Fiscal Policy in the Bundestag: Textual Analysis and Macroeconomic Effects[*]

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February 27, 2023

Abstract

Fiscal policy is made in parliament. We go to the roots of changes of fiscal policy in Germany and use a novel data set on all parliamentary speeches in the Bundestag from 1960 to 2021. We propose an embedding-based approach, which allows the representation of words and documents in a shared vector space, in order to measure fiscal policy-related sentiment in parliamentary debates at a scale from contractionary to expansionary. For this purpose, a dictionary containing terms related to expansionary and contractionary policy measures is created. We put fiscal sentiment into a series of recursively-identified vector autoregressive (VAR) models to show that a change in fiscal sentiment causes a change in government spending and has strong effects on the macroeconomy. The results support the notion that the debate in parliament contains information for the identification of government spending shocks.

Key Words: text mining, word embeddings, VAR models, identification, government spending
JEL classification:C89, E60, E62

[*]We thank Leif Anders Thorsrud for helpful discussions of an earlier draft. Financial support from the German Research Foundation (DFG) (TI 594/4-1 and WI 2024/8-1) for the project MaFiText is gratefully acknowledged. The project also benefited from cooperation within HiTEC Cost Action CA 21163.
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1 Introduction

Fiscal policy is made in parliaments. Legislating to raise or cut federal public spending or taxes is a key prerogative of parliaments. This implies that changes in government spending or taxation are usually preceded by extensive debates in parliament and beyond, often stretching several quarters or even years. Hence, shifts in the tone of the parliamentary debate should indicate changes in government spending further down the road.

The empirical literature on the identification of government spending shocks and the estimation of their effects on the macroeconomy, see Ramey (2016) for a recent survey, has not yet made use of this information. In this paper, we use data on all speeches delivered in the Bundestag, the federal parliament of Germany, in order to measure fiscal policy at its roots. We argue that the measurement and the identification of fiscal policy impulses can be improved by examining the roots of fiscal policy-making, namely the parliamentary process itself. We believe that households and firms monitor the parliamentary process and adjust their expectations and decisions well before the law is eventually passed and comes into effect.

As a matter of fact, parliamentary speeches are multi-dimensional objects. Extracting quantitative information about fiscal policy is not straightforward. We exploit recent advances in natural language processing (NLP) to tackle this complex NLP task of automatically quantifying fiscal sentiment in parliament based on a large parliamentary text data set.

We proceed as follows: First, we propose an embedding-based approach, which allows the representation of words and documents in a shared vector space, in order to measure fiscal policy-related sentiment in parliamentary debates at a scale from contractionary to expansionary. For this purpose, a dictionary containing terms related to expansionary and contractionary fiscal policy measures is created. Specifically, we adopt Doc2Vec, an unsupervised method to represent natural language in a high-dimensional vector space. The resulting text vectors (also called embeddings) capture semantic characteristics of the texts. These word and text vectors are characterized by the additive property and the interpretability of the distances between them. As the context in which fiscal policy measures are discussed may change over time, we adapt and refine the approach proposed by Kapfhammer et al. (2020) and propose a rolling forecast architecture. This provides us with three series of fiscal sentiment: for the full Bundestag, the governing parties and the opposition. We find large shifts in fiscal sentiment that fit the established historical narrative.

To the best of our knowledge, we are the first paper to use a large body of parliamentary texts to measure shifts in fiscal sentiment and, eventually, to estimate its effect on the macroeconomy.[1] Abercrombie and Batista-Navarro (2020) provide a comprehensive literature review of 61 studies, all of which deal with the automatic analysis of sentiments and opinions as well as the positions of speakers in parliamentary debates. In their research outlook, the authors regret that most of the studies only perform a rough positional analysis (e.g. left vs. right), instead of identifying policy preferences, so that no targeted question can be researched for real-world applications. Furthermore, almost all studies in Abercrombie and Batista-Navarro (2020) are limited to the analysis of a single election period. This makes this work one of the few existing studies that deals with the automated identification of political preferences over several election periods.

A recent strand of the macroeconomic literature proposes a "narrative approach" to the identification of exogenous changes to fiscal policy, i.e. Romer and Romer (2010), Mertens and Ravn (2012) and Cloyne (2013). These authors derive tax policy shocks from text documents such as presidential speeches or parliamentary reports.[2] Guajardo et al. (2014) use historical records such as budget speeches, central bank writings, IMF staff reports and OECD documents to identify changes in fiscal policy designed to consolidate public finances. Our paper goes beyond the selected numbers of text documents used in this studies. Instead, we use data on *all* parliamentary speeches to derive a measure of fiscal sentiment.

[1] Allard et al. (2013) and Dybowski and Adämmer (2018) quantify fiscal sentiment in central bank documents and the communication of U.S. presidents. Instead, our paper is based on a much larger text corpus.

[2] See Hayo and Uhl (2014), Hayo and Mierzwa (2022) and Christofzik et al. (2022) for similar approaches to tax policy shocks in Germany.

Second, we put the resulting sentiment series in a battery of standard Bayesian VAR models. The models also include variables such as real government spending, real GDP, real private consumption or real investment. Our aim is to evaluate whether fiscal sentiment causes government expenditure and, hence, macroeconomic responses. Following the pioneering work of Blanchard and Perotti (2002), a large literature uses a recursive identification scheme in order to estimate the causal effects of government spending. This draws on the notion that within a quarter government spending is predetermined such that a feedback from GDP or other macro aggregates on the level of government spending should be excluded. Fortunately, our series of fiscal sentiment lends itself to a straightforward extension of this identification scheme: we order sentiment last such that a change in sentiment cannot contemporaneously drive government spending. Sentiment, on the other hand, can immediately respond to economic developments.

We find that an unexpected increase in sentiment towards a more expansionary fiscal stance causes higher government spending, an expansion of real economic activity and an increase in private consumption. Several extensions of the model show that fiscal sentiment also increase investment and the price level and reduces unemployment. These responses are in line with standard (New-)Keynesian business cycle models. Furthermore, fiscal sentiment has consequences for Germany as an open economy: more expansionary sentiment leads to a real appreciation and a deterioration of the trade balance. Hence, sentiment measured from parliamentary speeches has strong and robust macroeconomic effects.

Third, we revisit the problem of fiscal foresight, which is often put forward as an argument to invalidate a recursive identification of government spending shocks, e.g. Ramey (2011), Ramey (2016) and Ellahie and Ricco (2017).[3] From a standard recursively-identified VAR model in the spirit of Blanchard and Perotti (2002), Fatás and Mihov (2001), Galí et al. (2007), Born and Müller (2012), Auerbach and Gorodnichenko (2012), Ilzetzki et al. (2013) and others we obtain a series of structural government spending shocks. We

[3] An alternative approach to address this issue is to identify anticipated fiscal "news shocks", see Ben Zeev and Pappa (2017).

then show that fiscal sentiment predicts these structural shocks six to eight quarters in advance. Hence, supposedly unanticipated government spending shocks are in fact anticipated once information from the parliamentary debate is taken into account.

The remainder of this paper is structured as follows. Section 2 describes the data from the German Bundestag as well as the preprocessing steps applied to this data in order to render the data usable for further analysis. Section 3 presents our approach for constructing the text-based fiscal sentiment indicator. In Section 4, we estimate a range of VAR models to understand the effects of fiscal policy on the German economy. Section 5 revisits the problem of fiscal foresight. Finally, Section 6 concludes.

2 Text data

This section introduces the textual data from which we derive a measure of fiscal sentiment. Subsection 2.1 describes the underlying text data, i.e. the full set of parliamentary speeches. In subsection 2.2, we describe specific text data preprocessing steps which are needed for the text mining methods applied later.

2.1 Bundestag speeches as novel data source

The Bundestag is the German federal parliament. At the time of writing, it has more than 700 members with the exact number varying over time. Although we later focus on fiscal policy, we start from the full set of all parliamentary debates. The digitized debates of the plenary sessions, not the committees, are made available to the public by the German Bundestag.[4]

Unfortunately, this text data is not directly suitable for the application of NLP methods as the parliamentary speeches up to election period 18, i.e. until October 2017, are available in an unstructured form only. This means that the XML documents only have one “TEXT” tag in addition to the

[4]All stenographic reports can be downloaded from this website as XML files packed in .zip files: https://www.bundestag.de/services/opendata.

tags “ELECTION PERIOD”, “DOCUMENT TYPE”, “NR”, “DATE” and “TITLE” on the meta-information of a session, the contents of which can be easily extracted. The content of the “TEXT” tag comprises the entire stenographic report – including the agenda items, the actual meeting and the annexes. Therefore, it is necessary to further structure the content of the “TEXT” tag so that each speech contribution can be assigned to a speaker. Furthermore, each speaker should be assigned with his or her role and party affiliation. To structure the XML files, we use the workflow documented in more detail in Latifi (2023) that proceeds as follows:

First, we parse and clean the XML documents provided using a set of regular expressions. Second, a Named Entity Recognition (NER) model with a customised entity, which usually consists of a speaker’s first and last name followed by his or her party affiliation in brackets, a colon and a newline, is developed to identify the begin of each speech. Thereby, a small hand-labelled data set is created to train the NER model. Eventually, the cleaned stenographic protocols can be split by each identified beginning of a speech. After that, one can extract roles and party affiliations corresponding to the speaker of each individual contribution.

With the aim of promoting computer-assisted research on parliamentary data, the German Bundestag has been publishing the XML files in a very finely structured form since election period 19, so that the precise extraction of relevant information involves comparatively little effort and little manual reworking.[5] We convert these plenary protocols into a file format that can be used for further processing by using the python package `pybundestag` (Hruzik, 2019). In a final step, we unify the data set of election periods 1-18 with the data set of election period 19 in a consistent structure. The complete data set of the election periods 1 to 19 comprises a total of $877,140$ speeches.

[5] Further information on the structure of the XML documents as of election period 19 are described here: https://www.bundestag.de/resource/blob/577234/f9159cee3e045cbc37dcd6de6322fcdd/dbtplenarprotokoll_kommentiert-data.pdf.

2.2 Corpus and text preprocessing

The time-stamped data set, structured following Latifi (2023), also contains meta-information on party affiliation, government participation and the role of the speaker. We now describe the specific preprocessing steps we apply in order to prepare the data for the subsequent steps.

Since most macroeconomic time series are available from 1970 onward and as we need a rolling 10-year training data set for our embedding approach, our data set begins in 1960. In a first step, speeches by the President of the Bundestag or an office holder of a similar function are excluded, as their main task is primarily to chair and moderate (including announcing voting results, calling up items on the agenda, calling up speakers) the plenary sessions. Furthermore, we exclude speeches from state ministers representing the federal states of Germany, guest speakers such as foreign dignitaries and other irregular speakers.

