# Can Machine Learning Change Our Opinion on Euler's Consumption Model?


## Abstract

This paper evaluates the performance of consumption Euler model, while introducing a novel high-frequency time series measure of inflation expectations derived from online news outlet in the UK. We evaluate and compare the performance of various Euler models both with the traditional data and the news-based data extracted using machine learning techniques and analyze the results for various consumption components.


## Why do Euler Consumption Models Fail?

Euler's consumption model is one of the key fundamental equations in modern macroeconomics and is a key ingredient in understanding the relationship between consumer spending and the real interest rate that is relevant to consumption and saving decisions. The real interest rate itself is determined by inflation expectations. The relationship between consumption, interest rate and inflation expectations is intuitive: an expected increase in inflation will lead to lower interest rate (given sticky nominal rates assumption), which then will reduce the savings through a boost in consumption.

In the early classical literature on Euler's consumption model (see Hansen and Singleton 1996, Breeden 1979) the representative household maximizes their intertemporal utility $U_t$ subject to β budget constraint (i.e. discount factor) according to

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

$c_{t+1}$ is the consumption, u is the instantaneous utility function and the $E_t$ acts as both the methematical expectation and consumer's subjective expectations, since the expectations are assumed to be rational. 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 interest rate between *t* and *t+1*.

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

In the simplest case the intertemporal consumption path is determined by the baseline Euler equation (3) which can be achieved by log linearizing (2) and slight arithmetic modifications.

$$E_t\widehat{\Delta c_{t+1}} = \sigma \hat{r}_t \qquad (3)$$

Where $\widehat{c_{t+1}}$ and $\hat{r}_t$ are respectively the log deviations of next period consumption and gross real interest rates from steady state. $\Delta c_{t+1} = c_{t+1} - c_t$ and $r_t = i_t - \pi_{t+1}$. $\sigma$ is the marginal rate of substitution or the intertemporal elasticity of substitution (EIS)[1] between current and future consumption and is negative as predicted by the standard theory: a lower real interest rate creates an incentive for consumers spend now and therefore reduce current savings. For riskless assets, the EIS is derived by dividing the elasticity of consumption in two period $t$ and $t+1$ by the relative price of consumption in these two periods, with a minus sign. Under uncertainty, EIS is computed similarly, except using the ratio of current-period consumption to certainty equivalent of the future consumption in the nominator (see Epstein and Zin (1989)), while for the constant relative risk aversion utility, the expectations of both the consumption growth rate and expected real returns on the asset are used for calculating the EIS (see Hansen and Singleton (1983))

While, the standard Euler's model of consumption is the building block of many macroeconomic models, yet a sizable literature has shown that it fails to hold at the aggregate consumption level. Consumption is poorly forecastable which leads to weak instruments. When estimating EIS, instruments should be exogenous and relevant, that is, correlated with the consumption. Intuitively, estimated value of EIS has important economic implications, but most papers find no evidence of intertemporal substitution: for example, Yogo (2004) then estimates EIS for 11 developed countries based on linearized Euler equation by using recent methods (at the time) designed by Stock and Yogo (2003) to handle weak instruments by formally testing the first stage F-statistic and a statistical tests by Kleibergen (2002) and Moreira (2001, 2003) designed to test coefficients in the structural equation regardless of the strength of identification. Main findings of the paper point to weak identification resulting from correlation between instruments and the dependent variable resulting in the estimates of EIS for all countries ranging from 0 to 0.5, therefore they are too small to have a significant effect on consumption.

Yogo (2004) paper follows a plethora of research done previously that yield similar results for the models linking consumption and asset returns. Noteworthy, the literature on interpreting the relationship between consumption (aggregate or components) and expected returns have come a long way. In mid 1970s Lucas (1976) argued that consumption function generally is not useful for evaluating the effects of alternate policies. The problems pointed out in the study were addressed once the postulate of rational expectations came around, which modelled the first order conditions for forward-looking fully rational agent and studies based on this assumption became known as "Euler equation approach" (Campbell and Mankiw (1989). Even though further studies developed the assumption and models, yet the consumption function did not seem to work well. For instance, Hall (1988) that finds virtually no evidence for the intertemporal substitution when estimating the relationship between consumption growth rate and expected real interest rates. The conclusion is that "there is little basis for a conclusion that the behaviour of aggregate consumption in the United States

[1] EIS is one of the most important determinants of the consumers' intertemporal consumption choices, since it measures the elasticity of the marginal substitiytion between cosnumption today versus consumption in the next period.

in the twentieth century reveals an important positive value of the intertemporal elasticity of substitution". In a similar study, Hansen and Singleton (1983) study the distribution of the aggregate consumption and asset returns and estimate the relative risk aversion (which is the reciprocal of the intertemporal substitution parameter, however authors choose not to use this wording in the paper) using maximum likelihood technique and find that the estimated coefficient is not informative about the risk aversion were essentially zero for models of individual Dow Jones and treasury Bills returns. Campbell and Mankiw (1989) also find an evidence against the permanent income hypothesis for the US data when examining both the non-durable and durable consumer spending. At the same time, paper also challenges the robustness of Hall's (1988) results when introducing the current-income consumers by arguing that the substantial fraction of income goes to rule-of-thumb consumers, therefore Hall's (1988) the theory behind the conclusions on the EIS cannot be empirically valid. While they find the elasticity of intertemporal substitution is close to zero for permanent income consumers, they do not provide definite conclusions for rule-of-thumb consumers.

More recent literature, that expands on the classical model while still aiming to estimate the EIS and address the weak identification problem More recently, Campbell (2003) find the 95% confidence interval for the estimated EIS to be close to 0 for non-durable consumption. Canzioneri et al. (2007) provide an alternative way of characterizing the extent by which the data on consumption and returns is inconsistent with the model and argue that for most Euler equation specifications the implied interest rates are strongly and negatively correlated with the federal funds rate (the money market rate targeted by central banks).

However, it is noteworthy that there are number of papers that also found significant and positive values for the EIS, for example Attanasio and Weber 1993, ….. , so there is no consensus in the literature as to what is the value of EIS and how significantly different from above zero it is. 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. Vissing-Jørgensen (2002) uses US Consumer Expenditure Survey micro data to argue that in order to obtain consistent estimates for EIS in the Euler's model, one needs to account for limited asset market participation and that 'the Euler equation should hold for a given household only if the household holds a nonzero position in the asset'. What this implies, is that, if a household does not hold any assets , then including their consumption in the Euler equation will lead to inconsistent estimates for the EIS, since these agents will not be adjusting their consumption growth rate in response to any expected changes for asset returns. The study eventually finds the EIS to be between 0.3 & 0.4 for stockholder households, and 0.8-1 for bondholder households, while for households that do not hold any stocks of assets, the EIS are small and close to zero. Similar findings are reported in Attanasio, Banks and Tanner (2002) and Gross and Souleles (2002)[2]. However, as Vissing-Jørgensen (2002) notes, one should be cautious as to not interpret these results as evidence of heterogeneity in the EIS across households. Attanasio and Low (2000) aim to understand the conditions under which the Euler equation will fit the data well, starting with testing overidentifying restrictions and estimating consistent parameters. They also suggest that log-linear approximation of Euler model is important to get linear equation in parameters and additive residuals, at the same time stressing the importance of using of micro-data and

[2] Gross and Souleles (2002) find EIS is significantly positive for credit card borrowers supported by singificant negatvie relation between the credit card interest rates and the amount of borrowing.

