Going Viral: Inflation Narratives and the Macroeconomy

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Abstract

In recent years, there has been increasing interest in the analysis of narratives in macroeconomic research. Our paper contributes to this research by proposing a way to identify and extract economic narratives from media reports. Therefore, this paper applies state-of-the-art text analysis methods to a large news corpus covering five years of news coverage in combination with results from a survey study on recent inflation narratives (Andre et al., 2023) in the US. This approach enables us to measure the prevalence and spread of inflation narratives over time and to examine the role of these narratives in aggregate macroeconomic expectations. Using Granger causality tests and local projections, we provide empirical evidence on the dynamics between inflation narratives and inflation expectations. Moreover, the paper highlights the vast heterogeneity across short-term and mid-term inflation expectations as well as socioeconomic groups.

JEL codes: D84, E31, E32, E52, E71
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1 Introduction

For the first time in decades, numerous countries world-wide, including the United States, are facing high inflation rates. This is important because households generally perceive high inflation as one of the most important (economic) policy issues (Shiller, 1997; Stantcheva, 2024). While some inflation might be desirable, rates way above the two percent target impose substantial costs on society (Romer, 2012). Consequently, its origin and the underlying mechanisms have been and continue to be subject of ongoing debate. Blanchard and Bernanke (2023) attribute the increase in inflation to a combination of supply constraints and robust aggregate demand. Reis (2022) highlights an "overly long period of expansionary policy", and central banks tolerating higher inflation rates. Weber and Wasner (2023) discuss the role of market power to hike prices, which indicates "sellers' inflation". On a theoretical level, Lorenzoni and Werning (2023) provide a decomposition of inflation and argue that the general cause of inflation is conflict or disagreement. Expectations are of great importance in their conceptualization, as they shape the aspirations of workers and firms.

In standard New Keynesian models, this idea of forward-looking agents is essential, as Werning (2022) demonstrates. In these models, expectations are seen as a driver of inflation dynamics. Influential on forward-guidance was the work by Krugman et al. (1998), who proposed that during a liquidity trap, central banks should be able to stimulate the economy by raising inflation expectations through credibility. This is why central banks closely monitor the expectations of households, firms, and experts— or, as Jerome Powell, the current Chair of the Federal Reserve, puts it: "Our monetary policy framework emphasizes the importance of well-anchored inflation expectations, both to foster price stability and to enhance our ability to promote our broad-based and inclusive maximum employment objective." (Powell, 2021).

A long tradition of empirical economic research addresses the question of whether and to what extent the expectations of households influence economic decisions. Two moments are subjects of interest: the consumption-saving nexus in the Euler-Equation and inflation uncertainty as a precautionary saving motive (D'Acunto et al., 2023). Regarding the former, work by Juster and Wachtel (1972) suggested already in the 1970s that inflation expectations influence expenditure spent on durable goods, while the findings fo Burch and Werneke (1975) indicate a strong relationship between inflation expectations and the national saving rate. More recent research by Bachmann et al. (2015) is also in line with both moments. The authors do report a significant negative relationship between expectations and savings, but only for a subset of households, whose expectations are within one percentage point of the actual realized inflation. By linking survey data on inflation expectations of households to administrative data, Vellekoop and Wiederholt (2019) report a negative relationship between inflation expectations and net worth. With a pseudo-panel study, the results of Duca-Radu et al. (2021) are in line with the Euler equation for all participants, however, smaller effect sizes for more inaccurate expectations. Further supporting evidence comes from Dräger and Nghiem (2021), who report positive correlation between current spending and inflation expectations for a German sample. Their results further indicate the importance of attention to monetary news as an amplifier of this channel. However, regarding the actual spending, the findings by Burke and Ozdagli (2023) suggest that the expectation effect applies only to spending on durable goods.

While the introduction of rational expectations by Muth (1961), Lucas (1972), Lucas and Sargent (1979) led to a revolution in economic modeling, the last two decades have been marked by strong criticism of the "full information rational expectations" (FIRE) model (Coibion and Gorodnichenko, 2012). Alternative approaches to the formation of expectations include "sticky information" (Mankiw and Reis, 2002; Carroll, 2003, 2005; Döpke et al., 2008b,a), "rational inattention" (Woodford, 2001; Sims, 2003), "learning" (Evans and Honkapohja, 2001) and "bounded rationality" (Gabaix, 2014; Fuster et al., 2010; Evans and Honkapohja, 2001). Regarding the heterogeneity of expectations, Weber et al. (2022) identify four different channels that affect subjective inflation expectations:

1. Exposure to heterogeneous price signals (D'Acunto et al., 2021b),

2. different media information sets (Carroll, 2003, 2005; Döpke et al., 2008b; 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).

This observed heterogeneity and subjectivity of inflation expectations is largely undisputed nowadays, however, there is still no consensus in economics as to what determines these expectations. To some extent, "narrative economics" (Shiller, 2017, 2019) has created a link to modern social science and psychological analysis of expectations and uncertainty (Beckert, 2016; Beckert and Bronk, 2018; Tuckett and Nikolic, 2017). The theoretical argument is based on findings from literary studies, sociology, anthropology, and psychology that highlight the importance of narratives for human beings and human decision-making (Shiller, 2017). It states that narratives about the economy pervade and guide decisions in uncertain moments. Therefore, they incorporate "[...] causal, temporal, analogical, and valence information about agents and events, which serve to explain data, imagine and evaluate possible futures, and motivate and support action over time" (Johnson et al., 2023). This highlights the importance of expectations, i.e. narratives for imagining and evaluating the future (Johnson et al., 2023; Beckert and Bronk, 2018).

In microeconomic models (Eliaz and Spiegler, 2020; Eliaz et al., 2022), the narrative approach has been implemented, establishing a connection with the statistical and epistemological literature on causality (Pearl, 2009). Eliaz and Spiegler (2020) refer to political debates and suggest that actors are encouraged to strategically adopt political stances aligned with narratives, which both perceive to have more positive and promising outcomes. From a macroeconomic perspective, Shiller (2017, 2019) emphasizes the role of "going viral" for narratives by focusing on the spread and dynamic of economic narratives. Following Shiller (2019), this aspect is crucial because narratives are closely linked to "animal spirits" (Shiller and Akerlof, 2009, 17). Thus, viral narratives may lead to fundamental shifts and turning points, being active drivers of the economy and of activity in the economy (Roos and Reccius, 2024). Research should therefore focus on the spread and dynamics of economic narratives.

In a recent paper, Andre et al. (2023) take the existing strand of research on expectations and link it to the strand of "narrative economics": Based on a working definition of economic narratives as "causal accounts of past economic events" (Andre et al., 2023, 5), the authors focus on measuring backward-looking narratives through open-ended questions. In order to classify narratives, the authors use the concept of "directed acyclic graphs" (DAG) (Pearl, 2009). Their findings suggest that narratives among households substantially differ from those of experts. This is partly explained by different political attitudes and news consumption. Moreover, they provide experimental evidence that expectations respond to narrative priming and that mass media is an important source of narratives.

The relevance of the media as an intermediary of narratives (Ter Ellen et al., 2022) is considered by some empirical research. Larsen et al. (2021) analyze news coming from the Dow Jones Newswire by means of a Latent Dirichlet Allocation (LDA) model (Blei et al., 2003). Their results suggest that media news reports are a good predictor of inflation expectations. Müller et al. (2022) use an augmented version of the static LDA, which allows for a dynamic analysis of news about inflation in German newspapers, yet without considering them as determinants of expectations. Related work comes from Hong et al. (2022), who combines LDA modeling with forecasting techniques. Macaulay and Song (2022) measure narratives by means of LDA on social media and investigate their effects on consumer sentiments with a high-frequency event study. All these papers have one aspect in common: They rely on (dynamic) exploratory LDA topic models to measure narratives in the media, which limits their methodological approach to a broad definition of narratives. Therefore, the previous approaches were unable to identify concrete predefined concepts of narratives (Roos and Reccius, 2024).

Building upon the existing research, this paper addresses the following research objectives:

1. Provide a methodological approach that goes beyond existing research to identify narratives in large text corpora and enables researchers to measure their prevalence according to predefined concepts.

2. Focus on the predominant inflation narratives in media reports during the recent inflationary period.

3. Investigate if inflation narratives are potential causal determinants of expectations. In order to do that, the paper utilizes the existing methodological approach to measure narratives a step further and proposes a combination of results coming from the survey study by Andre et al. (2023) and a "keyword-assisted topic model" (keyATM) in a variant called "dynamic keyATM", proposed by Eshima et al. (2024). This allows us to provide prior information about the narratives into the Bayesian estimation. This novel method overcomes the common problem of measuring specific concepts while using explorative topic models, e.g. LDA by Blei et al. (2003); it enables the researcher to specify a number of keywords to label topics prior to fitting the model on the data. For our purpose, we construct thirteen keyword-specified topics, that incorporate demand and supply narratives, as well as miscellaneous narratives, e.g., pandemic or war narrative, based on the findings by Andre et al. (2023). We refine our measurements by applying a Latent

Semantic Scaling (LSS) technique (Watanabe, 2021) to identify the direction of the narratives' argument and to construct corresponding indices. To investigate their predictive power over macroeconomic variables, we conduct multivariate Granger causality tests. Further, we study the diffusion of each narrative by applying "local projections" techniques (Jordà, 2005).

4. Finally, this paper examines whether certain narratives have a stronger impact on certain socio-economic groups (e.g. by income, education, age, numeracy) than other narratives.

Our empirical findings suggest that during the current inflationary period, narratives about demand recovery and shifts, supply chain, energy prices, labor shortage, monetary policy, corporate profits, and the pandemic in general as causes of rising inflation were of great importance. Moreover, stories about the war in Ukraine recorded a sudden and strong increase, which, however, did not persist. As our time series analysis indicates, in numerous cases the measured narratives do contain predictive power to macroeconomic variables, especially households' inflation expectations. Supplementary, by analyzing the impulse responses of a shock in the narratives, we provide evidence that narrative diffusion elevates households' inflation expectations, 1-year-ahead expectations in particular. When comparing shocks across narratives, we notice more anchored expectations with respect to a shock in the supply chain, demand shift, and profits narratives. Along the various socioeconomic determinants, such as income, education, age, etc., we find clear differences in the way narratives affect inflation expectations. For example, our analysis indicates that the energy narrative is the main driver of medium-term expectations for households with lower annual incomes, while several demand narratives Granger-cause the expectations of middle- and high-income households. This suggests a strong group-specific susceptibility to narratives and underlines the need for interdisciplinary (social science) analyses when it comes to explaining heterogeneous inflation expectations (Beckert, 2016). Finally, our results emphasize the spread and change of narratives over a short period of time, highlight economic narratives as a determinant of expectation building.

The paper is structured as follows: Firstly, Section 2 briefly describes the datasets and some of the preceding pre-processing steps. Further, we provide a short overview of the narratives identified by Andre et al. (2023) with corresponding pre-selected keywords, and further describe the applied empirical methods, namely keyATM, LSS, Granger causality tests, and local projections. Subsequently, section 3 offers a first outline of the dynamic keyATM results. Secondly, we report results from the LSS and provide constructed indices of narratives. Lastly, we present estimation results from the Granger causality tests and local projections. Further background information, the Online Appendix and the replication code will be made available via a repository at https://github.com/ValweM/InflationNarratives [1]

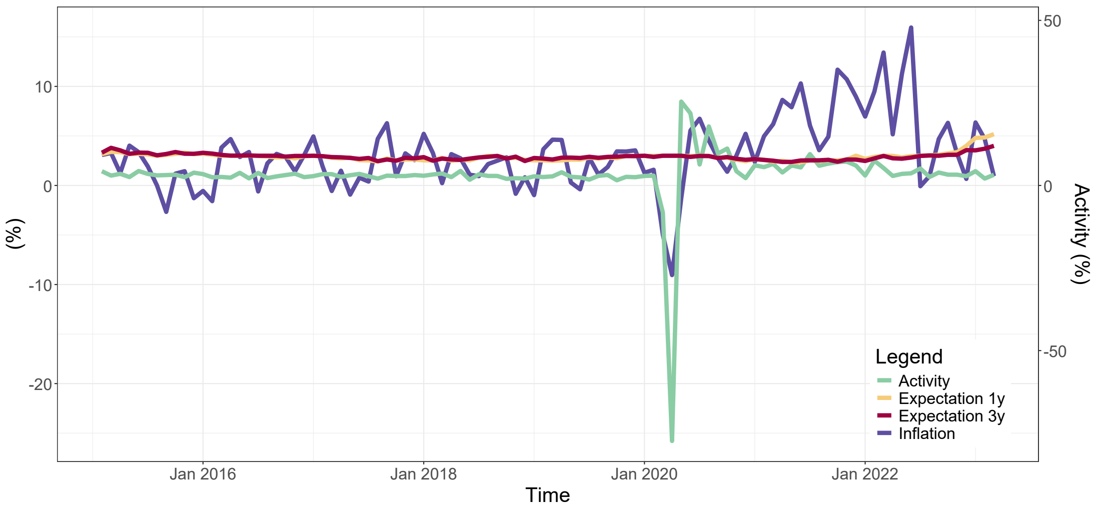
[1]All calculations in the paper were performed using R software (R Core Team, 2022) version 4.4.1. The software is licensed under GPL-2/GPL-3. Furthermore Python version 3.12.2 (Van Rossum and Drake, 2009) was used for several NLP pre-processing tasks (e.g lemmatization).

2 Data and Methods

2.1 Data

Two different datasets are used for the analysis: First, the time series of the occurrence of certain narratives described by Andre et al. (2023) in a news corpus from the *Dow Jones Newswires Machine Text Feed and Archive* database.[2] The dataset includes content of the following areas: market-moving M&A, exclusives, and earnings news; full-text feeds from Dow Jones sources (Newswires, The Wall Street Journal, Barron's, MarketWatch); global company news; central bank, macroeconomic, political, FX, commodities and energy news; third-party press release wires (BusinessWire, PR Newswire, Globe Newswire and others). It is important to note that the corpus includes one of the largest newspapers in the US; the Wall Street Journal.

Figure 1: Macroeconomic time series



Note: 'Activity' refers to the 'Coincident Economic Activity Index for the United States', monthly, seasonally adjusted at annual rates. 'Expectation 1y' and 'Expectation 3y' refers to 'New York Fed: Median 1- and 3-year ahead expected inflation rate', monthly, not seasonally adjusted. 'Inflation' refers to 'Consumer Price Index for All Urban Consumers: All Items in U.S. City Average', monthly, seasonally adjusted at annual rates. Source: https://fred.stlouisfed.org/ and https://www.newyorkfed.org/microeconomics/sce.html

For the investigation, we use a subset of news content taken from the full corpus, filtered by keywords such as "inflation" for the period January 2018 to January 2023 to cover the recent inflation period. Further, the period is limited to five years due to the constrained timeliness of the survey-based measured inflation narratives in Andre et al. (2023) and filtered by subject codes to select only relevant news sources. This amounts to a corpus of 159,440 documents. Prior to the analysis, further transformations and preprocessing steps are applied to the selected corpus, which are common when working with bag-of-words methods (Grimmer et al., 2022), e.g. lemmatization, stop words removal, constructing a document-feature matrix (see description in section A.2).

[2] See https://developer.dowjones.com/site/docs/newswires_feeds/dow_jones_text_feed_and_archive/ for details.

