Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

Lars Erik Kleiven
Emil Johan Verlo Ifwarsson

Measuring Economic Policy Sentiment and its effect on the economy

Master's thesis in Industrial Economics and Technology Management
Supervisor: Lars Sendstad
June 2020

NTNU
Norwegian University of
Science and Technology

Lars Erik Kleiven
Emil Johan Verlo Ifwarsson

Measuring Economic Policy Sentiment and its effect on the economy

Master's thesis in Industrial Economics and Technology Management
Supervisor: Lars Sendstad
June 2020

Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

NTNU
Kunnskap for en bedre verden

Problem description

The purpose of this thesis is to expand upon current techniques for measuring economic policy uncertainty. As policy uncertainty is not directly observable, stakeholders seek the most accurate proxies. Our approach is twofold:

i) We seek to improve the methods currently available for measuring economic policy uncertainty. Through several innovations, exploiting recent advances in computer science, we aim to capture nuances and additional information to make our policy uncertainty index more accurate than its peers.

ii) While several studies address policy uncertainty in large economies, and especially in the US, few look at small, open economies. We seek to geographically expand the literature by exploiting our native knowledge and network available in the Scandinavian region. We further address the economic impact of policy uncertainty by analyzing the response of key economic indicators to uncertainty shocks, and whether policy uncertainty holds information relevant to predicting recessions.

Preface

This thesis is submitted to fulfill the requirements of our Master of Science degree in Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU). The Master's thesis consists of one paper, aiming to expand the current literature on measuring policy uncertainty and its impact on the economy. This research area came to our attention through our project thesis, "Policy Uncertainty in the Scandinavian Countries" in collaboration with Lars Sendstad and Verena Hagspiel.

We would like to thank our supervisor, Lars Sendstad at the Department of Industrial Economics and Technology Management for valuable input and support. His interest in our work has been crucial to making this thesis possible. We also thank our co-supervisor Verena Hagspiel at the Department of Industrial Economics and Technology Management for constructive feedback during the initial phase of this thesis. Finally, we would like to thank our fellow students, friends and family for constructive comments and support.

Abstract

We contribute to the growing number of newspaper-based economic policy uncertainty indices by introducing the Economic Policy Sentiment index (EPS). Contrary to existing policy uncertainty indices the EPS index adjust the importance of each news article by the tone of writing captured through advanced sentiment analysis. Furthermore, the EPS index includes information from the region a country lies within, which could be particularly relevant for small, open economies, such as the Scandinavian countries. Although the methodology is applicable to any country, we implement the EPS index for the Scandinavian countries; Norway, Denmark and Sweden.

Furthermore, we perform a narrative validation that shows how the EPS indices for the Scandinavian countries capture both local events such as referendums and general elections, but also global, systemic crises in all three countries. Then, we compare the EPS index against already existing policy uncertainty indices, by analyzing how key economic indicators respond to each of them. Our results indicate that in the case of Norway and Sweden, the stock markets respond stronger to the EPS than the existing economic policy uncertainty indices. Similarly, we find that the Purchasing Manager's Index (PMI) responds more negatively to an increase in the EPS index, consistent across all three countries. Through further analysis we show that the EPS index, in general, has a higher explanatory power in predicting key economic variables than other policy uncertainty measures. These results could be of interest to policy makers, corporations and investors, seeking a tool to properly measure economic policy uncertainty. Furthermore, the EPS index allows researchers to include policy uncertainty in wider economic prediction models.

Sammendrag

Denne oppgaven er et bidrag til den stadig økende litteraturen om nyhetsbaserte politiske usikkerhetsindekser, ved å introdusere Economic Policy Sentiment indeksen (EPS). I motsetning til eksisterende indekser, justerer EPS vektingen av hver nyhetsartikkel etter skrivemåte, målt ved avansert sentiment-analyse. Videre inkluderer EPS indeksen informasjon fra hele regionen et land ligger i, som kan vise seg å være spesielt relevant for små, åpne økonomier slik som i de Skandinaviske landene. Merk at metoden vi har utviklet er anvendbar på alle land, selv om vi i denne artikkelen implementerer en EPS indeks for hvert av de Skandinaviske landene; Norge, Danmark og Sverige.