‘large-T’ asymptotics. The results of the Euler model derived from a dynamic optimization problem suggest that if the sample is long enough, the estimates are relatively efficient and ‘well-behaved’, even with the variability in the time series of the stochastic variables.

Most recent paper on this topic by Ascari, Magnussen and Mavroeidis (2021) summarizes results from various baseline and extension Euler models, as well as of 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 case of risk-free interest rate being using in the estimation of the Euler model the aggregate EIS is well-identified and low for several loglinear and nonlinear models but is virtually zero for semi-structural model. Most of the variation in results arises from weak instruments in the extension models: in models that include consumer habits the instruments are weak for consumption, while in models with hand-to-mouth consumers instruments are weak for labour income growth. On the contrary, in models that use the stock market return, the EIS are not well identified and are quite large (the confidence sets are very wide and exclude zero). Lastly, further models also fail to validate the assumptions of EIS being less or greater than zero.

In this paper, we contribute to the above-mentioned literature addressing the problems of failing Euler’s consumption model by proposing a new measure of inflation expectations. In our view, the real interest rate used in the literature is misspecified, because it does not reflect the agent’s true perceptions about the economy. Consumers and households have more information on the current and future consumption than an econometrician, therefore when estimating the EIS one should not treat current and future consumption as exogenous to avoid correlated residuals and inconsistent estimates. As this chapter already summarized, these EIS are usually not robust to weak identification and the estimates are unreliable. Poor estimates fail to explain sufficient variation and lead to the failure of first order asymptotics.

The importance of understanding household inflation expectations formation process for monetary authorities in their attempt to influence the household’s decisions is well documented. As highlighted by Blanchard (1993) consumer sentiment and inflation expectations are crucial in household decision making related to spending and spontaneous fall in household consumption is an important determinant of economic recessions. This is quite intuitive, since the sentiment reflects households’ perceptions about the economy and when the overall economic prospects are poor, not only agents defer from spending, but this is also reflected in their survey answers. The problem with the survey data is that the information is vast and costly to obtain. Agents receive only very partial information while doing everyday shopping and build their expectations through personal experiences and prior memories, which however can be inaccurate, irrational and diverse. Household surveys often indicate that the perception of the current inflation and expectations about the future are different from actual inflation values and differ strongly from the surveys of professional forecasters and implied inflation rates of financial markets, see for example Coibion et al. (2018). A growing literature supports the idea on information rigidities (Larsen, Thorsrud, Zhulanova (2020), Armantier et al. (2016), Coibon and Gorodnichenko (2012), Dovern et al (2015)).

Remarkably, however, to the best of our knowledge, at the time of writing this paper, there is no study on Euler's equation, that uses actual empirical data on expectations. The importance of capturing the true consumer's expectation for accurate estimation of Euler's model is also shown in Lamla and Maag (2004), where they find that households and professional forecasters have different idea about where the inflation over the next 12 months is heading. Similarly, Mankiw et al. (2004) (Mankiw, Reis, and Wolfers) also find considerable heterogeneity in household's inflation expectations.

In our proposed solution, we consider the standard theoretical model of Euler equation proposed by Hall (1988) and use the specification (3) for estimating the equation. The novelty of our approach is possible thanks to the technological advances that allow us to build a real-time high frequency indicator that captures true consumer inflation expectations that can be used to estimate Euler's equation.

## Inflation expectations and the news media

### Role of Media in Inflation Expectation Formation Process

Media's role and power in a society is well established and, in most cases, news are primary sources and preferred delegates for information. An average consumer does not typically have resources or time to constantly track the latest statistics and monitor all events in the economy to get a full understanding of the macroeconomic models behind macroeconomic 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 sentiments about the economy. Blinder and Krueger (2004) conduct a survey on determinants of public opinion in US and find that the television is the dominant source of information on economic policy issues, followed by newspapers. Fullone et al. (2007) supports these finding through conducting surveys in Italy.

More specifically, it has been shown in the literature that media coverage directly affects inflation expectations. Intuitively, to some extent, media coverage reflects the current state of the economy and it is possible to understand the importance of given topic for economy and its future based on the intensity and the extent of how much it is discussed in that news. Frequency of the news and the tone of the text can drive consumer perceptions and allow us to understand consumers' inflation expectations. Lamla and Lein (2008) investigate two channels through which media affects inflation expectations: intensity of the news coverage and the tone of this coverage, while Lamla and Maag (2012) adopt a Bayesian learning model investigate the heterogeneity of inflation expectations and forecast disagreement between German households and professional forecasters motivated by consumer price related media on inflation. They find that media coverage does affect the disagreement of households and tends to increase the with the heterogeneity of media coverage. On the other hand, the forecast disagreement declines as the amount of report pointing to inflation rise increases. Similar results are reported in Lamla and Lein (2008) study. In addition, Carroll (2003) contributes to these findings through analysis of two US newspapers and establishing a link between the amount of news reporting on inflation and accuracy of consumer expectations.

Our Analysis also support these findings, with more details to follow in the upcoming sections. Figure 1 illustrates the relationship between sentiment index constructed based on news coverage tone (SI) and compares it to UK's official Consumer Confidence Index (CCI)[3] from January 2000 to December 2020. Similarity in shape and trend of the curves, as well as strong visual correlation can be observed. The correlation of 0.6 exists between the SI-2 and CCI, which is even further improved to 0.7 when the SI-2 index is shifted 1 month forward, indicating that the sentiments consumers built are reflected in the consumer surveys with slight lags.

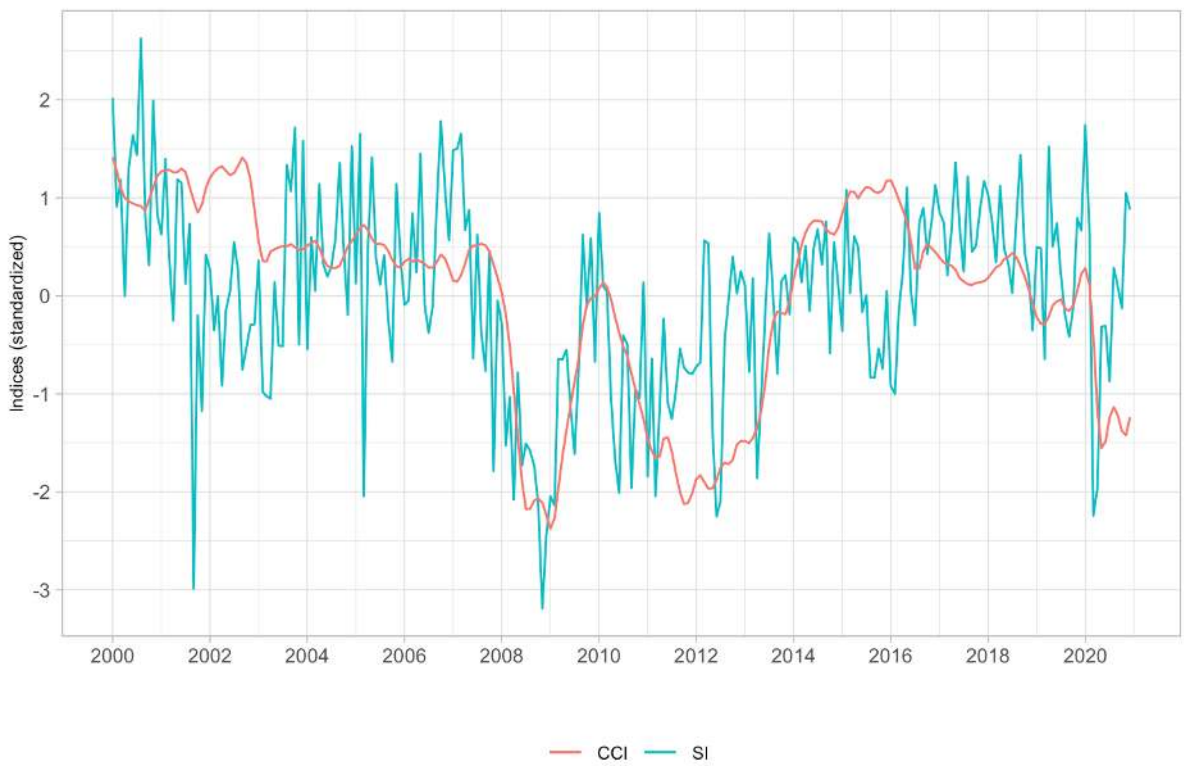


Figure 1: UK Consumer Confidence Index vs Sentiment Index Constructed from newspaper data

