1. Introduction

Inflation expectations play a vital role in affecting our everyday economic decisions. Yet, measuring inflation perceptions and expectations is one of the complicated tasks, as they are not directly observable. Euler's consumption model is one of the key fundamental concepts in modern macroeconomics. It is a key ingredient in understanding the relationship between consumer spending and the real interest rate. The relationship between inflation expectations and consumption is intuitive – an increase in the expected inflation will lead to a lower interest rate given the nominal interest rate. It boosts consumption relative to the future consumption.

In addition to their usefulness in portraying the economic relationship, the focus on the Euler equation allows to avoid explicitly solving the full optimization problem, instead focusing on specific first-order conditions of this optimization problem. One can estimate preference parameters without having to explicitly solve the model. The baseline Euler equation consists of a forward-looking consumption component and an inversely related real interest rate.

Though in theory a simple relationship, the estimations of Euler equations suffer from problem of weak identification, endogeneity issues and poor parameter estimates. As a result, consumption is often found unresponsive to the real interest rate. Can machine learning and its application in economics change our opinion of Euler's consumption model? Can technological advances help fix one of the key relationships in modern macroeconomics that has been failing over and over?

In this paper we address issues related to real interest rates that is the difference between the nominal interest rate and inflation expectations. While the nominal interest rate is observable, inflation expectations are not, making the (expected) real rate unobservable. We propose a new, news-topic driven inflation perception measure (NTDI). We suggest that the media and the news they report on have the potential to capture consumer inflation perception and expectations as an alternative to traditional survey measures.

Our contribution is therefore twofold. Our first contribution is to the rapidly growing research on the impact of news on inflation perceptions and perception. The news forms a major driver of inflation perception and expectations and decisions and in recent years a number of studies have used news data for macroeconomic modelling. So far, the focus has largely been on variables like GDP growth, unemployment, business cycles and even cryptocurrency returns (see Thorsrud, 2020; Soric et al., 2019; Corbet et al. 2020 and Saiz et al., 2021) and less on consumption and inflation expectations (Sapiro et al., 2018 and Larsen et al., 2021).

By using novel data from online news, we also take advantage of real-time data. When participating in household surveys, consumers give answers on their planned consumption levels based on their perceptions at the time when the surveys are being conducted. Our measure covers not only the particular period of the survey, but the average perception of the full period. Actual changes in consumption differ from planned levels and this difference is somewhat unpredictable. As major events unfold in the economy (e.g. Brexit vote, Covid19 pandemic, general elections), consumer perceptions and expectations change, but understandably, these changes have not been incorporated into their answers of months ago. The strong co-movement of news tone indices and official consumer confidence survey measures for the UK gives us the necessary reassurance for using news-based inflation perception measures as an alternative to survey-based inflation expectations. In addition, as Duca-Radu et al. (2021) suggests, using inflation perceptions allows to control for unobserved heterogeneity arising from emotions, sentiments etc., which influence perceptions and expectations about inflation.

Second, we contribute to the literature on Euler models by estimating various extensions of the baseline model and conducting empirical analysis on their performance, while evaluating the strength of instruments and values of structural parameters. Contrary to existing literature that mainly uses survey-based measures of inflation expectations or actual inflation for calculating the real interest rate (see for example Campbell and Mankiw, 1989; Coibon et al., 2020 and Dräger and Nghiem, 2021) we use a novel news-based measure of inflation perceptions.

In our view, the real interest rate used in the literature could be mis-specified as it does not reflect the agent's perceptions about the economy. Households and firms have potentially different information on the future path of inflation from news. Therefore, when estimating the structural parameter of the model, one should not treat current and future consumption as exogenous to avoid correlated residuals and inconsistent estimates.

Compared to the previous literature the paper contributes by novel estimates of the inflation measure for the Euler equation analysis. The importance of understanding the process of the formation of household inflation expectations for monetary authorities in their attempt to influence household decisions is well documented. When the overall economic prospects are poor, this affects households' perceptions of the economy and leads to potentially biased survey answers.

Agents receive only partial information while doing everyday shopping and build their expectations through personal experiences and memories, which however can be inaccurate, irrational and diverse. Household surveys often indicate that the perception of current inflation and expectations about the future are different from actual inflation values and differ strongly from surveys of professional forecasters and the inflation rates implied by financial markets (see for example Coibion et al., 2018). A growing body of literature provides evidence in favour of information rigidities rather than full-information rational expectations (Larsen et al., 2021; Armantier et al., 2015; Coibon and Gorodnichenko, 2012 and Dovern et al., 2015).

Differently from other papers this study adds novel empirical data on the inflation part in estimating the Euler equation. The importance of capturing true consumer expectations for estimation of the Euler model is also shown in Lamla and Maag (2012), where they find that households and professional forecasters have different ideas about where inflation is heading over the next year. In our proposed solution, we consider the standard theoretical model of the Euler equation proposed by Hall (1988) and use extensions to the baseline model from Ascari et al. (2021) to estimate the equation. The novelty of our approach is possible thanks to technological advances that allow us to build a real-time high frequency indicator that captures consumer inflation perceptions that can be used to estimate the Euler equation.

Our approach starts with extracting the textual data from one of the UK's leading online newspapers from January 2000 to December 2023 and performing text selection, pre-processing and cleaning on this data to reduce the dimensionality and noise. The resulting transformed textual data is then converted into quantitative indices that capture the intensity of the topics being discussed in the news. To finalise the construction of the novel news-based topic indices, the latter time series are augmented using sentiment indices that reflect the tone expressed by the authors of the news articles[1].

The final indices are used as measures of inflation perception in Euler equations. We also incorporate various components of consumption for robustness and analyse which topics have significant impact on household consumption decisions. As inflation expectations are unobservable, there is no other data to compare our newly created indexes with. The ultimate test for the goodness of the new series is how they behave in the estimation of empirical economic models.

The Euler models and specifications in this paper follow closely those suggested by Ascari et al. (2021). They undertake an extensive analysis of the Euler models and the different variants, such as models including consumer habits, hand-to-mouth consumers, recursive preferences etc. They contribute to research addressing the problems of weak identification by identifying structural parameters in both linear and non-linear form. Our aim, however, is different, as we focus on model estimation and performance evaluation using a novel news-based measure of inflation.

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[1] In this paper, the words 'sentiment analysis' and 'sentiment indices' refer to the tone of the news, rather than the economic sentiment.

The answer to the question of the usefulness of news and machine learning is positive. We show that when building the real interest rate using novel news-based sources of inflation perception in a Euler model, instead of traditional inflation expectation estimates for the real interest rate, the Euler models pass econometric tests and improve economic estimates. While not all models yield precise estimates for the structural parameters, for non-durable goods and services consumption components, most models result in strong instruments and improved estimates of the elasticity of intertemporal substitution. We show that when the novel measure of the real interest rate is used in the Euler models, they are not rejected, while they fail when traditional real interest rate measures are used.

We also find that with the novel measure of inflation perceptions many models pass instrument and endogeneity tests. The goodness of fit for all models improve when news-topic driven indices are used instead of official inflations measures. Also, the elasticity of intertemporal substitution (EIS) values improves upon benchmark models, albeit with values remain close to zero. Overall, our results provide information for evidence in favour of Euler models.

A topic-based classification of news yields the most important insights on the role of particular news topics on inflation perceptions and allows us to evaluate which news affects consumer spending the most. For instance, our results are particularly encouraging for news topics discussing UK, USA and Chinese economies, as well as financial markets. This is not surprising but an important contribution both as a validation of our results from the intuitive point of view, as well as a contribution allowing the use of news-based inflation perceptions for macroeconomic modelling and real-time predictions.

The paper proceeds as follows: The next section reviews the literature on Euler models and why often various empirical estimations fail. We also address the household optimisation problem and the role of the media in the formation of inflation expectations. Section 3 describes the estimation approach and presents the textual analysis. Section 4 provides the results and robustness analysis for the Euler equation estimation. Section 5 concludes.

2. Literature review

2.1 Why Euler equation estimations fail

In a standard model households maximise a direct intertemporal utility function of the form:

$$U_t = \sum_{i=0}^{\infty} \beta^i E_t[u(c_{t+1})], \tag{1}$$

where c_{t+1i} is consumption at period $t+i$, u is the utility function following certain properties, β is the discount factor and the E_t consumer's expectations at time t. For example, the utility function can exhibit Constant Relative Risk Aversion (CRRA), that is $u(c_{t+1}) = \frac{C_t^{1-\frac{1}{\sigma}}}{1-1/\sigma} - 1$, with σ being the inverse of the degree of risk aversion. Emerging from consumers' utility maximization problem are the first order conditions (2), where for the purposes of this paper, $\beta^i \left[\frac{u(c_{t+1})}{u(c_t)}\right]$ is the stochastic discount factor and the r_t is the risk-free real interest rate between *t* and *t+1*:

$$1 = E_t[\, \beta^i \left[\frac{u(c_{t+1})}{u(c_t)}\right] (1 + r_t)]. \tag{2}$$

Once log-linearized, these moment conditions become $\widehat{c_t} = E_t \widehat{c_{t+1}} - \sigma\, \widehat{r_t}$, which leads to the simplest case of the Euler model:

$$E_t \widehat{\Delta c_{t+1}} = \sigma\, \widehat{r_t}, \tag{3}$$

where $\Delta c_{t+1} = c_{t+1} - c_t$ and $\widehat{c_{t+1}}$ and $\widehat{r_t}$ are respectively the log deviations of $\widehat{c_t}$ and $\widehat{r_t}$. σ is the marginal rate of intertemporal substitution ($\sigma \geq 0$). In this simple model, σ is also the elasticity of intertemporal substitution[2] between current and future consumptions and tells us how the marginal rate of substitution between these consumptions reacts to the changes in interest rate.

The Euler equation implies that low interest rates bring higher current consumption in the cost of lower future consumption since savings lose worth. Different consumption components may be affected differently, and consumers may decide to spend on a particular type of goods, such as real estate, building, etc. For example, Ichiue and Nish Iguchi (2015) test the link between household consumption and the inflation expectations of Japanese households and find that when these households report higher inflation expectations, they increase current consumption by reducing planned savings. Dräger and Nghiem (2021) estimate the Euler equation using expected inflation and confirm that macroeconomic expectations matter for economic decisions for German households. There are other papers that report on the link between consumer inflation expectations and consumer readiness to spend on particular goods (see for example Coibon et al., 2021, Duca-Radu et al., 2019, Burke and Ozdagli, 2021, Bachmann et al., 2015, Ryngaert, 2022).

While the standard Euler model of consumption is one of the main building blocks of many macroeconomic models, a sizeable literature, some of which is described in this section, has had difficult times estimating the model, as it often fails to hold at the aggregate level. There are several possible explanations. One is that the real interest rate used in the Euler equation is mis-specified and does not capture the consumer inflation expectations and perceptions. Imperfect information may affect the Euler equation leading to inconsistent estimates. In addition, any structural changes arising from policy shifts have a weaker impact on real variables, such as consumption. Contrary the impact is stronger on nominal variables, such as future inflation expectations.

Another explanation for failing Euler models is that consumption is difficult to forecast, leading to instruments being weak. When estimating EIS, instruments should be exogenous and relevant;

[2] It is one of the most important determinants of the consumers' intertemporal consumption choices, since it measures the elasticity of the marginal substitution between consumption today versus consumption in the next period.

that is, correlated with consumption growth Δc_{t+1}. Intuitively, the estimated value of EIS has important economic implications, but most papers find no evidence of intertemporal substitution. For example, Yogo (2004) estimates of EIS for 11 developed countries are ranging from 0 to 0.5 and are too small to have a significant effect on consumption.

Yogo's paper follows a plethora of research conducted previously that yield similar results. An influential paper by Hall (1988) finds virtually no evidence for intertemporal substitution when estimating the relationship between consumption growth rate and expected real interest rates for the United States. Similarly, Campbell and Mankiw (1989) also find evidence against the permanent income hypothesis for the US when examining both non-durable and durable consumer spending. However, at the same time, the paper also challenges the robustness of Hall (1988) results when introducing the current-income consumers and arguing that the substantial fraction of income goes to rule-of-thumb consumers; therefore, Hall's theory behind the conclusions on the EIS cannot be empirically valid. As Attanasio and Weber (1993) point out, an aggregation bias may lead to such results of a low estimate of the consumption growth response to interest rates, and that as a result, the lagged consumption growth is being invalidated as an instrument. Once this is fixed, their value of EIS increases.

It is noteworthy that there are several papers that also found significant and positive values for the EIS; for example, Attanasio and Weber (1993), Vissing-Jørgensen (2002), so there is no consensus in the literature as to what the value of EIS and how significantly different from zero it should be. There is, however, a relatively wide strand of literature studying the conditions under which the structural preference parameters can be identified in the Euler equation (see Attanasio et al., 2002 and Gross and Souleles, 2002).

The most recent paper published on this topic by Ascari et al. (2021) summarizes the results from various baseline and extension Euler models, using both newly developed robust-to-weak-identification methods and well-established traditional methods. Their results vary depending on the choice of model (e.g. baseline or extension), as well as choice of interest rate parameter. For example, in the case of a risk-free interest rate being used in the estimation of the Euler model, the aggregate EIS is well-identified and low for several log-linear and nonlinear models but is virtually zero for the semi-structural model.

2.2 The role of the media in the process of forming inflation perceptions and expectations

One of the necessary steps in the analysis is linking media information to perception of the state and expectations of the future of the economy and inflation. The key to this relies on media theory and the power of media in a society. This link is well established and, in most cases, it is found that the news act as the primary source and is the preferred delegate for information. An average consumer does not typically have the resources or time to constantly track the latest statistics and monitor all the events in the economy to get a full understanding of the various economic indicators. In other words, it is primarily through the media (e.g. newspapers, television, online news) that consumers receive and interpret macroeconomic information, form beliefs and opinions, as well as build perceptions about inflation and sentiments about the economy and its future. The period of the study does see a rise in the role of social media, but for the most part newspapers still play a major role for investigating macroeconomic relationships over time, news is still the most widely used information source.

Blinder and Krueger (2004) find that television is the dominant source of information on economic policy issues, followed by newspapers. Fullone et al. (2007) support these findings through surveys in Italy and Nimark and Pitschner (2019) conclude that agents' beliefs and actions in the economy are affected by the reported information. As agents steadily move away from television and traditional newspapers to online news, more recent research papers particularly focus on examining the relationship between online news and consumers economic sentiments, see for example Thorsrud (2020), Bauer (2015), Barbaglia et al. (2022). The latter, for instance, evaluates the sentiment from news and its informational content, finding that when sentiment is considered in addition to macroeconomic factors, then the forecasting of major macroeconomic variables significantly improves. The overall idea from these studies is that news is in one way, or another consumed by households through various online channels, whether directly or through other media outlets.

A strand of the above-described literature is specifically focused on how media coverage affects inflation expectations. Intuitively, to some extent, media coverage reflects the current state of the economy. It is possible to understand the importance of this topic for the economy and its future based on the intensity and the extent of how much it is discussed in the news.

The frequency of the news and the tone of the text can drive consumer perceptions and allow us to understand consumer inflation expectations. Carroll (2003) contributes to this literature through an analysis of two US newspapers and establishes a link between the amount of news reporting on inflation and the accuracy of consumer expectations. Findings imply that more news leads to more rational household forecasts. Lamla and Lein (2008) investigate how the media affects inflation expectations through the intensity of the news coverage and the tone of this coverage.

Later, Lamla and Maag (2012) adopt a Bayesian learning model to investigate the heterogeneity of inflation expectations and forecast disagreement between German households and professional forecasters, motivated by media reporting on inflation. They challenge Carroll's results and find that media coverage does affect the forecast disagreement and tends to increase with the heterogeneity of media coverage. However, the forecast disagreement declines with the increase of the number of reports pointing to a rise in inflation.

