The Components of Uncertainty*

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Abstract

I create measures of uncertainty by first classifying news articles according to theme, and then quantifying uncertainty by the count of uncertainty terms within the different types of news. The uncertainty measures are available at a daily frequency and capture well-known events linked to uncertainty both at an aggregate and a category-specific level. However, different news categories often capture similar events. Do deal with this I compute four orthogonal components of uncertainty using principal component analysis. An uncertainty shock to these four components yields different responses in investment and GDP. This indicates that both good (positive response) and bad (negative response) types of uncertainty exist.

JEL-codes: D80, E32, E66

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1 Introduction

A large and growing literature investigates the effect of elevated uncertainty on aggregate macroeconomic fluctuations. Most uncertainty measures tend to be countercyclical, and several studies document that an increase in uncertainty is followed by worsening economic conditions, see, e.g., Bloom (2009), Jurado et al. (2015), and Baker et al. (2015). Common to these studies is the construction of uncertainty measures that capture similar types of events related to episodes of financial and economic distress. This paper contributes to the literature by introducing an identification strategy to disentangle different types of uncertainty. The approach enables me to construct several different measures of uncertainty. Doing so I show that, depending on the source, uncertainty may have different effects on the same macroeconomic variables.

I create measures of uncertainty by first classifying news articles according to theme, and then quantifying uncertainty by the count of uncertainty terms within the different types of news articles. I rely on machine learning techniques to uncover the content of a large set of documents. The method I use belongs to the field of topic modeling, where the objective is to identify hidden patterns in textual data. I estimate the content of news articles using a model called Latent Dirichlet Allocation (LDA), introduced by Blei et al. (2003). The method is an unsupervised learning algorithm, meaning that there is no pre-training of the model or labeling of the news articles before the classification. An advantage with this method is that the classification does not rely on the article containing a particular set words. Instead, the mixture of all the words in an article provide information on the theme of that article. I identify well-defined uncertainty measures related to categories such as Oil price, Monetary policy, Politics, and Stock market.

This paper relate to a growing literature that uses textual data to answer economics-related questions. Papers such as Gentzkow and Shapiro (2010) and Gentzkow et al. (2011) have been influential in their use of newspaper data to study the relationship between politics and media. In the finance literature, papers such as Tetlock (2007) and Boudoukh et al. (2013) have established a link between written news and stock returns. Moreover, several papers use textual data to create measures of uncertainty: Manela and Moreira (2016) use machine learning techniques to extract uncertainty from front-page articles of the Wall Street Journal. The paper then creates a news implied volatility index (NVIX) by linking textual data to the US VIX. Alexopoulos and Cohen (2009) create an uncertainty measure based on the number of New York Times articles that write about both uncertainty and economic activity. Baker et al. (2015) creates Economic Policy Uncertainty (EPU) indices for various countries by counting articles about uncertainty, the economy, and policy, all at the same time. The latter two papers classify articles by a set of pre-determined keywords, and if an article contains words from all categories, it contributes to the index. Baker et al. (2015) also identify narrower category-specific uncertainty measures by identifying and counting articles with words from specific categories such as National security and Health care.
I contribute to this literature by proposing to use a topic model to classify different types of news instead of specifying a set of keywords. Very few papers in economics use a topic model to extract information from textual data, but some exist: Larsen and Thorsrud (2015) create a topic-based news index, where the index is used to study the impact of news and noise shocks on the business cycle in Norway. Another example is Hansen et al. (2014), that study how transparency affects monetary policymakers deliberations by using a topic model to classify textual data from the Fed.

To collect the topics, I use news articles from Norway’s largest business newspaper, Dagens Næringsliv. The goal is to capture the underlying uncertainty in the economy in relation to different categories. An advantage of using a business newspaper is that most news stories are related to finance, business, and economics. Using more broadly themed newspapers would call for some pre-selection of relevant sections of the newspaper before the classification is performed. The data set is large, containing 27 years of news articles, spanning from 1988 to 2015.

I investigate the validity of this topic-based approach by evaluating the uncertainty measures in two ways: First, I do a narrative exercise evaluating whether the uncertainty measures capture known historical events where we expect uncertainty to be high. Second, I compare the uncertainty measures to other proxies for uncertainty such as the US VIX, realized stock market volatility in Norway, and some of the economic policy uncertainty measures created by Baker et al. (2015). Overall, there is a tendency for positive correlations between the topic-based measures and the alternative ones.

Despite the fact that the topic-based measures capture uncertainty in relation to different categories, common periods of high uncertainty, such as during the Global Financial Crisis, are reflected in many of the measures. To examine if distinct types of uncertainty underly the topic-based measures, I next construct a few orthogonal uncertainty measures using principal component analysis (PCA). Although the PCA makes orthogonal components, it does not assign any label to the components. To be able to give the components an interpretation, I give them a label based on which topics they correlate most with. The components are related to “economic and financial distress”, “the institutional framework of monetary policy”, “Norway’s relationship with the EU”, and “technology and firm expansion”. One implication from this finding is that when counting uncertainty terms in monetary policy news to identify uncertainty related to monetary policy, one mixes together uncertainty related to the response to economic and financial distress and uncertainty regarding the framework of monetary policy.

There is a large literature suggesting theories about how uncertainty affects the economy. Most theories suggest that uncertainty shocks have a negative effect on the economy. Uncertainty shocks can have real and substantial negative effects on firm investment and hiring, because firms delay taking action. This is often referred to as “wait and see” behavior, see e.g., Bernanke (1983), McDonald and Siegel (1986) and Bloom (2009). Uncertainty also affects households: Elevated uncertainty can increase precautionary savings and thereby deflate aggregate demand in the economy, see, e.g., Basu and Bundick (2012), Leduc and Liu (2015) and Fernandez-Villaverde et al. (2011). Uncertainty can affect finan-
cial markets, where higher firm risk leads to increased cost of capital and more cautionary behavior by investors, see, e.g., Gilchrist et al. (2014) and Arellano et al. (2010). On the other hand, there are also papers arguing for a positive effect of uncertainty, so called “growth options” theories, where willingness to invest can increase due to an improved upside in the economy, see e.g. Segal et al. (2015) and Kraft et al. (2013).

Previous empirical studies have analyzed different types of uncertainty, such as macroeconomic uncertainty (Bloom (2009) and Jurado et al. (2015)), economic policy uncertainty (Baker et al. (2015)), and fiscal policy uncertainty (Fernandez-Villaverde et al. (2015)). However, the uncertainty measures tend to be correlated and capture similar events. I analyze the impact of shocks to different (orthogonal) uncertainty measures, on aggregate economic fluctuations.¹ I find that different types of uncertainty have different implications for the economy. A shock to uncertainty related to “economic and financial distress” foreshadows declines in investment and GDP in line with previous studies. The effects are sizable and economically important. I find no effect on the Norwegian economy after an uncertainty shock related to “the institutional framework of monetary policy”, while an uncertainty shock related to “Norway’s relationship with the EU”, gives a large decline in investment. A shock to uncertainty related to “technology and firm expansion”, leads to an increase in investment. The effect is sizable and of economic importance. The finding that uncertainty can have both positive and negative effects indicates that both good and bad types of uncertainty exist.

The rest of the paper is organized as follows: Section 2 describes the newspaper data, the topic model and how the uncertainty measures are constructed. Section 3 discuses and evaluates the uncertainty measures. Section 4 creates orthogonal uncertainty components. In Section 5, I investigate the effect of uncertainty shocks on aggregate macroeconomic variables and Section 6 presents some robustness checks. Section 7 concludes.

2 Creating category-specific uncertainty

Uncertainty is not observable and researchers have suggested various proxies for uncertainty: Bloom (2009) uses options-based stock market volatility, Jurado et al. (2015) use an unforecastable component of a large set of economic variables, Bachmann et al. (2013) use forecast disagreement from firm-survey data, and Baker et al. (2015) count news articles that contain words from three categories, uncertainty, economy, and policy. I follow the latter paper in creating uncertainty measures using textual data. I depart from Baker et al. (2015) in the way news articles are classified. To classify the news articles, I make use of a text classification model called Latent Dirichlet Allocation (LDA). The LDA was introduced by Blei et al. (2003) and is heavily used in natural language processing and also for other classification tasks. I start this section by describing the newspaper data and the LDA model. Then I describe how the output from the classification exercise is com-

¹For Norway, Gudmundsdson and Natvik (2012) create an uncertainty measure in the same way as Alexopoulos and Cohen (2009) and find negative effects of uncertainty shocks on consumption.
bined with the count of uncertainty terms in the news articles to generate topic-specific measures of uncertainty.

2.1 The newspaper data

The raw data used is all the articles from a newspaper called *Dagens Næringsliv*, which is Norway’s largest business newspaper and also the fourth largest newspaper overall. *Dagens Næringsliv* has a right-wing and neoliberal political stance.

I use all articles published in the paper version of *Dagens Næringsliv* from May 2 1988 to October 15 2015. The data consists of close to 500 000 articles, spread over a period of more than 8000 days. This is a large amount of data that is highly unstructured, and before starting the classification exercise, several steps are performed to clean and reduce the data to a more manageable form. First, I remove words that would not convey any important meaning for the underlying theme of a news story, examples of such words are *the*, *is*, and *are*. I also remove common Norwegian surnames and given names. Next, each word is reduced to its word stem. Lastly, I calculate a corpus measure called the *tf–idf* score which stands for term frequency – inverse document frequency. This is a way of scoring all the words in the corpus based on how important they are in explaining single documents, relative to how frequently the word occurs in the whole text corpus. I select a cutoff for this *tf–idf* score and discard the words with the lowest relative importance in explaining single documents. Calculating the *tf-idf* score is not absolutely necessary since the LDA does a similar job when selecting the relevant words for the various topics. The main reason for doing this is to reduce the number of words in the corpus, to ease the computational burden when estimating the LDA. I keep around 250 000 of the stems with the highest *tf–idf* score, and move on to the classification using the LDA.

2.2 Latent Dirichlet allocation

Now I have a cleaned data set of news articles, and the goal is to classify all these articles by their underlying theme. The words in the documents convey the meaning of the text, and one possible approach to classify an article is by identifying specific keywords that I have linked to specific categories. Searching through all the articles and looking up these keywords, we can classify the articles according to some pre-specified categories. This is the approach taken by Baker et al. (2015), and a similar index is created for Norway in this paper. I create an Economic Policy Uncertainty (EPU) index for Norway to compare against the category-specific uncertainty measures created in this paper. The details of this Norwegian EPU can be found in Appendix E.

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2The word stem is the part of a word that is common to all the words inflections, an example is the word *production*, which has the word stem *produc*.