Results in Figure 1 support our hypothesis that sentiments from news are indeed very strong indicator of consumer expectations about the economy. As can be observed from the figure the CCI and sentiment indices build 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 the news about the coronavirus pandemic broke. The CCI also had a slight drop in the periods leading to the Brexit vote (June 23, 2016) and for some months afterwards, as is expected. However, no significant drop was reflected in the news-based inflation indices. In section 4.3, we extend and apply the sentiment analysis on news topic level.

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

## News as Novel Data Source

However, the empirical literature on using news-based data for modelling the economy is relatively small. Yet, there has been increasing interest in the literature with Thorsrud (2018) even stating that “words are the new numbers. For example, Hendry and Madeley (2010) use Latent Semantic Analysis to extract information from Bank of Canada communication statements and analyze which time of information affects returns and volatility in short-term and long-term interest rate markets. El-Shagi and Jung (2015) find that the minutes of Bank of England’s Monetary Policy Committee have contributed to markets expectation formations on the future of monetary policy. Lucca and Trebbi (2009) measure the content of central bank communication about future interest rate decisions based on information from news sources and Internet. Onsumran et al (2015) develop a gold price volatility prediction model using text mining approach to analyze how news articles influence gold price volatility. Thorsrud (2018) constructs a perfectly accurate new business cycle index based on quarterly GDP growth as well as information from daily business newspaper that classifies the phases of the business cycle and provides meaningful insights on which types of news drive or reflect economic fluctuations. Sapiro, Sudhof and Wilson (2018) use computational text analysis of economic and financial news articles to assess time series measures of economic sentiment that drive consumption. Larsen, Thorsrud and Zhulanova (2020) use large news corpus and machine learning algorithms to investigate the role played by the media in the expectation’s formation process of households and conclude that the news topics media report on are good predictors of both inflation and inflation expectations.

This paper contributes to this literature by similarly taking advantage of technological advances and building a real-time high dimensional indicator that captures the consumer inflation expectations from online news website. We build a high frequency multidimensional news-based measure of household inflation expectations which is then infused to Euler’s model as a novel measure of inflation. Current literature mainly focuses on expectation formation processes and less to finding quantitative evidence on consumers’ spending decisions based on these expectations.

Our approach starts off with extracting the textual data from a popular UK online newspaper and performing text selection, pre-processing and cleanup on this data to reduce the dimensionality. The transformed textual data is then converted to quantitative frequency indices that capture the intensity of the topics being discussed in the news. In the last step, these time series are augmented by sentiment indices that reflect the tone expressed by the authors of the news articles. The resulting final indices are used as a measure of inflation expectations in Euler’s equation. More detailed on these steps are provided in this section as well as in the appendix A.

We collect two types of data: from tradition published datasets and from the novel newspaper source. The former includes the consumption and inflation attitude surveys data collected from Bank of England. The consumption data includes the data on total household consumption, as well as separately, the expenditure on consumption on goods.

The novel data source used in our analysis comes from a rich textual data environment of online news and is collected from the one of the UK's leading newspapers[4], the Guardian using its open-source API[5]. The choice of the news outlet is due to relevance to our research in terms of content and readership. In April 2011, it was the fifth most popular newspaper in the world[6], while in May 2013, it was one of the most popular UK newspaper websites with 8.2 million unique visitors per months. We do not address or take into account the political bias of the newspaper nor the proportion of readers of Guardian in the population. We argue that the news stories relevant for the household expectations formation are most probably covered by Guardian (or any other major newspaper for that matter) regardless of the potential skew in the coverage due to political bias or readership. King et. al (2007) performed a real-world randomized experiment to understand the causal effects of news coverage in various news outlets across the U.S. in nationwide discussions on a range of topics and find that even the smaller media outlets news coverage can have an impact on increasing public discussion on specific topics and that this increase was uniformly distributed across political affiliation, gender and regions of the U.S.

Any news in Guardian is public and readable by anyone by default. The Guardian API is a public web service for accessing all the content the Guardian creates, categorised by tags and section. Users can query content database for articles with full content by tags and sections. While different news can drive consumer expectations, e.g., rumors, scandals, entertainment etc., 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 last 20 years. We also filter out the articles based on subjectively chosen keywords, such as inflation, deflation, cheaper, cheap, expensive, price, prices, cost, expense, salary, wage, salaries, wages. Arguable, this is only subset of news that affect household's decisions, yet main news stories relevant for household sentiment or expectation formation will be undoubtedly covered by articles that include these keywords.

The data comes in unstructured form, that is, the data is in a text form 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 2020, which is sufficient amount of 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 and co-authors (2015) at the same time adding more steps and more developed methods. We use the text mining's bag of word approach in the text, which means all words are analyzed as a single token and their structure, grammar or part of lexicon does not matter. Pre-processing results in a document term matrix, which includes all occurrences of the words in the corpus and their respective frequencies. At this step, the dimensionality of the corpus is reduced, and we get more understandable results. Full description of the steps to clean up the data is given in Appendix A1. Figure A1 in the appendix visualizes the most common words in the Guardian corpus.

[4] See https://www.pressgazette.co.uk/uk-newspaper-and-website-readership-2018-pamco/. In addition, see https://pamco.co.uk/pamco-data/latest-results/ for comparison among UK newspapers.
[5] See https://open-platform.theguardian.com
[6] Guardian.co.uk most read newspaper site in UK in March. www.journalism.co.uk.

# Can Machine Learning Change Our Opinion on Euler's Consumption Model

## Modelling News into Topics and Time

We hypothesize that certain topics news write about have significantly different degrees of impact on the consumer's sentiment and expectations formation process. 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 is a branch of unsupervised natural language processing that provides a simple way to analysed large volumes of uncategorized text clustering words that frequently occur together and best explain 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, patters 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 general introduction to topic modelling see Steyvers and Griffiths (2007) and Blei and Jordan (2003). The latter were the first to suggest the use of Latent Dirichlet Allocation (LDA) for this purpose. LDA is a statistical model that identifies each document as a mixture of topics (related to multiple 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 A2.

Generally, in text mining, researchers do not know the topic structure of a set of documents a priori. Different model iterations and different parameters result in different document clustering. However, the goal is finding 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 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.  Additional tests and analysis can confirm the topic structure uncovered by LDA. For our analysis, we follow method by Thorsrud (2018) and compare perplexity scores across various LDA models estimated using different number of topics, as it allows inspection of scores across 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". 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.