Similar results are reported in Pfajfar and Santoro (2013), where using Michigan Survey data, the authors show that more news coverage may widen the forecast gap between professional forecasters and consumer's mean forecast: more negative news tends to decrease the accuracy of consumer expectations, but favourable news has no statistically significant impact on them. What these results imply is that agents persistently deviate from the mean expectations of professional forecasters and the news is most likely to blame for this and causes distorted expectations.

A recent paper by Larsen et al. (2021) analyses about 5 million news articles published over 20 years and finds that many news topics have high predictive power for inflation expectations.

results of Blinder and Krueger (2004) and Fullone et al. (2007) show that television and newspaper reports are the most important sources of economic information for households. In sum, these results suggest that it is primarily through the transmission and interpretation of information by the media that macroeconomic information becomes useful for consumers results of Blinder and Krueger (2004) and Fullone et al. (2007) show that television and newspaper reports are the most important sources of economic information for households. In sum, these results suggest that it is primarily through the transmission and interpretation of information by the media that macroeconomic information becomes useful for consumers results of Blinder and Krueger (2004) and Fullone et al. (2007) show that television and newspaper reports are the most important sources of economic information for households. In sum, these results suggest that it is primarily through the transmission and interpretation of information by the media that macroeconomic information becomes useful for consumers.

2.3 News as novel data source

While it is clear that the media has a direct impact on consumer sentiments and perceptions about the economy and the inflation expectation process, the empirical literature on using news-based data for modelling the economy is relatively small, albeit growing consistently, with Thorsrud (2020) even adding to his title “words are the new numbers”.

Applications are numerous, from financial markets to central banking and consumer sentiments (see for example, Hendry and Madeley, 2010 and El-Shagi and Jung, 2015). Thorsrud (2020) uses articles from the Norwegian daily business newspaper and constructs a new business cycle index that classifies the phases of the business cycle and provides meaningful insights on which types of news drive or reflect economic fluctuations.

Larsen et al. (2021) use large news corpus and machine learning algorithms to investigate the role played by the media in the process of households forming expectations and conclude that certain news topics that the media reports on are good predictors of both inflation and inflation expectations.

3. Method and Data for The Euler Equation and Text Analysis with Machine Learning

3.1 Empirical Euler models

The simple Euler model in Table 1 labelled Baseline I represents the standard log-linearised Euler equation. The common consensus about this model is that it generally does not behave well due to the predictability of consumption by other series' lags and its unresponsiveness to the real interest rate. The latter is generally computed as the difference between nominal interest rate i_t and inflation measure π_t. The econometric specification of (3) within the IV-GMM framework can be rewritten as shown in Table 1.

TABLE 1
Models estimated in the paper

Baseline (I)	$\Delta \boldsymbol{c}_{t+1} = \alpha + \boldsymbol{\sigma}\,(\boldsymbol{i}_t - \pi_{t+1}) + \varepsilon_{t+1}$
Model with External Habits (II)	$\Delta \boldsymbol{c}_{t+1} = \alpha + \boldsymbol{\gamma} \Delta \boldsymbol{c}_t + \boldsymbol{\sigma}(\boldsymbol{1} - \boldsymbol{\gamma})(\boldsymbol{i}_t - \pi_{t+1}) + \varepsilon_{t+1}$
Model with Internal Habits (III)	$\Delta \boldsymbol{c}_{t+1} = \alpha + \frac{\boldsymbol{\gamma}}{\boldsymbol{1} + \boldsymbol{\gamma}^2 \boldsymbol{\beta}}(\Delta \boldsymbol{c}_t + \boldsymbol{\beta} \boldsymbol{E}_t \Delta \boldsymbol{c}_{t+2}) + \boldsymbol{\sigma} \frac{(\boldsymbol{1} - \boldsymbol{\gamma})(\boldsymbol{1} - \boldsymbol{\gamma}\boldsymbol{\beta})}{\boldsymbol{1} + \boldsymbol{\gamma}^2 \boldsymbol{\beta}}(\boldsymbol{i}_t - \pi_{t+1}) + \varepsilon_{t+1}$

$(i_t - \pi_{t+1})$ is the ex-post real interest rate, is an unrestricted constant and the elasticity of the intertemporal substitution. ε_{t+1} is the error term that can be serially correlated up to order 1. c_t and c_{t+1} are current and next period consumption respectively. In models with habits, $\gamma \in [0,1)$ is the parameter indicating the degree of habits, c_{t+2} is the consumption in period $t + 2$. For benchmark models, π_t is the UK's inflation expectations (measured by 5-year Inflation Implied Forward rates), while for all other models, it is replaced with news-topic driven inflation perceptions. By our definition, our NTDI reflects the inflation perceptions of consumers.

For the results in the main paper, we focus on total consumption. We present the findings on non-durable goods and services consumption in additional results. We do not estimate the Euler model for durable consumption: not only are they included in the calculations of aggregate consumption, but we also believe that durables do not respond as significantly to inflation, as does the spending on non-durable or semi-durable goods. It is worth noting, however, that the actual impact of not taking durable goods into our Euler models depends on the elasticity of substitution between durables and non-durables and whether the marginal utility of non-durables consumption is affected by the consumption of durables. We do not check for this in this paper.

The specifications of all models used in this paper are provided in Table 1 and follow closely those in Ascari et al. (2021). In addition to the baseline model, we also test two popular variants of the Euler equation that take external and internal consumer habits into consideration. Including consumer habits allows us to account for agents' response to various shocks and for the consumption path persistence in different periods. As commonly described in the literature and highlighted in Ascari et al. (2021), internal habits are those where the consumer is concerned with their current consumption relative to the consumption in the previous period. At the same time, external habits are influenced by external 'factors'[3], and therefore, the consumer's current consumption is affected by the aggregate consumption in the previous period instead of its own consumption in the same period, which is the case with internal habits. External habits are

[3] Commonly in the Euler literature, this type of habit formation is described as the 'keeping up with the Joneses' effect, which essentially means that consumers reduce their savings by increasing their consumption to keep up with the level of consumption in their peer group.

characterised by the introduction of the lagged term of c_t, which affects the forward-looking nature of the Euler equation and the relationship between EIS and aggregate consumption.

While there are somewhat contrasting results in the literature on the impact of habits of various consumption components and their importance in explaining the key patterns in household consumption decisions. Still, there seems to be consensus that habits capture consumption persistence, and therefore should be accounted for, especially in the presence of time-varying risk premia.

The official data used in the models comes from a variety of sources and undergoes a number of transformations to make all data aligned with each other and in a format comparable to other studies. Detailed descriptions of transformations to the official data are given in Table A1 of Appendix A.

News-topic driven indices are in a quarterly format and include a great deal of time-variation due to the nature of the data. To account for the economic size of the index, we standardise the NTDI by means of inflation expectations series.[4]

To support our empirical analysis, we evaluate the value and sign of EIS, the significance of regressors' coefficients and apply popular robust-to-weak-identification tests to ensure the validity of the instruments. The restriction $E_{t-1}\varepsilon_{t+1} = 0$ is imposed on the models, so that only variables that are determined at time t can be used as instruments. Endogeneity is addressed using an IV regression approach and taking lagged endogenous variables as instruments. As such our instrument set consists of three lags of both Δc_t and $(i_{t-1} - \pi_t)$, as well as a constant. News driven sentiment indices S_z(t) are also added as additional instruments based on the assumption that they are correlated with consumption (coefficient is -0.3) and would also allow more use of the novel data.

[4] To validate our results, we also standardize NTDI using alternative measures of inflation, such as inflation attitudes survey data or official inflation series.

However, we do not find any significant improvement in model performance when the sentiments are added or not as instruments.

Common tests in the literature for handling weak instruments are used, such as first-stage F-statistic test for weakness of instruments, Hausman test for checking the consistency of OLS estimates under the assumption that IV is consistent, as well as Stock and Watson's test of instrument exogeneity using overidentifying restrictions, which is only applicable to models where the number of instruments is more than the number of endogenous regressors. Overall, if all three tests hold, then we consider the instrument valid and non-weak.[5]

3.2 Modelling news

We hypothesise that certain topics written about in the news have different degrees of impact on consumer sentiments and the process of forming expectations and inflation perceptions. This means that certain events happening in the economy could potentially have economy-wide effects. In turn, this means some topic distribution is needed for the news corpus.

Topic modelling provides a simple way to analyse large volumes of uncategorised text clustering words that frequently occur together and best explain the underlying information of a particular document. In other words, it is the process of looking into a large collection of documents and identifying clusters of words based on similarity, patterns, and multitude.

Since any document can be assigned to several topics at a time, the probability distribution across topics for each document is therefore needed. For a general introduction to topic modelling see Steyvers and Griffiths (2007) and Blei and Jordan (2003). The latter were the first to suggest Latent Dirichlet Allocation (LDA) for this purpose. LDA is a statistical model that identifies each

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[5] There are other tests available for checking the instruments relevance, such as Kleibergen (2002)'s statistical test for instrument validity and Moreira (2003, 2009)'s coefficient test designed to test coefficients in the structural equation regardless of the strength of identification.

document as a mixture of topics and attributes each word to one of the document's topics; therefore, clustering words into topics. For more information on how LDA works see Appendix B2.

Generally, researchers do not know the topic structure of a set of documents a priori. Different model iterations and parameters result in different document clustering. However, the goal is to find unknown patterns; therefore, there is no perfect value for numbers of topics and the solution will most likely differ for different values. Hence, the choice of the number of topics to be extracted from the corpus is based on the researcher's intuition, domain knowledge and literature.

As such, we classified 80 different topics. To validate this number of topics, we follow the method by Thorsrud (2020) and compare perplexity scores across various LDA models estimated using different numbers of topics, as this allows us to inspect scores across the Markov chain Monte Carlo. The benefit of this approach comes in comparing perplexity across different models with varying topic numbers. The model with the lowest perplexity is generally considered the "best".[6]

To proceed with building a high-frequency news-topic-driven inflation index, we calculate the frequency of each topic, or in other words, the intensity of how much each topic is discussed in the news for a given day or period. Empirically, we first sum together all articles for a given day into one document, grouping them into one plain text. Next, based on the top 20 most frequent words in each topic the article's daily frequency is calculated. The news volume $I_z(t)$ of topic z is given by:

$$I_z(\mathrm{t}) = \sum_{d \in I(t)} \sum_{w} N(d, w, z), \tag{4}$$

where $N(d, w, z)$ is the frequency with which the word w tagged with topic z appears in document d. As such, we build 80 daily series for each topic using topic decompositions and distributions.

Since our aim is to build the inflation perceptions measure of consumers, sentiment analysis and its ability to classify articles into positive, negative, or neutral sentiments, is a key step in our methodology. We start by computing thousands of sentiment values which capture the tone

[6] Additionally, one can choose the number of topics that provide the best statistical decomposition by using the maximum likelihood method to find the model with the best score.

expressed by the authors of the news. The problem can be defined as a sentiment prediction problem: for each day all articles are aggregated into one document and a sentiment score is calculated for it as the difference between the frequencies of positive and negative words in the text normalized by the total number of words. This approach is widespread in the literature as can be seen also in Larsen et al. (2021) and Arslan-Ayaydin et al. (2016).

There are several available methods and ways to conduct sentiment analysis (see Ravi and Ravi, 2015; Ardia et al., 2019; Bai, 2011; Schumacher et al., 2012), each with its own limitations and advantages. To make our analysis more robust, we use two different methods. The first method uses a standard dictionary-based sentiment analysis approach to classify words based on their polarity (e.g., positive, negative, or neutral). We chose the Loughran-McDonald (2011) financial dictionary that has 354 positive words and 2355 negative words as the most suitable ready dictionary for text analysis in the economic domain. For the second approach, we apply an extension of the dictionary-based classification, which also considers valence-shifting words. These are words like 'very', 'barely', 'mustn't', 'nor', 'not', that may affect the context of nearby words. The sentiment indices in both approaches are calculated as the difference between positive and negative words (according to their sentiment polarity lexicon) divided by total number of the words.

We build two sentiment indices using the methods described above, but do not find significant differences in the results[7] and chose to proceed with the second approach in further calculations and denote the calculated sentiment index SI. Once SI time series are calculated for each topic, we multiply them with intensity indices to get NTDI:

$$\overline{NTDI_z}(\mathrm{t}) = I_z(\mathrm{t}) * S_z(\mathrm{t}). \tag{5}$$

This concludes the calculation of news-based measures of inflation perceptions.

[7] The correlation of sentiment indices built using the second method with the official consumer confidence index is slightly higher than for sentiment indices built using the dictionary-based methods only. The difference, however, is minor.

3.3 Analysis of the textual data

We use textual data and infuse the ready data to Euler models to analyse their performance. We collect two types of data: those downloaded from traditional published datasets and those manually[8] extracted from the novel newspaper source. Traditional published datasets were collected from the Bank of England and include data on inflation, consumption and inflation attitude surveys. The consumption data itself includes total household consumption series, as well as its components.

The novel newspaper data source comes from a rich textual data environment of online news and is collected from one of the UK's leading newspapers,[9] the Guardian, using its open-source API.[10] The choice of the news outlet is due to its relevance to our research in terms of content and readership.

The Guardian is known to have views that lie from liberal to left-wing in the political spectrum. This may bias the views on the economy and inflation. However, it is a newspaper that covers all main news. The bias on the direction of the views is not relevant when it only concerns the average position or the extent at which topics are covered. We standardize the data by taking away the mean and use the variance of the inflation expectations series. Therefore, bias and extent of news do not affect our results. It is only when some topics would not be covered about inflation, our results would turn out weaker than using another source that covers the topic.

King et al. (2007) performed a real-world randomized experiment to understand the causal effects of news coverage in various news outlets across the US in nationwide discussions on a range of topics and find that even the news coverage of smaller media outlets can have an impact on increasing public discussion on specific topics and that this increase was uniformly distributed across political affiliations, gender and regions of the US. Similarly, Nimark and Pitschner (2019)

[8] Here the word manually means that the data was not readily available for download. Instead, a connection to the newspaper's API is established and some coding is required to extract the data from the newspaper's website.

[9] See https://www.pressgazette.co.uk/uk-newspaper-and-website-readership-2018-pamco/, as well as https://pamco.co.uk/pamco-data/latest-results/ for comparison among UK newspapers.

[10] See https://open-platform.theguardian.com

highlight in their paper that while different news outlets typically emphasise different topics, major events are covered in all outlets quiet homogeneously.

Any news in the Guardian is public and readable by anyone by default. While different news can drive consumer expectations, and affect both sentiments and perceptions, we consider business section articles to be more suitable for the purposes of the analysis of this paper. Therefore, we take the articles only from the Guardian's business section for the 21 years between January 2000 to December 2023. We also filter out articles based on subjectively chosen keywords, such as inflation, deflation, price(s), cost(s). Arguably, this is only a subset of the news that affects household decisions, yet the main news stories related to inflation that are relevant for household perceptions formation will be covered by articles that include these keywords.

The data extracted from the Guardian is in a text format and does not have a given structure. Overall, our news corpus consists of around 23,000 English language articles with well above 20 million words in total from January 2000 to December 2023, which is enough data to conduct our analysis.

However, this amount of data also makes statistical computations a challenge. We therefore apply data pre-processing steps suggested by Bholat et al. (2015), at the same time adding more steps and more developed methods. We use the text mining bag of word approach when working with textual data, which means all words are analysed as a single token and their structure, grammar or part of lexicon does not matter. Pre-processing results in a so-called document term matrix, which consists of all unique words in the corpus and their respective frequencies. At this step, the dimensionality of the corpus is reduced, and we get results that have a clearer meaning. A full description of the steps used to clean up the data is given in Appendix B1. Figure B1 in the appendix visualises the most common words in the Guardian corpus.