Second, for the time series analysis we use a macroeconomic time series on CPI inflation (U.S. Bureau of Labor Statistics), inflation expectations (Median survey-based inflation expectations of US households one and three years ahead, New York Fed Survey) and economic activity (Coincident Economic Activity Index (CEI), Federal Reserve of Philadelphia) on a monthly basis (see figure 1).

CPI inflation and the economic activity index are seasonally adjusted at annual rates, while the inflation expectations are not seasonally adjusted. Moreover, as figure 1 shows, the economic activity time series contains several outliers, caused by the first Covid-19 lockdown in 2020. This may introduce a bias tp our estimations. Therefore, we treat these outliers with a dummy variable after they have been detected with the tsoutlier() function as implemented in Hyndman et al. (2022).

2.2 Methods

2.2.1 Semi-supervised Keyword-assisted Topic Model (keyATM)

Eshima et al. (2024) proposed the keyATM model as a semi-supervised alternative to the benchmark latent dirichlet allocation (LDA) topic model (Blei et al., 2003). They argue: "[u]nfortunately, although topic models can *explore* themes of a corpus [...], they do not necessarily *measure* specific concepts of substantive interest." (Eshima et al., 2024, 1). Furthermore, benchmark LDA topic models -as an unsupervised method-suffer from the post-hoc interpretability problem (Boyd-Graber et al., 2014).

The semi-supervised approach introduced by Eshima et al. (2024) enables researchers to label topics by specifying keywords before fitting the model. The authors describe it as a "semi-supervised topic model that combines a small amount of data with a large amount of unlabelled data."(Eshima et al., 2024, 2). The baseline keyATM is visualized as a plate representation in figure A.1 in the Online Appendix.

Specifically, the corpus has D documents and each document has N_d words. w_{di} stands for the i^{th} word in the d^{th} document. The model formulation of keyATM considers two types of topics: keyword topics ($\tilde{K}$) and non-keyword topics (K). For each keyword topic k the researcher has to specify a set L_k of keywords. The model is flexible enough to allow keywords to be assigned to different keyword topics simultaneously. The data generation process is modeled in such a way that at first, a latent topic variable z_{di} is sampled from the topic distribution of the document θ_d. If the sampled topic belongs to the non-keyword group, then the word is drawn from the corresponding word distribution of the topic (ϕ_k). If the topic belongs to the keyword group, a Bernoulli random variable s_{di} is drawn with probability π_k. This serves as an indicator variable to determine whether the word should be drawn from a set of keywords based on the probability vector $\tilde{\phi}_k$ or from the standard topic-word distribution ϕ. As the estimation is based on standard Bayesian approaches, $\eta, \beta, \gamma, \tilde{\beta}$ indicate priors (see Eshima et al. (2024, 4 f.) for a more detailed exposition).

Since the model is now based on a mixture of distributions, one with positive probabilities only for keywords on the keyword list and one with positive probabilities for all words, this implies greater prior means for the frequency of the predefined keywords than for the non-keywords in a given topic. As a result, the method is encouraged to give greater importance to keywords *prior* to estimation, but to learn the exact degree of importance from the data. Thus, researchers introduce *a priori* qualitative information into the estimation process of the topic model.

For this paper we make use of specific variant of the keyATM, namely the dynamic keyATM (Eshima et al., 2020, 22 ff.). Figure A.2 in the Online Appendix provides a plate representation of the model. As shown in the plate representation, the baseline keyATM is now extended by a hidden Markov model (HMM) with R states where $h_{t[d]}$ denotes the latent state of document d for time t. The transition probability matrix of the HMM is sparse, allowing only a one-step forward transition (to simplify the estimation). The dynamic keyATM allows the topic proportion θ_d to evolve over time by letting α vary across the different latent states. The authors argue that "(m)odeling α instead of θ_d makes (the model) less sensitive to short-term temporal variation".

For the selection of the pre-specified keywords, we follow the approach of Eshima et al. (2024) and guide our selection of keywords by the definition and example quotes by the survey study of Andre et al. (2023). Moreover, we take into account their results from a penalized logistic regression, which predicts whether or not a DAG factor was manually assigned to a response based on the text data. Finally, we conducted word embeddings of these keywords to optimize our selection. Accordingly, we applied an unsupervised learning algorithm for obtaining vector representations for words called GloVe by using the R Package text2vec (Selivanov et al., 2022). In table 2, all prior-selected keywords are listed, additionally with explanations coming from Andre et al. (2023). In contrast to their definitions, we use less restrictive definitions due to methodological limitations of the bag-of-words approach, which prevent us from further narrowing them down. Therefore, we treat government mismanagement as "politics", the tax increase narrative as "taxes" and the price-gouging narrative as "profits". Moreover, we do not consider base effect and inflation expectations narratives, due to their non-appearance in the households' sample in the original study.

2.2.2 Latent Semantic Scaling

Our semi-supervised topic model approach allows us to quantify the prevalence of stories about the potential causes of inflation. To measure a narrative, it is important to identify the direction of its argument, e.g., whether monetary policy is causing rising or falling inflation. Both narratives may exist. Thus, it is essential to distinguish between arguments attributing the different factors to either rising or falling inflation rates. In a way, we follow the idea of "tone-adjusted time series" by (Larsen and Thorsrud, 2019). To ensure a distinction, simple n-gram prefiltering could be applied, utilizing n-grams such as "rising inflation" or "rising prices". This, however, would only ensure that rising inflation rates are discussed at least once in each document. A more nuanced and accurate measurement of the argument is needed. Therefore, we apply the recently proposed semi-supervised document scaling technique "Latent Semantic Scaling" (LSS, Watanabe (2021)) which is based on a word embedding approach. This allows us to develop a content-related polarity dictionary to indicate if a document is mainly about falling or rising inflation rates.

Classification	"Positive" (= increasing)	"Negative" (= decreasing)
	accelerate	decline
	acceleration	decrease
	elevate	deflation
	high	fall
	increase	low
	persist	lower
	persistent	reduce
	pressure	persistent
	rise	reduction
	surge	weak

Table 1: Seed words for LSS initialization

Sentiment or polarity analyses are traditionally conducted by means of a dictionary approach (Grimmer et al., 2022, 180). Consequently, the major challenge is to select a domain specific dictionary or construct an own dictionary. To our knowledge, the former does not exist for the context of inflation, while the latter would be extremely time consuming. Then again, supervised machine learning methods could by applied to predict the sentiment of each document. This involves manual coding of a sufficiently large corpus, to insure reappearance of words in the training and test set, which again is time and cost intensive (Watanabe, 2021, 84). In contrast, LSS allows us to construct our own polarity dictionary using seed and target words. Based on the proximity to a selection of seed words for each semantic dimension, polarity scores of words are computed. To estimate the semantic closeness of words, LSS recalls on singular value decomposition (SVD) of a document-feature matrix. The selected seed words are listed in table 1. For further refinement of the polarity analysis on inflation, relevant target words are selected. Therefore, we opt for glob pattern "infla*" and "price*". Following our selection, the LSS method generates a collection of statistically significant words that occur within a window of five words around the target words. Polarity scores of words are computed as follows:

$$g_f = \frac{1}{|s|} \sum_{s \in S} cos(v_s, v_f) P_s \tag{1}$$

where g_f are words, s seed words, p_s user-provided polarity of seed words, and $cos(v_s, v_f)$ the cosine similarity between the seed word vector and the word vector associated with the word f (Watanabe, 2021, 86). Subsequently, the polarity scores of the documents are predicted by weighting word polarity scores by their frequency in the document:

$$y = \frac{1}{N} \sum_{f \in F} g_f h_f \tag{2}$$

where h_f is the frequency of words and N the total number of words in the model. The documents' scores are symmetrically distributed around the mean ($\mu = 0$), and rescaled by standard deviation ($\sigma = 0$). In our case, a negative score indicates that

Category	Explanation	Keywords
Demand		
Government Spending	Increases in government spending (e.g., stimulus payments)	infrastructure, agreement, biden, spending, deficit, bipartisan, package
Monetary Policy	Loose monetary policy by the Federal Reserve	fed, quantitative, easing, loose, monetary, interest
Pent-up Demand	Reopening of the economy and the associated higher incomes, new spending opportunities, and optimism about the future	demand, surge, activity, recover, pandemic
Demand Shift	Shift of demand across sectors (particularly increases in durables).	change, consumer, good, durable, trend, service, shift, vehicle,
Supply		
Supply chain issues	Disruption of global supply chains	supply, supplier, chain, producer, bottleneck
Labor shortage	Shortage of workers, e.g., due to some workers dropping out of the labor force, and higher wage costs	worker, employment, labor, wage, workforce, labour, job, strike, union, hire
Energy crisis	The global energy crisis, leading to shortages of, e.g., oil and natural gas and higher energy prices	crude, gas, gasoline, oil, fuel
Miscellaneous		
Pandemic	The COVID-19 pandemic, the global pandemic recession, lockdowns, and other policy measures	pandemic, covid-19, virus, coronavirus, infection, outbreak, case
Politics	Policy failure, mismanagement by policymakers, policymakers are blamed	part, republican, trump, congress, senate, president, biden, democrats, government
Russia-Ukraine war	The Russian invasion of Ukraine, the international economic, political, and military response	russia, war, ukraine, invasion, moscow, putin, military
Government debt	High level of government debt	debt, public, national, federal, deficit, borrowing, government, balance
Tax increases	Tax increases, such as VAT hikes	tax, raise, reform, legislation, overhaul, reduction
Profits	Greedy companies exploiting opportunities to increase profits, companies trying to make up for the money they lost during the pandemic	margin, corporate, profitability, profit, growth

Table 2: Narratives, explanations, and keywords

the document is mainly about falling inflation rates, while a positive score indicates that the document is mainly about rising inflation rates. For our further analysis, we constructed narrative indices based on the document scores and the topic prevalence time series from our keyATM analysis. For this, we multiply the topics' proportions on the document level with the document polarity score. Finally, we aggregated our index on monthly level.

2.2.3 Granger Causality Tests

In order to study the macroeconomic dynamics of our narratives, we first conducted a series of Granger causality test using our constructed narrative indices as a proxy for the narratives' virality. This allows us to study the predictive power of our narrative time series on macroeconomic variables (inflation expectations, CPI inflation, economic activity) and test their (weak) exogeneity. The Granger causality tests are constructed as multivariate tests in a vector autoregressive model (VAR) setting. The hypotheses of no Granger causality is tested by means of F test for joint significance. We follow the argument of Lütkepohl (2005), that an χ^2-distribution is often a poor approximation when working with a small sample size as ours. For our purpose we again consider five macroeconomic variables: the households' 1- and 3-year inflation expectations, the CPI inflation, the economic activity. The Granger causality statistics are used to examine whether the lagged values of one variable help to predict another one. In a more general sense we say that variable z Granger causes y if:

$$\mathbb{E}(y_t|I_{t-1}) \neq \mathbb{E}(y_t|J_{t-1}) \tag{3}$$

Here, the vector I_{t-1} contains past values of y and z, while the vector J_{t-1} only contains past information on y (Wooldridge, 2013). Granger causality thus follows the idea that a cause cannot succeed the effect (Lütkepohl, 2005, 41).

2.2.4 Local Projections

To further investigate the effects of increasing narrative diffusion at the macroeconomic level, we resort to dynamic time series models and, in particular, impulse response functions (IRF). Classical tools are VARs (Sims, 1980). This method, however, has some drawbacks: it is prone to mis-specification, difficult to apply to non-linear cases, and usually necessitates a relatively long lag length to ensure proper calculation (Jordà, 2005, 161). The latter is of particular importance for the present study, since a rather short observation period is used. We therefore decided to estimate the dynamic response sequences on the basis of "local projections" (LP) method (Jordà, 2005). Plagborg-Møller and Wolf (2021) recently proved that under reasonable assumptions, VAR and LP estimate the same IRFs.

The basic idea of LP is to compare a conditional forecast of an event using currently available information at the time of a shock to a forecast without the shock (Jordà, 2005, 163):

$$IR(t, s, \boldsymbol{d}_i) = \mathbb{E}(\boldsymbol{y}_{t+s}|\boldsymbol{v_t} = \boldsymbol{d}_i; \boldsymbol{X}_t) - \mathbb{E}(\boldsymbol{y}_{t+s}|\boldsymbol{v}_t = O; \boldsymbol{X}_t),\ s = 0, 1, 2, ..., S \tag{4}$$

The operator $\mathbb{E}(.|.)$ denotes the best predictor of the mean square deviation, $X_t \equiv (y_{t-1}, y_{t-2}...)$ and d_i is a vector containing all relevant shocks. Unlike in the VAR method, the LP method estimates the impulse response using least squares regressions for each time horizon s with $s = 0, 1, 2, ...S$ (Adämmer, 2019, 423):

$$\boldsymbol{y}_{t+s} = \boldsymbol{\alpha}^s + \boldsymbol{\beta}_1^{s+1} y_{t-1} + \boldsymbol{\beta}_2^{s+1} y_{t-2} + ... + \boldsymbol{\beta}_p^{s+1} y_{t-p} + \boldsymbol{u}_{t+s}^s, \ s = 0, 1, 2..., S \tag{5}$$

Here, α^s is a vector of constants and β_i^{s+1} are matrices with coefficients for each lag i and forecast horizon $s+1$ (Jordà, 2005, 163). The β coefficients derived from the regressions are used to construct the impulse responses. Therefore, the collection of all regressions from equation 5 are called *Local Projections* (Adämmer, 2019, 423). The impulse responses of these local linear projections are defined as:

$$\widehat{IR}(t, s, \boldsymbol{d}_i) = \hat{\boldsymbol{B}}_1^s \boldsymbol{d}_i, \ s = 0, 1, 2, ..., h \tag{6}$$

where $\hat{\boldsymbol{B}}_1^s$ contains the coefficients of the impulse response and $\boldsymbol{d}_i$ is the vector of all relevant shocks.

2.2.5 Stationarity and De-trending

The modelling of time series in VAR or ARDL models is typically based on the assumption of weak stationarity (Kirchgässner and Wolters, 2007, 13). If this property is not present, there are several options: any long-run relationships that may exist can be taken into account by modelling as an error correction model, or the time series can be transformed into a stationary representation using appropriate transformations.

Due to the short time series and the simultaneous consideration of unit root tests (see A.1 in Online Appendix), we had to choose a trend removal approach. Simple differencing may come at costs, as such an approach may lead to information loss and spurious independence, which could result in insignificant coefficients or downward biased results (Kirchgässner and Wolters, 2007, 201). However, modelling the time series at the level only makes sense if the long-term relationships are stable. We have therefore chosen another form of trend adjustment.

As Hamilton (2018); Phillips and Jin (2021) have shown, applying the popular HP filter (Hodrick and Prescott, 1997) has the potential of causing an inadequate statistical trend removal leading to (worsening) spurious results, especially when the default tuning parameter is used. Several alternatives have been suggested in the literature, including the Hamilton-Filter (Hamilton, 2018) and a boosted HP-Filter (Phillips and Shi, 2021). We opt for the latter, because it enables us to achieve stationarity without a loss of observation and its proved robustness with shorter sample sizes (Phillips and Jin, 2021). Thus, we report our baseline estimations with trend-cycle filtered time series by means of the boosted HP-Filter.