Once the number of topics is chosen, the LDA procedure derives the topic probability distribution by assigning probabilities to each word and document. Table A2 in Appendix A2 presents the results from topic modelling with LDA for all 80 topics.  The next step is to extract time concept from topics in order to capture true inflation expectations (which by definition show an expectation of the future). Since not all topics in the news coverage may refer to events in the same period, therefore, in addition to classifying words and documents into topics, we also group the latter according to the timing of events they represent and classify topics by those referring to the past events, present and future. Our method is quite simple, yet, to the best of our knowledge, there are no studies at the time of writing this paper that are extracting time from news topics. From empirical point of view, for each topic we extract the time by counting the occurrence of the keywords in it that represent past, present of future. If there are more than 2 of the keywords presented for given time period, then the topic is considered to represent that time period. For example, if a given topic contains any two of these keywords, future, expect, will, forecast, soon, then this topic is classified as representing the future. This means that the new-based inflation expectations that we build (see section 4.2) for this particular topic will represent true inflation expectations.

One characteristic of LDA procedure is that it does not assign labels to the topics. We do that ourselves, based on the most frequent words computed 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. Exact name, however, plays minor role in the actual analysis or results., while Figure 2 below plots a chosen sample of 15 topics from news coverage discussing the future of the economy and the frequency distribution of the most probable 10 words in them.

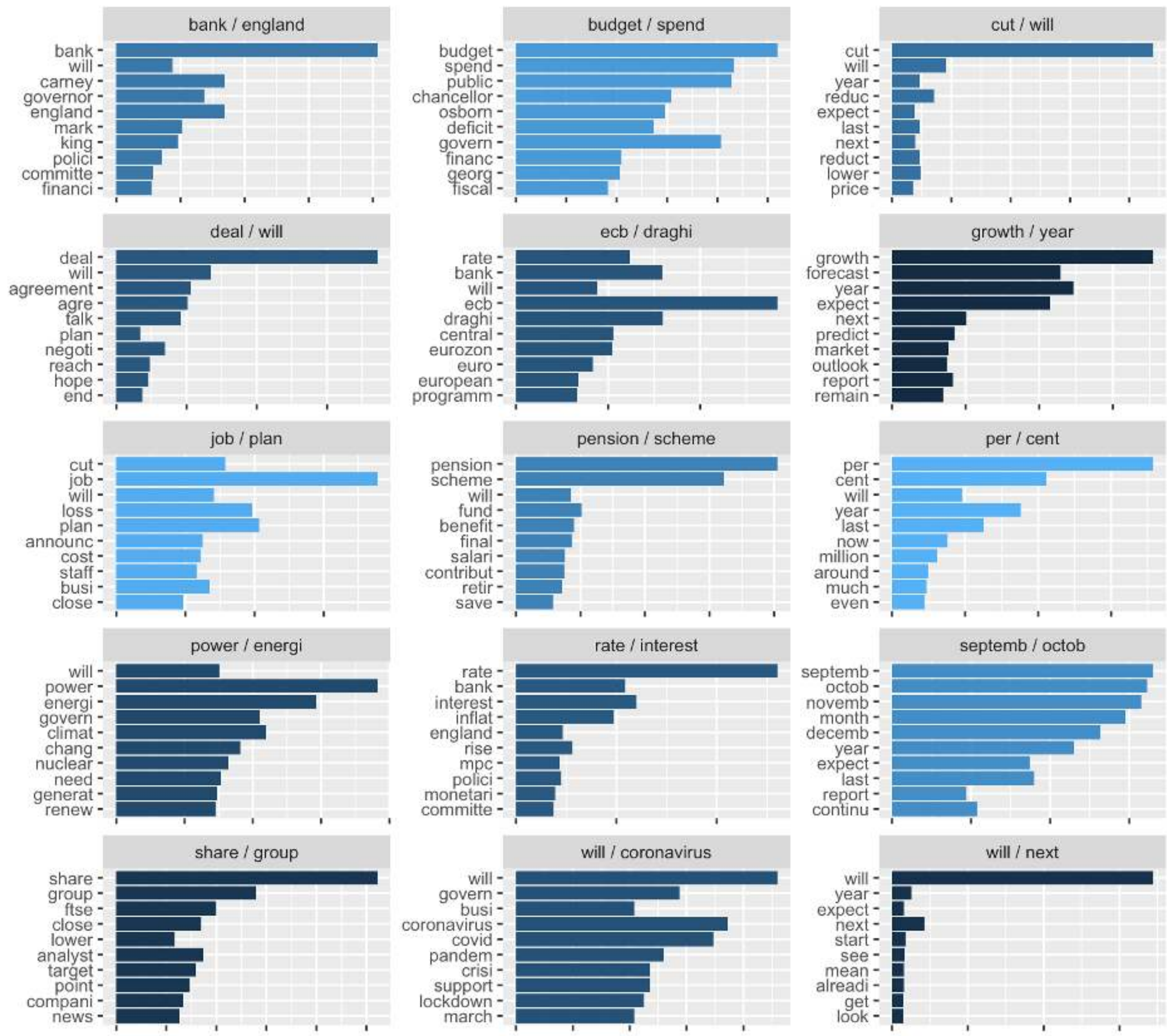


Figure 2: Sample of topics representing future with top 10 frequent words in them. Topic labels are assigned by a concatenation of two most frequent words within the topic. All words are in stemmed format.

## News-Topic-Driven Price Index

To proceed with building high-frequency news-topic-driven inflation index (NTDI), 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 given topic $z$ is given by

$$I_z(\mathrm{t}) = \sum_{d \in I(t)} \sum_w N(d, w, z) \qquad (1)$$

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 the topic decompositions and distribution. Figure 3 plots the results of frequency indices built using (1) of topics representing the news on the future of the UK economy.