Once the number of topics is chosen, the LDA procedure derives the topic probability distribution by assigning probabilities to each word and document. Table B2 in Appendix B2 presents the results from topic modelling with LDA for all 80 topics.

LDA procedure does not assign labels to the topics. We do that ourselves based on most frequent words for the given topic and based on our subjective understanding of the topics and the economy. By exploring top words within each topic that have the highest probability of belonging to that topic gives a good description of what the topic is about. The exact name, however, plays a minor role in the actual analysis or results.

Several recent papers find that the combination of the intensity of news topics and corresponding implied sentiment of these news and topics is important for better capturing inflation expectations (see Larsen et al., 2021 and Thorsrud, 2020). Therefore, to get the final measure NTDI, which will capture consumer inflation perceptions, we augment the intensity indices with sentiment indices.

The output for the sentiment analysis of all 80 topics is provided in Appendix C. The quantitative values of the inflation perception series shown in the figure are not of importance for us since the series will be standardised by the mean of consumption series before being used in the Euler model estimations. Instead, the trends and peaks for specific topics and correlations among topics are worth observation. For instance, one can note that the topic titled 'growth/forecast/year' (labelled based on its three most frequent words) has a low peak before and around 2008, corresponding to consumer inflation perceptions drop related to the global financial crisis. Similarly, it seems that topics discussing the tax budgets have caused a slightly more downward trend in the consumer perceptions around 2014.

Figure 1 illustrates News-Topic Driven Inflation Indices (NTDI) constructed using (5) for a sample of topics that contain words referring to the future of the UK economy. Such a sample of topics was chosen to 'mimic' the future part of inflation in the UK, since inflation perceptions are not easily measurable. To extract the topics referring to the future of the UK economy, a simple filtering exercise was performed on LDA results that chose the topics that contain both temporal elements, such as words like 'next', 'will', 'future', 'forecast', 'soon', as well as keywords indicating that the topic indeed refers to the UK economy. Out of the inflation keyword series there are 13 out of 80 that are clearly related to future keywords and 6 that refer to the past. For the economic sentiment indices there are 15 that relate to the future and five that relate to the past.

In the selected topics, there is no perfect match with the frequency of the macroeconomic data used and the news coverage. While there might be some reports in the newspaper that refer to future far away, the benefit of using a newspaper with wide reach is that it is more dealing with immediate issues rather than long-run prospects. And even if long-run prospects are covered, this is still likely to leave a more urgent feeling to the reader than the actual situation might refer to. This is also related to the past events. The process of interpretation of the news is not covered in the paper. The index captures the informational background at which decisions are formed against.

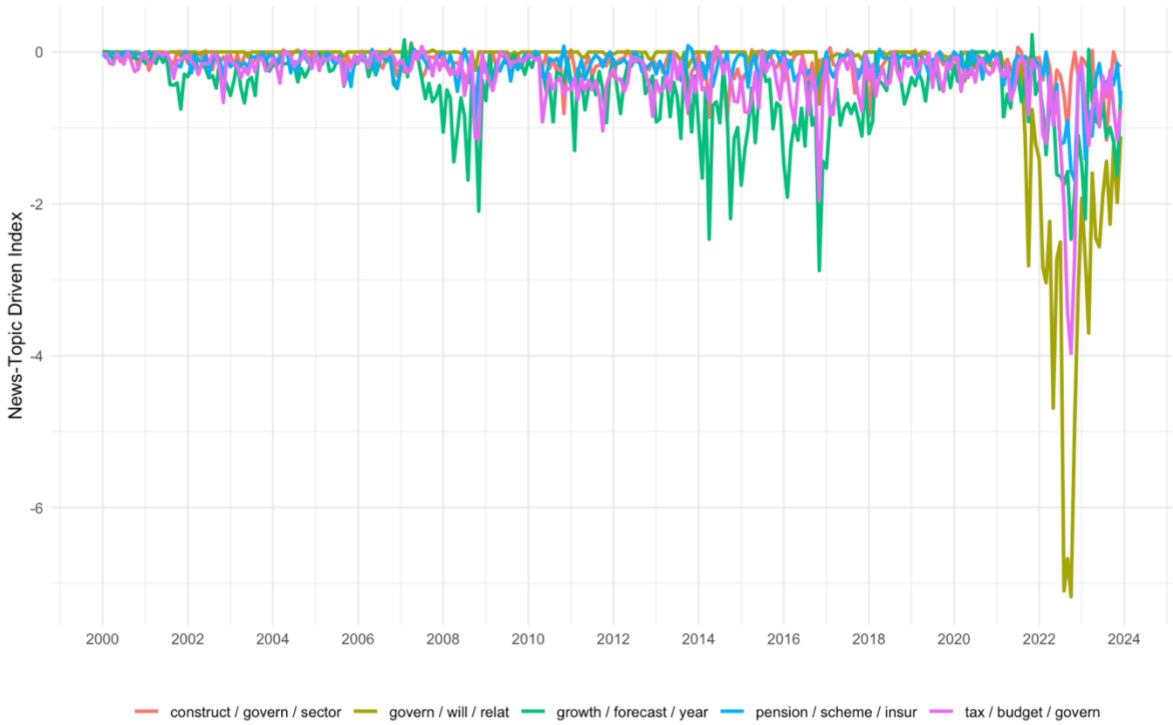

Figure 1. News-Topic Driven Inflation indices for topics representing news covering on the future of the UK economy.

The figure can be interpreted as follows: highly negative values of indices means that the media writes more about the topic and the tone of such news is mostly negative. The figure clearly highlights impactful economic events. The indexes are strongly negative at the time of the global financial and economic crisis of 2007-2009, the sovereign debt crisis of the euro area and economic worries of the mid 2010s, as well as starting with early 2022, which coincides with Russian invasion of Ukraine. These were all clearly disinflationary or even deflationary episodes that the data analysis is able to pick up.

Since we are using simple dictionary-based methods to compute the tone of the news, it appears that the number of negative words in the news are more prominent, which explains the higher negative values for the indices. This is not surprising, as the research suggests that people usually pay more attention to negative news rather than to positive news (Soroka et al. 2019). More sophisticated sentiment classification techniques exist (see for example Pang et al., 2012) and our methods for building the inflation indices could be developed. However, not only our approach is common in the literature (Larsen et al., 2021, Angelico et al., 2022), but also, as can be seen from figures above, our news-based inflation indices provide sufficient confidence on news-based topic indices in their ability to capture the inflation perceptions.

While more results and discussion will follow in the upcoming sections, Figure 2 illustrates the relationship between the UK's official Consumer Confidence Index (CCI)[11] and the sentiment index we constructed based on the tone of news coverage (NSI).

A similarity in shape and trend of the curves, as well as a strong visual correlation can be observed from Figure 2. The correlation of 0.7 is displayed between the NSI and CCI on average. Both the CCI and sentiment indices built from the news both fell strongly around the financial crisis of 2008, then gained an upwards trend as the economy started recovering. The confidence started dropping again around 2012 before reaching pre-crisis levels and did not drop until early 2020 when

[11] Source: https://data.oecd.org/leadind/consumer-confidence-index-cci.htm

the news about the coronavirus pandemic broke, then dropped again in 2022 related to Russia and Ukraine war.

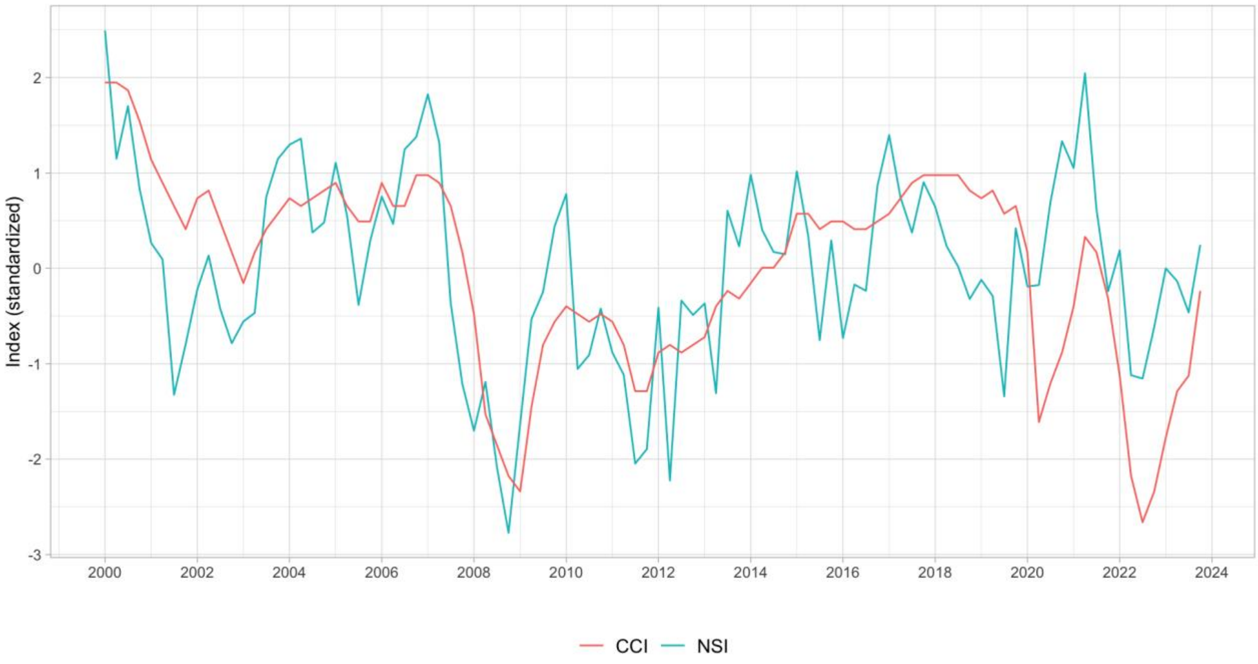

Figure 2**.** UK Consumer Confidence Index (CCI) vs News-based Sentiment Index (NSI). All indices are converted to quarterly series and standardized.

The CCI also had a slight drop in the periods leading to the Brexit vote (23 June 2016) and for some months afterwards, as expected. However, no significant drop was reflected in the news-based inflation indices. Some divergences between the series are expected and more thorough analysis would be required to identify the causes. Still, the results in Figure 2 support our hypothesis that sentiments from the news are indeed a very strong indicator of consumer perceptions about the economy and have a significant impact on them.

3.4 Analysis of the news-based sentiment indices

The idea of the news-based sentiment indices is to capture the latent perception of the discussion in the media. There is no correct counterpart to measure the success of the created indices to reach the goal. However, it is interesting to see how the data generated from news compares against data on prices and economic activity and confidence. This section presents the results of the dynamic correlation analysis of the indices with various macroeconomic data.

As stylised facts about the data we calculate contemporaneous correlation with a set of macroeconomic series and four leads and lags. The list of macroeconomic variables selected are those that are used as inputs in the Euler equation estimation. We use official CPI inflation, inflation attention, inflation attention, consumption deflators for the aggregate and non-durable consumption, and for consumption aggregate and non-durable consumption series.

Table 2 presents the dynamic correlation patterns for the inflation keyword indices. First column presents the share of created indexes for inflation keywords where the maximum leading correlation coefficient for the four quarters is stronger than the maximum lagging correlation coefficient. Values higher than 50 indicate therefore that most of the generated series have stronger leading patterns. For example, for the 83.8 percent of the series the correlation coefficient is higher for leads than for the lags. The average lead for all the topics is 2.4 quarters (see the third column). For the topics that are related to the future, the lead is even stronger, reaching 3.3 quarters the last column. The topics that are related more to the past still have a lead of 1.3 quarters in the fourth column.

TABLE 2
Inflation indices correlation summary

	Share of leading indices relative to lagged (%) (1)	Share of leading relative to contemporaneous (%) (2)	Average lead/lag (quarters)	Average lead/lag in quarter for past topics (quarters)	Average lead/lag in quarter for future topics (quarters)
Prices					
Inflation	83.8	93.8	-2.4	-1.3	-3.3
Inflation expectations	70.0	65.0	-0.5	-1.7	-1.1
Inflation attention	68.6	95	-1.5	0.0	-2.0

Consumption deflator	92.5	97.5	-3.3	-2.7	-3.9
Non-durable consumption deflator	90.0	95.0	-2.9	-2.3	-3.2
Economic activity					
Consumption	37.5	90	1.0	-1.2	1.3
Non-durable consumption	25.0	87.5	2.0	1.3	2.6
CCI	67.5	34	-0.4	-1.2	-0.3

Notes: (1) Share of leading indices is calculated by taking the maximum value of the correlation of four leading correlations and compared to the maximum of four lagged correlations. A percentage higher than 50 means that there are more series that have a stronger leading correlation than lagging correlation. (2) Share of leading indices relative to contemporaneous is calculated by taking the maximum value of the correlations of the four leading correlations and compared to the contemporaneous correlation. A percentage higher than 50 means that there are more series that have a stronger leading correlation than contemporaneous correlation.

In fact, the series created are leading on average for all the inflation related time-series. The relationships are especially strong for the consumption deflator that we use in the Euler equation analysis. All the future-related topics have on average also a longer lead than for all the series indicating that the keywords used to select future related indices has some predictive power.

The picture is completely different when one looks at the consumption and non-durable consumption correlations. The share of series leading drops to 37.5 for the aggregate consumption and even 25.0 for the non-durable consumption showing that most of the indices are in fact lagging consumption. The average lag is 1 quarter for the aggregate consumption and even 2 for the non-durable consumption. The consumer sentiment index

For completeness, Table 3 carries out a similar exercise for the economic sentiment keyword indices, showing the same descriptive statistics. The picture is somewhat different and is consistent with the view that the words and indices capture more economic sentiment and less inflation sentiment. The share of indices that have leading properties are lower for all but one index which is inflation attention. The same holds for the average lead which is smaller for inflation measures with the exception of inflation attention.

TABLE 3
Economic sentiment indexes correlation summary

	Share of leading indices relative to lagged (%) (1)	Share of leading relative to contemporaneous (%) (2)	Average lead/lag (quarters)	Average lead/lag in quarter for past topics (quarters)	Average lead/lag in quarter for future topics (quarters)
Prices					
Inflation	71.3	66.3	-0.8	-0.2	-1.5
Inflation expectations	40	12.5	0.6	0.4	0.5
Inflation attention	86.3	91.3	-2.5	-2.2	-3.3
Consumption deflator	81.3	86.3	-2.0	-1.4	-2.5
Non-durable consumption deflator	88.8	86.3	-1.5	-2.4	-1.7
Economic activity					
Consumption	48.8	66.3	0.1	-0.6	0.4
Non-durable consumption	41.3	65.0	0.8	1.6	0.5
CCI	18.8	15.0	0.4	0.8	0.7

Notes: (1) Share of leading indices is calculated by taking the maximum value of the correlation of four leading correlations and compared to the maximum of four lagged correlations. A percentage higher than 50 means that there are more series that have a stronger leading correlation than lagging correlation. (2) Share of leading indices relative to contemporaneous is calculated by taking the maximum value of the correlations of the four leading correlations and compared to the contemporaneous correlation. A percentage higher than 50 means that there are more series that have a stronger leading correlation than contemporaneous correlation.

When comparing the leading patterns of economic sentiment indices with economic activity, one can see also that the keywords of economic sentiment are more likely to be leading consumption are the keywords of inflation. Still the leading patterns is not strong as less than half are stronger correlated than lagged values. On average economic sentiment keyword indices lag consumption series.