Vi validerer EPS indeksene ved en gjennomgang av historiske begivenheter i de Skandinaviske landene, som viser at indeksene fanger både lokale hendelser som folkeavstemninger og stortingsvalg, men også globale systemiske kriser. Deretter sammenligner vi EPS indeksen med eksisterende mål for politisk usikkerhet, ved å analysere hvordan økonomiske nøkkelindikatorer reagerer på endringer i hver av dem. Resultatene våre viser at for både Norge og Sverige, reagerer aksjemarkedene kraftigere på endringer i vår politiske usikkerhetsindeks enn de eksisterende indeksene. Tilsvarende finner vi at innkjøpssjefenes indeks (PMI) synker kraftigere ved en økning i EPS indeksen, konsekvent i alle tre landene. Ved videre analyser viser vi at EPS indeksen generelt har en høyere forklaringskraft når man predikerer økonomiske nøkkelvariabler enn noen av de alternative politiske usikkerhetsindeksene. Resultatene i denne artikkelen kan være av interesse for både styresmakter, selskap og investorer som søker et godt verktøy for å måle politisk usikkerhet. Tilsvarende tillater EPS indeksen dem som ønsker å predikere makroøkonomiske bevegelser å inkludere politisk usikkerhet i kvantitative modeller.

1 Introduction

The consequences of policy uncertainty have received a considerable amount of attention not only from academia but also from Wall Street and policy makers. Recently, we have witnessed the policy uncertainty related to Brexit having a major impact on business conditions both in the UK and the remainder of Europe. The unclear outcome halted investments and depressed UK economic activity for several years (Financial Times, 2019b). However, recent progress through signing of the Withdrawal Agreement, passed by both the UK and the European Parliament finally provides some clarity. Indeed, even without addressing the outcome of the deal, simply stabilizing business conditions allow firms to move forward in their investments decisions (Financial Times, 2020).

Furthermore, trade policies have been on the agenda for many major economies following the 2016 US election. President Trump promised to renegotiate several trade deals, for instance the NAFTA agreement between the US, Mexico and Canada. Later efforts to decrease the US trade deficit towards China triggered a trade war starting in 2017. Throughout the following years, we saw stock markets responding instantly to developments in the negotiations. For instance, the Dow Jones dropped 600 points following President Trump's announcement to retaliate Chinese tariffs in August 2019 (Business Insider, 2019). Similarly, Asian stock markets tumbled on the following Monday (BBC, 2019). The trade war also affected the GDPs of both countries, leading to lower growth than previously expected (Forbes, 2020a). In contrast, as policy uncertainty declined through the signing of the Phase 1 trade agreement, the S&P500, Dow Jones and Nasdaq index reached record highs (Forbes, 2020b).

These examples emphasize the importance of policy uncertainty. It is, however, less clear *how* policy uncertainty should be taken into consideration, or to what extent it affects economic activity. Bremmer (2005) points at the need for a toolkit to systematically address policy uncertainty, which is the aim of this paper. In line with Kleiven & Ifwarsson

(2019), we define policy uncertainty as the risk of unexpected changes in policies, affecting the current business conditions. Throughout this work, policy uncertainty and policy risk will be used interchangeably.

The effect of policy uncertainty on investments has been subject to a profound academic interest. Theoretical models tend to agree that as uncertainty rise, so does the value of waiting for new information, often referred to as the "real options effect". As a result, irreversible investments are delayed which, in turn, leads to reduced economic growth (see, for instance, Dixit & Pindyck (1994); McDonald & Siegel (1986); Rodrik (1989); Bernanke (1983)). More specifically, the effect of policy uncertainty has been shown to incentivise deferrals of investment decisions, for instance in the energy sector (see Boomsma & Linnerud (2015); Boomsma et al. (2012); Ritzenhofen & Spinler (2016)). While the overall effect of policy uncertainty is known to be negative, a strand of literature emphasizes the positive effect of government interventions. More specifically, the effect of "Government put protection" also called the "Greenspan put", meaning that as uncertainty rise in a weak economy so does the chance of a government bailout (Pástor & Veronesi, 2013). Indeed, this promotes riskier and earlier investments.

More recently, a growing literature of empirical studies on policy uncertainty and its impact on key economic indicators have emerged. Baker et al. (2016) were one of the first to gain traction on their method of measuring economic policy uncertainty. They create the EPU index based on textual analysis of newspapers in the US.[1] Their findings indicate that as policy uncertainty rises, the US industrial production growth and employment decline. Furthermore, Gulen & Ion (2015) find that an increase in the EPU index of Baker et al. depresses corporate investments in the US, in line with real options theory.

[1] Baker et al. (2016) measure policy uncertainty based on the frequency of articles regarding this topic. Relevance is binary and determined from whether an article contains a combination of the following words: "economic" or "economy", "uncertainty" or "uncertain", "congress" or "deficit" or "Federal Reserve" or "legislation" or "regulation" or "White House". The optimal set of search words are determined from a human study in which over 10,000 articles were classified.

