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Narratives on the causes of inflation in Germany

First results of a pilot study

Lisa Demgensky[*] Ulrich Fritsche[†]

July 19, 2023

Abstract

Since 2021, the inflation rate in Germany and the euro area has increased significantly. At the same time, there are increasing signs of "de-anchoring" of inflation expectations in Germany. This paper - building on the approach of Andre et al. (2022a) - examines in a pilot study survey-based narratives for the rising inflation together with socio-economic factors. A mixed-methods approach is used to classify the narratives, with clustering based on statistical criteria. A regression analysis is used to examine the relationship between socio-economic factors and narratives on the one hand, and the relationship between narratives/clusters of narratives and a de-anchoring of inflation expectations on the other hand. We can associate certain narratives with socio-economic characteristics and political partisanship. Narrative complexity is a function of education and literacy. Narrative clusters correspond to certain milieus and dimensions of socio-economic stratification. Narratives of supply shortages and price gouging are positively correlated with anchored expectations; demand and government plus other narratives are negatively correlated with anchored expectations.

JEL codes: E31, E32, E71

Keywords: Narratives, expectation formation, inflation, Germany

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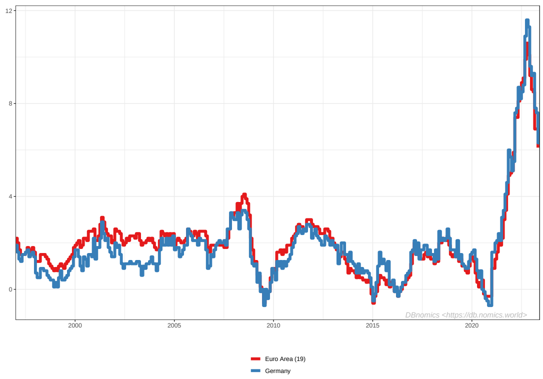
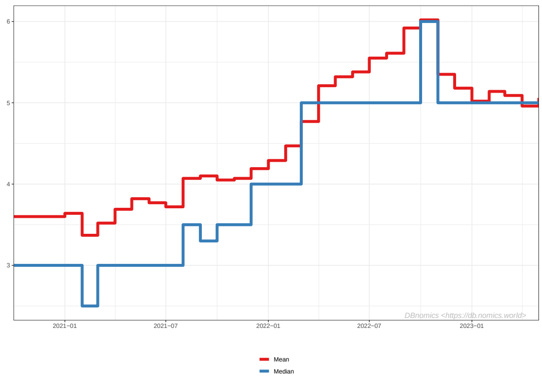
1 Introduction

The past two years in many countries, and also in Germany, have been characterised by a significant increase in the inflation rate, which started in 2021 but accelerated significantly in 2022. Medium-term inflation expectations over a 5-year horizon have also increased significantly (see figure 1).

Figure 1: Inflation and medium-run inflation expectations



(a) Inflation rate, year-over-year, Germany (blue) and Euro Area (19) (red)



(b) Survey-based 5 years ahead inflation expectations (Germany)

Note: The inflation rate is calculated on the basis of the year-on-year rates of change in the Harmonised Index of Consumer Prices. Inflation expectations refer to the median (blue) and mean (red) of the survey of quantitative inflation expectations for the 5-year horizon in the Survey of Consumer Expectations of the Deutsche Bundesbank (https://www.bundesbank.de/en/bundesbank/research/survey-on-consumer-expectations). The data were obtained using the R package rdbnomics, see Brand (2020).

The increase in households' medium-term inflation expectations is consistent with the pre-2021 findings of a "de-anchoring" (Coleman and Nautz, 2023; Strohsal et al., 2016; Nautz et al., 2017, 2019; Hachula and Nautz, 2018) of inflation expectations as compared to the Central Bank's reference value.[1] A process of "de-anchoring" already started after the 2008 financial crisis, and medium-term inflation expectations have since become even more detached from the inflation target. This is relevant for monetary policy because in all modern macroeconomic models the expected inflation plays a central role for the resulting inflation rate and other macroeconomic variables (Gürkaynak et al., 2005; Bauer, 2015).

The analysis of inflation expectations of households, experts and firms, usually collected through surveys, has increased significantly in recent decades. The decades-long dominance of the "fully informed rational expectations" assumption, going back to Muth (1961) and Lucas (1972), was broken by the work of Mankiw and Reis (2002), Woodford (2001) and Sims (2003) on "information rigidities" and "rational inattention". Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015a) provided convincing and

[1] The reference value for the European Central Bank's inflation target had been defined in 2003 as "below, but close to, 2%", and in July 2021 as "aiming for two per cent inflation over the medium term". See European Central Bank (2021).

widely validated evidence for the existence of information rigidities. While Manski (2004) back in 2004 diagnosed a strong scepticism of economists towards the use of survey data, the heterogeneity and subjectivity of inflation expectations is now a well-accepted fact and survey-based expectation data are used all over the place (Bachmann et al., eds, 2023).

While the heterogeneity and subjectivity of inflation expectations is now largely undisputed, there is still no consensus in economics as to what determines these expectations.

Weber et al. (2022a) identify four channels that affect subjective inflation expectations: (1) exposure to heterogeneous price signals (D'Acunto et al., 2021b), (2) different media information sets (Carroll, 2003; Doepke et al., 2008; Bachmann et al., 2021; D'Acunto et al., 2021a; Dräger et al., 2016), (3) cognitive ability, education and the usage of heuristics (D'Acunto et al., 2019a; D'Acunto et al., 2022; Gennaioli and Shleifer, 2010), and (4) heterogeneous incentives to obtain information (Cavallo et al., 2017).

In a recent paper, Andre et al. (2022a) takes the existing strand of research and links it to the strand of "narrative economics" research that has gained momentum especially after the work of Shiller (2017) and Shiller (2019): Based on a working definition of economic narratives as "causal accounts for past economic events" (Andre et al., 2022a, p. 5), the authors focus on measuring backward-looking narratives by means of open-ended questions. For the classification of narratives, the concept of "directed acyclic graphs" (DAG) is used (Pearl, 2009), which is also used in the work of Eliaz and Spiegler (2020) and Macaulay and Song (2022) and allows a direct connection to economic discourses, especially to expectation formation under Bayesian learning. At the same time, the concept of narrative expectations is interdisciplinary. It can be linked to discourses in other social science disciplines (Beckert, 2016) or psychology (Tuckett and Nikolic, 2017).

The findings of Andre et al. (2022a) for the U.S. can be summarized as follows: Households' narratives differ markedly from those of economists. They place much more emphasis on supply effects and political factors as causes of the inflation process. Heterogeneity of reported narratives can be explained mainly by political attitudes (ideology) and news consumption. In an experimental part of the study, the authors show that expectations respond to priming with narratives, that narratives influence the interpretation of news, and that mass media coverage is an important source of narratives.

As part of a pilot study, this paper used the methodology of Andre et al. (2022a) as the basis for a survey of German households. Based on Eliaz and Spiegler (2020)'s methodology, narratives are interpreted as DAG and retrospective narratives are measured with open-ended questions and coded with qualitative social research methods, strongly following Andre et al. (2022a)'s methodology. The research focused on the following questions: Which narratives are reported in connection with the current rise in inflation? What is the relationship between individual narratives, narrative clusters and socio-economic variables? Is there a relationship between certain narratives and the "de-anchoring" of inflation expectations? Because of the pilot nature of the survey, causal experiments with an randomized controlled trial design were not conducted, and the size of our survey does not yet meet the requirements for representativeness. The research was conducted in Germany between August, 12^{th}, 2022, and October, 1^{st}, 2022, via an online questionnaire. This suggests a much stronger effect of the Russian war of aggression against Ukraine compared to the reference study and had to be taken into account in the coding. Cluster analysis was used to reduce the dimensionality of the narratives. Regression analysis is used to analyse the relationships between narratives and socio-economic factors on the one hand and between narratives and de-anchoring on the other hand.

Based on the regression results, we can associate certain narratives with socio-economic characteristics and political partisanship. To give just a few examples: The monetary policy narrative is more likely to be reported by older and male respondents, while the climate crisis narrative is more likely to be reported by female and more educated respondents. The pandemic and war narratives appear to be less unpopular among respondents who lean to the far right of the political spectrum. The government mismanagement narrative is also clearly popular among these respondents. Price gouging, on the other hand, seems to be a more popular narrative on the left of the political spectrum. Furthermore, and in line with the hypothesis and findings in Andre et al. (2022a), narrative complexity is a function of education and literacy. Narrative clusters correspond to particular milieus and dimensions of socio-economic stratification. To take a few examples, cluster 5 (see figure A.F.3e), with a strong focus on supply chain issues as the dominant narrative for inflation, is associated with respondents who tend towards the centre of the political spectrum, are financially literate and have a higher probability of correctly reporting inflation perceptions, while cluster 9 ("government mismanagement") aggregates respondents mainly from the far right of the political spectrum. Regarding the anchoring of medium-term inflation expectations, males and the better educated are more likely to have anchored expectations. Narratives of supply shortages and price gouging are positively correlated with anchored expectations, while narratives of demand problems and government mismanagement are negatively correlated with anchored expectations.

The paper is structured as follows: Section 2 gives a brief overview of existing research strands. Section 3 briefly describes the survey instrument, the qualitative analysis and the clustering algorithm. Section 4 presents the regression results and section 5 concludes. Some background material is given in the Appendix (section A) of the paper. Further background information, the detailed survey questionnaire, anonymised data and the replication code will be made available via a repository at `https://www.openicpsr.org/openicpsr/search/studies`. All calculations in the paper were performed using R software (R Core Team, 2022). The software is licensed under GPL-2/ GPL-3.

2 Literature Review and Research Contributions

Given the recent inflation developments, the question arises as to which policy measures and interventions governments and central banks use in response to rising inflation in order to maintain price stability. In order to answer this question, it is necessary to understand the mechanisms behind inflation and to have an overview of the variables that influence it. It is widely accepted in macroeconomics that expectations of future inflation have a significant impact on actual inflation developments. This effect is part of most canonical New Keynesian models (Werning, 2022). Central banks, for example, try to influence these expectations by means of communicative interventions. In this respect, information about how and why economic agents develop certain expectations is of central importance (Bernanke, 2007; Yellen, 2015).