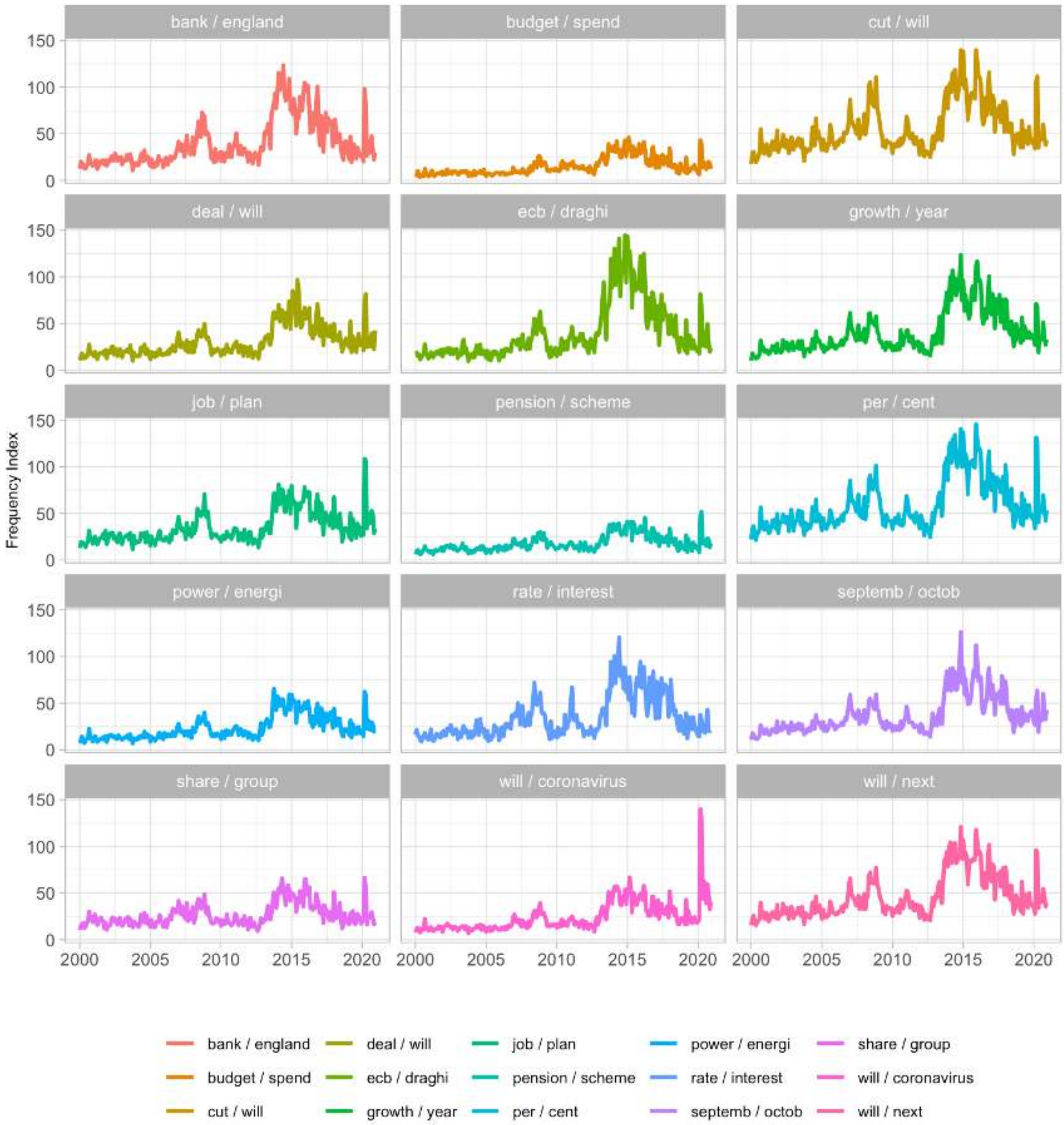

*Figure 3: News-based monthly inflation indices for topics representing news covering about the future of the UK economy*

These time series $I_z(\mathrm{t})$ are measures of volume or intensity. As literature finds (see Larsen et. al. (2020) and Thorsrud (2018)) the combination of intensity news topic and sentiment identification is important for better capturing of inflation expectations. In order to get the NTDI, we augment the intensity indices with sentiment indices by multiplying intensity indices with the corresponding sentiment indices as given below:

$$\overline{NTDI_z}(\mathrm{t}) = I_z(\mathrm{t}) * S_z(\mathrm{t}) \tag{2}$$

where $S_z(\mathrm{t})$ is constructed in section 4.3.

## Adding Sentiment

Since our aim is to build the consumers' inflation expectations, sentiment analysis and its ability to classify articles into positive, negative or neutral sentiment, is a key step of our analysis. In this sub-section we describe sentiment analysis method used in this paper.

Our methodology starts by computing thousands of sentiment values which capture the tone expressed by the authors of the news. The problem can be defined as a sentiment prediction problem, where the *N* articles from the Guardian corpus are aggregated as a single text for each day *t*. Therefore each document $d_i$ in $\{d_1 \dots \dots d_N\}$, that consists of collection of $n$ words $\{w_1 \dots \dots w_n\}$, is aggregated into $\{D_1 \dots \dots D_t\}$ for each day *t,* where $D_i$ is the collection of document for day *i.* Each of these $D_i$ can take a sentiment value $s_i$ that can any value and are calculated as the difference between the frequencies of positive and negative words in the text normalized by the total number of words. This is a widespread approach in the literature (Thorsrud (2020), Arslan-Ayaydin, Boudt (2016)).

There are number of available methods and ways to do sentiment analysis (see Ravi and Ravi (2015), Ardia, Bluteau and Boudt (2019), Bai (2011), Schumacher et. Al (2012)). Each of the methods has limitations and advantages and differ by the way each item is classified as word, sentence or paragraph and by the aggregation method used to obtain a single sentiment index per text. Methods can also be either supervised or unsupervised. We build sentiments for Guardian news data using two different method. The first method uses bag-of-words, standard lexicon-based sentiment analysis approach to classify linguistics patters based on their polarity, e.g. positive, negative or neutral. While many papers use Harvard IV dictionary, we chose Loughran-McDonald (2010) financial dictionary (354 positive words and 2355 negative words), as it is most suitable for text analysis in economic domain. The second method is an extension of the dictionary-based method, that also captures valence-shifting words, such as 'very', 'barely', 'mustn't', 'nor', 'not', etc., that may affect the context of nearby words. Built in packages in R provide powerful toolchains facilitating the sentiment analysis of such textual contents. As a result of this approach, we build two sentiment indices SI-1 or SI-2 using two methods described, each corresponding to topic *z* and day *t*. In the further calculation we only use SI-2 and denote it as SI, as its correlation to official consumer confidence index is higher than for SI-1, even though the difference is insignificant. The final indices are built using (2) and using SI-2 for the value of $S_z$(t). The results for the sample of topics for future are plotting in Figure 4.

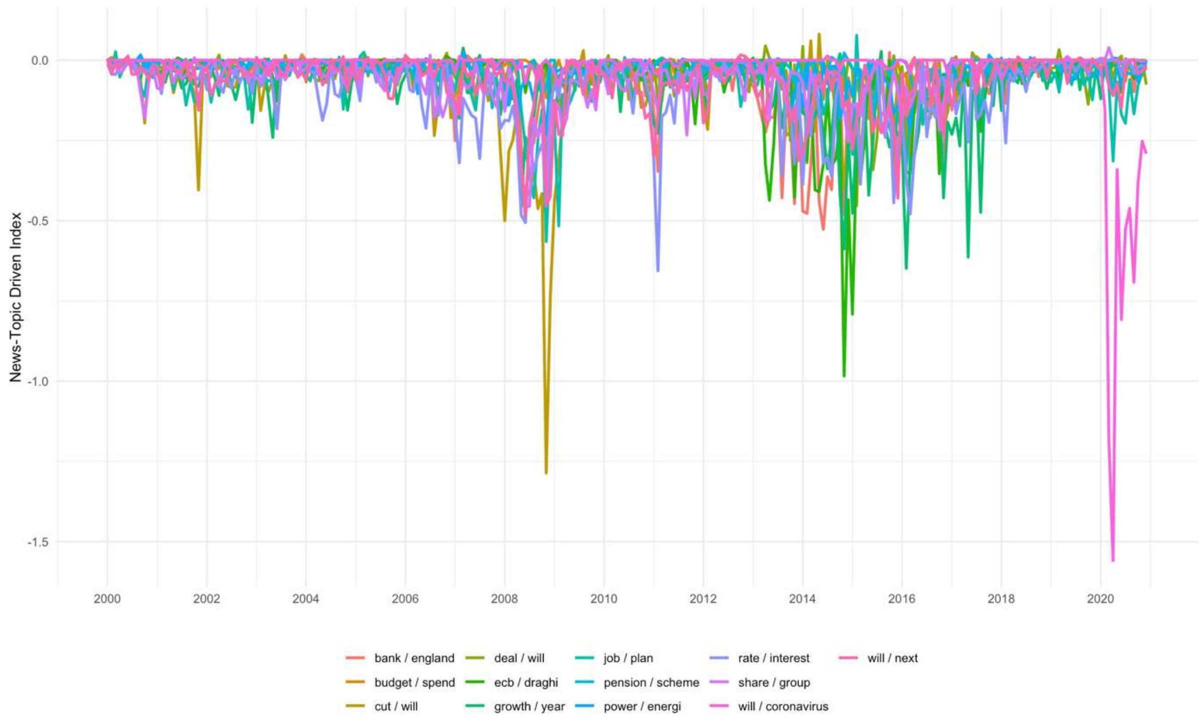


*Figure 4: News-Topic Driven Inflation indices for topics representing news covering about the future of the UK economy*

More sophisticated sentiment classification techniques (see Pang et. al (2012) exist and therefore our methods of building the inflation indices can be improved. However, as can be seen from figures 1 and 4, our news-based inflation indices provide good enough results and are able to capture the true inflation expectations quite well.