Extensions of the US EPU index include geographical expansion to new regions. In the original paper, Baker et al. (2016) extend their policy uncertainty index to 11 major economies.[2] More recent extensions include smaller economies such as the Swedish EPU by Armelius et al. (2017), the Norwegian EPU by Kleiven & Ifwarsson (2019), the Croatian EPU by Soric & Lolic (2017), as well as the EPUs for Ireland by Zalla (2017) and Greece by Fountas et al. (2018). A wide range of applications have emerged as well, including Brogaard & Detzel (2015) using the US EPU index to forecast excess market returns, Stockhammar & Österholm (2016) looking at the spillover effect of US policy uncertainty on small, open economies and Tarassow (2019) combining multiple uncertainty measures to forecast real M2 money growth in the US. The EPU of Baker et al. (2016) has also gained traction outside the academic world, being carried out by most financial data platforms, used in news coverage of politics and in reports from investment banks and international organizations.[3] Other related uncertainties have also been subject to empirical research, for instance Jurado et al. (2015) measuring macroeconomic risk, Caldara & Iacoviello (2018) measuring geopolitical risk, and the VIX index by the Chicago Board Options Exchange (CBOE) measuring market risk.

Similar to policy uncertainty, news sentiment[4] has shown to hold valuable information in predicting output and stock prices. For example, Tetlock (2007) use a pre-trained model to capture news sentiment from analyzing the popular column "*Abreast of the Market*" in the Wall Street Journal. He finds that high levels of negative or weak words in a firm-specific article is followed by lower returns the next day. Further, Loughran & McDonald (2011) measure the sentiment in 10-K fillings to capture the expressed feelings of the CFO, as an indication of how business is going. This study further illustrates the importance of

[2] **Additional EPU regions (number of news sources used):** India (7), Canada (6), South Korea (6), France (2), Germany (2), Italy (2), Japan (2), Spain (2), United Kingdom (2), China (1), Russia (1)

[3] The Economic Policy Uncertainty index is carried by Bloomberg, Haver, FRED, and Reuters (Baker et al., 2016). Examples of news coverage include The Wall Street Journal (2019); Financial Times (2019a). The index is used by major investment banks in their financial market reports (e.g. Deutsche Bank (2018); Goldman Sachs (2012)) and by international organizations (e.g. World Trade Organization (2019); OECD (2016)).

[4] Sentiment is defined as the expressed feelings towards a subject. In this context, the tone of writing in a news article.

individual adjustments to the sentiment analysis model, as words such as "tax" should be neutral while having a negative sentiment value in general lexicons. Hence, Boudoukh et al. (2013) combine information on both the topic and sentiment of news articles improves the predictive power on stock returns compared to a topic-only measure. Thorsrud (2018) creates time series indices based on both the topic, identified using LDA[5] and the sentiment of news articles to predict sector specific stock movements as well as GDP in Norway. The choice of method for capturing sentiment is crucial in this work. Although others have analyzed news sentiment using simple bag-of-words methods, no one currently exploits state-of-the-art Natural Language Processing (NLP) models, accounting for negation and context.

In this article, we introduce the Economic Policy Sentiment index (EPS) as an extension of the EPU index of Baker et al. (2016). The EPS index presents two inventions to the existing methodology: adjusting the importance of news articles by their sentiment value, and including information from the wider region a country lies within. Our hypothesis is that the sentiment of news articles contains valuable information in measuring policy uncertainty, making our index more accurate than the EPU.

By not only accounting for whether an article involves policy uncertainty or not, but also incorporating information on the tone of the writing, we aim to improve the accuracy of our policy uncertainty index. To capture the tone of a news article we use sentiment analysis through pre-trained models and classified lexicons. Note that this information could be split into two indices: a standard EPU index and a separate news sentiment index. However, the simplicity of a single index to capture the relevant information could explain some of the broad marked adoption of the original EPU index. Therefore, our main contribution is the EPS index: a single, sentiment-weighted policy uncertainty index.

[5]Latent Dirichlet Allocation (LDA) is an unsupervised clustering algorithm used in textual analysis to generate topics across a large set of articles and generate the probability of each article belonging to a certain topic Blei et al. (2003).

Further, the EPS index presents a second invention, namely, to include a component of regional policy uncertainty to the index when considering small, open economies. These economies partake in international trade and are considered price takers in the world economy.[6] Thus, we believe their policies to be more influenced by foreign affairs than in the case of large economies. Hence, including a component reflecting the regional level of policy uncertainty is believed to further improve the accuracy of the EPS index for small, open economies.