The exception is the correlation with the economic sentiment index CCI. It is related stronger to inflation keywords than with the words of economic activity. This shows that the relationship between economic sentiment and inflation in the views of the public debate is worth separate investigation.

4. Results

4.1 Euler equation estimation

Baseline models are presented in Table 4 that show the output of the Euler models with the total consumption. The results for the non-durable goods and services, as well as for alternative measures of inflation for benchmark models are provided in Appendix D. For benchmark models' 'official' inflation expectations data is used for π_t and we compare these to the models infused by news-based topic driven indices as inflation perception measures. As can be observed from the diagnostic tests in Table 4, Euler models do not seem to provide solid evidence for total consumption, when using inflation expectations. The instruments pass the weakness test but fail on the other Wu-Hausman and Sargan tests indicating that the econometric approach does not solve endogeneity problem fully. EIS is 0 or negative, indicating that its value is not informative. Therefore, the conclusion at this stage would be that Euler models for UK total consumption fail. So do the models for the other types of consumption, as is implied from the results in tables D1 and D2 in the appendices.

TABLE 4
IV regression results from benchmark models: total consumption

	Benchmark Models		
	(I)	*(II)*	*(III)*
$(i_t - \square_{t+1})$	0.001	0.001	0.002
	(0.007)	(0.006)	(0.007)

c_t		-0.253	-0.657*
		(0.240)	(0.348)
$E_t c_{t+2}$			-0.872*
			(0.479)
Constant	0.004	0.005	0.008
	(0.016)	(0.016)	(0.018)
Observations	91	91	90
EIS	0.0008	0.001	0.002
R^2	-0.001	0.104	-0.102
		Diagnostic tests	
Weak Instruments test	54.5 ***	54.7 *** 1.58	54.6*** 1.57 4.66***
Wu-Hausman	0.96 (0.33)	0.56 (0.57)	0.86 (0.46)
Sargan	6.93 (0.33)	6.58 (0.25)	1.83 (0.76)

Notes: *p<0.1; **p<0.05; ***p<0.01, all models include 6 instruments: $c_{t-1}, c_{t-2}, c_{t-3}, r_{t-1}, r_{t-2}, r_{t-3}, c_t$ corresponds to non-durable goods and services consumption.

Findings for the Euler models with news-based topic indices are presented in Table 5. Only models where all instruments are valid and an improvement upon benchmark models in terms of R^2, holding the number of estimated coefficient constant, is observed are shown. For the purposes of saving space, we cluster topics into larger groups and present the results as a range of minimum and maximum EIS and R^2 for the topics of that cluster.

TABLE 5

IV regressions results from benchmark models: total consumption

Model	*Topic Cluster*	R^2	R^2 *benchmark*	*EIS*	*Max Improvement*
External Habits	FINANCIAL MARKETS	0.12	0.10	-0.006	+2 pp
External Habits	OTHER	0.12	0.10	-0.001	+2 pp

External Habits	UK ECONOMY	0.12	0.10	-0.001	+2 pp
Internal Habits	FINANCIAL MARKETS	0.02 - 0.21	-0.10	-0.014 - 0.002	+21 pp
Internal Habits	INFLATION	0.09	-0.10	-0.006	+9 pp
Internal Habits	OTHER	0.04 - 0.24	-0.10	-0.012 - 0.009	+24 pp
Internal Habits	UK ECONOMY	0.12 - 0.2	-0.10	-0.009 - 0.002	+20 pp
Internal Habits	WORLD ECONOMY	0 - 0.19	-0.10	-0.013 - 0.009	+19 pp

The logic for clustering is simple: topics discussing any kind of price information are clustered under the group INFLATION. Topics containing words about the economy, such as GDP, recession, economic growth, bank rates, the unemployment rate are grouped under either UK or WORLD ECONOMY clusters, depending on the exact keywords. Topics that discuss financial markets, investments and stocks are grouped under the FINANCIAL MARKETS cluster and so on.

All other remaining and potentially insightful topics are clustered into the group OTHER. Detailed results for all three models and individual results for each topic can be found in Appendix D, tables D1–D4.

The most important condition is clearly the test on the validity of the instruments. The comparison of the goodness of fit R^2 is done for the purpose of getting intuition on the overall performance of the models as it is standard to report the parameter estimates and goodness of fit in the literature even for models that fail econometric tests. In a strict econometric interpretation, the estimates of the standard errors should be adjusted for the uncertainty of the first stage of the index estimation. This is however not feasible. The goodness of fit is part of the standard information reported on the regression in other papers. It is easily and intuitively interpretable. Therefore, the paper concentrates on the economic values of the parameter estimates and the improvement in the goodness of fit.

Summarizing the findings from Table 5, the Euler models based on the novel data source outperform the benchmark models as highlighted by the value of R^2. This means that the data from Table 5 fits the Euler consumption models. Compared to the internal and external models the improvement in R^2 is ranging between 2 or 6 percentage points, but both R^2 and EIS remain generally low. The internal habits model seems to outperform the external habits model. Overall, the goodness of fit and EIS values of all three models improves when NTDI are used instead of official inflation expectation measures. Most importantly all instruments are now valid and satisfy our test conditions, as opposed to the benchmark models.

Analysing the results on the topic of total consumption, interestingly, out of 80 topics, 90% of those selected contain words such as inflation, price increase, economic growth, recession, or losses. The Bank of England, expectedly, comes up often in the UK Economy cluster. Foreign economies, such as China and the USA also have an impact on household consumption decisions as per our results, which is not surprising with China and the USA being among major world economies.

Topics that include words like retail sales, Australian economy, bonus pays, drugs, sports, airlines and other miscellaneous topics were not selected by the models, indicating that news on these topics are irrelevant or have low impact on consumer spending decisions. A few of the topics that were excluded do contain useful words such as oil prices, job cuts and incomes and this is expected. First, model performance can always be improved by using better models and tools. Second, each topic generally contains around 1,000 words, while in the Euler models we use about the 100 most frequent words, without taking into account that the remaining 900 words might outweigh the top 100 by total quantity.

The topics selected by our algorithm represent news shocks affecting consumer consumption decisions and consequently the relationships between macroeconomic variables in the Euler models. We provide evidence for the NTDI based Euler models. Evidence shows that consumers who read the news will build their inflation perceptions and adjust their spending according to the relationship represented by the Euler model framework. From Table 5 and the UK Economy topic, it follows that all three consumption models are able to pass econometric tests and model consumers total consumption patterns through the Euler models. The EIS coefficient is the highest for the external habits model, implying a stronger relationship. This means that when reading the news on the UK economy, households take into the account the spending of others in their own spending and consumption decisions.

To further validate our results and support the above describe findings, we analysed the relationship between total consumption with novel news topic-based inflation perception indices. The results from dynamic correlation are presented in Figure E1 in Appendix E and show high levels of correlation between the two measures, highlighting the potential for NTDI to predict movements in consumption. Further analysis, however, is left for future research.

For other components of consumption, expectedly, the results are not as clear. The tests improve clearly. In economic terms the improvement for aggregate consumption is up to 3 points at best, while for the semi-durable goods consumption component, only the baseline model with a full instrument set gives reliable results. The remaining results cannot be considered satisfactory, as either R^2 or EIS are negative. The sensitivity of the Euler models' results on the consumption data we observe is common in the literature. For different types of consumption, the same models can yield contrasting results, which is intuitive. Numerous survey-data-based studies on different countries reach the same conclusion, that changes in inflation affect various components of consumption differently both by quantity and the direction of the change (see Drager and Nghiem, 2021 for the results using German household data, Coibon et al., 2019 for results on Dutch households and Bachmann et al., 2015 for results on US households). In a recent paper by Burke and Ozdagli (2023), actual spending data for the US households is used and again, different consumption components react differently to expected inflation. For instance, durable spending increases, but only for a specific type of households. However, the nondurables spending of US households does not respond to inflation. For Dutch consumers, the spending on durable goods falls sharply as inflation expectations rise (Coibon et al., 2019). It is therefore not surprising, and as expected, that the Euler models would not perform alike for all consumption types.

4.2 Robustness checks

Number of alternative models and measures have been employed to validate and reinforce our results. For instance, tables D5 and D6 in Appendix D show that when in benchmark Euler models implied deflator corresponding to consumption components is used as a measure of inflation π_t , news topic-based models still outperform benchmark modelling, highlighting the advantage that news-based inflation perception measures bring to Euler models.

We also replicated all analysis by filtering out news articles based on another keyword set, related to consumer specifically to consumer sentiment. Results, not included in this paper, but available upon request, are still better for news-based indices than for benchmark models. The ranges of EIS as well as improvements of R^2 are similar to the results from inflation related keywords.

Our results, including the value of EIS are almost insensitive to using 3-month interbank rates or end-of-quarter official bank rates[12]. Neither are they particularly sensitive to instrument set combinations. However, they are sensitive to the type of consumption and the number of lags in instruments. For reference, the results from Ascari et al. (2021) on US data are also insensitive to different instruments and specifications. However, in contrast to ours, their results do not change

[12] Results are not presented in the paper for the purposes of saving space but are available on request.

when a different consumption measure is used but instead are highly sensitive to asset returns: the value of EIS changes depending on whether risk-free returns or stock market returns are used. In particular, with stock market returns, EIS is significantly positive, but not precisely estimated. A similar observation about the sensitivity and precision of EIS can also be drawn from our results: it is not always precisely estimated, and its value varies a lot when the model and underlying data change.

The value of EIS across all our models is generally low and close to zero. These results are supported in the linear models of Ascari et al. (2021) and Campbell (2003), which find the 95% confidence interval for the estimated EIS to be close to zero for non-durable consumption. Yogo (2004) robust to weak-identification econometric methods also yield a small EIS that is not significantly different from zero.

There are numerous ways to improve model performance to support our results with even stronger empirical evidence. For example, there are a number of robust-to-weak identification tests for parameter stability or structural change that could be applied to our models. Similarly, there are potentially more efficient methods for further evaluating the sensitivity of our results to different heteroskedasticity and autocorrelation consistent estimates and the variance of moment conditions.

Attanasio and Low (2000) also suggest loglinear approximating Euler models and using a sample long enough to get ‘well-behaved’ estimates. While we believe our sample size is adequate, we are unable to extend the data length due to the limitations of the availability of online news data. It would also be interesting to deep dive into consumer data and better understand the demographics of UK households and the specific characteristics of news readers, such as age, income, wealth, education etc. However, we will leave this for further research.

5. Conclusions

There is a lot of discussion of Euler models and their potential failures in the literature. We argue that one reason why many authors have reached the conclusion that they fail is because the real interest rate in the model is mis-specified and fails to capture consumers' true perception of the economy. To tackle this, we propose news as a novel alternative source for capturing inflation perceptions.

Our hypothesis is that the news that consumers read has a direct impact on their perceptions and recent technological advances allow us to derive these perceptions directly from the news using machine learning techniques. Even though we do not solve all the problems related to Euler models, our results are empirically successful. We provide evidence in favour of Euler models when news-based inflation perceptions are used to calculate the real interest rate.

Using online news data for consumption modelling and predictions is relatively unexplored. Estimating Euler models with news-based inflation perception measures opens numerous opportunities for macroeconomists to make further progress not only in modelling, but also predicting consumption in real-time. Our positive findings also allow for the use of such novel data sources for other key macroeconomic relationships, for example, the New Keynesian Phillips curve.

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APPENDIX A: data description

We use quarterly data covering the sample period between January 2000 and December 2023 and apply seasonal adjustment and growth transformation where needed. Like (Ascari, Magnussen and Mavroeidis, 2021), we use per head measures of consumption. Household final consumption, HFCE_PH is available both as a total and per capita measure and is directly exported from the source, while for the consumption components we manually transform the series to per head measures using population time series POP from the UK Labour Force Survey. We also transform nominal measures of consumption, HFCE, NDE, NDG, SERV to real measures using corresponding implied deflators. The formulae are as follows:

For final consumption expenditure:

$$RHFCE = \frac{HFCE\_PH}{HFCE\_DEFL}. \tag{A.1}$$

For non-durable goods and services, we combine the two components into one real measure as follows:

$$RNDGSERV = \frac{NDG\_PH + SERV\_PH}{P_{NDGSERV}}. \tag{A.2}$$

Implicit deflator in (A.2) for nondurable goods and services $P_{NDGSERV}$ is computed as follows:

$$P_{NDGSERV} = \frac{NDG+SERV}{\frac{NDG}{NDG\_DEFL}+\frac{SERV}{SERV\_DEFL}}. \tag{A.3}$$

And the per capita measures for consumption components are computed using:

$$NDG_{PH} = \frac{NDG}{POP}, \tag{A.4}$$

$$SERV\_PH = \frac{SERV}{POP}. \tag{A.5}$$

As a last step for consumption related data, the per head measures RHFCE and RNDGSERV are log transformed to be used as consumption proxies in the Euler model.

For the interest rate we use 3-Month Interbank Rates for the United Kingdom for the main results and End of Quarter Official Bank Rates for robustness checks in additional results (see Appendix D). Both time series are monthly and are consequently converted to quarterly series by averaging.

To compare our results with the benchmark model we use 5-year Inflation Implied Forward rates, as well as official inflation data from the Bank of England and Inflation attitude surveys data in additional results for comparison.

Overall, at the final stage all data described in Table A1 is in quarterly values at annual rates, seasonally adjusted. Some are also log transformed.

Table A1
Data used in the paper

Mnemonic in the dataset	*Description*	*Transformation*	*Source*
INFL_ATT	Median value from survey indicating public attitudes to inflation and general expectation on inflation change over the next 12 months	Seasonal adjustment	Office for National Statistics
CPI_INFL	Official CPI inflation	Seasonal adjustment	Bank of England
INFL_EXP	Quarter average of yield from British Government Securities, 5-year Inflation Implied Forward	Seasonal adjustment	Bank of England
HFCE_DEFL	Real Household final consumption expenditure: Implied deflator	Seasonal adjustment	Office for National Statistics
HFCE	Household final consumption expenditure at current prices	-	Office for National Statistics
HFCE_PH	Household final consumption expenditure per head at current prices	-	Office for National Statistics
IB_3M	3-Month Interbank Rates for the United Kingdom, growth rates	Seasonal adjustment	Federal Reserve Economic Data
IB_EQR	End of Quarter Official Bank Rate	Seasonal Adjustment	Bank of England
NDG	Nominal non-durable goods expenditure at current prices		Office for National Statistics
NDG_DEFL	Implied Deflators for Nondurable goods, 2008 Index	Seasonal adjustment	Office for National Statistics

POP	LFS: Population aged 16+: UK: All: 4 quarter average	Seasonal adjustment	Labor Force Survey, ONS
SERV	Nominal services expenditure at current prices	-	Office for National Statistics
SERV_DEFL	Implied Deflators for Services, 2008 Index	Seasonal adjustment	Office for National Statistics
Calculated variables			
SERV_PH	Nominal services expenditure per head		
NDE_PH	Nominal non-durable goods expenditure per head		
RHFCE	Real Household final consumption expenditure per head	Log	
RNGSERV	Real Household non-durables and services consumption expenditure per head	Log	

APPENDIX B: textual data mining

B1: data preparation

All words are analysed as a single token using Natural Language Processing's bag of word (BOW) approach, which means their grammar or structure does not matter. This is a common, if not the most popular, approach applied in the literature (see Thorsrud, 2018; Thorsrud, 2020). Below are the techniques used to clean up the data, which include the most common steps of the BOW approach. However, we extended this approach by also stemming the words. Each of these techniques has its own pros and cons. For example, along with reducing dimensionality, these techniques might obscure meaning for some words or might count words that are written similarly but have different meanings.