For robustness checks, we follow the suggestion of the literature (Kirchgässner and Wolters, 2007, 159) and provide level and difference estimations in the Online Appendix. Further, sufficient consideration of lags of endogenous variables should help avoid the problem of "spurious regression" results. To select the system's lag order, we rely on the Schwarz information criterion (SC).

3 Empirical Analysis

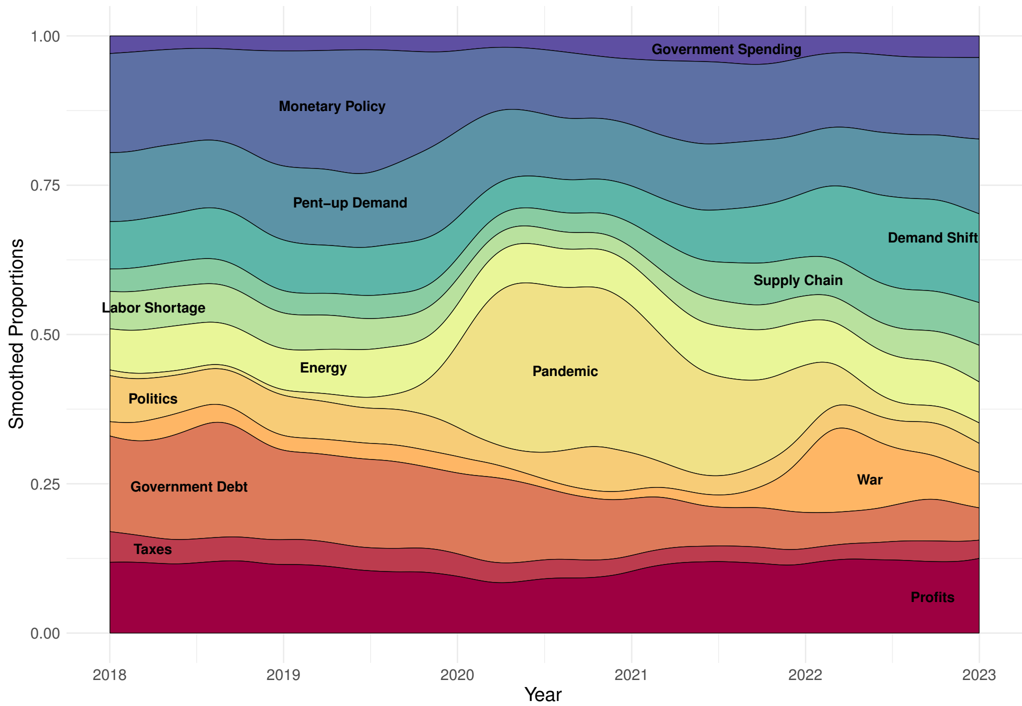
In this section, we present our empirical results, starting with a descriptive overview of the measured keyATM topics between 2019 and 2023. Next, we introduce our polarity score, which measures media reports on rising or falling inflation rates based on word embeddings. By integrating our polarity analysis with the results from the keyATM, we derive our final narrative indices. Utilizing these indices, we conduct multivariate Granger causality tests to assess the predictive power of our measured narratives. By disaggregating household expectations, we are able to identify differences based on a range of socio-economic factors. Finally, we employ local projections to study the effect of narrative diffusion on the macroeconomy.

3.1 Narrative Topics

We begin by examining the interpretability of the resulting topics, following the procedure recommended by Eshima et al. (2024), and provide an overview of the topic-word distribution. In other words, we highlight terms with high probabilities of topic selection. These terms are visualized in figure 3 as wordclouds for each of the considered topics. The wordclouds highlight the topics' consistency with the underlying narrative concept. Moreover, multiple pre-selected keywords are present for the vast majority of topics. The presence of multiple keywords and topic-consistent terms suggests a successful measurement of the respective concepts. To illustrate: terms like "unemployment", "work", and "growth" are close to the labor shortage narrative, while "share", "revenue", and "rise" are closely related to the profit narrative. An exception is the pent-up demand topic, for which none of the top 20 words includes a pre-selected keyword. Despite this, we observe a predominant use of words associated with the overarching narrative of economic recovery, featuring words like "rise", "growth", and "increase".

Following the discussion on consistency, we consider the development of topic proportions over time. As figure 2 illustrates, there are some major changes present over time. The pandemic topic surge stands out overall. It is marked by a sudden increase that is sustained with elevated shares until the conclusion of 2022. The strong increase in the war topic is also sudden, although of short duration. More generally, proportions start to shift in 2021, when inflation rates began to rise. Significant steady increases are observed for the demand shift, supply chain, energy, and profits topics. Among these, the most notable increases are reported for the supply chain and demand shift topics. Additionally, the government spending and labor shortage topics experience slight increases. However, the latter already starts declining in 2021. We observe more fluctuations for the pent-up demand topic. It is characterized by losses in early 2020 but recovers and gains importance, especially at the end of 2022.

Figure 2: Change of smoothed proportions

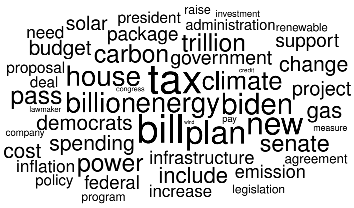


Note: The figure shows the development of the smoothed proportions. To calculate the relative proportions only the topics with pre-specified keywords were considered. To build this plot we employed the geom_stream() function by Sjoberg (2021). We organized the topics by following the code system provided by Andre et al. (2023).

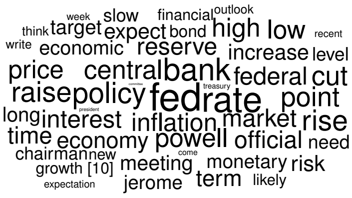
We observe a similar picture in the monetary policy topic. It also declines during the early phase of the pandemic, however, it shows recovery towards the end of the observation period. On the contrary, the debt topic shows a more steady decline. This topic is characterized by only occasional minor increases during the outbreak of the pandemic. The tax topics maintained relatively stable shares throughout the observation period, whereas the politics topic shows more fluctuations. It experiences an increase at the end of 2020, coinciding with the presidential election. Additionally, we observe a slight increase in relative importance towards the end of 2022.

To ensure robustness irrespective of the news structure, we provide a subsample comparison keyATM estimation that only includes Wall Street Journal (WSJ) articles, as illustrated in figure A.6 in the Online Appendix. The WSJ corpus includes approximately 25,500 documents. While most topics exhibit similar trajectories, a few minor differences are observed. On the one hand, smaller volumes for the pandemic and supply chain topics are found in the WSJ corpus. However, a simultaneous trend is present. On the other hand, the politics topic shares are greater with the WSJ corpus. Overall, the topics in the WSJ corpus appear to react more strongly to singular events compared to the baseline corpus, which includes more financial and corporate sources.

Figure 3: Wordclouds of keyATM keyword topics



(a) Government spending



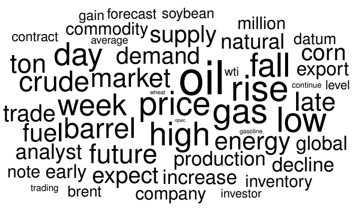
(b) Monetary policy

(c) Pent-up demand

(d) Demand shift

(e) Supply chain

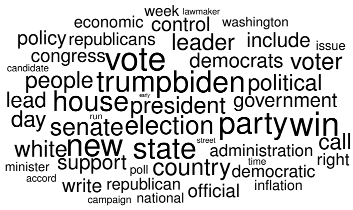
(f) Labor shortage



(g) Energy

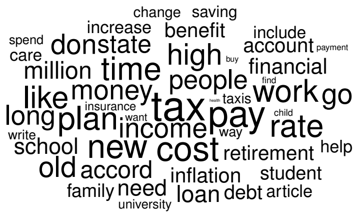
(h) Pandemic

(i) War



(j) Politics

(k) Debt



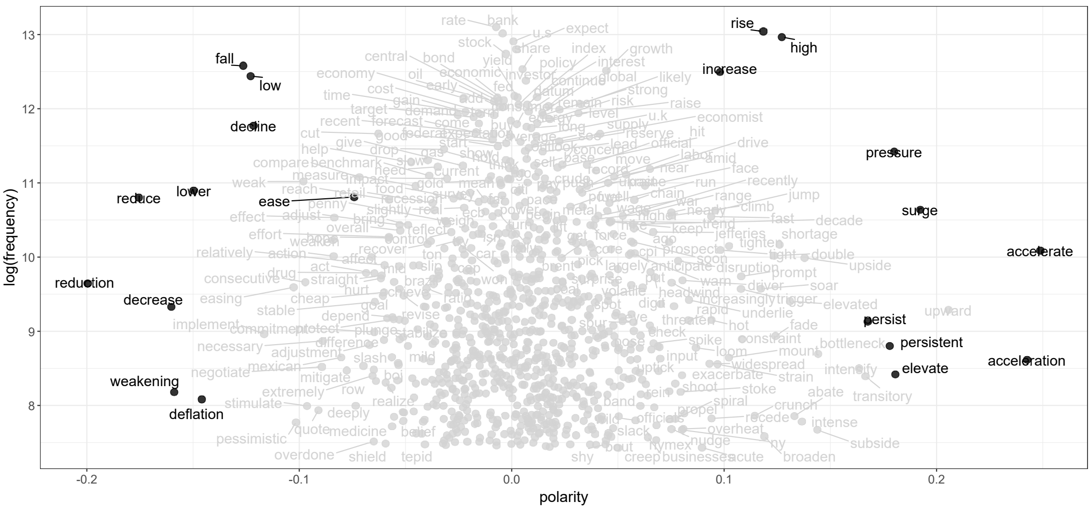
(l) Taxes

(m) Profits

3.2 Polarity-adjusted Narrative Time Series

So far, using a keyATM model enables us to measure reports on various causes of inflation. However, a key challenge lies in discerning the directions of these arguments, significantly impacting the subsequent econometric time series analysis. As detailed in 2.2, we address this issue by employing LSS to identify whether a document is mainly about (expected) rising or falling inflation rates. Ter Ellen et al. (2022) previously highlighted this methodological challenge. However, by applying a simple dictionary method, their approach falls short “[...] to identify the difference in tonality for specific narratives, for example, with respect to inflation, and not only the overall contribution” (Ter Ellen et al., 2022, 1533). In contrast, our approach enhances this methodology by employing semantic scaling to create a case-specific dictionary that identifies the narrative components’ tonality. Subsequently, we construct an index for each narrative by multiplying the sentiment score of a document by the relative proportions of the keyATM topics in each document. This is concluded by aggregating our data on monthly-level, resulting in the final indices of the narratives.

Figure 4: Polarity of words (seed words highlighted)

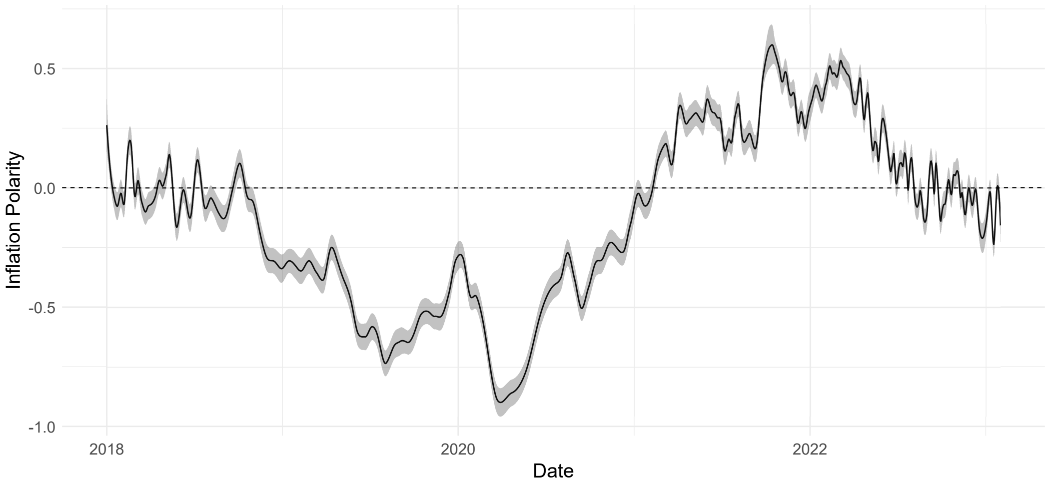


Note: The figure shows the polarity scores for all statistically significant words around the target words “infla*” and “price*”. To compute the polarity score, the semantic closeness towards pre-selected seed words are considered. To facilitate orientation, the utilized seed words are highlighted.

To evaluate the results of LSS, we plot the polarity scores constructed from our chosen seed words in figure 4. The pre-selected seed words are highlighted in the figure. Those terms associated with falling inflation rates, such as “deflation”, “negative”, or “downturn” possess a negative polarity score. In contrast, terms like ‘intensify,’ ‘tight,’ or ‘shortage’ have a positive score. Additionally, the majority of words is located around the midpoint of the polarity score line. This is reasonable because most words are not implicitly associated with changing inflation rates. Examples, such as ”affect,” ”likelihood,” and ”expect,” share the characteristic of not being explicitly aligned with discussions about increasing or decreasing inflation rates. Thus, this observed neutrality can be interpreted as further validation for how accurate the estimation is.

By weighting the polarity scores for each document, as described in 2.2, we construct an aggregated polarity score at the document level. Figure 5 shows the smoothed polarity score over time. As the plot demonstrates, the polarity score experiences strong fluctuations over the observation period. The figure shows a profound decline in the polarity score since the end of 2018. This trend corresponds with the realized CPI inflation, which began to decrease in mid 2018 and maintained low levels through October 2019. During this period, the US economy experiences a slowdown in growth. This is followed by a brief recovery of the inflation polarity, starting a the end of 2019. While the overall CPI inflation remained relatively low, an upward trend was still evident [3]. Following the first lockdowns, we observe an increase in the polarity score starting in mid-2020. The score turns overall positive in 2021 and remains so until late 2022, peaking in late 2021.