## Infusing New Inflation Measure to the Euler's Model

The choice of Eulers models and specification in this paper follow closely those suggested by Ascari, Magnussen and Mavroeidis (2021) paper, where an extensive analysis is done on various Eulers models, such as baseline model and extensions that include habits, hand to mout consumers and recursive preference. The aim of their paper is to help further research by reporting main conclusions of various models and methods used to address problems of weak identification. However, whereas Ascari and co-authors focus on identifying structural parameters in both linear and non-linear form, in our paper we focus only on the baseline loglinear model, similar to Yogo (2004), but use the methods presented in Ascari et al. (2021) for purposes of testing parameter stability, i.e. to test if these parameters are robust to weak instruments.

As such, we use baseline model's (3), which however has been shown not to work well in earlier literature due to unresponsiveness of consumption growth to the real interest rate and it being easily predictable by lags of other series (see Campbell 1999).

The econometric specification of (3) with IV (instrumental variable) regressions can be written as

$$c_t = E_t c_{t+1} + \sigma\,(i_t - E_t \pi_{t+1}) \qquad (4)$$

Or following specification in Ascari, Magnussen and Mavroeidis (2021) as

$$\Delta c_{t+1} = \alpha + \sigma\,(i_t - \pi_{t+1}) + \varepsilon_{t+1} \qquad (5)$$

where $c_t$ is the consumption, $E_t C_{t+1}$ is the expectation of consumption at t+1 formed at time t, $i_t$ is the one-period nominal interest rate and the $E_t \pi_{t+1}$ is the expectation of inflation at time t+1 formed at time t. Details on empirical moments of linear models is provided in Appendix B.

Official data used in (4) and (5) comes from a variety of sources and undergoes a number of transformations. Detailed description is given in Table C1 of Appendix C.

Results section is currently work in progress.

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# Appendix A: Textual Data

## A1. 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 common, if not the most popular, approach applied in the literature (Thorsrud 2018, Thorsrud 2020, Schumaker and Chen etc.). Below are the techniques used to clean up the data, which include 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 as same word.

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

*Step 3:* Next, all words are normalized, 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 incorrect picture of 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 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 part-of speech of each word is identified, and each word is converted into its base form, e.g., nouns, verbs, pronouns with same base into base word (e.g. reporting, reported and reporter will be reduced to report).

*Step 6:* The last step of 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, i.e. terms occurring only in very few documents. These are the tokens which are missing from more than 90% of the documents in the corpus[7]. The remaining 900 000 stems with the highest TDM score are used in the final analysis.

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


Figure A1: Word cloud representation of document-term-matrix.

[7] 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.

## A2. 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 allows to derive the topic probability distribution by assigning probabilities to each word and document. Assigning words and documents to multiple topics also has advantage of semantic flexibility (ex. the word 'rate' can relate both to inflation and unemployment topic). The term latent, has its name because the words are intended to communicate latent structure: the topic of the article, while the Dirichlet term is used because the topic mixture is drawn from a conjugate Dirichlet prior in order to ensure sparsity in the underlying multinomial distribution. Thorstrud (2018) notes that 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 $\theta$, a set of $N$ words $w$ is given by

$$p(\theta, z, w \mid \alpha, \beta) = p(\theta \mid \alpha) * \prod_{n=1}^{N} p(z_n \mid \theta) * p(w_n \mid z_n, \beta) \tag{1}$$

where parameters $\alpha$ and $\beta$ are $k$-vectors with components greater than zero, with $k$ being the dimensionality of Dirichlet distribution, that is the directionality of topic variable $z$. In addition, the topic distribution of each document is distributed as

$$\theta \sim \text{Dirichlet}(\alpha)$$

term distribution is modeled by

$$z_n \sim \text{Dirichlet}(\beta)$$

and

$$N \sim \text{Possion}(\xi)$$

LDA model's goal is therefore to estimate $\theta$ and $\varphi$ in order to estimate which words are important for which topic and which topics are important for a given document. For $\alpha$ and $\beta$, 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 and through specifications on the LDA model and topic modeling in general are provided in Blei (2003) and Griffiths and Steyvers (2004).

There are different approaches to LDA algorithm, and in this paper, we use the Gibbs sampling method. Gibbs sampling is an algorithm for successively sampling conditional distributions of variables, whose distribution over states converges to the true distribution in the long run. Gibbs sampling allows improving the topic representations within documents, as well as 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 (1) is sampled given other variables' full conditional distribution, which are as follows:

$$p(\mathrm{z}_{iv} = k \mid \pi_i, b_k) \propto \exp(\log \pi_{ik} + \log b_{k,\mathrm{y}_{iv}}) \tag{2}$$

$$p(\pi_i \mid \mathrm{z}_{iv} = k, b_k) = \text{Dirichlet}\ (\alpha + \textstyle\sum_k \mathbb{I}\ (\mathrm{z}_{iv} = k)) \tag{3}$$

$$p(b_k \mid \mathrm{z}_{iv} = k, \pi_i) = \text{Dirichlet}\ (\beta + \textstyle\sum_i \sum_k \mathbb{I}\ (\mathrm{y}_{il} = w, \mathrm{z}_{il} = k)) \tag{4}$$

