provision experiment using real-world newspaper excerpts demonstrates that exposure to news narratives significantly impacts qualitative inflation expectations, whereas quantitative expectations display greater rigidity. However, narrative exposure significantly reduces reliance on prior inflation perceptions, with treatment effects exhibiting mild heterogeneity across levels of financial literacy and prior inflation experience.

Samuel Drößler: University of Hamburg, email: samuel.droessler@studium.uni-hamburg.de. Ulrich Fritsche: University of Hamburg, email: ulrich.fritsche@uni-hamburg.de. Junbo Huang: University of Hamburg, email: junbo.huang@uni-hamburg.de. **Max Weinig (corresponding author)**: University of Hamburg, email: max.weinig@uni-hamburg.de. We thank colleagues for helpful comments, specifically Kai Carstensen, Lena Dräger, Philipp Lieberknecht, Davide Romelli, Johannes Wohlfahrt, Johannes Zahner, participants of the RSE Day 2026, the 57th Annual Conference of the Money, Macro and Finance Society, the research seminar on quantitative economics at the University of Hamburg, the seminar audience at the University of Kiel and the Bank of England for helpful comments. This work was partly funded by the Federal Ministry of Education and Research (BMBF) and the Free and Hanseatic City of Hamburg under the Excellence Strategy of the Federal Government and the Länder.

1. Introduction

Narratives, which are "instruments of mind in the construction of reality" (Bruner 1991, p. 6), matter. This insight establishes the foundation for the narrative turn across several disciplines (De Fina and Georgakopoulou 2011). More recently, the study of narratives, "the stories people tell to explain the world" (Andre et al. 2026, p. 1), has gained traction in empirical economic research (Shiller 2017, 2019; Eliaz and Spiegler 2020; Roos and Reccius 2023; Barron and Fries 2023).

The inflation surge of 2022–2023 provides a unique opportunity to examine how households construct macroeconomic narratives. Following more than a decade of low inflation, Germany experienced the strongest inflationary episode since reunification. While public debate featured a wide range of competing explanations, relatively little is known about which of these stories households adopted and how such narratives differ across individuals. At the same time, following the idea of Carroll (2003), previous studies have shown that news media serve as an information channel, shaping inflation expectations (e.g., Döpke et al. 2008a; Pfajfar and Santoro 2013; Lamla and Lein 2014). Although Andre et al. (2026) and Afrouzi et al. (2024) formally test the role of expert narratives in shaping inflation expectations and preferences, to our knowledge, no prior study explicitly estimates the effect of exposure to news narratives on households' expectations and preferences.

This paper studies causal narratives of inflation among German households using more than 4000 responses to open-ended questions from a largely representative survey of Germany conducted in December 2024. Following the common definitions of narratives in economics as a "sequence of causally linked events and their underlying sources" (Akerlof and Snower 2016, p. 58), or "causal models that map actions to consequences" (Eliaz and Spiegler 2020, p. 3787), the open-ended explanations are annotated into directed acyclical graphs (DAGs) through a combination of human coding and parameter-efficient fine-tuning of large language models. This approach allows us to recover both the content and structure of households' inflation narratives at scale. To study the media transmission channel, we construct a narrative provision experiment that randomly exposes participants to one of three causal narratives taken from real-world newspaper articles: (a) *pent-up demand*; (b) *energy crisis*; (c) *price-gouging*.

Our empirical analysis provides three main findings. First, German households predominantly explain inflation through supply-side narratives and geopolitical tensions. The war in Ukraine and the energy crisis are by far the most frequently cited drivers, while demand-side explanations such as monetary policy remain comparatively rare. Although this broad pattern resembles findings for the US reported by Andre et al. (2026), the German context exhibits an even stronger emphasis on energy-related and geopolitical explanations, reflecting the salience of the European energy shock and Germany's dependence on Russian gas during the period under study.

Second, building on the large body of literature on expectation formation, we examine how household narratives are systematically stratified across the population according to financial literacy, inflation experience, and institutional trust. Financially literate respondents construct more complex causal narratives and are more likely to emphasise supply-side explanations, while age-related differences suggest an important role for inflation experience: somewhat older respondents who experienced the global inflation in the 1970s and 1980s (often labelled as "Great Inflation" in the US context) are more likely to invoke the energy crisis, whereas younger cohorts more frequently emphasise demand drive or blame the government and firms. Further, we document the importance of institutional trust. Trust in public broadcasters, newspapers, and political institutions is associated with a lower probability of blaming the government, firms, or migration, while the latter is positively correlated with demand explanations. Taken together, these findings suggest that narratives are systematically related to individuals' cognitive resources, lived economic experiences, and the institutions they trust when interpreting macroeconomic events.

Third, random exposure to news narratives that highlight the rapid economic recovery after the pandemic or firms' price-setting behaviour as causes of inflation reduces households' qualitative short-term expectations, but does not shift quantitative expectations or preferences on average. Consistent with the existing literature, we document a strong dependence on prior inflation perceptions among our respondents when forming expectations. Our narrative treatment significantly reduces this dependence. Additional heterogeneity analyses reveal that quantitative updating is especially concentrated among financially literate households, who significantly revise their short- and long-term expectations downward when exposed to a pent-up demand narrative, potentially taking into account the transitory nature of the demand effect.

This paper builds on a growing literature examining expectation formation and the role of narratives. We contribute to several strands of literature. First, by studying households' causal inflation narratives, we build on Andre et al. (2026, 2022) and Binetti, Nuzzi, and Stantcheva (2024), who examine the content and structure of inflation narratives among US households and experts. They find that household accounts are coarser, more focused on supply, and more politically charged than expert explanations. Additionally, Demgensky and Fritsche (2023) conduct a pilot study using a small German sample, finding that narrative clusters correspond to socioeconomic and partisan divides. Building on this body of work, we present a large, representative German survey that elicits households' narratives about the causes of inflation.

Second, an extensive literature has studied the determinants of macroeconomic expectations. Previous studies find that financial literacy is associated with more accurate expectations, but also greater uncertainty (Bruine De Bruin et al. 2010; Rumler and Valder-

rama 2020, e.g.,). Malmendier and Nagel (2015) and Malmendier, Nagel, and Yan (2021) have further shown that inflation expectations of households and experts are driven by lived experience of previous inflation episodes. Other research building on the early work by Carroll (2003) has studied the role of media reporting on inflation expectations (Lamla and Lein 2014; Pfajfar and Santoro 2013; Dräger 2015; Larsen, Thorsrud, and Zhulanova 2021, e.g.,). Lastly, recent research on institutional trust indicates that inflation perceptions are correlated with trust in political institutions (Van Der Cruijsen, De Haan, and Van Rooij 2025; Guillochon and Ellen 2025). We build on these findings by exploring the narrative formation process, taking into account potential heterogeneity across financial literacy, prior experience, media consumption, and institutional trust.

Third, we contribute to the literature studying the causal role of narratives in the formation of inflation expectations and preferences. Andre et al. (2026) show that expert narrative treatments alter the expectations of US households, while Afrouzi et al. (2024) demonstrate their impact on inflation preferences. Building on Carroll (2003), we extend this research by investigating the causal effects of media narratives on inflation expectations and preferences, highlighting the role of the media as an information transmission channel for households.

Lastly, by extracting causal narratives from open-ended survey responses using state-of-the-art machine learning methods, we contribute to the literature on narrative extraction. While previous research has primarily relied on "bag-of-words" approaches, such as topic models or codebook-based sentiment analysis (Ter Ellen, Larsen, and Thorsrud 2022; Müller et al. 2022; Hong et al. 2025), we build on Andre et al. (2026) and Huang et al. (2026) by employing a DAG-based approach to extract inflation narratives from text. Thus, we extend the work of Heddaya et al. (2024) and propose a pipeline that combines human annotation with parameter-efficient, fine-tuned LLMs to extract multi-hop DAGs.

Section 2 describes the data collection, details the design of the information provision experiment, and explains the coding of the narratives. Section 3 provides an overview of the most frequent inflation narratives, describes the meta-clusters, and introduces our narrative formation study. Section 4 presents correlational evidence between narratives and households' inflation expectations and preferences, and in Section 5 we introduce our causal design to discuss the effects of media narrative provision. Section 6 concludes.

2. Data

2.1. Survey overview

To conduct our analysis, we draw on a preregistered online household survey[1] conducted in December 2024 in collaboration with *Kantar*, a leading panel provider. In total the

[1] Preregistration: `https://osf.io/w6efa/overview`

survey collected responses from 4,150 households living in Germany. Topics covered include, among others, inflation narratives, sociodemographic information, measures of trust, media usage, inflation expectations, and inflation preferences. We sampled based on gender, age, and education, and we post-stratify the data using iterative proportional fitting (raking) (DeBell and Krosnick 2009) on income, age, gender, education, and political identification. We benchmark these weights against the 2024 Microcensus and the 2025 German Longitudinal Election Study for our control group analysis.[2]

Following introductory and demographic questions, respondents report their level of financial constrain, answer two financial literacy questions regarding compound interest and inflation (Lusardi and Mitchell 2011). We then elicit respondents' inflation perceptions. Therefore, we provide first a basic definition of inflation and a corresponding example to illustrate its effects. Next we adopt a survey design informed by Leiser and Drori (2005), which, in contrast to Andre et al. (2026), splits the narrative elicitation into two distinct questions to reduce cognitive load. After providing historical context regarding the 2022 to 2023 inflation surge, the first question asks respondents to list the causal factors that come to mind first (Gennaioli and Shleifer 2010). The second question then invites them to describe how these factors are interconnected. We encourage respondents to write three to five sentences and emphasize the importance of this section to incentivize engagement. Finally, we administer a series of closed-ended questions using Likert scales to evaluate the perceived drivers of rising inflation.

To causally identify the effects of media narratives on inflation expectations and preferences, we randomly assign respondents to a control group or to one of three narrative treatment arms. The treatments present distinct causal narrative explanations for inflation: (a) pent-up demand following the post-pandemic recovery, (b) energy price shocks driven by the oil and gas crisis, and (c) corporate price gouging to increase profits. All quotes are drawn from real-world articles in the *Frankfurter Allgemeine Zeitung* authored by the same journalist. We slightly summarize these narratives and match them in length. The control group consists of 1,973 participants, with approximately 700 participants assigned to each treatment arm (see Table A6 in Appendix D). We subsequently elicit respondents' subjective inflation expectations for the next 12 and 60 months using point estimates (including upper and lower bounds) and qualitative Likert scales, alongside a point estimate of their preferred inflation rate (Afrouzi et al. 2024).

The final section includes comprehension checks, detailed socioeconomic and political background covariates, and post-treatment measures of institutional trust and media consumption, placed at the end to minimize priming effects. The questionnaire (see a flowchart in Figure A1 in the Appendix) was designed to take approximately 20 minutes (mean completion time: 18.5 minutes). We ensure data quality by excluding respondents

[2] `https://www-genesis.destatis.de/datenbank/online/statistic/12211/details`

who fail an attention check or complete the survey in less than one-third of the median duration, allowing us to filtering out inattentive responses.

2.2. Demographics and randomization

We provide an overview over the ranking-weighted descriptive statistics for the demographic and socioeconomic characteristics in Table A5. On average, respondents in the control group are 44 years old, 50 per cent are male, 40 per cent have at least one minor in their household, and approximately 20 per cent reside in East Germany. Around 40 per cent hold a university entrance qualification, while approximately 30 per cent have obtained a bachelor's degree or higher. The vast majority of respondents are currently employed, whereas 4 per cent are unemployed and 28 per cent are out of the labour force. The modal monthly net household income falls within the €1,300–€2,600 bracket, with approximately 13 per cent of households earning less and 57 per cent earning more. Regarding political identification, 26 per cent identify as left-wing and 30 per cent as right-wing. Overall, 50 per cent of the weighted sample correctly answered both financial literacy questions.

To evaluate the success of our randomization strategy, we report the standardized mean differences (SMDs) alongside p-values derived from ANOVA and χ^2 tests for the unweighted treatment groups and the control group in Table A6 in the Appendix D. Across all considered covariates, we do not observe any p-values that falls below the 5 per cent threshold. This is also supported by the SMD, which remains below 0.1 for eight of the ten covariates, with none exceeding 0.2. Taken together, both metrics confirm that the data are well-balanced across all treatment arms.

2.3. Measuring narratives in open-ended questions

The use of open-ended questions has become increasingly common in (macro-)economic research. While open-ended questions allow researchers to measure what is at the forefront of respondents' minds without unintentionally prompting a certain answer based on a predefined set of potential responses, they have the disadvantage of being more costly and time-intensive to analyse. Although there is no single best practice, researchers have implemented a wide range of methods to analyse the answers, including human annotations, word clouds, topic models and, more recently, Large Language Models (LLMs). (Haaland et al. 2025).

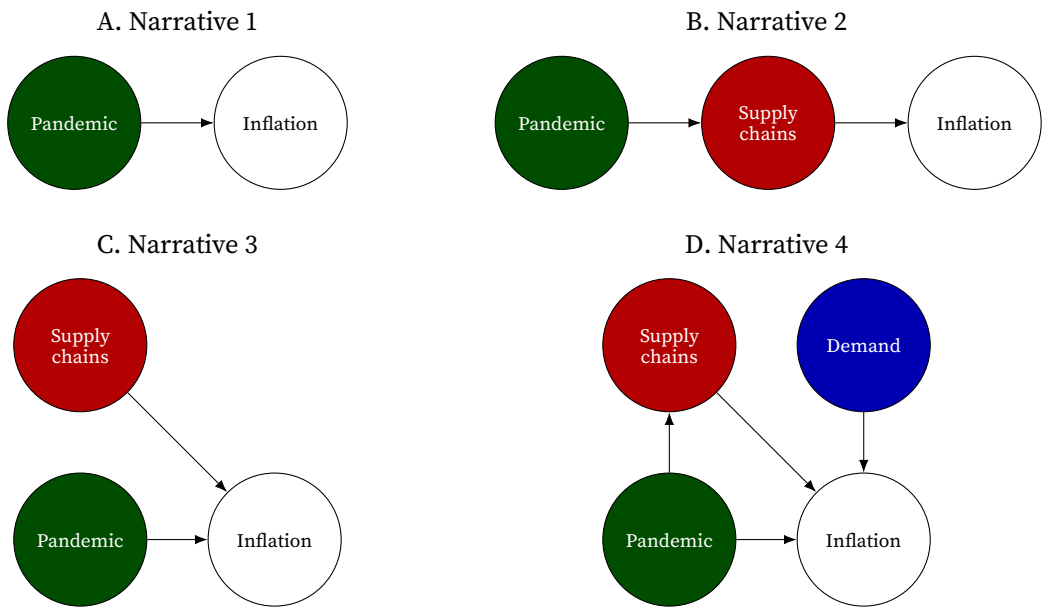
LLMs are particularly useful for researchers working with open-ended survey data. They offer greater generalisability than many commonly used text-analysis methods, provide substantial time savings relative to manual annotation, and are increasingly accessible through application programming interfaces (APIs). To the best of our knowledge,

existing applications of LLMs in the open-ended survey literature have primarily focused on tasks such as sentiment analysis or topic classification (e.g., Ferrario and Stantcheva 2025). However, analysing people's causal narratives requires moving beyond sentiment or topic analysis (Roos and Reccius 2023).

So far, Heddaya et al. (2024) is the only study to use LLMs to extract and model narratives in a manner that approximates a graph representation. Their application, however, is restricted to one-hop DAGs and focuses on newspaper articles rather than survey responses. More recently, Huang et al. (2026) introduce a methodological approach that draws on qualitative content analysis (QCA; see, e.g., Selvi (2019)) to annotate narratives as graphs and develop adjusted metrics for evaluating inter-annotator agreement (IAA) in graph-based settings.

Building on this work, we propose a pipeline for open-ended survey questions that maps causal inflation narratives into graph structures. The approach enables survey responses to be represented as unrestricted DAGs and facilitates the identification of narrated causal links between events across extended text segments. To this end, we implement a transparent two-stage annotation procedure and subsequently evaluate the classification performance of LLMs systematically.

FIGURE 1. Illustrative examples of narratives in DAG representation



Note: These figures presents a series of example DAGs. Blue nodes are demand-side factors, red nodes are supply-side factors, and green nodes are miscellaneous factors. The arrows indicate the direction of causality.

Methodologically, our framework builds closely on Andre et al. (2026). Figure 1 provides illustrative examples of these DAG structures to clarify the underlying framework.

Nodes represent the constitutive components of an inflation narrative, also called events, while directed edges denote the perceived causal linkages between these factors (so called relations). Narrative graphs can be highly parsimonious, as shown in Panel 1A. They may manifest as a linear sequence of arguments (Panel 1B), or exhibit non-linear complexities (Panels 1C and 1D) that complicate structural automated extraction.

We identify and extract narratives from open-answers by implement a two-stage annotation pipeline. To determine whether a survey response addresses the drivers of inflation, the first stage applies a classification framework across three distinct categories: (a) *Causal reasoning*: The respondent identifies relevant macroeconomic factors and articulates explicit causal mechanisms linking them. (b) *Factors of inflation*: The respondent identifies relevant drivers of inflation but does not explicitly or limited discuss how they are causally related. *Non-relevant*: The respondent's answer is either nonsensical or explicitly refuses to engage with the task.

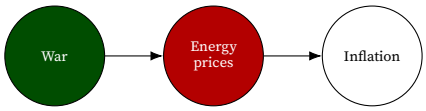
The second stage consists of two phases. First, using an iteratively refined taxonomy, the annotators identify and label the relevant event spans. Next, the causal linkages between previously labelled events are identified. During the annotation procedure, cyclical relations are excluded, with inflation being the only exception. However, we decided to exclude these cyclical relations from further analysis. Although the initial annotation is executed at the span level, these metrics are aggregated at the document level for subsequent empirical analysis. Our initial category system is based on the work by Andre et al. (2026) and inductively extended and adjusted during the annotation process. A detailed description of the codes can be found in the category system in Table A4 in the Appendix.

While LLMs have proven comparable to humans in many annotation tasks (Gilardi, Alizadeh, and Kubli 2023), recent literature has shown that they still struggle with complex tasks such as modelling narratives from texts (Antoniak et al. 2025; Schmidt et al. 2025). This makes a rigorous evaluation necessary. Thus, we create a benchmark based on carefully selected human annotations to study the performance of our modelling. In summary, our annotators agree in 88.6% of all cases on the same event label and in 72.2% of all cases on the relation. These levels of raw agreement are consistent with those reported by Andre et al. (2026). To further enhance the internal consistency and reliability of these annotations, we implement a conflict resolution process following Andre et al. (2026). This process requires a single researcher to review the response alongside the two independent annotations. The researcher then decides which of the two annotations to follow. The resulting dataset serves as the "gold standard" for all subsequent model training and testing. We provide an in-depth discussion of the evaluation including a graph-adjusted Krippendorff's α proposed by Huang et al. (2026) and a description of the conflict resolution in Appendix B.

To automate the annotation process of the full sample, we utilise open-weights LLMs to

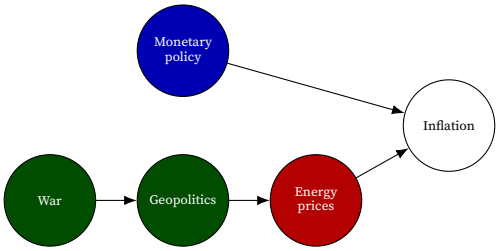
Survey Questions:

"In your opinion, which factors or reasons contributed to the sharp increase in the inflation rate in 2022-2023? How do you think these factors you mentioned are related to one another?"