Step 1: We remove any metadata such as images, links and any other data in an unknown format contained in the articles and convert any information contained in the article into an appropriate format. Duplication and empty entries should also be accounted for and such documents are removed. This can be done either manually or using methods similar to Echkely (2015). In our analysis, we used R language's powerful commands for duplicate and empty data removal.

Step 2: We then use tokenisation, which is a step which splits longer strings of text into smaller tokens, such as words, numbers, symbols and so on. Tokenisation is usually done by using blank spaces or punctuation marks as delimiters. Tokenisation is sometimes also referred to as lexical analysis. This breakdown process results exclusively in words.

Step 3: Next, all words are normalised; that is, all the words are converted into lower case, punctuation is removed, numbers are converted into their equivalent. This is an important step, otherwise same words, such as Rate and rate, which are written in upper, and lowercase respectively will be interpreted as different words. The downside is, however, that when written in uppercase, some words may refer to names of people or places, such as White and white. We assume, however, that the frequency of such words is not significant.

Step 4: A crucial step is removing stop words, otherwise they will appear in the frequently used words and will not give an incorrect picture of the core meaning of the document. Stop words are those words which are filtered out before further processing of text, since these words contribute little to the overall meaning, given that they are generally the most common words in a language. The list of these words is provided in the beginning of the analysis and includes common words in the English language that do not contain any information relating to the article. Examples of such words are the, like, can, I, also, are, in, on, this, that, gmt, pm etc.

Step 5: For further dimensionality reduction and better pre-processing results, we stem words, which involves cutting off affixes and suffixes and reducing all words to their respective word stems. This is a form of linguistic normalization, where the part of speech of each word is identified and each word is converted into its base form; for example, nouns, verbs, pronouns with the same base into base words (e.g. reporting, reported and reporter will be reduced to report).

Step 6: The last step in the pre-processing involves defining the document term matrix (DTM) based on the now clean text and computing the most common words across all the documents. Document Term Matrix (DTM) lists all occurrences of words in the corpus, by document. At this stage, we also remove the sparse terms; that is, terms occurring only in very few documents. These are the tokens which are missing from more than 90% of the documents in the corpus.[13] The remaining 900,000 stems with the highest TDM score are used in the final analysis.

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[13] Maximal allowed sparsity is in the range from 0 to 1. For this paper, the sparsity was chosen equal to 0.9, which means the token must appear in at least 10% of the documents to be retained. The sparsity value can be modified to higher or lower value, but that affects the number of terms remained in the corpus.

The visualisation summarising the results described above is given in a word cloud form in Figure A1. Word cloud visualises the most common words in the corpus by differentiating between word colour and size, indicating the frequency intervals by colour and size, with more frequent words having a bigger size.

Figure B1. Word cloud representation of document-term-matrix.

B2: topic modelling

Latent Dirichlet allocation (LDA) is an approach used in topic modelling based on probabilistic vectors of words, which indicate their relevance to the text corpus. LDA makes it possible to derive the topic probability distribution by assigning probabilities to each word and document. Assigning words and documents to multiple topics also has the advantage of semantic flexibility (e.g. the word ‘rate’ can relate both to inflation and unemployment topics). As Thorstrud **(**2018) notes, LDA shares many features with Gaussian factor models, with the difference being that factors here are topics and are fed through a multinomial likelihood at the observation.

In LDA, each document is given a probability distribution and for each word in each document, a topic assignment is made. The joint distribution of topic mixture θ, a set of N words w is given by:

$$p(\theta, z, w \mid \alpha,\beta) = p(\theta \mid \alpha) * \prod_{n=1}^{N} p(z_n) * p(w_n \; z_n,), \qquad \text{(B.1)}$$

where parameters α and β are k-vectors with components greater than zero, with k being the dimensionality of the Dirichlet distribution; that is, the directionality of topic variable $\boldsymbol{z}$. In addition, the topic distribution of each document is distributed as $\theta \sim$ Dirichlet(α). Term distribution is modelled using $z_n \sim$ Dirichlet(β) and N ~ Possion(ξ).

The goal of the LDA model is therefore to estimate θ and in order to estimate which words are important for which topic and which topics are important for a given document. For α and β, the higher they are, the more likely each document will contain a mixture of most topics instead of a single topic and the more likely each topic will contain a mixture of most of the words and not just single words. More technical detail and thorough specifications on the LDA model and topic modelling in general are provided in Blei (2003) and Griffiths and Steyvers (2004).

There are different approaches to the LDA algorithm. In this paper, we use the Gibbs sampling method, an algorithm for successively sampling conditional distributions of variables, whose distribution over states converges to the true distribution in the long run. Gibbs sampling makes it possible to improve the topic representations within documents, as well as the word distributions of all the topics. Gibbs method samples from this multinomial posterior distribution on the set of possible subset choices to identify those with higher probability by their more frequent appearance in the Gibbs sample (George and McCulloch, 1993). Each variable from formula (B.1) is sampled given the full conditional distribution of other variables, which are as follows:

$$p(z_{iv} = k \mid \square_i, b_k) \infty \exp(\log \square_{ik} + log\ log\ b_{k,y_{iv}}),$$
(B.2)

$$p(\square_i \mid z_{iv} = k, b_k) = \text{Dirichlet}\ (\alpha + \textstyle\sum_k^{\square} \square\ l\ (z_{iv} = k)),$$
(B.3)

$$p(b_k \mid z_{iv} = k, \square_i) = \text{Dirichlet}\ (+ \textstyle\sum_i^{\square} \square \sum_k^{\square} \square\ l\ (y_{il} = w, z_{il} = k)),$$
(B.4)

where k is the topic, w is a term, $\square_i$ is a vector defining a distribution over T topics and b_k is a vector defining a distribution over N words.

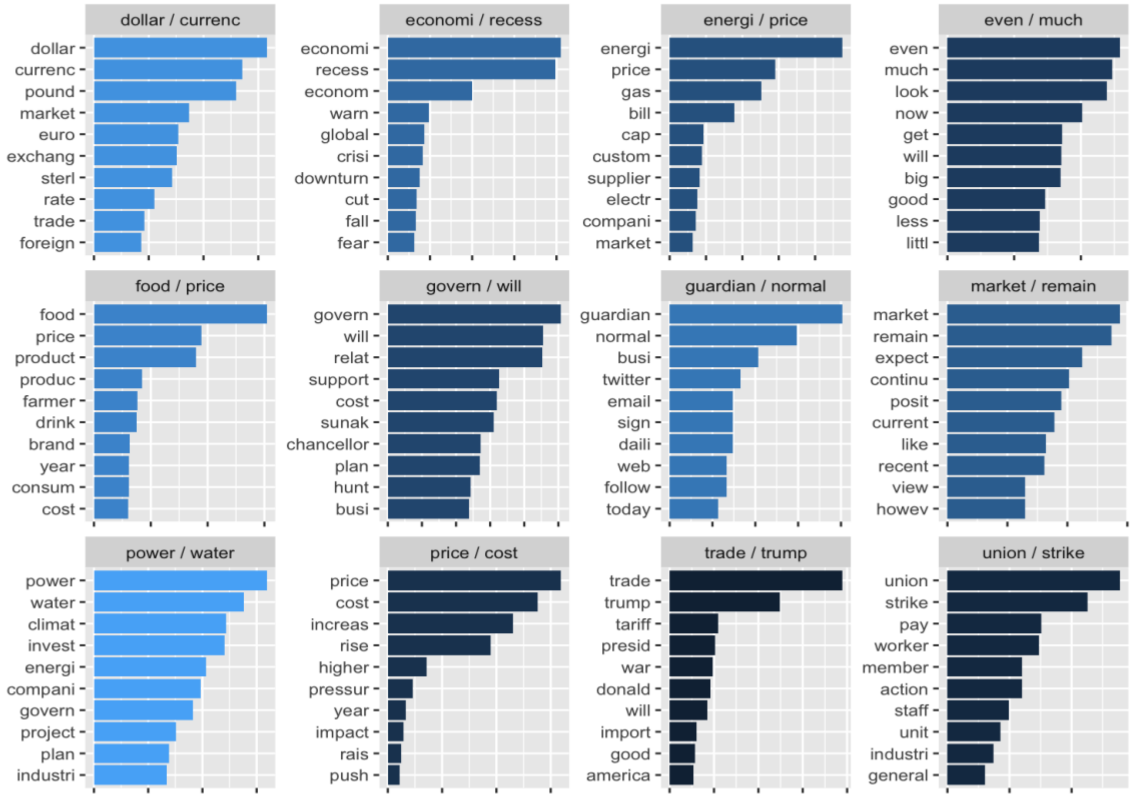
Griffiths and Steyvers (2004) were the first to suggest analytically integrating $\square_i$ and b_k and sample z_{iv} to get a better performance by perhaps adding something – better performance of what? Predictive performance? The logic is as follows: for each document d, for each word w, reassign a new topic k to w. The probability of this topic k is equal to the probability of word w given topic k multiplied by the probability of topic k given document d. The mathematical formula is given below:

$$p(z_i = j \mid z_{-i}, w_i, d_i) = \frac{C^{NT}_{w_i j} +}{\sum_{w=1}^{N} \square C^{NT}_{w_i j} + W\square} \text{ x } \frac{C^{DT}_{d_i j} +}{\sum_{t=1}^{T} \square C^{DT}_{d_i t} + T\square}, \qquad \text{(B.5)}$$

where C^{NT} is a word-topic matrix and C^{DT} is a document-topic matrix, while and are parameters that set the topic distribution for the documents and the words respectively.

Different model iterations and different parameters of α and β in (B.1) result in different document clustering. However, the goal is to find unknown patterns; therefore, there is no perfect value for numbers of topics and the solution will most likely differ for different values. Hence, the choice of the number of topics to be extracted from the corpus is based on the researcher’s intuition, domain knowledge and the literature.