3The corpus reduction and cleaning is standard in the text literature, maybe with the exception of removing the surnames and given names. This choice is made because many persons share the same names, and names often occur in the newspaper; including them will only pollute the underlying meaning of the article since the algorithm gives the same “meaning” to all unique names.
The LDA is a generative model that allow sets of observed documents to be explained by latent structures that explain why documents belong together. It is an unsupervised learning algorithm, meaning that there is no labeling of the articles or training of the model before the articles are classified. It is assumed that all documents are constructed by combining a given set of themes or topics and then drawing words from these topics. Each article is a random mixture of all the topics identified for the whole newspaper. The word “topic” is used frequently in this paper and it refers to a distribution over a fixed vocabulary. All the observed words in the newspaper have a positive probability of occurring in all the topics, and all the topics occur with a positive probability in all of the documents. When observing the documents, which in this case are the news articles, we can estimate the underlying theme structure that the documents were generated from. The generative algorithm is as follows:

1. Pick the overall theme of an article by randomly giving it a distribution over topics

2. For each word in the document
   i) From the topic distribution chosen in 1., randomly pick one topic
   ii) Given that topic, randomly choose a word from this topic

Iterating the second step generates a document, while iterating both the first and the second step generates a collection of documents. This is the way we imagine the documents were generated, but in reality, we only observe the outcomes, the published news articles. We use this model of how the articles were generated, together with the realized articles to infer the underlying topic structure. The estimation of the topics is done by starting out with a given set of word distributions where the probabilities of the different words occurring are random. Then we improve these distributions by changing the probabilities and evaluating how well they describe the documents. I use an Bayesian approach to estimate the topic model using Gibbs simulations. The estimation procedure follows the algorithm described in Griffiths and Steyvers (2004), and additional details can be found in Appendix A.

Before estimating the topic model, I need to specify the number of topics that I want to identify, and 80 topics is selected ($N_{\text{topics}} = 80$). What makes 80 the right number? I use a model measure called perplexity to compare different choices of $N_{\text{topics}}$. The perplexity is a predictive likelihood and measures how well the topic model predicts the data. I find that 80 topics is preferable to fewer topics. The goal in this paper is not to find the topic model that best describes the documents, but rather a model that delivers topics that give a reasonable description of the newspaper and the Norwegian economy. Increasing the number of topics would likely improve the perplexity score, but would also give us topics with a narrower meaning. I found that 80 topics gave a good result, where the topics were neither too broad nor too narrow. Chang et al. (2009) show that improving the perplexity of a topic model by e.g. increasing the number of topics can lead to semantically less meaningful topics. Increasing the number of topics is also problematic computationally.
The output from the topic model is two sets of distributions: one set of distributions over words, denoted by $\theta_j$, for all topics $j \in \{0, N_{\text{topics}}\}$, and one set of distributions over topics, denoted by $\varphi_i$, for all articles in $i \in \{0, N_{\text{articles}}\}$. In the topic model both $\theta_j$ and $\varphi_i$ come from a Dirichlet distribution, giving rise to the name Latent Dirichlet allocation.

### 2.3 The news topics

The output from the topic model is given by two sets of distributions. I plot four examples of the topic distributions, $\theta_j$, in Figure 3 in the next subsection. These distributions tell us how important the different news topics are in describing single news articles. I also get 80 distributions over words, $\varphi_i$, one for each of the topics $i$. Figure 1 shows two examples where the word distributions are represented as word clouds. The size of the word in the word cloud corresponds to the probability of that word occurring in the given topic. The topics are given by the word distributions, and are not given any label by the topic model. Since referring only to topic numbers gives very little meaning, and since I want an economic interpretation of the different topics, I manually label the topics. The labeling is done by visual inspection of the word distributions and then picking a word that I think gives a reasonable description of the distribution. Most topics convey a clear theme or category. A list of all the 80 topics and their labels, together with a list of the 10 most frequent words occurring in each topic, is given in Figure 5 in Appendix B. I get topics related to the aggregate economy such as Macroeconomics, Fiscal policy and Monetary policy, topics related to financial markets such as Banking and Funding, topics related to politics such as Politics and Elections, international topics such as USA and Asia, etc.

An important condition that needs to be satisfied for the approach in this paper to be valid is that the latent space underlying the news topics must be semantically meaningful. The topic labeled as Monetary policy must actually represent news about monetary policy. I do not make a formal evaluation of the semantic meaning of these topics, an example of a study doing this is Chang et al. (2009).

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**Figure 1.** Examples of topic distributions

(a) Macroeconomics

(b) Monetary policy

Note: The 150 words with the highest probabilities are shown, the size of the words corresponds to the probability of that word occurring in the topic distribution.

4All the word clouds are available at [http://www.vegardlarsen.com/uncertainty/Word_clouds/](http://www.vegardlarsen.com/uncertainty/Word_clouds/).
2.4 Topic-based measures of economic uncertainty

I create measures of uncertainty by combining two types of information about the news articles: First, the topic model allows me to classify all the textual content of the newspaper as probability distributions over news categories. Second, I calculate a measure of uncertainty for all the articles in the sample. To quantify how much a news article signals uncertainty, I count the words *uncertain* and *uncertainty* within that article.

2.5 Counting uncertainty terms in the news

Measuring uncertainty using written media can be done in several ways. One approach is to identify articles that satisfy certain criteria, such as containing specific words, and count the articles that satisfy this criterion. In this approach the number of times the uncertainty terms occur within an article does not matter; as long as the specified keyword occurs once or more, the article is counted once. This is the approach taken by Alexopoulos and Cohen (2009) and Baker et al. (2015). I take a slightly different route by counting the total occurrences of the words *uncertain* and *uncertainty* within the articles. The reason for this is that the classification of articles will be done using the topic model instead of identifying specific words.\(^5\) And, the frequency of the uncertainty terms within the articles should be correlated with the degree of uncertainty conveyed by the articles.

I start out by counting the term *uncertain* and its inflections for all the articles.\(^6\) The count of uncertainty terms in article \(i\) is given by

\[
v_i = \# \text{ of uncertainty terms in article } i. \tag{1}\]

This uncertainty count is calculated for all articles in the sample. To control for a varying amount of news coverage over time, I keep track of the total number of words in article \(i\) given by:

\[
\omega_i = \# \text{ of total words in article } i. \tag{2}\]

Then, as a first approach, I calculate an aggregate daily measure, that is the overall uncertainty count in the newspaper each day. Calculating an aggregate count reflects uncertainty about many different underlying concepts, such as sports, the economy, political elections etc. Even if the interpretation of this aggregate uncertainty measure is unclear, it is a point of departure, before looking at the more disaggregated measures. I calculate the aggregate uncertainty measure as follows:

\(^5\)Baker et al. (2015) identify and count articles related to economic policy uncertainty by identifying specific words that relate the article to the economy, to policy, and to uncertainty. In Appendix E I create an uncertainty index for Norway based on this approach and I do some comparisons between the Norwegian EPU and the topic-based measures in Section 3.

\(^6\)The words that are counted (given in Norwegian): *usikker, usikre, usikkert, usikkerhet, usikkerheter, usikkerheten, usikkerhetene*. I have also experimented with using a broader list of words including terms such as *risk* and *unpredictability*, and this gives indices that lie close to the ones created in this paper. An advantage of using a broader list is that more articles get a non-zero uncertainty term count, which gives us a richer measure. I choose to use only the terms directly affiliated with uncertainty to create a measure that is clean and easy to interpret.
Figure 2. *Dagens næringsliv* aggregate uncertainty

![Diagram showing aggregate uncertainty over time](image)

**Note:** The black line plots the 150 day backward-looking rolling mean, and the blue line plots the daily series (right axis). The series gives the share of uncertainty terms per 100 000 words in the newspaper.

\[ \gamma_{t}^{\text{Agg}} = \int_{i \in \text{day } t} \left( \frac{\nu_{i}}{\omega_{i}} \right) \, di. \]  

On each day, the total count of the uncertainty terms are divided by the total word count that day. Figure 3 plots this aggregate measure for the period 1988Q4 – 2015Q3. There are large variations between days, likely containing some noise, and I plot the 150 days backward-looking mean to get smooth a series. Over the sample the total count (for the 150 day backward-looking mean) of the word *uncertain* and *uncertainty* vary approximately between 1 out of 10 000 words and 25 out of 10 000 words. From the figure we see that there are large variations in the uncertainty measure and that there are clear episodes where aggregate uncertainty is high. I plot some events that coincided with significant increases in uncertainty. Based on the chosen events it appears that the uncertainty count in *Dagens Næringsliv* is driven mostly by foreign crises such as wars and international financial crises. The episodes that are displayed are the first and the second gulf war (GW1 and GW2), the Asian crisis, 9/11, the credit crunch, which is often considered as the start of the financial crisis, the collapse of Lehman Brothers, and the Greek referendum related to a bailout of the Greek government. The only specifically Norwegian events displayed in the figure are the referendum on joining the European Union, which ended with a no vote, and Norway depegging its currency from the European Currency Unit (ECU). Of course many of the episodes where uncertainty is high in the figure coincide with Norwegian events such as the banking crisis in the early 1990s, and a short recession in 2002–2003 and 2008–2009. The rest of this section is about disentangling this aggregate uncertainty measure by its category-specific components. And we will see that different news categories can have very different uncertainty profiles over time.

### 2.6 Calculating category-specific uncertainty

The category-specific uncertainty measures are created based on the uncertainty count within the categorized news articles. The topic model delivers the classification of all news articles. This classification is given as a probability distribution over all topics reflecting
content in the articles that relates to several topics at once. I calculate an uncertainty measure for all the different news topics. This is done by weighing the uncertainty counts by the relative contribution of all articles to the different topics. That is, article $i$ has an uncertainty count given by $v_i$, which then contributes by $\varphi_i(\text{topic } = j)$ to topic $j$. To see what these topic distributions, $\varphi_i$, may look like, Figure 3 plots such topic distributions for four news articles. These distributions tell us how much the uncertainty count from the articles they represent contributes to the uncertainty indexes for the various topics. We see that for some articles there is one or a few topics that explain the content of the article, while others are a broader mix of topics. The newspaper *Dagens Næringsliv* is a business newspaper, as can be seen by the large majority of topics that relate to business and economics$^7$. Thus, an article about the economy is likely to be a mix of economy-related topics. On the other hand, there are very few topics related to sports, so a sports-related article is more likely to be described by few topics.

The total amount of content in a newspaper varies over time, as does the coverage of an individual news topic. To control for this, I need to make a normalization with respect to the amount of news content on any given day. The more articles and words we observe in one day, the more uncertainty terms we expect to observe in total. For the baseline normalization, I divide the topic-specific uncertainty term count within one day by the total number of words that day.$^8$ This uncertainty measure is given by:

$^7$The topics are listed in Appendix B.

$^8$Dividing by the total daily count is in line with the literature, see e.g. Baker et al. (2015).
Table 1. Uncertainty share in different news categories

<table>
<thead>
<tr>
<th>Top 10</th>
<th># of words per 100 000</th>
<th>Bottom 10</th>
<th># of words per 100 000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monetary policy</td>
<td>6.5</td>
<td>Drinks</td>
<td>1.0</td>
</tr>
<tr>
<td>Stock market</td>
<td>5.4</td>
<td>Movies/Theater</td>
<td>1.0</td>
</tr>
<tr>
<td>Macroeconomics</td>
<td>5.0</td>
<td>Food</td>
<td>1.0</td>
</tr>
<tr>
<td>Fear</td>
<td>3.9</td>
<td>Literature</td>
<td>1.0</td>
</tr>
<tr>
<td>Oil price</td>
<td>3.6</td>
<td>Music</td>
<td>1.1</td>
</tr>
<tr>
<td>Debate</td>
<td>3.2</td>
<td>Art</td>
<td>1.1</td>
</tr>
<tr>
<td>Negotiation</td>
<td>2.8</td>
<td>Sports</td>
<td>1.2</td>
</tr>
<tr>
<td>Results</td>
<td>2.7</td>
<td>Family business</td>
<td>1.2</td>
</tr>
<tr>
<td>Oil production</td>
<td>2.6</td>
<td>Watercraft</td>
<td>1.3</td>
</tr>
<tr>
<td>Funding</td>
<td>2.6</td>
<td>Retail</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Note: The average number of uncertainty terms used in the different types of news. The count is per 100 000 words in the full newspaper.

\[ \Upsilon_{j,t} = \frac{\int_{i \in \text{day}_t} v_i \varphi_i(\text{topic} = t) di}{\int_{i \in \text{day}_t} \omega_i di} \] (4)

One alternative specification is to divide by the total number of words used within a specific news category.\(^9\) The denominator is important to consider because it in itself causes fluctuations in the uncertainty measure. I choose to use the normalization in Equation 4 as the baseline, because fluctuations in the coverage of a given news topic can vary substantially. Daily fluctuation in topic coverage can have large effects on the alternative uncertainty measure, and this variation is not driven by the uncertainty count.