This leaves us with all speeches delivered by members of parliament, Chancellors, Federal Ministers and State Secretaries.[6] Furthermore, we remove very short and very long speeches from the data set. Short remarks are often made during swearing-in ceremonies or as interposed questions. We count the words of each speech and remove all speeches containing less than 100 tokens, i.e words, or more than $3,573$ tokens. The latter threshold corresponds to the 99.5%-percentile of the word frequency distribution over the documents. After these exclusion steps, the data set contains $235,129$ speeches covering the period from January 20, 1960 to September 07, 2021.

Figure (1) shows the number of speeches on a quarterly basis. Over the entire period, the average number of speeches per quarter is 959.71, though the number of speeches increases over time. Furthermore, there are seasonal fluctuations. The third quarter contains by far the fewest speeches in the data set, with a total of $26,141$ speeches, which can be attributed to the summer break.[7] In addition, Figure (1) shows that members of the coalition

[6] Members of the government do not have to be members of parliament, though in most cases they are.

[7] For comparison, quarter 1 contains a total of $68,553$ speeches, quarter 2 contains $73,412$ speeches, and quarter 4 contains $67,023$ speeches.

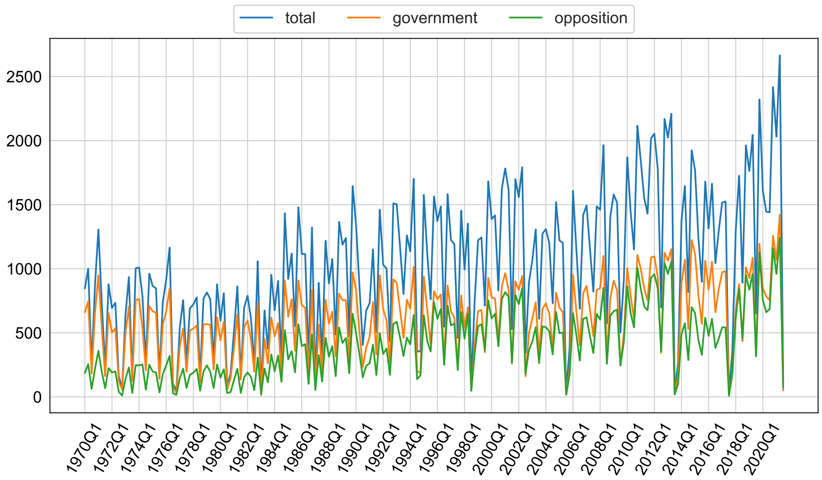
parties forming the government deliver more speeches than members of the opposition parties. This is plausible given the distribution of seats. However, these differences have become smaller in the recent past.

We then prepare the corpus using common text preprocessing steps, such as those described in detail in Grimmer and Stewart (2013) and in Denny and Spirling (2018). We first lemmatize all speeches using the model *"de_core_news_lg"* from the python package `spaCy` (Honnibal et al., 2020) so that all words in the speeches are traced back to their root words. This also reduces the complexity of the corpus. In the following, we refer to a word as a token and a speech as a document. The corpus is the collection of all documents.

After lemmatizing, we convert all German umlauts and the eszett to exclude encoding errors. In addition, we remove line breaks, digits, blank sentences and special characters and convert all letters to lower case. We remove single-element tokens and tokens with more than 30 elements. The removal of further short tokens is not advisable for this domain, because meaningful tokens such as "is", "eg", "eu", "ki", "db" etc. are included in this corpus.

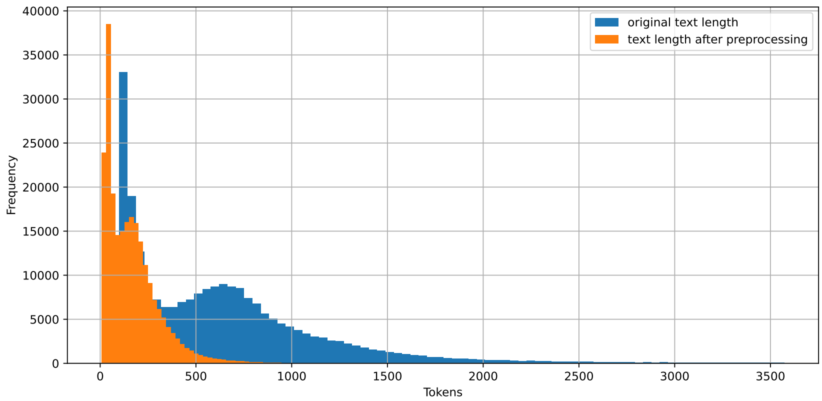
The next step is to create a list of stop words. Stop words are tokens that occur very frequently in the corpus, but contain little informational content and therefore do not provide the texts with much semantics (e.g. personal pronouns, conjunctions, etc.). In the `nltk` package (Bird and Klein, 2009) there is a predefined list of stop words for the German language. Since a general stop words list does not include domain-specific terms such as "Bundestag", "Abgeordneter", "Deutschland", "Redezeit", "Drucksache", etc., we create a list of stop words based on the inverse document frequency (*idf*) value of each unique word. The *idf* value is calculated using the package `scikit-learn` (Pedregosa et al., 2011). A low *idf* value implies that a word occurs in a very large number of documents and is therefore not very specific. All tokens that occur in 97% of all documents in each election period are considered potential stop words. The final list of stop words is manually expanded in an iterative process, so that it comprises a total of 1405 terms. We report the final list of stop words in Appendix A. These stop words were lemmatized analogously to the text and finally removed from the corpus.

Figure 1: Number of speeches



Notes: The figure shows the number of speeches over our sample period aggregated to quarterly frequency.

Figure 2: Length of speeches before and after preprocessing



Notes: The figure shows the distribution of the length of a document (speech) before and after preprocessing.

Figure (2) shows the distribution of the length of a document before and after applying the described preprocessing steps. A document contains an average of 637.10 tokens before preprocessing, but only 164.83 tokens after preprocessing. The entire corpus contains $149,800,737$ tokens before and $38,755,290$ tokens after preprocessing. This means that the size of the corpus is reduced by almost 75% after preprocessing.

3 A text-based fiscal sentiment indicator

This section first documents the construction of a dictionary with fiscal policy-specific terms. We then present the state-of-the-art word and text representation technique, the so-called word or document embeddings, and propose an approach to construct a fiscal sentiment indicator based on these text representations.

3.1 Compiling a dictionary on fiscal policy

Although dictionary-based approaches have been widely used in economics and finance lately, e.g. to quantify the sentiment of financial reports (Loughran and McDonald, 2011), central bank communication (Picault and Renault, 2017) or to construct newspaper-based indicators of economic policy uncertainty (Baker et al., 2016), there is no dictionary available for the field of fiscal policy. Therefore, we first need to assemble a fiscal policy-related dictionary for Germany.

We construct a preliminary list of terms relevant to fiscal policy through extensive study of the speeches in the Bundestag. Since some randomly selected speeches are more concerned with other detailed fiscal policy issues, such as real estate policy, economic crime or reducing bureaucracy in the tax system, in order to quickly identify particularly expressive words we also take advantage of data from the Manifesto corpus (Burst et al., 2020), which contains publicly available, thematically classified quasi-sentences from election manifestos of various parties from over 50 countries. The categories capture the most relevant political issues and goals and are assigned to the respective quasi-sentences according to a strict annotation scheme. The annotation scheme is described in Werner et al. (2011). The corpus can be downloaded via the R package `manifestoR` or as .csv files via the website.[8] We select 19 categories relevant to fiscal policy. This amounts to 39 .csv files of German election programs from 1998 to 2017. These files contain a total of 22,602 quasi-sentences classified with the selected categories.[9]

In this way, we construct a preliminary list of 163 keywords. This list is then labelled by us in terms of the categories expansionary, neutral, contractionary. It is important that we identify terms as uniquely as possible in terms of the expansionary or contractionary sentiment conveyed. In case an expression is ambiguous, we decide based on the majority vote.

Eventually, our list consists of 86 terms or compound terms, of which 47 are classified as "expansionary" and 39 as "contractionary". The list of expansionary and contractionary terms used in the current version can be found in Appendix B.[10]

3.2 Doc2Vec approach

Word2Vec is an unsupervised, neural network based method to represent natural language in a high-dimensional vector space (Mikolov, Chen, Corrado and Dean, 2013). The resulting text vectors (also called embeddings) are state-of-the-art in capturing semantic characteristics of words and texts. These word and text vectors have two key properties: they are additive and the distance between words and vectors is interpretable. Doc2Vec is an exten-

[8] The .csv files can be downloaded via this page: `https://visuals.manifesto-project.wzb.eu/mpdb-shiny/cmp_dashboard_dataset/`.

[9] The following categories are selected: [303] Governmental and Administrative Efficiency, [401] Free Market Economy, [402] Incentives, [403] Market Regulation, [404] Economic Planning, [408] Economic Goals, [409] Keynesian Demand Management, [410] Economic Growth: Positive, [412] Controlled Economy, [414] Economic Orthodoxy, [416] Anti-Growth Economy: Positive, [503] Equality: Positive, [504] Welfare State Expansion, [505] Welfare State Limitation, [501] Environmental Protection: Positive, [701] Labour Groups: Positive, [702] Labour Groups: Negative, [416.1] Anti-Growth Economy: Positive, [4012] Control of Economy: Negative.

[10] The dictionary is not final yet, as we are still working on expanding and refining the keywords considering also the characteristics specific to the German language, e.g. compounded words and synonyms.

sion of the Word2Vec approach that also allows to represent sentences, paragraphs, and documents as vectors (Le and Mikolov, 2014; Mikolov, Sutskever, Chen, Corrado and Dean, 2013).

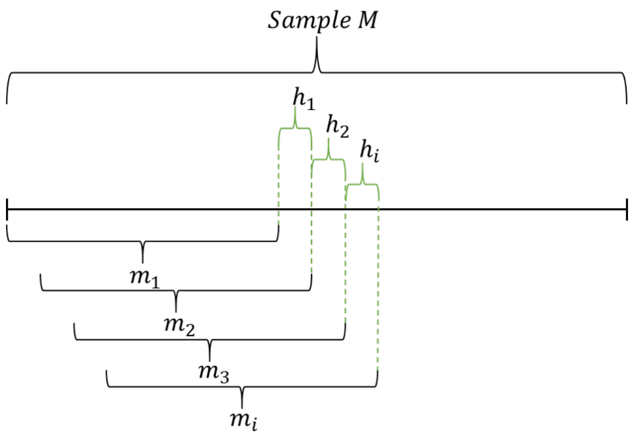
Such word and text vectors are successfully used in different text-as-data applications. Rheault and Cochrane (2020) highlight the potential of word embedding for the analysis of political texts. The authors propose a word embeddings-based model to examine latent concepts such as political ideology in political texts. Gennaro and Ash (2021) use word embeddings to study the use of emotion and reason in political discourse. Using word embeddings, the authors construct two poles corresponding to emotion and reason, respectively, and measure the similarity of digitised transcripts from the U.S. Congress to these poles. A recent work by Rodriguez and Spirling (2022) studies the performance of word embeddings in applied research, especially political sciences. The authors come to the conclusion that even pre-trained embeddings perform very well compared to human coders.