Figure B2 presents the results from topic modelling with LDA for all 80 topics. Each of the visuals in the figure represents a topic and its top 10 most frequently occurring words in the y axis. These words and corresponding frequency bars are plotted in descending order.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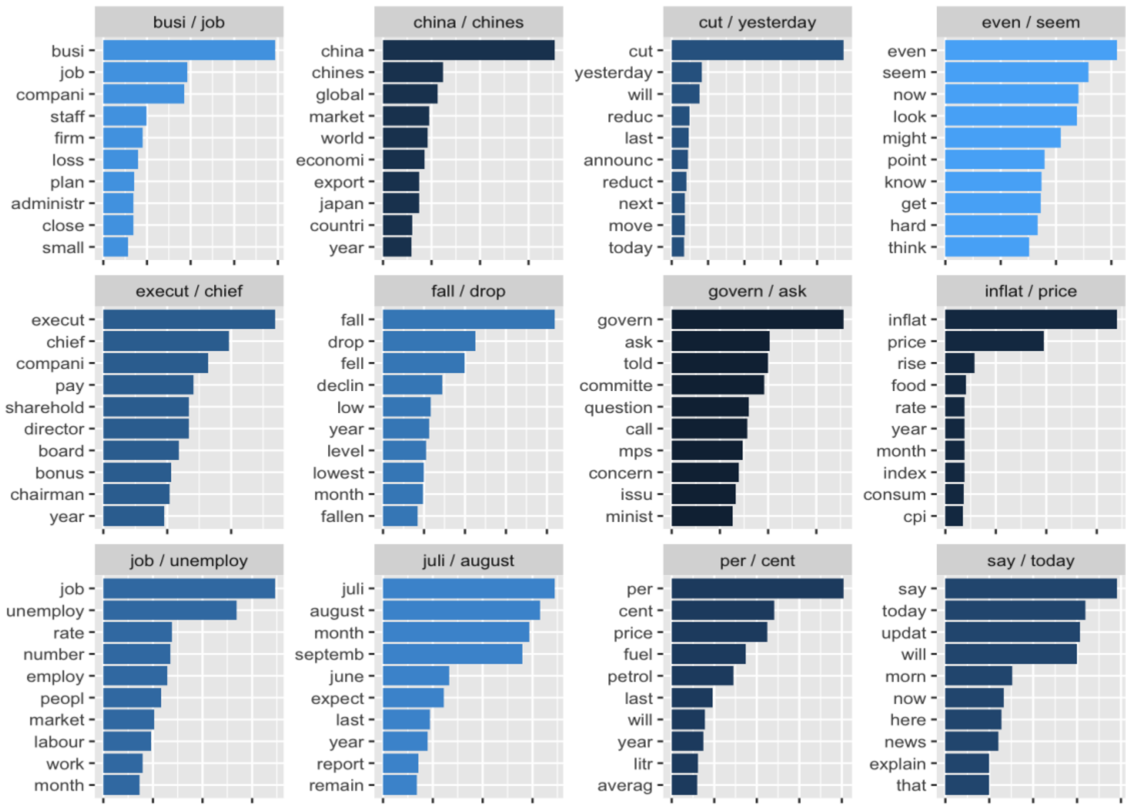
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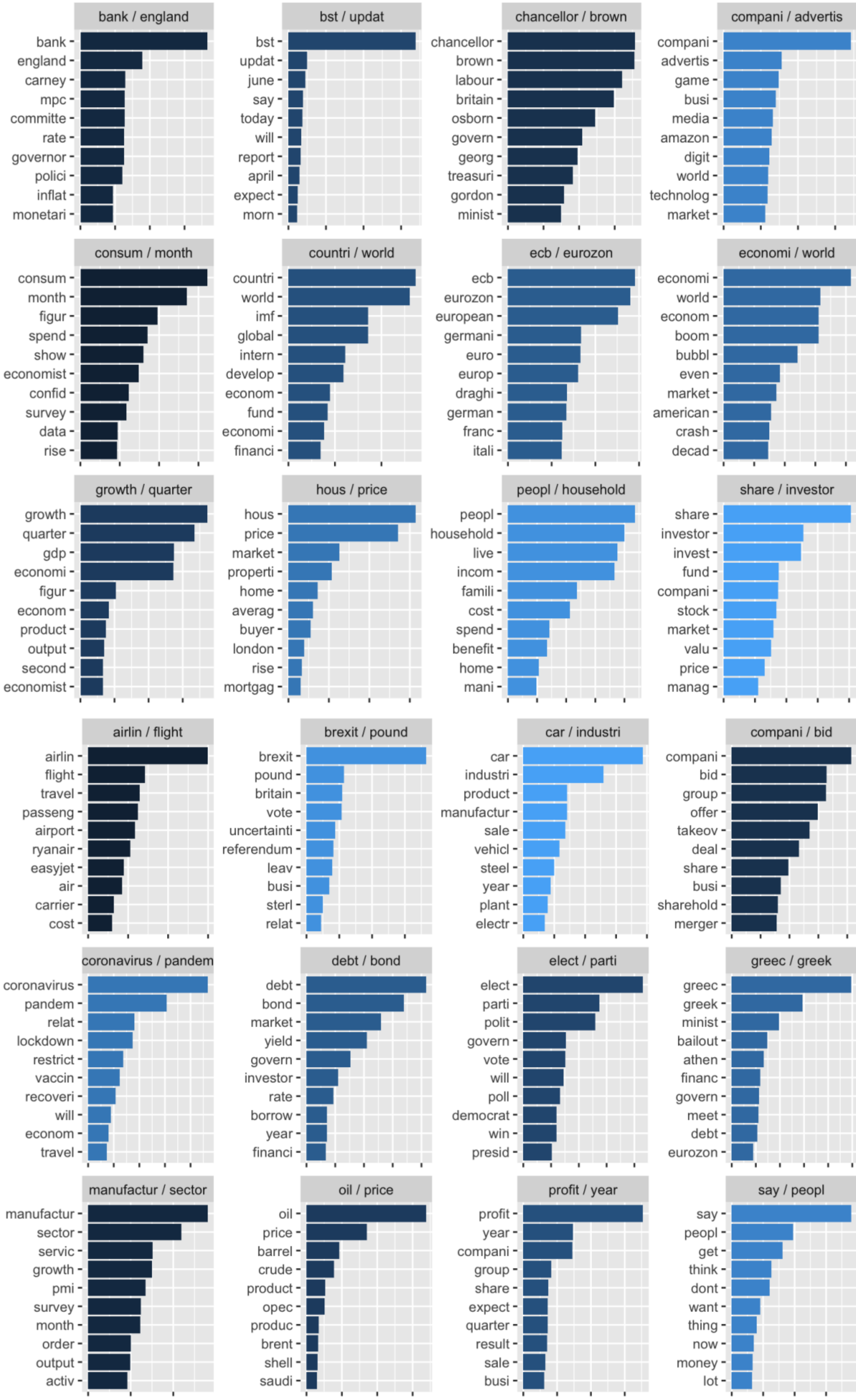
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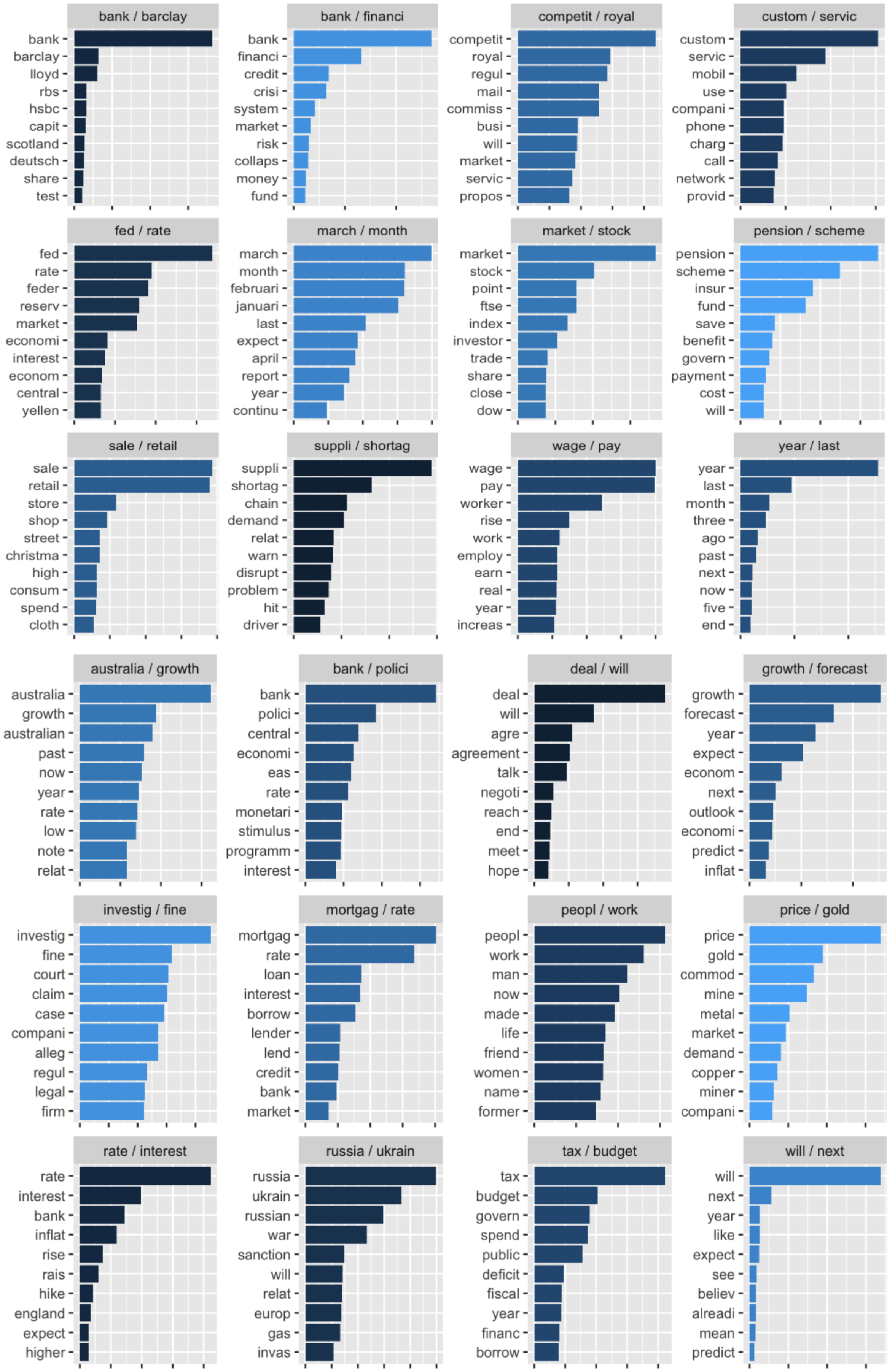
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growth
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past
now
year
rate
low
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bank / polici
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deal / will
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growth / forecast
growth
forecast
year
expect
econom
next
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economi
predict
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investig / fine
investig
fine
court
claim
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legal
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mortgag / rate
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borrow
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lend
credit
bank
market
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work
man
now
made
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friend
women
name
former
price / gold
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gold
commod
mine
metal
market
demand
copper
miner
compani
rate / interest
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interest
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rise
rais
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expect
higher
russia / ukrain
russia
ukrain
russian
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will
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europ
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invas
tax / budget
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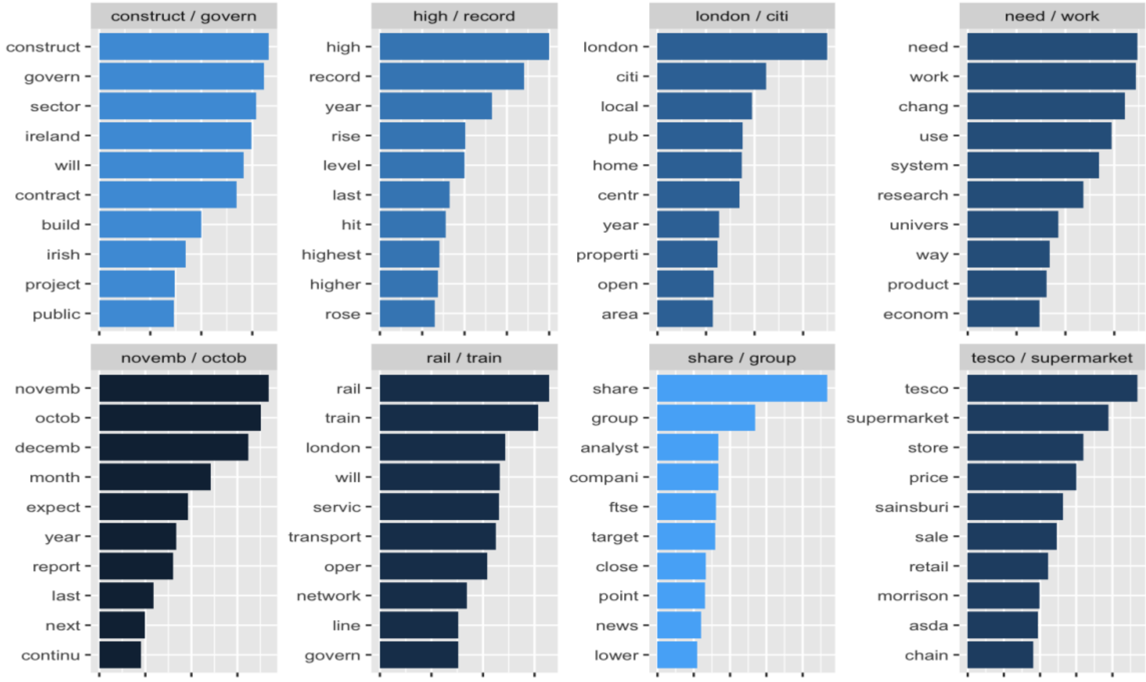
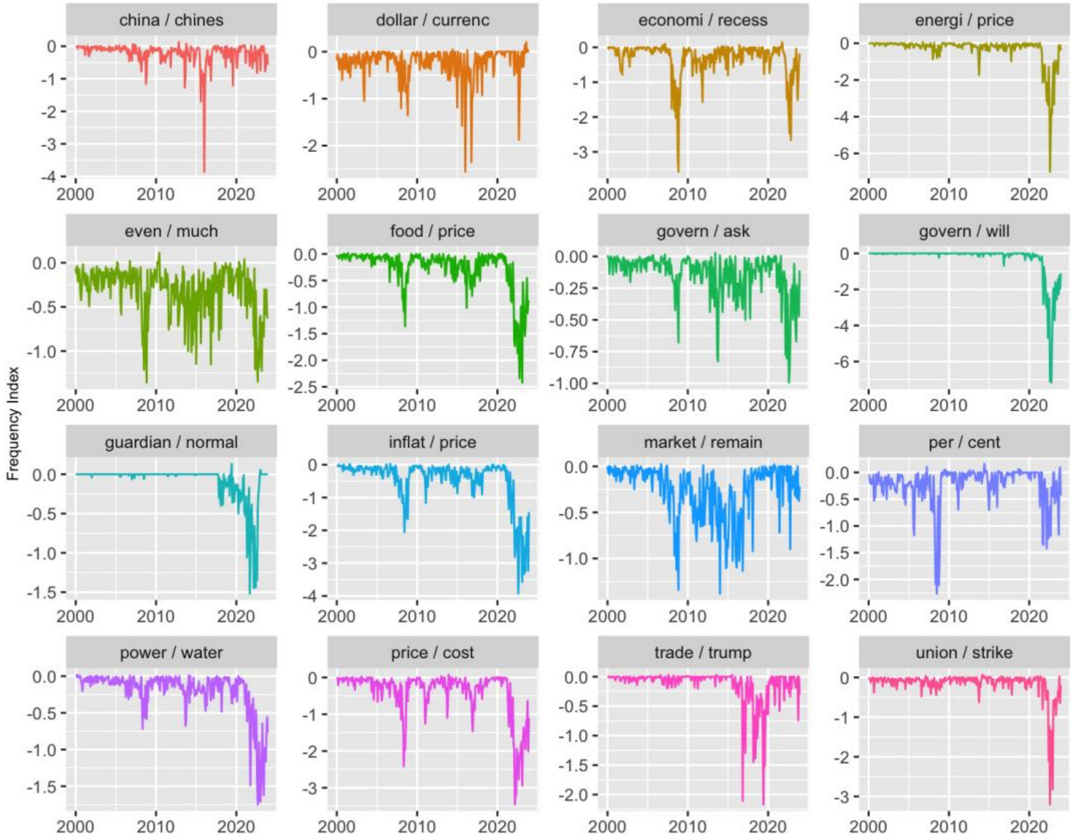
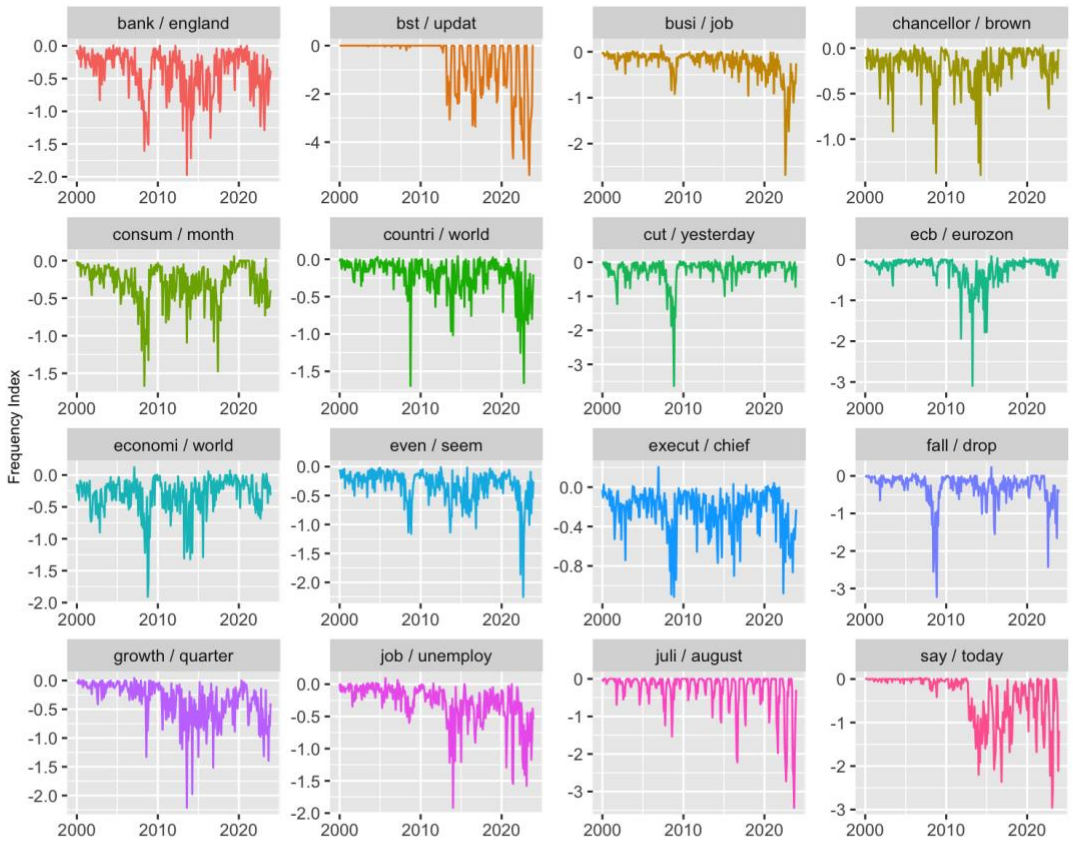
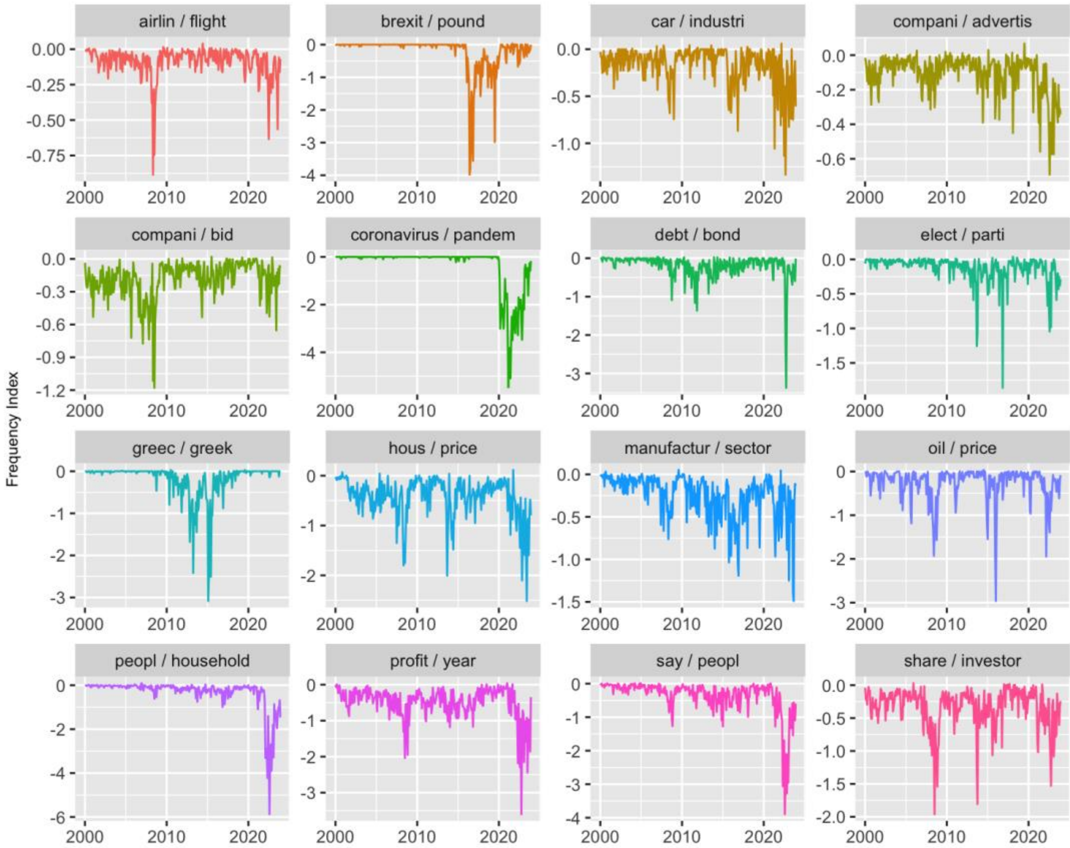


Figure B2. 80 topics resulting from LDA with top 10 frequent words in them. Topic labels are assigned by a concatenation of two most frequent words within the topic. All words are in stemmed format.