What types of news category use the uncertainty terms the most? Table 1 reports the 10 news categories with the largest number of uncertainty terms, and also the 10 news categories with the lowest count. The news category where the newspaper writes the most about uncertainty is Monetary policy. During the period studied, Norway has had five different monetary policy regimes, and this may have led to increased uncertainty. Also, since Dagens Næringsliv is a business newspaper, it gives extensive coverage of the the interest rate decision in Norges Bank, and there is often some uncertainty about this decision. The news category with the second highest uncertainty count is Stock market, followed by Macroeconomics, Fear, and Oil price. The Fear topic is actually a news topic where the word uncertainty is one of the words with the highest probability and the frequency of the Fear topic itself is as a possible proxy for uncertainty. On the other hand, the type of news where the uncertainty terms are the least frequent are Drinks, Movies/Theater and Food.

\(^9\)This alternative measure is calculated as

\[ \tilde{\Upsilon}_{j,t} = \int_{i \in \text{day}_t} \left( \frac{v_i}{\omega_i} \right) \varphi_i(\text{topic} = t) di \]

I have also calculated these measures, and for most topics they give very similar results. The average correlation between the two measures is 0.82.
3 Evaluating the topic-based uncertainty measures

The approach to creating uncertainty measures presented in this paper is mechanical. The topics are identified by an unsupervised learning algorithm, and uncertainty is identified as the frequency of uncertainty terms within news related to various news topics. There is no subjectivity involved other than the labeling of the topics, and this is only a way of referring to the underlying word distributions. Now, I evaluate whether the uncertainty measures capture what they are supposed to, which is the underlying uncertainty in the economy related to various themes or categories. I do a narrative exercise where I plot some of the uncertainty measures together with episodes where it is reasonable to think that uncertainty is high. To conserve space, I only discuss a subset of the 80 measures. I select eight measures based on two different criteria. The first four measures are selected based on the type of news that use the uncertainty terms with the highest frequency. Second, I choose four measures based on news categories that are easy to link to well-known historical events. An example is oil price uncertainty, which we expect to be high during episodes with conflicts in regions that produce oil. I also evaluate the full set of measures by comparing them to other proxies for uncertainty. Norway does not have many available measures, so part of this exercise compares the topic-based measures with uncertainty measures for other countries.

3.1 Narrative analysis of the uncertainty measures

The first four examples of category-specific uncertainty are chosen by selecting the news topics where the uncertainty terms are used with the highest frequency. These topics are Monetary policy, Stock market, Macroeconomics, and Fear. The 10 news topics with the highest frequency of uncertainty terms are reported in Table 4.1. The top four measures are plotted in Figure 4 together with some notable events where it is reasonable to think that uncertainty was high. The exact dates and a short description of the events can be found in Table 6 in Appendix B. I plot both the daily measures and the 150 day backward-looking mean in Figure 4. The reason for plotting the backward-looking mean instead of a monthly or quarterly series, is because it reduces noise and makes it easy to identify episodes when uncertainty was high. Also, I utilize the data at a daily frequency. This is done for visual clarity, and all empirical results presented are based on the measures at a daily, monthly or quarterly frequency. I start out by going through the first four examples of uncertainty measures:

In Panel (a) in Figure 4, I plot the measures for Monetary policy uncertainty. The measure is plotted together with the dates when the monetary policy regime changed, as well as when a new central bank governor assumed office. We see that uncertainty tends to be elevated around these events. Uncertainty was especially high during the second part of the 1990s. This was a period when Norway had a debate on what monetary policy regime that should be implemented. The monetary policy regime in Norway changed four times

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10 Figures for all the 80 topics can be found at http://www.vegardlarsen.com/uncertainty.
during the sample studied here. Uncertainty also increase in connection with global events such as the Lehman Brothers bankruptcy and the Greek government-debt crisis. Uncertainty tends to increase in times of large changes in the interest rate, see Figure 16 in Appendix C where the Monetary policy measure is plotted against the Norwegian interest rate.

In Panel (b) of Figure 4, I plot the series for Stock market uncertainty. This measure captures well-known events of heightened uncertainty, such as the debate in Norway on whether or not to join the EU, the Asian financial crisis, the short Norwegian recession in the early 2000s, and the Global Financial Crisis. Stock market uncertainty tends to increase when the stock market is in decline. I plot the Stock market measure together with the OSEBX in Figure 17 in Appendix C.

In, Panel (c) in Figure 4, I plot the Macroeconomic uncertainty measure. This series captures many of the same events as Stock market uncertainty, but there are a few exceptions where the two measures diverge: First, the Macroeconomics measure captures more uncertainty in the early 1990s during both the Norwegian banking crisis and the episodes of changing monetary policy regimes. Second, we see a large surge in Macroeconomics uncertainty after the oil price fall that started in the summer of 2014.

The Macroeconomics measure is countercyclical and has a negative correlation with the business cycle. I plot the Macroeconomics measure against the HP-filtered real GDP in Figure 18 in Appendix C. The correlation between the two measures is -0.50.

Lastly, Panel (d) in Figure 4 plots the frequency of uncertainty terms within news classified as Fear. The Fear topic is a type of news that gets considerable coverage during a crisis. The measure is especially high during the Global Financial Crisis and the Greek government-debt crisis. The first four examples often capture the same events. This shows us that uncertain times are reflected in different types of news. Now we turn to measures capturing more distinct types of uncertainty. The next four examples represent types of uncertainty that can be related to known events where it is reasonable to think that uncertainty was high. These four measures are uncertainty related to Oil price, Telecommunication, International conflicts, and Politics. The measures are plotted in Figure 5.

Panel (a) in Figure 5 shows the series for Oil price uncertainty. Norway is a large oil exporter, and the oil price is closely monitored by the media as well as policy makers. The oil price is usually considered exogenous from Norway’s perspective, and by inspecting some of the largest spikes in Oil price uncertainty, it looks like they are driven mostly by foreign events. The episodes of heightened uncertainty are often related to unrest in the Middle East or global financial crises. There is one Norway-specific event labeled as “Oil debate in Norway”. This reflects a special focus in the newspaper on a debate on the future of oil production in Norway. Hamilton (2013) identifies historical oil shocks, and all his shocks, during the period studied here, coincide with elevated Oil price uncertainty.

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12 The average correlation between the four components at a daily (quarterly) frequency is 0.29 (0.46).
Figure 4. Examples of uncertainty measures

(a) Monetary policy uncertainty

(b) Stock market uncertainty

(c) Macroeconomics uncertainty

(d) Fear uncertainty

Note: The black line plots the 150 day backward-looking mean, and the blue line plots the daily uncertainty measure. The series is the daily count of the uncertainty terms within the specified news type. This count is the number of uncertainty terms per 100,000 words. The right-hand axis is for the daily measures.
In Panel (b) of Figure 5, I plot uncertainty related to *Telecommunication*. The 1990s was a period of rapid technological advancements in the IT sector, which had substantial influence on the telecommunications industry. The value of IT companies on stock markets all over the world rose rapidly. The NASDAQ index, which is a US-based, technology-heavy index, grew from below 1000 in 1995 to over 5000 in the year 2000. This surge of technology and IT companies was part to the buildup of the dot-com bubble. The *Telecommunication* uncertainty measure grows with the NASDAQ, up until the peak of the index in March 2000. Using the peak of the NASDAQ as the peak of the dot-com bubble, we see that after the bubble burst uncertainty increases even more. NASDAQ reached a bottom, at slightly over 1100, in October 2002. *Telecommunication* uncertainty stayed high for some time after NASDAQ hit the bottom, before the uncertainty measure fell to pre-1995 levels in late 2003. I plot the *Telecommunication* measure together with the NASDAQ index in Figure 20 in Appendix C. This type of uncertainty increased again during the Global Financial Crisis.

Panel (c) in Figure 5 shows uncertainty related to *International conflicts*. The series picks up well-known conflicts such as the first and second Gulf war, and several episodes during the Arab spring. The uncertainty measure is especially high during the first and second Gulf wars (GW1 and GW2 in the figure), which affected Norway directly through the effect on the oil price.\(^{13}\)

Lastly, in Panel (d) in Figure 5, I show uncertainty related to *Politics*. The dates for the parliamentary elections and local elections in Norway are indicated by the red and green dashed lines respectively. I also indicate whether there is a left-leaning (red) or right-leaning (blue) central government in office. The uncertainty tends to increase around the parliamentary elections. We also see a large surge in uncertainty around the time of the local election in 2011. However, this is likely an increase in uncertainty in relation to the terrorist attacks on the government headquarters, and on the Workers’ Youth League summer camp on July 22.

### 3.2 Comparison to alternative uncertainty measures

Now I compare the topic-based uncertainty measures to some alternative measures of uncertainty. There is limited availability of uncertainty measures for Norway so I generate two alternative measures: First, Norway has no options-based stock market volatility index, and as an alternative, I calculate a realized stock market volatility (RSMV) measure. The RSMV series is calculated as the one-month backward-looking standard deviation of the Oslo stock exchange benchmark index (OSEBX). The second measure I generate, is a Norwegian version of the EPU created by Baker et al. (2015). The details on how the Norwegian EPU measure is computed can be found in Appendix E. In addition, I look at seven foreign measures. Those are: the US VIX, the macroeconomic and financial uncertainty measures from Jurado et al. (2015), and the EPU measures for the US, the

\(^{13}\)Since the newspaper used to create the uncertainty measures is a business newspaper, news stories within categories such as *International conflicts* have an angle towards the effect of the news on the economy.
Figure 5. Examples of uncertainty measures

(a) *Oil price* uncertainty

(b) *Telecommunication* uncertainty

(c) *International conflicts* uncertainty

(d) *Politics* uncertainty

*Note:* The black line plots the 150 day backward-looking mean, and the blue line plots the daily uncertainty measure. The series is the daily count of the uncertainty terms within the specified news type. This count is the number of uncertainty terms per 100,000 words. The right-hand axis is for the daily measures. In the plot for *Politics* uncertainty the vertical red dashed lines represent parliamentary, and the green dashed lines, local elections in Norway. The areas shaded in red represent periods with a left-leaning government, and the blue shaded areas represent right-leaning governments.
UK, Europe and China, created by Baker et al. (2015).14

Figure 4.6 displays the correlations between all the 80 topic-based measures and the nine alternative ones. The figure is a heat map where negative correlations are in shades of red, and positive correlations are in shades of blue. The highest correlation, 0.69, is between the \textit{Fear} measure and the US EPU. This observation is placed in the top left corner of the heat map, and I sort the rows and columns in descending order away from this point. The lowest correlation, -0.32, is between the \textit{Europe} and the RSMV measure. Some notable results emerge from Figure 6:

First, almost all the topic-based measures have a positive correlation with the alternative ones. This indicates that most of the measures, both the topic-based measures and the alternative ones, capture similar events. Two notable exceptions are the \textit{EU} and \textit{Europe} measures, which have a negative correlation with several of the alternative measures. In part of the sample, these measures capture a Norway-specific type of uncertainty related to the referendum on membership of the European Union.