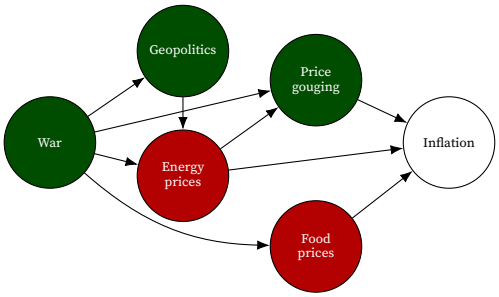
*"The **war in Ukraine**, **higher energy costs** – Due to the **war**, we had to look for **new energy sources**."(item-id 330, own translation)*

A. Example 1: War and Energy Crisis



*"**Energy prices have risen disproportionately**, **Ukraine war**, **interest rates of the ECB too low, interest rates of the FED too low** – A **too large money supply by the central banks at a low interest rate** fuels **inflation**. The **war in Ukraine** and the **embargo policy** of the EU and Germany have **made energy unnecessarily expensive**!" (item-id 559, own translation)*

B. Example 2: Sanctions and Monetary Policy



*"**War**, **energy became significantly more expensive**, **rise in food prices** well above the average increase in the cost of living – Causes: due to **Russia's war** against Ukraine and the resulting **boycott against Russia**. **Loss of cheap energy**. **"Windfall profits"** for the energy industry and arms manufacturers." (item-id 297, own translation)*

C. Example 3: War, Sanctions, and Price Gouging

FIGURE 2. Examples of Annotation. The left panels illustrate the extracted directed acyclic graphs (DAGs) representing the causal relationships. The right panels show the corresponding translated text excerpts, with key entities color-coded to match the nodes in the DAGs.

enhance reproducibility and mitigate potential data privacy risks. Specifically, we evaluate the performance of an *Llama-3.1 70B* model using zero-shot and few-shot learning settings and a *Llama-3.1 8B* using parameter-efficient fine-tuning. To evaluate the system, we hold out a random test set human-annotated documents from our gold standard dataset. A rigours comparison is provided in Appendix B. In short, in zero-shot and few-shot scenarios, the model struggles to identify narrative causal relationships that align with the human-annotated reference. This is consistent with previous findings (Heddaya et al. 2024). Therefore, we opt for the fine-tuned LLM approach that significantly improves overall performance, allowing for more reliable DAG-based narrative modelling. This results in final micro F1-scores of 0.87 for events and 0.64 for relation extraction.

2.4. Narrative clustering

Next, we move from identifying individual events and relations to asking whether the resulting DAGs exhibit systematic clustering across the survey. In other words, do certain factors and causal connections tend to co-occur systematically in distinct narrative patterns?

To identify groups of structurally similar narratives, we closely follow the approach outlined in Andre et al. (2026) and apply an agglomerative hierarchical clustering procedure. Each narrative is represented by its graphical edge list E, i.e. the set of causal connections contained in the respective directed acyclic graph (DAG). We then measure the dissimilarity between narratives i and j using the Jaccard distance:

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

This measure is zero for identical narratives and increases as narratives share fewer causal connections. Based on this distance metric, the clustering procedure groups narratives with similar causal structures together, while separating those with more dissimilar underlying relational patterns. To determine the appropriate number of clusters, we used silhouette plots and the average silhouette width. This resulted in a total of 23 clusters. We set the minimum number of observations per cluster to 30, thereby eliminating very small clusters and reducing the number of relevant clusters to 19. Further details on the clustering procedure can be found in Appendix G.

The resulting fine-grained clusters were subsequently examined qualitatively by the authors and consolidated into broader meta-clusters capturing overarching narrative families. These meta-clusters represent broader narrative families: a demand-side cluster, a supply-side cluster, a crisis cluster, and a political-blame/top-down-conflict cluster, each capturing a distinct mode of explaining inflation.

Our selection of these meta-clusters is guided by the theoretical framework in Andre

et al. (2026). Beyond the primary categories of demand and supply, we classify the remaining unassigned clusters into two additional, qualitatively distinct groups. First, we form a separate meta-cluster for geopolitical factors and global macroeconomic shocks (e.g., Covid-19, wars), which have gained empirical relevance in recent years. Second, motivated by the literature on political polarization and partisanship (Westheuser, Lux, and Mau 2026), we define a meta-cluster for anti-establishment narratives (e.g., "them up there/us down here" or"the people versus the government").

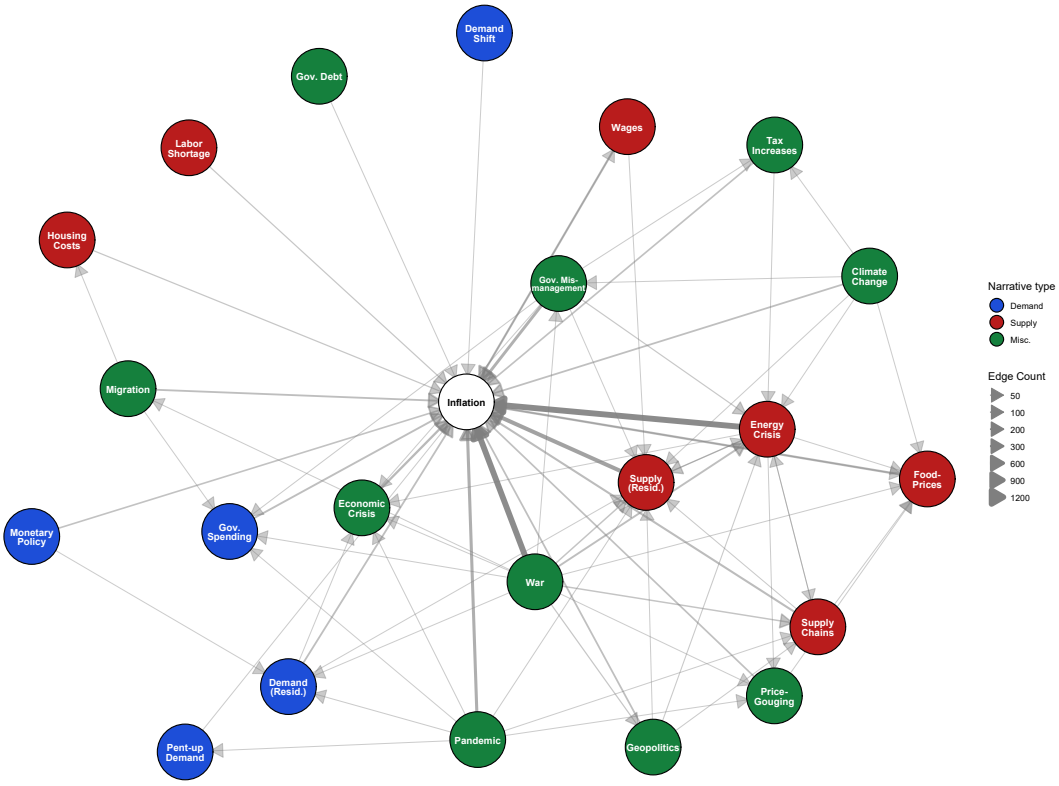
3. Individuals' inflation narratives

3.1. Descriptive findings

We begin by analysing the frequency of causes mentioned by the respondents within the open-ended questions. These causes are also referred to as events or drivers, representing nodes within the graph representations. Figure 4 provides the weighted share of respondents who mention a particular narrative event. In our sample, the most frequently cited driver (56%) is the war in Ukraine, followed by the global energy crisis (40%). Other commonly mentioned drivers include broader supply-side constraints (26%), the impact of the pandemic (24%), and government mismanagement (19%). Respondents rarely cite pent-up demand (<1%), high government debt (2%), or labour shortage (3%). In summary, the German sample cites supply and miscellaneous factors more frequently than demand factors. Consistent with the findings of Andre et al. (2026) for the US, our results demonstrate a similar popularity of several drivers. For example, both samples show a similar share of respondents mentioning the pandemic, political mismanagement, and supply chain disruptions. Conversely, our respondents place greater emphasis on the energy crisis and the war in Ukraine. This divergence is likely due to differences in Russian gas dependency between Germany and the US, as well as the distinct sampling periods. Moreover, during the annotation process, we add several drivers to our taxonomy not explicitly included in Andre et al. (2026), some of which may be captured within their residual categories, e.g., a code capturing food price inflation, alongside codes for wage growth and housing costs as drivers of aggregate price increases. As an additional robustness check, Figure A2 in Appendix C reports the weighted frequency of the hand-coded answers. This Figure confirms the reliability of our LLM-based codings.

To further investigate the argument structure and interconnection of the different narrated causes, we provide a full narrative graph analysis. Thus, we introduce the complete DAG-based narrative representations in Figure 3, which illustrates the "overall narrative" or "aggregate narrative" across all responses. This graph summarizes the DAGs derived from the open-ended responses, with edge weights reflecting the reporting frequency of the identified causal linkages. As the Figure shows, several supply-side drivers are

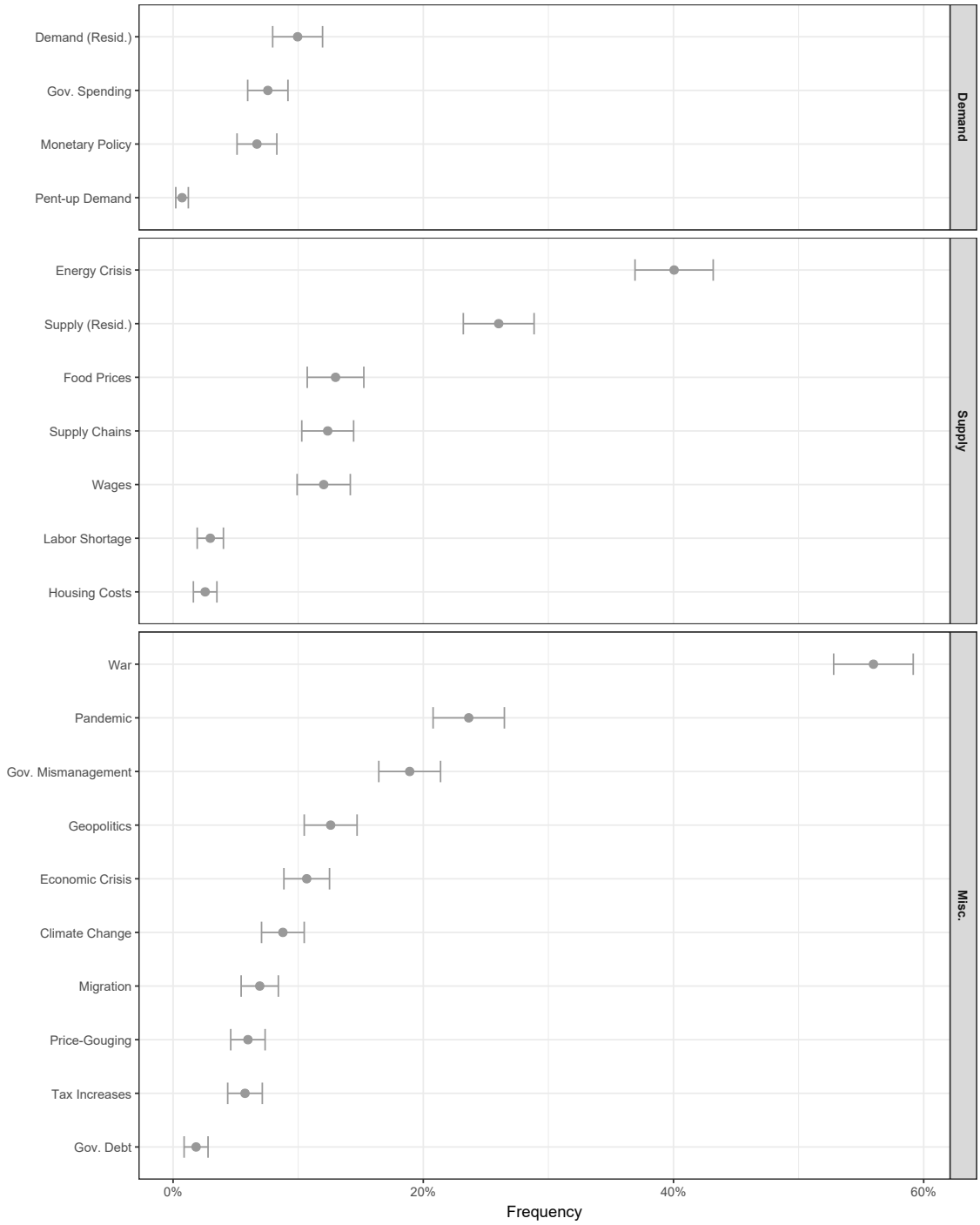
FIGURE 3. Full sample network



Note: This Figure shows the "average" narrative, displayed as causal network. The aggregated DAGs show which events and causal relations are most relevant in households' narratives. Red colour indicates supply-side factors, blue indicates demand-side factors, green indicates miscellaneous factors. The thickness of the edges is proportional to the share of narratives that refer to the respective node. For visibility, only edges occurring at least 5 times are displayed.

highly interconnected. For instance, causal chains proceed from supply chain disruptions to the energy crisis or other supply constraints. Furthermore, these supply-side drivers frequently enter causal chains involving exogenous shocks such as war or the COVID-19 pandemic. Another group of interconnected drivers involves demand-side factors (e.g., government spending and pent-up demand) alongside the pandemic and the government mismanagement. While this aggregate view captures the broad structure of inflation narratives, it necessarily abstracts from the patterns that recur across individual accounts, motivating a reduction in dimensionality that isolates the common configurations in which these drivers are causally linked. We operationalize this reduction in a second step, applying the clustering procedure detailed in Section 2.4 to render the individual DAGs more tractable and to identify common patterns across individuals. This results, following the exclusion of some very small clusters and the elimination of a self-referential cluster,

FIGURE 4. Frequency of events



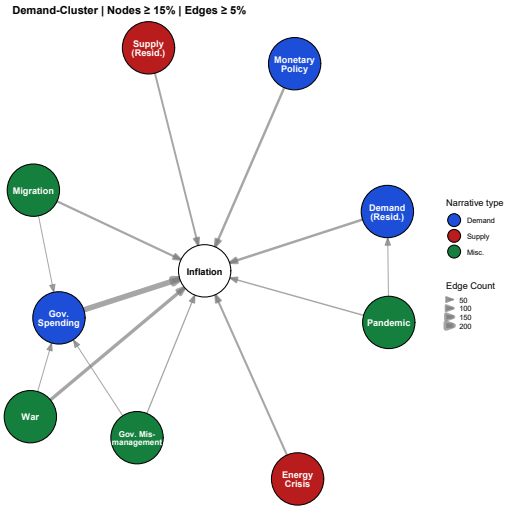
Note: The figures show the weighted frequency for different narrated causes of inflation. The band includes the 95 per cent coefficient intervals.

in a total of 19 narrative clusters for further analysis. A graphical representation of these clusters can be found in figures 5A-5D.

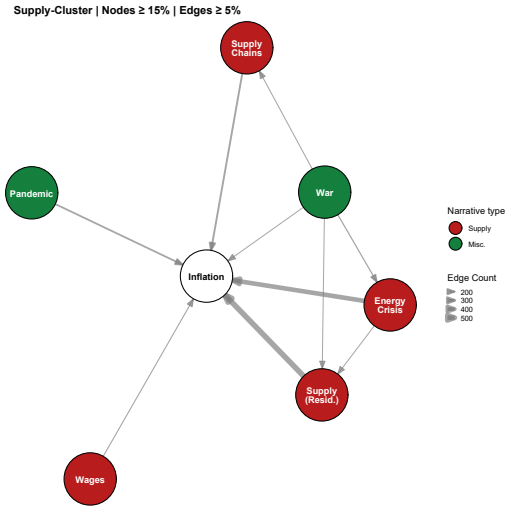
Building on the 19 clusters, we construct four theoretically motivated meta-clusters to capture the overarching narratives, accounting for approximately 90% of the sample. To derive these meta-clusters, we considered the main factors within each fine-grained cluster, focusing in particular on the most frequent causal connections. Based on these dominant narrative structures, we grouped the fine-grained clusters into four broader meta-clusters: demand-side, supply-side, geopolitics and crisis, and political blame/top-down conflict. The demand-side meta-cluster (see Figure 5A) captures narratives emphasising demand-driven inflationary pressures, most notably government spending, which respondents frequently associate with migration, political mismanagement, and the war in Ukraine. Residual demand factors constitute the second-largest component of this cluster. Respondents cite monetary policy less frequently; when mentioned, they typically present it as an isolated explanatory factor rather than as part of a broader causal chain. A broad set of supply-side explanations drives the supply meta-cluster (see Figure 5B), with the energy crisis, supply chain issues, and general supply frictions emerging as its most prominent components. Within this cluster, respondents frequently link the war to the energy crisis, and the war to supply chain disruptions, portraying the war in the Ukraine as a broader driver of aggregate supply-side pressures. The geopolitics and crisis meta-cluster (see Figure 5C) centres primarily on the war as the main driver of inflation. This is followed by the pandemic, government mismanagement, the energy crisis, and climate change. Further, respondents frequently invoke the economic crisis as a more general cause to inflation. Finally, the political blame/top-down conflict meta-cluster groups narratives attributing inflation to identifiable actors, primarily citing government mismanagement, price-gouging, and taxation. Respondents frequently mention the war in Ukraine in this cluster too, but usually as an additional explanation rather than as part of a more complex causal chain.

FIGURE 5. Meta-clusters

A. Demand



B. Supply



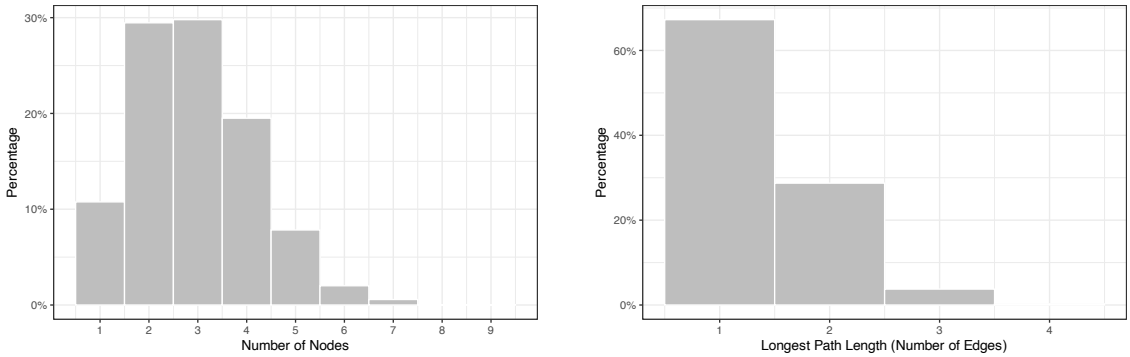
C. Geopolitics and crisis

D. Political-blame/top-down-conflict

Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 23 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The remaining 19 clusters are subsequently consolidated into four meta-clusters, labelled "Demand", "Supply", "Crisis", and "Political-blame/top-down-conflict". The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 15 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.

3.2. Narratives and financial literacy

Research on financial literacy and its impact on macroeconomic beliefs has shown that higher inflation literacy is associated with more accurate expectations and, notably, greater reported uncertainty (Bruine De Bruin et al. 2010; Rumler and Valderrama 2020). We contribute to this research by examining how financial literacy shapes the formation of narratives by incorporating questions from Lusardi and Mitchell (2011), while accounting for heterogeneity in the structure and complexity of individual narratives.



A. Distribution of number of measured nodes (events) within DAGs

B. Distribution of longest measured path within DAGs

FIGURE 6. Overview of DAG descriptive statistics.

We begin by estimating the relationship between financial literacy and the narrative content. Specifically, we regress binary narrative events and meta-cluster indicators on an indicator variable equal to one if a respondent correctly answered two financial literacy questions on compound interest and inflation, controlling for socioeconomic background characteristics (see Table 2 for the meta-clusters, and Table A7–A9 in the Appendix for the inflation events). Our results indicate that financially literate respondents have a significantly higher probability to highlight the supply channels, especially narratives involving energy crisis or wages as causes of inflation. Additionally being financially literate is associated with referring to climate change, and government mismanagement as causes of inflation.

Next, we introduce three complexity variables for the reported narratives, guided by the previous work of Andre et al. (2026): *number of nodes* measures the number of named events (besides inflation) within an answer; *longest path* measures the longest path of causal chains within a DAG and *demand and supply* is a dummy that takes the value one if a DAG contains demand and supply events at the same time (as a measure of the sophistication of arguments). In summary, on average a DAG consist two to three events. Around 35% provide answers with at least one path in their DAG consisting of two or three causal relations (see Figure 6). This means that approximately 65% of all answers

directly link events to inflation without providing any indirect causal explanations. Lastly, of all these answers, only 20% contain both demand and supply factors. Our additional regression analyses in Table 1 further indicate that complexity (measured by the *number of named events* or *longest path*) is, among others, a function of financial literacy. Moreover, our results suggest that left-leaning and right-leaning respondents provide a larger number of events, as well as older respondents.