APPENDIX C: news-based topic driven inflation perceptions



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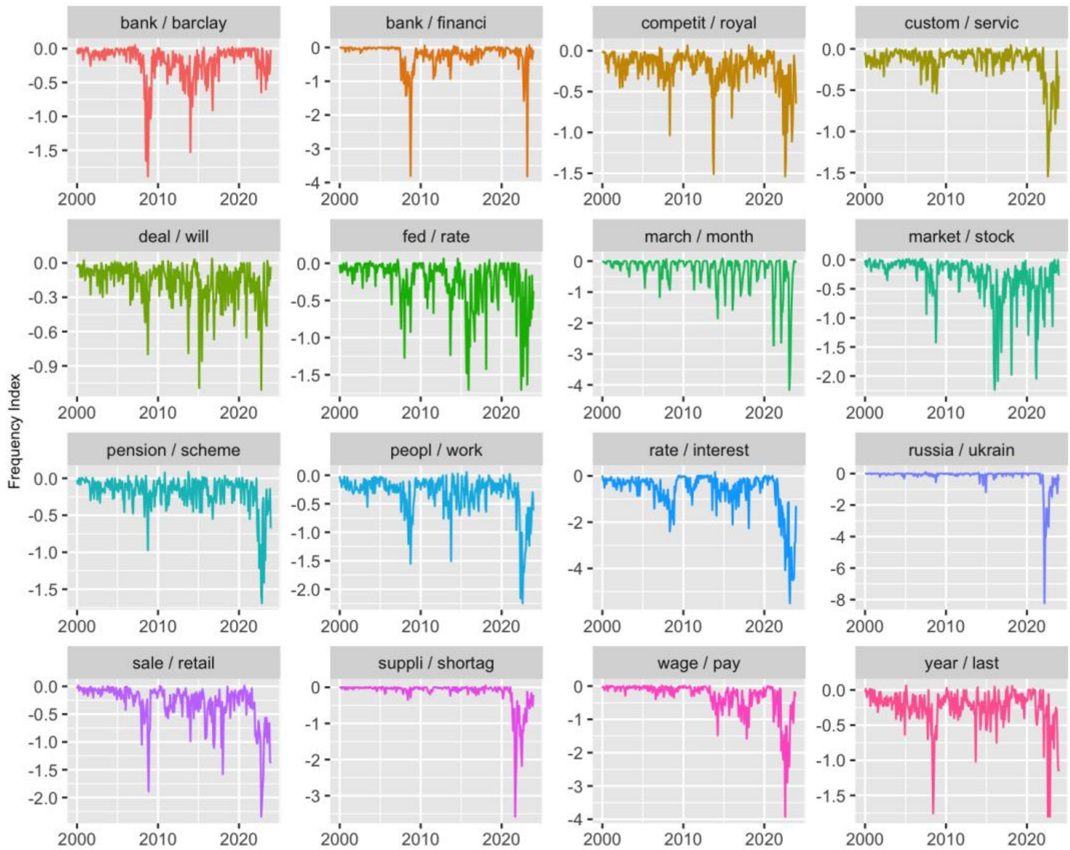
brexit / pound
car / industri
compani / advertis
compani / bid
coronavirus / pandem
debt / bond
elect / parti
greec / greek
hous / price
manufactur / sector
oil / price
peopl / household
profit / year
say / peopl
share / investor
Frequency Index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bank / financi
competit / royal
custom / servic
deal / will
fed / rate
march / month
market / stock
pension / scheme
peopl / work
rate / interest
russia / ukrain
sale / retail
suppli / shortag
wage / pay
year / last
Frequency Index

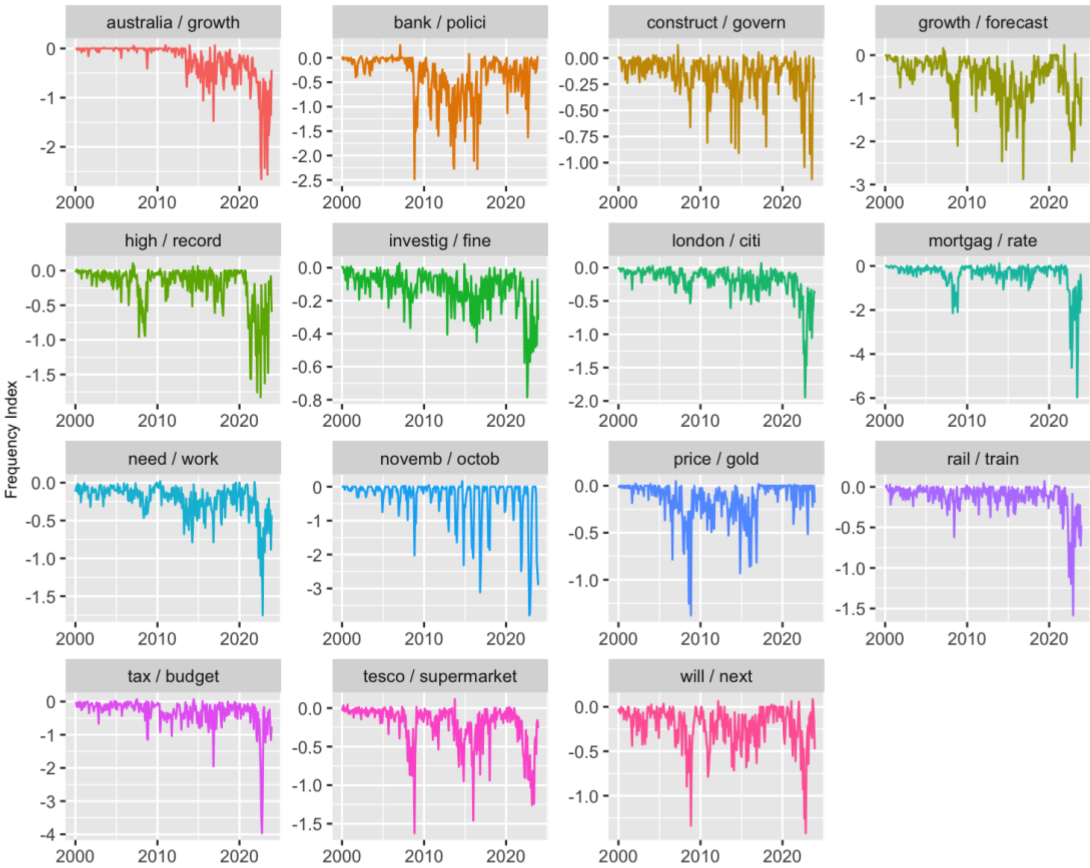


Figure C1. News-based topic driven indices for all 80 topics from January 2020 until December 2023. Topic labels are assigned by a concatenation of three most frequent words within the topic.

APPENDIX D: results

D1: Results from benchmark Euler models

TABLE D1

IV regression results from benchmark models / non-durable goods and services consumption

	Benchmark Models		
	(I)	*(II)*	*(III)*
$(i_t - \pi_{t+1})$	0.002	0.003	0.003
	(0.006)	(0.006)	(0.006)
c_t		-0.291	-0.308
		(0.302)	(0.350)
$E_t c_{t+2}$			-0.040
			(0.464)
Constant	0.009	0.012	0.012
	(0.014)	(0.014)	(0.015)
Observations	91	91	90
EIS	0.002	0.207	-1.12
R^2	0.0004	0.096	0.119
	Diagnostic tests		
Weak Instruments	48.5***	48.5*** 1.12	48.5*** 1.11 3.19**
Wu-Hausman	0.30 (0.59)	0.09 (0.91)	0.15 (0.92)
Sargan	3.42 (0.76)	2.82 (0.73)	2.85 (0.58)

*Notes: *p<0.1; **p<0.05; ***p<0.01, All models include 6 instruments:* c_{t-1}, c_{t-2}, c_{t-3}, r_{t-1}, r_{t-2}, r_{t-3}, c_t *corresponds to total consumption.*

TABLE D2

IV regression results from benchmark models / semi durable goods consumption

	Benchmark Models		
	(I)	*(II)*	*(III)*
$(i_t - \pi_{t+1})$	0.005	0.005	0.002
	(0.007)	(0.008)	(0.009)
c_t		-0.022	0.441
		(0.344)	(0.422)
$E_t c_{t+2}$			-0.097
			(0.310)
Constant	0.002	0.002	0.001
	(0.004)	(0.004)	(0.004)
Observations	81	81	80
EIS	0.005	-0.022	-3.289
R^2	0.044	0.056	-0.345
	Diagnostic tests		
Weak Instruments	3.698 (0.003) **	3.698 / 0.742 (0.003) ** / (0.618)	4.399 / 0.581 / 7.788 *** / / ***
Wu-Hausman	1.180 (0.280)	0.148 (0.862)	0.894 (0.448)
Sargan	16.121 (0.013) *	16.325 (0.006) **	1.320 (0.858)

*Notes: *p<0.1; **p<0.05; ***p<0.01, All models include 6 instruments:* c_{t-1}, c_{t-2}, c_{t-3}, r_{t-1}, r_{t-2}, r_{t-3}, c_t *corresponds to total consumption.*

D2: Results from NTDI based Euler models.

TABLE D3

IV regression results from NTDI models, total consumption

Topic	*Model*	*Instruments*	*EIS*	R^2	R^2 *benchmark*	*Improvement*
2	Internal Habits	All	0.00	0.2	-0.10	+20 pp
2	Internal Habits	All excl. sentiment	0.00	0.19	-0.10	+19 pp
3	Internal Habits	All	-0.01	0.24	-0.10	+24 pp
3	Internal Habits	All excl. sentiment	-0.00	0.17	-0.10	+17 pp
6	Internal Habits	All excl. sentiment	-0.02	-0.02	-0.10	+-2 pp
10	Internal Habits	All excl. sentiment	0.01	-0.03	-0.10	+-3 pp
11	External Habits	All	-0.00	0.12	0.10	+2 pp
11	Internal Habits	All	-0.00	-0.02	-0.10	+-2 pp
12	Internal Habits	All	0.00	0.02	-0.10	+2 pp
17	Internal Habits	All	0.00	0.2	-0.10	+20 pp
17	Internal Habits	All excl. sentiment	0.00	0.18	-0.10	+18 pp
31	Internal Habits	All	-0.01	0	-0.10	+0 pp

33	External Habits	All	-0.00	0.12	0.10	+2 pp
33	Internal Habits	All	-0.01	0.12	-0.10	+12 pp
34	Internal Habits	All	-0.00	0.13	-0.10	+13 pp
39	Internal Habits	All	0.01	0.16	-0.10	+16 pp
39	Internal Habits	All excl. sentiment	0.01	0.09	-0.10	+9 pp
42	External Habits	All	-0.01	0.12	0.10	+2 pp
42	Internal Habits	All	-0.01	0.21	-0.10	+21 pp
43	Internal Habits	All	-0.00	0.07	-0.10	+7 pp
44	Internal Habits	All	0.01	0.19	-0.10	+19 pp
48	Internal Habits	All	0.00	0.05	-0.10	+5 pp
48	Internal Habits	All excl. sentiment	0.00	0.13	-0.10	+13 pp
50	Internal Habits	All	-0.01	0.12	-0.10	+12 pp
50	Internal Habits	All excl. sentiment	-0.01	0.15	-0.10	+15 pp
53	Internal Habits	All	-0.00	0.21	-0.10	+21 pp
64	Internal Habits	All	0.01	0.1	-0.10	+10 pp
64	Internal Habits	All excl. sentiment	0.01	0.04	-0.10	+4 pp
68	Internal Habits	All excl. sentiment	-0.01	0.09	-0.10	+9 pp
69	Internal Habits	All	-0.00	-0.08	-0.10	+-8 pp
76	Internal Habits	All	-0.01	0.12	-0.10	+12 pp

TABLE D4

IV regression results from NTDI models, non-durable goods and services consumption

Topic	*Model*	*Instruments*	*EIS*	R^2	R^2 *benchmark*	*Improvement*
5	Internal Habits	All	-0.00	0.16	0.12	+4 pp
14	Baseline	All	-0.00	0.02	0.00	+2 pp
14	Baseline	All excl. sentiment index	-0.00	0.01	0.00	+1 pp
18	Baseline	Sentiment index only	-0.01	0.01	0.00	+1 pp
21	Baseline	All	0.00	0.01	0.00	+1 pp
26	Baseline	All	0.00	0.01	0.00	+1 pp
33	External Habits	All	-0.00	0.1	0.10	+0 pp
33	Internal Habits	All	-0.01	0.18	0.12	+6 pp
42	Baseline	All	-0.01	0.01	0.00	+1 pp
42	Baseline	All excl. sentiment index	-0.01	0.01	0.00	+1 pp
42	External Habits	All	-0.00	0.1	0.10	+0 pp
44	Baseline	All excl. sentiment index	0.01	0.06	0.00	+6 pp
50	Baseline	Sentiment index only	-0.01	0.02	0.00	+2 pp
69	Internal Habits	All	0.01	0.16	0.12	+4 pp
71	Baseline	All	0.00	0.01	0.00	+1 pp
71	Baseline	All excl. sentiment index	0.00	0.01	0.00	+1 pp
5	Internal Habits	All	-0.00	0.16	0.12	+4 pp
14	Baseline	All	-0.00	0.02	0.00	+2 pp
14	Baseline	All excl. sentiment index	-0.00	0.01	0.00	+1 pp
18	Baseline	Sentiment index only	-0.01	0.01	0.00	+1 pp
21	Baseline	All	0.00	0.01	0.00	+1 pp
26	Baseline	All	0.00	0.01	0.00	+1 pp

Topic	*Model*	*Instruments*	*EIS*	R^2	R^2 *benchmark*	*Improvement*
33	External Habits	All	-0.00	0.1	0.10	+0 pp
33	Internal Habits	All	-0.01	0.18	0.12	+6 pp
42	Baseline	All	-0.01	0.01	0.00	+1 pp
42	Baseline	All excl. sentiment index	-0.01	0.01	0.00	+1 pp
42	External Habits	All	-0.00	0.1	0.10	+0 pp
44	Baseline	All excl. sentiment index	0.01	0.06	0.00	+6 pp
50	Baseline	Sentiment index only	-0.01	0.02	0.00	+2 pp
69	Internal Habits	All	0.01	0.16	0.12	+4 pp
71	Baseline	All	0.00	0.01	0.00	+1 pp
71	Baseline	All excl. sentiment index	0.00	0.01	0.00	+1 pp

D3: Results from NTDI based Euler models when inflation π_t is measured by the deflator that corresponds to each of the series used for consumption components.