Second, the \textit{Fear} measure captures a type of uncertainty that is common to all the alternative measures. The topic-based measures do not seem to capture much heterogeneity between the alternative measures, but there are some exceptions: Financial measures such as \textit{Funding}, \textit{Banking}, and \textit{Stock market} have a relative high correlation with the US VIX of 0.50, 0.54, and 0.52 respectively. Political measures such as \textit{Politics} and \textit{Elections}, on the other hand, capture more Norway-specific events and have a relatively high correlation with the Norwegian EPU of 0.41 and 0.49 respectively. The \textit{USA} uncertainty measure also has a high correlation with the US EPU of 0.56.

Third, given that the topic-based measures capture relevant types of uncertainty, the RSMV measure does not look like a good measure for uncertainty: the average correlation between the topic measures and the RSMV is 0.11. Given that no options-based volatility measure exists for Norway, a measure such as \textit{Stock market} uncertainty can be a good alternative as a proxy for a Norwegian VIX.

The topic-based uncertainty measures do capture the type of events we expected them to, and different measures capture category-specific events. An example is \textit{Politics} uncertainty that tends to be high around the Norwegian parliamentary elections. Most measures are positively correlated with alternative measures of uncertainty, which suggests that there are some common components captured in most types of uncertainty measures. This motivates the next section, where I conduct an analysis of the underlying components of uncertainty.

\footnote{Jurado et al. (2015) creates an uncertainty measure based on the unforecastable component of a large set of economic variables. The Jurado et al. (2015) paper focuses on macroeconomic uncertainty. In a related paper, using similar data, Ludvigson et al. (2015) disentangles macro and financial uncertainty. I refer to both the macro and the finance measure as JLN-measures (Jurado, Ludvigson, and Ng), because I downloaded the measures from the supplementary material from Jurado et al. (2015) (\url{http://www.columbia.edu/~sn2294/pub.html}).}
Note: The correlations are computed at a quarterly frequency. Blue represents a positive correlation while red represents a negative one. The topics are sorted by the correlation with the US EPU, where the correlations range from 0.69 to 0.10.
Table 2. The component measures – descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Component 1</th>
<th>Component 2</th>
<th>Component 3</th>
<th>Component 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explained variation</td>
<td>35</td>
<td>15</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>Cumulative E.V.</td>
<td>35</td>
<td>50</td>
<td>58</td>
<td>63</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.50</td>
<td>0.76</td>
<td>0.78</td>
<td>0.44</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.13</td>
<td>0.71</td>
<td>1.37</td>
<td>0.34</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>1.85</td>
<td>0.40</td>
<td>1.58</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Note: Fisher’s definition of kurtosis is used where the kurtosis of a normal is zero. The components are normalized (mean zero and a standard deviation of one).

4 The underlying components of uncertainty

In times of high uncertainty, the uncertainty count in most types of news tends to increase. We saw in the previous sections that during the Global Financial Crisis, uncertainty increased in many of the topic-based measures. The measures are not orthogonal, and they have a between-topic correlation varying from -0.29 to 0.84. The goal of this section is to use the various topic-based measures to extract common components of uncertainty. I use Principal Component Analysis (PCA) to extract uncorrelated components from the topic-based measures. PCA is a method for reducing a set of potentially correlated variables down to a set of linearly uncorrelated variables. I run the PCA on a subset of the 80 uncertainty measures. I drop general topics that have an unclear theme, and I also drop topics that are not related to the economy, such as Sports and Art. I remove 20 measures and run the PCA on the remaining 60.

I run the PCA on data at a quarterly frequency. I will later include the components in a VAR using quarterly data, and extracting quarterly components ensures that the components are orthogonal when included in the VAR. I keep the four components that explain most of the variation in the topic-based measures. Selecting four components is motivated by keeping the components that explain five percent or more of the total variation in the topic-based measures. The four components explain a total of 65 percent of the variation in the 60 underlying measures. The first component is, by definition, the most important one, and it explains 35 percent of the total variation. The explained variation for all the components is given in Table 2 along with some descriptive statistics for the measures. The principal components are not identified with a sign, so whether an

15A heat map of all the between-topic correlations is given in Figure 12 in Appendix B. The correlations are calculated at a quarterly frequency, on a daily frequency they vary between 0.02 and 0.53.

16The removed topics are Calendar, Surroundings, Movies/Theater, Argumentation, Unknown (8), Negotiation, Unknown (27), Narrative, Sports, Drinks, Literature, Watercraft, TV, Music, Unknown (53), Weekdays, Food, Art, Disagreement, Life. Remember, these are labels representing the word clouds described in Section 2. See Table 5 in Appendix B for the 10 most important words in each topic, and for a better description of the content they represent.

17If I perform the PCA on daily or monthly values, and then do the aggregation, I get very similar results, but the aggregated components will not be orthogonal.
increase in the measures corresponds to more or less uncertainty is not defined. I normalize the sign of the four components so they have a positive correlation with the topic-based uncertainty measure where they have the highest correlation. The first component has the highest correlation with the Fear measure of ±0.82, and I rotate this component so that the correlation is positive. Figure 7 plots the measures using the final normalizations.

We saw in Figure 6 that most of the topic-based uncertainty measures had a positive correlation with the alternative measures. This is not surprising given that there are some common events, such as the Global Financial Crisis, where uncertainty was high across most topic-based measures and also across all the alternative measures. Now we have four distinct types of variation in the uncertainty measures and Figure 8 reports the correlations between the component measures and the alternative ones. The first component has a positive correlation with all the alternative measures. Looking at Component 1 in Figure 7, we see that it captures well-known events of heightened uncertainty, such as the Asian crisis, the 9/11 attacks, and the collapse of Lehman Brothers. This type of uncertainty is common in all the alternative measures. The second component has a negative correlation with all the alternative measures. The third component has a positive correlation with the EPU measures for Norway and the US and a negative correlation with

Note: A plot of the four principal components extracted from 60 topic-based uncertainty measures.
4.1 Labeling the components

The topic-based measures, discussed in Section 3, have a direct link to the news categories. This gives the measures a straightforward interpretation. However, the measures are not orthogonal, and they often capture the same type of uncertainty. The component measures on the other hand, are uncorrelated measures, capturing different types of variation in the uncertainty count, but they have no direct link to different types of news. To deal with this, I give the components a label by relating them back to the topic-based uncertainty measures. The relationship is based on the correlation between the components and the topic-based measures. Table 3 reports the five topic-based measures that have the highest correlation with the four components and also the five topics that have the lowest correlation. I give the four components a label by linking them to the topic-based measures where the absolute value of the correlation is high. A correlation coefficient above 0.5 is deemed important and is used for the interpretation of the components. Furthermore, the topic labels reported in Table 3 are only a way of referring to the underlying topic distributions. To get a deeper understanding of the content of the components, I show the three topic distributions with the highest absolute correlation for all the components in Figure 13 in Appendix B.

The first principal component is strongly correlated with many of the topic-based measures. All the topic-based measures have a positive correlation with Component
Table 3. The “content” of the components

<table>
<thead>
<tr>
<th>Component 1</th>
<th>Component 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correlation</td>
</tr>
<tr>
<td>1st  Fear</td>
<td>0.82</td>
</tr>
<tr>
<td>2nd  Stock market</td>
<td>0.82</td>
</tr>
<tr>
<td>3rd  Statistics</td>
<td>0.80</td>
</tr>
<tr>
<td>4th  Family business</td>
<td>0.77</td>
</tr>
<tr>
<td>5th  Goods and services</td>
<td>0.74</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>56th EU</td>
<td>0.22</td>
</tr>
<tr>
<td>57th Projects</td>
<td>0.21</td>
</tr>
<tr>
<td>58th Europe</td>
<td>0.19</td>
</tr>
<tr>
<td>59th Entitlements</td>
<td>0.19</td>
</tr>
<tr>
<td>60th Taxation</td>
<td>0.11</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Component 3</th>
<th>Component 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correlation</td>
</tr>
<tr>
<td>1st  EU</td>
<td>0.82</td>
</tr>
<tr>
<td>2nd  Agriculture</td>
<td>0.75</td>
</tr>
<tr>
<td>3rd  Europe</td>
<td>0.74</td>
</tr>
<tr>
<td>4th  Fiscal policy</td>
<td>0.58</td>
</tr>
<tr>
<td>5th  Nordic countries</td>
<td>0.56</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>56th Energy</td>
<td>-0.30</td>
</tr>
<tr>
<td>57th Asia</td>
<td>-0.35</td>
</tr>
<tr>
<td>58th Oil service</td>
<td>-0.37</td>
</tr>
<tr>
<td>59th Inst. investing</td>
<td>-0.38</td>
</tr>
<tr>
<td>60th IT technology</td>
<td>-0.46</td>
</tr>
</tbody>
</table>

Note: The five topic-based uncertainty measures with both the highest and the lowest correlation with the four components. The topic-based measures where the absolute value of the correlation exceeds 0.5 are marked in boldface.

1. The topic-based measures that have the highest correlation with Component 1 are the Fear and Stock market measures, with a correlation coefficient of 0.82. Component 1 uncertainty captures well-known events of heightened uncertainty such as the Asian crisis, 9/11 and the Global Financial Crisis. This component captures the type of uncertainty the literature has focused on when using the alternative measures. I label the first component as uncertainty related to “economic and financial distress”.

The second principal component increases with uncertainty related to Monetary policy, and decreases with uncertainty related to Macroeconomics, Organizations, and Employment. Having topic-based measures with a high correlation of opposite signs complicates
the labeling of the components. Component 2 uncertainty was particularly high during the second part of the 1990s, see Figure 7. This was a period where there was a debate about what type of monetary policy regime that should be implemented in Norway. The uncertainty terms used in news about monetary policy can emerge for at least three unrelated reasons: First, the usage of uncertainty terms in news about monetary policy increases during economic and financial distress because there is uncertainty related to how the monetary authorities will react. This type of uncertainty is captured by Component 1, which is orthogonal to Component 2. Second, when the newspaper writes about monetary policy, the uncertainty terms are common vocabulary in this type of news story, without relating to an uncertain environment. Third, in the sample studied here, there have been several changes in the monetary policy regime, so part of the monetary policy uncertainty can be related to what type of monetary policy regime that will be implemented. Given that Component 2 is highly correlated with the Monetary policy measure, it can capture increases in uncertainty that are caused by the two last reasons. However, this does not tell us why Component 2 with lower uncertainty related to Employment, Organizations, and Macroeconomics. Although the labeling of Component 2 is challenging, I select a label based on the topic-based measure with the highest correlation. I label Component 2 as uncertainty related to “the institutional framework of monetary policy”.