Exploiting our domain knowledge and data availability, we construct the EPS index for Norway, Sweden and Denmark, before comparing it to alternative policy uncertainty indices. We compare the EPS to indices with only one or neither of the presented innovations to the original EPU of Baker et al. (2016): including information from the wider region a country lies within and adjusting news articles importance by their sentiment scores. While there is no exact blueprint to measure the various methodologies against, our hypothesis is that as the index becomes more accurate, the economic response to the index becomes more profound. Hence, we estimate a series of bivariate VAR models including a policy uncertainty index and a key economic indicator.

For Norway and Sweden our findings indicate that stock markets respond more strongly to changes in the EPS index than towards existing policy uncertainty indices. Furthermore, looking at the Purchasing Manager's Index (PMI) we find a more pronounced response to changes in the EPS index, consistent across all three countries and lasting for several months. Next, by calculating the forecast error variance decomposition (FEVD)[7] we show that the EPS in general holds a higher explanatory power than the alternative indices. In conclusion, our results point in the direction of the EPS methodology being an improvement of the alternative methodologies.

[6]Source: Deardorffs' Glossary of International Economics

[7]FEVD is a measure of how much information each variable contributes to the other variables in a regression. See Section 2.5 for a full explanation.

Furthermore, we seek to address whether policy uncertainty holds additional value in wider prediction models. This could potentially increase the number applications for the EPS index. More specifically, we create an economic model to predict recessions and analyze whether including the EPS index significantly improves these models. Predicting US recessions has been a subject of interest to economists for a long time. Estrella & Mishkin (1998) examine the out-of-sample performance of economic variables in predicting US recessions. Their results indicate that the stock market performs well on short-term predictions. However, the yield curve seems to outperform other economic variables when predicting more than one quarter ahead. Further, Wright (2006) uses the shape of the US Treasury yield curve as an indication of the current state of the US economy. By applying probit models he finds that the yield curve holds additional information than simply using the term spread. Karnizova & Li (2014) use the US EPU index of Baker et al. (2016) to further improve probit models which include the term spread[8], stock market returns[9], corporate spread[10] and stock market volatility.[11] However, there are few empirical studies aiming to predict recessions in the Scandinavian region.

Our results indicate that policy uncertainty holds valuable information in predicting recessions. For Norway, we find evidence that including the EPS index in a multi-factor probit model improves predictions 1-3 and 8-10 quarters ahead. Similarly, for Denmark we find that the Danish EPS improves recession predictions 7-10 quarters ahead. For Sweden, we find that while the EPS index seem to improve predictions, the results are somewhat less conclusive.

[8] Term spread: Difference between the 10-year and 3-month Treasury yields.
[9] Stock market returns: Log-difference of the S&P500 index.
[10] Corporate spread: Aaa corporate bond yield less the 10-year Treasury yield.
[11] Stock market volatility is measured using the VXO index. The VXO index calculates stock market volatility based on S&P100 option prices 30-days ahead, and is calculated by the CBOE.

In Section 2 we present the data and methodology behind the EPS index. Section 3 validates the EPS indices through a narrative validation before comparing each index to corresponding indices using only one or neither of our innovations. Section 4 analyze the economic impact of policy uncertainty through VAR analysis, and introduce the probit model used to predict recessions in the Scandinavian countries. Section 5 concludes the article and offers guidance for further research.

2 Measuring policy uncertainty

Construction of the EPS index consist of two parts: classifying an article as relevant or not, and capturing the sentiment of the relevant articles. In this chapter we present the methodology and data behind the EPS index, as well as the methods of measuring the economic response to changes in policy uncertainty.

2.1 Data

We aim to capture policy uncertainty using a newspaper-based approach. Thus, we rely on the newspapers to capture key political events affecting the economy, scaling the coverage based on the importance, and writing in an objective manner not covered by the newspapers political views. The selection of newspapers is based on some key criteria: availability, quality of journalism, national coverage and close to neutral political view. Regarding availability, the newspaper needs to have a digitized archive, preferably accessible through Retriever's Atekst database in order to facilitate our analysis. Quality of journalism is based partially on the number of readers and partially on the newspapers reputation amongst native speakers. Moreover, we filter on political stance to avoid newspapers that might skew the index through political slant, thus the most left- and right-leaning news sources are excluded. The risk of unintended bias stemming from political slant is discussed further in Baker et al. (2016).

We use daily newspaper articles from 1980 across the leading newspapers covering Norway, Sweden and Denmark. See Table 1 for the full list of newspapers and summary statistics. The news sources for Norway include VG and Aftenposten, Norway's two largest newspapers by circulation, as well as Finansavisen covering financial news.[12] In Sweden, we use Svenska Dagbladet and Aftonbladet, two of the largest tabloid newspapers with a

[12]Newspaper circulation statistics were gathered from *www.medienorge.uib.no/statistikk*

national coverage. In Denmark, historical articles for their leading newspapers are currently unavailable. We thus include the archive of Denmark's leading news agency.