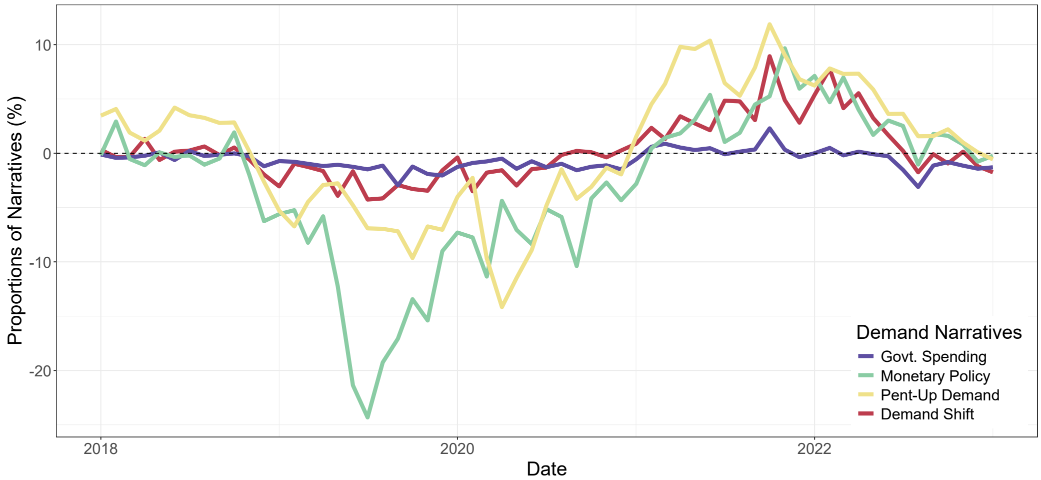
Figure 5: Change of polarity in corpus



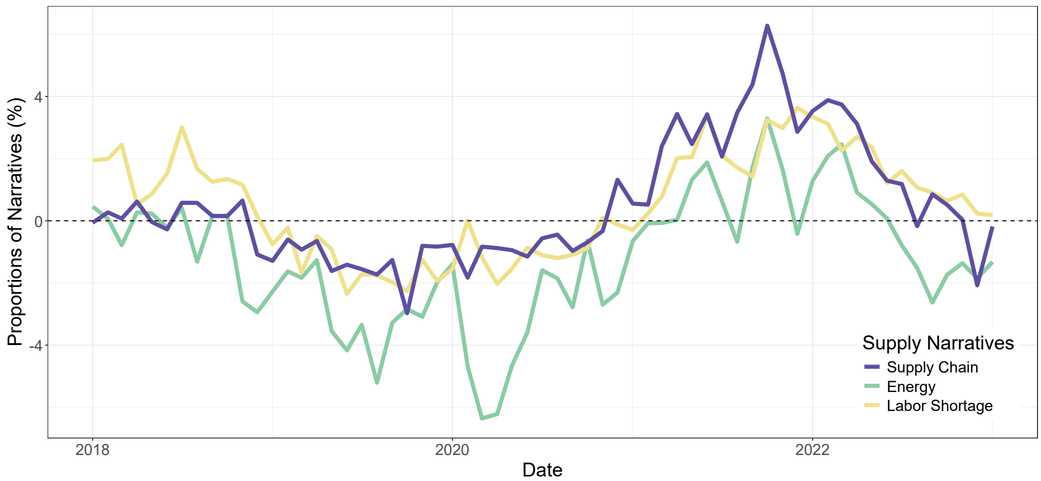
Note: The figure shows the development of the aggregated polarity score computed by LSS. To ensure readability, the time series is smoothed by applying a local polynomial regression (Watanabe, 2023) with 95% confidence intervals.

Lastly, by combining our keyATM and LSS results, we construct the final narrative indices. We begin with the demand narratives, which are visualized in figure 6a. As the figure illustrates, the demand inflation narratives are present during two considered periods: the non-inflationary (pre- and early pandemic) and the inflationary period (particularly since 2021). Until mid-2020, narratives highlighting monetary policy and pent-up demand factors are particularly prominent. The importance of the monetary policy narrative is exceptionally strong in mid-2019, meaning that a large number of reports about falling inflation rates were discussing aspects of monetary policy. This coincides with the previously discussed fall of the CPI rate under the inflation target. It also marks the first interest rate cut by the Fed in eleven years (Board of Governors of the Federal Reserve System, 2019). In late 2021, the narrative reaches positive values and gains relative significance in the media coverage about rising inflation rates.

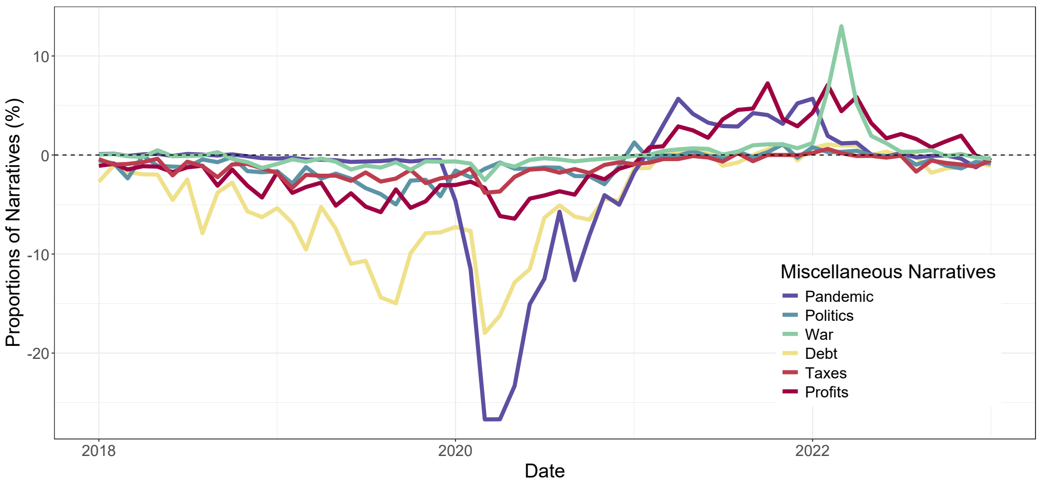
[3]For comparison: U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, February 21, 2024.



(a) Indices of demand narratives



(b) Indices of supply narratives



(c) Indices of miscellaneous narratives

Note: The figures show the constructed narrative time series. Negative values signify the relative importance of a narrative in the context of falling inflation rates, whereas positive values represent the relative importance in the context of rising inflation rates.

In contrast, the pent-up demand narrative reaches its minimum in early 2020, during the first announced economic lockdown following the COVID-19 outbreak. However, only a few months later, the narrative experiences significant positive growth. By 2021, it reaches relatively high positive values. The demand shift narrative also contributes to the media discourse about rising inflation rates but peaks with a lag compared to the pent-up demand narrative. Media reports on government spending as cause of inflation was not widespread during this entire period. We report only minor growth in late 2020 and early 2021. During this time, there were controversial discussions about large-scale infrastructure programs, which were questioned by Republicans and centrist Democrats (e.g., Peterson, 2021). In conclusion, we report positive values for all demand narratives from the beginning of 2021, but we observe significant differences in volume and timing.

Turning to the supply narratives, a similar trend becomes evident, with less negative values during the non-inflationary period. As Figure 6b shows, only the energy narrative reaches profound negative values. In contrast, all three narratives show significant positive growth in 2020 and reach positive values in early 2021. Overall, all three narratives follow a similar path, with the supply chain reporting the steepest increase, whereas the energy narrative is more volatile. Additionally, it is the first among supply narratives to experience negative values already in mid-2022. Only the labor shortage narrative reports a positive score until the end of the observation period.

Larger differences among the narratives do we report for the miscellaneous. As figure 6c shows, the tax and politics narratives experience only minor changes, however, there is a slight increase from the end of 2020 to early 2021 for the politics narrative. In contrast, the pandemic narrative records pronounced changes and is highly polarized. While non existing until end of 2019, it experienced a remarkable decline during early 2020. This is in line with the spread of the COVID-19 virus and the associated non-pharmaceutical measures. However, the pandemic narrative is also rapidly recovers, besides a smaller setback in late 2020. The debt narrative is primarily experiencing a profound negative score in 2020, while it remained more or less insignificant during the inflationary period. Characterized by fewer extremes, the profit narrative is present in both periods. Further, the narrative is more persistent during the inflationary period with a comparably late peak in 2022. Lastly, the war narrative is not existing until early 2022, which coincides with the invasion of Russia in the Ukraine. It rapidly declines afterwards.

3.3 Granger Causality

So far, our analysis has revealed two key findings. First, combining survey study results with a semi-supervised topic model and a latent sentiment scaling technique enables us to measure and quantify known concepts of inflation narratives. Thus we are able to describe their evolution over time and identify narrative-specific polarity. Second, we provide descriptive evidence on the spread of inflation narratives. For the considered time period, those emphasizing changes in demand and its strong recovery, monetary policy, and supply issues as causes of inflation are particularly notable. Additionally, our descriptive analysis has shown that narratives on profits and specific crisis-related aspects, such as pandemic or war in Ukraine, are highly featured in news media articles.

In contrast, other narratives, including those on government spending, politics, debt, and taxes, are less often featured in reports about rising inflation rates.

To deepen our understanding of how inflation narratives interact with the macroeconomy, especially inflation expectations, we first construct multiple multivariate VAR models to test for potential Granger causalities in our system. The VAR models include short-term and mid-term expectations, CPI inflation, economic activity and one of the measured narrative indices. Even tough the procedure is based on predictability, and not on direct causal effects, we follow Granger's argument that predictive power can serve as an indicator for potential causalities (Shojaie and Fox, 2022). Additionally, by applying the test procedure in a more restrictive VAR setting we control relevant information beyond a bivariate relationship. In a second step we take existing economic research into account that indicates strong variations of inflation expectations among different socioeconomic groups (e.g., European Central Bank (2021); Weber et al. (2022)). Further, pioneer survey studies suggest that the narratives of households are diverse and systematically related to individual characteristics (e.g., Andre et al. (2023); Demgensky and Fritsche (2023)). To address this variation, we analyze disaggregated household expectations based on income, education, age, and numeracy, employing data from the New York Fed Survey of Consumer Expectations. Afterwards, we re-estimate our multivariate Granger causality tests by incorporating the expectations of subgroups (e.g. low income or high educated households) from each socioeconomic category to identify any potential Granger causal relationships.

3.3.1 Aggregated Expectations

As discussed in Chapter 2, we treat all variables as trend-cycle filtered series and use them as baseline estimates. For robustness, we provide level and difference estimations in the Online Appendix. The results of the baseline estimation are shown in table **??**. It provides a comprehensive overview of all p-values of the Granger causality analysis, indicating whether or not a narrative is Granger-causing 1-year or 3-year expectations. Thus, we test whether the integration of a narrative lag into a system of lagged variables improves the prediction of the households' expectations. As the table shows, we report several significant Granger-causal relationships.

For the demand narratives, we report significant results exclusively for the demand shift narrative at the aggregate level. For short-term expectations, we identify Granger-causal relationships for the supply chain and labor shortage narratives. For medium-term expectations, we confirm these results, but only for the supply chain narrative. Further Granger causalities are evident for the miscellaneous narratives, in this case for both expectations. This includes the war and profits narratives for short- and medium-term expectations. In summary, we find several highly significant Granger causalities for the narratives considered, with only minor changes between 1-year and 3-year expectations. In addition, we examine potential feedback relationships in table **??**. We test the exogeneity of the narratives with respect to aggregate expectations. Among the previous Granger causalities, our estimation suggests a feedback relationship with 3-year expectations only for the supply chain narrative. We also find some reverse Granger causality for the pent-up demand and energy narratives from 1-year expectations and for energy from 3-year expectations.

Narratives	**One-Year Expectations** (Pr(>F))	**Three-Year Expectations** (Pr(>F))
Demand		
Government Spending	0.20	0.25
Monetary Policy	0.77	0.19
Pent-up Demand	0.80	0.82
Demand Shift	<0.01 ***	0.08 *
Supply		
Supply Chain	0.05 **	0.13
Energy	0.80	0.44
Labor Shortage	<0.01 ***	0.17
Miscellaneous		
Pandemic	0.36	0.21
Politics	0.72	0.65
War	0.05 *	0.04 **
Debt	0.32	0.78
Taxes	0.66	0.83
Profits	0.05 **	0.04 **
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3: Granger causality analysis (boosted HP-Filter)

To ensure robustness, we provide additional level and difference estimations in the Online Appendix in tables **??** and **??**. Overall, the results with the boosted HP filter are confirmed by the level estimates, although more significant relationships are reported. In contrast to the trend-cycle filtered estimation, these results suggest Granger causality for monetary policy, labor shortage, and politics on 3-year expectations. The results are supported for the demand shift, supply chain, labor shortage (1-year expectations), and profit narrative for short- and/or medium-term expectations. In comparison, the difference estimations give a more restrictive picture, but all of the Granger causalities for short-term expectations are supported. In contrast, for medium-term expectations, the estimation only supports the initial results for the demand shift. In addition, we report significant results for the government spending narrative.

At last, our results suggest that narratives featured in media reports possess inherent statistical predictive power for household expectations. This can be interpreted as an indicator of potential causalities Shojaie and Fox (2022). Moreover, our findings suggest that Granger causalities are present in all categories, but there are slight differences in the data between short-term and medium-term expectations. To address the challenge of potential nonstationarity, we consider results with three different estimation strategies. Although we find some differences between these estimations, most of the results, especially for short-term expectations, are confirmed. Moreover, correlative evidence from Andre et al. (2023) and Stantcheva (2024) backs our findings regarding how important supply and profit narratives are for 1-year expectations. In contrast to these survey studies, we do not report significant p-values for the politics, monetary policy, and government spending narratives on aggregate expectations. This could be partly explained by the considered news source, which targets financial market actors and experts.

Narratives	**One-Year Expectations** (Pr(>F))	**Three-Year Expectations** (Pr(>F))
Demand		
Government Spending	0.11	0.07 *
Monetary Policy	0.62	0.58
Pent-up Demand	<0.01 ***	0.18
Demand Shift	0.90	0.31
Supply		
Supply Chain	0.04 **	0.09 *
Energy	0.03 **	0.12
Labor Shortage	0.65	0.10
Miscellaneous		
Pandemic	0.17	0.21
Politics	0.90	0.93
War	0.98	0.72
Debt	0.32	0.88
Taxes	0.81	0.90
Profits	0.95	0.68
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: Reverse granger causality analysis (boosted HP-Filter)

3.3.2 Socioeconomic Heterogeneity

Heterogeneity by Income - We begin the discussion of socioeconomic heterogeneity by looking at differences in income. The New York Fed survey distinguishes three income groups: below $50k, $50k to $100k, and above $100k per year. The results in table **??** in the Online Appendix show some differences between the considered groups. With respect to short-term expectations, our results suggest only small distinctions between the different income groups. What is significant for all groups are the demand shift, supply chain, labor shortage, and profit narratives. However, for the lower- and middle-income groups, we additionally report significant results for the war narrative. We report significant results for the pandemic narrative solely for middle- and upper-income households. In contrast, we observe stronger heterogeneity across incomes for medium-term expectations. Our results emphasize the significance of demand narratives for middle- and high-income households, while significant effects appear only for the energy narrative among lower-income households. Our analysis suggests that the 3-year expectations of middle-income households appear to respond only to demand narratives. In contrast, we report multiple Granger causal relationships for high income-households, including narratives demand, supply, and miscellaneous narratives.

Heterogeneity by Education - To access further potential heterogeneity of narratives across socioeconomic groups, we conduct Granger tests for different educational backgrounds of households. Accordingly, we consider the household groups with a high school degree or less, some college, and a BA or higher. The results are shown in table **??** in the Online Appendix. As our analysis suggests, households with high levels of education are more responsive to narratives that emphasize demand shifts, supply chain issues, or profits. However, we find partly similar results for all household groups. The pandemic and war narratives are also important for high educated households' medium-term expectations. In contrast, we observe significant results for households with some college education or less with regard to government spending. Interestingly, this is the only Granger causality to 3-year expectations we observe for this group. Lastly, the data suggest that the labor shortage narrative Granger-causes short-term expectations of households with some college degree or less.

Heterogeneity by Age - Pronounced variations with respect to age are visible in **??** in the Online Appendix. As before, we observe less heterogeneity across different ages for short-term expectations than for medium-term expectations. For the analysis, we consider three groups: under 40, 40 to 59, and over 59. Overall, we find fewer Granger causality relationships for the oldest households. Moreover, for households aged 40 and older, demand narratives are significant. Further, for these households numerous supply narratives are particularly important for short-term expectations. In contrast, we observe the most Granger-causal relationships for miscellaneous narratives among the youngest cohort. Overall, this analysis highlights the relevance of age as a determinant of heterogeneity across households.