Kapfhammer et al. (2020) use word embeddings to measure climate change transition risk. The authors investigate how the media speaks about risk and how the context changes over time. To address the issue of changeability of the context, the authors divide the considered time period into sub-periods and estimate separate Word2Vec models for each sub-period. Kapfhammer et al. (2020) argue that making the word embedding methodology dynamic can capture changes of the relationships between specific words over time.

In the current project, we propose a Doc2Vec approach to construct a fiscal policy sentiment index for the German Bundestag. This approach is advantageous for at least two reasons. First, we receive vector representations for each speech in the corpus as a single semantic unit.[11] This allows us to compare speeches with each other. Second, we also obtain vector representations for single words in the corpus vocabulary that we then use to construct vectors representing expansionary and contractionary fiscal policy measures. Thereby, we follow the ideas of a dynamic approach presented by Kapfhammer et al. (2020). New concepts with regard to fiscal policy

[11] An alternative approach would be to use Word2Vec and aggregate the constituent words to speeches representations.

Figure 3: Rolling-window Doc2Vec



Notes: This figure represents the training procedure of the dynamic Doc2Vec approach. In the presented scheme, each training period m covers the same period of time (e.g. quarter, year, 10 years). Each forecast period h is also of fixed size. In the proposed procedure, the shift length equals the defined forecast length.

may occur and some of them may disappear over time. Also, the general context in which fiscal policy measures are discussed may also change over time. In the following, We describe the dynamic Doc2Vec approach to the construction of a fiscal policy sentiment indicator.

We propose a rolling forecast architecture to the defined problem. Figure (3) represents the training procedure for the rolling window setting. Given the sample M that correspond to the corpus presented in Subsection 2.2, we divide the period into training periods m_i. For each period m_i, we train a Doc2Vec model using lemmatized and preprocessed texts. For the subsequent period, h_i document vectors are inferred based on the trained Doc2Vec model. This means that documents in the forecast period h are actually new to the model. The vectors for these documents can be predicted based on the trained word dependencies and relationships. Each training and forecast period is of fixed size. However, the number of observations in each period m_i and h_i might differ depending on the number of documents.

The proposed dynamic approach can be divided into four steps:[12]

[12]In this context, an alternative static Doc2Vec approach would imply using all available text data in the training process of text embeddings. It means that steps 1 and 2 are not

1. For a defined period of time, train the Doc2Vec model using preprocessed texts.[13] Doc2Vec models are trained using Python's `gensim` package (Řehůřek and Sojka, 2010).

2. For the given training sub-period, construct an expansionary and a contractionary vector as the average vector of the identified fiscal policy-related terms. Thereby, their representation is different in each training period depending on which words occur in the learned vocabulary. For two-words terms such as "Steuern senken", "Arbeitsplätze schaffen" and others, the average of the corresponding word vectors is used to represent these terms.

3. Based on the pre-trained model, infer speeches vectors for the subsequent forecast period. Calculate the cosine similarities between the inferred document vectors and the fiscal policy vectors. Each document/speech receives two scores: similarity to expansionary stance of fiscal policy and similarity to a contractionary stance of fiscal policy.

4. Construct a continuous indicator by taking the difference between the similarity to the expansionary vector and the contractionary vector. This results in a value that ranges from -1 (very contractionary) to 1 (very expansionary).

This procedure is fully unsupervised and language agnostic. It can be applied to other corpora and other languages in case a fiscal policy dictionary is available.

3.3 Results

We use a training length of 10 years (40 quarters) and a forecast length of one quarter. As mentioned before, this limits the sample for which we will obtain the sentiment series to 1970 to 2021. Each training sub-period

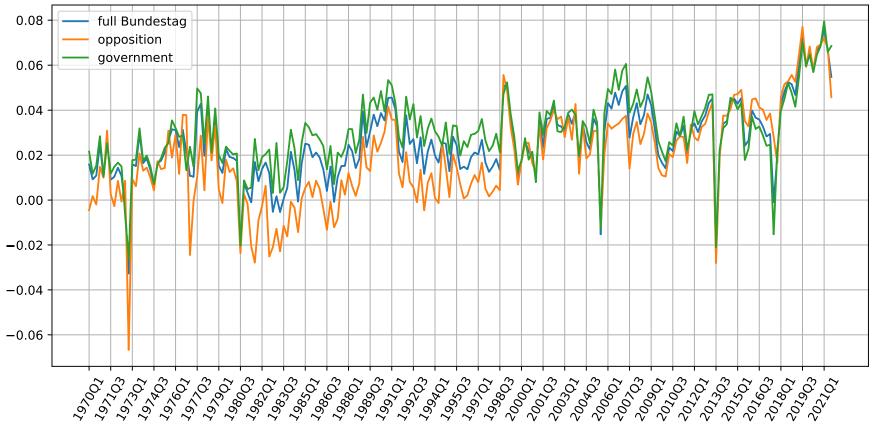
performed iteratively for several sub-periods, but only once for the entire sample.

[13] We use the following parameters for the training: vector_size = 100, min_count = 1, epochs = 50. We keep the remaining parameters at the default level.

contains $37,889$ speeches on average. Each forecast period contains $1,037$ speeches on average. As described in the previous subsection, each speech receives two scores that correspond to the cosine similarity values between the single speeches and the constructed expansionary and contractionary vectors. We build a continuous fiscal policy index by subtracting the similarity to the contractionary vectors from the similarity to the expansionary vector. For example, a fiscal sentiment of zero could imply that a speech discusses both expansionary and contractionary fiscal policy measures and the cosine scores to both fiscal vectors cancel out.

Figure (4) shows the final sentiment series at quarterly frequency. These series will enter the estimated VAR models in the next section. We show one series for the full Bundestag, i.e. for speeches of all members, one for speeches delivered by members of the governing parties and one based on speeches from opposition members. We find a close co-movement of government and opposition sentiment. The evolution of sentiment is consistent with the established historical narrative: First, the shift from a center-left to center-right coalition in 1982, which was also motivated by concerns about fiscal sustainability, is clearly visible as drop in fiscal sentiment of the government towards a more restrictive policy stance. Second, when the European Commission triggered the excessive deficit procedure against Germany, which is specified in the Stability and Growth Pact, fiscal sentiment deteriorated. Third, we spot a fall in fiscal sentiment starting in 2014 when the coalition government pushed its policy of budget surpluses ("schwarze Null"). Towards the end of our sample period, i.e. after the 2017 election, there is a remarkable upward trend in sentiment.

Figure 4: Fiscal policy sentiment

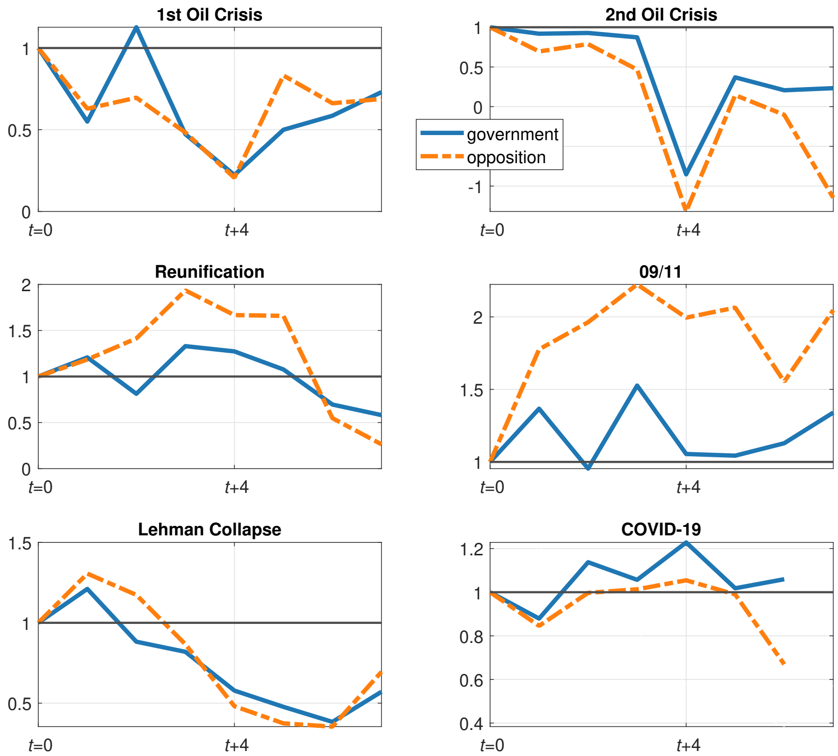


Notes: The figure shows the fiscal sentiment of the full Bundestag as well as the government and the opposition.

To further illustrate the evolution of fiscal sentiment, Figure (5) highlights selected episodes. We show sentiment following six large shocks that could be considered exogenous: the two oil crisis in the 1970s, the collapse of the German Democratic Republic leading the way to German reunification, the 09/11 terrorist attacks, the collapse of Lehman Brothers at the peak of the global financial crisis and the COVID-19 pandemic. Since we normalize sentiment to one at the beginning of each episode, this figure is not informative about the level of sentiment. Rather, it showcases the responses to these events. During the two oil crisis, both the government and the opposition respond by a hawkish sentiment. After 09/11 and the reunification, in contrast, government and opposition strike a much more dovish tone. These episodes also exhibit the largest discrepancy between government and opposition. Within a year after the Lehman collapse, the Bundestag turns very hawkish, which certainly also reflects the parliamentary debate about fiscal policy in the euro area.