In Figure 7 we see that Component 3 uncertainty was high during the first part of the 1990s and that the elevated uncertainty coincides with two events during this period: First, the spike in 1992 coincides with Norway depegging its currency from the ECU. Second, this was a period when Norway considered joining the EU, and the second spike in 1994 coincides with the Norwegian referendum on joining the European Union, which ended with Norway staying on the outside. The topic-based measures with the highest correlation with Component 3 are EU, Agriculture, and Europe. The agriculture industry was strongly opposed to Norway joining the EU. I label Component 3 as uncertainty related to “Norway’s relationship with the EU”.

The fourth component has a high correlation with IT systems, Telecommunication, and Stock listings. Within the sample studied in this paper, the IT sector has grown exponentially. An example is the Norwegian telecommunications company Telenor, which is Norway’s second largest company and also one of the largest telecommunications companies in the world, with 211 million mobile subscriptions.\(^\text{18}\) I label the fourth component as uncertainty related to “technology and firm expansion”.

In this section, I have extracted four orthogonal components of uncertainty. The correlations are given a label based on which topic-based measures they correlate the most with. I relate the four components to, “economic and financial distress”, “the institutional framework of monetary policy”, “Norway’s relationship with the EU”, and “technology and firm expansion”. In the next section, I study how the economy responds to shocks to these four orthogonal measures.

5 Uncertainty and the economy

A robust finding in the uncertainty literature is that uncertainty proxies are counter-
cyclical. Bad economic times are also times of high uncertainty. I have identified four
components of uncertainty with different properties. Now I investigate the response of
investment and GDP after shocks to the different components.

The standard modeling framework in the literature is to estimate the effects of un-
certainty shocks in a structural VAR model, using a recursive identification scheme. The
main finding from these studies is that, using various proxies, uncertainty shocks are
followed by a decline in real activity, see e.g. Bloom (2009), Jurado et al. (2015), and
Baker et al. (2015). Using a VAR to investigate uncertainty shocks is challenging due
to the endogeneity issues between the uncertainty measures and the macroeconomic vari-
ables. The impulse responses presented in this section cannot necessarily be interpreted
as causal, but the goal is to learn something about how different types of uncertainty
relate to aggregate quantities in the economy. A more thorough study of the causal links
between the different uncertainty measures and the economy is left for future work.

I follow Baker et al. (2015) and specify a structural VAR model where the identification
is achieved using a Cholesky decomposition. The uncertainty measure is ordered on top in
the VAR, meaning that uncertainty cannot react to the other variables within the same
period. I also report impulse responses from a model where the uncertainty measure
is ordered below asset prices. This ordering implies that asset prices cannot react to
uncertainty within the quarter. \(^{19}\) The VAR model is specified as follows

\[
A_0 y_t = \sum_j A_j y_{t-j} + B \varepsilon_t, \tag{5}
\]

where \(y_t \equiv \begin{bmatrix} \text{Uncertainty} \\
\log(\text{OSEBX}) \\
\text{Interest rate} \\
\log(\text{Investment}) \\
\log(\text{GDP}) \end{bmatrix}_t\) and \(\varepsilon_t \sim i.i.d. N(0,1)\).

The \(A_0\) matrix is lower triangular and the \(B\) matrix is diagonal. The topic-based uncertainty measures are available daily, but for most macroeconomic time series, data
is available at a lower frequency. I estimate a model using quarterly data because I
want to include investment and GDP. The OSEBX is the Oslo stock exchange benchmark
index, downloaded from Yahoo Finance. I include a nominal interest rate where I use the
3-month Norwegian interbank offered rate (NIBOR), downloaded from Norges Bank. I
also include real gross investment in mainland Norway and real GDP in mainland Norway
both variables downloaded from Statistics Norway. In the baseline specification, the model
includes three lags and the data sample used is 1988Q2–2015Q3.

\(^{19}\)Bloom (2009) estimates a similar structure at a monthly frequency for the US.
What is a relevant size of an uncertainty shock? Different studies use different values for the initial shock. Bloom (2009) creates a shock series based on the periods when the US VXO index exceeds 1.65 standard deviation from the mean. To make their results comparable to the VXO shocks in Bloom (2009), Jurado et al. (2015) record responses to a four standard deviation shock to their uncertainty measures. Baker et al. (2015) report responses to a shock that correspond with the increase in the mean of the newspaper-based economic policy uncertainty measure between 2005–2006 and 2011–2012. These are all studies for the US, and my shocks are not directly comparable. I report impulse responses from a one standard deviation shock to the uncertainty measures. What does a one standard deviation increase imply for some of the topic-based measures? The Fear measure increased by close to three standard deviations from 2006 to 2008, while the mean of the Politics measure is about one standard deviation higher in the years of parliamentary elections relative to the years without elections.

As a point of reference, I start out by including the aggregate uncertainty measure, $\Upsilon_{\text{Agg}}^t$, in the VAR. This measure is the overall uncertainty count in the newspaper, and the series is plotted in Figure 4.2. Since the newspaper covers business and economics news, this measure is a proxy for the overall uncertainty related to business and economics. Figure 9 plots the impulse responses to investment and GDP after a shock to the aggregate uncertainty measure. We see a significant drop in GDP. The drop is gradual, and reaches its bottom, of -0.4 percent, after three quarters. There is no significant drop in investment. We see that the ordering of the variables matters. When placing the uncertainty measure below asset prices, the negative effect on GDP disappears. This aggregate measure captures uncertainty within all types of news. Unexpected volatility in the stock market can lead the newspaper to write about uncertainty and the stock market in the subsequent period. In this scenario, ordering the uncertainty measure above asset prices does not make much sense. The finding that the ordering matters indicates that the aggregate uncertainty measure is not an exogenous source of variation. In a model using monthly data, the results are less sensitive to the ordering of the variables, see, Section 6.

Now I estimate the VAR using the four components as uncertainty measures. Including the topic-based measures directly in the VAR yields a range of different responses, but given the high correlation among many of them, the responses often look similar. Figure 15 in Appendix B plots the eight most and the eight least negative responses of GDP and investment using the topic-based measures directly in the VAR. I estimate the baseline VAR by include the components in the model one at a time.

First, a Component 1 shock, labeled as uncertainty related to “economic and financial distress”, gives a significant fall in investment and GDP. These responses resemble those after a shock to the aggregate uncertainty measure in Figure 9. Investment falls by more than one percent and GDP by close to -0.4 percent. The responses reach their minimum after 3–4 quarters. In Appendix B, I estimate the same VAR using some of

---

20 The VXO is similar to the US VIX, but is based on the narrower S&P 100 index rather than the S&P 500 index for the US VIX.
the alternative uncertainty measures discussed in Section 3 and show that they give very similar responses. The first component does, at least along some dimensions, capture the same type of uncertainty as the literature has focused on and the impulse responses do resemble those in the literature. We see that the ordering of the uncertainty measure matters for the impulse responses, and when ordering the first component below asset prices, the negative responses disappear. Both orderings are problematic, and I do not think Component 1 uncertainty captures pure exogenous uncertainty.

Second, a Component 2 shock, labeled as uncertainty related to “the institutional framework of monetary policy”, gives no significant responses in either investment or GDP. This type of uncertainty might be especially noisy, since the uncertainty terms are used frequently in this type of news for various reasons (see the discussion when labeling Component 2 in the previous section). The uncertainty about the institutional framework of monetary policy was prevalent in the 1990s. In 2001, Norway implemented inflation targeting, which is still in place in 2016. There has not been much discussion on moving away from this regime, and uncertainty regarding the institutional framework of monetary policy has been low in this period. We see in Figure 4.7 that Component 2 uncertainty declines in late 2007 and during 2008, coinciding with the start of the Global Financial Crisis. Lower Component 2 uncertainty might be driven by increased uncertainty related to Macroeconomics and Employment, see, Table 3. Component 2 has both a strong negative and a strong positive correlation with some of the topic-based measures, making the interpretation of the uncertainty shock difficult. Third, a Component 3 shock, labeled as uncertainty related to “Norway’s relationship with the EU”, gives a significant drop in investment, reaching a bottom of more than -1.5 percent after one year. This component gives a slightly stronger negative effect on investment relative to Component 1. Also, the investment response is more persistent. At the same time, we observe an increase in GDP, but this is not a significant response. We can see in Figure 4.7 that this type of uncertainty was especially high during the first part of the 1990s, when Norway was depegging its currency from the ECU and also considered joining the EU.

21 I use four alternative measures: The Norwegian version of the EPU (see Appendix E), the US EPU, Norwegian realized stock market volatility, and the US VIX.
Figure 10. Impulse responses using the four components

(a) Component 1 – “economic and financial distress”

(b) Component 2 – “the institutional framework of monetary policy”

(c) Component 3 – “Norway’s relationship with the EU”

(d) Component 4 – “technology and growing companies”

Note: The uncertainty components are introduced in the model one at a time. The orange dashed line is the response from a model where the uncertainty measure is ordered below asset prices.
Table 4. The contribution to the variance

<table>
<thead>
<tr>
<th>Component 1</th>
<th>Component 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizon</td>
<td>0-year</td>
</tr>
<tr>
<td>Investment</td>
<td>0.01</td>
</tr>
<tr>
<td>GDP</td>
<td>0.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Component 3</th>
<th>Component 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizon</td>
<td>0 year</td>
</tr>
<tr>
<td>Investment</td>
<td>0.01</td>
</tr>
<tr>
<td>GDP</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Note: The contribution to the variance of investment and GDP from the four components. The contribution to variance is computed as the forecast error variance decomposition.

Fourth, a Component 4 shock, labeled as uncertainty related to “technology and firm expansion”, gives a significant increase in investment of around one percent. Investment stays elevated for 1.5 years after the uncertainty shock. This result is positive evidence for “growth options” theories. If increased uncertainty represents a higher potential upside in the IT sector, we have a good type of uncertainty, that leads to increased investment. There is no effect on GDP after a Component 4 shock. For the fourth component, there is no difference between the baseline and the alternative ordering of the uncertainty measure, indicating that movements in asset prices do not influence the uncertainty measure.

The contribution to the variance of investment, and GDP from the four components is reported in Table 4. Uncertainty related to “economic and financial distress” explains the most for GDP at the five-year horizon at six percent. For investment, uncertainty related to “Norway’s relationship with the EU” explains the most at seven percent at the five-year horizon.

Component 1 uncertainty, related to “economic and financial distress”, gives a significant fall in both investment and GDP. Given the negative response, Component 1 uncertainty can be categorized as a bad type of uncertainty. This type of uncertainty has a similar profile as other uncertainty measures used in the literature, and it gives similar responses as the alternative measures when included in a structural VAR. However, higher uncertainty can also yield a positive economic response. An uncertainty shock related to “technology and firm expansion” gives a boom in investment. Given the positive response, Component 4 uncertainty, can be categorized as a good type of uncertainty.

6 Robustness

I have estimated a number of models using alternative specifications. The results presented in the previous section are robust to most of the alternative specifications. Details are discussed below.