In summary, these findings are consistent with previous work on financial literacy by Rumler and Valderrama (2020) and Dräger and Nghiem (2025), suggesting that financial literacy facilitates more nuanced economic reasoning. Additionally, these results extend the findings of Andre et al. (2026) by showing that household narratives are more coarsely structured than those of experts.

3.3. Narratives and inflation experience

While financial literacy has been shown to influence how individuals reason about inflation and the complexity of their explanations, the content of these narratives may also reflect their lived economic experiences. This perspective builds on the findings of Malmendier and Nagel (2015); Malmendier, Nagel, and Yan (2021), who show that inflation expectations of households and experts are strongly influenced by personal exposure to past inflation episodes. More recently, Malmendier (2026) provide initial evidence that such exposure may also shape the narratives individuals use to explain economic developments. Motivated by this insight, we examine whether exposure to different inflationary environments over the life cycle is associated with systematic differences in narrative content.

To examine this relationship, we regress binary indicators for each inflation event respectively narrative meta-clusters on indicators for three age cohorts, controlling for a range of socioeconomic characteristics. The results of the meta-clusters are reported in Table 2, while we report the results for the narrative events in Table A7–A9 in the Appendix D. Our findings underscore the importance of age and accumulated inflation experiences, in shaping inflation narratives. Specifically, older respondents are significantly more likely to refer to the energy crisis or crisis related factors, while they are less likely to refer to demand or blame government and firms.

One interpretation is that individuals who experienced the inflation surge of the 1970s and 1980s - predominantly attributed to energy-price shocks - are more likely to perceive contemporary inflation as being driven by the energy crisis. In contrast, younger cohorts, are more likely to emphasise demand-side pressures and blame government or firms. These findings are consistent with the evidence reported by Malmendier (2026) for the US. She shows that individuals who remember the "Great Inflation" episode refer more frequently to energy-related explanations, whereas cohorts whose experiences are shaped

by the recent inflation episode are more likely to mention factors such as government spending. In this sense, personal experience could provide persistent narrative templates for understanding the causes of inflation.

TABLE 1. Complexity of narratives (OLS/LPM)

	Dependent variable:		
	Number of Events	Longest Path	Demand and Supply
	(1)	(2)	(3)
Inflation Perception	−0.007***	−0.003***	−0.001***
	(0.002)	(0.001)	(0.0002)
Age 40-59	0.143*	0.002	−0.065***
	(0.087)	(0.042)	(0.025)
Age 60-69	0.179**	−0.040	−0.061**
	(0.085)	(0.041)	(0.026)
Male	−0.084	−0.040	−0.032**
	(0.061)	(0.029)	(0.016)
University Education	0.114*	0.012	0.029*
	(0.063)	(0.031)	(0.017)
Unemployed	−0.333**	−0.094	0.010
	(0.146)	(0.058)	(0.046)
Out of Labor-Force	−0.001	0.039	0.006
	(0.073)	(0.035)	(0.019)
Children in Household	−0.041	−0.013	−0.006
	(0.071)	(0.034)	(0.019)
High Income	0.057	0.005	0.023
	(0.062)	(0.031)	(0.018)
Right-Leaning	0.204***	0.075**	−0.0005
	(0.069)	(0.035)	(0.018)
Left-Leaning	0.206***	0.095***	−0.011
	(0.071)	(0.033)	(0.019)
Financial Literate	0.457***	0.148***	−0.008
	(0.068)	(0.030)	(0.018)
East Germany	0.014	−0.004	−0.004
	(0.070)	(0.036)	(0.017)
Regular Expenses	0.048	0.001	0.003
	(0.063)	(0.030)	(0.018)
Constant	2.380***	1.266***	0.192***
	(0.108)	(0.048)	(0.035)
Observations	3,073	3,073	3,073

Note: This table reports regressions relating respondents' characteristics to the complexity of their inflation narratives extracted from the open-ended responses. The dependent variable in column (1), Number of Events, measures the number of narrative events other than inflation contained in a respondent's DAG. Longest Path in column (2) measures the maximum number of causal edges along a path in the DAG. Demand and Supply in column (3) is an indicator equal to one if the narrative contains both demand- and supply-side factors. Columns (1) and (2) are estimated by OLS and column (3) by a linear probability model. All regressions are estimated using survey weights constructed by iterative proportional fitting (raking) based on income, age, gender, education, and political identification. Standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.4. Narratives, political trust, and media consumption

As the previous sections have shown, financial literacy and personal inflation experiences shape how individuals understand and explain inflation. While these factors are important determinants of inflation beliefs and perceptions, they provide only a partial account of narrative formation. Individuals also acquire information about economic developments through external sources, most notably the media, which serves as a key channel for the transmission of economic information.

The framework developed by Carroll (2003) highlights this mechanism within an epidemiological model of expectation formation. Challenging the assumption of full-information rational expectations (FIRE), Carroll argues that households update their expectations only gradually as information diffuses from experts to the broader public. This process generates sticky expectations and has been examined empirically by, among others, Döpke et al. (2008a,b). A central component of this framework is media coverage. Several studies have shown that media reporting plays an important role in shaping inflation perceptions and expectations (Lamla and Lein 2014; Dräger 2015; Pfajfar and Santoro 2013). More recently, Andre et al. (2026) demonstrate that media consumption is associated not only with inflation expectations but also with the economic narratives individuals adopt. Their findings suggest that narratives are shaped not only by financial literacy and personal experiences, but also by the information environment to which individuals are exposed.

The influence of information, however, is likely to depend not only on exposure but also on the credibility individuals assign to its source and political actors. Previous studies have examined both the determinants and consequences of trust in political institutions, including the ECB (Brouwer and De Haan 2022; Ehrmann 2026). At the same time, recent research suggests that the level of perceived inflation is associated with trust in fiscal and monetary policy (Van Der Cruijsen, De Haan, and Van Rooij 2025; Guillochon and Ellen 2025). Together, these findings indicate that trust may play an important role in shaping how individuals process and interpret economic information. We therefore hypothesise that individuals who differ in their trust in political institutions and the media may also differ in the inflation narratives they find plausible. Accordingly, we examine whether political trust is associated with systematic differences in narrative content.

To investigate the potential relationships between media consumption, trust, and the measured narratives more systematically, we estimate LPMs where the dependent variables are binary measures for our inflation events or the four meta-clusters. The primary explanatory variables are the media consumption and trust in media and political institutions. Specifically, we measure media consumption as the average across standard Likert-scales items measuring news consumption of traditional media (newspapers, radio, and TV) and new media (social media, messengers, and YouTube). Trust in political

institutions averages across standard Likert-scale measures for the ECB, the government, and the Eurosystem, while trust in public broadcasters and newspapers averages across standard Likert-scale measures for newspapers and public broadcasters. Trust in private broadcasters is measured separately, the correlation with the other two media trust items is only moderate.

Our measures of trust in institutions are statistically significant predictors of these narratives, even conditional on media consumption. As Table 2 suggests, higher trust in newspapers and public media is associated with a significantly lower probability of blaming the government or firms. In addition, Tables A7–A9 in the Appendix highlight that trust in public broadcasters and newspapers is related to a lower likelihood of referring to migration as a cause of inflation. We observe similar patterns for our measure of trust in political institutions: A negative correlation between this measure and the likelihood of attributing inflation to government action and firms price-setting behaviour and a positive correlation with demand explanation. In contrast, having higher trust in private media increases the likelihood of referring to migration as potential cause.

In line with Andre et al. (2026), we also observe some significant relationships between media consumption and narrative formation; e.g., above-average new media consumption is associated with a lower likelihood of explaining inflation with the energy crisis or residual supply factors, while higher consumption of traditional media is associated with higher likelihood of citing government spending and supply channels as cause of inflation. In summary, our results suggest that trust in political and media institutions plays a prominent role in how individuals conceptualise the drivers of inflation, even when controlling for media consumption. Our findings therefore contribute to the existing literature on trust by highlighting that institutional trust does not merely dampen expectation levels but might also shapes the causal structure through which households interpret inflationary episodes, a mechanism consistent with the cross-country evidence reported in D'Acunto and Weber (2024) that trust in economic institutions increases reliance on aggregate, less biased signals.

4. Narratives and the formation of inflation beliefs

4.1. Descriptive findings

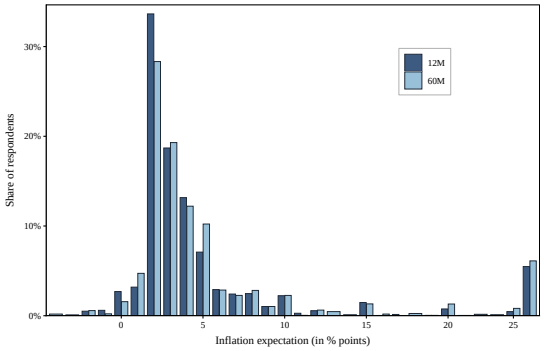
This section describes our descriptive findings regarding individuals' beliefs, expectations, and preferences. We begin by providing a detailed discussion of expected and preferred inflation rates. We present the distributions of quantitative short- and long-term inflation expectations and inflation preferences in figures 7A and 7B. In summary, households anticipate rising short- and long-term inflation in December 2024, with weighted mean expected short- and long-term inflation rates of 3.7% and 4.0%, respectively. In contrast

TABLE 2. Meta narrative clusters (LPM)

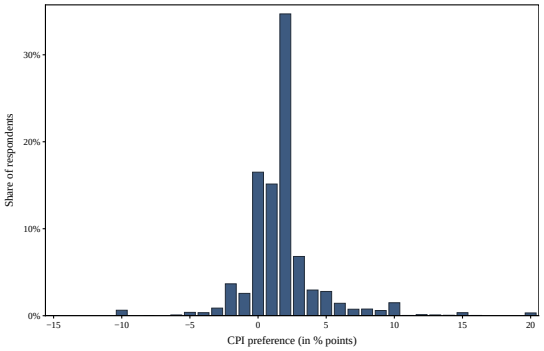
	Dependent variable:			
	Demand Cluster	Supply Cluster	Blame Cluster	Crisis Cluster
	(1)	(2)	(3)	(4)
Inflation Perception	−0.001	−0.002**	0.003***	−0.001
	(0.0005)	(0.001)	(0.001)	(0.001)
Age 40-59	−0.103***	0.014	−0.085**	0.169***
	(0.038)	(0.046)	(0.040)	(0.048)
Age 60-69	−0.104***	0.055	−0.094**	0.130**
	(0.040)	(0.051)	(0.041)	(0.052)
Male	−0.005	−0.032	0.094***	−0.070**
	(0.021)	(0.033)	(0.021)	(0.035)
University Education	0.012	0.061*	0.0003	−0.066*
	(0.023)	(0.034)	(0.025)	(0.036)
Unemployed	−0.096***	0.073	−0.032	0.027
	(0.026)	(0.086)	(0.058)	(0.092)
Out of Labor-Force	0.026	−0.025	−0.021	−0.016
	(0.028)	(0.042)	(0.021)	(0.043)
Children in Household	0.003	−0.035	0.001	0.014
	(0.027)	(0.039)	(0.029)	(0.041)
High Income	0.001	−0.032	−0.008	0.036
	(0.025)	(0.034)	(0.023)	(0.036)
Right-Leaning	−0.049**	−0.011	0.037	0.027
	(0.024)	(0.037)	(0.027)	(0.039)
Left-Leaning	−0.039	0.050	0.006	−0.010
	(0.025)	(0.040)	(0.027)	(0.043)
Financial Literate	0.011	−0.006	0.067***	−0.043
	(0.025)	(0.036)	(0.022)	(0.039)
East Germany	0.013	−0.032	0.046	−0.037
	(0.025)	(0.034)	(0.030)	(0.038)
Regular Expenses	0.010	−0.025	0.013	−0.012
	(0.024)	(0.034)	(0.021)	(0.036)
Trust in Political Institutions	−0.022***	0.011	−0.014	0.020
	(0.008)	(0.015)	(0.011)	(0.015)
Trust in Public and Newspaper Media	−0.013	−0.001	−0.027**	0.035**
	(0.008)	(0.015)	(0.011)	(0.016)
Trust in Private Media	−0.005	0.022*	0.013	−0.026*
	(0.008)	(0.012)	(0.011)	(0.014)
Old Media	0.011**	−0.007	−0.002	−0.001
	(0.004)	(0.007)	(0.004)	(0.007)
New Media	−0.002	−0.005	−0.005	0.006
	(0.005)	(0.007)	(0.004)	(0.007)
Constant	0.304***	0.280***	0.222***	0.227***
	(0.070)	(0.079)	(0.054)	(0.081)
Observations	1,466	1,466	1,466	1,466

Note: This table reports linear probability models relating respondents' characteristics, institutional trust, and media consumption to the content of their inflation narratives. The dependent variables are binary indicators for whether a respondent's extracted narrative is assigned to the Demand, Supply, Political-blame/top-down-conflict, or Geopolitics and Crisis meta-cluster. The analysis is restricted to respondents in the control group. Trust in Political Institutions averages respondents' reported trust in the ECB, the government, and the Eurosystem; Trust in Public and Newspaper Media averages trust in newspapers and public broadcasters. Old Media measures consumption of traditional media (newspapers, radio, and television), while New Media measures consumption of social media, messengers, and YouTube. All regressions are estimated using survey weights constructed by iterative proportional fitting (raking) based on income, age, gender, education, and political identification. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

to the findings of Afrouzi et al. (2024), the weighted mean preferred inflation rate in our German sample is 1.9%, which is well above the rate observed in their US sample.



A. Distribution of short and long-term inflation expectations



B. Distribution of preferred inflation rates among respondents

4.2. Correlative evidence

The variety and heterogeneity observed in the explanations given by people in our German sample for the rise in inflation during 2022 and 2023 is interesting from the perspective of belief formation. This may also be relevant for macroeconomic development and policymakers, particularly with regard to inflation expectations, as recent research has shown (Flynn and Sastry 2024; Hong et al. 2025; Andre et al. 2026). The idea is that different stories provide different interpretations of whether the rise in inflation is persistent or transitory, depending on the nature of the narrated shock. Depending on the reasons given, people may perceive inflation differently, either as something to be avoided at all costs or as something that might be acceptable up to a certain level (Afrouzi et al. 2024).

We examine the association of backward-looking narratives with qualitative and quantitative inflation expectations and preferences by conducting an OLS and LPM regression analysis. This analysis uses individuals' short- and long-term expectations or inflation preferences as the dependent variable, while narrative clusters and event dummies serve as the explanatory variables. Our estimation results for the narrative clusters are shown in Table A10 and for the narrative events in Table A11, both in the Appendix D. To control for outliers, we follow the literature and apply Huber weights (Coibion, Gorodnichenko, and Weber 2022).

Our results highlight that the energy crisis narrative is associated with lower inflation expectations. This pattern holds for short- and long-term expectations. Furthermore, respondents that cite monetary policy have significant lower expectations. For the pandemic do we find similar patterns, but only for short-term expectations, while for pent-up demand only for long-term expectations. Conversely, we observe higher expectations predominantly among respondents that refer to non-standard explanations, such as gov-

ernment mismanagement or firms price-setting. Large coefficients do we also observe for respondents that mention migration as causes of inflation: mentioning migration as cause is associated with an roughly 0.7 percentage point increase in short- and long-term expectations.

Next, we examine the relationship between inflation narratives and the preferred inflation rate. Following Afrouzi et al. (2024), we elicit a point estimate of respondents' preferred inflation rate for a typical year. Our results show that the preferred inflation rate is strongly correlated with individuals' narratives. Our results indicate that respondents who refer supply chain issues, the pandemic, price-gouging, tax increases or government mismanagement report significant lower preferred rates. Even larger, statistically significant coefficients do we observe for respondents who believe that high government debt contributed to the rise in inflation. Specifically, citing high public debt is associated with respective decreases in the preferred inflation rate of 0.8 percentage points.

5. Causal effect of media narratives

In this section, we examine the impact of a media narrative intervention on individuals' inflation expectations and preferences. Three different treatments are introduced to distinguish between demand, supply and miscellaneous narratives.

The experiment is embedded within the primary survey, which is described in Section 2.1. Of our total sample of 4,150 respondents, 50 per cent are randomly assigned to one of three treatment groups, while the remaining 50 per cent serve as the control group. This results in approximately 700 participants per treatment arm. Respondents in the treatment groups received a summary of a real-world newspaper article from *Frankfurter Allgemeine Zeitung*. These articles were written by the same journalist, are fairly the same length and differ only in the narrative presented: (a) *Pent-up demand* highlights the impact of an atypically rapid economic recovery following the pandemic, where demand for goods and services exceeded supply, resulting in higher inflation; (b) *Energy crisis* attributes inflation to surging energy prices, which increased production and transport costs; and (c) *Price-gouging* frames inflation as the result of firms expanding their profit margins by raising prices beyond cost increases due to specific market conditions. None of these texts provide information regarding the persistence or future path of inflation; they only propose a potential cause of inflation. Appendix F provides the three quotes used in the study. Subsequently, we elicit inflation expectations and preferences in order to compare these outcomes across the different treatment arms and the control group.

5.1. Average treatment effect

In order to study the causal effect of narratives on inflation expectations and preferences rigorously, we estimated the following regression:

$$Y_i = \beta_0 + \beta_1 T_{\text{pent-up demand}} + \beta_2 T_{\text{energy crisis}} + \beta_3 T_{\text{price-gouging}} + X_i\gamma + \varepsilon_i, \tag{1}$$

where Y_i our the outcome of interest for individual i (individuals' quantitative/qualitative expectations or quantitative preferences), and β_1, β_2 and β_3 measure the mean differences in the outcome between the pent-up demand, energy crisis, and price-gouging treatment groups, respectively, and the control group. X_i contains a number of socioeconomic controls, ε_i is the error term. As mentioned earlier we use Huber robust weights for both short- and long-run expectations and for inflation preferences regressions.

TABLE 3. Average treatment effects (OLS/LPM)

	Dependent variable:				
	Expectations 12M (Quan)	Expectations 12M (Qual)	Expectations 60M (Quan)	Expectations 60M (Qual)	CPI Preferences
	(1)	(2)	(3)	(4)	(5)
Pent-up Demand	−0.093	−0.049**	−0.122	−0.033	−0.008
	(0.074)	(0.022)	(0.089)	(0.022)	(0.090)
Energy Crisis	0.018	−0.024	−0.042	−0.006	0.054
	(0.073)	(0.022)	(0.089)	(0.022)	(0.090)
Price-Gouging	−0.053	−0.047**	0.034	−0.003	−0.175*
	(0.074)	(0.023)	(0.090)	(0.023)	(0.093)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,602	3,876	3,595	3,876	3,622
R^2	0.503	0.010	0.436	0.015	0.294

Note: This table reports estimates of the average effects of the three randomly assigned narrative treatments on respondents' inflation expectations and inflation preferences. Quan denotes respondents' quantitative point forecasts of inflation in percentage points over the next 12 and 60 months, respectively. Qual denotes binary indicators constructed from the corresponding qualitative inflation-expectation questions. CPI Preferences denotes respondents' preferred inflation rate for a typical year, measured in percentage points. Columns (1), (3), and (5) are estimated by OLS, while columns (2) and (4) are estimated using linear probability models. Huber weights are applied to the regressions with quantitative expectations and inflation preferences to reduce the influence of outliers. All specifications include age, gender, education, income, employment status, region, and financial literacy as controls. Standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

For the expectations measure, we estimate the treatment effect on both the qualitative (*Qual*) and quantitative (*Quan*) responses. The results of our experiment are shown in Table 3, beginning with the average treatment effects on qualitative inflation expectations. As the Table shows, we find significant negative effects of providing the pent-up demand and price-gouging narratives on individuals' one-year expectations. Both narratives decrease the probability of respondents answering that inflation one year ahead will increase or strongly increase by approximately 5 percentage points. Although the point estimate

is negative, the effect of providing an energy crisis media narrative on respondents' expectations is not statistically significant. We do not confirm any similar significant effects for long-term qualitative inflation expectations. Next, we analyse the treatment effects on quantitative inflation expectations. We find no similar statistically significant effects on long-term qualitative inflation expectations. Next, we analyse the treatment effects on quantitative inflation expectations. Using Huber-weighted regressions, we find no statistically significant treatment effects on either short- or long-term quantitative inflation expectations. However, we find a weakly statistically significant treatment effect of the price-gouging narrative on inflation preferences. Exposure to the price-gouging narrative reduces the preferred inflation rate by approximately 0.18 percentage points. These results indicate that our narrative treatments, drawn from a real-world news article, primarily affect inflation sentiment rather than quantitative inflation expectations. Thus, our results partially contrast with the findings of Andre et al. (2026) and Afrouzi et al. (2024). We argue that this difference might be explained by three factors. First, our narratives are drawn from a newspaper article rather than expert statements, which may increase interpretation uncertainty and reduce the perceived authority of the narrative. Second, our survey was fielded in December 2024, when inflation had largely converged to the ECB's 2 percent target. Lastly, recent research by Ludolph, Nghiem, and Tonzer (2026) has shown that communication without numbers has a weaker effect on respondents' estimates than communication that combines numbers with stories.