An extensive survey-based literature on households' inflation expectations also refutes the assumption of rational expectations that has long dominated macroeconomics. According to this assumption, agents in a market do not have complete information at their disposal, which is not processed in the same rational way independently of individual factors (Muth, 1961, p. 316 f.). A number of recent research findings confirm that, in the specific case of inflation expectations, differences can be demonstrated with regard to various factors of households. For example, inflation expectations differ according to demographic factors such as gender (Armantier et al., 2016; Bryan and Venkatu, 2001; D'Acunto et al., 2021, 2022; Jonung, 1981; Pfajfar and Santoro, 2008) and age cohorts (Blanchflower and MacCoille, 2009; Bruine de Bruin et al., 2010; Bryan and Venkatu, 2001; D'Acunto et al., 2022; Diamond et al., 2020; Johannsen, 2014; Lombardelli and Saleheen, 2003; Malmendier and Nagel, 2016). In addition, socio-economic factors such as income and education (Armantier et al., 2016; Blanchflower and MacCoille, 2009; Bruine de Bruin et al., 2010; Bryan and Venkatu, 2001; D'Acunto et al., 2022; Johannsen, 2014; Pfajfar and Santoro, 2008; Weber et al., 2022b) as well as occupation (Lombardelli and Saleheen, 2003; D'Acunto et al., 2021) have an impact on agents' inflation expectations. Furthermore, specific education in terms of understanding economic and financial relationships also has an impact on expectations (Bruine de Bruin et al., 2010; Burke and Manz, 2014; D'Acunto et al., 2019a,b; Rumler and Valderrama, 2020). Other factors include, for example, the actors' voting behaviour as well as the preferred political party and its status in government (Bachmann et al., 2021; Berlemann and Elzemann, 2006; Gillitzer et al., 2021) or experience with prices as well as previous consumption behaviour (Cavallo et al., 2017; Coibion and Gorodnichenko, 2015b; D'Acunto et al., 2019b, 2021a; D'Acunto et al., 2021b; Jonung, 1981; Weber et al., 2022b).

As Andre et al. (2022a) were able to show, in addition to heterogeneous inflation expectations and the resulting economic decisions, there is also heterogeneity in inflation narratives, as the causes of the current rise in inflation that individuals have assumed in the past. This paper is related to the emerging field of narrative studies, which has gained general attention in economics circles following Shiller (2017)'s presidential address at the American Economic Association. According to this view, narratives are understood as contagious and popular stories that spread virally and are seen as a central cause of economic fluctuations, as people align their economic actions and adjust their expectations for the future on the basis of the world views associated with (Shiller, 2017, p. 967 f.).[2]

In addition to numerous methodological approaches to studying the dynamics of narratives in economics, Shiller (2017) stresses the importance of survey-based data, which are generated using open-ended questions "that ask the respondent to write a sentence or two. The questions are designed to get the respondent thinking about what motivates them, so that their answers can be analysed in the future." (Shiller, 2017, p. 998). At the heart of Andre et al. (2022a)'s survey of households and experts in the US is an open-ended question asking participants to explain relevant causal principles that lie in the past and explain the recent rise in inflation. Others, such as (Borup et al., 2022), use this elicitation method by exploring subjective beliefs about the perceived impact of the COVID-19 pandemic on financial markets (Borup et al., 2022).

Furthermore, the concept of narrative in relation to this research project borrows heavily from the work of Eliaz and Spiegler (2020), who define narratives as simplified causal models. The authors refer thematically to political debates where different positions are taken because of competing narratives that collide. They suggest that actors position themselves politically on the basis of narratives that they perceive as having the more hopeful outcomes. Accordingly, emotions in particular are a driving force in the formation of beliefs. Thus, it is not only objective facts or the preferences of actors that contribute to beliefs. To illustrate the causal nature of narratives, they are represented in the form of a "Directed Acyclic Graph" (DAG).[3] Accordingly, narratives may differ in terms of which variables are included in the causal model. Furthermore, the causal structure may differ, with variables playing different roles in the causal sequence of causes and effects (Eliaz and Spiegler, 2020, p. 3786 ff).

Based on this representation, the heterogeneity of narratives regarding rising inflation in Andre et al. (2022a) can be elaborated. Furthermore, these results are associated with heterogeneous inflation expectations. Again, the heterogeneity of inflation narratives with respect to demographic and socio-economic factors is confirmed. There has been ample evidence in the past that expectations of future events are heterogeneous. The work of Andre et al. (2022a) shows that past events and related narratives and evaluations influence expectations and the evolution of the current inflation rate.

[2] It is worth noting that the concept of narratives is defined differently in different strands of economic research. For example, Roos and Reccius (2021) divide the current research literature into categories with respect to different definitions of the concept of narratives. Much of the literature, such as Shiller (2017, 2020), assumes that narratives influence the economic actions of actors and thus the economy as a whole (Roos and Reccius, 2021, p. 12).

[3] The foundational work of Pearl (2009) on causality in statistics underpins the concept of DAG.

This paper contributes to the field by presenting a mixed-methods study of inflation narratives for a sample of German households during the most recent inflation period in 2022, after historical events such as the start of Russia's invasion of the Ukraine are a few months in the past. Further research should go beyond the scope of a pilot study and examine a more representative sample.

Furthermore, Robert Shiller advocates the adoption of an interdisciplinary perspective, specifically a greater convergence of economics with the social sciences (Shiller, 2020, p. 375-379). Therefore, the theoretical concept of narratives is extended by a sociological perspective, following Beckert (2018, p. 509-516), by assuming that narratives, as stories about the future, are related to social interactions, positions as well as systems of norms and values. Also Roos and Reccius (2021, p.13 ff.) emphasize the aspect of social interaction. According to her, narratives are passed on between individuals and groups with similar belief systems, which is why groups with different belief systems hold different narratives and consequently adapt their actions and expectations.Therefore, as in Andre et al. (2022a), socio-demographic factors as well as the political positioning of the participants are also collected in order to examine whether the narratives differ with regard to these factors.

The paper adds to the literature by jointly analysing narratives, socio-demographic factors and long-term inflation expectations. Special attention is paid to the correlation between de-anchoring, socio-demographic factors and narratives. Furthermore, it is important to compare the results with those of Andre et al. (2022a) in order to check whether similar as well as specific structures can be worked out for the case of Germany at another time. Further studies should go beyond the scope of the survey and examine the relationships in an appropriate causal inference framework.

3 Survey Design, Coding of Narratives, and Clustering

3.1 Survey Design

The survey was conducted between August 12^{th} and October 1^{1st} 2022, using the online survey tool *LimeSurvey* to classify the narratives and collect other background variables. Independently recruited participants received an online link to the questionnaire and were able to participate in the survey. The only requirement to participate in this survey was a minimum age of 18 years. A total of 168 respondents participated in the study. Of these, 133 datasets can be analysed (see section A for further details on data selection). The study is seen as a pre-test of the stated method of results and evaluation, in order to find out what adjustments can be made within the framework of an equivalent study on a larger scale.

Accordingly, the sample has a high proportion of women (62%). In addition, the participants are above average young, 57% are between 18 and 34 years old, and tend to be better educated, with 75% having a high school diploma or equivalent and 52% having a university degree. 55% of respondents are in full-time employment and 15% are unemployed. 56% have a net monthly income of more than 2,000 Euros, 38% less.

The questionnaire is structured as follows: All participants first see a welcome page with introductory words on the purpose of the survey, notes on anonymity, the average response time required and a provision of contact details. It is pointed out that the survey asks for personal views and assumptions on the development of the inflation rate, as there are very different opinions and associations on this topic. The aim is to motivate participants, including those who feel they have too little background knowledge.

Some demographic and socio-economic background variables of the respondents are then collected to check whether the narratives differ with respect to these factors. The wording and response categories are based on the recommendations of the German Federal Statistical Office (Statistisches Bundesamt, 2016) for oral and written surveys in Germany, which can be used to assess the representativeness of the surveyed sample and ensure the comparability of data, as they are also used in the microcensus, the instrument of official statistics (Statistisches Bundesamt, 2016, p. 5 f., 73). The questionnaire collects data on age, gender, highest school-leaving qualification, highest vocational qualification, employment status and average monthly net income.

The next step is to determine the respondents' political attitudes in order to identify differences with regard to the narratives mentioned. Participants are asked to name the party they would vote for with their second choice if a general election were to be held in Germany next Sunday. Six of the parties represented in the Bundestag are listed as response categories. There is also an option to name a party that is not listed in an open answer category.

In order to analyse the influence of respondents' financial literacy on inflation expectations and narratives about the recent rise in inflation, the level of financial literacy is measured within the questionnaire. (Lusardi and Mitchell, 2006, p. 3) developed a three-question module in the 2004 wave of the Health and Retirement Study (HRS) "to assess respondents' level of financial literacy" (Lusardi and Mitchell, 2006, p. 3). These have since been used in various surveys and are considered a benchmark for measuring financial literacy (Lusardi and Mitchell, 2011, p. 499 f.). The questions cover the following three dimensions, which are central to financial decision-making "(i) understanding of compound interest; (ii) understanding of inflation; and (iii) understanding of risk diversification" (Lusardi and Mitchell, 2011, p. 499).

The following sections of the questionnaire are devoted to the rate of inflation. In this respect, a definition of the inflation rate is first given, according to (Andre et al., 2022b, p. 6). An example is then given of how consumer prices change over a 12-month period for a basket of typical monthly purchases. This ensures that respondents have a basic understanding of the inflation rate and can refer to the same facts in relation to the following questions.

Then, as Andre et al. (2022b, p. 7), the respondent's estimate of the inflation rate over the past 12 months is recorded. This is asked both quantitatively, in the form of the inflation rate as a percentage, and qualitatively, by asking respondents to assess whether the inflation rate over the past 12 months was higher, lower or about the same as the year before. Finally, these questions can be used to determine whether respondents have a realistic perception of recent inflation developments. It also allows us to see whether this assessment or perception has an impact on the narratives about the rise in inflation and on expectations about future inflation developments.

A central component of this research project is to identify the causal narratives that respondents use to justify the recent rise in inflation. Within the questionnaire there is a preliminary indication that this is about expressing personal thoughts and opinions in one's own words. Respondents are first asked to read the following text carefully and to take a few minutes to answer the question. In the context of the text, the event of the recent rise in inflation is described as follows Andre et al. (2022b, p. 8). This has the advantage that the answers refer to the same event, which has been clearly defined beforehand, thus allowing for comparability. It is mentioned that, according to the Federal Statistical Office, the inflation rate in the years 2000-2020 was between 0.3-2.6%. These values refer to the consumer price index as a percentage change from the previous year's level (Statistisches Bundesamt, 2022a, p. 5).