Country	Newspaper	Type	First article	EPU articles
Norway	Aftenposten	Newspaper	30.10.1983	12,652
Norway	Finansavisen	Newspaper	31.01.2011	1,913
Norway	VG	Newspaper	30.10.1983	2,612
Denmark	Ritzau	News agency	27.07.1988	15,017
Sweden	Aftonbladet	Newspaper	01.09.1994	1,799
Sweden	Svenska Dagbladet	Newspaper	01.01.1995	9,954

Table 1: Statistics on the data set extracted from Retriever's Atekst database, after duplicate articles are removed. Articles with identical headlines for the same newspaper and date are considered duplicates. EPU articles refer to the total number of articles marked relevant by following the method of Baker et al. (2016).

In order to classify articles as relevant to economic policy uncertainty we follow the method of Baker et al. (2016), also used by Kleiven & Ifwarsson (2019). For an article to be considered as relevant it must contain the words "economy" or "economic", "uncertainty" or "uncertain" as well as one of the following policy words: "Congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". We translate these search words to the three Scandinavian languages using academic dictionaries and later verifying these translations by native speakers. See Appendix A for details and the exhaustive list of search words used.

2.2 Sentiment analysis

Once the news articles are classified as relevant to policy uncertainty or not, the next step involves capturing the sentiment of each article's content. This section explains the procedure of the sentiment analysis in more detail.

Recent advances in the field of sentiment analysis allow us to easily extract the sentiment of large amounts of text, however there are multiple possible sentiment engines. Explained briefly, there are two main categories of sentiment analysis: machine-learning and lexical models. The machine-learning models have no preset rules but learns from its training set. Such models are good at capturing complex relationships between words, but require extensive, domain specific and labeled training sets.[13] A major drawback to a machine-learning approach, in the case of measuring the sentiment of newspaper articles, is that labelled training sets are neither available nor easy to build from scratch.

The lexical methods use a predefined lexicon of words assigned with a score reflecting its positiveness.[14] Within Lexical models we find two main categories: Bag-of-words and more advanced rule-based methods. Bag-of-words models simply map each word in a text to its predefined score before returning the sum or average of each sentence (see Godbole et al. (2007), Bautin et al. (2008)). A shortcoming of the bag-of-words method is that it discards all information about the context in which the word is used. In contrast, rule-based methods seek to better understand the dynamics of human language, such as Vader by Hutto & Gilbert (2015). Vader mitigates the weaknesses of bag-of-words models by analyzing entire sentences rather than single words. In addition to a lexicon, Vader has a set of heuristic rules accounting for the word's context within the sentence. Journalists tend to use negation, sarcasm and otherwise advanced language, hence words should be interpreted conditionally on the context it is used. Hence, we will proceed with Vader in order to improve our measurement of policy uncertainty compared to bag-of-words methods. While bag-of-words methods have previously been used to analyze news articles, no one currently use state-of-the-art Natural Language Processing techniques such as Vader. A more in-depth review of how Vader captures the sentiment from entire sentences can be found in Appendix B.

[13]See for instance Pang et al. (2002) training machine-learning models to predict movie reviews based on the users comments.

[14]Most lexicons assign each word with a score of 1 (positive), 0 (neutral) or -1 (negative), although more nuanced scoring regimes work fine such as in the case of the lexicon Vader by Hutto & Gilbert (2015). Vader uses a score from -4 to 4, see *https://github.com/cjhutto/vaderSentiment*.

As the vast majority of sentiment analysis tools are available in English only, researchers have tried to translate other languages before applying sentiment analysis. Bautin et al. (2008) translate articles from nine different languages to English, before applying sentiment analysis. This study shows that the translator engines occasionally fail in translating certain keywords, leaving them in their original language. However, they run a parallel corpus analysis on the EU's JRC-Acquis[15] corpus for five languages showing a significant Pearson correlation between most languages and English.[16] A more recent study by de Vries et al. (2018) uses transcripts from debates in the European Parliament to evaluate the performance of Google's translate engine. From each of the five languages addressed[17], more than 2,000 transcripts are translated and compared to their English versions. Comparisons based on bag-of-words vectors and similarity in results from topic modeling indicate that the content is well-preserved post-translation. Motivated by the results of de Vries et al. (2018), we adopt a translation-based approach for sentiment analysis on newspapers. The translation engine used in this work is Google Translate, and we manually verify a sample of the translated articles to ensure the content and tone of writing is preserved.