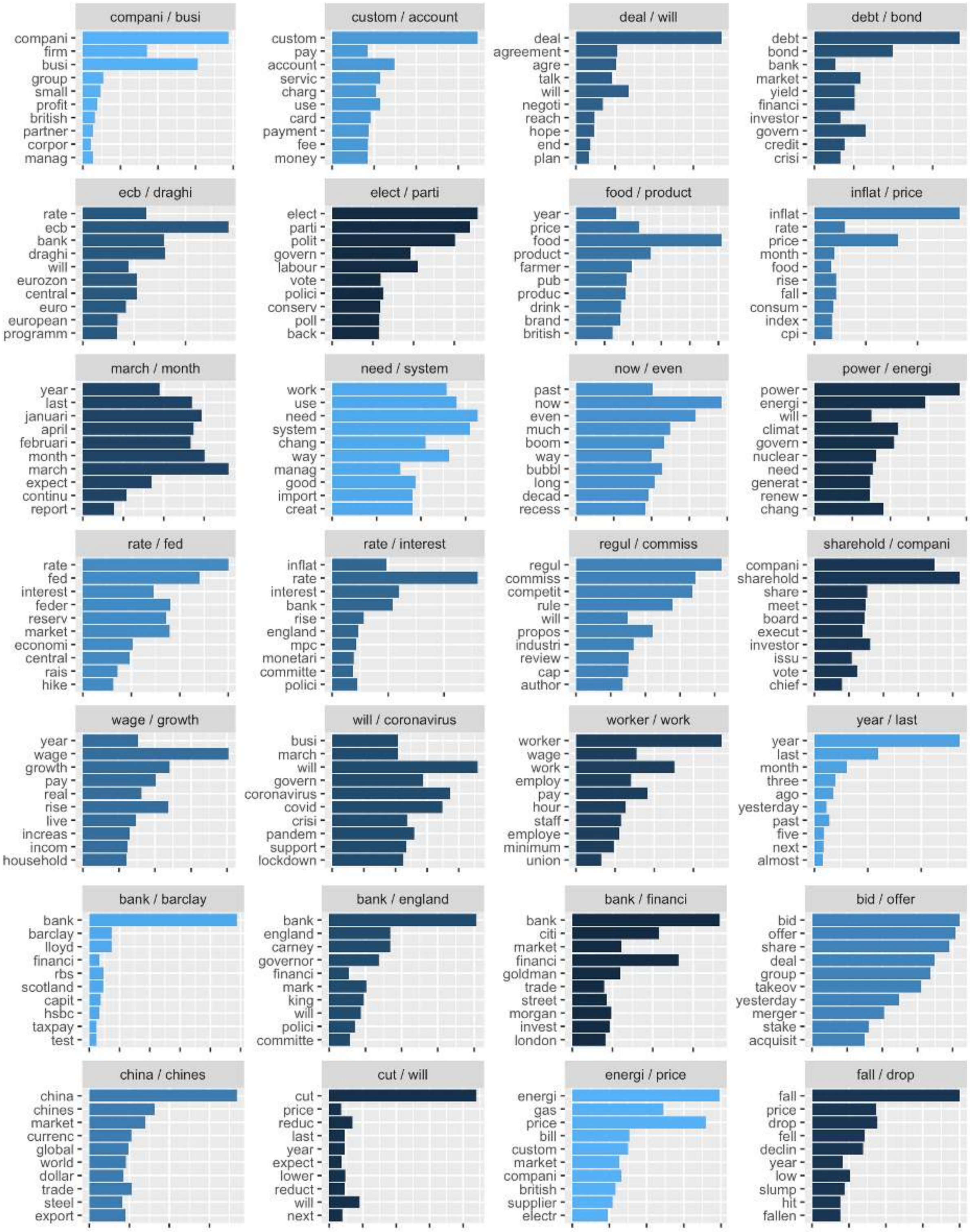
where $k$ is the topic, $w$ is a term, $\pi_i$ is a vector defining a distribution over $T$ topics and $b_k$ is a vector defining a distribution over $N$ words.

Griffiths and Steyvers (2004) were the first to suggest to analytically integrate $\pi_i$'s and $b_k$'s and sample $\mathrm{z}_{iv}$'s to get a better performance perhaps add 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:

$$p(\mathrm{z}_i = j \mid z_{-i}, w_i, d_i) = \frac{C^{NT}_{w_i j} + \beta}{\sum_{w=1}^{N} C^{NT}_{w_i j} + W_\beta} \text{ x } \frac{C^{DT}_{d_i j} + \alpha}{\sum_{t=1}^{T} C^{DT}_{d_i t} + T_\alpha} \tag{5}$$