It is then mentioned that the latest inflation rate (as of June 2022) was 7.6%. This is the value of the consumer price index compared to the same month of the previous year (Statistisches Bundesamt, 2022b). A period of 20 years is described to illustrate that the inflation rate has not been subject to major fluctuations over a long period of time compared with the recent rise in inflation. Again, additional examples of price changes in baskets of goods are added. The retrospective survey is conducted by means of an open-ended question. The wording has been tailored to encourage respondents to provide a detailed description of the presumed causal factors behind the recent rise in inflation. Respondents are asked to write 3-5 sentences to encourage not just bullet points but several full sentences, ideally capturing multi-layered thoughts and a relationship between causes and effects. In addition, the survey tool reiterates that personal thoughts are requested at this point as there are different opinions on the subject and therefore no right or wrong answers.

According to Gennaioli and Shleifer (2010), it is assumed that people make judgements and decisions based on the information and thoughts that first come to mind. In the case of spontaneous decisions, memory functions selectively, as complete knowledge is not accessed (Gennaioli and Shleifer, 2010, p. 1429 f.). Thus it is possible that although respondents have been exposed to different narratives, only those that have a stronger weighting are spontaneously remembered. By asking respondents to write a few coherent sentences, the aim is to capture these spontaneous trains of thought, without directing respondents in a thematic direction or restricting their thoughts, as may be the case with predetermined answer options (Züll and Menold, 2019).

It also looks at which narratives are used to form expectations about the future path of inflation. As mentioned in section 2, expectations about the future influence the economy. Therefore, the following question provides information on how agents assess the future development of inflation and on the basis of which narratives these expectations are formed. From this, conclusions can be drawn, for example, on how central banks can act in order to gain public confidence, which is an important basis for ensuring price stability. Respondents are asked to assess whether the current high inflation rate is temporary or whether it will remain high in 3-5 years' time.[4]

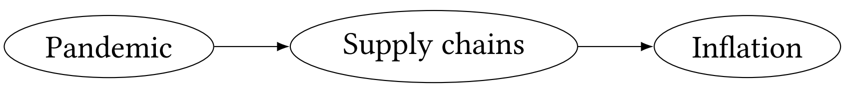
3.2 Coding of Narratives

For the purpose of comparability, the narratives are converted into a simple and quantifiable structure and, according to Andre et al. (2022a, p. 1), presented in the form of "directed acyclic graph[s] (DAG)". DAGs graphically represent causal relationships and consist of vertices or nodes, which represent variables, and links, which establish a relationship between these nodes. Links are called "directed" (Pearl, 2009, p. 13) if they are represented by an arrow. The direction of the arrow indicates the direction of the causal link. The variable from which the arrow originates is therefore the cause of the variable to which the arrowhead is directed. A sequence of several links or arrows between variables is called a path (Pearl, 2009, p .12f.).

In the context of the research project, the nodes or variables of the DAGs describe the factors that are proposed to be the cause of the rise in inflation. These are determined by evaluating the open-ended text answers of the respondents within the framework of a largely quantitatively oriented, category-guided text analysis. Relevant text passages are assigned to appropriate categories.

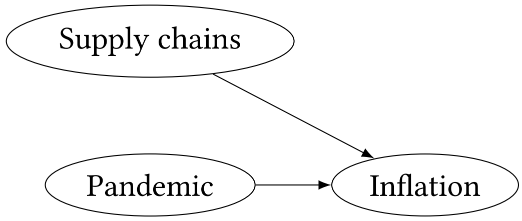
The following examples in figures 2 and 3 show two different narratives in the form of the DAG representation. These are fictional examples, consisting of factors that appear frequently in the dataset of this survey. In both cases the same factors 'pandemic', 'supply chains' and 'inflation' are present, but they have a different relationship to each other. Figure 2 shows all 3 factors of a path. It shows that the consequences of the pandemic lead to supply chain problems, which in turn are seen as a trigger for inflation. In figure 3, supply chain problems and the pandemic are seen as independent causes, each having an impact on the development of inflation.

Figure 2: Example narrative 1, represented by DAG



[4] At the end of the questionnaire, data are also collected on the consequences for savings and consumption behaviour, but these are not discussed in detail in this paper as they are not the subject of this study.

Figure 3: Example narrative 2, represented by DAG



In addition to the quantitative recording of the factors, qualitative approaches must also be pursued in order to maintain openness and flexibility with regard to the data material. Within a category system the factors are arranged thematically. According to Andre et al. (2022a, p. 10), the factors are grouped into three main categories. These include supply and demand related factors. Factors that are neither supply nor demand related are assigned to a third, upper category. Based on the arguments in Andre et al. (2022a), this system of categories claims to represent key factors that have been identified in the academic theoretical literature as the cause of rising inflation, as well as factors that have been identified in the media and equivalent household surveys. It is therefore a structured content analysis in which the category system is deductively given and theory-guided (Mayring and Fenzl, 2019, p. 638). This makes it possible to compare the different samples.

Furthermore, the analysis process is characterised by inductive category formation, in which subcategories are formed from the data material. As this study deals with specific data material, in which the sample differs both geographically and temporally, it is important to maintain openness and flexibility, as central principles of qualitative research (Lamnek and Krell, 2016, p. 33 f., p. 37 f.), towards the data material. Compared to the category system in Andre et al. (2022a), new categories are added, existing ones are modified or combined or removed. Section A provides an overview of categories and anchor examples, a more detailed analysis will be made available in the repository of the project.

Coding describes a circular process in which the category system has been continuously modified. Already coded data are re-examined, interpreted and adapted in the context of the transformed coding system. Finally, the data material was worked through again independently of the coding system to check whether the results are consistent when carried out repeatedly in order to ensure intra-coding agreement (Mayring and Fenzl, 2019, p. 637) and reliability (Krebs and Menold, 2019, p. 490 f.).

The factors identified in the narratives are then transferred into a DAG representation. It should be noted that individual factors occur only once within a DAG. Multiple mentions within a narrative are therefore not coded twice. An exception to this is the categories "demand", "supply" and "other" (section A), as these categories are used to combine different factors. For example, if globalisation and public debt are mentioned together in a narrative and each is grouped under the category "other", there are two nodes in the DAG.

The problem with extracting causal structures from the narratives is that many respondents answered the open-ended question with only a few key words or were imprecise. The identification of causal relationships is therefore open to interpretation. In the context of cluster analysis, the DAGs take on a linear form in which the order of the mentions plays a central role. According to the arguments in Gennaioli and Shleifer (2010, p. 1400), the order of the DAG connection is chosen according to the order in which the factors are mentioned by the respondents, reflecting their importance or weighting. Occasionally, analysis practice shows that it is not always clear in which order the DAG links can be cited, as they are sometimes implicit and not given in the textual responses. In this case it is up to the researcher to make an interpretation and choose a logical order. All answers and their codings are therefore transparently documented in a repository at https://www.openicpsr.org/openicpsr/search/studies.

A first descriptive analysis of the resulting aggregated DAG structures across the entire sample provides the network representation based on Andre et al. (2022a) in figure 4. It represents an "average narrative" across all responses. All resulting DAGs are shown here, with the strength of the arrow connections being directly proportional to the number of mentions. Several aspects stand out: First, there are clear differences in the naming of narratives. "War", "resources", "pandemic" are mentioned much more often than other narratives. On the other hand, certain narratives are "exogenous" in this network in the sense that there are no causal factors pointing to these edges. This is (understandably) true for "war", "climate crisis" and "pandemic". But it is also true for "government mismanagement". Other narratives are not entirely exogenous if the average across all responses is considered.

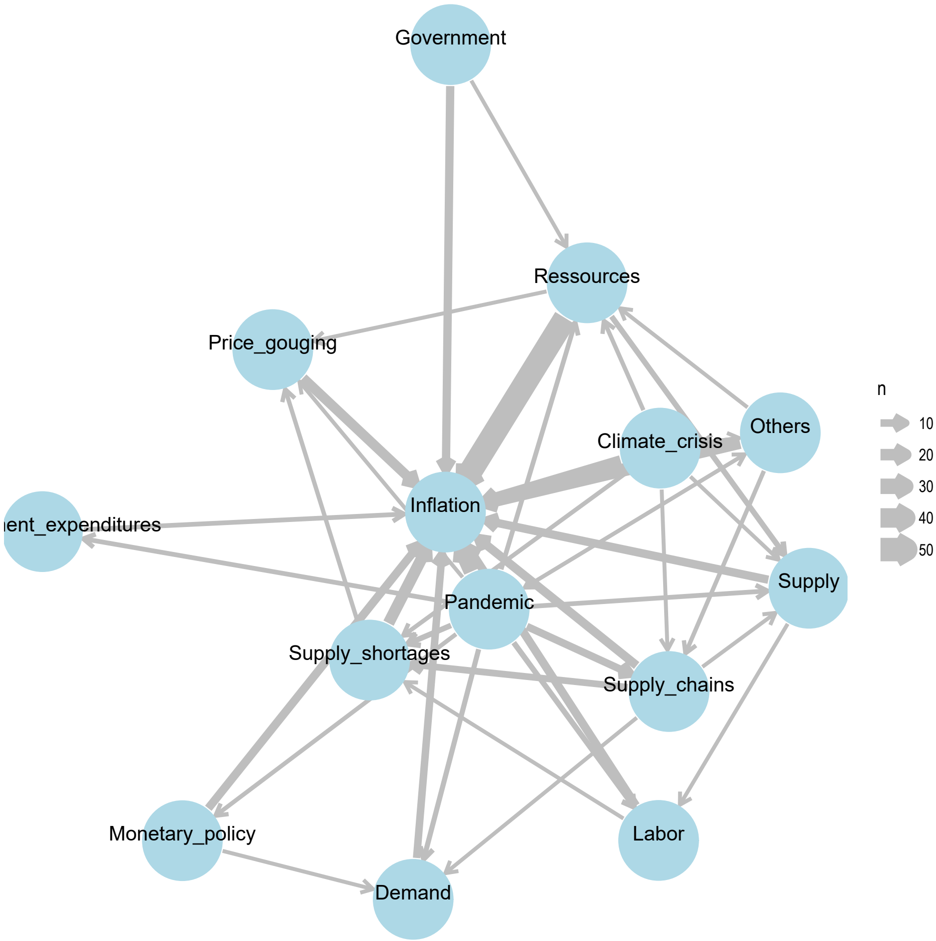
3.3 Clustering

In calculating the distances between the narratives, we closely follow Andre et al. (2022a, Appendix D). Each narrative is entirely represented by the edge list of its DAG. The edge list E is the set of causal connections of a narrative, e.g. $E_i = \{A \rightarrow B, B \rightarrow C\}$. Andre et al. (2022a) suggest to use the *Jaccard distance* between two edge lists E_i, E_j to measure the distance $D_{i,j}$ as:

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

$D_{i,j}$ is an appropriate measure for clustering categorical data. Based on the pairwise distances, a standard agglomerative hierarchical clustering procedure is applied using the pairwise mean distance method. The number of clusters was set to $k = 10$ by checking the corresponding silhouette plots (Rousseeuw, 1987). Dendrogram and silhouette plots for the selected number of clusters are shown in figures A.F.1 and A.F.2. Results with slightly more

Figure 4: Average DAG Representation of Narratives: Full Sample



Note: The network plot shows the results of the qualitative coding over the whole sample as a summary of all directed acyclic graphs (DAGs). The nodes are labelled with the narrative terms of the codebook. The direction of the arrows indicates the direction of the DAG. The strength of the arrows is proportional to the occurrence of the narrative in the sample.

or less clusters resulted in only small changes in the average silhouette width.[5]

For the regression analysis, only clusters with $n > 5$ were considered to avoid spurious results. Clusters 6, 7 and 9 were therefore excluded from further analysis. Figures A.F.3a to A.F.3g show the visualisation for the respective "average" cluster narratives of the clusters examined.