---

22 For an economic model of good and bad types of uncertainty, see Segal et al. (2015).
Figure 11. Alternative VAR – Monthly data

*Note:* The orange dashed line represents a model where the uncertainty measure is ordered below the asset prices. 70 and 90 percent confidence bands are plotted.

During the available sample, the Norwegian economy underwent several structural changes. First, the monetary policy regime changed several times, and in 2001, Norway adopted an inflation-targeting regime. Second, Norway is a large exporter of petroleum, and government petroleum revenues are saved in a sovereign wealth fund (SWF). In 2001 the Norwegian parliament decided on a fiscal rule. The rule restricted the allocation of funds from the SWF to the government budget to four percent of the total value of the fund. The rise in oil prices in the 2000s vastly increased the value of the fund, which has changed the constraints on fiscal policy in the post-2001 period. Then, to account for these changes, I estimate the models on a post-2001 sample. Also to test whether the results are driven by the Global Financial Crisis, I estimate the model on a sample ending in 2007. The impulse responses from this exercise are plotted in Figure 21 in Appendix D.

In the baseline specification there is no significant effect after a Component 2 shock. In the pre-2001 sample, we see a positive response in investment and GDP. The high correlation between Component 2 and *Monetary policy* uncertainty is used as a rationale for labeling Component 2 as uncertainty related to “the institutional framework of monetary policy”. As alluded to earlier, uncertainty about the monetary policy regime in Norway was prevalent in the 1990s, and less so after the introduction of an inflation target. The high negative correlation between Component 2 and *Macroeconomics* and *Employment* uncertainty, see Table 3, may be an explanation for the positive effect on investment and GDP in the post-2001 sample, when uncertainty related to the monetary policy regime was reduced. For a Component 3 shock, the response in investment is more negative when using the post-2001 sample. Also in the post-2001 sample, instead of getting an insignificant positive response in GDP, we now get a negative response. Overall, the results are robust to the alternative specifications and also strengthened along some dimensions.

In the baseline specification of the VAR, I follow Baker et al. (2015) and choose three lags. Using the Akaike information criteria the preferred number of lags is two. I report impulse responses using both two and four lags in Figure 22 in Appendix D. The results in the previous section are robust to different lag lengths.

---

23 The first deposit into the fund was in 1996.
Using a recursive ordering to identify the uncertainty shocks is problematic because of the potential endogenous relationship between the uncertainty measure and the economy. Using quarterly data can amplify the problem because the restrictions on the contemporaneous relationships, implied by the Cholesky identification, are stronger using quarterly data. I estimate a monthly model where I include employment and industrial production instead of investment and GDP. Figure 11 plots the impulse responses to employment and industrial production after a shock to the aggregate uncertainty measure. We see a significant drop in both employment and industrial production. The ordering of the variables matter for industrial production, but to a lesser extent than for GDP in the quarterly model.

7 Conclusion

This paper introduces a text-based approach to create category-specific measures of uncertainty, taking advantage of text classification tools from the machine learning literature. I classify more than 26 years of newspaper articles from Norway’s largest business newspaper. The articles are classified according to their underlying meaning using a topic model. I measure the degree of uncertainty conveyed by the different articles by counting the uncertainty terms within the articles. I get uncertainty measures related to a wide range of categories such as Oil price, Monetary policy, Politics, and Stock market.

The uncertainty measures capture well-known episodes of heightened uncertainty both at an aggregate level and at a more category-specific level. Comparing the topic-based uncertainty measures to alternative measures used in the literature, many of the topic-based measures capture similar types of events. There is limited heterogeneity across the alternative measures, and they often capture the same events. In contrast the topic-based measures can capture more heterogeneous events.

Even if the topic-based measures do capture heterogeneous events, different types of news often capture the same type of uncertainty, such as the increased uncertainty during the Global Financial Crisis. To be able to capture distinct types of uncertainty, I do an orthogonalization of the topic-based uncertainty measures. I identify four distinct types of uncertainty related to “economic and financial distress”, “the institutional framework of monetary policy”, “Norway’s relationship with the EU”, and “technology and firm expansion”. These four components capture orthogonal types of variation in the uncertainty count in the newspaper.

I use a structural VAR model to investigate the effect of the four different uncertainty components on investment and GDP for the Norwegian economy. I find that shocks to the different components have different effects. A shock to uncertainty related to “economic and financial distress” is followed by a contraction in the Norwegian economy; this type of uncertainty resembles the bad type of uncertainty the empirical literature has focused on. In contrast to this bad type of uncertainty, a shock to uncertainty related to “technology and firm expansion” leads to increased investment.

The data is downloaded from Statistics Norway.
References


Gjedrem, S. (2008). Monetary policy from a historical perspective. Address at the conference to mark the 100th anniversary of the Association of Norwegian Economists in Oslo, Norway, 16 September 2008.


Appendices

Appendix A Latent Dirichlet Allocation Model

The LDA model was developed in Blei et al. (2003). I follow the model setup presented in Griffiths and Steyvers (2004). Let $T$ be the number of topics. The probability of word $i$ occurring in a given document is written as

$$P(w_i) = \sum_{j=1}^{T} P(w_i | z_i = j)P(z_i = j),$$  \hspace{1cm} (6)

where $w_i$ is word $i$, $z_i$ is a latent variable denoting which topic word $i$ was drawn from. The term $P(w_i | z_i = j)$ denotes the probability that word $i$ is drawn from topic $j$. The last term $P(z_i = j)$ gives the probability that we draw a word from topic $j$ in the current document. Different documents will have different probabilities for drawing words from the various topics.

Let $D$ be the number of documents in our corpus and $W$ is the number of unique words. Then we can represent the importance of the words for the different topics as

$$P(w_i | z = j) = \phi^{(j)}_w, \text{ for all } j \in [1,T] \text{ and } w_i \in \{w_1, w_2, \ldots, w_W\} \hspace{1cm} (7)$$

where $\phi$ is a set of $T$ multinomial distributions over the $W$ words. The importance of a topic within a given document can be represented as

$$P(z = j) = \theta^{(d)}_j, \text{ for all } j \in [1,T] \text{ and } d_i \in \{d_1, d_2, \ldots, d_D\} \hspace{1cm} (8)$$

where $\theta$ is a set of $D$ multinomial distributions over the $T$ topics.

With the new notation we can imagine that we have the generating algorithm for the documents, this is a two step algorithm

1. Pick a distribution over topics by randomly choosing $\theta$ from a Dirichlet distribution, which then determines $P(z)$

2. For each word in the document

   (a) Pick a topic $j$ from $\theta$

   (b) Given that you have topic $j$, pick a word from $\phi^{(j)}$, which is assumed to be fixed.

Then if we know the algorithm the documents was generated from, and we have the final documents, it is possible to estimate the distribution $\phi$ and $\theta$. We use Gibbs sampling to estimate the distributions.
Estimating the LDA Model

Griffiths and Steyvers (2004) gives a complete specification LDA-model with the additional Dirichlet prior on \( \phi \) as

\[
\begin{align*}
  w_i | z_i, \phi^{(z_i)} & \sim \text{Discrete}(\phi^{(z_i)}) \quad (9a) \\
  \phi & \sim \text{Dirichlet}(\beta) \quad (9b) \\
  z_i | \theta^{(d_i)} & \sim \text{Discrete}(\theta^{(d_i)}) \quad (9c) \\
  \theta & \sim \text{Dirichlet}(\alpha) \quad (9d)
\end{align*}
\]

where \( \alpha \) and \( \beta \) are hyperparameters specifying the prior distribution for \( \phi \) and \( \theta \)…. When estimating a topic model we need to set three parameters; That is the number of topics, \( T \), and the two hyperparameters of the Dirichlet priors, \( \alpha \) and \( \beta \). We follow Griffiths and Steyvers (2004) when selecting priors

\[
\alpha = \frac{50}{T}, \quad \text{and} \quad \beta = \frac{200}{W}.
\]

We select 80 topics and the number of words in our corpus is 250834. Then we can start sampling topics, we use burn a burn in period in before we start keeping samples. When keeping samples we use a thinning interval of 50. Then we keep as many samples as is computational feasible. We have a very large text corpus and sampling topics from this corpus demands allot of memory, the algorithm runs in \( \mathcal{O}(W) \) space. The complexity of each iteration of the Gibbs sampling algorithm is linear in topics and documents and runs in \( \mathcal{O}(TD) \) time.\(^{25}\)

Model selection

Given values for the hyperparameters \( \alpha \) and \( \beta \), the only variable we can change is the number of topics, \( T \). Choosing the right value for \( T \) is a model selection problem. A measure we use to evaluate the performance of our topic model is perplexity (equivalent to predictive likelihood) defined as follows

\[
\text{Perplexity}(w) = \exp \left\{ -\frac{L(w)}{W} \right\},
\]

(10)

where

\[
L(w) = \log P(w|z).
\]

(11)

\(^{25}\)Is this correct? See ?.
Appendix B  Additional results

Table 5 gives the labels for the 80 news topics and also a list of the most frequent words for all the news topics. All the news topics are represented as word clouds, as shown in Figure 1. Word clouds for all the 80 topics can be found at [www.vegardlarsen.com/Word_clouds](http://www.vegardlarsen.com/Word_clouds).

Table 6 gives a short description of the historical events plotted together with the uncertainty measures in Figure 4 and 5 in the main text.

Figure 12 displays the correlations between all the 80 topic-based measures. The figure is a heat map where negative correlations are in shades of red, and positive correlations are in shades of blue.

Figure 13 shows the word distributions, as word clouds, for the three topics where the topic-based uncertainty measure has the highest (absolute) correlation with the four components.

Figure 14 plots impulse responses using four alternative measures of uncertainty. The first alternative measure is a Norwegian version of the economic policy uncertainty (EPU) measure created by Baker et al. (2015). This measure is created using the same data as for the topic-based measures and details can be found in Appendix E. The second measure is the US EPU. The third is a measure of Norwegian real stock market volatility calculated as the five day backward-looking rolling standard deviation of the Oslo stock exchange benchmark index (OSEBX). The last measure is the US VIX.