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

Different model iterations and different parameters of $\alpha$ and $\beta$ in (1) result in different document clustering. However, the goal is finding 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 number of topics to be extracted from the corpus is based on the researcher's intuition, domain knowledge and literature. As such, we classified 100 different topics. Additional tests and analysis can confirm the topic structure uncovered by LDA. For our analysis, we follow method by Thorsrud (2018) and compare perplexity scores across various LDA models estimated using different number of topics, as it allows inspection of scores across Markov chain Monte Carlo. The benefit of this approach comes in comparing perplexity across different models with varying $k$. The model with the lowest perplexity is generally considered the "best".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custom / account
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year price food product farmer pub produc drink brand british
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need / system
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power / energi
power energi will climat govern nuclear need generat renew chang
rate / fed
rate fed interest feder reserv market economi central rais hike
rate / interest
inflat rate interest bank rise england mpc monetari committe polici
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worker wage work employ pay hour staff employe minimum union
year / last
year last month three ago yesterday past five next almost
bank / barclay
bank barclay lloyd financi rbs scotland capit hsbc taxpay test
bank / england
bank england carney governor financi mark king will polici committe
bank / financi
bank citi market financi goldman trade street morgan invest london
bid / offer
bid offer share deal group takeov yesterday merger stake acquisit
china / chines
china chines market currenc global world dollar trade steel export
cut / will
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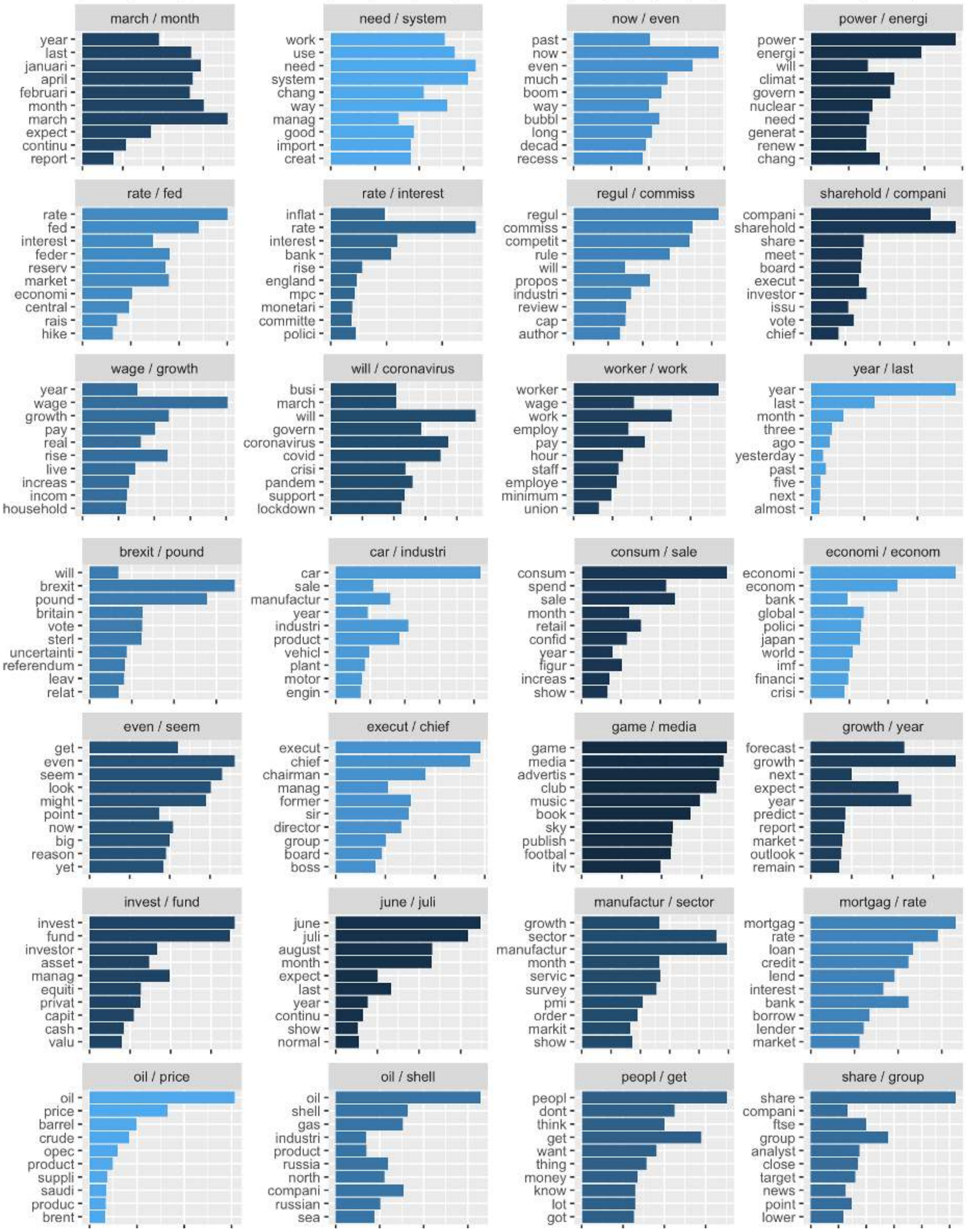
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need / system
work use need system chang way manag good import creat
now / even
past now even much boom way bubbl long decad recess
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inflat rate interest bank rise england mpc monetari committe polici
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regul commiss competit rule will propos industri review cap author
sharehold / compani
compani sharehold share meet board execut investor issu vote chief
wage / growth
year wage growth pay real rise live increas incom household
will / coronavirus
busi march will govern coronavirus covid crisi pandem support lockdown
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consum spend sale month retail confid year figur increas show
economi / econom
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even / seem
get even seem look might point now big reason yet
execut / chief
execut chief chairman manag former sir director group board boss
game / media
game media advertis club music book sky publish footbal itv
growth / year
forecast growth next expect year predict report market outlook remain
invest / fund
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growth sector manufactur month servic survey pmi order markit show
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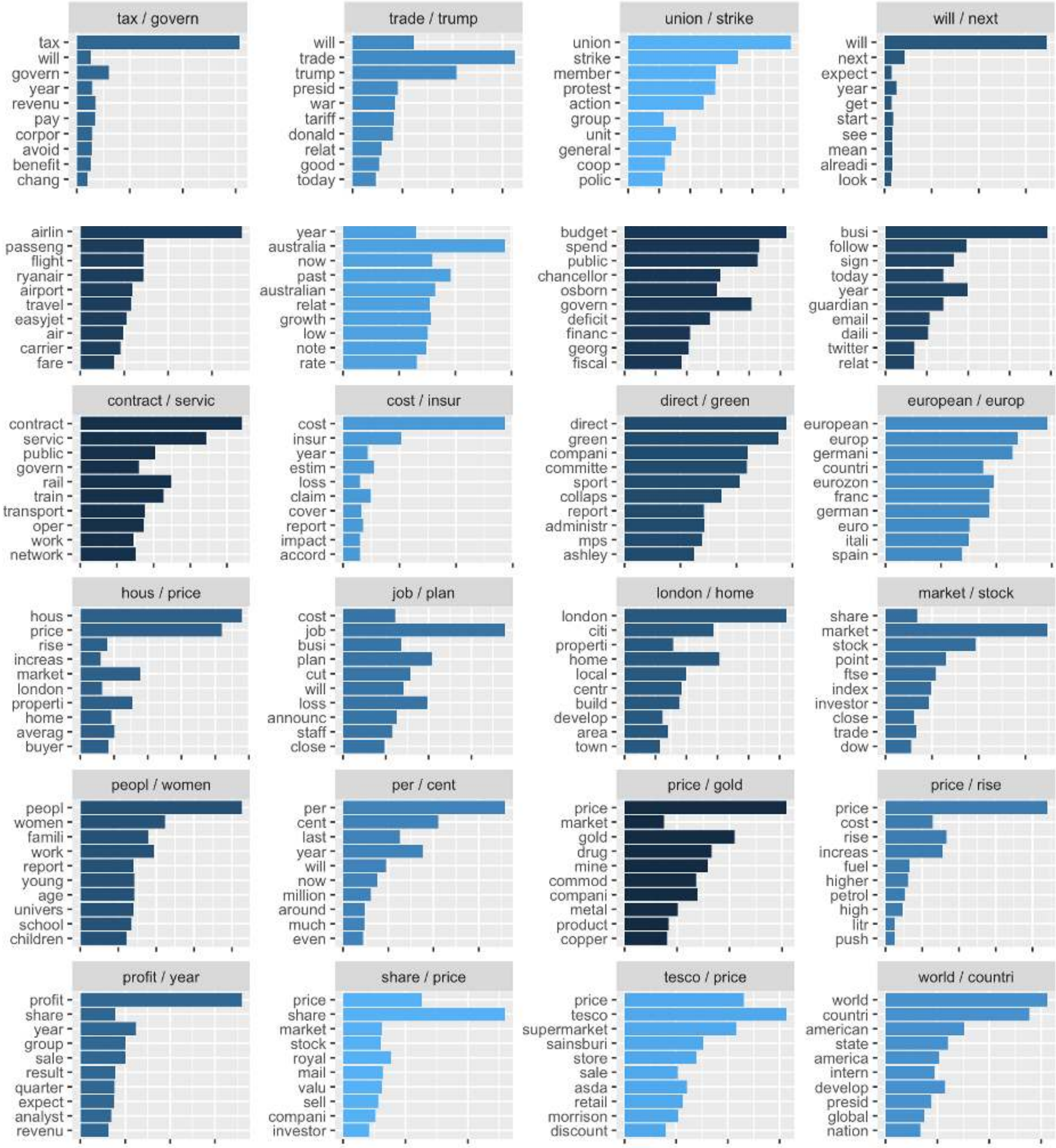


Figure A2: 80 topics resulting from LDA with top 10 frequent words in them. Topic labels are assigned by a concatenation of two most frequent words within the topic. All words are in stemmed format.

## Appendix B: GMM

## Appendix C: Data Description

Table C1 lists the series used in the Euler's consumption model. We use quarterly data covering the sample period between January 2000 and December 2020 and apply seasonal adjustment where needed. Like Ascari, Magnussen and Mavroeidis (2021), we the 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 Labor Force Survey. We also transform nominal measures of consumption, HFCE, NDE, NDG, SERV to real measures. In other words we inflation adjust theses variables using corresponding implied deflators. Formulae are as follows:

For final consumption expenditure:

$$RHFCE = \frac{HFCE\_PH}{HFCE\_DEFL}$$

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

$$RNDGSERV = \frac{NDG\_PH + SERV\_PH}{P_{NDGSERV}}$$

where the implicit deflator for nondurable goods and services $P_{NDGSERV}$ is computed as follows

$$P_{NDGSERV} = \frac{NDG + SERV}{\frac{NDG}{NDG\_DEFL} + \frac{SERV}{SERV\_DEFL}}$$

And the per capita measures for consumption components are computed using

$$NDG\_PH = \frac{NDG}{POP}$$

$$SERV\_PH = \frac{SERV}{POP}$$

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 interest rate we use 3-Month Interbank Rates for the United Kingdom, which are monthly series and are converted to quarterly by averaging.

Table C1: Data used in the paper

| **Data from various sources** | | | |
|---|---|---|---|
| **Mnemonic in the dataset** | **Description** | **Transformations applied** | **Source** |
| *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* | 3-Month Interbank Rates for the United Kingdom, growth rates | Seasonal adjustment | Federal Reserve Economic Data |
| *NDE* | 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 |
| **Variables calculated by us** | | | |
| *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 transformation | |
| *RNGSERV* | Real Household non-durables and services consumption expenditure per head | Log transformation | |