[5]We used the function `hclust` from the `R` native package `stats` and the function `silhouette` from the `cluster` package. See R Core Team (2022) and Maechler et al. (2022) for more details.

4 Regression Analysis

To conduct a more rigorous quantitative analysis, we recoded several items of our survey as well as qualitative coding and cluster procedure results into binary variables. A full description of the coding rules can be found in table A.T.2 in section A. Due to the elimination of observations with *NA*s in individual variables we ended up with exactly 100 observations.[6]

4.1 Selected variables

We use the following groups of variables in the regression analysis:

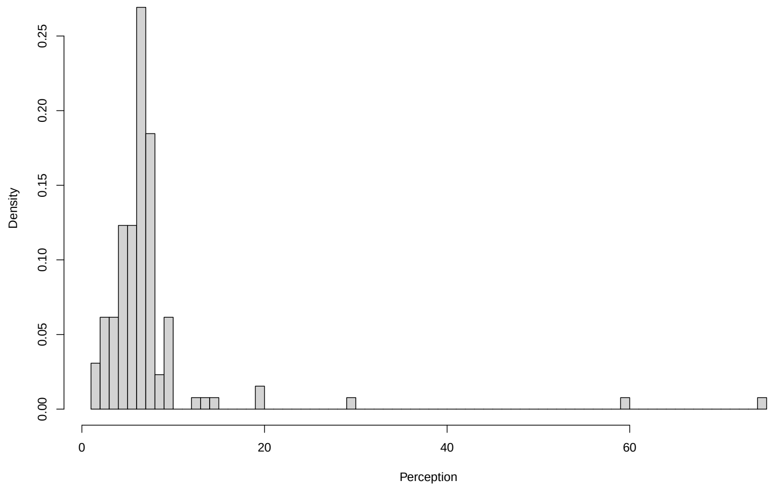
Socio-demographic variables (incl. financial literacy levels) and political attitudes Here we recoded information on gender (*male*), age (*old*), education (*school* and *high_edu*), employment status (*employment* and *fulltime*) and income (*high_income*). Furthermore, we follow Lusardi and Mitchell (2011) and use their well-established instrument to construct a variable *fin_literacy* which indicates a high level of financial literacy. Last but not least, the variables *left* and *right* indicate self-reported political attitudes at the tails of the political spectrum.

Inflation perception and anchoring of inflation expectations The variables *perception_quant* and *perception_quali* contain recoded information from the questions on past inflation rates – in quantitative and qualitative form (see section 3.1). It could be argued that the current inflation rate is not known to many respondents and therefore the data could be very "noisy". Figure 5 shows a histogram of reported quantitative inflation perceptions. The bulk of answers is in a range close to actual inflation. For the analysis, an answer is classified as a "correct" perception if the reported number falls in a range from 6 to 10 % for the quantitative question or if the correct sign of the change in inflation is implicitly reported in the qualitative question. The variable *anchor* as a proxy for "anchored" inflation expectations is classified as 1 if the rise in inflation over 3-5 years is considered to be temporary in nature.

Reported narratives, narrative complexity and assignment to narrative clusters The variables ranging from *fin_literacy* to *others* in table A.T.2 indicate the occurrence of respective narratives (see section 3.2 and table A.T.1) in the open-ended question. Furthermore, we added three complexity variables for the reported narratives as in Andre et al. (2022a): *complex* indicates at least 4 connections within the DAG structure, *supply_demand* indicates the simultaneous mentioning of supply and demand factors in a DAG and *longest_path* is set to 1 if the longest path in the DAG has at least 2 connections. The

[6] The balanced sample was necessary for the applied stepwise procedure of the predictive modelling approach to work.

Figure 5: Histogram of quantitative inflation perceptions



variable *cluster_i* contains the cluster membership information. We only considered the clusters with more than 5 units (see figure A.F.1 for dendrogram and A.F.2 for cluster membership information) for the regression.

4.2 Modelling approach

As the dependent variable is binary, binomial class models (e.g. logit) are well suited, but interpreting the coefficients is not straightforward, so odds ratios or (average) marginal effects are usually used. Linear probability models (LPM) are a useful alternative. Greene (2019, p. 780 ff.) argue that results from LPM provide approximate results for the average marginal effects of the corresponding logit models. This argument is supported, for example, by the results in Jacob and Levitt (2003). The major advantages of LPM are robustness and simplicity (Greene, 2019, p. 781). We follow Andre et al. (2022a) and use LPM with heteroscedasticity robust standard errors as the main tool of analysis. Following the suggestions in Long and Ervin (2000), we chose "HC3" as a modified version of the original White estimator (White, 1980).

Given the small number of observations, we are faced with a relatively large number of predictors and possible multicollinearity problems. We opted for a stepwise approach to select a smaller set of predictors to consider. For the selection of variables, we relied on a *predictive modelling approach* as described in James et al. (2013, p. 79) and used a combination of forward and backward selection. We used the AIC criterion to assess the quality of our selection. For all regressions, we report both results - for the full set of variables and for the reduced set of variables after the predictive modelling selection procedure. In the section below, we focus on the results from the predictive modelling approach and report further results for the full set of variables in section A.

As a robustness check, logit models were fitted instead of the linear probability model and predictive modelling was carried out. The results are available in a separate appendix in the repository at `https://www.openicpsr.org/openicpsr/search/studies` and are qualitatively to a large extent identical to the results presented here.

4.3 Results

Inflation narratives First, we analyse the correlation between narratives (dependent) and demographic, socio-economic and literacy background variables. The results are presented in tables 1 and A.T.3. In a nutshell: For the monetary policy narrative, being male or older is associated with a higher likelihood of reporting the monetary policy narrative. The demand narrative is more likely to be reported by those with high financial literacy and higher incomes, while the supply chain narrative is less likely to be reported at both ends of the policy spectrum. Supply shortages as an explanatory narrative are reported by those with high incomes, high financial literacy and those whose perceptions are in line with official statistics. The same is true of the resource narrative. The narratives relating to labour and supply issues in general are less likely to be held by people whose perceptions of inflation are correct. The pandemic narrative appears to be less popular with people who are politically right of centre (although this result does not hold at the usual levels of significance). The same is true of the Russian war on Ukraine narrative. In the latter case, highly educated people and people with right-wing perceptions are less likely to report this narrative. Men are less likely to refer to the climate crisis narrative, while people with more years of schooling are more likely to refer to the climate crisis as an explanatory narrative. People over the age of 45 and those with left-leaning political attitudes are slightly more likely to refer to price gouging as an explanatory factor (although this result does not hold at the usual levels of significance). Finally, there is a high probability for people holding positions at the extreme right of the political spectrum to mention the government narrative as an explanatory factor for the recent rise in inflation. There seems to be a slight tendency for people holding left-wing positions to refer to the narrative of other sources beyond the scope of the narratives previously analysed (though again, this is not found to be a significant effect at usual levels).

Narrative complexity Second, using the complexity measures as dependent variables and the same set of explanatory variables as in the first set of regressions, we tested whether socio-demographic variables and literacy were systematically related to the complexity of reported narratives. The results are shown in tables 2 and A.T.4. We found significant effects for the complexity proxies *complex* and *longest_path*. For the first proxy *complex*, the regressors age, employment, high income and (at low levels of significance) correct inflation perceptions show a positive effect on the probability of high complexity. In the case

Table 1: Correlation between narratives and demographic, socioeconomic and literacy background variables (predictive modelling)

	Dependent variable:												
	mon_policy	demand	supply_chain	supply_short	ressources	labor	supply	pandemic	war	climate_crisis	price_gouging	govt	others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
male	0.145*	−0.099		−0.114			0.127*			−0.142**			
	(0.078)	(0.062)		(0.082)			(0.073)			(0.064)			
old	0.148		0.166								0.147	0.092	
	(0.105)		(0.111)								(0.102)	(0.074)	
high_edu			−0.146*		0.220**				0.182*				
			(0.088)		(0.100)				(0.103)				
fulltime	−0.091		0.124*									0.109**	
	(0.073)		(0.075)									(0.052)	
high_income		0.106*		0.125*									
		(0.058)		(0.074)									
fin_literacy		0.141***		0.186*									
		(0.048)		(0.112)									
left			−0.171**								0.149		0.170
			(0.071)								(0.119)		(0.126)
right			−0.271***					−0.301	−0.308			0.609***	
			(0.077)					(0.190)	(0.249)			(0.208)	
perception_quali				0.434*	0.304*								
				(0.248)	(0.177)								
perception_quant						−0.107	−0.191**		−0.147*				
						(0.081)	(0.083)		(0.088)				
school										0.166***			−0.220
										(0.045)			(0.160)
Constant	0.092	−0.054	0.184**	−0.050	0.284***	0.194***	0.197***	0.468***	0.709***	0.052	0.055*	−0.030	0.348**
	(0.066)	(0.039)	(0.077)	(0.094)	(0.077)	(0.073)	(0.075)	(0.052)	(0.107)	(0.032)	(0.030)	(0.029)	(0.155)
Observations	100	100	100	100	100	100	100	100	100	100	100	100	100
R^2	0.091	0.058	0.102	0.130	0.070	0.023	0.098	0.021	0.101	0.058	0.075	0.305	0.054
Adjusted R^2	0.063	0.029	0.055	0.093	0.051	0.013	0.079	0.011	0.073	0.038	0.055	0.284	0.035
Note:													*p<0.1; **p<0.05; ***p<0.01

of the proxy *longest_path* correct perceptions, higher income and (at low levels of significance) higher education are positively correlated with the probability of higher complexity. The results are consistent with the hypothesis of a positive relationship between levels of education (including economic and financial literacy) and higher complexity of reported narratives. This is also consistent with the findings of Andre et al. (2022a). No significant results can be reported for the third proxy variable *supply_demand*.