5.2. Narratives and the perception pass-through

An increasing body of research highlights the importance of perceptions in the expectation formation process, suggesting that temporary perceived price level increases can have persistent effects on expectations (Huber, Minina, and Schmidt 2023; Weber, Gorodnichenko, and Coibion 2023; D'Acunto et al. 2025). In line with these previous findings, Table 4 shows that prior inflation perceptions are significantly higher among respondents who expects higher inflation. Specifically, a 1-percentage-point increase in inflation perceptions is associated with an increase in short- and long-term inflation expectations of 0.632 and 0.596 percentage points, respectively.

Next, we investigate whether the treatment induces belief updating by altering the dependence on prior inflation perceptions. We find that prior perceptions significantly moderate the narrative treatment effect. Our research design closely follows previous work by Nghiem, Dräger, and Dalloul (2024) and Coibion, Gorodnichenko, and Weber (2022). However, rather than focusing on prior expectations, we explore treatment heterogeneity with respect to prior inflation perceptions. Thus, posterior expectations are assumed to be formed as a combination of prior perceptions and narrative framing. Our results suggest that exposure to the pent-up demand or price-gouging narrative reduces

TABLE 4. Heterogeneous treatment effects inflation perceptions (OLS)

	Dependent variable:		
	Expectations 12M (Quan)	Expectations 60M (Quan)	CPI Preferences
	(1)	(2)	(3)
Pent-up Demand	0.730***	0.720***	0.287
	(0.153)	(0.191)	(0.187)
Energy Crisis	0.297*	0.113	−0.470*
	(0.169)	(0.185)	(0.240)
Price-Gouging	0.786***	0.920***	0.778***
	(0.167)	(0.162)	(0.166)
Perceived Inflation	0.632***	0.596***	0.430***
	(0.021)	(0.022)	(0.026)
Pent-up Demand x Perceived Inflation	−0.231***	−0.220***	−0.077*
	(0.038)	(0.046)	(0.044)
Energy Crisis x Perceived Inflation	−0.076*	−0.037	0.142**
	(0.042)	(0.044)	(0.060)
Price-Gouging x Perceived Inflation	−0.224***	−0.221***	−0.235***
	(0.040)	(0.036)	(0.036)
Controls	Yes	Yes	Yes
Observations	3,602	3,595	3,622
R^2	0.496	0.444	0.315

Note: This table reports heterogeneous treatment effects with respect to respondents' prior inflation perceptions. The dependent variables are quantitative 12-month and 60-month inflation expectations and respondents' preferred inflation rate, all measured in percentage points. The interaction terms capture how exposure to each narrative treatment changes the association between perceived inflation and the respective outcome relative to the control group. Huber weights are applied to all regressions to reduce the influence of extreme quantitative responses. All specifications include age, gender, education, income, employment status, region, and financial literacy as controls. Standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

respondents' reliance on their perceptions for their own inflation point forecasts. To give an example: Being randomly exposed to pent-up treatment reduces the pass-through from inflation perception to 12-months expectations by 36.6%. Thus, especially respondents with relatively high inflation perceptions report lower expectations than in the control group. In contrast, the effect of the energy crisis treatment is only weakly statistically significant for short-term expectations. Overall, even without providing actual numeric information about the current or professionally forecasted inflation level, providing causal explanations reduces reliance on prior perceptions and induces different forecasts.

Furthermore, our findings suggest that respondents update their inflation preferences. Again, we document that respondents who have higher prior inflation perceptions also report higher inflation preferences. While somewhat surprising, this might reflect a simple adaptation to their already higher perceived inflation rates. However, after being exposed to the price-gouging narrative, this channel is significantly weakened. Respondents who are exposed to this narrative reduce their reliance on prior perceptions by more than 50%. The effects of the pent-up demand narrative are in the same direction, but smaller in magnitude and only weakly statistically significant. Conversely, we document a positive

and statistically significant coefficient for the interaction between the energy crisis narrative and prior perceptions. Following Coibion, Gorodnichenko, and Weber (2022), we interpret this as a less informative signal for respondents, which increases their reliance on prior perceptions. This finding may be explained by the energy crisis narrative being the most prevalent narrative in our sample, whereas only a small number of respondents cite price-gouging or pent-up demand in response to the open-ended question.

5.3. Additional heterogeneous treatment effects

While the previous section showed that our narrative provision treatment affects short-term qualitative inflation expectations, we did not find any statistically significant effects on quantitative inflation expectations. However, our correlational analysis revealed that the structure and content of individuals' narratives are associated with financial literacy, personal inflation experience, and trust in public institutions. Motivated by these findings, we hypothesize that the treatment effect might vary across these dimensions. Thus, we estimate heterogeneous treatment effects with respect to respondents' financial literacy, age, and institutional trust using the standard interaction-term specification. Consistent with our baseline findings, we find evidence of heterogeneity in the treatment responses.

We begin with studying the heterogeneity across financial literacy. We observe a statistically significant reduction in both short- and long-term expectations among financially literate households (see Table 5). Exposure to a media narrative that attributes inflation to the rapid economic recovery after the COVID-19 pandemic statistically significantly reduces inflation expectations among financially literate. More specifically, their expectations are 0.69, respectively 0.62 percentage points, lower than those of non-financial literate households. This effect offsets the corresponding increase in expectations among respondents with lower financial literacy, resulting in a net treatment effect of -0.21, respectively -0.23 percentage points. Thus, exposing financially literate respondents to a pent-up demand narrative leads to a reduction in inflation expectations by potentially highlighting the transitory nature of the pent-up demand effect.

Next, we examine whether the treatment effect is moderated by prior inflation experience. As Table A12 in the Appendix D shows, we do not document any heterogeneous effects with respect to inflation experience for inflation expectations. However, our results indicate that 40–59-year-old respondents respond differently in their preferences to the pent-up demand narrative than 18–39-year-old respondents.

Finally, we explore treatment heterogeneity by trust in political institutions or the media. As reported in Tables A13–A14 in Appendix D, higher levels of trust in political institutions are in general associated with lower inflation expectations and higher inflation preferences. Furthermore, we find some indications that responses to treatment might differ between respondents who trust and do not trust political institutions or newspapers.

TABLE 5. Heterogeneous treatment effects for financial literacy (OLS)

	Dependent variable:		
	Expectations 12M (Quan)	Expectations 60M (Quan)	CPI Preferences
	(1)	(2)	(3)
Pent-up Demand	0.166	0.109	−0.063
	(0.156)	(0.185)	(0.179)
Energy Crisis	−0.004	−0.132	0.292
	(0.148)	(0.172)	(0.180)
Price-Gouging	−0.012	0.065	−0.131
	(0.155)	(0.188)	(0.186)
Financial Literacy	−0.318***	−0.448***	−1.237***
	(0.090)	(0.111)	(0.111)
Pent-up Demand x FinLit	−0.381**	−0.344*	0.082
	(0.174)	(0.207)	(0.203)
Energy Crisis x FinLit	0.034	0.141	−0.358*
	(0.168)	(0.200)	(0.205)
Price-Gouging x FinLit	−0.061	−0.047	−0.066
	(0.174)	(0.212)	(0.212)
Controls	Yes	Yes	Yes
Observations	3,602	3,595	3,622
R^2	0.503	0.437	0.295

Note: This table reports heterogeneous treatment effects with respect to respondents' financial literacy. The dependent variables are quantitative 12-month and 60-month inflation expectations and respondents' preferred inflation rate, all measured in percentage points. Financial Literacy is an indicator equal to one if a respondent correctly answers both financial-literacy questions. The treatment coefficients therefore report the estimated treatment effects among respondents classified as not financially literate, while the interaction terms measure the additional treatment effect for financially literate respondents. The total treatment effect for financially literate respondents is given by the sum of the respective treatment coefficient and interaction coefficient. Huber weights are applied to all regressions to reduce the influence of extreme quantitative responses. All specifications include age, gender, education, income, employment status, region, and financial literacy as controls. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

First, for respondents with low trust in political institutions, exposure to the price-gouging treatment decreases inflation expectations. Conversely, having higher trust in political institutions partly weakens this negative response. This may be because respondents with higher trust exhibit stickier expectations, causing them to respond less strongly to a single narrative exposure. We observe similar effects for inflation preferences. Respondents with low reported trust exhibit a statistically significant response when exposed to the energy crisis narrative. Again, reporting higher trust in political institutions attenuates this effect. We run the same heterogeneity analysis for self-reported trust in public broadcasters and newspapers. In contrast to trust in political institutions, we find no statistically significant treatment heterogeneity along these dimensions. As trust in political institutions and the media is measured post-treatment, these results should be interpreted with caution, even though we observe no treatment effect on respondents' trust.

6. Discussion

This paper examines how German households made sense of the 2022–23 inflation surge, how these causal accounts differ across individuals, and whether exposure to real-world media narratives changes inflation beliefs. Combining open-ended survey responses from more than 4,000 households with DAG-based narrative extraction and a preregistered information experiment, we show that news media inflation narratives have causal effects on qualitative expectations and preferences and that the exposure to inflation narratives reduces partially the reliance on prior inflation perceptions.

First, households' explanations of the recent inflation episode are dominated by supply-side factors and global crisis. The war of Russia against Ukraine and the energy crisis features far more prominently than demand-side explanations. This pattern underscores the importance of the specific historical context and discourse in which beliefs are formed: in Germany, the European energy shock appears to have provided a particularly salient lens through which households interpreted rising prices.

Second, narratives are not randomly distributed across the population. Financial literacy, past inflation experience, and institutional trust are systematically associated with both the content and complexity of households' causal explanations. More financially literate respondents are more likely to articulate complex narratives; younger cohorts emphasize demand channels and blame government or firms; and trust is associated with a lower probability to attribute inflation to government action or firms' inappropriate pricing behaviour ("price gouging"). These associations do not establish a causal process of narrative formation, but they indicate that education and subsequent cognitive resources, personal experience, and trust in institutions jointly structure how households interpret inflation.

Third, the experiment shows that news narratives based on real-world examples can affect households' qualitative short-run inflation expectations. Exposure to narratives centred on post-pandemic demand or price gouging reduces qualitative expectations, while no average treatment effects on quantitative expectations are observed. However, narrative exposure reduces the reliance on prior inflation perceptions when forming quantitative expectations. Furthermore, quantitative updating is heterogeneous with respect to financial literacy and trust in political institutions and media. These findings suggest that real-world media narratives can shape inflation beliefs causally, but that their effects are neither uniform across outcomes nor homogeneous across households.

Taken together, the results place causal narratives at the intersection of expectation formation, experience, and information acquisition. Our results imply that households do not merely receive inflation expectation updates passively as isolated numbers. They interpret information through causal stories that differ in content, structure, and economic meaningfulness across socioeconomic groups. With this result, the paper goes beyond

the implications of first-generation epidemiological models of information transmission (Carroll 2003, 2005). For research on household expectations, this points to the value of classifying the narratives underlying expectations rather than treating those expectations as self-contained beliefs. For communication by policymakers and the media, the results highlight that the framing of causal explanations may matter alongside the information provided. At the same time, the heterogeneous experimental effects caution against assuming that one-and-only common narrative produces a common quantitative response. Prior knowledge, literacy, trust and experience may condition how households process, interpret, and update from inflation news.

Our research highlights a number of paths for future research. The observed heterogeneity within the clusters is analytically interesting and calls for further research, i.e. examination through the lens of political sociology and the "arenas of conflict" framework of Mau, Westheuser, and Lux (2024). Furthermore, future research should vary source credibility and format, including the presence or absence of numerical anchors, as highlighted by Ludolph, Nghiem, and Tonzer (2026). Lastly, the survey was conducted at a single point in time, which prevents analysis of how narratives evolve. Longitudinal or panel designs would allow us to examine narrative updating on the individual level and its macroeconomic consequences on the aggregate level.

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Appendix A. Measuring Narratives in Open-Ended Questions

A.1. Qualitative Content Analysis

To develop the category system and annotation guidelines, we draw on principles of Qualitative Content Analysis (QCA), a systematic and transparent approach to text interpretation widely used in the social sciences (Selvi 2019). In contrast to purely deductive annotation frameworks, QCA combines theoretical concepts with insights emerging from the empirical material, allowing coding schemes to be refined throughout the research process.

Our initial category system is based on the inflation narrative taxonomy proposed by Andre et al. (2026), which distinguishes between *supply*, *demand*, and *miscellaneous* explanations of inflation. Following the iterative logic of QCA (Mayring and Fenzl 2019; Przyborksi and Wohlrab-Sahr 2022), we continuously refined this initial taxonomy during the annotation process. Additional categories were introduced whenever recurrent narrative elements could not be adequately captured by the existing coding scheme, and annotation guidelines were revised through regular discussions between annotators and the research team. The resulting category system consists of 23 fine-grained narrative event categories and forms the basis for all subsequent annotations. A detailed description of the final taxonomy is provided in Appendix A4. In our application, QCA primarily served two purposes. First, it guided the iterative development of the category system and annotation guidelines during the pilot phase. Second, it facilitated a shared understanding of the coding scheme among annotators throughout the final annotation stage, thereby improving transparency and consistency in the annotation process.

A.2. Annotator Recruitment

Given the complexity of the annotation task and the domain-specific knowledge required, we recruited two research assistants enrolled in a master programme with a substantial economics component. Both annotators held undergraduate degrees in economics and had prior training in QCA. Their role was to independently identify event mentions and causal relations before participating in structured discussions aimed at refining annotation guidelines and resolving ambiguities in the category system. The hourly wage is 14.37€.

A.3. Pilot Study

Before we conducted our final survey with Kantar a first round of interviews in a pilot study was conducted (Demgensky and Fritsche 2023). The pilot survey was conducted in 2022, using the online survey tool *LimeSurvey*. In total 168 non-random recruited respondents participated in the study. Of these, 133 answers contained an answer that engaged with

the question. In contrast to the final study design, the pilot study used one question only to elicit the narratives, closely following the design by Andre et al. (2026). As in the final study, the pilot study build on the principals of QCA. Thus, during the iterative process of annotating, a complex category system has been developed. This pilot category system contained among the three upper categories (supply, demand, miscellaneous) in total 12 categories.

A.4. Inter-Annotator-Agreement

Narrative extraction is a complex annotation task that requires identifying both events and the causal relationships between them. Recent research has shown that even expert annotators may disagree when interpreting narratives, making a rigorous assessment of annotation reliability essential (Schmidt et al. 2025; Huang et al. 2026). To evaluate the consistency of our annotations, we employ Krippendorff's α for the document-level classification task and a graph-adjusted variant of Krippendorff's α proposed by Huang et al. (2026) for narrative graph annotations.

Task 1: Narrative Identification. We begin by evaluating agreement in the narrative identification task. Of the 998 annotated responses, both annotators assigned the same label in 814 cases, corresponding to a raw agreement of 81.6%. To account for chance, we additionally compute Krippendorff's α using a nominal distance function, yielding $\alpha = 0.717$. This level of agreement indicates substantial consistency between annotators in distinguishing between causal narratives, non-causal inflation explanations, and non-relevant responses. Because the first stage aims primarily to identify responses suitable for narrative extraction, the second annotation stage restricts the sample to observations classified by both annotators as containing either reasons for inflation or causal reasoning. This ensures that all retained observations exhibit an identifiable causal mechanism for inflation.

Task 2: Narrative Extraction. To evaluate agreement in the narrative extraction task, we employ the graph-adjusted Krippendorff's α proposed by Huang et al. (2026) on our narrative graph annotations. This framework enables reliability assessment across different narrative representations and distance specifications. We consider three categorical representations and two graph-based representations. The categorical representations include **All Events**, which contains all annotated event categories, **Adjacent Events**, which is restricted to events directly linked to inflation, and **Relations**, which captures the annotated causal relations. The graph-based representations are **Full Story**, consisting of all annotated nodes and edges, and **Adjacent Story**, a one-hop subgraph centred on the inflation node. Table A1 reports inter-annotator agreement for three distance specifications introduced by Huang et al. (2026): *lenient* metrics, which measure partial overlap

between two sets of nodes, edges or graphs; *moderate* metric, which provide a graded measure of similarity based on Jaccard and Graph Edit Distance; and *strict* metrics, which measure similarity with exact match. In summary, agreement ranges from modest under strict graph matching to very high under lenient matching criteria, with Krippendorff's α ranges from 0.321 to 0.961.

TABLE A1. Inter-annotator agreement metrics

	Distance Metric Type		
Narrative Repr.	Lenient	Moderate	Strict
Category			
All Events	**0.961**	**0.729**	**0.477**
Adj. Events	0.869	0.597	0.372
Graph			
Full Story	**0.897**	**0.595**	0.321
Adj. Story	0.869	0.548	**0.372**

Note: This table reports inter-annotator agreement for narrative events and causal relationships using the graph-adjusted Krippendorff's alpha proposed by Huang et al. (2026). Agreement is evaluated across categorical and graph-based narrative representations using three distance metrics. Lenient metrics allow partial overlap, moderate metrics capture graded similarity, and strict metrics require exact matches. Adjacent Events and Adjacent Story are restricted to events and narrative structures directly connected to the inflation node.

The results suggest that annotators largely agree on the relevant narrative elements (i.e., events) and their causal structure (i.e., *event-relation-event* triples), although disagreement naturally increases as stricter matching criteria are applied. While an α of 0.321 might typically be considered unreliable, in this context, the exact graph match serves as a conservative lower bound, as even the slightest difference in the graph structure results in no agreement. Compared to the findings of Huang et al. (2026) for a news dataset, our inter-annotator agreement (IAA) is strictly higher across all specifications. This suggests that the interpretation of causal narratives in open-ended survey responses exhibits lower variance, indicating greater uniformity across respondents. In terms of raw agreement, annotators assign the same event label in 88.6% of cases and identify the same relation in 72.2% of cases. These estimates are comparable to those reported by Andre et al. (2026), highlighting both the feasibility and the inherent subjectivity of narrative annotation.

To obtain a consolidated gold-standard dataset, we rely exclusively on fully agreed labels from the first stage and implement a conflict-resolution procedure for the second stage following Andre et al. (2026). In cases of disagreement, a member of the research team reviewed the independent annotations and selected the final annotation. The resulting dataset serves as the reference standard for all subsequent modelling experiments.

Appendix B. Narrative modelling

To automate the annotation of the full survey sample, we employ a combination of transformer-based and large-language-model approaches. We focus exclusively on open-weights models to enhance reproducibility and mitigate potential data privacy concerns. Since our annotation framework consists of two distinct tasks, we evaluate separate modelling strategies for narrative identification and narrative extraction.

Task 1: Narrative Identification. We formulate the narrative identification task as a document-level classification problem. To determine whether a response contains causal reasoning, inflation-related factors, or non-relevant content, we fine-tune several language transformer models that have been specifically trained on a German corpus. All models are trained on 70% of the annotated data (537 documents) and evaluated on the remaining 30% of the sample, which is split equally into validation and test sets. As our classes are moderately imbalanced, we report Micro F1 and Weighted Macro F1 scores. Table A2 shows that all tested models perform comparably well, achieving F1 scores of approximately 0.9. The best overall performance is obtained by *gbert-large*[3], although the differences between models are relatively small. Overall, the results suggest that identifying whether a response contains any reasoning about inflation is a comparatively straightforward classification task.