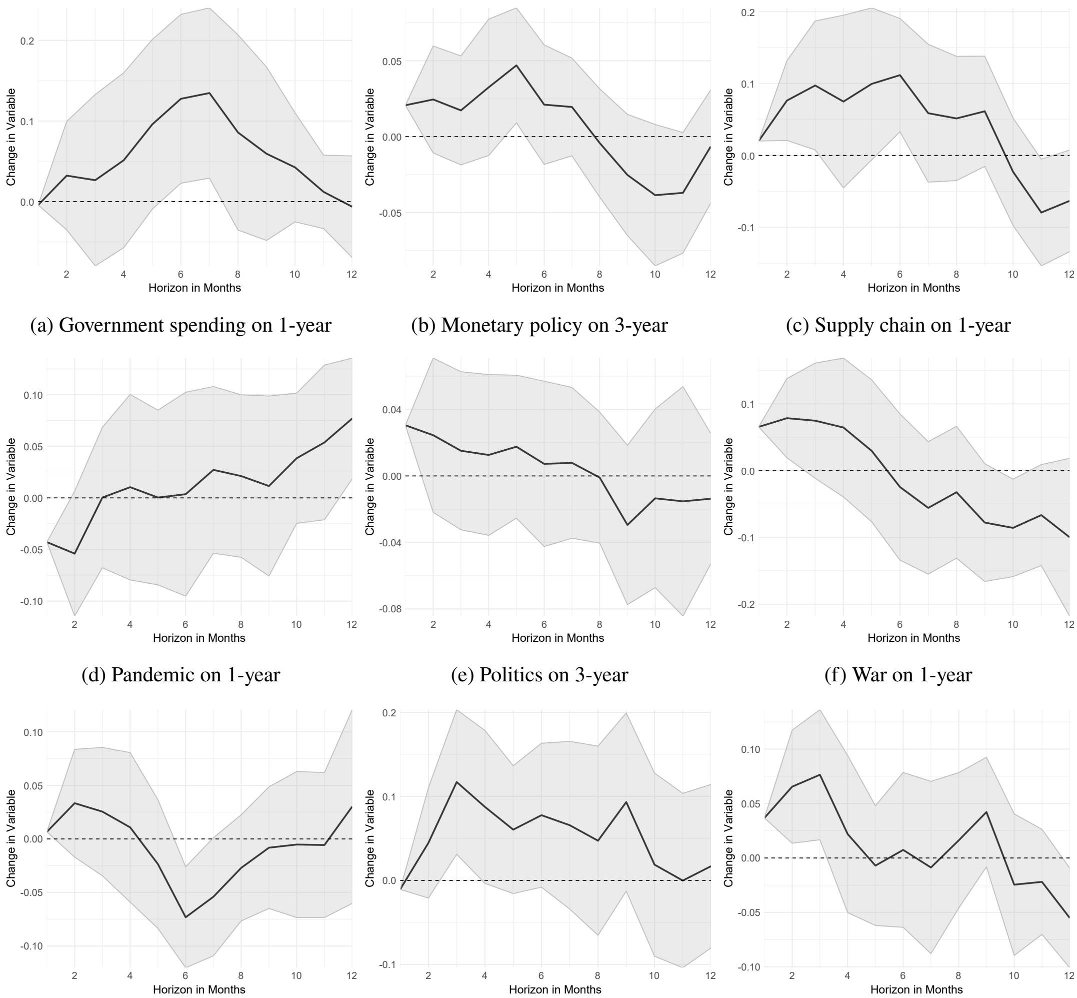
Heterogeneity by Numeracy - Finally, we examine potential heterogeneity between households with low and high numeracy in table **??** in the Online Appendix. Overall, our analysis indicates only minor differences for 3-year expectations. Comparatively, our results indicate strong differences among households' short-term expectations. For households with a lower numeracy, our analysis highlights the importance of the war and pandemic narratives. For high numeracy households, more Granger-causal relationships for the supply and demand narratives are present. Furthermore, we again identify that the profit narrative is relevant for short-term expectations.

3.3.3 Dynamic Responses

To further investigate potential causal relationships between our narratives and households' expectations, we estimate impulse responses. This approach allows us to gain a more comprehensive understanding of the impact that an increasing diffusion of narratives has at the macroeconomic level. In the following section, we provide an overview of the impulse responses that we conducted by means of Jordà (2005)'s local projections. In this process, the impulse responses measure the effect of an impulse to the system, i.e. how an impulse at a specific point of time t_0 in one equation proceeds through a system (Kirchgässner and Wolters, 2007, 138). In this case, we consider a shock the size of one standard deviation of the error term. We conduct several multivariate models that contain five different variables: 1-year and 3-year expected inflation by households, CPI inflation, economic activity, and one of our constructed narrative indices. Again, as mentioned in chapter 2.2, we treat all variables as trend-cycle filtered time series and use them as a baseline. For the robustness, we estimated the local projections with levels and differences. To ensure readability and an efficient use of the limited space, we included all graphical illustrations of the impulse responses in the Online Appendix. The complete set of baseline impulse responses are illustrated in figure A.7, A.8, A.9, and A.10 in the Online Appendix. Figure 7 reports a selection of significant responses. The x-axis represents the forecast horizon s, with a maximum of 12 months, while the y-axis shows the change in 1- or 3-year household expectations in response to a standardized deviation innovation. The black line represents the mean response to a shock, while the gray area around the line visualizes the 90% confidence interval.

We begin by examining the response to demand narrative shocks. In doing so, we observe statistically significant positive responses for all demand narratives. Comparatively, we note some differences in the paths of the responses. The shock in the government spending narrative is the longest lasting among the demand narratives. The response to a shock in the demand shift narrative is of the same magnitude but of shorter duration, while we also observe a smaller magnitude for the monetary policy narrative. Only initially positive reacts the medium-term expectations to a shock in the pent-up demand narrative. These findings are consistent with the positive coefficients for the monetary policy and government spending narratives in Andre et al. (2023). The impulse responses for the supply chain narrative are in line with the discussion about its anchoring tendency in Andre et al. (2023); Demgensky and Fritsche (2023). The response is short-lived and temporarily negative. While there is a primarily statistically significant reaction only for the energy narrative, the relevance of the supply chain and labor shortage narrative for household expectations is again highlighted. For the latter, the response is profound and comparatively persistent. Finally, the ways in which the miscellaneous narratives react to a shock are more diverse, with a large number of responses being insignificant. We establish only partially significant results for short-term expectations to a shock in the pandemic narrative, which are initially negative, before they turn positive over time. In contrast, a shock to the politics narrative seems to initially raise expectations, especially in the medium-term, and then return to the baseline. Furthermore, the war narrative and the profits narrative should be emphasized. The profits narrative indicates positive responses in both expectations, which are also relatively strong in terms of magnitude, with a rather transient effect on 3-year expectations. The response to the war narrative is exceptional considering its strong decreasing tendency after an initial increase. Overall, the results are roughly in line with our previous findings and the results of the survey conducted by Andre et al. (2023); Stantcheva (2024); Demgensky and Fritsche (2023).

Figure 7: Selection of narratives' impulse responses



(a) Government spending on 1-year

(b) Monetary policy on 3-year

(c) Supply chain on 1-year

(d) Pandemic on 1-year

(e) Politics on 3-year

(f) War on 1-year

(g) War on 3-year

(h) Profits on 1-year

(i) Profits on 3-year

Note: The graphs show the mean responses and 90% confidence bands. The x-axis shows months (s) after narrative diffusion event; t = 0 is the month of the shock event. The y-axis shows the change in expectations as a response to the shock event. The shock considered is of the size of one standard deviation.

To summarize the analysis of aggregate expectations, it can be concluded that a (positive) narrative shock is followed by an initial positive response of households' expectations. At the same time, a closer look reveals differences in the paths of the responses. Comparing 1-year and 3-year expectations, the response in 1-year expectations is more pronounced in terms of magnitude and, in many cases, more persistent. The results also highlight some important differences between the narratives. While our results indicate significant positive responses for most demand and supply narratives, the responses of the latter are less persistent and in some cases insignificant for 3-year expectations, suggesting a stronger anchoring tendency of these narratives. On the other hand, the responses to a shock in the other narratives are more diverse. Among these, the profit narrative stands out for its profound effect on short-term expectations.

As for the Granger causality tests, we provide robustness estimates again using levels and differences. The results for the selected impulse responses from figure 7 are shown in the Online Appendix with level specification in figure A.11, and figure A.12 visualized the results with the differences. While the responses under level specification are more persistent, the responses with differences time series are more ambivalent and unstable. In general, the robustness estimations support our findings. However, for the pandemic narrative only, both robustness estimations indicate no significant reaction in household expectations. It should be noted, that the baseline estimation indicates an overall stronger anchoring tendency of expectations.

4 Conclusion

This paper proposes a new methodological approach to measure known inflation narratives in news reports. The combination of survey information on inflation narratives with a supervised topic model and a latent semantic scaling approach provides information on the prevalence and spread of narratives in a large text corpus, including the Wall Street Journal. For the recent inflationary period, our descriptive results highlight the presence of narratives about changing demand, supply factors including the supply chain, energy prices, and labor shortages, as well as stories about the war in Ukraine and corporate profits. Conversely, narratives about monetary policy, energy, government debt, and the pandemic were prevalent in the preceding period of low inflation and deflation, respectively. To further investigate the relevance for macroeconomic development, additional time series analyses were conducted. As suggested by the multivariate Granger causality tests, the considered narratives contain relevant information for households' expectations. This is in line with the theoretical arguments presented in Shiller (2017); Tuckett et al. (2020) and Beckert (2016). While our estimates suggest only small differences between short- and medium-term aggregate expectations, we highlight heterogeneity across socioeconomic groups. We document notable differences in income, education, age, and numeracy, especially for medium-term expectations. For example, our results imply that the energy narrative is the main driver of 3-year expectations for households with lower annual incomes, while several narratives Granger-cause the expectations of high-income households. In addition, our analysis points to the importance of age as a driver of heterogeneity. To further investigate potential differences in the pathways of responses to narrative diffusion, we conduct impulse responses. Our estimates show that the responses to 1-year expectations are more pronounced and often more persistent. Moreover, when comparing shocks across narratives, we notice more anchored expectations with respect to a shock in the supply chain, demand shift, and profits narratives.

In summary, our paper reveals the powerful role that media narratives play in shaping economic expectations, potentially anchoring or unanchoring inflation expectations over time. This impact varies by narrative type and socioeconomic backgrounds of households, making it particularly relevant for monetary policymakers, who may pay even more attention to media coverage. By recognizing the diverse impact of these narratives, policymakers can develop more targeted communication strategies. Future advances in narrative analysis hold the promise of enabling even more responsive and adaptable policy interventions, aligned with the evolving narratives captured in media.

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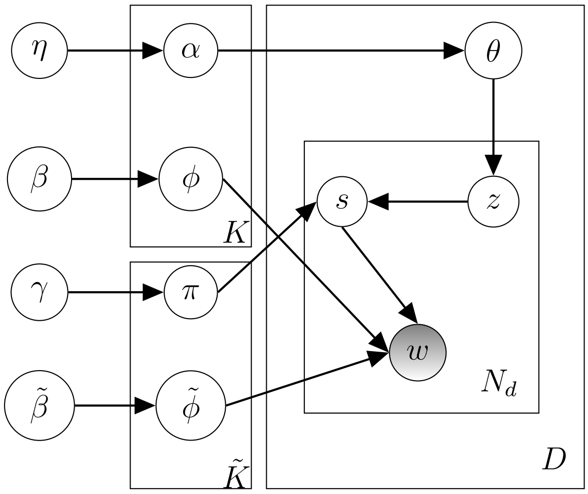
A Appendix - Going Viral: Inflation Narratives and the Macroeconomy

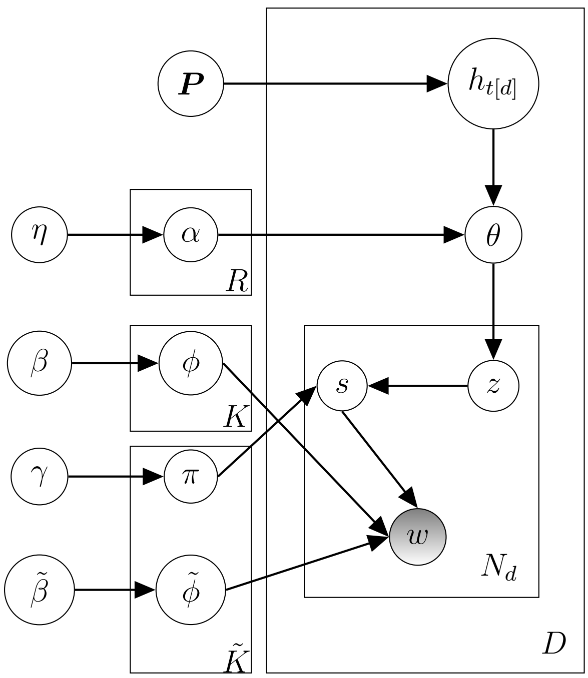
A.1 Supplementary Figures and Tables

Figure A.1: Graphical model of base keyATM



The shaded node (w) denotes observed variables, while other transparent nodes denote latent variables. Source: (Eshima et al., 2020, 40)

Figure A.2: Graphical model of dynamic **keyATM**



The shaded node (w) denotes observed variables, while other transparent nodes denote latent variables. Source: (Eshima et al., 2020, 41)