Table 2: Correlation between narrative complexity and demographic, socioeconomic and literacy background variables (predictive modelling)

	Dependent variable:		
	complex	supply_demand	longest_path
	(1)	(2)	(3)
old	0.380***		
	(0.130)		
employment	0.189*		
	(0.114)		
fulltime	−0.154		
	(0.110)		
high_edu			0.166
			(0.104)
high_income	0.323***		0.170*
	(0.106)		(0.102)
perception_quali	0.299		0.336*
	(0.230)		(0.189)
Constant	−0.038	0.130***	0.187**
	(0.080)	(0.034)	(0.084)
Observations	100	100	100
R^2	0.274	0.000	0.101
Adjusted R^2	0.236	0.000	0.072
Note:			*p<0.1; **p<0.05; ***p<0.01

Narrative clusters Third, rather than focusing on individual narratives, we analyse the correlation between narratives (dependent) and demographic, socio-economic and literacy background variables. The results are presented in tables 3 and A.T.5. In brief: For clusters 2 and 3 we cannot find plausible results and we also report very low R^2 values. For cluster 1, being male reduces the probability of belonging to the cluster and being in full-time employment increases the probability (it is basically related to the female full-time employees in the survey). Cluster 4 is associated with being male, better educated, left-leaning and younger. Being in cluster 5 is less likely for people who report political attitudes at both ends of the spectrum and more likely for people with higher financial literacy and correct inflation perceptions (it could be described as a “middle class” cluster). Cluster 8 is negatively related to higher education and high income (so it is again more likely for people with lower education and income to be in this cluster). Cluster 9 is strongly positively related to holding right-wing political positions and at the same time negatively related to correct inflation perceptions (the latter results are again not significant at the usual levels).

Anchoring expectations Finally, we are interested in analysing the factors that are systematically associated with the anchoring of inflation expectations. We run three regressions with the variable *anchor* as the dependent variable. First, we run a regression on socio-demographic and literacy variables. Second, we use the reported narratives as explanatory variables and third, we do the same with measures of complexity. The results are presented in tables 4 and A.T.6. Regarding the first set of regressor variables, being male, younger, more educated and holding correct perceptions, as well as not being in full-time employment (due to the nature of the pilot study at the University of Hamburg, we suspect a high number of students among the participants), increase the likelihood of having anchored expectations. Using the reported narratives as explanatory variables, we see a positive relationship between the narratives of supply shortages, labour (market) problems and price gouging with anchoring, and a negative relationship between demand factors, the mention of government problems as an inflation narrative and the reporting of other problems as inflation cause with anchoring. It is noteworthy that the strongest effect on the probability of "de-anchoring" is observed for people who hold the government narrative. Finally, we do not find any effects of the complexity measures.

5 Conclusion

The pilot study focused on the following questions: What narratives are reported in relation to the current inflationary episode? What is the relationship between narratives (including narrative clusters) and socio-economic variables? Is there a relationship between the narratives people report to make sense of the recent inflation episode and the "de-anchoring" of inflation expectations?

In summary, we can report the following findings: First, we can associate certain narratives with socio-economic characteristics and political partisanship. The effects are pronounced at the tails of the political spectrum which is in line with Eliaz and Spiegler (2020)'s idea of "competing narratives". Second, in line with Andre et al. (2022a) we find that narrative complexity is associated with educational attainment and (financial) literacy. This is consistent with the literature on the role of "financial literacy" for expectation formation Burke and Manz (2014). Third, narrative clusters correspond to certain milieus and dimensions of socio-economic stratification. Fourth, we found that certain narratives are predictive of anchored/unanchored inflation expectations. On the one hand, supply shortages and price gouging as reported narratives seem to be correlated with anchored inflation expectations. Demand narratives other than government demand and narratives of government mismanagement are correlated with de-anchored inflation expectations.

Table 3: Demographic, socioeconomic and literacy variables on DAG cluster (predictive modelling)

	Dependent variable:						
	cluster_1	cluster_2	cluster_3	cluster_4	cluster_5	cluster_8	cluster_9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
male	-0.105^{*}			0.188^{**}			
	(0.061)			(0.089)			
fulltime	0.160^{***}	-0.151			0.088^{*}		0.051
	(0.058)	(0.100)			(0.050)		(0.032)
old			0.083	-0.166			
			(0.068)	(0.106)			
high_edu				0.332^{***}			
				(0.076)			
left				0.221^{*}	-0.110^{***}		
				(0.118)	(0.041)		
right					-0.161^{**}		0.462^{**}
					(0.079)		(0.233)
fin_literacy					-0.153		-0.094
					(0.143)		(0.082)
perception_quali					-0.158^{**}		
					(0.071)		
school						-0.265^{*}	
						(0.147)	
high_income						-0.061	
						(0.043)	
Constant	0.053	0.439^{***}	0.013	-0.019	0.205	0.312^{**}	0.067
	(0.032)	(0.079)	(0.013)	(0.054)	(0.146)	(0.156)	(0.076)
Observations	100	100	100	100	100	100	100
R^2	0.077	0.024	0.039	0.197	0.094	0.198	0.393
Adjusted R^2	0.058	0.014	0.029	0.163	0.046	0.181	0.374
Note:					*p<0.1; **p<0.05; ***p<0.01		

Table 4: Anchoring regressions (predictive modelling)

	Dependent variable:		
	anchor		
	(1)	(2)	(3)
male	0.192*		
	(0.102)		
old	−0.321**		
	(0.126)		
school	0.343***		
	(0.118)		
fulltime	−0.211**		
	(0.101)		
perception_quali	0.301		
	(0.231)		
demand		−0.296**	
		(0.141)	
supply_short		0.228*	
		(0.127)	
labor		0.286**	
		(0.136)	
price_gouging		0.278*	
		(0.155)	
govt		−0.507***	
		(0.086)	
others		−0.261**	
		(0.107)	
Constant	0.239*	0.456***	0.440***
	(0.140)	(0.068)	(0.050)
Observations	100	100	100
R^2	0.183	0.248	0.000
Adjusted R^2	0.139	0.199	0.000
Note:	*p<0.1; **p<0.05; ***p<0.01		

In general, the study confirms that a mixed-methods approach provides interesting insights into the underlying heuristics in interpreting the world and forming expectations (e.g. when it comes to the prevalence of high inflation). As recently argued by Ferrario and Stantcheva (2022), the study of narratives using open-ended questions could be a promising approach for several issues: fiscal policy, redistribution, and many more. It could also be a promising area for central bank communication research.

Further research should address the representativeness of the survey to further validate the results statistically. Second, methods of computer-assisted text analysis and supervised learning should be tested to facilitate the identification and classification of narratives and to be able to evaluate larger text corpora. Thirdly, the surveys should be repeated over time to track changes in the narratives.