TABLE D5

IV regression results from NTDI models, total consumption

Topic	*Model*	*Instruments*	*EIS*	R^2	R^2 *benchmark*	*Improvement*
2	Internal Habits	All	0.00	0.2	-0.12	+20 pp
2	Internal Habits	All excl. sentiment	0.00	0.19	-0.12	+19 pp
3	External Habits	All	-0.00	0.09	0.08	+1 pp
3	Internal Habits	All	-0.01	0.24	-0.12	+24 pp
3	Internal Habits	All excl. sentiment	-0.00	0.17	-0.12	+17 pp
6	Internal Habits	All excl. sentiment	-0.02	-0.02	-0.12	+-2 pp
10	Internal Habits	All excl. sentiment	0.01	-0.03	-0.12	+-3 pp
11	External Habits	All	-0.00	0.12	0.08	+4 pp
11	Internal Habits	All	-0.00	-0.02	-0.12	-
12	External Habits	All	0.00	0.09	0.08	+1 pp
12	Internal Habits	All	0.00	0.02	-0.12	+2 pp
17	External Habits	All	0.00	0.09	0.08	+1 pp
17	Internal Habits	All	0.00	0.2	-0.12	+20 pp
17	Internal Habits	All excl. sentiment	0.00	0.18	-0.12	+18 pp
31	Internal Habits	All	-0.01	0	-0.12	+0 pp
31	Internal Habits	All excl. sentiment	-0.01	-0.12	-0.12	+-12 pp
33	External Habits	All	-0.00	0.12	0.08	+4 pp
33	Internal Habits	All	-0.01	0.12	-0.12	+12 pp
34	Internal Habits	All	-0.00	0.13	-0.12	+13 pp
39	External Habits	All	0.01	0.08	0.08	+0 pp
39	Internal Habits	All	0.01	0.16	-0.12	+16 pp
39	Internal Habits	All excl. sentiment	0.01	0.09	-0.12	+9 pp
42	External Habits	All	-0.01	0.12	0.08	+4 pp
42	Internal Habits	All	-0.01	0.21	-0.12	+21 pp
43	External Habits	All	-0.00	0.1	0.08	+2 pp
43	Internal Habits	All	-0.00	0.07	-0.12	+7 pp
44	Internal Habits	All	0.01	0.19	-0.12	+19 pp

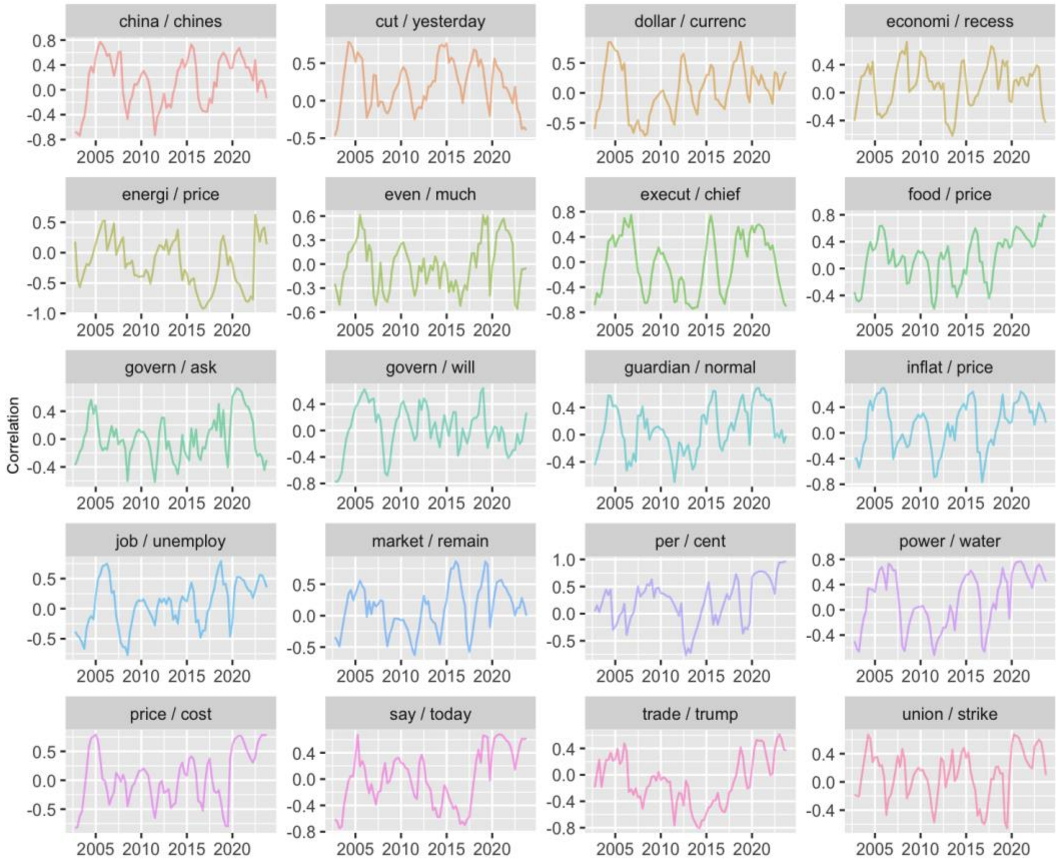
Topic	*Model*	*Instruments*	*EIS*	R^2	R^2 *benchmark*	*Improvement*
48	Internal Habits	All	0.00	0.05	-0.12	+5 pp
48	Internal Habits	All excl. sentiment	0.00	0.13	-0.12	+13 pp
50	Internal Habits	All	-0.01	0.12	-0.12	+12 pp
50	Internal Habits	All excl. sentiment	-0.01	0.15	-0.12	+15 pp
53	External Habits	All	-0.00	0.09	0.08	+1 pp
53	Internal Habits	All	-0.00	0.21	-0.12	+21 pp
64	Internal Habits	All	0.01	0.1	-0.12	+10 pp
64	Internal Habits	All excl. sentiment	0.01	0.04	-0.12	+4 pp
68	Internal Habits	All excl. sentiment	-0.01	0.09	-0.12	+9 pp
69	Internal Habits	All	-0.00	-0.08	-0.12	+-8 pp
76	External Habits	All	-0.01	0.1	0.08	+2 pp
76	Internal Habits	All	-0.01	0.12	-0.12	+12 pp

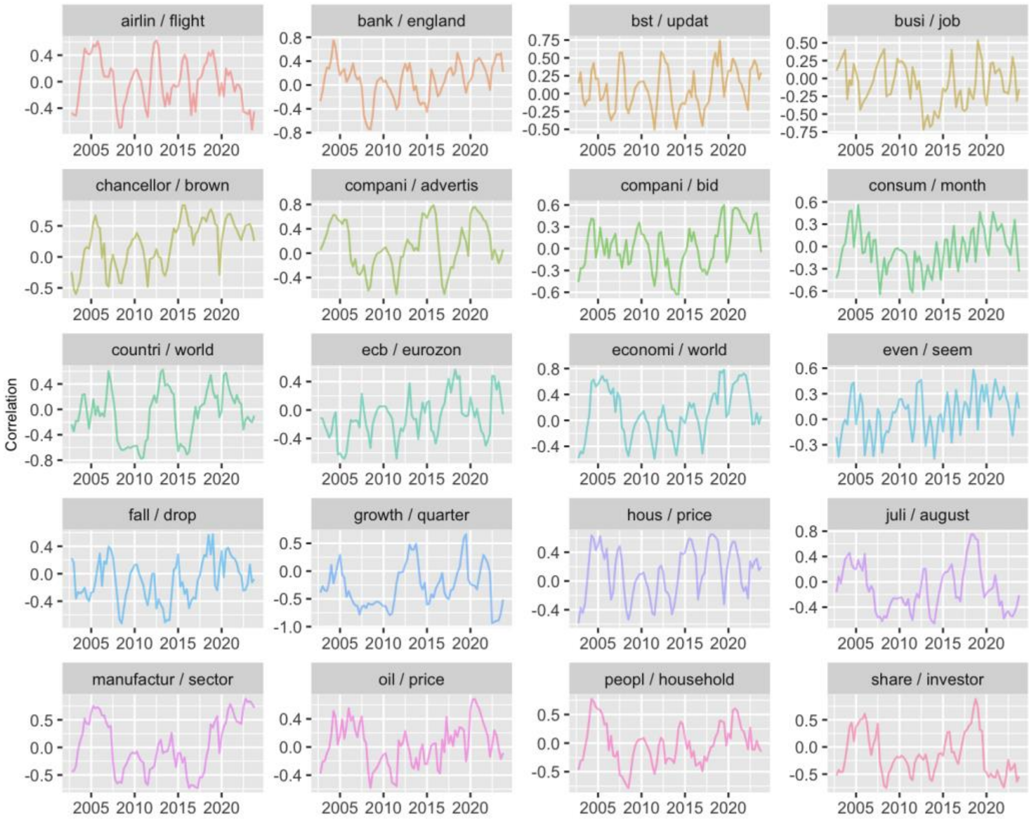
TABLE D6

IV regression results from NTDI models, non-durable good and services consumption

Topic	*Model*	*Instruments*	*EIS*	R^2	R^2 *benchmark*	*Improvement*
5	External Habits	All	-0.00	0.09	0.06	+3 pp
5	Internal Habits	All	-0.00	0.16	0.11	+5 pp
11	External Habits	All	-0.00	0.07	0.06	+1 pp
33	External Habits	All	-0.00	0.1	0.06	+4 pp
33	Internal Habits	All	-0.01	0.18	0.11	+7 pp
42	External Habits	All	-0.00	0.1	0.06	+4 pp
43	External Habits	All	-0.00	0.09	0.06	+3 pp
53	External Habits	All	-0.00	0.07	0.06	+1 pp
55	External Habits	All	-0.00	0.08	0.06	+2 pp
57	External Habits	All	-0.00	0.09	0.06	+3 pp
69	External Habits	All	0.01	0.07	0.06	+1 pp
69	Internal Habits	All	0.01	0.16	0.11	+5 pp

APPENDIX E: results from dynamic correlation

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compani / bid
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countri / world
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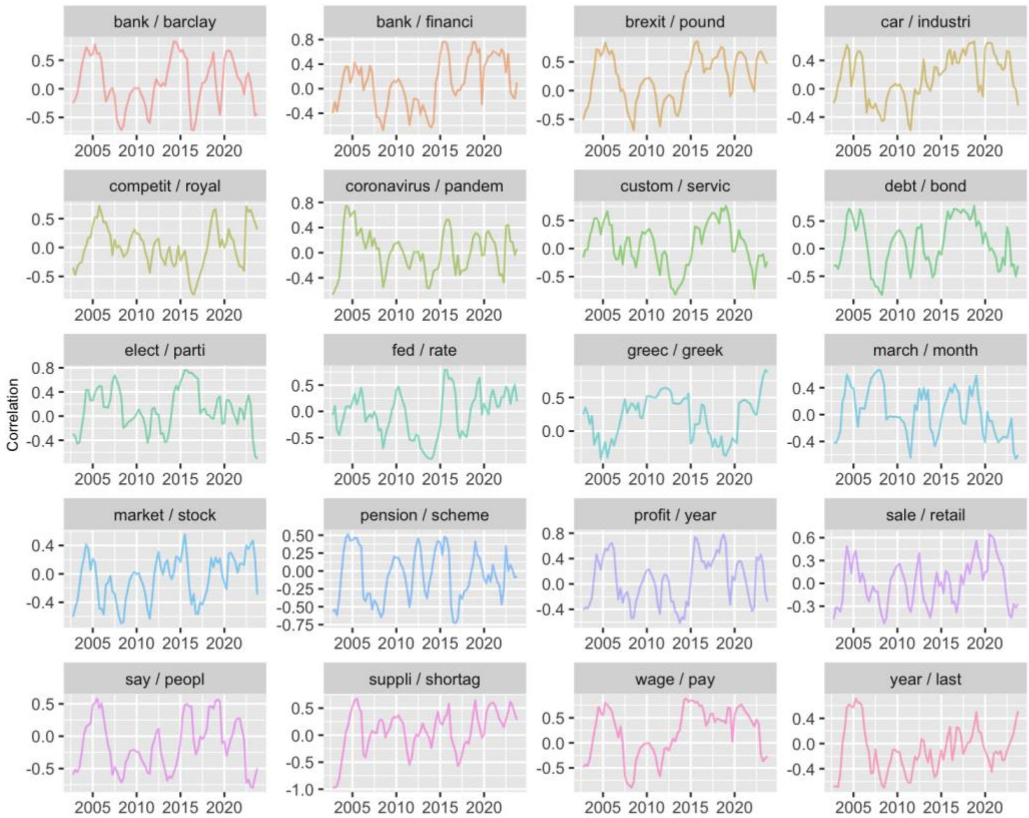
even / seem
fall / drop
growth / quarter
hous / price
juli / august
manufactur / sector
oil / price
peopl / household
share / investor
Correlation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elect / parti
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sale / retail
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year / last
Correlation

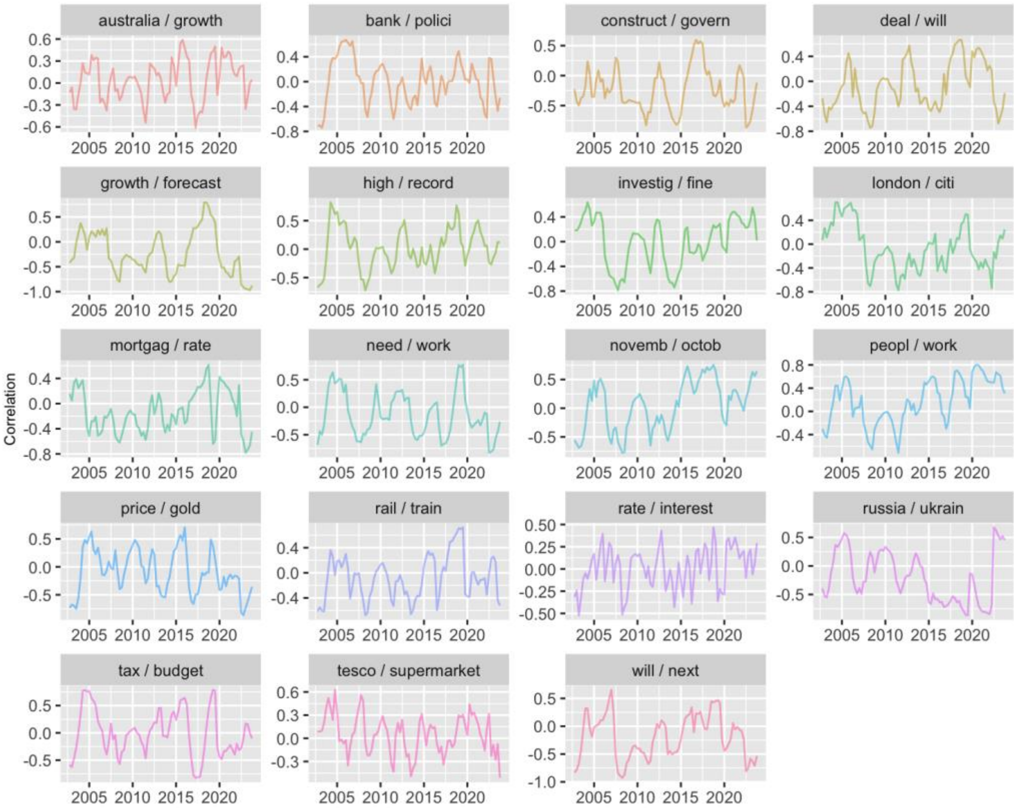

Figure E1. 12-month rolling correlation between news-based topic driven indices for all 80 topics and non-durable goods and services consumption. Topic labels are assigned by a concatenation of three most frequent words within the topic.