Figure A.3: Modelfit

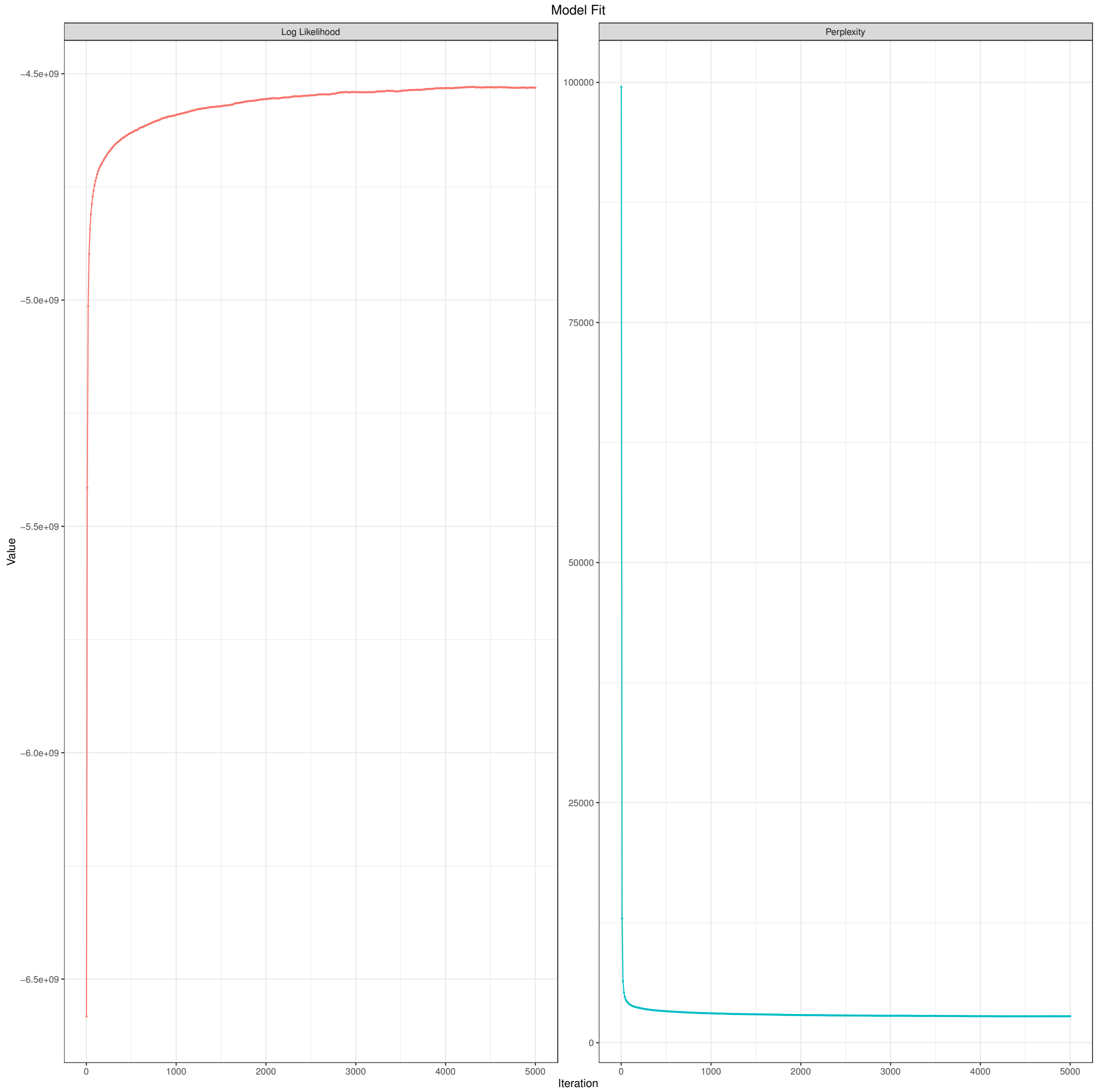


Figure A.4: Estimated alpha

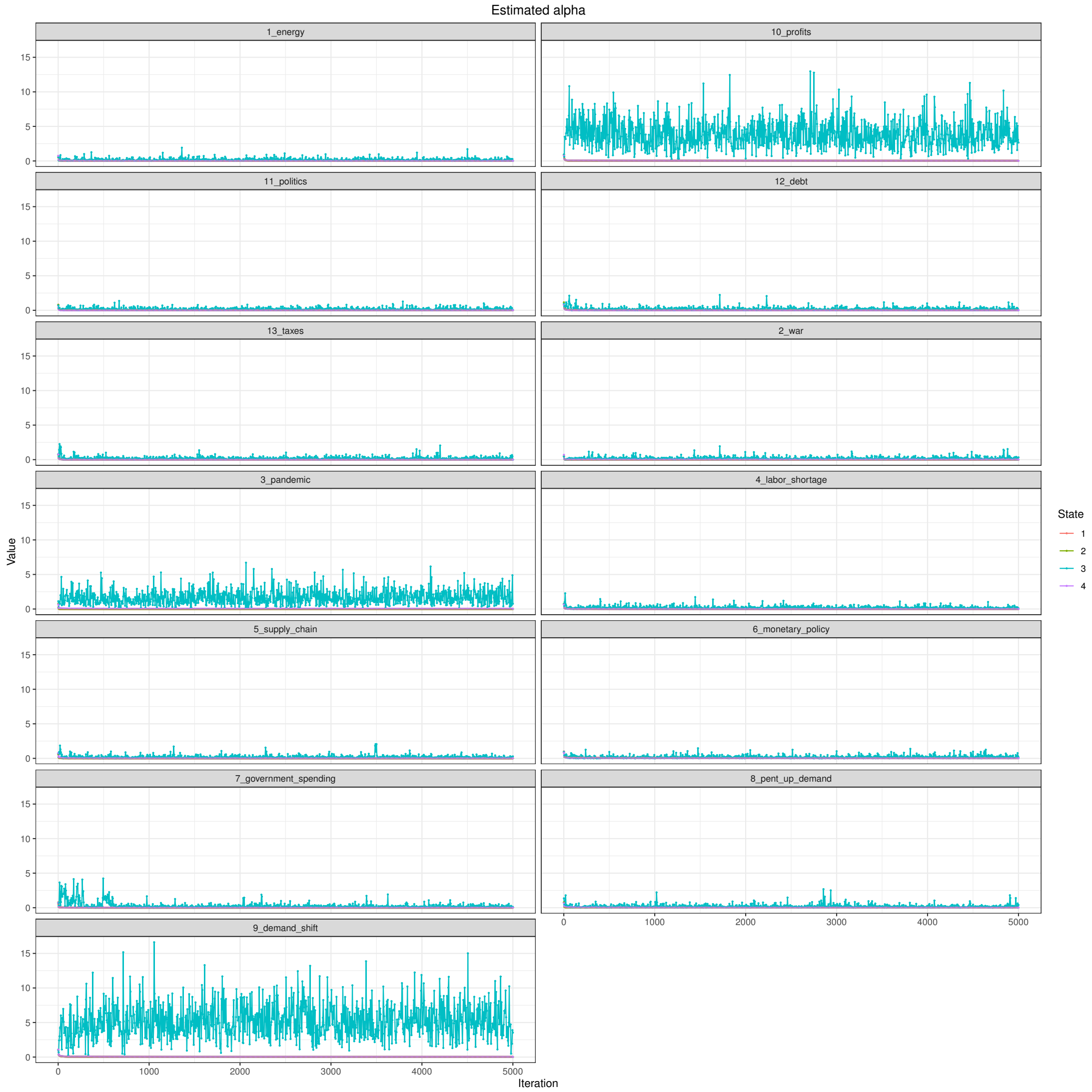
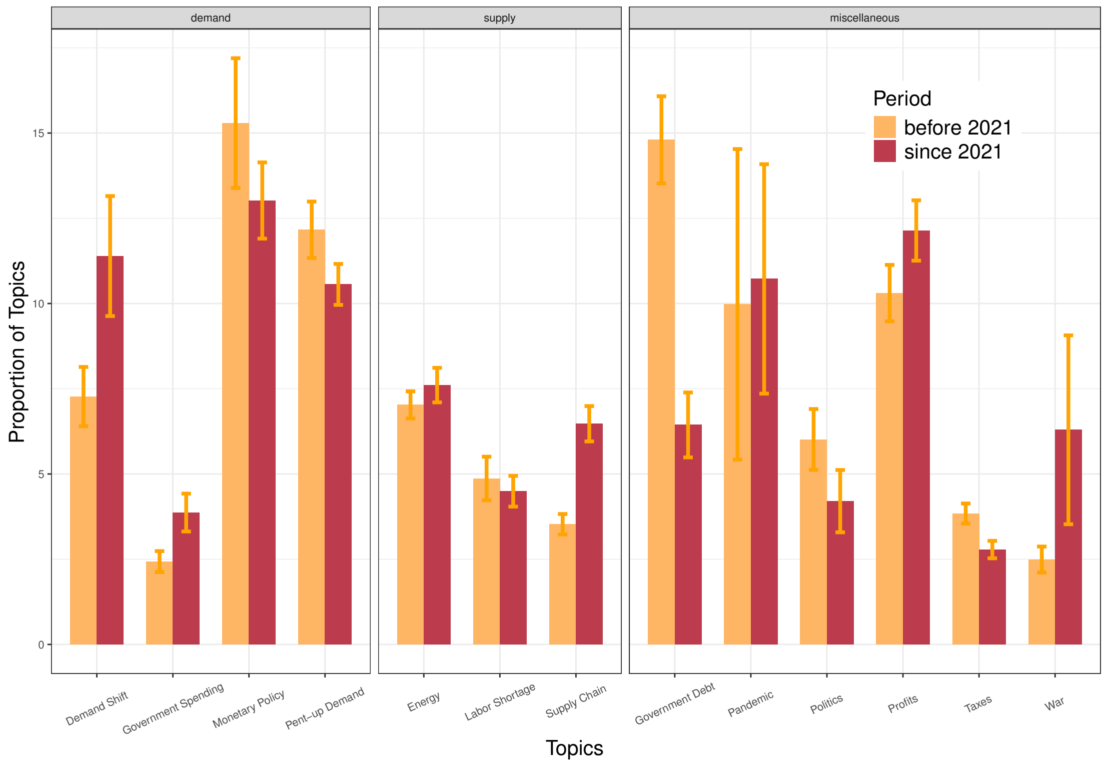


Figure A.5: Change of mean proportions



Note: The Figure shows the change in mean proportions since 2021 with the 95% confidence intervals. To calculate the relative proportions only the topics with pre-specified keywords were considered, so that the sum of the proportions of all keyword topics equals 1. All other non-keyword topics were excluded. We organized the topics by following the code system provided by Andre et al. (2023).

Figure A.6: Change of mean proportions

Variable	**Statistic**	**Critical Value 1%**	**Critical Value 5%**	**Critical Value 10%**
Government Spending	2.33	1.95	3.11	4.17
Monetary Policy	4.85	1.95	3.11	4.17
Pent-up Demand	3.44	1.95	3.11	4.17
Demand Shift	4.51	1.95	3.11	4.17
Supply Chain	4.97	1.95	3.11	4.17
Energy	2.72	1.95	3.11	4.17
Labor Shortage	7.01	1.95	3.11	4.17
Pandemic	2.01	1.95	3.11	4.17
Politics	3.14	1.95	3.11	4.17
War	0.92	1.95	3.11	4.17
Debt	3.86	1.95	3.11	4.17
Taxes	3.56	1.95	3.11	4.17
Profits	7.27	1.95	3.11	4.17

Table A.1: Elliott, Rothenberg and Stock unit root test results

Narratives	**One-Year Expectations** (Pr(>F))	**Three-Year Expectations** (Pr(>F))
Demand		
Government Spending	0.09 *	0.19
Monetary Policy	0.69	<0.01 ***
Pent-up Demand	0.27	0.15
Demand Shift	<0.01 ***	<0.01 ***
Supply		
Supply Chain	<0.01 ***	<0.01 ***
Energy	0.98	0.17
Labor Shortage	0.17	0.08 *
Miscellaneous		
Pandemic	<0.01 ***	0.22
Politics	0.27	0.09 *
War	0.70	0.15
Debt	0.86	0.27
Taxes	0.36	0.18
Profits	<0.01 ***	<0.01 ***
Note:		*p<0.1; **p<0.05; ***p<0.01

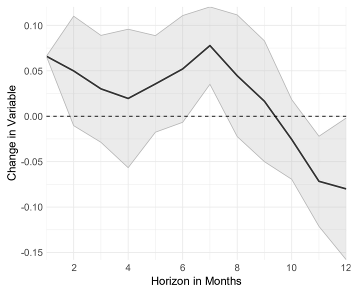
Table A.2: Granger causality analysis (level)

Narratives	**One-Year Expectations** (Pr(>F))	**Three-Year Expectations** (Pr(>F))
Demand		
Government Spending	0.01 **	0.15
Monetary Policy	0.68	0.26
Pent-up Demand	0.91	0.86
Demand Shift	<0.01 ***	0.12
Supply		
Supply Chain	0.02 **	0.08 *
Energy	0.96	0.27
Labor Shortage	0.12	0.94
Miscellaneous		
Pandemic	0.58	0.71
Politics	0.59	0.55
War	0.51	0.12
Debt	0.07 *	0.97
Taxes	0.86	0.73
Profits	0.22	0.55
Note:		*p<0.1; **p<0.05; ***p<0.01

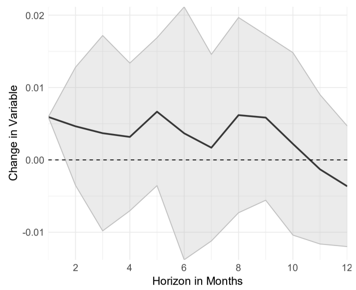
Table A.3: Granger causality analysis (differences)

Figure A.7: Demand narratives' impulse responses

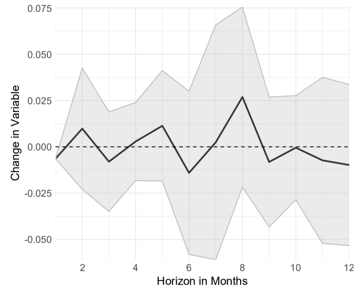
(a) Government spending on 1-year expectations



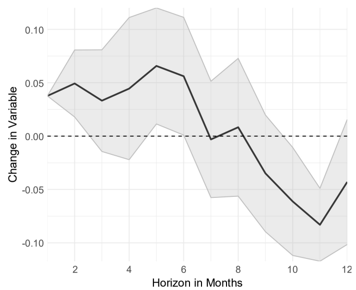
(b) Government spending on 3-year expectations



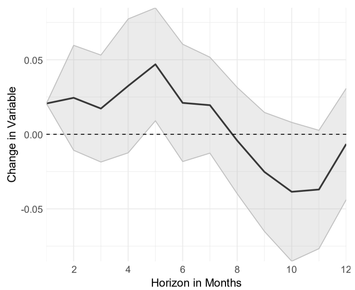
(c) Government spending on CPI inflation



(d) Government spending on economic activity

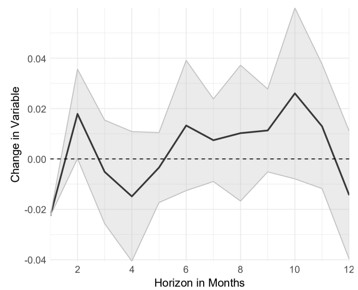


(e) Monetary policy on 1-year expectations

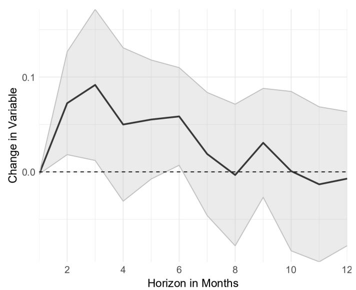


(f) Monetary policy on 3-year expectations

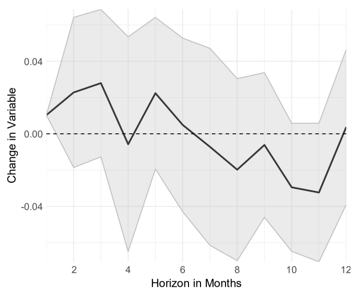
(g) Monetary policy on CPI inflation



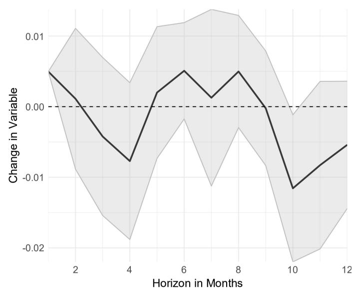
(h) Monetary policy on economic activity



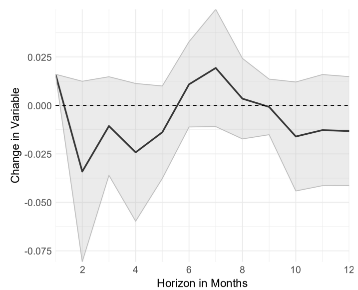
(i) Pent-up demand on 1-year expectations



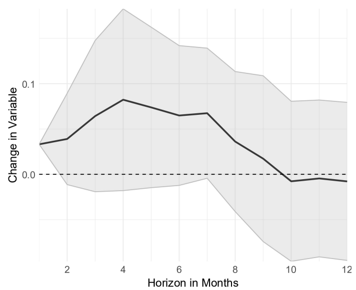
(j) Pent-up demand on 3-year expectations