TABLE A2. Performance metrics for fine-tuned German language models.

Model	Micro F1	Weighted F1
gbert-base	0.85	0.85
gbert-large	**0.89**	**0.89**
bert-base-german-cased	0.88	0.88
GermanFinBert_FP	0.88	0.87

Note: This table reports the classification performance of fine-tuned German-language transformer models for identifying causal reasoning, inflation-related explanations, and non-relevant responses. Models are trained on 70 percent of the annotated sample, with the remaining observations used for validation and testing. Performance is evaluated using Micro F1 and Weighted F1 scores to account for differences in class frequencies.

Task 2: Narrative Extraction. Unlike narrative identification, narrative extraction requires recovering the underlying graph structure of respondents' explanations. We construct this task as a generative task: identifying narrative events and predicting causal relations between them in a generation approach. To evaluate different modelling strategies, we compare three commonly used LLM-based approaches: zero-shot prompting, few-shot

[3] `https://huggingface.co/deepset/gbert-large`

prompting, and parameter-efficient fine-tuning using Low-Rank Adaptation (LoRA) (Hu et al. 2021).

Our prompts consist of a task description, an overview of the narrative taxonomy, and formatting constraints that ensure a valid graph representation. For the few-shot setting, we additionally provide three annotated examples. The complete prompt templates are provided in Appendix E. For our benchmark, we restrict our evaluation to Llama models that have been specifically trained on a German corpus. Furthermore, Llama models have proven to be promising candidates to extract narratives from texts (Heddaya et al. 2024). Specifically, we use *Llama-3.1 70B*[4] for the zero-shot and few-shot experiments and *Llama-3.1 8B*[5] for parameter-efficient fine-tuning. We select Llama models because they outperformed other models in previous narrative extraction tasks (Heddaya et al. 2024). Furthermore, comparing different specifications of the same model family ensures comparability. We evaluate model performance on a held-out test set of 143 human-annotated responses from the gold-standard dataset.

TABLE A3. Event and relation extraction performance across learning settings

	Zero-shot (Llama-3.1 70B)		Few-shot (Llama-3.1 70B)		LoRA (Llama-3.1 8B)	
Metric	Event	Relation	Event	Relation	Event	Relation
Micro F1	0.52	0.33	0.70	0.43	**0.87**	**0.64**
Weighted F1	0.49	0.30	0.68	0.42	**0.88**	**0.61**

Note: This table compares the performance of zero-shot prompting, few-shot prompting, and Low-Rank Adaptation (LoRA) fine-tuning for extracting narrative events and causal relationships. Zero-shot and few-shot results are based on Llama-3.1 70B, while the fine-tuned model uses Llama-3.1 8B. Performance is evaluated on a held-out test set of 143 human-annotated responses. Micro F1 and Weighted F1 scores are reported separately for event and relation extraction.

Table A3 reveals two main findings. First, event extraction consistently outperforms relation extraction across all learning settings. Even in a zero-shot setting, *Llama-3.1 70B* achieves reasonable performance in identifying narrative events, suggesting that large language models can generalise relatively well to the detection of inflation-related topics in open-ended survey responses. However, identifying the causal links that connect these events proves considerably more challenging. This finding is consistent with previous work showing that current LLMs struggle to recover narrative structure from text (Heddaya et al. 2024; Schmidt et al. 2025).

Second, task-specific fine-tuning substantially improves performance. To address the class imbalance in our training data, we synthetically oversample minority categories using LLM-based paraphrasing. These synthetic observations are used exclusively during training and are never included in the validation or test sets. After LoRA fine-tuning, event

[4]VAGOsolutions/Llama-3.1-SauerkrautLM-70b-Instruct
[5]VAGOsolutions/Llama-3.1-SauerkrautLM-8b-Instruct

extraction improves from a weighted macro F1 of 0.68 to 0.88, while relation extraction increases from 0.42 to 0.61. Notably, the fine-tuned *Llama-3.1 8B* outperforms the substantially larger prompted *Llama-3.1 70B*, indicating that task-specific adaptation is more important than model size for narrative graph extraction.

Overall, our results suggest that modern LLMs are capable of identifying inflation-related narrative events in zero- and few-shot settings, but struggle to recover the causal structure connecting these events. Parameter-efficient fine-tuning substantially narrows this gap and produces considerably more reliable DAG representations. We therefore recommend fine-tuned models over out-of-the-box prompting approaches when extracting narrative graphs from open-ended survey responses.

Appendix C. Figures

FIGURE A1. Survey design

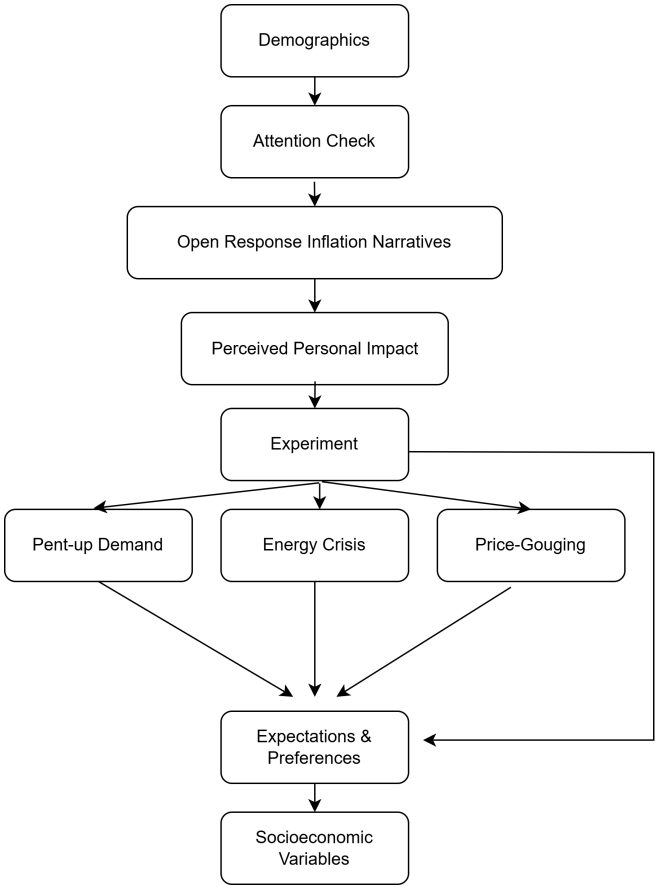
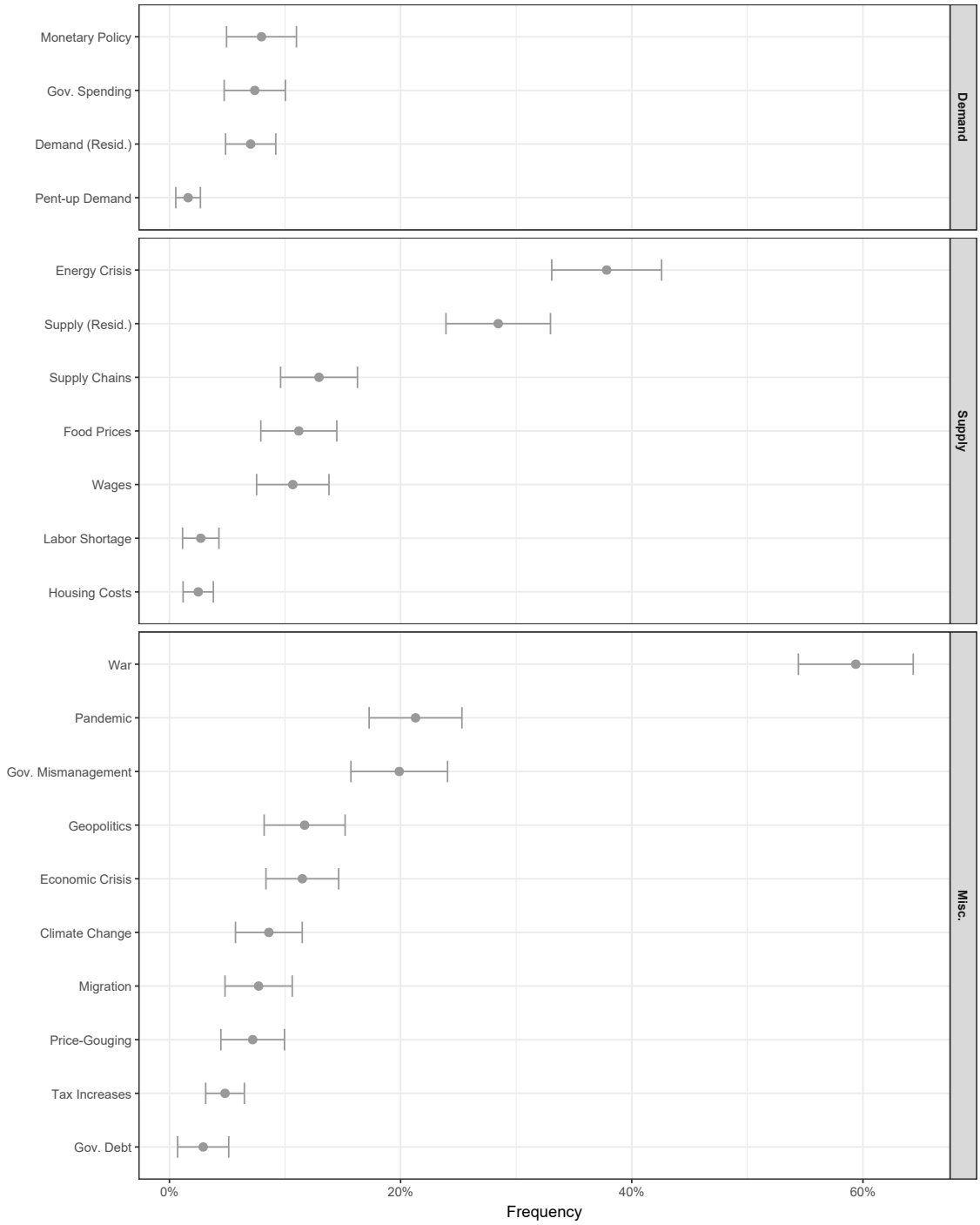
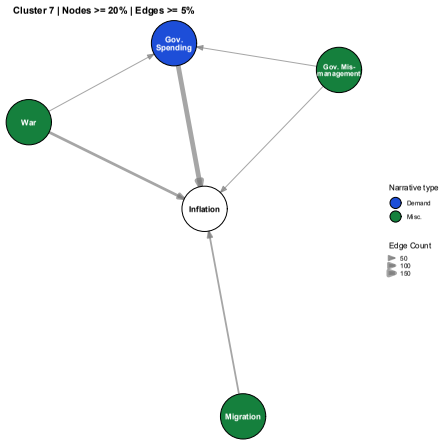


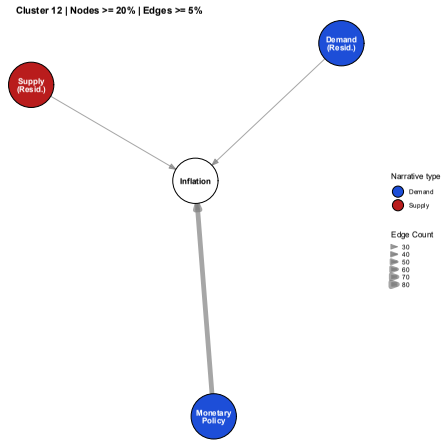
FIGURE A2. Frequency of hand-coded events



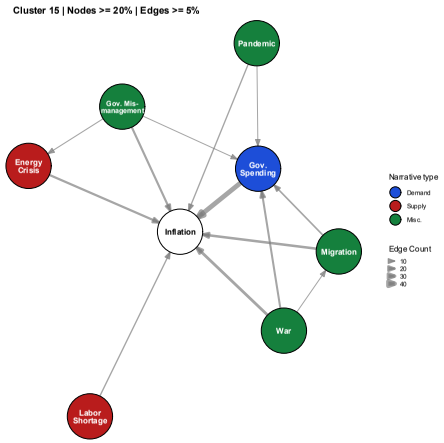
Note: The figures show the weighted frequency for different narrated causes of inflation in the hand-coded data. The band includes the 95 per cent coefficient intervals.



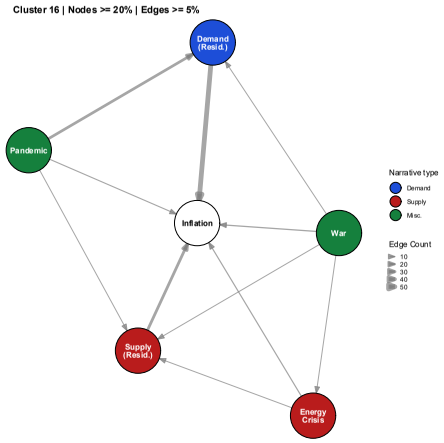
A. Cluster 7



B. Cluster 12



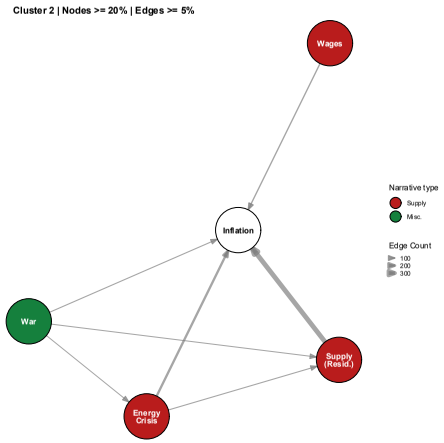
C. Cluster 15



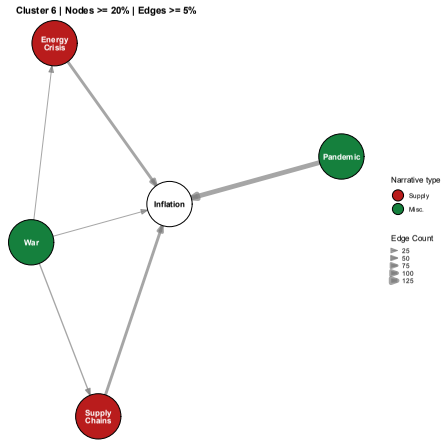
D. Cluster 16

FIGURE A3. Demand-side clusters

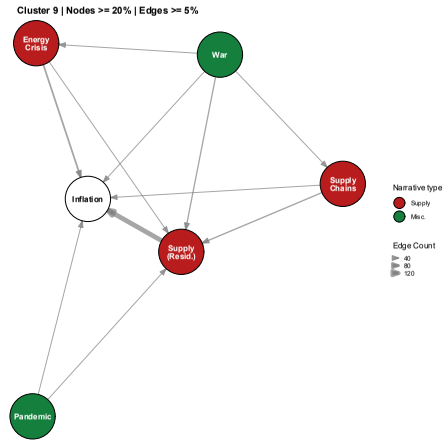
Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 23 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 20 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.



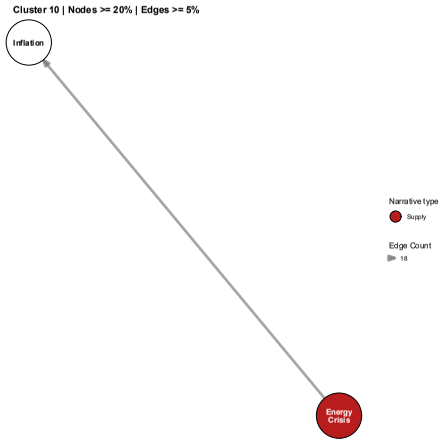
A. Cluster 2



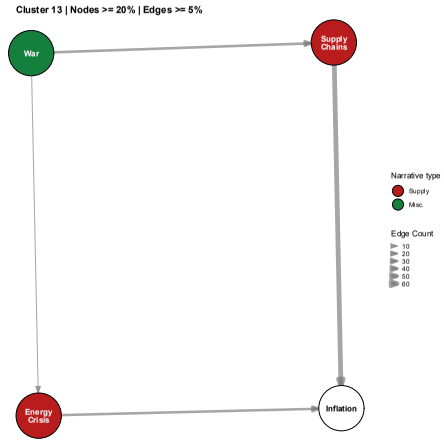
B. Cluster 6



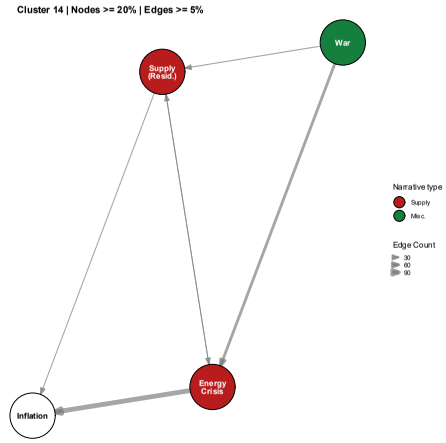
C. Cluster 9



D. Cluster 10



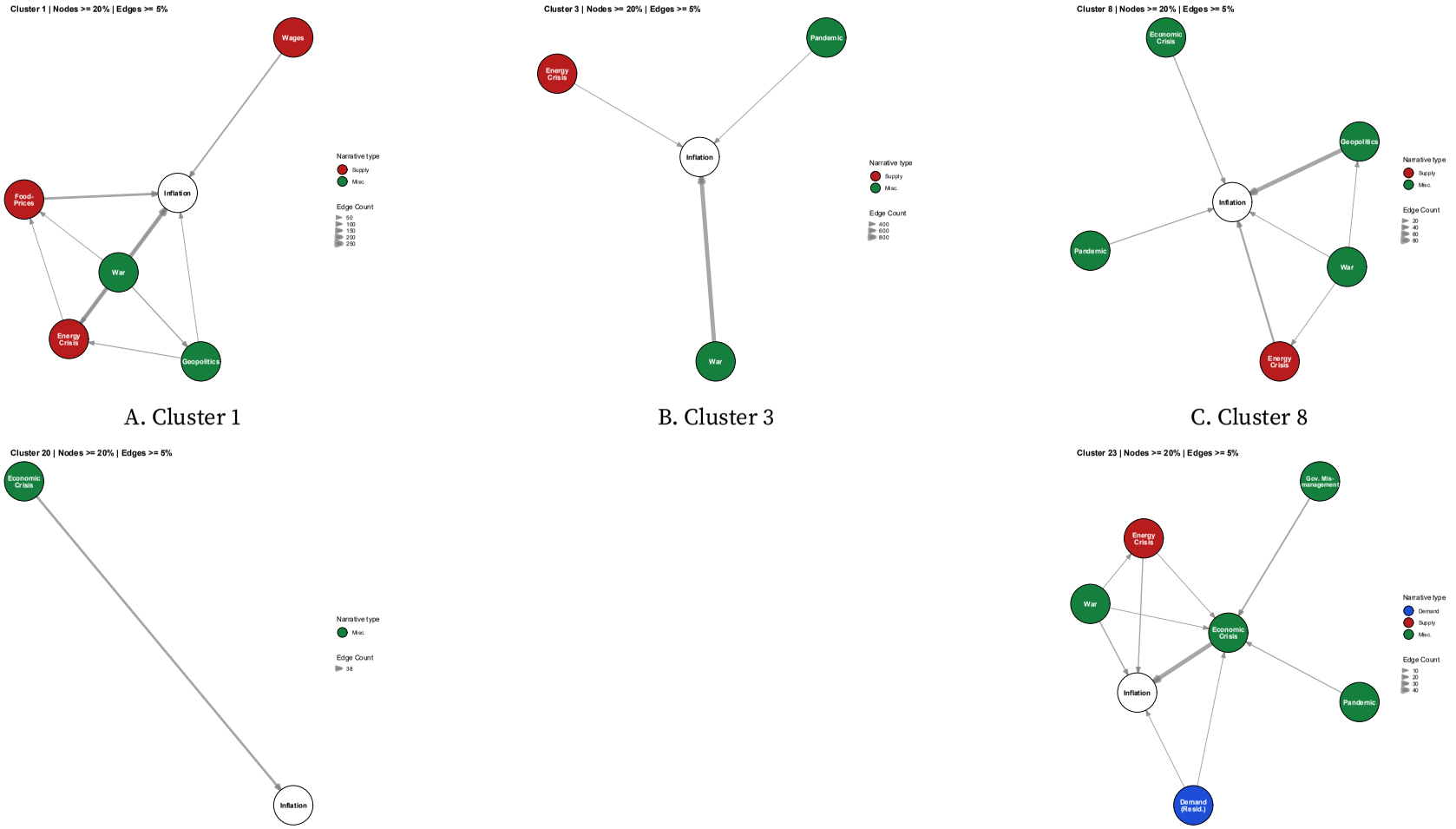
E. Cluster 13



F. Cluster 14

FIGURE A4. Supply-side clusters

Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 23 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 20 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.