We further analyse fiscal sentiment with regard to the changing coalition governments. Figure (6) presents the average sentiment in the German Bundestag for each election period. In most periods, the government exhibits a more expansionary sentiment than the opposition. The only exception to this

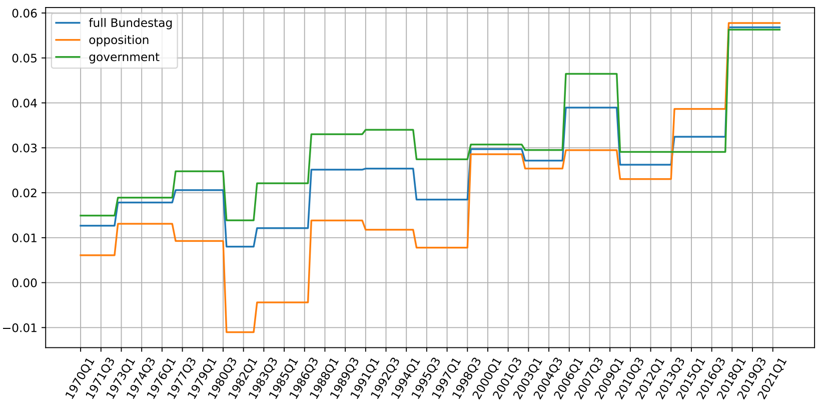
Figure 5: Fiscal sentiment in selected episodes



Notes: The figure shows the standardized fiscal sentiment for the government and the opposition during selected episodes. We normalize both sentiment series to one in 1973Q3 (1st oil crisis), 1979Q3 (2nd oil crisis), 1990Q1 (when reunification became more likely), 2001Q3 (09/11), 2008Q3 (collapse of Lehman Brothers) and 2020Q1 (COVID-19).

is the 2017-2021 coalition with Finance Minister Wolfgang Schäuble pushing the “schwarze Null”. The distance between government and opposition varies over time and reaches a maximum in the early 1980s.

Figure 6: Average fiscal sentiment per election period



Notes: The figure shows the average fiscal sentiment of the full Bundestag the government and the opposition in each election period from 1970Q1 to 2021Q3.

Finally, we want to compare our index to alternative measures derived from textual information. However, as our paper is the first to construct a long time series reflecting the fiscal sentiment of the German Bundestag, no further indices are available for comparison. In standard sentiment analysis, sentiment scores are often obtained based on counting the occurrence of specific words, e.g. words carrying a positive vs negative meaning. Here, we use these dictionary-based approaches for comparison. Instead of applying Doc2Vec and working with text representations, we count the relevant expansionary ($\#expansionary$) and contractionary ($\#contractionary$) terms and divide this count by the total number of words ($\#words$) in the document as in equation (1) or by the sum of expansionary and contractionary words as in equation (2), i.e.

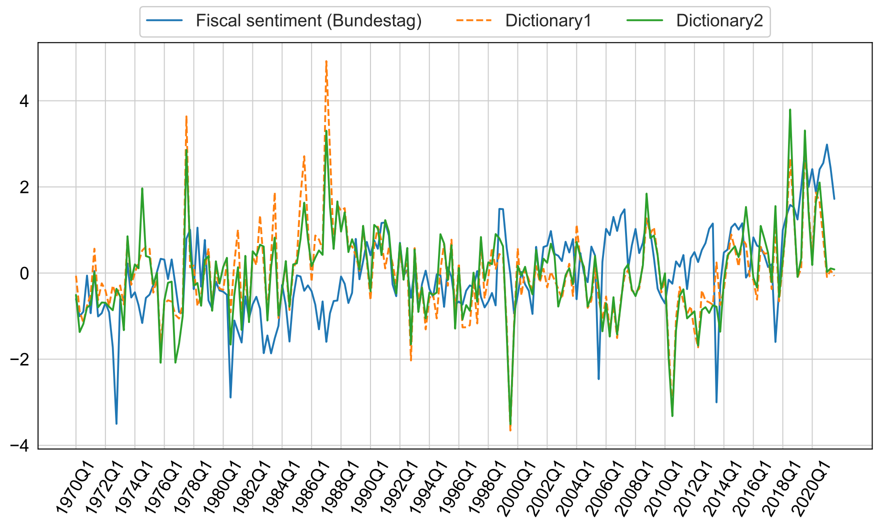
$$Dictionary_1 = \frac{\#expansionary - \#contractionary}{\#words} \tag{1}$$

or

$$Dictionary_2 = \frac{\#expansionary - \#contractionary}{\#expansionary + \#contractionary}. \quad (2)$$

We then aggregate the series to quarterly frequency. Figure (7) presents the standardized fiscal policy sentiment indicator for the full Bundestag and two frequency-based alternatives. The overall evolution of the two dictionary-based series is similar to our benchmark. However, both series are only weakly correlated with our Doc2Vec-based sentiment. The contemporaneous correlation is 0.14 (p=0.04) with $Dictionary_1$ and 0.27 (p=0.00) with $Dictonary_2$. In addition, there are notable and persistent discrepancies between them, e.g. in the mid-1980s or the 2000s.

Figure 7: Comparing fiscal policy sentiment in the Bundestag across methods



Notes: The figure shows the standardized Doc2Vec-based fiscal policy sentiment indicator for the full Bundestag as well as the two dictionary-based reference series.

4 Estimating the macroeconomic effects

We now study the macroeconomic effects of exogenous changes in fiscal sentiment as reflected in the textual data. For that purpose, we augment a relatively standard VAR model by our new sentiment series.

4.1 VAR model

We estimate a reduced-form VAR model with p lags

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + C x_t + \varepsilon_t, \tag{3}$$

where y_t is the $n \times 1$ vector of endogenous variables, $A_1, ..., A_p$ are $n \times n$ coefficient matrices and x_t is a vector of exogenous regressors such as constant terms, dummies and a time trend. The vector of error terms, ε_t, follows a multivariate normal distribution, $\varepsilon_t \sim N(0, \Sigma)$, where Σ is the variance-covariance matrix with $E(\varepsilon_t \varepsilon_t') = \Sigma$. The residuals are mutually uncorrelated at all leads and lags.

The VAR model is estimated using Bayesian methods, thus treating parameters as random variables drawn from an underlying probability distribution. We assume a Normal-Wishart prior, though our results remain unchanged for alternative priors specifications.[14]

As discussed before, we adopt a recursive identification scheme. Let us write the model in its structural form

$$D_0 y_t = D_1 y_{t-1} + ... + D_p y_{t-p} + F x_t + \eta_t, \tag{4}$$

where $\eta \sim N(0, \Gamma)$ is the vector of structural shocks and the D matrices are defined appropriately. With $D = D_0^{-1}$, the reduced-form error terms and the structural shocks are linked by $\varepsilon_t = D\eta_t$. We assume that D is lower triangular, thus imposing restrictions on the contemporaneous interdependencies between the endogenous variables.

4.2 Data

In our baseline model, we include four endogenous variables: the log of real government expenditure, Gov_t, the log of real GDP, GDP_t, the log of real private consumption, $Cons_t$, and one of the three alternative indicators of fiscal sentiment derived in the previous sections, $Senti_t^j$, with

[14] In order to estimate the model, we rely on the BEAR toolbox for MATLAB, see https://www.ecb.europa.eu/pub/research/working-papers/html/bear-toolbox.en.html.

$j \in (Bundestag, Government, Opposition)$. In order to smooth the extreme fluctuations of the sentiment series, we include them as (backward) four-quarter moving averages. Below, we show that the results also hold for the non-smoothed sentiment series. Hence, the vector of endogenous variables is

$$y_t' = \begin{bmatrix} Gov_t & GDP_t & Cons_t & Senti_t^j \end{bmatrix}. \tag{5}$$

In three alternative specifications, we augment the baseline VAR by additional variables. First, we include the log of real private investment and the log of employment as two additional variables reflecting the domestic business cycle. Second, we include the unemployment rate as well as the log of the consumer price index. Third, we add two variables to the model that reflect the open-economy transmission of fiscal policy, i.e. the log of the real effective exchange rate and the trade balance relative to GDP. All log series are multiplied by 100. The estimation frequency is quarterly and the data spans 1970Q1 - 2021Q3.

We also include a time trend and an impulse dummy that is one in 2020Q2 and zero otherwise. This dummy capture the extreme drop in real economic activity due to the COVID-19 pandemic and the ensuing lockdown. As Germany went into lockdown in the second half of March 2020, we choose to set the dummy to one in the second quarter of 2020. We estimate the VAR model for $p = 8$ lags.

The core time series are taken from the OECD data file: real GDP, real private consumption, real government consumption and real gross fixed capital formation, i.e. investment. These series are seasonally adjusted. Employment is measured as the employed population, aged 15 and over. The seasonally adjusted series is available on the FRED database of the Federal Reserve Bank of St. Louis (series ID: LFEMTTTTDEQ647S). Likewise, the unemployment rate (ID: LRUNTTTTDEQ156S) applies to persons aged 15 and over. The consumer price index (ID: DEUCPIALLMINMEI) is also taken from FRED. Finally, we include open-economy variables: the real effective exchange rate is also available on FRED (series ID: CCRETT01DEQ661N), while Germany's trade balance as a share of GDP is constructed from seasonally adjusted nominal exports (series ID: DEUGDPNQDSMEI), imports (series ID: DEUIMPORTQDSMEI), and nominal GDP (series ID: DEUEXPORTQDSMEI).

4.3 Identification

We draw on the extensive literature on the identification of exogenous fiscal policy shocks pioneered by Blanchard and Perotti (2002) and applied, among others, by Fatás and Mihov (2001), Galí et al. (2007), Born and Müller (2012), Auerbach and Gorodnichenko (2012) and Ilzetzki et al. (2013) and impose a recursive ordering onto the variables. The ordering of the variables as in (5) implies that in a given quarter government expenditure is predetermined. Changes in GDP or consumption, respectively, do not contemporaneously affect government spending. Our specific application lends itself to a straightforward extension of this line of literature. The starting point of our analysis is that fiscal policy is made in parliaments and that parliamentary decisions take time. This is exactly why spending is predetermined in a given quarter. Our text data reflects this parliamentary debate. In fact, as argued by Mertens and Ravn (2010), Ramey (2011) and Ramey (2016), among others, changes in government spending could be anticipated several quarters in advance. Ordering government spending first thus implies that VARs do not identify unanticipated government spending shocks. We will revisit this issue in the next section.

Including information on the fiscal sentiment expressed in parliament alleviates this concern. We order sentiment last. Hence, a change in fiscal sentiment as expressed in Bundestag speeches should not contemporaneously drive either government expenditure, nor real GDP or real consumption. At the same time, fiscal sentiment is contemporaneously responding to the business cycle. If sentiment is informative about fiscal policy, we should expect that an exogenous increase in sentiment, i.e. a shift towards a more expansionary policy stance, raises government expenditure and economic activity. This effect should be more pronounced for the sentiment of speakers of the parties forming the government compared to opposition speakers.