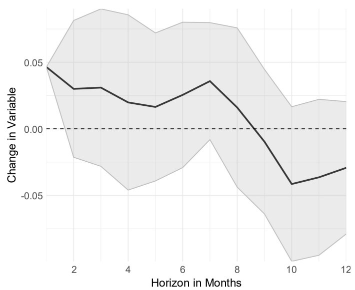
(k) Pent-up demand on CPI inflation



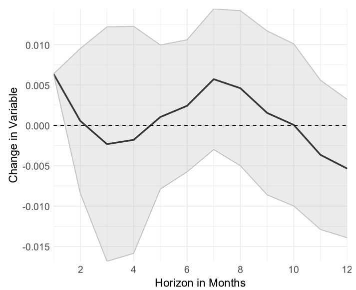
(l) Pent-up demand on economic activity



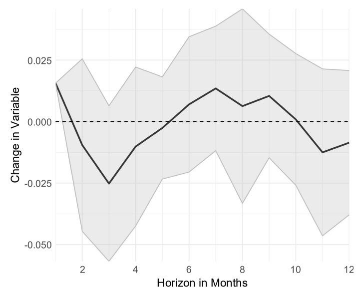
(m) Demand shift on 1-year expectations



(n) Demand shift on 3-year expectations

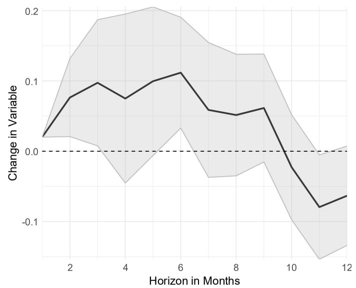


(o) Demand shift on CPI inflation

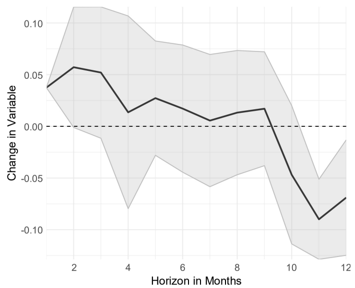


(p) Demand shift on economic activity

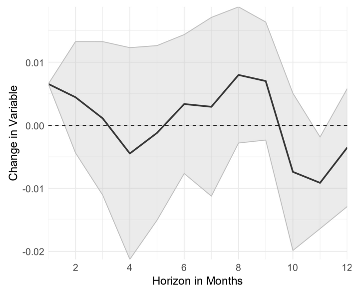
Figure A.8: Supply narratives' impulse responses



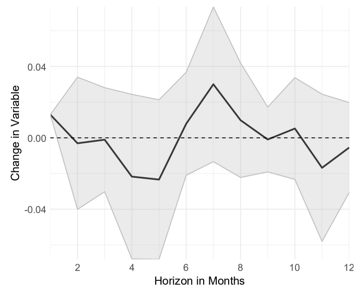
(a) Supply chain on 1-year expectations



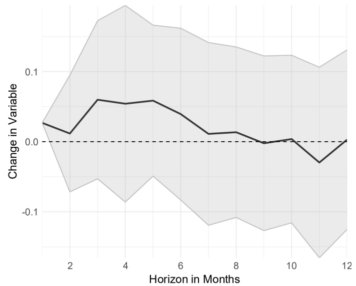
(b) Supply chain on 3-year expectations



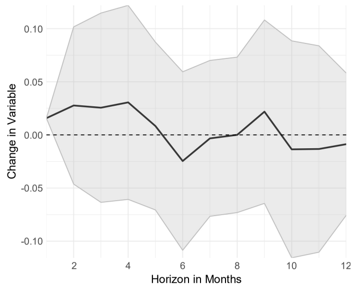
(c) Supply chain on CPI inflation



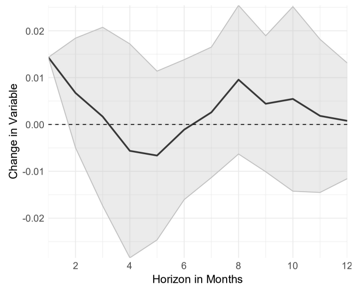
(d) Supply chain on economic activity



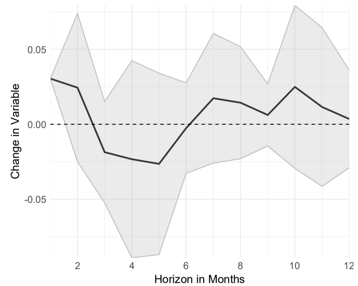
(e) Energy on 1-year expectations



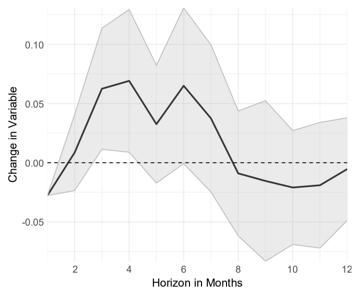
(f) Energy on 3-year expectations



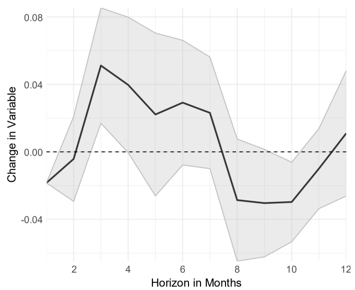
(g) Energy on CPI inflation



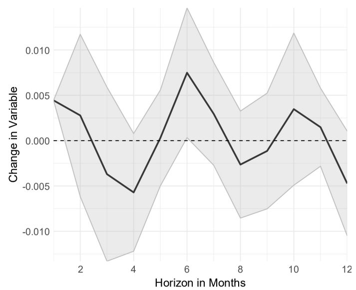
(h) Energy on economic activity



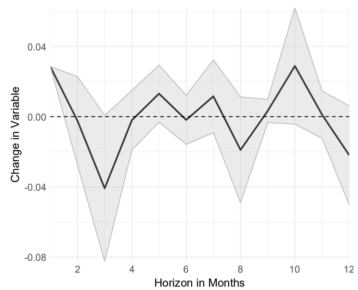
(i) Labor shortage on 1-year expectations



(j) Labor shortage on 3-year expectations

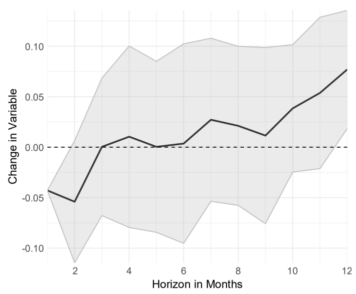


(k) Labor shortage on CPI inflation

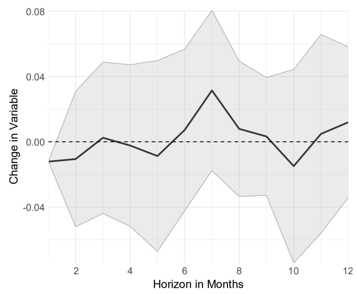


(l) Labor shortage on economic activity

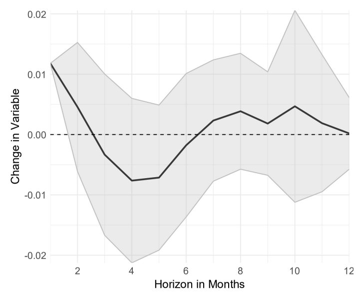
Figure A.9: Miscellaneous narratives’ impulse responses



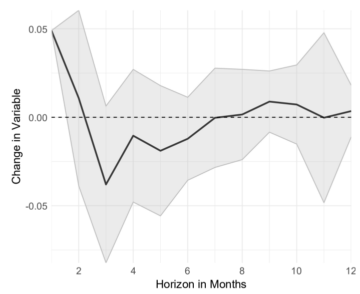
(a) Pandemic on 1-year expectations



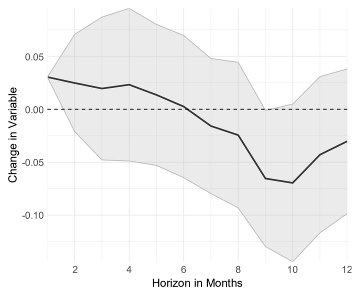
(b) Pandemic on 3-year expectations



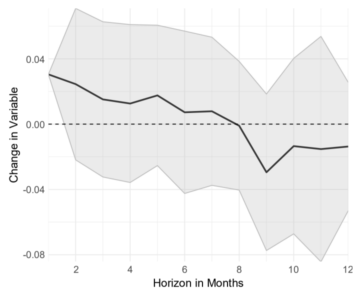
(c) Pandemic on CPI inflation



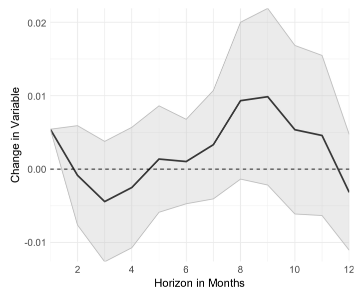
(d) Pandemic on economic activity



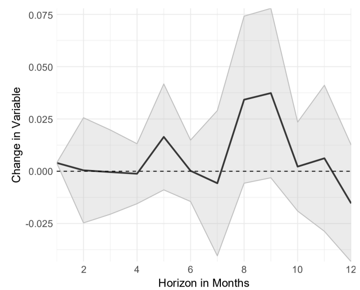
(e) Politics on 1-year expectations



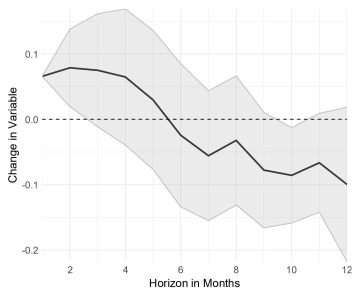
(f) Politics on 3-year expectations



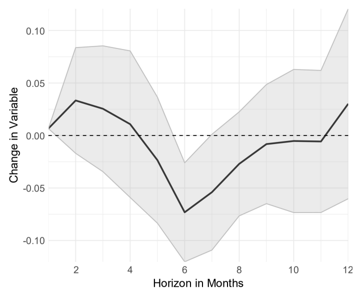
(g) Politics on CPI inflation



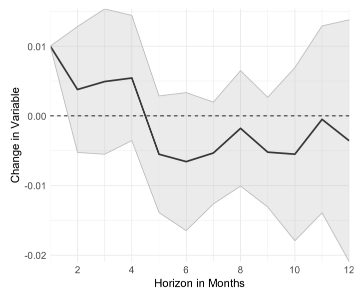
(h) Politics on economic activity



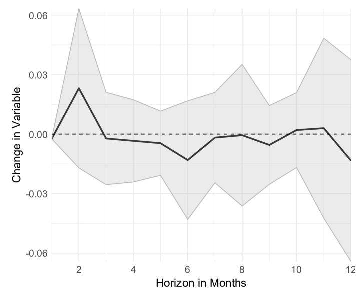
(i) War on 1-year expectations



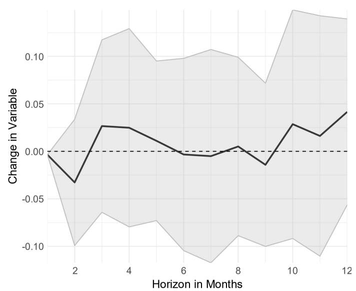
(j) War on 3-year expectations



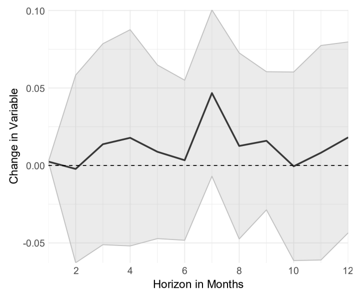
(k) War on CPI inflation



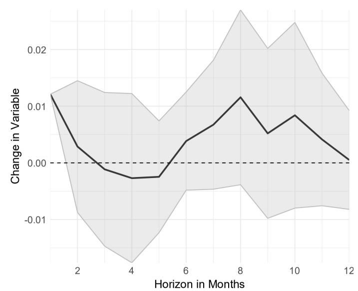
(l) War on economic activity



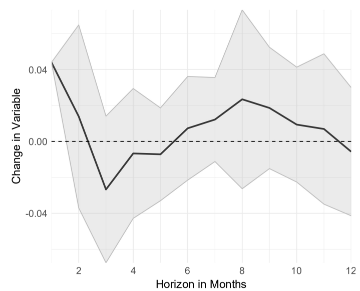
(m) Debt on 1-year expectations



(n) Debt on 3-year expectations

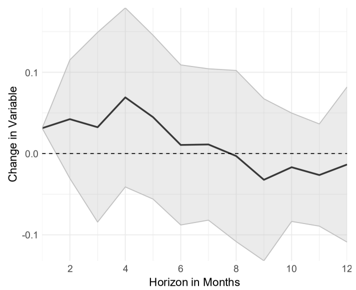


(o) Debt on CPI inflation

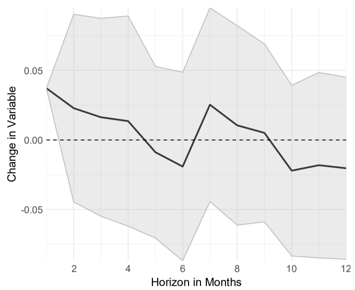


(p) Debt on economic activity

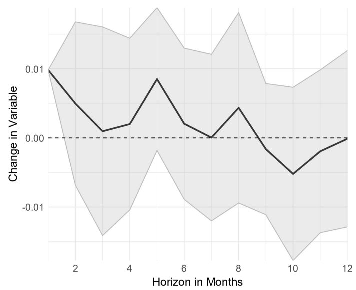
Figure A.10: Miscellaneous narratives' impulse responses



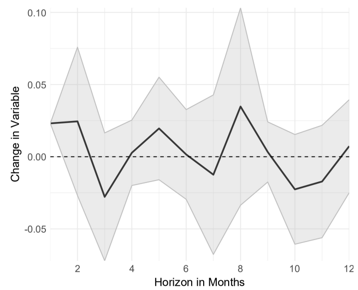
(a) Taxes on 1-year expectations



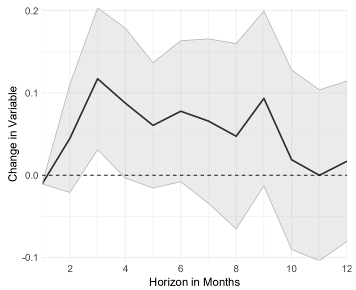
(b) Taxes on 3-year expectations



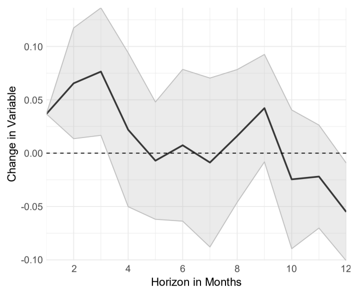
(c) Taxes on CPI inflation



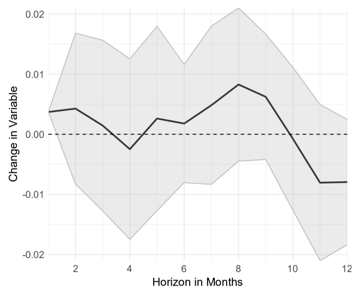
(d) Taxes on economic activity



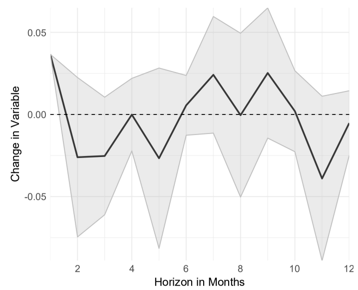
(e) Profits on 1-year expectations



(f) Profits on 3-year expectations

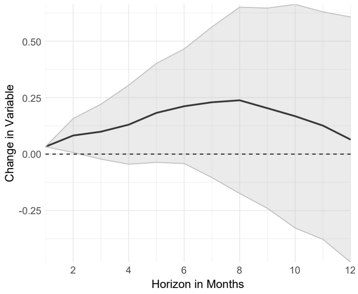


(g) Profits on CPI inflation



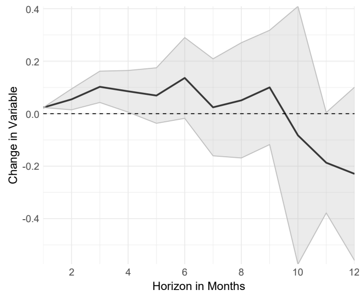
(h) Profits on economic activity

Figure A.11: Selection of narratives' impulse responses (Level)