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A Appendix

Figure A.F.1: Cluster dendrogram

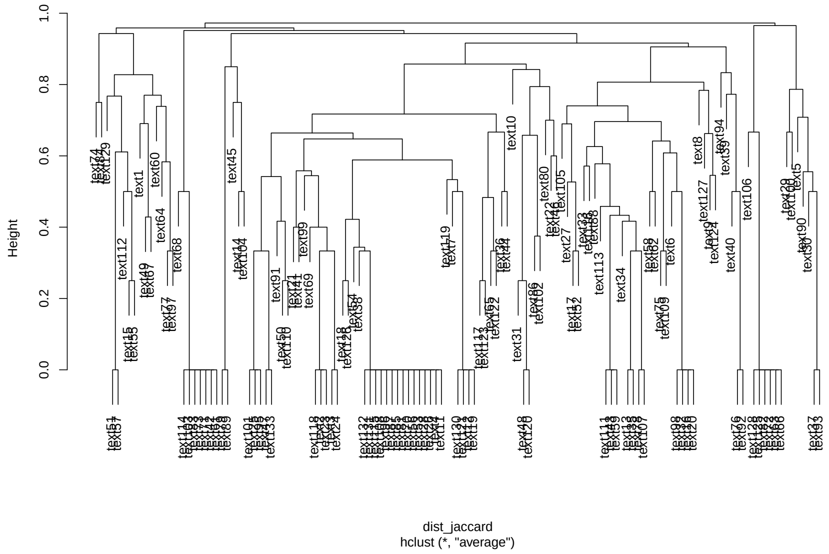


Figure A.F.2: Silhouette plot with $k = 10$

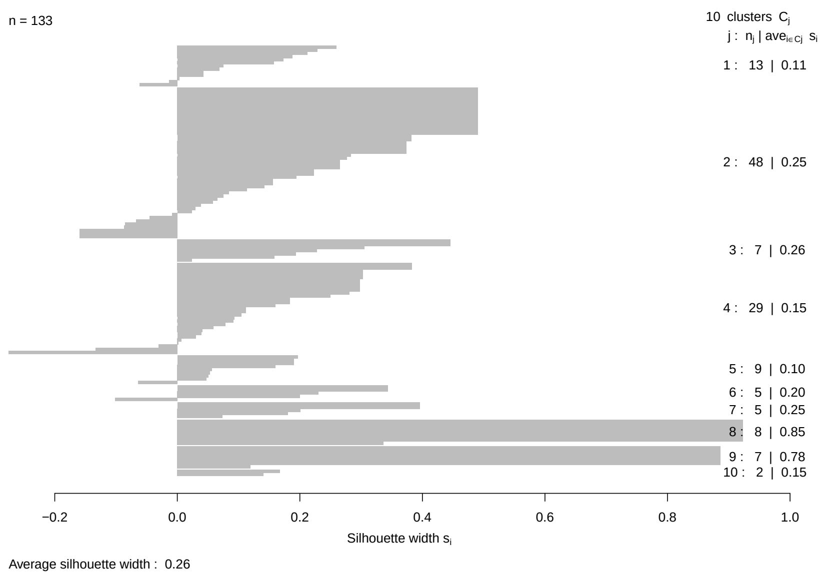
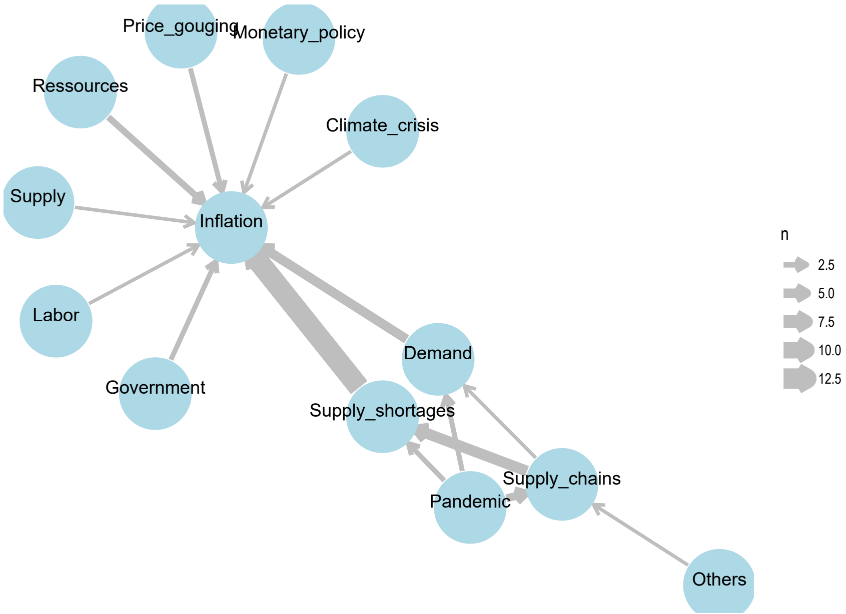
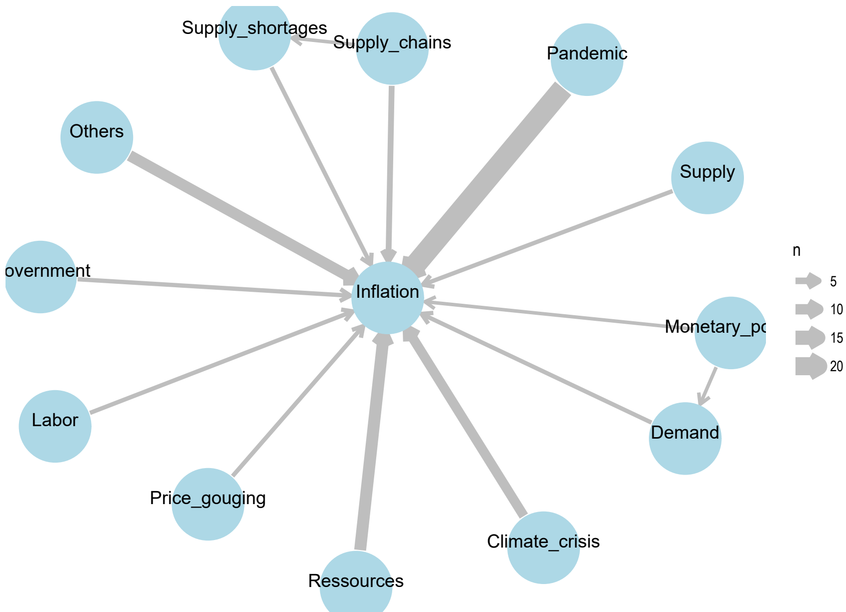


Figure A.F.3: Average DAG Representation of Narratives



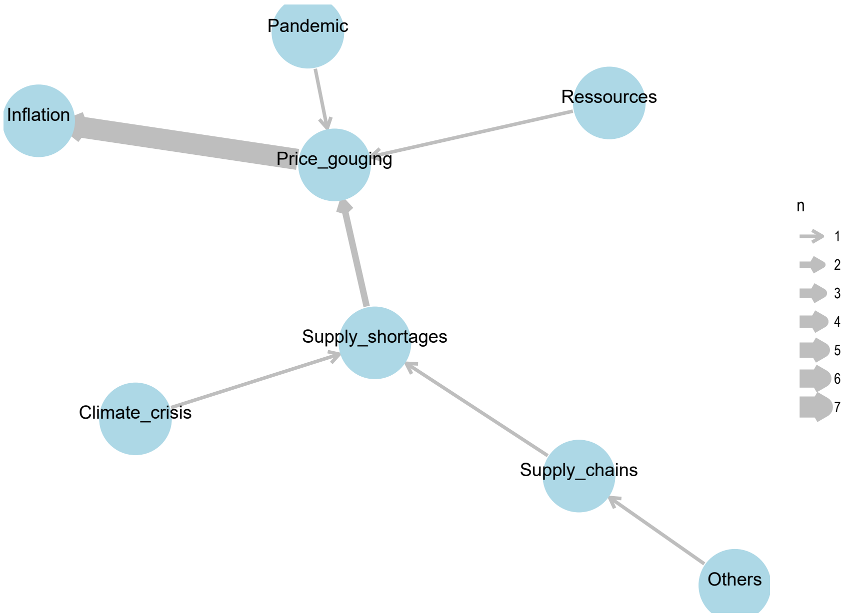
(a) Cluster 1



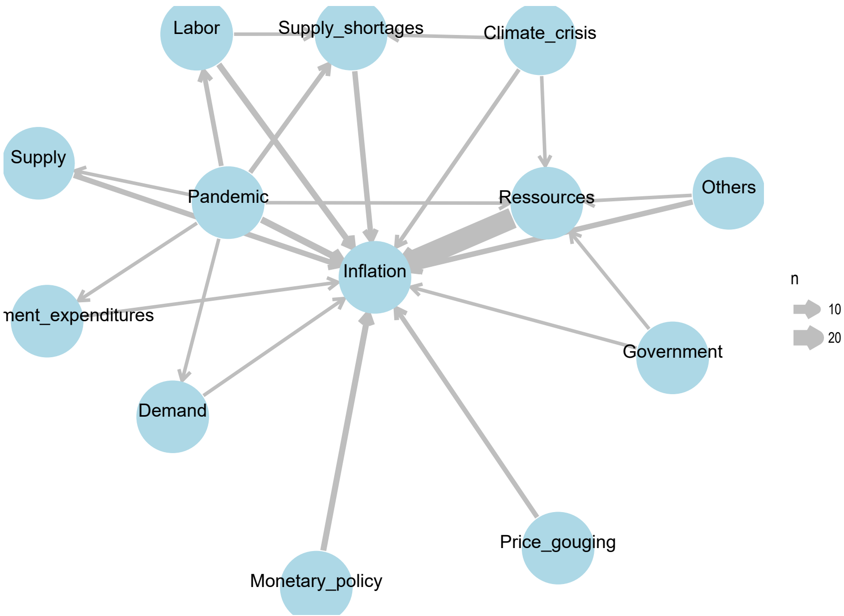
(b) Cluster 2

Note: The network plot shows the results of the qualitative coding over the respective cluster as a summary of all directed acyclic graphs (DAGs). The nodes are labelled with the narrative terms of the codebook. The direction of the arrows indicates the direction of the DAG. The strength of the arrows is proportional to the occurrence of the narrative in the cluster.

Figure A.F.3: Average DAG Representation of Narratives



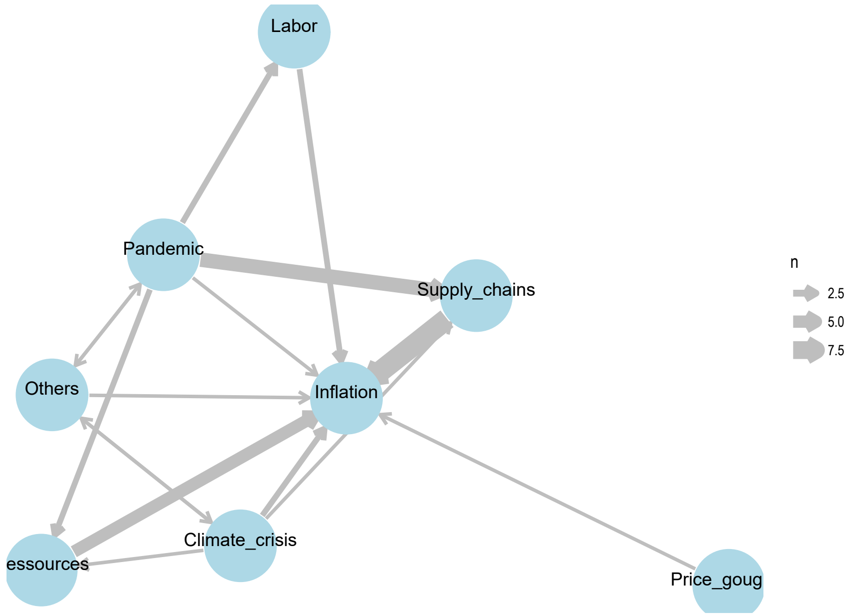
(c) Cluster 3



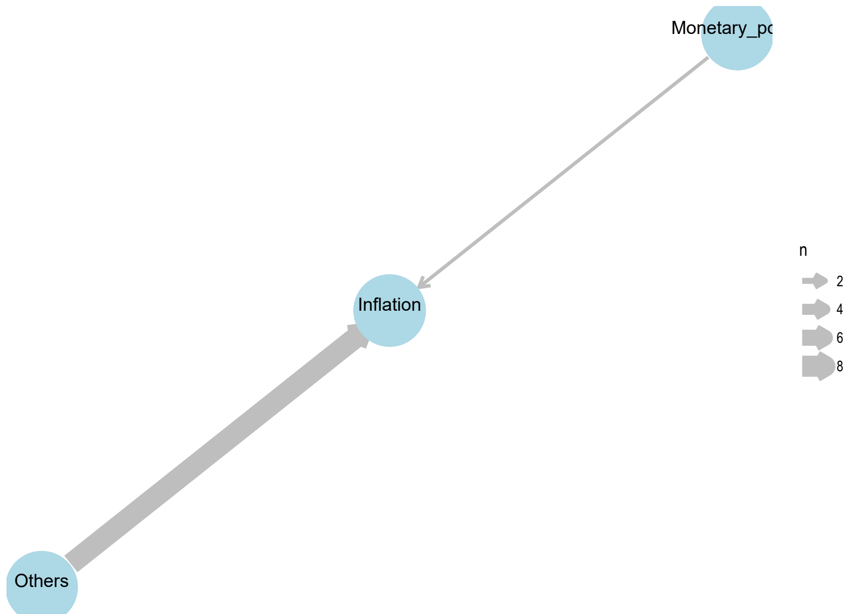
(d) Cluster 4

Note: The network plot shows the results of the qualitative coding over the respective cluster as a summary of all directed acyclic graphs (DAGs). The nodes are labelled with the narrative terms of the codebook. The direction of the arrows indicates the direction of the DAG. The strength of the arrows is proportional to the occurrence of the narrative in the cluster.