4.4 Results

Figure (8) shows the responses of our endogenous variables to an increase in the fiscal sentiment of the full Bundestag one standard deviation in size. All figures also include 68% probability bands. As a consequence of the shock, government expenditure increase strongly by about 0.4%. This response is highly significant and very persistent. Hence, a shift towards a more expansionary policy stance as reflected in the speeches held in the Bundestag does indeed cause a subsequent increase in government spending. The additional spending has real economic effects: real GDP as well as real private consumption increase by about 0.3%.

In Figure (9), we depict the responses to fiscal sentiment as reflected in the speeches of the members of parliament who belong to the governing parties. While the increase in government spending is slightly smaller than in Figure (8) with expenditure increasing by about a quarter of a percent, the overall macroeconomic effects are very similar. Again, expansionary fiscal policy has a strong impact on income and consumption. Somewhat surprisingly, the results also remain unchanged if we include only sentiment in those speeches that are delivered by the opposition parties, see Figure (10). The strong macroeconomic effects appear robust with respect to the parliamentary origin of more expansionary fiscal sentiment. As a matter of fact, this reflects the close co-movement of the sentiment series as shown in Figure (7).

We now extend the baseline model by additional variables. In the first alternative model, we include real investment and employment. Both variables are also ordered behind government expenditure but before our sentiment indicator. Figure (11) reports the corresponding impulse response functions. We show these model extensions for the sentiment of the coalition parties forming the government only. The shift in sentiment causes a strong increase in government expenditure and a significant increase in private consumption and investment. As expected, the response of investment is much larger than the response of consumption, which is consistent with the logic of standard intertemporal business cycle models. In contrast to the baseline results, the GDP response is no longer different from zero. In line with that, employment exhibits only a tiny increase indistinguishable from zero.

In the second alternative model, we augment the baseline variables by the unemployment rate and the consumer price index. Figure (12) shows that a fiscal expansion leads to a drop in unemployment after two years. Furthermore, consumer prices start to increase after 18 months by about 0.2%. Hence, the expansionary fiscal impulse is leading to inflationary pressure.

We study a third alternative model specification that reflects the open-economy transmission of fiscal policy. In addition to the four variables of the baseline model, we include the real effective exchange rate and the trade balance relative to GDP. Again, both variables are ordered after government expenditure but before fiscal sentiment. Textbook models of an open economy suggest that a fiscal expansion, here reflected by a shifts towards a more expansionary sentiment, causes a real appreciation of the domestic currency and a deterioration of the trade balance. Figure (13) shows that the impulse responses are perfectly in line with standard models. Germany experiences a real appreciation of about 0.3% after 10 months as well as a drop in the trade balance by 0.2 percentage points.[15]

Taken together, these findings suggest that a change in the fiscal sentiment expressed in the Bundestag does indeed have real economic effects. Our results lend support to the Keynesian paradigm, i.e. suggesting that expansionary fiscal policy does indeed increase income and consumption.

4.5 Robustness

In our baseline model, we include the log-levels (times 100) of macroeconomic aggregates such as GDP, consumption and government expenditure. An alternative would be to detrend the three macroeconomic variables. We follow Gordon and Krenn (2010), Ramey (2016), Ramey and Zubairy (2018) and Ilori et al. (2012) and detrend each variable using the trend in real GDP, i.e. we include variable x_t, which is either real GDP, real consumption or real government expenditure, as $100 \times (\ln x_t - \ln y_t^{trend})$, where y_t^{trend} is the

[15]Thus, our findings are in line with theory and do not exhibit a puzzling depreciation after an expansionary policy, see Forni and Gambetti (2016) and Ferrara et al. (2021) for this debate.

estimated trend in real GDP. We derive y_t^{trend} either from fitting a quadratic trend to log GDP as in Gordon and Krenn (2010), Ramey (2016) and Ramey and Zubairy (2018) or from applying the Hamilton (2018) filter to log real GDP as in Ilori et al. (2012).

The results based on the quadratic trend in GDP are shown in Figure (14). An unexpected increase in fiscal sentiment raises government expenditure, GDP as well as private consumption. All responses are distinct from zero and look very similar to the results based on the log-level variables presented in the previous section. In Figure (15), we show the impulse responses based on the GDP trend derived from the Hamilton (2018) detrending procedure. Interestingly, the response of government expenditure and GDP is now smaller and no longer different from zero. Nevertheless, the change in fiscal sentiment still pushes up private consumption.

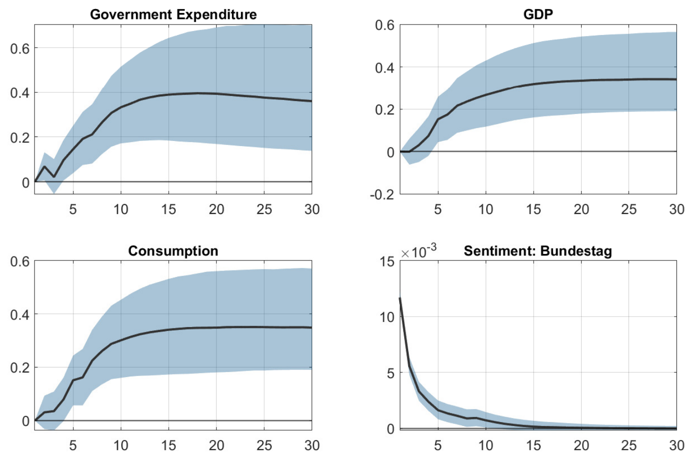
To shed light on the impact of the estimation method on our findings, Figures (14) and (15) also depict the resulting impulse responses when the model is estimated by OLS. While the results are qualitatively similar to the Bayesian estimates, we see that our baseline responses tend to be somewhat smaller than the OLS-based responses.

Finally, we assess the robustness of the findings with respect to the lag order p of the VAR model. Figure (16) reports the impulse responses for the baseline model with $p = 8$ as well as three alternative models with $p \in 4, 6, 10$. While the responses of the three macroeconomic variables tend to be smaller for $p = 4$, they remain qualitatively unaffected when changing the lag order from $p = 8$ to $p = 6$ or $p = 10$. We conclude that our results are robust with respect to plausible alternative lag orders.

5 Fiscal foresight revisited

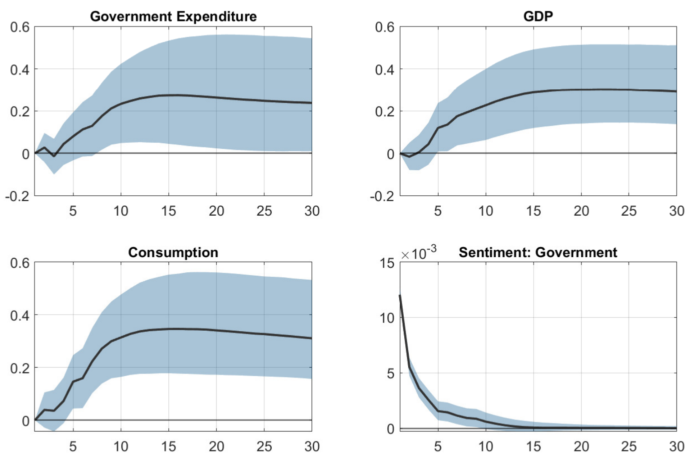
The literature on government spending shocks argues that fiscal foresight invalidates the recursive Blanchard-Perotti identification, see Mertens and Ravn (2010), Ramey (2011) and Ramey (2016) and Ellahie and Ricco (2017). Our data set allows us to examine the degree to which fiscal sentiment expressed in parliamentary speeches allows the public to forecast government

Figure 8: Response to fiscal sentiment (full Bundestag)



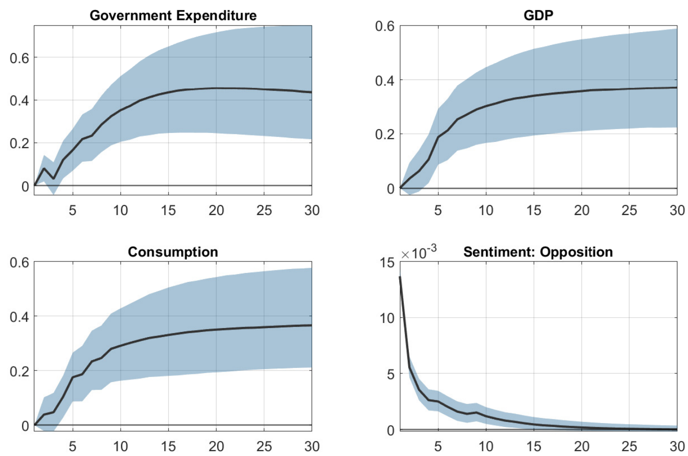
Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment as reflected in speeches of all members of the Bundestag. All responses are derived from a recursively identified Bayesian VAR model with 8 lags and Normal-Wishart priors. The shaded areas reflect 68% probability bands.

Figure 9: Response to fiscal sentiment (government)



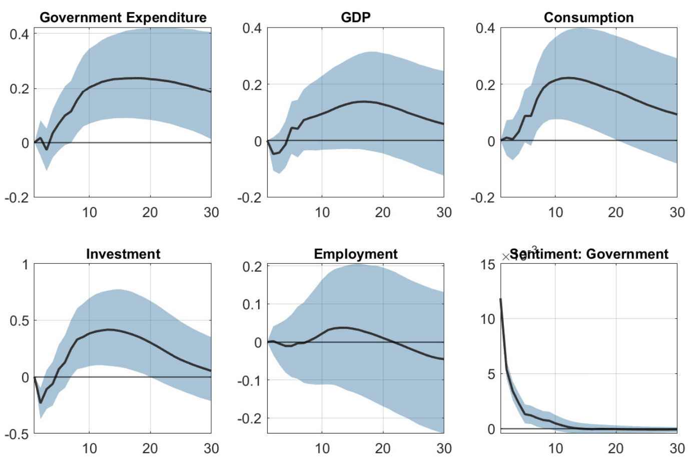
Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment as reflected in speeches of members of the parties forming the government. All responses are derived from a recursively identified Bayesian VAR model with 8 lags and Normal-Wishart priors. The shaded areas reflect 68% probability bands.