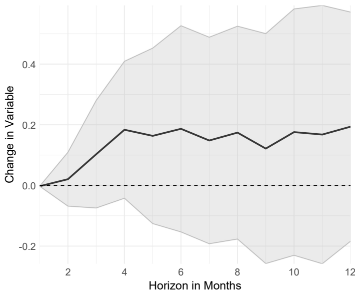


(a) Government spending on 1-year

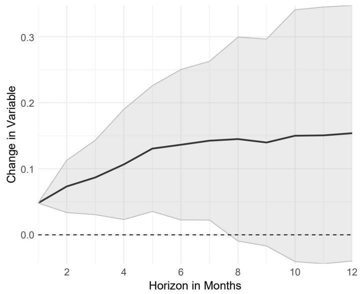
(b) Monetary policy on 3-year



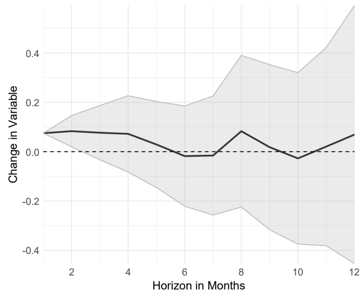
(c) Supply chain on 1-year



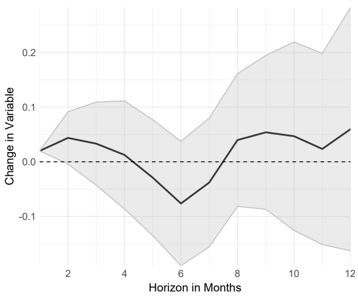
(d) Pandemic on 1-year



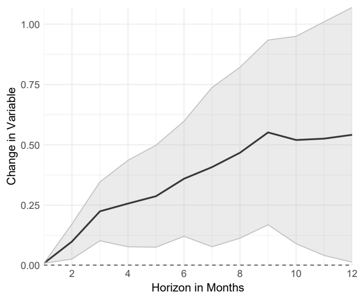
(e) Politics on 3-year



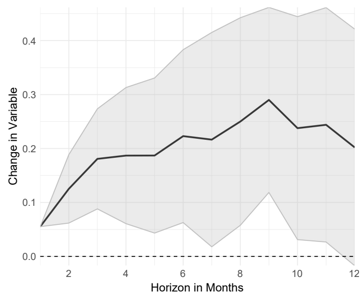
(f) War on 1-year



(g) War on 3-year



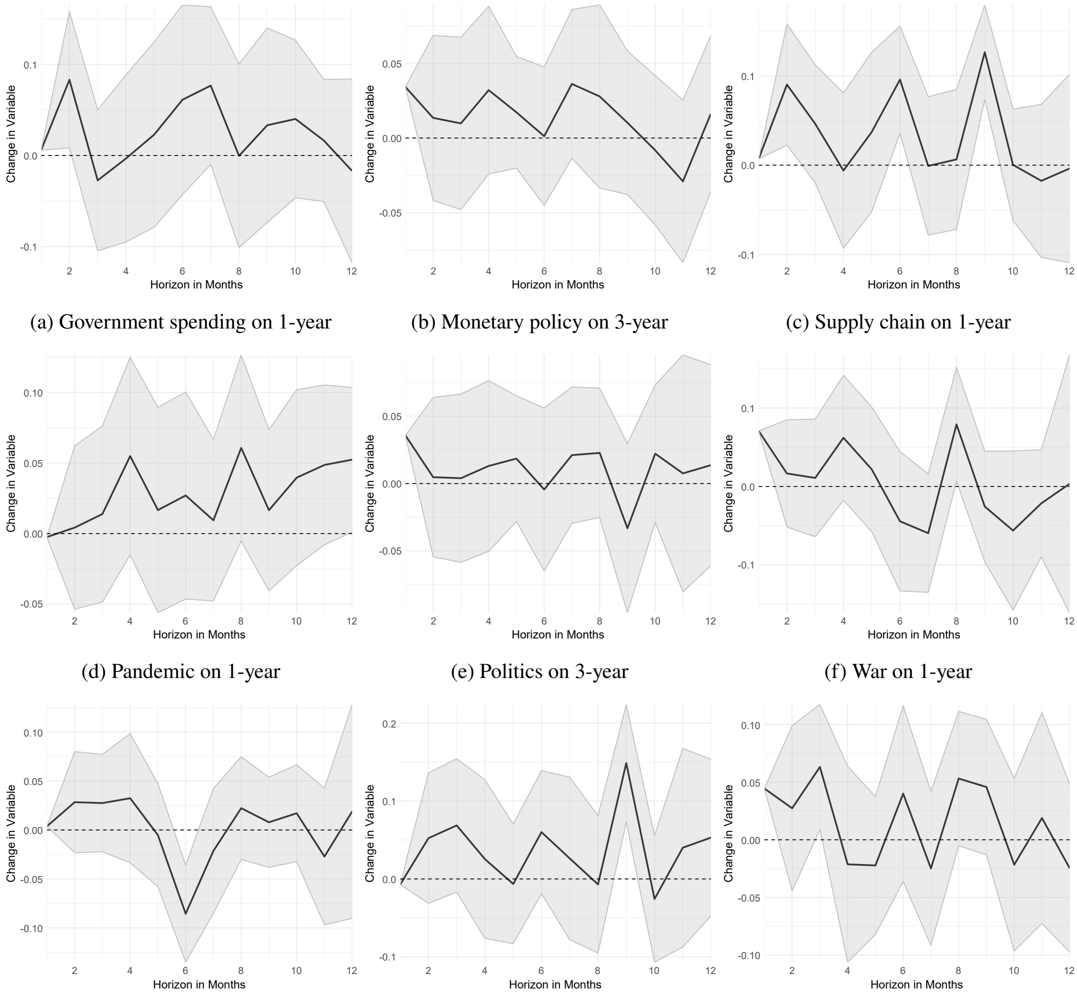
(h) Profits on 1-year



(i) Profits on 3-year

Note: The graphs show the mean responses and 90% confidence bands. The x-axis shows months (s) after narrative diffusion event; t = 0 is the month of the shock event. The y-axis shows the change in expectations as a response to the shock event. The shock considered is of the size of one standard deviation..

Figure A.12: Selection of narratives' impulse responses (differences)



(a) Government spending on 1-year (b) Monetary policy on 3-year (c) Supply chain on 1-year

(d) Pandemic on 1-year (e) Politics on 3-year (f) War on 1-year

(g) War on 3-year (h) Profits on 1-year (i) Profits on 3-year

Note: The graphs show the mean responses and 90% confidence bands. The x-axis shows months (s) after narrative diffusion event; t = 0 is the month of the shock event. The y-axis shows the change in expectations as a response to the shock event. The shock considered is of the size of one standard deviation.

A.2 Data preprocessing

In this section we describe the data pre-processing steps prior to the keyATM estimation. The Dow Jones Newswire is stored in .nml data files, that contain Extensible Markup Language (XML) Files. The raw Dow Jones Newswire contains roughly eight million documents for the observation period. This amount of documents and terms alone makes it computationally challenging. Moreover, many of these documents may not be of interest for the underlying research question(s) of this paper. To shrink the data set and at the same time allows for a greater focus on economic news about inflation, we pre-filtered the raw corpus in two ways: first, by using the subject codes from Dow Jones Newswire, we only selected relevant news sources, see A.8. This left us with approximately 350,000 documents. Additionally we explicitly removed articles that report tables, calendars, technical reports or press releases. Second, by applying a simple keyword filtering to generate a dataset only containing documents, which, in some way, report on inflation. The selected keywords are: “inflation”, “deflation”, “rising price[s]”, “increasing price[s]”, “price increase”, “rise of prices” and “stagflation”. The final corpus includes 163030 documents.

Subject Code	**Description**
DJIB	Dow Jones Investment Banker
DJG	Dow Jones Institutional News
GPRW	Dow Jones Global Press Release Wire
DJAN	Dow Jones Australian/New Zealand Report
AWSJ	Wall Street Journal Asia
WSJE	Wall Street Journal Europe
PREL	Press Release Wires
NRG	Dow Jones Energy Service
DJBN	Dow Jones Global News Select
AWP	AWP News
BRNS	Barron’s
JNL	Wall Street Journal - Online Versions of Print Articles
WAL	Wall Street Journal (domestic) stories filed direct to Newswires
WLS	Wall Street Journal (all) on Newswires
WSJ	The Wall Street Journal - PB

Table A.8: Selected News Sources

As customary when using text-as-data methods, we reduce the dimensionality of the dataset according to Grimmer et al. (2022) . Therefore, we first proceeded with an lemmatization. By lemmatization we mean a mapping process from words to lemmas, whereby a lemma is the canonical form of a set of by inflection related words (Grimmer et al., 2022). Accordingly, we used the Python package spaCy (Honnibal and Montani, 2017). This was followed by removing all punctuation, numbers, symbols, separators and urls. After removing these characters, we filtered out stop words, i.e. common words which have little to none information relating an article’s subject. Additionally, time marks were taken out, as well as corpus-specific terms, which are relatively frequent but contain no information about the subject of an article like “quot” or “newswires”. Finally, very rare terms were removed, as we are not able to use those efficiently in our model.

Narratives	1-Year Low Income	3-Year Low Income	1-Year Mid Income	3-Year Mid Income	1-Year High Income	3-Year High In
Demand						
Government Spending	0.48	0.19	0.52	0.06 *	0.73	0.28
Monetary Policy	0.50	0.63	0.44	0.15	0.10 *	0.11
Pent-up Demand	<0.01 ***	0.25	0.13	0.15	0.05 *	0.30
Demand Shift	0.33	0.18	0.50	0.74	0.59	0.49
Supply						
Supply Chain	<0.01 ***	0.08 *	0.02 **	0.32	0.01 **	0.08 *
Energy	0.37	0.11	0.96	0.26	0.94	0.60
Labor Shortage	0.25	0.44	0.11	0.99	0.17	0.94
Miscellaneous						
Pandemic	0.43	0.74	0.15	0.45	0.25	0.07 *
Politics	0.85	0.81	0.57	0.33	0.88	0.56
War	<0.01 ***	0.10 *	0.03 **	0.59	0.10 *	0.25
Debt	0.36	0.74	0.35	0.95	0.27	0.36
Taxes	0.26	0.65	0.46	0.91	0.92	0.56
Profits	<0.01 ***	0.04 **	0.04 **	0.28	0.12	<0.01 ***
Note:						*p<0.1; **p<0.05; ***p

Table A.4: Income: Granger causality analysis (bHP-Filter)

Narratives	1-Year Low Education	3-Year Low Education	1-Year Mid Education	3-Year Mid Education	1-Year High Education
Demand					
Government Spending	0.07 *	0.01 **	0.79	<0.01 ***	0.50
Monetary Policy	0.13	0.63	0.99	0.17	0.33
Pent-up Demand	<0.01 ***	0.71	0.06 *	0.85	0.11
Demand Shift	0.04 **	0.11	0.83	0.54	0.47
Supply					
Supply Chain	<0.01 ***	0.59	0.22	0.02 **	<0.01 ***
Energy	0.45	0.79	0.26	0.11	0.19
Labor Shortage	0.37	0.59	0.04 **	0.94	0.69
Miscellaneous					
Pandemic	0.17	0.76	0.19	0.98	0.28
Politics	0.44	0.72	0.77	0.35	0.90
War	<0.01 ***	0.72	<0.01 ***	0.14	0.22
Debt	1.00	0.26	0.51	0.52	0.66
Taxes	0.06 *	0.16	0.92	0.76	0.74
Profits	<0.01 ***	0.28	0.09 *	0.07 *	0.05 **

Note: *p<0.

Table A.5: Education: Granger causality analysis (bHP-Filter)

Narratives	1-Year Low Age	3-Year Low Age	1-Year Mid Age	3-Year Mid Age	1-Year High Age	3-Year High Age
Demand						
Government Spending	0.15	0.34	0.21	0.01 **	0.46	0.01 **
Monetary Policy	0.73	0.58	0.16	0.72	0.44	0.12
Pent-up Demand	<0.01 ***	0.14	0.07 *	0.56	0.45	0.67
Demand Shift	0.76	0.21	0.22	0.97	0.62	0.05 **
Supply						
Supply Chain	0.08 *	0.01 **	<0.01 ***	<0.01 ***	0.08 *	0.05 **
Energy	0.54	0.23	0.31	0.70	0.48	0.10 *
Labor Shortage	0.73	0.86	0.27	0.62	0.13	0.35
Miscellaneous						
Pandemic	0.13	0.14	0.89	0.35	0.22	<0.01 ***
Politics	0.53	0.64	0.95	0.31	0.50	0.95
War	0.02 **	<0.01 ***	0.15	0.06 *	0.04 **	0.75
Debt	0.08 *	0.81	0.93	0.46	0.45	0.92
Taxes	0.48	0.07 *	0.52	0.92	0.28	0.76
Profits	0.22	0.01 **	0.02 **	<0.01 ***	0.07 *	0.09 *
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A.6: Age: Granger causality analysis (bHP-Filter)

Narratives	**1-Year Low Numeracy**	**3-Year Low Numeracy**	**1-Year High Numeracy**	**3-Year High Numeracy**
Demand				
Government Spending	0.69	0.05 *	0.54	0.04 **
Monetary Policy	0.41	0.36	0.17	0.38
Pent-up Demand	0.27	0.92	0.01 **	0.84
Demand Shift	0.96	0.42	0.30	0.31
Supply				
Supply Chain	0.04 **	0.44	$<$0.01 ***	0.44
Energy	0.81	0.20	0.96	0.16
Labor Shortage	0.13	0.98	0.09 *	0.92
Miscellaneous				
Pandemic	0.16	0.89	0.36	0.71
Politics	0.36	0.41	0.57	0.47
War	$<$0.01 ***	0.02 **	0.10	0.05 **
Debt	0.19	0.30	0.35	0.20
Taxes	0.30	0.22	0.65	0.18
Profits	0.04 **	0.10	0.12	0.10 *
Note:				*p$<$0.1; **p$<$0.05; ***p$<$0.01

Table A.7: Numeracy: Granger causality analysis (bHP-Filter)