Figure 15 plots impulse responses from the baseline VAR explained in Section 5. The figure plots the eight most and the eight least negative responses in GDP and investment from an uncertainty shock where I use the topic-based uncertainty measures directly in the VAR.
## Table 5. Estimated topics and labeling

<table>
<thead>
<tr>
<th>Topic</th>
<th>Label</th>
<th>First words</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Calendar</td>
<td>january, march, october, september, november, february</td>
</tr>
<tr>
<td>1</td>
<td>Family business</td>
<td>family, foundation, name, dad, son, fortune, brothers</td>
</tr>
<tr>
<td>2</td>
<td>Institutional investing</td>
<td>fund, investments, investor, return, risk, capital</td>
</tr>
<tr>
<td>3</td>
<td>Justice</td>
<td>lawyer, judge, appeal, damages, claim, supreme court</td>
</tr>
<tr>
<td>4</td>
<td>Surroundings</td>
<td>city, water, meter, man, mountain, old, outside, nature</td>
</tr>
<tr>
<td>5</td>
<td>Housing</td>
<td>housing, property, properties, apartment, square meter</td>
</tr>
<tr>
<td>6</td>
<td>Movies/Theater</td>
<td>movie, cinema, series, game, producer, prize, audience</td>
</tr>
<tr>
<td>7</td>
<td>Argumentation</td>
<td>word, besides, interesting, i.e., in fact, sure, otherwise</td>
</tr>
<tr>
<td>8</td>
<td>Unknown</td>
<td>road, top, easy, hard, lift, faith, outside, struggle, fast</td>
</tr>
<tr>
<td>9</td>
<td>Agriculture</td>
<td>industry, support, farmers, export, production, agriculture</td>
</tr>
<tr>
<td>10</td>
<td>Automobiles</td>
<td>car, model, engine, drive, volvo, ford, molder, toyota</td>
</tr>
<tr>
<td>11</td>
<td>USA</td>
<td>new york, dollar, wall street, president, usa, obama, bush</td>
</tr>
<tr>
<td>12</td>
<td>Banking</td>
<td>dnb nor, savings bank, loss, brokerage firm, kreditkassen</td>
</tr>
<tr>
<td>13</td>
<td>Leadership</td>
<td>position, chairman, cco, president, elected, board member</td>
</tr>
<tr>
<td>14</td>
<td>Negotiation</td>
<td>solution, negotiation, agreement, alternative, part, process</td>
</tr>
<tr>
<td>15</td>
<td>Newspapers</td>
<td>newspaper, media, schibsted, dagbladet, journalist, vg</td>
</tr>
<tr>
<td>16</td>
<td>Health care</td>
<td>hospital, doctor, health, patient, treatment, medication</td>
</tr>
<tr>
<td>17</td>
<td>IT systems</td>
<td>it, system, data, defense, siem, contract, tandberg, deliver</td>
</tr>
<tr>
<td>18</td>
<td>Stock market</td>
<td>stock exchange, fell, increased, quote, stock market</td>
</tr>
<tr>
<td>19</td>
<td>Macroeconomics</td>
<td>economy, budget, low, unemployment, high, increase</td>
</tr>
<tr>
<td>20</td>
<td>Oil production</td>
<td>statoil, oil, field, gas, oil company, hydro, shelf, stavanger</td>
</tr>
<tr>
<td>21</td>
<td>Wage payments</td>
<td>income, circa, cost, earn, yearly, cover, paid, salary</td>
</tr>
<tr>
<td>22</td>
<td>Regions</td>
<td>trondheim, llc, north, stavanger, tromso, local, municipality</td>
</tr>
<tr>
<td>23</td>
<td>Family</td>
<td>woman, child, people, young, man, parents, home, family</td>
</tr>
<tr>
<td>24</td>
<td>Taxation</td>
<td>tax, charge, revenue, proposal, remove, wealth tax, scheme</td>
</tr>
<tr>
<td>25</td>
<td>EU</td>
<td>eu, eea, commission, european, brussel, membership, no</td>
</tr>
<tr>
<td>26</td>
<td>Industry</td>
<td>hydro, forest, factory, production, elkm, industry, produce</td>
</tr>
<tr>
<td>27</td>
<td>Unknown</td>
<td>man, he, friend, smile, clock, evening, head, never, office</td>
</tr>
<tr>
<td>28</td>
<td>Mergers and acquisitions</td>
<td>orkla, storebrand, merger, bid, shareholder, acquisitions</td>
</tr>
<tr>
<td>29</td>
<td>UK</td>
<td>british, london, great britain, the, of, pound, england</td>
</tr>
<tr>
<td>30</td>
<td>Narrative</td>
<td>took, did, later, never, gave, stand, happened, him, began</td>
</tr>
<tr>
<td>31</td>
<td>Shipping</td>
<td>ship, shipping, dollar, shipowner, wilhelmsen, fleet, proud</td>
</tr>
<tr>
<td>32</td>
<td>Projects</td>
<td>project, nsb, development, fornebu, entrepreneurship</td>
</tr>
<tr>
<td>33</td>
<td>Oil price</td>
<td>dollar, oil price, barrel, oil, demand, level, opec, high</td>
</tr>
<tr>
<td>34</td>
<td>Sports</td>
<td>olympics, club, football, match, play, lillehammer, sponsor</td>
</tr>
<tr>
<td>35</td>
<td>Organizations</td>
<td>leader, create, organization, challenge, contribute, expertise</td>
</tr>
<tr>
<td>36</td>
<td>Drinks</td>
<td>wine, italy, taste, drinks, italian, fresh, fruit, beer, bottle</td>
</tr>
<tr>
<td>37</td>
<td>Nordic countries</td>
<td>swedish, sweden, danish, denmark, nordic, stockholm</td>
</tr>
<tr>
<td>38</td>
<td>Airline industry</td>
<td>sas, fly, airline, norwegian, braathens, airport, travel</td>
</tr>
<tr>
<td>39</td>
<td>Entitlements</td>
<td>municipality, public, private, sector, pension, scheme</td>
</tr>
<tr>
<td>40</td>
<td>Employment</td>
<td>cut, workplace, measures, salary, labor, working, employ</td>
</tr>
<tr>
<td>41</td>
<td>Politics</td>
<td>conservatives, party, ap, labor party, stoltenberg, parliament, frp</td>
</tr>
</tbody>
</table>

Continued on next page
<table>
<thead>
<tr>
<th>Topic</th>
<th>Label</th>
<th>First words</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topic 42</td>
<td>Funding</td>
<td>loan, competition, creditor, loss, bankruptcy, leverage</td>
</tr>
<tr>
<td>Topic 43</td>
<td>Literature</td>
<td>book, books, read, publisher, read, author, novel, wrote</td>
</tr>
<tr>
<td>Topic 44</td>
<td>Statistics</td>
<td>count, increase, investigate, share, average, decrease</td>
</tr>
<tr>
<td>Topic 45</td>
<td>Watercraft</td>
<td>ship, boat, harbor, strait, shipowner, on board, color</td>
</tr>
<tr>
<td>Topic 46</td>
<td>Results</td>
<td>quarter, surplus, deficit, tax, group, operating profit, third</td>
</tr>
<tr>
<td>Topic 47</td>
<td>TV</td>
<td>tv, nrk, channel, radio, digital, program, media</td>
</tr>
<tr>
<td>Topic 48</td>
<td>International conflicts</td>
<td>war, africa, irak, south, un, army, conflict, troops, attack</td>
</tr>
<tr>
<td>Topic 49</td>
<td>Elections</td>
<td>election, party, power, politics, vote, politician, support</td>
</tr>
<tr>
<td>Topic 50</td>
<td>Music</td>
<td>the, music, record, of, in, artist, and, play, cd, band, song</td>
</tr>
<tr>
<td>Topic 51</td>
<td>Oil service</td>
<td>rig, dollar, contract, option, offshore, drilling, seadrill</td>
</tr>
<tr>
<td>Topic 52</td>
<td>Tourism</td>
<td>hotel, room, travel, visit, stordalen, tourist, guest A</td>
</tr>
<tr>
<td>Topic 53</td>
<td>Unknown</td>
<td>no, thing, think, good, always, pretty, actually, never</td>
</tr>
<tr>
<td>Topic 54</td>
<td>Engineering</td>
<td>aker, kværner, røkke, contract, shipyard, maritime</td>
</tr>
<tr>
<td>Topic 55</td>
<td>Fishery</td>
<td>fish, salmon, seafood, norway, tons, nourishment, marine</td>
</tr>
<tr>
<td>Topic 56</td>
<td>Europe</td>
<td>german, russia, germany, russian, west, east, french, france</td>
</tr>
<tr>
<td>Topic 57</td>
<td>Law and order</td>
<td>police, finance guards, aiming, illegal, investigation</td>
</tr>
<tr>
<td>Topic 58</td>
<td>Week days</td>
<td>week, financial, previous, friday, wednesday, tdn, monday</td>
</tr>
<tr>
<td>Topic 59</td>
<td>Supervision</td>
<td>report, information, financial supervision, enlightenment</td>
</tr>
<tr>
<td>Topic 60</td>
<td>Retail</td>
<td>shop, brand, steen, rema, reitan, as, group, ica, coop</td>
</tr>
<tr>
<td>Topic 61</td>
<td>Startups</td>
<td>bet, cooperation, establish, product, party, group</td>
</tr>
<tr>
<td>Topic 62</td>
<td>Food</td>
<td>food, restaurant, salt, nok, pepper, eat, table, waiter</td>
</tr>
<tr>
<td>Topic 63</td>
<td>Stock listings</td>
<td>shareholder, issue, investor, holding, stock exchange listing</td>
</tr>
<tr>
<td>Topic 64</td>
<td>Asia</td>
<td>china, asia, chinese, india, hong kong, south, authorities</td>
</tr>
<tr>
<td>Topic 65</td>
<td>Art</td>
<td>picture, art, exhibition, gallery, artist, museum, munch</td>
</tr>
<tr>
<td>Topic 66</td>
<td>Disagreement</td>
<td>criticism, express, asserting, fault, react, should, alleging</td>
</tr>
<tr>
<td>Topic 67</td>
<td>Debate</td>
<td>degree, debate, context, unequal, actually, analysis</td>
</tr>
<tr>
<td>Topic 68</td>
<td>Life</td>
<td>man, history, dead, him, one, live, church, words, strokes</td>
</tr>
<tr>
<td>Topic 69</td>
<td>Goods and services</td>
<td>customer, post, product, offers, service, industry, firm</td>
</tr>
<tr>
<td>Topic 70</td>
<td>Telecommunication</td>
<td>telenor, mobile, netcom, hermansen, telia, nokia, ericsson</td>
</tr>
<tr>
<td>Topic 71</td>
<td>IT technology</td>
<td>internet, net, pc, microsoft, technology, services, apple</td>
</tr>
<tr>
<td>Topic 72</td>
<td>Monetary policy</td>
<td>interest rate, central bank, euro, german, inflation, point</td>
</tr>
<tr>
<td>Topic 73</td>
<td>Education</td>
<td>school, university, student, research, professor, education</td>
</tr>
<tr>
<td>Topic 74</td>
<td>Regulations</td>
<td>rules, authorities, competition, regulations, bans</td>
</tr>
<tr>
<td>Topic 75</td>
<td>Trade organizations</td>
<td>lo, nho, members, forbund, strike, organization, payroll</td>
</tr>
<tr>
<td>Topic 76</td>
<td>Fear</td>
<td>fear, emergency, hit, severe, financial crisis, scared</td>
</tr>
<tr>
<td>Topic 77</td>
<td>Fiscal policy</td>
<td>suggestions, parliamentary, ministry, selection, minister</td>
</tr>
<tr>
<td>Topic 78</td>
<td>Energy</td>
<td>energy, emissions, statkraft, industry, environment</td>
</tr>
<tr>
<td>Topic 79</td>
<td>Foreign</td>
<td>foreign, abroad, japan, japanese, immigration, games</td>
</tr>
</tbody>
</table>