Figure 10: Response to fiscal sentiment (opposition)



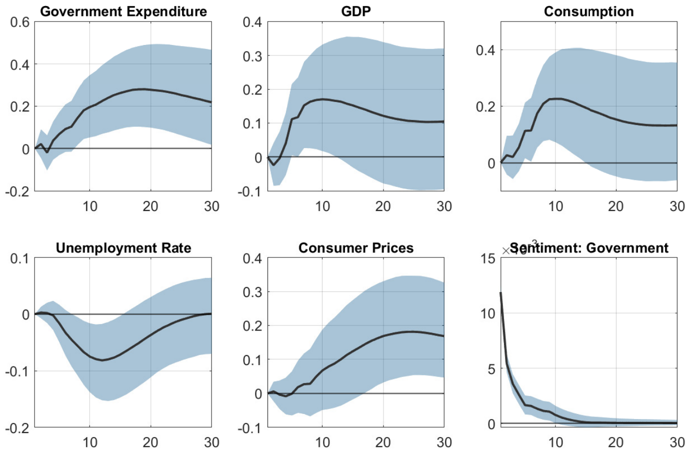
Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment as reflected in speeches of all members in the opposition. All responses are derived from a recursively identified Bayesian VAR model with 8 lags and Normal-Wishart priors. The shaded areas reflect 68% probability bands.

Figure 11: Response to fiscal sentiment (government): extended VAR



Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment as reflected in speeches of members of the parties forming the government. All responses are derived from a recursively identified Bayesian VAR model with 8 lags and Normal-Wishart priors. The shaded areas reflect 68% probability bands.

Figure 12: Response to fiscal sentiment (government): extended VAR

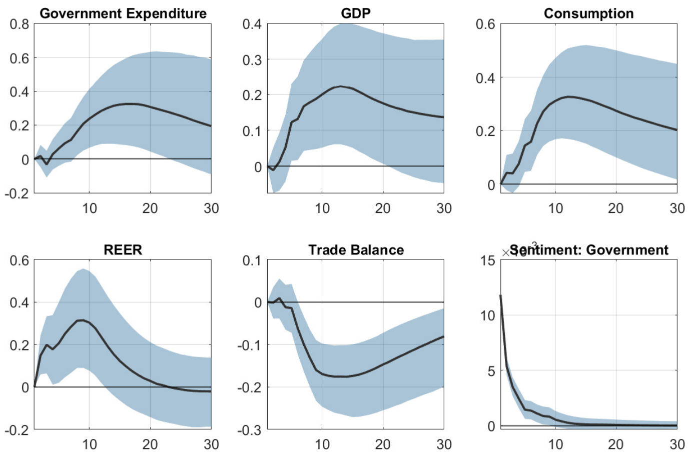


Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment as reflected in speeches of members of the parties forming the government. All responses are derived from a recursively identified Bayesian VAR model with 8 lags and Normal-Wishart priors. The shaded areas reflect 68% probability bands.

spending shocks. In other words, we can study whether unanticipated government spending shocks are in fact anticipated. We estimate a VAR model with the three core variables used before: government spending, GDP and consumption. We use all three alternative treatments of the variables, i.e. log-levels, quadratic detrending and Hamilton-detrending and do not include sentiment at this stage. Importantly, we adopt the recursive Blanchard-Perotti identification scheme that orders government spending first. Hence, government spending is predetermined with respect to output and consumption. This provides us with three alternative series of structural government spending shocks - one for each treatment of the endogenous variables.

In the next step, we assess whether sentiment contains information that allows us to predict future government spending shocks. The following model in the spirit of Jordà (2005) regresses the government spending shock for

Figure 13: Response to fiscal sentiment (government): open-economy VAR



Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment as reflected in speeches of members of the parties forming the government. All responses are derived from a recursively identified Bayesian VAR model with 8 lags and Normal-Wishart priors. The shaded areas reflect 68% probability bands.

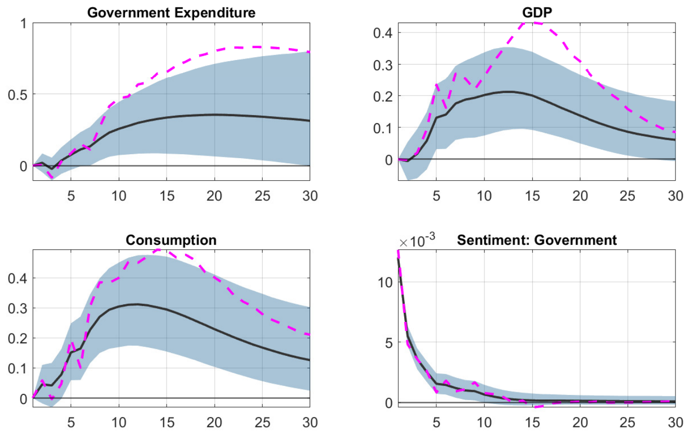
model k at time $t+h$ on the parliamentary sentiment at time t

$$shock_{t+h}^{k} = \alpha_h + \beta_h Senti_t^j + \gamma_h X_{t-1} + \varepsilon_{t+h} \tag{6}$$

with $Senti_t^j$, with $j \in (Bundestag, Government, Opposition)$. A significant β_h would indicate that current sentiment predicts future government spending shocks. We estimate this model for each shock k as well as for the standardized sentiment of the government, the opposition and the full Bundestag. The vector X_t contains contemporaneous and lagged realizations of GDP, consumption and government expenditure as control variables. As the dependent variable is the result of a structural identification, it should be orthogonal to these control variables. Nevertheless, we include these variables as controls.

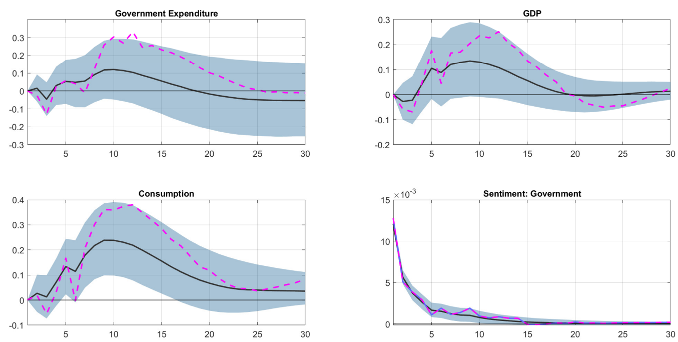
Panel (a) of Figure (17) plots the estimated β_h as a function of h for the sentiment of the full Bundestag. The results are consistent across the alternative treatments of the variables: A shift towards a more expansionary

Figure 14: Response to fiscal sentiment (government): detrending



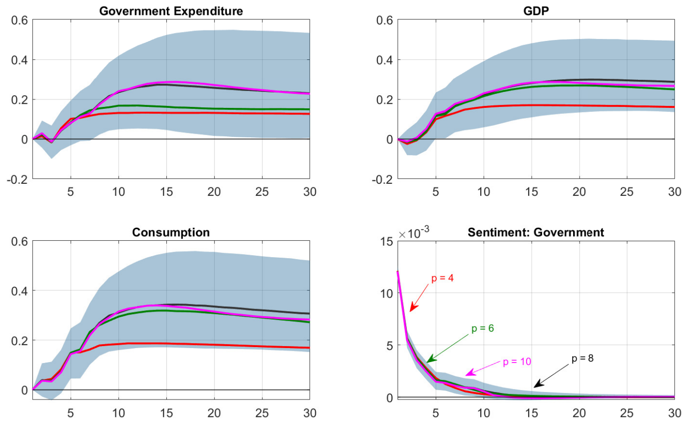
Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment. The three macroeconomic variables are detrended by the quadratic trend in GDP. All responses are derived from a recursively identified Bayesian VAR model with alternative lags orders p and Normal-Wishart priors. The pink responses are derived from the model estimated by OLS. The shaded areas reflect 68% probability bands.

Figure 15: Response to fiscal sentiment (government): detrending



Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment. The three macroeconomic variables are detrended by the Hamilton (2018) trend in GDP. The black responses are derived from a recursively identified Bayesian VAR model with alternative lags orders p and Normal-Wishart priors. The pink responses are derived from the model estimated by OLS. The shaded areas reflect 68% probability bands.

Figure 16: Response to fiscal sentiment (government): lag order



Notes: The figure shows the responses of the endogenous variables to an increase in fiscal sentiment. All responses are derived from a recursively identified Bayesian VAR model with alternative lags orders p and Normal-Wishart priors. The shaded areas reflect 68% probability bands.

fiscal sentiment in t predicts an increase in government spending six to eight quarters later. Hence, the government spending shocks are predictable from parliamentary speeches. The results are weekly significant at the 90% level. When we narrow the set of speeches to the members of the governing parties, see panel (b) of the figure, we obtain similar results. Information from speeches of politicians from the opposition parties, see panel (c), does not predict future government spending shocks.

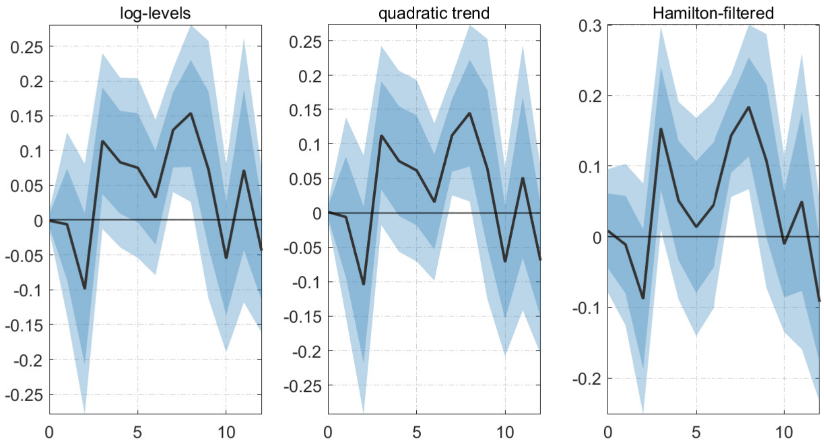
Overall, this sections supports the notion that government spending shocks identified from a recursive ordering can indeed be anticipated. This also underlines the relevance of the parliamentary process as a source of information for upcoming changes to fiscal policy.