Next, when applying Vader, we have to decide which parts of the article to include when defining its overall sentiment score. Each sentence is considered equally important, independent of whether it comes from the headline, subheadings or main body of the article. However, we acknowledge the fact that most sentences in an article likely contains noise. As we are mainly interested in whether the policy uncertainty mentioned in each article is referring to increased, declining or absence of policy uncertainty, some filtering is appropriate before applying sentiment analysis. Hence, we only account for sentences containing the words "uncertainty" or "uncertain", holding a sentiment score of -1.4 and

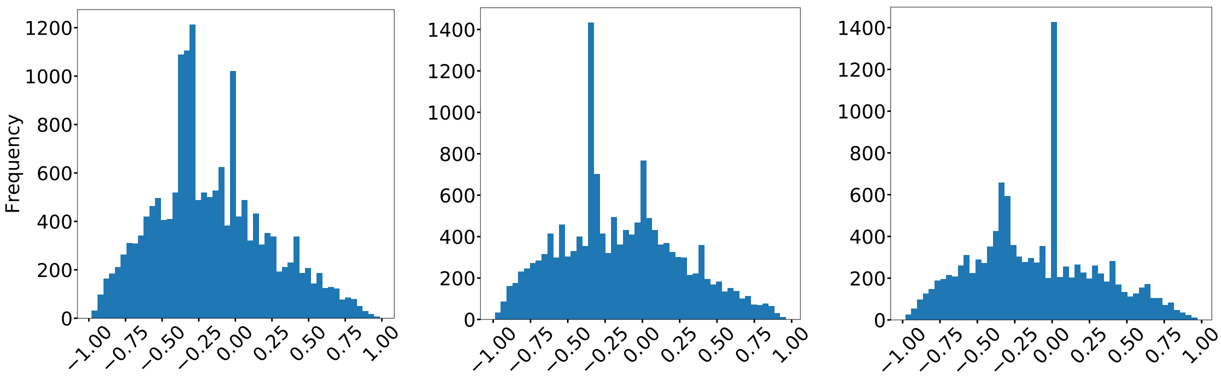
[15]The European Commission Joint Research Centre's Acquis multilingual parallel corpus (EU's JRC-Acquis) is the body of all EU law applicable to its member countries, in the member states' official languages

[16]Besides German polarity correlation to English is below the 95% significance level, all languages are significant measured in frequency, polarity and subjectivity. Languages looked at are English, French, German, Italian, and Spanish

[17]Danish, German, Spanish, French and Polish

-1.2 in the [-4, 4] range of the Vader lexicon.[18] As described in Appendix B, Vader adjusts these scores if combined with intensifying words or negation. Note also that while each word in the Vader lexicon is in range [-4, 4], the sentiment engine returns an overall score of entire sentences which are normalized to a [-1, 1] scale.

Figure 1 shows the distribution of sentiment scores for articles in the EPS index, showing a high frequency around the neutral context of the words "uncertain" and "uncertainty". Further, in 5-10% of the articles, Vader is unable to find any sentiment leaving the sentences with a score of zero. Table 2 shows the descriptive statistics for the sentiment distribution for the three countries. Note that there is a negative mean, explained by the negative sentiment of key words in the sentences analyzed. Moreover, we find a slight positive skewness indicating that a majority of the observations are more negative than the mean of the distribution. From Table 2 we find that the sentiment distributions are highly similar across all three countries when looking at the first two moments; the mean and standard deviation. Thus, it seems as the tone of writing is consistent across the Scandinavian news sources.



(a) Norwegian articles **(b)** Danish articles **(c)** Swedish articles

Figure 1: Distribution of sentiment scores using Vader on articles from the Scandinavian countries. Note that approximately 5-10% of the articles have a neutral sentiment value of zero in each of the three countries.

[18]The full Vader lexicon can be found at https://github.com/cjhutto/vaderSentiment/

	Norway	Denmark	Sweden
Mean	-0.165	-0.147	-0.112
Std. dev.	0.388	0.408	0.409
Min	-0.980	-0.988	-0.982
Max	0.986	0.961	0.971
Skewness	0.422	0.300	0.257
Kurtosis	-0.271	-0.501	-0.530

Table 2: Descriptive statistics of sentiment values for the newspaper articles. Kurtosis shows excess kurtosis, meaning that the normal distribution holds a value of zero.

2.3 Regional impact on open economies

Similar to the additional value held in the sentiment of news articles, we believe that the overall level of policy uncertainty in the entire region a country lies within, is of interest. Thus, we seek to measure the overall uncertainty to a region and letting it weigh in on each country's EPS index.