A. Cluster 1

B. Cluster 3

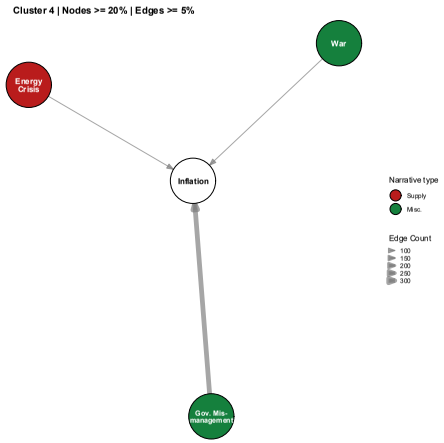
C. Cluster 8

D. Cluster 20

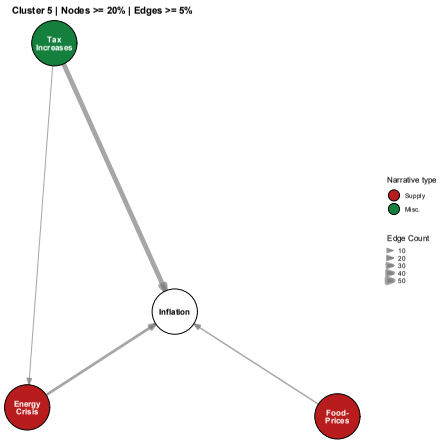
E. Cluster 23

FIGURE A5. Crisis clusters

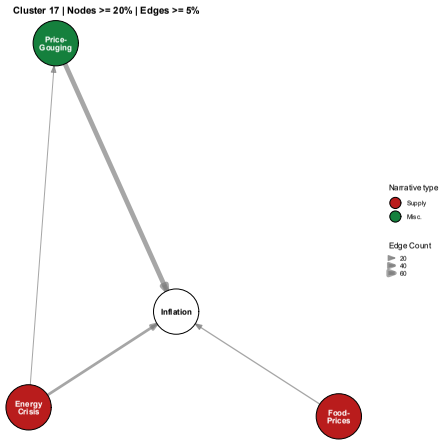
Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 23 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 20 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.



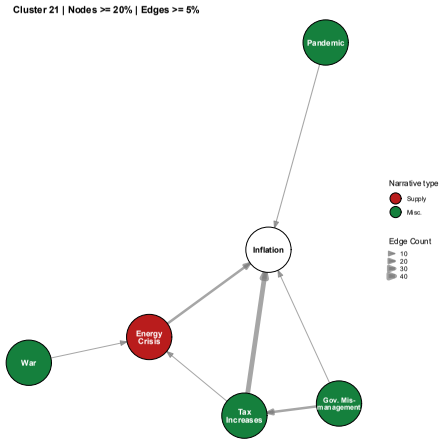
A. Cluster 4



B. Cluster 5



C. Cluster 17



D. Cluster 21

FIGURE A6. Political-blame/ top-down-conflict clusters

Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Jaccard distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 23 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 20 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.

Appendix D. Tables

TABLE A4. Classification of Inflationary Channels and Explanations

Category	Explanation
Inflation	General increase in prices
Demand-Side Channels	
Government Spending	Increase in or high level of government spending
Monetary Policy	Expansionary monetary policy of the central bank(s)
Pent-up Demand	Economic reopening or a sudden surge following an event associated with higher spending, optimism, and/or income
Demand Shift	Shift in demand between sectors (e.g., from services to specific goods)
Demand (Residual)	General increase in demand that cannot be attributed to any other channel
Supply-Side Channels	
Supply Chain Disruptions	Disruption of global supply chains
Labor Shortage	Shortage of labor, e.g., due to workers exiting the labor force, and higher wage costs
Wages	Rising and/or high wages of workers
Energy Crisis	Global energy crisis leading to shortages (e.g., in crude oil and natural gas) and higher energy prices
Housing Costs	High costs of housing and property
Food Prices	Rising food prices
Supply (Residual)	Negative impacts on supply other than labor shortages, wages, supply chain issues, or the energy crisis
Miscellaneous Channels	
Pandemic	The COVID-19 pandemic, global pandemic recession, lockdown measures, and other policy interventions
Political Mismanagement	Policy failure and political mismanagement, where government policy is blamed
War	The Russian invasion of Ukraine and other armed conflicts, as well as international economic, political, and military responses
Government Debt	High level of public debt
Tax Increases	Tax increases, such as an increase in the value-added tax (VAT)
Price Gouging	Corporate price gouging or profit-led inflation, where companies exploit opportunities to increase profits or recoup losses incurred during the pandemic
Climate Change	The impact of climate change on the economy
Migration	(Increasing) migration and refugee movements (leading to higher demand for goods, increased labor supply, etc.)
Geopolitics	Geopolitical tensions (e.g., trade wars, diplomatic crises, sanctions, and unstable international relations)
Exchange Rates	Exchange rate fluctuations
Economic Crises	Severe macroeconomic downturns or structural crises that disrupt production capacities, distort market dynamics, or necessitate extraordinary inflationary policy responses

TABLE A5. Weighted Descriptive Statistics: Control Group

	Control group
Observations (n)	1973
Demographics	
Age	44.01 (14.79)
Male	0.50 (0.50)
Highest School Degree (\%)	
Univ. Entrance Degree	808.5 (40.3)
Other Degree	57.7 (2.9)
Basic Degree	389.1 (19.4)
No Degree	77.5 (3.9)
Middle School Degree	616.4 (30.7)
Still in School	58.9 (2.9)
Advanced Educ. Attainment (\%)	
Other Adv. Degree	91.2 (4.5)
Bachelor	297.9 (14.8)
Currently in Education	148.5 (7.4)
No Adv. Degree	389.9 (19.4)
Apprenticeship	751.5 (37.4)
Master/Diploma	292.9 (14.6)
Doctorate/PhD	38.8 (1.9)
Employment Status (\%)	
Employed	1362.0 (67.7)
Unemployed	82.1 (4.1)
Out of Labour Force	567.6 (28.2)
Income (\%)	
Until 1300€	241.3 (12.7)
1300–2600€	569.4 (30.0)
2600–3600€	343.4 (18.1)
3600–5000€	344.8 (18.1)
5000€ and more	401.3 (21.1)
Demographics	
Minors	0.39 (0.49)
Political Identification (\%)	
Center	814.9 (43.8)
Right	568.8 (30.6)
Left	475.9 (25.6)
Other Covariates	
FinLit	0.54 (0.50)
Demographics	
Region East	0.19 (0.39)

Note: This table reports weighted descriptive statistics for respondents in the control group. Survey weights are constructed using iterative proportional fitting (raking) based on income, age, gender, education, and political identification. Continuous variables are reported as weighted means with standard deviations in parentheses; categorical variables as weighted frequencies with percentage shares in parentheses. Financial Literacy equals one if both financial-literacy questions are answered correctly.

TABLE A6. Unweighted Descriptive Statistics by Treatment Group

	Treatment Group					
	Pent-up Demand	Energy Crisis	Price-Gouging	No-Treatment	p-value	SMD
Observations (n)	729	749	699	1973		
Demographics						
Age	45.25 (14.28)	44.87 (14.55)	44.72 (14.87)	44.90 (14.50)	0.917	0.018
Male	0.54 (0.50)	0.49 (0.50)	0.49 (0.50)	0.48 (0.50)	0.087	0.057
Highest School Degree (\%)						
Univ. Entrance Degree	337 (46.2)	325 (43.4)	334 (47.8)	864 (43.8)	0.379	0.115
Other Degree	13 (1.8)	28 (3.7)	22 (3.1)	54 (2.7)		
Basic Degree	118 (16.2)	140 (18.7)	99 (14.2)	341 (17.3)		
No Degree	9 (1.2)	9 (1.2)	5 (0.7)	19 (1.0)		
Middle School Degree	238 (32.6)	233 (31.1)	222 (31.8)	658 (33.4)		
Still in School	14 (1.9)	14 (1.9)	17 (2.4)	36 (1.8)		
Advanced Educ. Attainment (\%)						
Other Adv. Degree	44 (6.0)	37 (4.9)	27 (3.9)	93 (4.7)	0.405	0.118
Bachelor	94 (12.9)	93 (12.4)	110 (15.8)	249 (12.6)		
Currently in Education	35 (4.8)	41 (5.5)	43 (6.2)	95 (4.8)		
No Adv. Degree	35 (4.8)	46 (6.1)	37 (5.3)	135 (6.8)		
Apprenticeship	411 (56.4)	408 (54.5)	367 (52.6)	1091 (55.3)		
Master/Diploma	100 (13.7)	118 (15.8)	108 (15.5)	285 (14.5)		
Doctorate/PhD	10 (1.4)	6 (0.8)	6 (0.9)	24 (1.2)		
Employment Status (\%)						
Employed	505 (69.3)	517 (69.0)	491 (70.2)	1367 (69.3)	0.619	0.048
Unemployed	33 (4.5)	44 (5.9)	29 (4.1)	82 (4.2)		
Out of Labour Force	191 (26.2)	188 (25.1)	179 (25.6)	524 (26.6)		
Income (\%)						
Until 1300€	103 (14.8)	117 (16.5)	97 (14.7)	271 (14.5)	0.876	0.072
1300–2600€	221 (31.7)	214 (30.1)	211 (32.0)	584 (31.3)		
2600–3600€	158 (22.7)	155 (21.8)	133 (20.2)	406 (21.8)		
3600–5000€	125 (17.9)	140 (19.7)	128 (19.4)	384 (20.6)		
5000€ and more	90 (12.9)	84 (11.8)	91 (13.8)	219 (11.7)		
Demographics						
Minors	0.37 (0.48)	0.36 (0.48)	0.37 (0.48)	0.38 (0.49)	0.906	0.016
Political Identification (\%)						
Center	273 (39.9)	281 (39.7)	284 (43.2)	774 (42.2)	0.550	0.061
Right	234 (34.2)	247 (34.9)	198 (30.1)	594 (32.4)		
Left	177 (25.9)	180 (25.4)	176 (26.7)	465 (25.4)		
Other Covariates						
FinLit	0.54 (0.50)	0.56 (0.50)	0.58 (0.49)	0.56 (0.50)	0.496	0.041
Demographics						
Region East	0.23 (0.42)	0.25 (0.43)	0.23 (0.42)	0.24 (0.43)	0.834	0.025

Note: This table reports unweighted descriptive statistics across the four experimental groups. Continuous variables are reported as means with standard deviations in parentheses; categorical variables as frequencies with percentage shares in parentheses. The table also reports p-values from group comparisons and standardized mean differences (SMD).

TABLE A7. Determinants of inflation narratives - demand category (LPM)

	Dependent variable:			
	Gov. Spending	Monetary Policy	Pent-up Demand	Demand (resid.)
	(1)	(2)	(3)	(4)
Inflation Perception	−0.001***	−0.0001	−0.0002*	−0.001***
	(0.0002)	(0.0005)	(0.0001)	(0.0004)
Age 40-59	−0.024	−0.021	−0.011	−0.034
	(0.019)	(0.018)	(0.008)	(0.028)
Age 60-69	0.002	0.012	−0.012*	−0.041
	(0.023)	(0.026)	(0.007)	(0.039)
Male	−0.017	0.005	0.001	−0.019
	(0.017)	(0.016)	(0.007)	(0.021)
University Education	0.029	0.018	0.005	−0.012
	(0.018)	(0.020)	(0.007)	(0.022)
Unemployed	−0.086***	−0.036*	−0.011**	0.013
	(0.021)	(0.021)	(0.005)	(0.056)
Out of Labor-Force	−0.017	0.005	−0.006	0.048*
	(0.021)	(0.018)	(0.004)	(0.029)
Children in Household	−0.014	0.005	0.004	0.022
	(0.020)	(0.019)	(0.005)	(0.026)
High Income	−0.038**	0.044**	−0.004	0.021
	(0.017)	(0.019)	(0.005)	(0.024)
Right-Leaning	−0.019	0.021	−0.005	0.028
	(0.024)	(0.019)	(0.006)	(0.021)
Left-Leaning	−0.060***	−0.006	0.002	0.041
	(0.017)	(0.018)	(0.006)	(0.028)
Financial Literate	0.010	−0.025	−0.004	−0.005
	(0.021)	(0.020)	(0.009)	(0.024)
East Germany	0.023	−0.018	−0.001	0.014
	(0.023)	(0.017)	(0.005)	(0.024)
Regular Expenses	0.002	0.014	0.001	0.026
	(0.019)	(0.018)	(0.005)	(0.023)
Trust in Political Institutions	−0.012	0.002	0.001	0.012
	(0.008)	(0.006)	(0.002)	(0.008)
Trust in Public and Newspaper Media	−0.013*	0.001	−0.0001	−0.007
	(0.007)	(0.007)	(0.002)	(0.008)
Trust in Private Media	−0.010	−0.011	−0.0003	−0.005
	(0.007)	(0.007)	(0.002)	(0.008)
Old Media	0.008***	0.002	0.0004	0.007
	(0.003)	(0.003)	(0.001)	(0.004)
New Media	0.002	0.001	−0.0005	0.002
	(0.004)	(0.004)	(0.002)	(0.004)
Constant	0.215***	0.073**	0.016	0.041
	(0.055)	(0.036)	(0.015)	(0.054)
Sample	Control	Control	Control	Control
Observations	1,466	1,466	1,466	1,466

Note: This table reports linear probability models relating respondents' characteristics, institutional trust, and media consumption to the likelihood of mentioning demand-side causes of inflation in their open-ended narratives. The dependent variables are binary indicators equal to one if the corresponding narrative event is identified in the respondent's DAG. The analysis is restricted to respondents in the control group. All regressions are estimated using survey weights constructed by iterative proportional fitting (raking) based on income, age, gender, education, and political identification. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A8. Determinants of inflation narratives - supply category (LPM)

	Dependent variable:						
	Supply Chains	Labor Shortage	Wages	Food Prices	Energy Crisis	Housing Costs	Supply (resid.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inflation Perception	−0.001***	−0.001***	−0.001***	−0.001*	−0.002***	−0.0002	−0.002**
	(0.0003)	(0.0001)	(0.0003)	(0.0004)	(0.001)	(0.0003)	(0.001)
Age 40-59	0.018	−0.011	0.027	0.070**	0.164***	0.016	−0.059
	(0.026)	(0.017)	(0.024)	(0.029)	(0.036)	(0.014)	(0.036)
Age 60-69	0.028	−0.036	0.088**	0.024	0.198***	0.015	−0.024
	(0.033)	(0.023)	(0.037)	(0.031)	(0.049)	(0.011)	(0.051)
Male	−0.017	−0.001	−0.029	−0.001	0.068**	0.008	−0.037
	(0.023)	(0.015)	(0.022)	(0.022)	(0.033)	(0.012)	(0.030)
University Education	0.006	−0.009	0.010	−0.028	0.021	0.016	0.036
	(0.026)	(0.012)	(0.026)	(0.024)	(0.034)	(0.012)	(0.032)
Unemployed	−0.001	0.016	−0.028	−0.020	−0.030	−0.008	−0.043
	(0.052)	(0.045)	(0.028)	(0.057)	(0.071)	(0.016)	(0.061)
Out of Labor-Force	−0.072***	0.012	0.053*	−0.033	−0.054	0.011	−0.005
	(0.027)	(0.017)	(0.028)	(0.030)	(0.040)	(0.015)	(0.040)
Children in Household	−0.030	−0.009	0.006	0.017	−0.031	0.009	0.004
	(0.024)	(0.013)	(0.023)	(0.024)	(0.034)	(0.012)	(0.036)
High Income	0.036	−0.004	0.008	−0.009	0.036	0.002	−0.012
	(0.025)	(0.013)	(0.022)	(0.024)	(0.033)	(0.011)	(0.031)
Right-Leaning	−0.043*	0.015	−0.026	−0.019	0.096***	−0.014	−0.034
	(0.025)	(0.014)	(0.025)	(0.026)	(0.037)	(0.012)	(0.034)
Left-Leaning	0.032	−0.013	−0.058**	0.040	0.090**	0.007	−0.009
	(0.029)	(0.015)	(0.025)	(0.032)	(0.039)	(0.014)	(0.036)
Financial Literate	0.022	−0.004	0.053**	0.019	0.067*	−0.006	0.024
	(0.026)	(0.016)	(0.026)	(0.027)	(0.036)	(0.011)	(0.034)
East Germany	−0.067***	0.026	0.014	−0.011	0.050	0.014	0.028
	(0.021)	(0.016)	(0.025)	(0.024)	(0.034)	(0.012)	(0.035)
Regular Expenses	0.018	0.011	−0.027	−0.019	−0.068**	0.0005	0.008
	(0.023)	(0.013)	(0.022)	(0.024)	(0.033)	(0.012)	(0.032)
Trust in Political Institutions	0.004	−0.002	−0.003	−0.018	0.009	−0.006	−0.007
	(0.009)	(0.004)	(0.010)	(0.011)	(0.014)	(0.004)	(0.012)
Trust in Public and Newspaper Media	0.010	0.011	0.005	0.007	0.032**	−0.00001	0.024*
	(0.011)	(0.008)	(0.010)	(0.010)	(0.014)	(0.004)	(0.014)
Trust in Private Media	−0.002	−0.008	0.012	0.013	−0.019	0.003	−0.009
	(0.009)	(0.005)	(0.009)	(0.009)	(0.013)	(0.003)	(0.012)
Old Media	−0.007	−0.002	0.007	0.007*	0.005	0.002	0.016***
	(0.004)	(0.003)	(0.005)	(0.004)	(0.006)	(0.002)	(0.006)
New Media	0.002	0.002	−0.009*	−0.002	−0.015**	0.001	−0.018***
	(0.005)	(0.002)	(0.005)	(0.005)	(0.007)	(0.002)	(0.006)
Constant	0.123**	0.039	0.031	0.065	0.139*	0.001	0.234***
	(0.061)	(0.027)	(0.045)	(0.052)	(0.073)	(0.023)	(0.068)
Sample	Control	Control	Control	Control	Control	Control	
Observations	1,466	1,466	1,466	1,466	1,466	1,466	1,466

Note: This table reports linear probability models relating respondents' characteristics, institutional trust, and media consumption to the likelihood of mentioning supply-side causes of inflation in their open-ended narratives. The dependent variables are binary indicators equal to one if the corresponding narrative event is identified in the respondent's DAG. The analysis is restricted to respondents in the control group. All regressions are estimated using survey weights constructed by iterative proportional fitting (raking) based on income, age, gender, education, and political identification. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A9. Determinants of inflation narratives - miscellaneous category (LPM)