Note: The topics are labeled based on the meaning of the most important words, see the text for details. The “# of articles” column reports the number of articles, in the full sample which, according to the model, belong to that specific topic. The words are translated from Norwegian to English using Google Translate. This table and Table 3.B.1 are the outcomes from two separately estimated topic model, the results in this table is from a estimation with around half a year more date. Most of the topics overlap (the topic numbers does not match), and we find mostly the same news topics in both models.
<table>
<thead>
<tr>
<th>Event</th>
<th>Date</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1990s</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GW1</td>
<td>1990-08-02</td>
<td>Gulf war 1 (2 Aug. 1990 – 28 Feb 1991)</td>
</tr>
<tr>
<td>Fixed rate (ECU)</td>
<td>1990-10-01</td>
<td>MPR: Fixed exchange rate pegged to ECU</td>
</tr>
<tr>
<td>Bank bailout</td>
<td>1991-12-20</td>
<td>The nationalization of several Norwegian banks</td>
</tr>
<tr>
<td>Bosnian War</td>
<td>1992-04-06</td>
<td>Armed conflict that took place in Bosnia and Herzegovina</td>
</tr>
<tr>
<td>Free float</td>
<td>1992-12-01</td>
<td>MPR: Free float exchange rate</td>
</tr>
<tr>
<td>Moland</td>
<td>1994-01-01</td>
<td>New central bank governor: Moland</td>
</tr>
<tr>
<td>Stability t.w. EU</td>
<td>1994-05-01</td>
<td>MPR: Stability t.w. EU currencies</td>
</tr>
<tr>
<td>EU vote</td>
<td>1994-11-28</td>
<td>Norwegian referendum for EU membership</td>
</tr>
<tr>
<td>Storvik</td>
<td>1996-01-01</td>
<td>New central bank governor: Storvik</td>
</tr>
<tr>
<td>Asian crisis</td>
<td>1997-11-01</td>
<td>The Asian financial crisis</td>
</tr>
<tr>
<td>Russian default</td>
<td>1998-09-01</td>
<td>Russian Default</td>
</tr>
<tr>
<td>LTCM Default</td>
<td>1998-09-23</td>
<td>Collapse of Long-Term Capital Management</td>
</tr>
<tr>
<td>Gjedrem</td>
<td>1999-01-01</td>
<td>New central bank governor: Gjedrem</td>
</tr>
<tr>
<td><strong>2000s</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak of NASDAQ</td>
<td>2000-03-10</td>
<td>NASDAQ peak before the burst of the dot-com bubble</td>
</tr>
<tr>
<td>Inflation tgt.</td>
<td>2001-03-01</td>
<td>MPR: Inflation target and floating FX</td>
</tr>
<tr>
<td>9/11</td>
<td>2001-09-11</td>
<td>The Al-Qaeda attack on 9/11</td>
</tr>
<tr>
<td>WorldCom bankruptcy</td>
<td>2002-07-21</td>
<td>WorldCom goes bankrupt</td>
</tr>
<tr>
<td>Bottom of NASDAQ</td>
<td>2002-10-01</td>
<td>NASDAQ bottom after the burst of the dot-com bubble</td>
</tr>
<tr>
<td>GW2</td>
<td>2003-03-20</td>
<td>Gulf war 2 (20 Mar 2003 – 01 May 2003)</td>
</tr>
<tr>
<td>Credit crunch</td>
<td>2007-08-01</td>
<td>Start of the Global Financial Crisis</td>
</tr>
<tr>
<td>Lehman</td>
<td>2008-09-15</td>
<td>The collapse of Lehman Brothers</td>
</tr>
<tr>
<td><strong>2010s</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flash crash</td>
<td>2010-05-06</td>
<td>The flash crash stock crash</td>
</tr>
<tr>
<td>Arab spring</td>
<td>2010-12-18</td>
<td>Start of the Arab spring</td>
</tr>
<tr>
<td>Fall of Tripoli</td>
<td>2011-08-28</td>
<td>Gaddafi government collapses</td>
</tr>
<tr>
<td>Olsen</td>
<td>2011-01-01</td>
<td>New central bank governor: Olsen</td>
</tr>
<tr>
<td>Stock market crash</td>
<td>2011-08-01</td>
<td>Stock market crash</td>
</tr>
<tr>
<td>Greek prop. refer.</td>
<td>2011-10-31</td>
<td>Greek proposed economy referendum</td>
</tr>
<tr>
<td>Egyptian coup</td>
<td>2013-07-03</td>
<td>Egyptian coup d’état</td>
</tr>
<tr>
<td>OPEC meeting</td>
<td>2014-11-28</td>
<td>OPEC chose not to reduce production</td>
</tr>
<tr>
<td>Greek referendum 2</td>
<td>2015-07-05</td>
<td>Greek vote on financial bailout</td>
</tr>
</tbody>
</table>

Note: Details on the historical events that are indicated in the plots of the uncertainty indexes. MPR is an abbreviation for Monetary Policy Regime.
Figure 12. Correlation between the topic-based measures

Note: The correlations are computed at a quarterly frequency. See Figure 5 for the corresponding topic labels. Blue represents a positive correlation while red represents a negative one.
Figure 13. Giving content to the components

Component 1 – economic and financial distress
Fear (0.82)  Stock market (0.82)  Statistics (0.80)

Component 2 – the institutional framework of monetary policy
Monetary policy (0.68)  Employment (-0.54)  Organizations (-0.51)

Component 3 – Norway’s relationship with the EU
EU (0.82)  Agriculture (0.75)  Europe (0.74)

Component 4 – technology and growing companies
IT systems (0.53)  Telecommunication (0.53)  Stock listings (0.52)

Note: The 150 words with the highest probabilities are shown, the size of the words corresponds to the probability of that word occurring in the topic distribution. The correlation with the components is given in the parentheses.
Figure 14. Impulse responses using alternative measures

Norwegian EPU

Investment  | GDP
--- | ---
0 | 0
-0.5 | -0.0
-1 | 0.0
-1.5 | 0.1
-2 | 0.2
-2.5 | 0.3
0 | 0
2 | 0
4 | 0
6 | 0
8 | 0
10 | 0
12 | 0
14 | 0
16 | 0

US EPU

Investment  | GDP
--- | ---
-3 | 0
-2 | 0
-1 | 0
0 | 0
1 | 0
2 | 0
3 | 0
0 | 0
2 | 0
4 | 0
6 | 0
8 | 0
10 | 0
12 | 0
14 | 0
16 | 0

Norwegian real stock market volatility

Investment  | GDP
--- | ---
-3 | 0
-2 | 0
-1 | 0
0 | 0
1 | 0
2 | 0
3 | 0
0 | 0
2 | 0
4 | 0
6 | 0
8 | 0
10 | 0
12 | 0
14 | 0
16 | 0

US VIX

Investment  | GDP
--- | ---
-2.5 | 0
-2 | 0
-1.5 | 0
-1 | 0
-0.5 | 0
0 | 0
0.5 | 0
1 | 0
1.5 | 0
2 | 0
2.5 | 0
0 | 0
2 | 0
4 | 0
6 | 0
8 | 0
10 | 0
12 | 0
14 | 0
16 | 0

Note: Impulse responses from VAR model as described in the text. The alternative uncertainty measures are introduced in the model one at a time. The orange dashed line is the responses from a model where the uncertainty measure is ordered below asset prices.
**Figure 15.** The most and least negative responses

<table>
<thead>
<tr>
<th>Eight most negative responses</th>
<th>Eight least negative responses</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Investment</strong></td>
<td><strong>GDP</strong></td>
</tr>
<tr>
<td><img src="image1" alt="Investment Graph" /></td>
<td><img src="image2" alt="GDP Graph" /></td>
</tr>
<tr>
<td><img src="image3" alt="Investment Graph" /></td>
<td><img src="image4" alt="GDP Graph" /></td>
</tr>
</tbody>
</table>

**Note:** The eight most, and the eight least, negative responses in investment and GDP using the topic-based measures.
Appendix C  Uncertainty measures and related variables

The Figures 16 to 20 plot some of the uncertainty measures discussed in Section 5 along with some related time series.

**Figure 16.** Monetary policy uncertainty and the interest rate

*Note:* The interest rate series, 3-Month Interbank Rates for Norway, is downloaded from FRED (St. Louis Fed).

**Figure 17.** Stock market uncertainty and asset prices

*Note:* The OSEBX series is the Oslo stock exchange benchmark index, downloaded from Yahoo finance.

**Figure 18.** Macroeconomics uncertainty and HP-filtered GDP

*Note:* The real GDP series is the Hodrick Prescott (HP, $\lambda = 40000$) filtered Norwegian real GDP, downloaded from FRED (St. Louis Fed).
Figure 19. *Oil price* uncertainty and the oil price

Note: The oil price series is the global price of Brent Crude, downloaded from FRED (St. Louis Fed).

Figure 20. *Telecommunication* uncertainty and the NASDAQ

Note: The NASDAQ series is the Nasdaq Composite downloaded from Yahoo finance.
Appendix D  Robustness

Figure 21. Robustness – Estimation using alternative samples

(a) Component 1

(b) Component 2

(c) Component 3

(d) Component 4

Note: Impulse responses from the VAR model as described in the text. 90 percent confidence intervals from the baseline model are plotted.
Figure 22. Robustness – Estimation using alternative lag lengths

(a) Component 1

(b) Component 2

(c) Component 3

(d) Component 4

Note: Impulse responses from VAR the model as described in the text. 90 percent confidence intervals from the baseline model are plotted.
Appendix E  Norwegian index of economic policy uncertainty

Baker et al. (2015) creates an economic policy uncertainty (EPU) index for 11 countries. These indices have proven to be popular and are available through commercial data resources such as Bloomberg, FRED, and Reuters. This index is not available for Norway, and this section will follow Baker et al. (2015) and create this index based on the Norwegian newspaper DN. The index is created by counting the articles that contain fords from the following three categories: uncertainty or uncertain; economic or economy; and Baker et al. (2015) use the following policy terms: congress, deficit, Federal reserve, legislation, regulation or white house. These three categories are named: uncertainty, economy, and policy. The counted articles contain words from all of them. Each day the final count is divided by the total number of articles that day to control for changes in total news coverage over time. The words need to be translated into their Norwegian counterparts to suit a Norwegian setting, the translations used are given in Table 7.

Table 7. Term Sets for the Norwegian EPU index

<table>
<thead>
<tr>
<th>Category</th>
<th>English</th>
<th>Norwegian</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>uncertainty or uncertain</td>
<td>usikker or usikkerhet</td>
</tr>
<tr>
<td>Economy</td>
<td>economic or economy</td>
<td>økonomisk or økonomi</td>
</tr>
<tr>
<td>Policy</td>
<td>government</td>
<td>regjering</td>
</tr>
<tr>
<td></td>
<td>parliament</td>
<td>storting</td>
</tr>
<tr>
<td></td>
<td>authorities</td>
<td>myndigheter</td>
</tr>
<tr>
<td></td>
<td>tax</td>
<td>skatt</td>
</tr>
<tr>
<td></td>
<td>regulation</td>
<td>regulering</td>
</tr>
<tr>
<td></td>
<td>budget</td>
<td>budsjett</td>
</tr>
<tr>
<td></td>
<td>deficit</td>
<td>underskudd</td>
</tr>
<tr>
<td></td>
<td>ministry of finance</td>
<td>Finansdepartementet</td>
</tr>
<tr>
<td></td>
<td>central bank</td>
<td>sentralbank</td>
</tr>
</tbody>
</table>

Note: I also include variations of the words given in this table such as taxation and regulations.
Figure 23. Economic Policy Uncertainty Index for Norway

Note: The index is calculated by counting articles that contain words from the uncertainty terms, the economy terms, and the policy terms. The large spike between GW2 and the Credit crunch coincide with the 2004 Indian Ocean earthquake and tsunami.