Some work has already been done in identifying the spillover-effects of policy uncertainty between countries. The findings of Stockhammar & Österholm (2016) suggest that the US EPU holds predictive power for Sweden's GDP, while Colombo (2013) identifies spill-over effects from US EPU to the Euro-area. Kleiven & Ifwarsson (2019) compares the economic effect of US EPU compared to local EPUs in the Scandinavian region. Their findings indicate that foreign policy uncertainty has a considerable impact on key economic indicators across all countries in this region. However, no-one, to the best of our knowledge, address the potential spill-over effects from policy uncertainty in neighboring countries or the region a country lies within.

From a global perspective, the Nordic countries[19] are often addressed as one region rather than five different countries, and especially so within Scandinavia.[20] The Scandinavian

[19]Norway, Sweden, Denmark, Iceland and Finland constitute the Nordic countries.
[20]Norway, Sweden and Denmark constitute the region named Scandinavia.

countries, besides their physical closeness, share a common history of unions.[21] In addition, the Scandinavian countries are all integrated in the European Single Market and have similar public policies often referred to as "the Nordic model". Lastly, while the three economies are dominated by different industries[22] they can be categorized as small, open economies. This means that while they partake in international trade, their policies will not largely affect the world economy.[23] The similarities between the Scandinavian countries can further be shown through indicators of wealth distribution and level of democracy.

A well-known measure of wealth distribution is the GINI coefficient by the World Bank Development Research Group. The coefficient values range from 0 to 100, where 0 indicates perfect equality in terms of income, wealth and/or consumption. Contrary, a value of 100 indicates the extreme of one person in the population having all the income, wealth and/or consumption. Table 3 shows the GINI coefficients for the Scandinavian, as well as other European countries and the US from 2004 to 2016. The Nordic countries average scores range from 26.9 to 27.7, while other European countries lie above 31 and the US above 40. From these numbers it seems clear that the wealth distribution in the Nordic countries differ substantially from the US as well as the rest of Europe.

[21]Norway was a part of the Danish kingdom for 434 years up until 1814, when handed over to Sweden. Once liberated from Sweden in 1905 a Danish price was asked to take the throne, under the name Haakon VII. His grandson is the current regent of Norway.

[22]Norway's main export is oil & gas accounting for 58% of total exports. Denmark exports mainly machines and chemical products accounting for 22% and 18% of total exports. Sweden exports machines and vehicles accounting for 26% and 16% of total exports. Numbers are from 2017. Source: The Observatory of Economic Complexity, *https://oec.world/en/resources/about/*

[23]Source: Deardorffs' Glossary of International Economics

Country	2004	2016	Average
Norway	31.6	28.5	**27.3**
Denmark	24.9	28.2	**26.9**
Sweden	26.1	29.6	**27.7**
Finland	27.9	27.1	**27.5**
France	30.6	31.9	**32.1**
Germany	30.4	31.9	**31.1**
Italy	34.3	35.2	**34.4**
Spain	33.3	35.8	**34.8**
United Kingdom	36.0	34.8	**34.2**
United States	40.5	41.4	**40.8**

Table 3: GINI coefficients calculated by the World Bank Development Research Group. Historical values from the first and last date reported for all the selected countries, as well as the historical average over the period 2004 to 2016 (World Bank Development Research Group, 2020).

Further, the Democracy Index of The Economist Intelligence Unit rank and label 167 countries political systems. The scale goes from 0 to 10, where 10 indicates a "full democracy" while 0 indicates a "authoritarian regime". Key elements evaluated are the electoral process, political participation, functioning of government democratic political culture, and civil liberties (The Economist Intelligence Unit, 2019). We present the numerical democracy scores as well as the associated regime type in Table 4. The Nordic countries all have a score above 9, significantly higher scores than the US as well as other European countries. A high democracy score indicates that the public trust the political system to respond properly to local and international events. Thus, the Democracy Index points at yet another similarity between the Scandinavian countries, which motivates us to use Scandinavia as the region of interest when measuring policy uncertainty in Norway, Denmark and Sweden.

Country	Democracy score	Regime type
Norway	9.87	Full democracy
Denmark	9.22	Full democracy
Sweden	9.39	Full democracy
Finland	9.14	Full democracy
France	7.80	Flawed democracy
Germany	8.68	Full democracy
Italy	7.71	Flawed democracy
Spain	8.08	Full democracy
United Kingdom	8.53	Full democracy
United States	7.96	Flawed democracy

Table 4: Democracy scores from The Economist Intelligence Unit (2019) Democracy Index.