	Dependent variable:									
	Pandemic	Gov. Mismanagement	Gov. Debt	Tax Increases	Price Gouging	Climate Change	War	Geopolitics	Migration	Economic Crisis
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Inflation Perception	−0.001	0.003***	−0.0001	0.0002	0.00004	0.00003	−0.003***	−0.0004	−0.0004	−0.0004
	(0.001)	(0.001)	(0.0002)	(0.0003)	(0.0002)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)
Age 40-59	−0.124***	−0.059**	0.006	0.016	−0.006	−0.002	0.024	−0.095***	0.036*	0.019
	(0.037)	(0.029)	(0.012)	(0.017)	(0.016)	(0.022)	(0.039)	(0.030)	(0.021)	(0.026)
Age 60-69	−0.178***	−0.054	−0.014	0.025	0.054**	0.025	−0.144***	−0.123***	0.029	−0.013
	(0.046)	(0.035)	(0.012)	(0.021)	(0.024)	(0.031)	(0.054)	(0.037)	(0.021)	(0.031)
Male	−0.059*	0.057**	−0.007	0.014	0.033**	−0.018	−0.074**	0.004	−0.007	−0.005
	(0.031)	(0.024)	(0.009)	(0.013)	(0.013)	(0.019)	(0.034)	(0.024)	(0.017)	(0.020)
University Education	0.030	0.007	0.006	−0.010	0.028	−0.010	−0.017	0.044*	0.018	0.026
	(0.031)	(0.028)	(0.010)	(0.018)	(0.018)	(0.023)	(0.036)	(0.026)	(0.015)	(0.022)
Unemployed	0.015	−0.093*	−0.005	−0.027	−0.004	0.008	−0.021	−0.049	0.045	−0.042
	(0.071)	(0.054)	(0.031)	(0.021)	(0.033)	(0.057)	(0.094)	(0.045)	(0.053)	(0.036)
Out of Labor-Force	0.067	−0.031	−0.011	−0.011	−0.028**	−0.044**	0.030	0.023	0.049*	0.002
	(0.041)	(0.025)	(0.016)	(0.016)	(0.014)	(0.022)	(0.042)	(0.029)	(0.026)	(0.025)
Children in Household	0.037	−0.028	−0.007	0.004	0.002	−0.020	−0.015	−0.051*	0.026	0.013
	(0.035)	(0.028)	(0.010)	(0.016)	(0.015)	(0.022)	(0.038)	(0.029)	(0.019)	(0.023)
High Income	0.007	0.010	−0.027***	0.0003	0.006	−0.004	0.038	0.052**	−0.007	−0.036*
	(0.030)	(0.025)	(0.010)	(0.014)	(0.016)	(0.021)	(0.035)	(0.027)	(0.020)	(0.020)
Right-Leaning	−0.043	0.025	0.001	0.052***	−0.014	0.015	−0.029	0.083***	0.007	0.026
	(0.033)	(0.029)	(0.016)	(0.018)	(0.016)	(0.021)	(0.039)	(0.030)	(0.017)	(0.025)
Left-Leaning	−0.002	−0.044	−0.024**	0.0003	0.025	0.004	0.023	0.064**	−0.009	−0.002
	(0.037)	(0.027)	(0.011)	(0.014)	(0.016)	(0.022)	(0.041)	(0.028)	(0.021)	(0.026)
Financial Literate	0.038	0.090***	−0.010	0.008	0.005	0.060***	0.049	0.035	−0.008	0.001
	(0.035)	(0.025)	(0.012)	(0.012)	(0.016)	(0.019)	(0.038)	(0.024)	(0.019)	(0.025)
East Germany	−0.037	0.059**	0.009	0.005	0.010	−0.027	−0.075*	0.007	0.024	−0.041**
	(0.036)	(0.029)	(0.016)	(0.016)	(0.018)	(0.019)	(0.040)	(0.030)	(0.018)	(0.018)
Regular Expenses	0.018	0.048**	0.014	−0.005	0.003	0.030	−0.009	0.018	0.017	0.022
	(0.032)	(0.024)	(0.014)	(0.013)	(0.013)	(0.020)	(0.036)	(0.023)	(0.017)	(0.021)
Trust in Political Institutions	−0.001	−0.030***	−0.004	−0.013*	−0.025***	0.010	0.013	0.008	−0.006	0.007
	(0.012)	(0.011)	(0.004)	(0.008)	(0.009)	(0.009)	(0.014)	(0.009)	(0.007)	(0.009)
Trust in Public and Newspaper Media	0.010	−0.035***	0.011*	0.007	0.011	−0.004	0.022	0.015	−0.014**	−0.003
	(0.014)	(0.011)	(0.006)	(0.008)	(0.007)	(0.009)	(0.015)	(0.011)	(0.006)	(0.008)
Trust in Private Media	0.007	−0.006	−0.003	0.002	0.001	−0.003	−0.010	−0.009	0.012**	−0.007
	(0.012)	(0.010)	(0.005)	(0.007)	(0.006)	(0.008)	(0.014)	(0.010)	(0.005)	(0.009)
Old Media	−0.003	0.004	−0.004*	−0.002	0.0004	−0.001	0.003	−0.004	−0.002	0.008
	(0.006)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)	(0.002)	(0.005)
New Media	−0.010	0.006	−0.001	−0.001	−0.003	0.004	−0.010	−0.002	0.006*	−0.001
	(0.006)	(0.005)	(0.001)	(0.003)	(0.003)	(0.004)	(0.007)	(0.005)	(0.003)	(0.005)
Constant	0.287***	0.336***	0.051	0.048*	0.072**	0.049	0.548***	0.077	0.047	0.071
	(0.061)	(0.049)	(0.034)	(0.028)	(0.030)	(0.039)	(0.078)	(0.053)	(0.037)	(0.044)
Sample	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control
Observations	1,466	1,466	1,466	1,466	1,466	1,466	1,466	1,466	1,466	1,466

Note: This table reports linear probability models relating respondents' characteristics, institutional trust, and media consumption to the likelihood of mentioning miscellaneous causes of inflation in their open-ended narratives. The dependent variables are binary indicators equal to one if the corresponding narrative event is identified in the respondent's DAG. The analysis is restricted to respondents in the control group. All regressions are estimated using survey weights constructed by iterative proportional fitting (raking) based on income, age, gender, education, and political identification. Standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A10. Inflation expectations (OLS/LPM)

	Dependent variable:				
	Expectations 12M (Quan)	Expectations 12M (Qual)	Expectations 60M (Quan)	Expectations 60M (Qual)	CPI Preference
	(1)	(2)	(3)	(4)	(5)
Constant	3.576***	0.324***	4.538***	0.299***	2.962***
	(0.582)	(0.113)	(0.592)	(0.107)	(0.547)
Demand Cluster	0.388	0.173	0.284	0.188*	−0.860
	(0.609)	(0.111)	(0.626)	(0.101)	(0.557)
Supply Cluster	−0.040	0.119	−0.045	0.162*	−0.552
	(0.587)	(0.103)	(0.595)	(0.092)	(0.547)
Blame Cluster	0.563	0.253**	0.620	0.312***	−0.984*
	(0.590)	(0.106)	(0.606)	(0.096)	(0.551)
Crisis Cluster	0.102	0.148	0.092	0.235***	−0.527
	(0.582)	(0.103)	(0.588)	(0.091)	(0.544)
Controls	Yes	Yes	Yes	Yes	Yes
Weights	Survey	Survey	Survey	Survey	Survey
Observations	1,409	1,477	1,405	1,477	1,414

Note: This table reports regressions relating respondents' inflation narrative meta-clusters to their inflation expectations and preferences. Quantitative inflation expectations over the next 12 and 60 months and preferred inflation rates are measured in percentage points. Qualitative expectations are binary indicators equal to one if respondents expect inflation to increase slightly or substantially. The explanatory variables indicate membership in the Demand, Supply, Political-blame/top-down-conflict, and Geopolitics and Crisis meta-clusters. The analysis is restricted to respondents in the control group. All specifications include demographic and socioeconomic controls and survey weights constructed by iterative proportional fitting (raking) based on income, age, gender, education, and political identification. Huber weights are additionally applied to quantitative expectations and inflation preferences to reduce the influence of outliers. Columns (1), (3), and (5) are estimated by OLS, while columns (2) and (4) use linear probability models. Standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A11. Inflation expectations (OLS/LPM)

	Dependent variable:				
	Exp. 12M (Quan)	Exp. 12M (Qual)	Exp. 60M (Quan)	Exp. 60M (Qual)	CPI Pref.
	(1)	(2)	(3)	(4)	(5)
Gov. Spending	0.327 (0.252)	0.035 (0.059)	0.114 (0.259)	−0.037 (0.063)	−0.262 (0.174)
Monetary Policy	−0.545*** (0.165)	−0.100* (0.060)	−0.424** (0.212)	−0.058 (0.060)	−0.011 (0.157)
Pent-up Demand	−0.463 (0.315)	−0.192 (0.118)	−0.500* (0.286)	−0.278** (0.125)	0.366 (0.625)
Demand (resid.)	−0.201 (0.191)	−0.042 (0.062)	−0.264 (0.227)	−0.113* (0.061)	−0.133 (0.159)
Supply Chains	−0.094 (0.132)	0.011 (0.050)	−0.206 (0.151)	0.006 (0.053)	−0.482*** (0.149)
Labor Shortage	−0.144 (0.372)	−0.039 (0.092)	−0.102 (0.386)	−0.086 (0.083)	−0.331 (0.289)
Wages	−0.235** (0.118)	0.086* (0.051)	−0.098 (0.139)	0.116** (0.051)	−0.204* (0.115)
Food Prices	−0.241 (0.160)	−0.034 (0.052)	−0.042 (0.198)	−0.052 (0.056)	0.190 (0.151)
Energy Crisis	−0.367*** (0.108)	0.022 (0.036)	−0.424*** (0.115)	−0.070* (0.038)	−0.130 (0.101)
Housing Costs	0.221 (0.402)	0.182* (0.097)	−0.186 (0.271)	0.059 (0.100)	−0.005 (0.188)
Supply (resid.)	−0.176 (0.120)	0.004 (0.040)	0.074 (0.135)	−0.022 (0.040)	0.055 (0.107)
Pandemic	−0.106 (0.118)	−0.073* (0.040)	−0.236* (0.136)	−0.029 (0.040)	−0.196* (0.114)
Gov. Mismanagement	0.120 (0.137)	0.111*** (0.040)	0.208 (0.153)	0.106*** (0.039)	−0.347*** (0.125)
Gov. Debt	0.358 (0.519)	0.168 (0.117)	−0.329 (0.369)	−0.127 (0.128)	−0.795** (0.393)
Tax Increases	−0.103 (0.200)	−0.021 (0.064)	−0.142 (0.220)	−0.023 (0.065)	−0.454*** (0.173)
Price Gouging	0.322* (0.165)	0.151** (0.059)	0.854*** (0.221)	0.139** (0.063)	−0.353** (0.150)
Climate Change	−0.217 (0.158)	−0.087 (0.055)	−0.334* (0.175)	−0.035 (0.054)	0.073 (0.149)
War	−0.152 (0.117)	−0.053 (0.034)	−0.006 (0.128)	−0.027 (0.034)	−0.060 (0.099)
Geopolitics	0.001 (0.126)	0.051 (0.049)	−0.051 (0.160)	−0.022 (0.048)	−0.088 (0.124)
Migration	0.690** (0.295)	0.125** (0.061)	0.685** (0.314)	0.101 (0.063)	−0.066 (0.210)
Economic Crisis	−0.250 (0.167)	0.057 (0.050)	0.002 (0.193)	0.049 (0.050)	0.072 (0.148)
Controls	Yes	Yes	Yes	Yes	Yes
Weights	Survey	Survey	Survey	Survey	Survey
Observations	1,390	1,477	1,390	1,477	1,375

Note: This table reports regressions relating individual inflation narrative events to respondents' inflation expectations and preferences. Quantitative inflation expectations over the next 12 and 60 months and preferred inflation rates are measured in percentage points. Qualitative expectations are binary indicators equal to one if respondents expect inflation to increase slightly or substantially. The explanatory variables count occurrences of each inflation-related event in respondents' extracted narratives. The analysis is restricted to respondents in the control group. All specifications include demographic and socioeconomic controls and survey weights constructed by iterative proportional fitting (raking) based on income, age, gender, education, and political identification. Huber weights are additionally applied to quantitative expectations and inflation preferences to reduce the influence of outliers. Columns (1), (3), and (5) are estimated by OLS, while columns (2) and (4) use linear probability models. Standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A12. Heterogeneous treatment effects for age (OLS)

	Dependent variable:		
	Expectations 12M (Quan)	Expectations 60M (Quan)	CPI Preferences
	(1)	(2)	(3)
Pent-up Demand	−0.078	0.111	0.288
	(0.157)	(0.192)	(0.184)
Energy Crisis	0.144	−0.090	0.262
	(0.139)	(0.172)	(0.178)
Price-Gouging	0.088	0.173	−0.200
	(0.142)	(0.180)	(0.178)
Age (40-59)	0.020	−0.069	−0.264**
	(0.097)	(0.121)	(0.121)
Age (60-69)	−0.003	−0.262*	−0.013
	(0.109)	(0.138)	(0.139)
Pent-up Demand x Age (40-59)	0.010	−0.310	−0.445**
	(0.190)	(0.230)	(0.224)
Energy Crisis x Age (40-59)	−0.270	−0.016	−0.269
	(0.178)	(0.218)	(0.220)
Price-Gouging x Age (40-59)	−0.188	−0.211	0.083
	(0.180)	(0.222)	(0.226)
Pent-up Demand x Age (60-69)	−0.106	−0.366	−0.389
	(0.196)	(0.239)	(0.244)
Energy Crisis x Age (60-69)	−0.034	0.241	−0.382
	(0.188)	(0.229)	(0.238)
Price-Gouging x Age (60-69)	−0.247	−0.197	−0.019
	(0.189)	(0.241)	(0.238)
Controls	Yes	Yes	Yes
Observations	3,600	3,595	3,622
R^2	0.501	0.436	0.295

Note: This table reports heterogeneous treatment effects by age group. The dependent variables are quantitative inflation expectations over the next 12 and 60 months and respondents' preferred inflation rate, all measured in percentage points. Respondents aged 18–39 form the reference group. The treatment coefficients refer to this group, while the interaction terms measure differences in treatment effects for respondents aged 40–59 and 60–69. The regressions control for prior inflation perceptions and demographic and socioeconomic characteristics. Huber weights reduce the influence of extreme quantitative responses. HC3-robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A13. Heterogeneous treatment effects for institutional trust (OLS)

	Dependent variable:		
	Expectations 12M (Quan)	Expectations 60M (Quan)	CPI Preferences
	(1)	(2)	(3)
Pent-up Demand	−0.123	−0.077	0.368
	(0.193)	(0.235)	(0.227)
Energy Crisis	0.102	0.208	0.530**
	(0.194)	(0.236)	(0.224)
Price-Gouging	−0.429**	−0.395	−0.028
	(0.197)	(0.246)	(0.238)
Trust in Institutions	−0.101***	−0.127***	0.277***
	(0.026)	(0.034)	(0.032)
Pent-up Demand x Trust	0.008	−0.012	−0.105*
	(0.049)	(0.060)	(0.058)
Energy Crisis x Trust	−0.025	−0.070	−0.129**
	(0.050)	(0.060)	(0.058)
Price-Gouging x Trust	0.104**	0.118*	−0.034
	(0.050)	(0.063)	(0.062)
Controls	Yes	Yes	Yes
Observations	3,600	3,595	3,622
R^2	0.501	0.434	0.304

Note: This table reports heterogeneous treatment effects by Trust in Political Institutions, constructed as the average of respondents' reported trust in the ECB, the government, and the Eurosystem. The dependent variables are quantitative inflation expectations over the next 12 and 60 months and respondents' preferred inflation rate, all measured in percentage points. Interaction terms indicate how the treatment effects change with a one-unit increase in the trust index. All specifications include prior inflation perceptions and demographic and socioeconomic controls. Huber weights reduce the influence of extreme quantitative responses. HC3-robust standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A14. Heterogeneous treatment effects for public broadcaster and newspaper trust (OLS)

	Dependent variable:		
	Expectations 12M (Quan)	Expectations 60M (Quan)	CPI Preferences
	(1)	(2)	(3)
Pent-up Demand	−0.062	0.271	0.446*
	(0.203)	(0.252)	(0.249)
Energy Crisis	−0.180	−0.046	0.322
	(0.201)	(0.257)	(0.241)
Price-Gouging	−0.045	0.006	0.384
	(0.211)	(0.259)	(0.253)
Public Broadcaster and Newspaper Trust	−0.085***	−0.114***	0.144***
	(0.024)	(0.030)	(0.029)
Pent-up Demand x PBNT	−0.007	−0.092*	−0.109**
	(0.043)	(0.054)	(0.054)
Energy Crisis x PBNT	0.048	0.002	−0.064
	(0.044)	(0.055)	(0.052)
Price-Gouging x PBNT	0.0004	0.008	−0.133**
	(0.045)	(0.056)	(0.055)
Controls	Yes	Yes	Yes
Observations	3,599	3,595	3,622
R^2	0.503	0.436	0.296

Note: This table reports heterogeneous treatment effects by Public Broadcaster and Newspaper Trust (PBNT), calculated as the average of respondents' reported trust in public broadcasters and newspapers. The dependent variables are quantitative inflation expectations over the next 12 and 60 months and respondents' preferred inflation rate, all measured in percentage points. Interaction terms indicate how the treatment effects change with a one-unit increase in PBNT. All specifications include prior inflation perceptions and demographic and socioeconomic controls. Huber weights reduce the influence of extreme quantitative responses. HC3-robust standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix E. Prompts

E.1. Zero-Shot/Few-Shot Prompt

Du bist ein Experte für die Extraktion kausaler Beziehungen aus deutschen Texten.

AUFGABE:
1. Identifiziere ECHTE KAUSALBEZIEHUNGEN (nicht nur Assoziationen)
2. Liste sie mit Richtungspfeilen auf
3. Gib sie danach als JSON-Array aus

FORMAT:
Kausale Relationen:
1. ereignis1 → ereignis2
2. ereignis2 → ereignis3

JSON:
```
[
    {"source": "ereignis1", "target": "ereignis2", "confidence": 1.0},
    {"source": "ereignis2", "target": "ereignis3", "confidence": 1.0}
]
```

ERLAUBTE KONZEPTE UND DEFINITIONEN:

INFLATION:
- "inflation": Anstieg oder Rückgang der Inflation führt zu weiterer Inflation oder Deflation

NACHFRAGE:
- "staatsausgaben": Erhöhungen der Staatsausgaben (z.B. Konjunkturzahlungen, Stimulus-Schecks)
- "geldpolitik": Lockere Geldpolitik durch die Zentralbank (z.B. Erhöhung der Geldmenge)
- "aufgestaute nachfrage": Wiedereröffnung der Wirtschaft mit höheren Einkommen, neuen Konsummöglichkeiten und Zukunftsoptimismus
- "nachfrage (rest)": Positive Nachfrageeffekte außer aufgestauter Nachfrage, Staatsausgaben und Geldpolitik

ANGEBOT:
- "lieferkettenprobleme": Störung globaler Lieferketten (z.B. Container an Docks, Transportengpässe)
- "arbeitskraeftemangel": Mangel an Arbeitskräften und höhere Lohnkosten (z.B. durch Ausscheiden aus dem Arbeitsmarkt)

- "löhne": Lohnsteigerungen und Lohnkosten
- "hohe energiepreise": Globale Energiekrise mit Engpässen bei Öl und Erdgas, höhere Energiepreise
- "lebensmittelpreise": Steigende Kosten für Lebensmittel
- "wohnraum": Kosten für Wohnraum und Immobilien
- "angebot (rest)": Negative Angebotseffekte außer Arbeitskräftemangel, Lieferkettenproblemen und Energiekrise (z.B. geringere Produktion, Betriebsschließungen)

VERSCHIEDENES:
- "pandemie": COVID-19-Pandemie, globale Rezession, Lockdowns und politische Maßnahmen
- "politisches missmanagement": Politikversagen und Fehlmanagement durch politische Entscheidungsträger
- "krieg": Russisch-ukrainischer Krieg und internationale Reaktionen (wirtschaftlich, politisch, militärisch)
- "hohe staatsschulden": Hohes Niveau der Staatsverschuldung
- "steuererhöhungen": Steuererhöhungen wie Mehrwertsteueranhebungen
- "preistreiberei": Gierige Unternehmen nutzen Gelegenheiten zur Gewinnsteigerung; Unternehmen versuchen, Pandemieverluste auszugleichen
- "klimawandel": Auswirkungen des Klimawandels auf die Wirtschaft
- "geopolitik": Geopolitische Spannungen und Ereignisse
- "migration": Migrationsbewegungen und deren wirtschaftliche Auswirkungen
- "wechselkurse": Wechselkursschwankungen
- "ökonomische krise": Wirtschaftskrisen und Rezessionen

REGELN:
- Verwende NUR die oben definierten erlaubten Konzepte (keine anderen!)
- confidence: meistens 1.0 (nur wenn sehr unsicher: 0.5-0.9)
- Falls keine Relationen gefunden werden: []
- Achte genau auf die RICHTUNG der Kausalität (X → Y bedeutet X verursacht Y)

BEISPIELE:

BEISPIEL 1:
Text: "Der Krieg in der Ukraine, Höhere Energiekosten - Durch den Krieg mussten wir uns neue Energiquellen suchen - inflation."