6 Conclusions

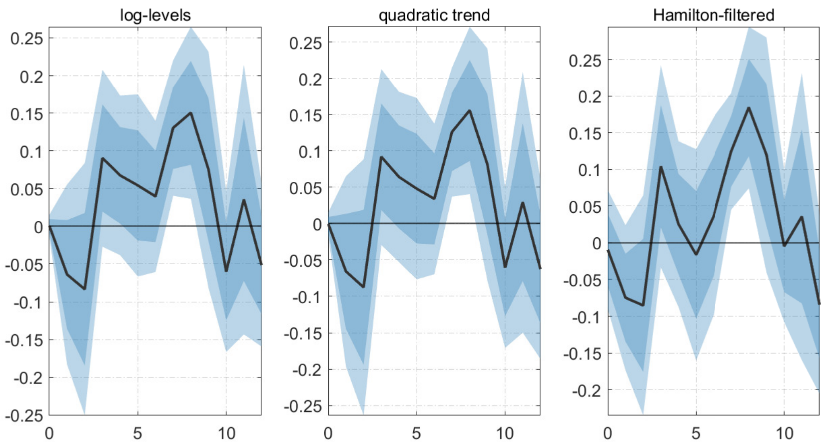
This paper went to the roots of fiscal policy-making - the debate in parliament. We use the full set of parliamentary speeches delivered in the German

Figure 17: Response of government expenditure shock to sentiment

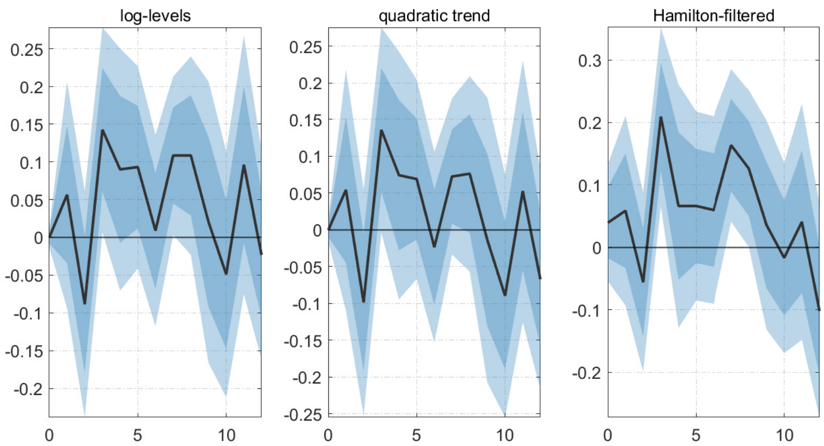
(a) full Bundestag



(b) Government



(c) Opposition



Notes: The figure shows the responses of the recursively identified government expenditure shock to an increase in fiscal sentiment. The shaded areas reflect 68% and 90% confidence bands constructed from Newey-West standard errors.

Bundestag as a source of information about fiscal preferences. An embedding-based approach using the latest advances in text mining provides us with a sentiment index on a scale from expansionary to restrictive that summarizes the debate about fiscal policy. This sentiment series has real economic effects: recursively identified VAR models suggest that an increase in fiscal sentiment towards a more expansionary policy stance increases government spending, output and consumption. Hence, a change in fiscal sentiment has macroeconomic effects consistent with standard New-Keynesian business cycle models.

We draw two main conclusions: First, we believe textual data to be very informative about economic policy-making. The rich information incorporated in parliamentary speeches is particularly promising for researchers interested in fiscal policy. In this paper, we focused on the consequences of fiscal sentiment for government expenditure and the macroeconomy. In follow-up work, we will study the consequences of disagreement about fiscal policy between the government and the opposition. Using this data set to assess the consequences of sentiment on the revenue side of public finances could also be an interesting way forward.

Second, the identification of government spending shocks often rests on the assumption that the part of government spending not forecastable from lags of the endogenous variable is a suitable exogenous shock. Information from parliamentary debates about fiscal policy might help enhance this identification. As parliamentary speeches partly forecast future expenditure, only the part of government expenditure that is orthogonal to lags of business cycle variables as well as lags of textual information from the parliamentary debates should qualify as a government expenditure shock.

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Appendices

Appendix A Stop words

The following list contains stop words:

> ab, aber, abg, abgegeben, abgelehnt, abgeordnete, abgeordneten, abgeordneter, abs, absicht, abstimmen, abstimmung, abzulehnen, aendern, aenderung, aenderungsantrag, aktuellen, all, alle, allein, allem, allen, aller, allerdings, alles, allgemein, allgemeine, allgemeinen, als, also, alten, am, an, ander, andere, anderem, anderen, anderer, andererseits, anderes, anderm, andern, anderr, anders, anfang, anfrage, angeht, angelegenheit, angenommen, angesichts, angesprochen, anlage, anlass, anliegen, annahme, annehmen, ansatz, ansicht, anspruch, anteil, antraege, antrag, antrage, antrags, antwort, antworten, april, arbeit, arbeiten, arbeitnehmer, arbeitsplaetze, art, artikel, auch, auf, auffassung, aufgabe, aufgaben, aufgrund, aufmerksam, aufmerksamkeit, auftrag, augen, augenblick, august, aus, ausdruck, ausdrucklich, ausdruecklich, ausfuehrungen, ausgaben, ausgefuehrt, ausgehen, ausgesprochen, ausschuessen, ausschuss, ausschusse, ausschusses, ausschuss, aussprache, auswaertigen, auswirkungen, ausserdem, ausserordentlich, bald, beamten, beantragt, beantworten, bedarf, bedenken, bedeutet, bedeutung, bedingungen, befasst, beginn, begruenden, begruendet, begruendung, begruessen, behandeln, behandelt, behandlung, bei, beide, beiden, beim, beispiel, beispiele, beispielsweise, beitrag, bekannt, bekommen, bemerkung, bemerkungen, bemuehen, bemueht, bemuehungen, beraten, beratung, beratungen, bereich, bereichen, bereit, bereits, bericht, berichterstatter, berlin, beruecksichtigt, beschaeftigen, beschaeftigt, beschlossen, beschluss, beschlussempfehlung, besondere, besonderen, besonders, besser, bessere, bestehen, besteht, bestimmt, bestimmte,