Figure A.F.3: Average DAG Representation of Narratives



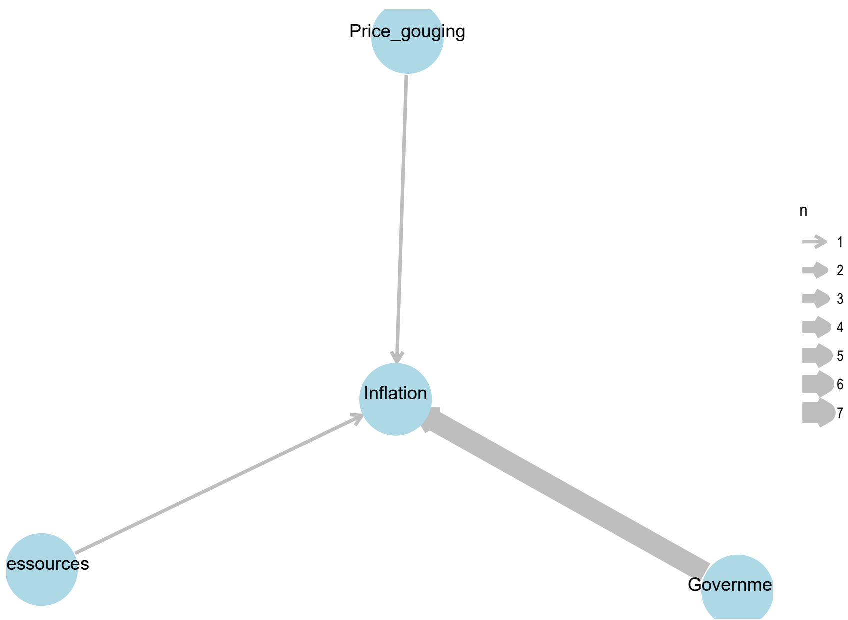
(e) Cluster 5



(f) Cluster 8

Note: The network plot shows the results of the qualitative coding over the respective cluster as a summary of all directed acyclic graphs (DAGs). The nodes are labelled with the narrative terms of the codebook. The direction of the arrows indicates the direction of the DAG. The strength of the arrows is proportional to the occurrence of the narrative in the cluster.

Figure A.F.3: Average DAG Representation of Narratives



(g) Cluster 9

Note: The network plot shows the results of the qualitative coding over the respective cluster as a summary of all directed acyclic graphs (DAGs). The nodes are labelled with the narrative terms of the codebook. The direction of the arrows indicates the direction of the DAG. The strength of the arrows is proportional to the occurrence of the narrative in the cluster.

Table A.T.1: Categories and examples

Categories	Explanation	Label of respective narrative	Representative example	Translation (DeepL)
Demand	monetary policy	Comprises all monetary policy measures, such as an adjustment of the key interest rate or an increase in the money supply.	"Die (e)xpansive Geldpol[i]tik hat über mehrere Jahre in der EU dazu geführt, dass die Inflationsrate immer stetig angestiegen ist. […]" (ID: 34)	The (e)xpansionary monetary policy has led to a steady increase in the inflation rate in the EU over several years. […]" (ID: 34)
	demand	This category includes further demand-related factors.	"[…] Angepasste Nachfrage nach bestimmten Gütern, die vorher weniger stark nachgefragt waren, während der Lockdowns, die bis jetzt anhält." (ID: 70)	"[…] Adjusted demand for certain goods that were previously in less demand during the lockdowns, which continues until now." (ID: 70)
Supply	supply chain issues	Disruptions, delays or interruptions in supply chains.	"[…] Viele Produktionsstätten werden daher ins Ausland verlegt. Wenn dann Kriege und Pandemien ganze Lieferketten unterbrechen oder ganz verhindern kommt es zu einem Mangel an Produkten und eine erhöhte Nachfrage dieser, lässt die Preise rasant nach oben steigen." (ID: 160)	"[…] Many production facilities are therefore relocated abroad. When wars and pandemics interrupt or prevent entire supply chains, there is a shortage of products and an increased demand for them causes prices to rise rapidly." (ID: 160)
	supply shortages	Shortages, bottlenecks or declines in production of goods and services. This category is distinct from the category "resources", which includes supply shortages in the context of resources such as energy sources.	"[…] auch große Gesellschaften […] kamen mit ihrer Produktion nicht hinterher. Wenn die Anfrage an Produkten aber dieselbe bleibt, dann muss im gewissem Maße auch der [P]reis für diese Produkte erhöht werden. […]" (ID: 176)	"[…] even large companies […] could not keep up with their production. But if the demand for products remains the same, then to a certain extent the [price] for these products must also be increased. […]" (ID: 176
	ressources	Summary category for mentioning shortages, scarcities, supply bottlenecks and rising prices of resources (e.g. energy resources such as oil and gas, other raw materials, building materials, etc.) and the energy crisis in general.	"[…] Verknappung von Rohstoffen auf dem Weltmarkt da die Nachfrage stark gestiegen ist […]" (ID: 122)	"[…] shortage of raw materials on the world market as demand has risen sharply […]" (ID: 122)
	labor-related issues	The category summarises labour-related issues, including labour or skills shortages, wage increases, rising wage costs, the wage-price spiral, and unemployment or job losses.	"[…] Arbeitskräfte fielen für längere (Z)eiten aus oder waren nicht mehr flexibel abrufbar, Unternehmen mussten mit den Mitarbeitern haushalten, die sie hatten und nicht nur kleine Unternehmen gingen zu Grunde, auch große Gesellschaften mussten Menschen entlassen oder kamen mit ihrer Produktion nicht hinterher. […]" (ID: 176)	"[…] workers were absent for longer periods of time or could no longer be called up flexibly, companies had to manage with the employees they had and not only small companies went under, but also large companies had to lay off people or could not keep up with their production. […]" (ID: 176)
	further supply-related factors	This category includes further supply-related factors, which are summarised due to the low number of mentions	"[…] höhere (B)eschaffungskosten" (ID: 169)	"[…] higher acquisition costs" (ID: 169)
Other factors	pandemic	Price increases as a result of the Covid-19-pandemic and related policies.	"Ich denke durch die Pandemie sind viele Sachen teurer geworden. […]" (ID: 132)	"I think the pandemic has made many things more expensive. […]" (ID: 132)
	war	Both wars and global political crises in general as well as the explicit mentioning of the Russian war against Ukraine and associated political measures, e.g. sanctions. If the latter are also negatively evaluated or criticised, the additional code "government" is used.	"Ich denke, dass unter anderem die Kriege und Konflikte auf der Welt Schuld an der Inflation sind. […]" (ID: 88)	"I think that, among other things, the wars and conflicts in the world are to blame for inflation. […]" (ID: 88)
	climate crisis	All aspects related to the climate crisis and natural disasters, as well as related environmental and economic consequences.	"[…] Klimakrise und einhergehende Dürren und klimatischen Veränderungen" (ID: 158)	"[…] climate crisis and accompanying droughts and climatic changes" (ID: 158)
	price gouging	Artificial price increases by political actors or companies for the purpose of profit maximisation. At this point, the existing economic system is not questioned, but a market failure is assumed. This category is therefore distinct from "capitalism".	"Geldgier der Unternehmen. Durch Krisen (Corona) und Kriege haben die Milliardenunternehmen (Amazon, Ölkonzerne,...) wahnsinnigen Gewinn gemacht und dann die Preise angehoben. Es gibt eigentlich keinen Grund für die Inflationsrate." (ID: 11)	"Corporate greed. Due to crises (Covid) and wars, the billionaire companies (Amazon, oil companies,...) have made insane profits and then raised prices. There is actually no reason for the inflation rate." (ID: 11)
	government (mismanagement)	Mismanagement of the government and criticism of political decisions and decision-makers.	"Die Politiker und der Staat sind daran schuld" (ID: 111)	"The politicians and the state are to blame" (ID: 111)
	other	This category includes "other" factors that are summarised due to the low number of mentions, like globalisation, capitalism as economic system, economic crises and upheavals, price increases as a result of speculation and fluctuations in the stock market, ...	"[…] Der Mensch, besonders der wohlhabende Teil der Welt lebt über seine Verhältnisse, Wohlstand wird für immer weniger Menschen erreichbar sein..." (ID: 19)	"[…] Man(kind), especially the wealthy part of the world, lives beyond his means, prosperity will be attainable for fewer and fewer people..." (ID: 19)

Table A.T.2: Variable labels used in the regression outputs

Variable label	**Definition**
male	Variable = 1 if male, = 0 if female, = NA else
old	Variable = 1 if age > 45 years, = 0 if age < 45, NA else
school	Variable = 1 if schooling is college or higher
high_edu	Variable = 1 if professional education is study graduation or higher
employment	Variable = 1 if actually employed (not further defined)
fulltime	Variable = 1 if employed full-time
high_income	Variable = 1 if net income >= 2.000 € (median income in Germany; status: 2019), =0 if < 2.000 €
left	Variable =1 if preferred party is "Die Linke" (The Left)
right	Variable = 1 if preferred party is "AfD" (Alternative for Germany)
perception_quant	Variable = 1 if estimated inflation rate of last 12 months is between 6-10%, = 0 if < 6% or > 10%
perception_quali	Variable = 1 if inflation rate of last 12 months is assumed lower than today, = 0 if assumed higher than today or equal
anchor	Variable = 1 if rise in inflation rate over 3-5 years is considered to be temporary, = 0 if inflation is expected to remain high
cluster_*i*	Variable = 1 if DAG is part of cluster *i*
fin_literacy	Variable = 1 if financial literacy is high - answered at least 2/3 questions correctly, = 0 if 1 question correctly or none
mon_policy	Variable = 1 if narrative adresses monetary policy
demand	Variable = 1 if narrative adresses demand
supply_chain	Variable = 1 if narrative adresses supply chain
supply_short	Variable = 1 if narrative adresses supply shortages
ressources	Variable = 1 if narrative adresses ressources
labor	Variable = 1 if narrative adresses labor
supply	Variable = 1 if narrative adresses supply
pandemic	Variable = 1 if narrative adresses pandemic
war	Variable = 1 if narrative adresses war
climate_crisis	Variable = 1 if narrative adresses climate change or climate crisis
price_gouging	Variable = 1 if narrative adresses price gouging
govt	Variable = 1 if narrative adresses government
others	Variable = 1 if narrative adresses other issues
complex	Variable = 1 if >=4 connections within DAG, =0 if <4 connections
supply_demand	Variable = 1 if supply and demand factors are mentioned together in DAG, = 0 if not
longest_path	Variable = 1 if the longest path within the DAG has >=2 connections

Table A.T.3: Correlation between narratives and demographic, socioeconomic and literacy background variables