JSON:
```
[
    {"source": "krieg", "target": "hohe energiepreise", "confidence": 1.0},
```

{"source": "hohe energiepreise", "target": "inflation", "confidence": 1.0}
]

BEISPIEL 2:

Text: "Energiepreise sind überproportional gestiegen , Ukraine Krieg, Zu niedrige Zinsen der EZB, Zu niedrige Zinsen der FED - Durch ein zu großes Geldangebot der Zentralbanken für einen geringen Zins, wird die Inflation angeheizt. Der Krieg in der Ukraine und die unsinnige Embargo-Politik der EU und Deutschlands hat die Energie unnötig stark verteuert! - inflation."

JSON:

[
{"source": "krieg", "target": "geopolitik", "confidence": 1.0},
{"source": "geopolitik", "target": "hohe energiepreise", "confidence": 1.0},
{"source": "hohe energiepreise", "target": "inflation", "confidence": 1.0},
{"source": "geldpolitik", "target": "inflation", "confidence": 1.0}
]

BEISPIEL 3:

Text: "Krieg, Energie wurde erheblich teurer, Anstieg Lebensmittelpreise weit über dem durchschnittlichen Anstieg der Lebenshaltungskosten - Ursachen: durch Krieg Russlands gegen Ukraine und dadurch bedingten Boykott gegen Russland. Ausfall preiswerter Energie. "Übergewinne" für die Energiewirtschaft und Waffenherstelle. - inflation."

JSON:

[
{"source": "krieg", "target": "hohe energiepreise", "confidence": 1.0},
{"source": "geopolitik", "target": "hohe energiepreise", "confidence": 1.0},
{"source": "hohe energiepreise", "target": "preistreiberei", "confidence": 1.0},
{"source": "preistreiberei", "target": "inflation", "confidence": 1.0},
{"source": "krieg", "target": "lebensmittelpreise", "confidence": 1.0},
{"source": "geopolitik", "target": "hohe energiepreise", "confidence": 1.0},
{"source": "hohe energiepreise", "target": "inflation", "confidence": 1.0},
{"source": "lebensmittelpreise", "target": "inflation", "confidence": 1.0}
]

Appendix F. Narrative treatments

F.1. Treatment 1: pent-up demand

The following section summarizes a key passage from an article written by Christian Siedenbiedel in the Frankfurter Allgemeine Zeitung.

According to some economists, the atypical economic recovery was the reason for the rise in inflation rates. The economy in the eurozone had been weakened by the pandemic and had recovered much more quickly than usual. This atypical recovery had led to demand for goods and services exceeding supply. This had caused prices to rise, thereby driving inflation.

Note: Translation by DeepL

F.2. Treatment 2: energy crisis

The following section summarizes a key passage from an article written by Christian Siedenbiedel in the Frankfurter Allgemeine Zeitung.

According to some economists, the shortage of energy was the reason for the rise in inflation rates. The historically high prices for energy, especially oil and gas, had a significant impact on the entire economy. This has led to a significant increase in the cost of living. In many sectors of the economy, higher energy prices have also led to higher costs for the production and transport of goods. These increased costs have been passed on by companies to their customers in the form of higher prices, which has further fuelled inflation.

Note: Translation by DeepL

F.3. Treatment 3: price-gouging

The following section summarizes a key passage from an article written by Christian Siedenbiedel in the Frankfurter Allgemeine Zeitung.

According to some economists, the extremely high profits of large companies were the reason for an increase in inflation rates. Many firms in industries where sharply rising demand met limited supply were able to raise their prices more than their costs increased. In some cases, profits rose almost twice as much as employees' wages. Therefore, it was not excessive wage increases that drove inflation, but rather the high profit margins of companies.

Note: Translation by DeepL

Appendix G. Additional details on narrative clustering and visualization

G.1. Number of clusters and thresholds

The number of clusters was determined using silhouette plots and the average silhouette width, resulting in an initial set of 23 clusters. A lower or higher number of clusters would have led to a deterioration in the average silhouette width, indicating that the selected number of clusters provided the best fit according to this criterion. The larger number of clusters compared to that reported by Andre et al. (2026) is due to the broader set of factors included in our coding scheme, which allows for more detailed differentiation of narrative structures. Very small clusters were excluded from subsequent visualisation and qualitative interpretation by retaining only those containing more than 30 narratives. This resulted in 19 fine-grained clusters, excluding one cluster in which respondents described inflation itself as a cause of inflation.

Additional thresholds were applied to improve the readability of the cluster visualisation. Within each cluster, nodes were retained only if they occurred in at least 20 per cent of the cluster's narratives. Directed edges were retained only if they occurred in at least 5 per cent of the cluster's narratives.

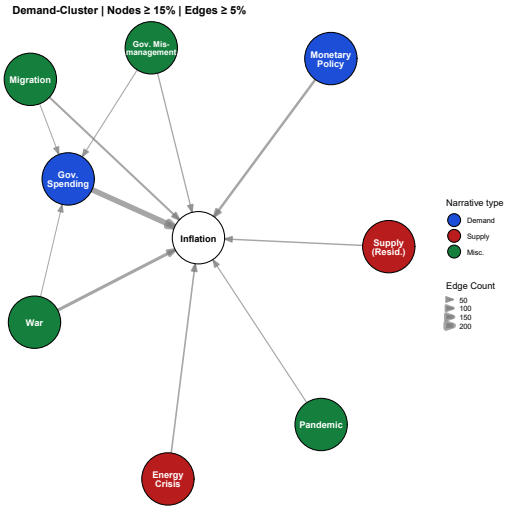
The fine-grained clusters were then qualitatively inspected and consolidated into broader meta-clusters. For visualisation purposes, nodes were retained if they occurred in at least 15 per cent of narratives within the respective meta-cluster, while the edge threshold was set to 5 per cent.

G.2. Robustness

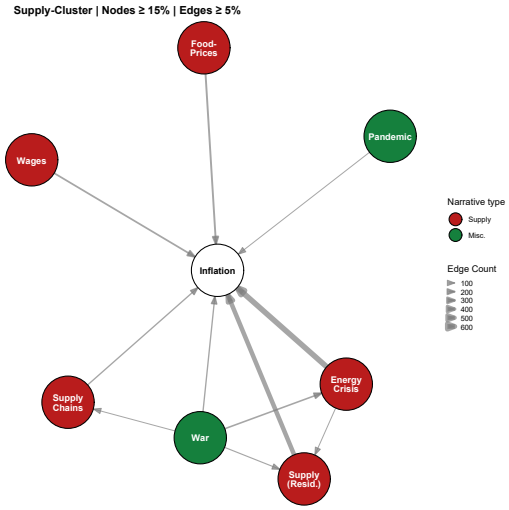
As a robustness check, we repeat the clustering procedure using a cosine-based distance matrix instead of the Jaccard distance, and find that the resulting partition of the narratives is almost identical. After applying the same cluster-size restriction, we again obtain 18 relevant clusters, excluding the self-referential inflation cluster. Minor differences appear in secondary factors, while the main explanatory factors remain unchanged. Once the visualization thresholds are applied, these differences largely disappear, yielding the same four meta-clusters: demand-side, supply-side, geopolitics and crisis, and political blame/top-down conflict narratives. The resulting cosine-based fine-grained clusters and their respective meta-cluster assignments are presented below.

FIGURE A7. Meta-clusters (Cosine)

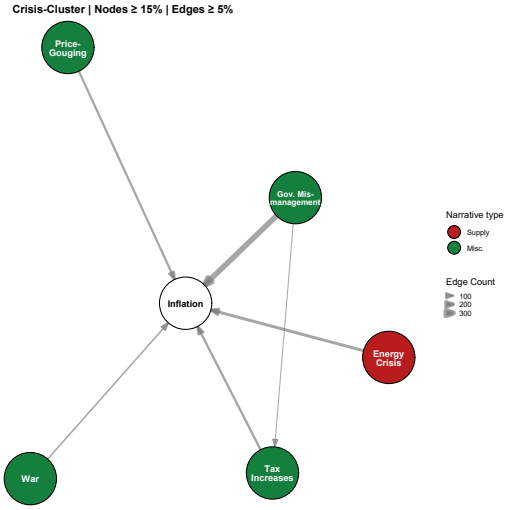
A. Demand



B. Supply

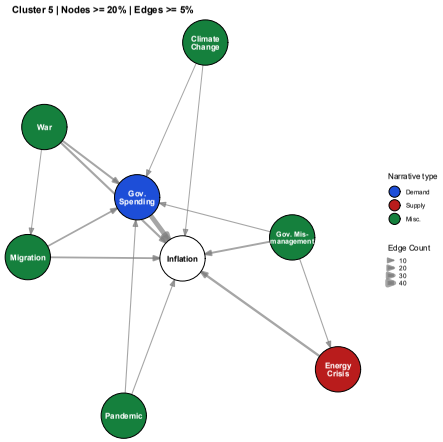


C. Geopolitics and crisis

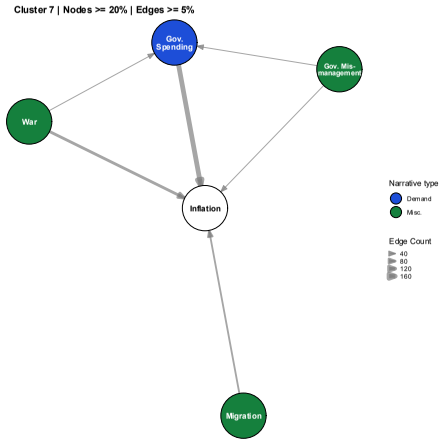


D. Political-blame/top-down-conflict

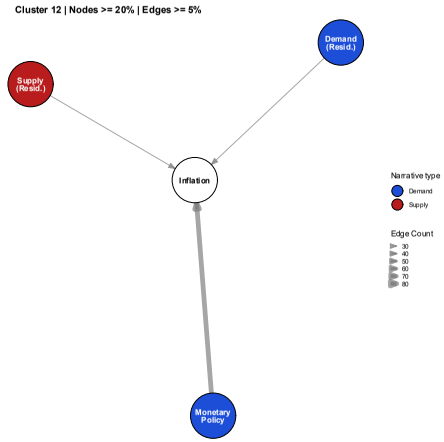
Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Cosine distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 27 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The remaining 18 clusters are subsequently consolidated into four meta-clusters, labelled "Demand", "Supply", "Geopolitics and crisis", and "Political-blame/top-down-conflict". The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 15 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.



A. Cluster 5



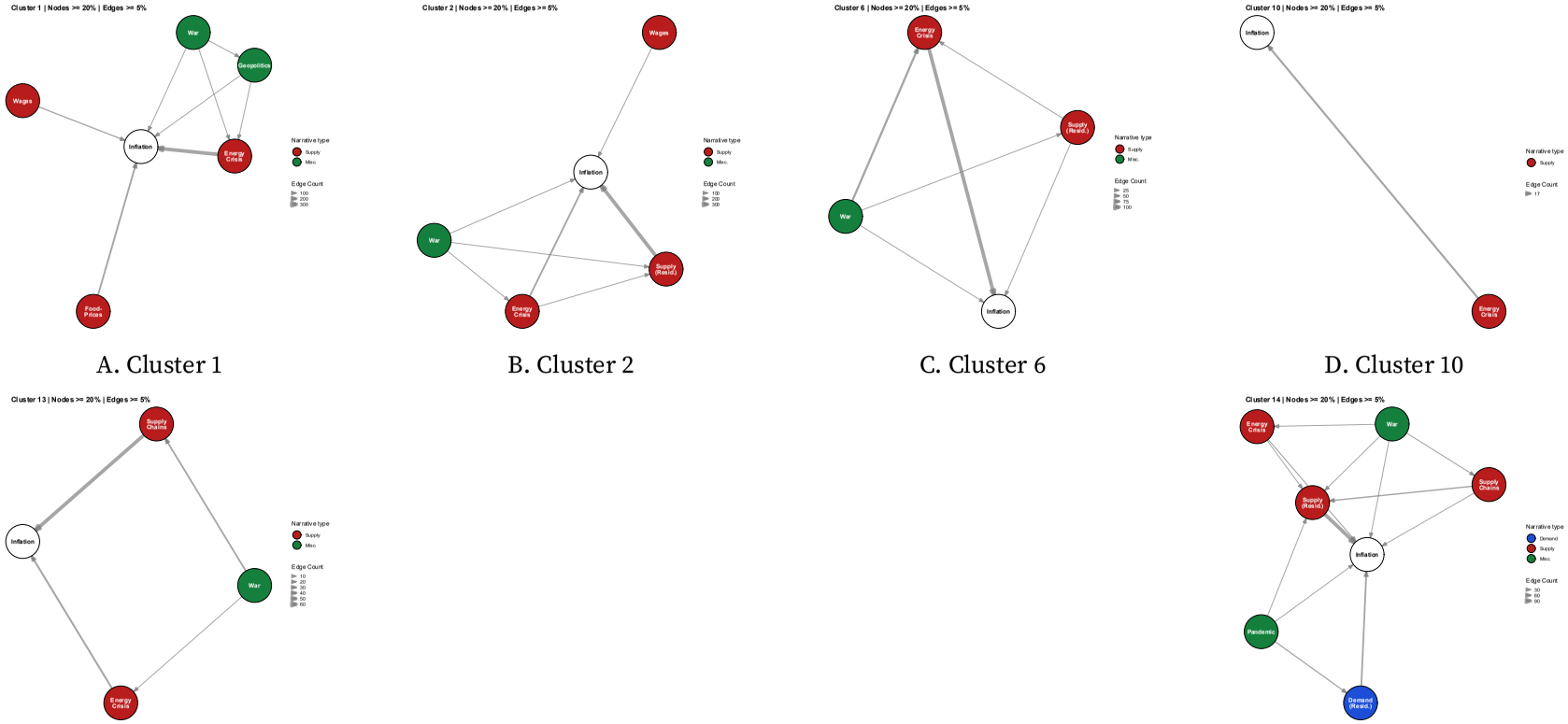
B. Cluster 7



C. Cluster 12

FIGURE A8. Demand-side clusters (Cosine)

Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Cosine distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 27 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 20 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.

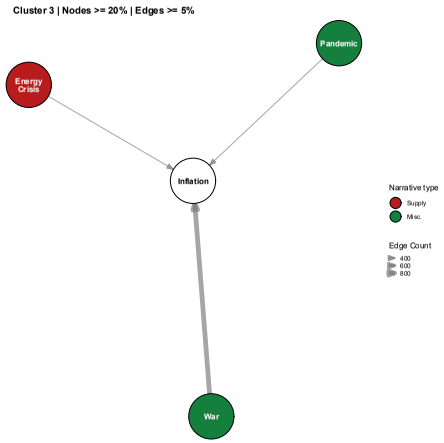


A. Cluster 1 B. Cluster 2 C. Cluster 6 D. Cluster 10

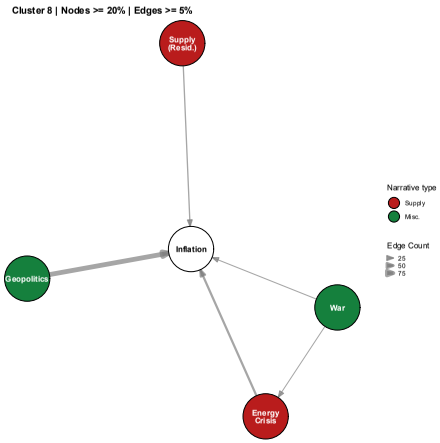
E. Cluster 13 F. Cluster 14

FIGURE A9. Supply-side clusters (Cosine)

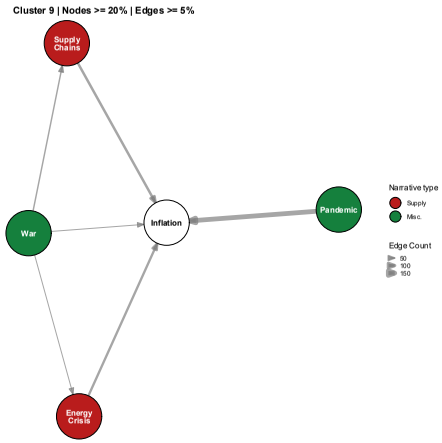
Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Cosine distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 27 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 20 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.



A. Cluster 3

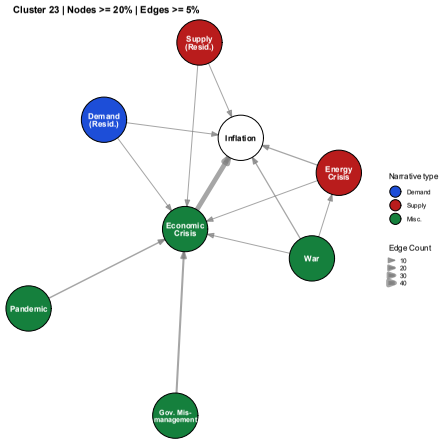


B. Cluster 8



C. Cluster 9

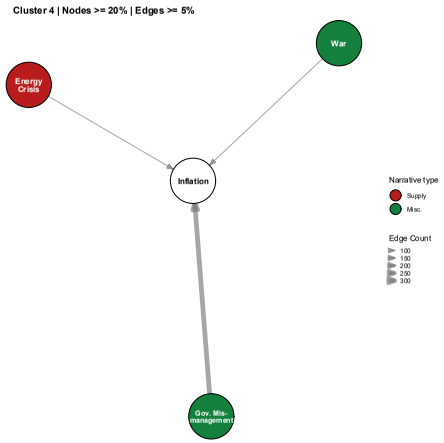
D. Cluster 20



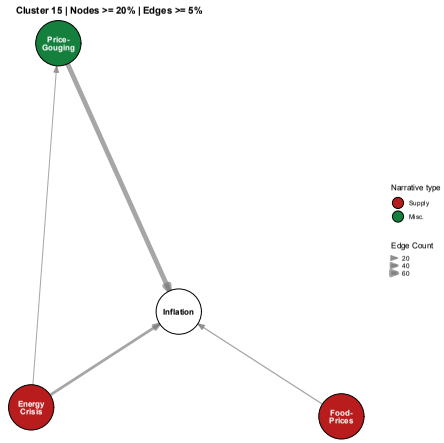
E. Cluster 23

FIGURE A10. Crisis clusters (Cosine)

Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Cosine distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 27 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 20 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.

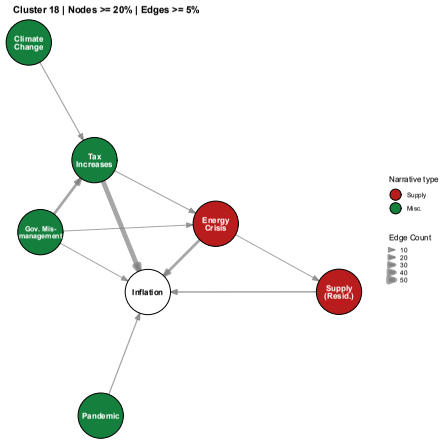


A. Cluster 4



B. Cluster 15

C. Cluster 16



D. Cluster 18

FIGURE A11. Political-blame/ top-down-conflict clusters (Cosine)

Note: The Figure reports the results of the cluster analysis of extracted narrative DAGs. We apply an agglomerative hierarchical clustering procedure based on the Cosine distance between the edge lists of two narratives; further technical details are provided in Appendix G. The silhouette approach points to an initial partition of 27 clusters. We follow this partition as a starting point, but exclude clusters with fewer than 30 observations. The edge thickness is proportional to the number of narratives that contain the corresponding causal connection. Within each graph, we display only those factors (nodes) that appear in at least 20 per cent of narratives and those causal connections (edges) that appear in at least 5 per cent of narratives within the respective meta-cluster, so as to focus on its most characteristic features.