bestimmten, bestimmung, bestimmungen, beteiligt, beteiligten, betrag, betreiben, betriebe, betrieben, betrifft, betroffenen, bevoelkerung, bevolkerung, bevor, bewusst, bewusst, beziehungen, bezueglich, bezug, bin, bis, bisher, bisherigen, bisschen, bist, bitte, bitten, bisschen, bleiben, bleibt, blick, bonn, brauchen, braucht, bringen, bringt, buendnis, buerger, buergerinnen, bund, bundes, bundeskanzler, bundeskanzlerin, bundeslaender, bundeslaendern, bundesminister, bundesministerium, bundesrat, bundesregierung, bundesrepublik, bundestag, bundestages, bundnis, burger, burgerinnen, but, bzw, cdu, chance, cronenberg, csu, da, dabei, dadurch, dafuer, dafur, dagegen, daher, dahin, damals, damen, damit, danach, dank, dankbar, danke, dann, daran, darauf, daraus, darf, darin, daruber, darueber, darum, das, dass, dasselbe, davon, dazu, dass, debatte, dehler, dein, deine, deinem, deinen, deiner, deines, dem, dementsprechend, demokratie, demokratischen, demselben, den, denen, denke, denken, denn, dennoch, denselben, der, deren, derer, derselbe, derselben, derzeit, des, deshalb, desselben, dessen, deswegen, deutlich, deutsche, deutschen, deutscher, deutschland, deutschlands, dezember, dich, die, diejenigen, dienen, dienst, dienstag, dies, diese, dieselbe, dieselben, diesem, diesen, dieser, dieses, dieter, dinge, dingen, dir, diskussion, diskutieren, diskutiert, dm, doch, donnerstag, dort, dr, draussen, drei, dringend, dritte, dritten, drittens, drucksache, drucksachen, du, duerfen, durch, durchaus, durchfuehrung, durchgefuehrt, durfen, eben, ebene, ebenfalls, ebenso, egal, ehemaligen, eher, ehlers, ehrlich, eigene, eigenen, eigentlich, ein, eindeutig, eindruck, eine, einem, einen, einer, eines, einfach, einfuehrung, eingebracht, eingehen, eingehend, eingeraumt, eingesetzt, einheit, einig, einige, einigem, einigen, einiger, einiges, einkommen, einmal, einstimmig, eintreten, einverstanden, einzelne, einzelnen, einzige, ende, endlich, enthalten, enthaltungen, entscheiden, entscheidende, entscheidung, entscheidungen, entschieden, entsprechend, entsprechende, entsprechenden, entspricht, entstehen, entwicklung, entwurf, entwurfs, er, erfahrungen, erfolg, erfolgen, erfolgt, erforderlich, erfuellen, erfuellt, ergeben, ergebnis, ergibt, erhalten, erheben, erhebliche, erhoehung, erinnern, erkennen, erklaeren, erklaert, erklaerung, erklaren, erleben, erledigt, ermoglichen, erneut, ernst, erreichen, erreicht, erscheint, erst, erste, ersten, erstens, erster, erwaehnt, erwahnt, erwarten, es, etwa, etwas, euch, euer, eure, eurem, euren, eurer, eures, euro, europa, europaeische, europaeischen, europaische, europaischen, faelle, faellen, fall, falle, fallen, falsch, familie, fassung, fast, fdp, februar, ferner, fest, festgestellt, feststellen, feststellung, festzustellen, finde, finden, findet, foerderung, folge, folgen, folgende, folgendes, fordern, forderung, forderungen, form, formuliert, forsten, frage, fragen, fraktion, fraktionen, frankreich, frau, frauen, freien, freiheit, freitag, freue, freunde, froh, frueher, frueheren, fuehren, fuehrt, fuenf, fuer, fuhren, fuhrt, funcke, funf, funktioniert, fur, fuer, gab, ganz, ganze, ganzen, gar, geaendert, gebe, geben, gebiet, gebiete, gebieten, gebracht, gedanken, geehrte, geehrten, geehrter, gefahr, gefordert, gefragt, gefuehrt, gefuhrt, gefunden, gegeben, gegen, gegenprobe, gegenteil, gegenuber, gegenueber, gehabt, gehalten, gehen, gehoeren, gehoert, gehoren, gehort, geht, gekommen, gelegenheit, geleistet, gelingt, gemacht, gemeinden, gemeinsam, gemeinsame, gemeinsamen, gemeinschaft, genannt, genannten, genau, genauso, genommen, genug, gerade, gerecht, gern, gerne, gerstenmaier, gesagt, gesamte, gesamten, geschaeftsordnung, geschaffen, geschehen, geschichte, geschieht, gesehen, gesellschaft, gesetz, gesetze, gesetzentwurf, gesetzes, gesetzt, gesichtspunkt, gesprochen, gestatten, gestellt, gestern, getan, getragen, getroffen, gewesen, gewisse, gewissen, geworden, gewuenscht, gezeigt, gibt, gilt, ging, glaube, glauben, gleich, gleiche, gleichen, gleichermassen, gleichzeitig, grosse, grossen, grosser, gruende, gruenden, gruenen, grund, grunde, grunden, grundgesetz, grundgesetzes, grundlage, grundsaetzlich, grundsatz, grune, grunen, gut, gute, guten, guter, gutes, hab, habe, haben, haelt, haette, haetten, halte, halten, haltung, hand, handeln, handelt, handzeichen, hans, hat, hatte, hatten, haus, hause, hauses, heisst, helfen, her, heraus, herr, herren, herrn, herzlichen, heute, heutigen, hier, hierher, hierzu, hilfe, hin, hinaus, hinblick, hingewiesen, hinsichtlich, hinter, hintergrund, hinweisen, hinzu, hoch, hoehe, hoere, hoeren, hoffe, hoffen, hohe, hohen, horen, ich, ihm, ihn, ihnen, ihr, ihre, ihrem, ihren, ihrer, ihres, im, immer, immerhin, in, indem, inhalt, innerhalb, innern, ins, insbesondere, insgesamt, insofern, interesse, interessen, internationale, internationalen, inzwischen, ist, ja, jaeger, jahr, jahre, jahren, jahres, januar, je, jede, jedem, jeden, jedenfalls, jeder, jedes, jedoch, jemand, jene, jenem, jenen, jener, jenes, jetzt, juli, junge, juni, kam, kann, kaum, kein, keine, keinem, keinen, keiner, keines, keineswegs, kennen, kenntnis, klar, klare, klaren, klaus, kleine, kleinen, koalition, koenne, koennen, koennte, koennten, kohl, kollege, kollegen, kollegin, kolleginnen, komme, kommen, kommenden, kommission, kommt, kommunen, konkret, konnen, konnte, konnten, konzept, kosten, kraft, kritik, kuenftig, kunftig, kurz, koennen, koennte, laender, laendern, laengst, laesst, laesst, lage, land, lande, lander, landern, landes, lange, langer, langst, lassen, lasst, last, laufe, laut, least, leben, lediglich, legen, legislaturperiode, leicht, leider, leisten, leistungen, lesen, lesung, letzte, letzten, leute, liebe, lieber, liegen, liegt, linie, linke, linken, loesen, loesung, losen, losung, machen, macht, maerz, mag, mai, mal, man, manche, manchem, manchen, mancher, manches, manchmal, mann, mark, masse, massnahmen, mehr, mehrfach, mehrheit, mein, meine, meinem, meinen, meiner, meines, meinung, meisten, menschen, mich, milliarden, millionen, mindestens, minister, ministerin, ministerium, mir, mit, miteinander, mitglieder, mittel, mitteln, mittlerweile, mittwoch, mochte, moechte, moechten, moeglich, moeglicherweise, moeglichkeit, moeglichkeiten, moeglichst, moglich, monaten, montag, morgen, mueller, muesse, muessen, muesste, muessten, muss, mussen, musste, mussten, muss, musste, nach, nachdem, nachgefragt, nachher, nachste, nachsten, nachster, naechsten, naemlich, namen, namens, namlich, natuerlich, naturlich, neben, nehme, nehmen, nein, nennen, neu, neue, neuen, nicht, nichts, nie, niemand, nimmt, noch, noetig, not, notwendig, notwendige, notwendigen, notwendigkeit, november, nr, nun, nunmehr, nur, nutzen, ob, obwohl, oder, oeffentliche, oeffentlichen, oeffentlichkeit, of, offen, offenbar, offensichtlich, offentlichen, oft, ohne, ohnehin, ok, oktober, opposition, ordnung, ort, ost, paar, parl, parlament, parlamentarischer, parlaments, partei, parteien, passiert, pds, peter, pflicht, plenum, politik, politiker, politisch, politische, politischen, position, praesident, praesidenten, praesidentin, praktisch, prasident, prasidentin, praxis, presse, pro, problem, probleme, professor, programm, prozent, pruefen, pruefung, punkt, punkte, rahmen, rahmenbedingungen, raum, rechnen, rechnung, recht, rede, reden, redezeit, redner, reform, regelung, regelungen, regierung, reicht, reihe, renger, richtig, richtige, richtung, rolle, ruecksicht, rufe, rund, sache, sage, sagen, sagt, sagte, sagten, samstag, satz, schaffen, schauen, scheint, schliesslich, schluss, schluss, schmid, schmidt, schmitt, schnell, schoen, schoettle, schon, schritt, schutz, schwer, schwierigkeiten, sehe, sehen, sehr, sei, seien, sein, seine, seinem, seinen, seiner, seines, seit, seitdem, seite, seiten, selber, selbst, selbstverstaendlich, september, setzen, setzt, sich, sicher, sicherheit, sicherlich, sicht, sie, sieht, sind, sinn, sinne, sinnvoll, situation, sitzung, so, soeben, sofort, sogar, sogenannte, sogenannten, solche, solchem, solchen, solcher, solches, soll, sollen, sollte, sollten, sondern, sonntag, sonst, sorge, sorgen, soweit, sowie, sowohl, sozialdemokraten, soziale, sozialen, spaeter, spater, spd, sprechen, spricht, staat, staaten, staatsminister, staatssekretaer, staatssekretar, staerker, stand, standpunkt, stark, starken, starker, statt, stehen, steht, stelle, stellen, stellt, stellung, stellungnahme, stimme, stimmen, stimmkarte, stimmt, strauss, stuck, stuecklen, stunde, suessmuth, system, taetigkeit, tag, tage, tagen, tagesordnung, tat, tatsache, tatsachlich, tatsaechlich, teil, teilen, teilweise, the, thema, themen, tragen, treffen, treten, trotz, trotzdem, tun, tut, uber, uberhaupt, ubrigen, ubrigens, ueber, ueberhaupt, ueberlegen, ueberlegungen, ueberzeugt, ueberzeugung, uebrigen, uebrigens, uhr, um, umdruck, umfang, umgesetzt, umsetzung, umstaenden, umwelt, unbedingt, und, union, unmoeglich, uns, unser, unsere, unserem, unseren, unserer, unseres, unter, unterhalten, unternehmen, unterschied, unterstuetzen, unterstuetzung, usw, verabschiedet, verabschiedung, verantwortung, verbessern, verbesserung, verehrte, verehrten, vereinbart, verfahren, verfuegung, verfugung, vergangenen, vergangenheit, vergessen, vergleich, verhaeltnis, verhaeltnisse, verhalten, verhandlungen, verhindern, verlangen, verlangt, verordnung, verpflichtet, verpflichtung, verschiedenen, verstaendnis, verstanden, verstehen, versuch, versuchen, versucht, vertrag, vertreten, vertreter, verwaltung, verwiesen, viel, viele, vielen, vieles, vielleicht, vielmehr, vier, vizepraesident, vizepraesidentin, vizeprasidentin, vockenhausen, voellig, volk, volkes, voll, vollig, vom, von, vor, voraussetzung, voraussetzungen, vorgelegt, vorgenommen, vorgeschlagen, vorgesehen, vorgetragen, vorhanden, vorher, vorhin, vorlage, vorliegen, vorliegenden, vorliegt, vorschlaege, vorschlag, vorschlage, vorschriften, vorstellen, vorstellungen, vorwurf, waehrend, waere, waeren, wahl, wahlperiode, wahrend, wahrheit, wahrscheinlich, wann, war, ware, waren, warst, warum, was, weder, weg, wege, wegen, wehner, weil, weise, weit, weiter, weitere, weiteren, weiterer, weiteres, weiterhin, weiternun, weiterreden, weitgehend, weiss, welche, welchem, welchen, welcher, welches, welt, weltweit, wenig, wenige, wenigen, weniger, wenigstens, wenn, wer, werde, werden, wert, wesentlich, wesentliche, wesentlichen, wichtig, wichtige, wichtigen, wichtiger, widerspruch, wie, wieder, wiederholen, wiederholt, will, willen, wir, wird, wirklich, wirklichkeit, wirst, wirtschaft, wirtschaftliche, wirtschaftlichen, wissen, wo, wobei, woche, wochen, wohl, wolfgang, wollen, wollte, wollten, womoglich, worden, wort, worte, worten, wortmeldungen, woruber, wuenschen, wuenscht, wuerde, wuerden, wunsch, wurde, wurden, waehrend, wuerde, wuerden, zahl, zahlen, zehn, zeigen, zeigt, zeit, zeitpunkt, ziehen, ziel, ziffer, zitiere, zitieren, zitiert, zu, zudem, zugestimmt, zukunft, zuletzt, zum, zumindest, zunachst, zunaechst, zur, zuruck, zurueck, zusaetzlich, zusaetzliche, zusaetzlichen, zusammen, zusammenarbeit, zusammenhang, zusatzfrage, zusatzlich, zustaendigen, zustand, zustimmen, zustimmung, zuzustimmen, zwar, zweck, zwei, zweifel, zweifellos, zweite, zweiten, zweitens, zwischen, zwischenfrage, ueber

Appendix B Terms Related to Fiscal Policy

Terms reflecting expansionary policy

The following list contains terms reflecting expansionary fiscal policy:

Abgabenlast, Akzelatoreffekt, Arbeitnehmersparzulage, Arbeitsbeschaffungsmaßnahme, Arbeitsplätze schaffen, Auftragsvergabe, Beschäftigungsprogramm, crowding in, deficit spending, Entlastung, Entlastungsvolumen, expansiv, fiskalische Belastung, Fördermaßnahmen, Förderpaket, Förderprogramm, Hilfspaket, Hilfsprogramm, höhere Neuverschuldung, Investitionen, Investitionslücke, Kaufanreiz, Keynes, keynesianisch, Konjunkturmaßnahme, Konjunkturpaket, Konjunkturprogramm, Konsum erhöhen, Konsumanreiz, Mehrwertsteuersenkung, Multiplikatoreffekt, nachfragesteigernd, Neuverschuldung, öffentliche Aufträge, schuldenfinanziert, Sozialprogramm, Staatshilfen, staatliche Fördermaßnahmen, staatliche Investitionen, Steuerentlastung, Steuererleichterung, Steuern senken, Steuersenkung, Stimulation, stimulieren, Stimulus, Subventionen

Terms reflecting contractionary policy

The following list contains terms reflecting contractionary fiscal policy:

Abbau des Defizits, Ausgaben kürzen, Boom, crowding out, Defizitabbau, Einführung der Steuer, Einsparungen, Fiskalpakt, Haushaltsdefizit, Haushaltskonsolidierung, Haushaltsregel, Haushaltsstabilität, Hochkonjunktur, Investitionsstopp, Konsolidierung, kontraktiv, Maastricht, Mehrwertsteuererhöhung, nachfragesenkend, Nullneuverschuldung, prozyklisch, restriktiv, Schuldenregel, Schuldenabbau, Schuldenbremse, Schuldlast, schwarze Null, Sparanstrengung, sparen, Sparmaßnahme, Sparpolitik, Sparprogramm, Stabilitätspakt, Steuereinführung, Steuererhöhung, Steuern erhöhen, Vermögensabgabe, Verschuldungsregel, Verschuldungspolitik