	Dependent variable:												
	mon_policy	demand	supply_chain	supply_short	ressources	labor	supply	pandemic	war	climate_crisis	price_gouging	govt	others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
male	0.128	−0.122*	−0.041	−0.119	0.149	0.030	0.136*	0.009	−0.046	−0.132*	0.047	−0.025	0.002
	(0.083)	(0.071)	(0.090)	(0.102)	(0.122)	(0.076)	(0.079)	(0.122)	(0.113)	(0.077)	(0.079)	(0.077)	(0.090)
old	0.162	0.054	0.117	0.038	0.087	−0.001	−0.013	0.102	0.008	0.064	0.128	0.094	0.100
	(0.130)	(0.102)	(0.135)	(0.147)	(0.167)	(0.096)	(0.073)	(0.177)	(0.151)	(0.114)	(0.131)	(0.096)	(0.138)
school	−0.084	−0.139	−0.100	0.125	0.098	0.147*	0.041	0.110	0.199	0.162	0.020	−0.012	−0.260
	(0.170)	(0.149)	(0.203)	(0.207)	(0.211)	(0.089)	(0.086)	(0.217)	(0.227)	(0.106)	(0.147)	(0.161)	(0.197)
high_edu	0.047	0.009	−0.120	−0.128	0.158	0.015	−0.039	0.059	0.122	0.022	0.017	0.019	0.064
	(0.072)	(0.072)	(0.103)	(0.115)	(0.132)	(0.082)	(0.097)	(0.136)	(0.127)	(0.088)	(0.079)	(0.055)	(0.089)
employment	0.097	0.111	0.030	0.011	0.164	0.151	0.064	0.241	−0.044	−0.040	−0.059	−0.019	−0.058
	(0.136)	(0.076)	(0.107)	(0.102)	(0.173)	(0.136)	(0.099)	(0.197)	(0.191)	(0.144)	(0.136)	(0.093)	(0.128)
fulltime	−0.143	−0.010	0.059	0.009	−0.119	−0.079	−0.020	−0.134	0.031	0.049	0.007	0.096	0.135
	(0.106)	(0.094)	(0.115)	(0.117)	(0.139)	(0.107)	(0.101)	(0.153)	(0.140)	(0.120)	(0.091)	(0.065)	(0.101)
high_income	0.047	0.096	0.074	0.154	0.105	−0.036	0.005	0.055	0.064	0.008	0.018	0.049	−0.112
	(0.081)	(0.082)	(0.113)	(0.109)	(0.140)	(0.075)	(0.092)	(0.143)	(0.135)	(0.111)	(0.087)	(0.084)	(0.096)
left	−0.074	0.007	−0.146*	−0.153	0.127	0.027	0.116	−0.102	−0.100	0.015	0.140	−0.007	0.155
	(0.083)	(0.097)	(0.085)	(0.100)	(0.147)	(0.099)	(0.124)	(0.167)	(0.153)	(0.124)	(0.133)	(0.068)	(0.133)
right	0.056	−0.123*	−0.297***	−0.187*	−0.124	−0.069	−0.102	−0.301	−0.338	−0.137	−0.057	0.592**	−0.032
	(0.204)	(0.063)	(0.112)	(0.111)	(0.187)	(0.066)	(0.071)	(0.230)	(0.296)	(0.117)	(0.090)	(0.231)	(0.222)
fin_literacy	0.044	0.116*	−0.104	0.186	0.047	−0.021	−0.010	−0.194	−0.097	−0.083	0.063	−0.034	−0.006
	(0.059)	(0.062)	(0.193)	(0.160)	(0.198)	(0.152)	(0.160)	(0.196)	(0.152)	(0.178)	(0.079)	(0.090)	(0.157)
perception_quant	−0.024	0.075	0.061	−0.040	−0.081	−0.115	−0.200**	0.111	−0.123	−0.031	0.055	0.008	−0.083
	(0.077)	(0.062)	(0.088)	(0.102)	(0.120)	(0.092)	(0.092)	(0.120)	(0.097)	(0.090)	(0.073)	(0.058)	(0.095)
perception_quali	−0.171*	−0.187**	0.121	0.417	0.375*	0.091	0.102	−0.082	0.017	−0.034	0.035	−0.124*	−0.158
	(0.103)	(0.095)	(0.257)	(0.312)	(0.197)	(0.181)	(0.152)	(0.266)	(0.237)	(0.218)	(0.241)	(0.073)	(0.143)
Constant	0.060	−0.032	0.294	−0.057	0.031	0.001	0.135	0.271	0.653**	0.130	−0.043	0.009	0.436*
	(0.220)	(0.139)	(0.247)	(0.238)	(0.301)	(0.190)	(0.168)	(0.347)	(0.307)	(0.258)	(0.217)	(0.154)	(0.255)
Observations	100	100	100	100	100	100	100	100	100	100	100	100	100
R^2	0.143	0.126	0.143	0.174	0.130	0.072	0.135	0.074	0.130	0.082	0.104	0.325	0.101
Adjusted R^2	0.025	0.006	0.024	0.060	0.010	−0.056	0.016	−0.054	0.010	−0.044	−0.020	0.232	−0.023

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.T.4: Correlation between narrative complexity and demographic, socioeconomic and literacy background variables

	Dependent variable:		
	complex	supply_demand	longest_path
	(1)	(2)	(3)
male	−0.089	0.005	0.011
	(0.098)	(0.091)	(0.113)
old	0.373**	0.066	0.081
	(0.147)	(0.131)	(0.161)
school	0.116	−0.002	−0.035
	(0.165)	(0.145)	(0.216)
high_edu	0.077	0.069	0.139
	(0.108)	(0.086)	(0.131)
employment	0.225*	0.065	0.125
	(0.116)	(0.133)	(0.167)
fulltime	−0.143	−0.060	0.060
	(0.115)	(0.119)	(0.142)
high_income	0.311***	0.054	0.120
	(0.113)	(0.107)	(0.137)
left	0.071	0.070	−0.076
	(0.138)	(0.121)	(0.155)
right	−0.068	0.102	−0.175
	(0.170)	(0.208)	(0.202)
fin_literacy	−0.033	0.097	0.116
	(0.190)	(0.062)	(0.189)
perception_quant	0.003	0.005	−0.050
	(0.105)	(0.079)	(0.119)
perception_quali	0.323	−0.116	0.284
	(0.274)	(0.095)	(0.240)
Constant	−0.167	−0.076	0.057
	(0.246)	(0.208)	(0.300)
Observations	100	100	100
R^2	0.304	0.059	0.133
Adjusted R^2	0.208	−0.071	0.013
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.T.5: Demographic, socioeconomic and literacy variables on DAG cluster

	Dependent variable:						
	cluster_1	cluster_2	cluster_3	cluster_4	cluster_5	cluster_8	cluster_9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
male	−0.123	−0.111	−0.008	0.215**	−0.056	0.030	−0.010
	(0.096)	(0.113)	(0.037)	(0.097)	(0.054)	(0.045)	(0.047)
old	−0.025	0.085	0.080	−0.191	0.038	−0.045	−0.021
	(0.132)	(0.143)	(0.073)	(0.131)	(0.082)	(0.079)	(0.053)
school	−0.038	0.207	−0.076	0.104	0.011	−0.255	0.019
	(0.188)	(0.183)	(0.102)	(0.133)	(0.138)	(0.163)	(0.097)
high_edu	−0.064	−0.088	−0.017	0.354***	−0.056	−0.022	0.005
	(0.107)	(0.130)	(0.032)	(0.110)	(0.071)	(0.050)	(0.050)
employment	0.003	−0.019	−0.028	0.029	0.013	−0.070	0.011
	(0.061)	(0.197)	(0.073)	(0.149)	(0.065)	(0.091)	(0.055)
fulltime	0.142	−0.112	−0.024	0.015	0.104	0.005	0.054
	(0.101)	(0.143)	(0.034)	(0.117)	(0.071)	(0.049)	(0.051)
high_income	0.041	0.004	0.026	−0.108	−0.012	−0.045	−0.011
	(0.093)	(0.136)	(0.048)	(0.109)	(0.072)	(0.054)	(0.067)
left	−0.066	−0.031	−0.062	0.262**	−0.131**	0.043	−0.006
	(0.084)	(0.147)	(0.044)	(0.126)	(0.054)	(0.063)	(0.021)
right	−0.147*	−0.218	−0.068	0.214	−0.183*	0.078	0.465*
	(0.080)	(0.211)	(0.052)	(0.182)	(0.099)	(0.177)	(0.252)
fin_literacy	0.110	−0.118	0.020	0.166	−0.132	0.002	−0.094
	(0.155)	(0.194)	(0.028)	(0.116)	(0.155)	(0.112)	(0.089)
perception_quant	0.035	−0.025	0.003	−0.065	0.040	0.040	−0.028
	(0.079)	(0.123)	(0.047)	(0.096)	(0.065)	(0.031)	(0.034)
perception_quali	0.137	−0.087	−0.099	0.301	−0.188**	0.058	−0.027
	(0.261)	(0.240)	(0.084)	(0.209)	(0.087)	(0.126)	(0.041)
Constant	0.007	0.467*	0.119	−0.245	0.187	0.317*	0.072
	(0.221)	(0.274)	(0.123)	(0.249)	(0.173)	(0.192)	(0.140)
Observations	100	100	100	100	100	100	100
R^2	0.125	0.071	0.092	0.251	0.116	0.252	0.405
Adjusted R^2	0.004	−0.057	−0.033	0.147	−0.006	0.149	0.323
Note:							*p<0.1; **p<0.05; ***p<0.01

Table A.T.6: Anchoring regressions

	Dependent variable:		
	anchor		
	(1)	(2)	(3)
male	0.186		
	(0.118)		
old	−0.292*		
	(0.156)		
school	0.328**		
	(0.167)		
high_edu	−0.065		
	(0.138)		
employment	0.028		
	(0.172)		
fulltime	−0.151		
	(0.135)		
high_income	−0.097		
	(0.132)		
left	−0.056		
	(0.151)		
right	−0.173		
	(0.197)		
fin_literacy	0.194		
	(0.205)		
perception_quant	−0.071		
	(0.107)		
perception_quali	0.291		
	(0.275)		
mon_policy		−0.048	
		(0.147)	
demand		−0.293*	
		(0.170)	
supply_chain		−0.014	
		(0.172)	
supply_short		0.235	
		(0.152)	
ressources		−0.057	
		(0.114)	
labor		0.343*	
		(0.189)	
supply		−0.115	
		(0.179)	
pandemic		−0.035	
		(0.115)	
war		0.100	
		(0.126)	
climate_crisis		−0.136	
		(0.165)	
price_gouging		0.284	
		(0.173)	
govt		−0.523***	
		(0.102)	
others		−0.277**	
		(0.126)	
complex			−0.120
			(0.134)
supply_demand			−0.033
			(0.170)
longest_path			0.142
			(0.122)
Constant	0.179	0.464***	0.424***
	(0.286)	(0.122)	(0.068)
Observations	100	100	100
R^2	0.217	0.268	0.018
Adjusted R^2	0.109	0.158	−0.013
Note:			*p<0.1; **p<0.05; ***p<0.01