2.4 Constructing the EPS index

In order to construct the Economic Policy Sentiment index, we start by applying the method of Baker et al. (2016). Each article is already marked as relevant to policy uncertainty or not, according to the criteria presented in Section 2.1. For each country $c \in C$, we create a variable x_{ijt} as defined in (1), for each news source $i \in I_c$, each article in that news source $j \in J_{it}$, and each day $t \in T$.

$$x_{ijt} = \begin{cases} 1, & \text{if relevant to policy uncertainty} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Further, in order to combine news sources and compare across countries, we adjust the time-series to a unit standard deviation. This adjustment is shown in (2), where σ_i is the standard deviation for each newspaper.

$$y_{ijt} = \frac{x_{ijt}}{\sigma_i} \tag{2}$$

So far, we have followed the methodology of the original EPU index of Baker et al. (2016). However, to adjust for the articles sentiment values we calculate the sentiment score of each article, γ_{ijt} which is obtained using Vader as described in Section 2.2. Note that the sentiment scores, γ_{ijt} are in range [-1, 1], where +1 indicates a highly positive sentiment and -1 indicates a highly negative sentiment. We use information about the sentiment to adjust y_{ijt} by scaling up the importance of an article if it holds a negative sentiment, and vice versa, where the sentiment adjusted variable z_{ijt} is calculated according to (3). Note that we subtract the sentiment score from the adjustment factor as positive sentiment indicates lower policy uncertainty and vice versa.

$$z_{ijt} = y_{ijt} \cdot (1 - \gamma_{ijt}) \tag{3}$$

We further aggregate z_{ijt} to an average value for each newspaper per day as shown in (4), where $|J_{it}|$ is the number of articles in newspaper i at day t.

$$u_{it} = \frac{1}{|J_{it}|} \cdot \sum_{j \in J_{it}} (z_{ijt}) \tag{4}$$

Similarly, we create an aggregate value for each country as shown in (5), where $|I_c|$ is the number of news sources for country c.

$$v_{ct} = \frac{1}{|I_c|} \cdot \sum_{i \in I_c} (u_{it}) \tag{5}$$

As we would like to compare the values of the final indices to the corresponding EPU index, we adjust the mean of v_{ct} to a value of 100 according to (6) & (7), where $|T|$ is the total number of days in period T.

$$M_c = \frac{1}{|T|} \cdot \sum_{t \in T} (v_{ct}) \tag{6}$$

$$w_{ct} = v_{ct} \cdot \left(\frac{100}{M_c}\right) \tag{7}$$

While the sentiment adjusted EPU stops at this point, we propose a second adjustment to the framework, which is specific for small, open economies. To include the impact of policy uncertainty in the region, we first construct a combined index for the countries $c \in C$ by weighting each country by their GDP. The combined index is calculated according to (8), where G_{ct} is the GDP of country c at time t.

$$q_{ct} = \frac{\sum_{c\in C}(G_{ct} \cdot w_{ct})}{\sum_{c\in C}(G_{ct})} \tag{8}$$

While a combined regional EPS index might be of interest to some, we find highly limited use cases compared to a country-specific measure, which by definition should be dominated by local information. Thus, the final, country-specific EPS index is calculated according to (9), where λ determines the weighting of local versus regional information.

$$EPS_{ct} = \lambda \cdot w_{ct} + (1 - \lambda) \cdot \frac{\sum_{c\in C}(G_{ct} \cdot w_{ct})}{\sum_{c\in C}(G_{ct})} \tag{9}$$

2.5 VAR analysis of economic response

Next, by utilizing the EPS indices created in Section 2.4, we now measure the economic response to changes in policy uncertainty. A popular method for measuring the response of a time-series on another, is through the use of vector autoregression models, hereby referred to as VAR models. By applying a VAR model, we run a regression on each time series included, allowing the variables to depend on lagged observations of themselves, as well as from the other time-series.

The specifications of a k-dimensional $VAR(p)$ model is shown in (10), where $y_t = (y_{1t}, ..., y_{Kt})'$ denote the variables, C is a $(1 \times K)$ intercept matrix, A_i are the

$(K \times K)$ coefficient matrices while $u_t = (u_{1t}, ..., u_{Kt})'$ are the error terms. Note that the error terms are assumed to be white noise, meaning $E(u_t) = 0$ and variance as defined in (11), where Σ_u is assumed to be positive definite.

$$y_t = C + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \tag{10}$$

$$E(u_t, u_s') = \begin{cases} \Sigma_u, & \text{if t=s} \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

Further, as we are interested in the response of policy uncertainty on an economic indicator, we calculate the impulse response function from the VAR model. Thus, we change the fitted VAR to a moving average (MA) representation, as shown in (12). $\Phi_0 = I_K$ which is the $(K \times K)$ identity matrix, and Φ_i is defined according to (13). Note that $A_j = 0$ for $j > p$ where p is the number of lags in the $VAR(p)$ specification. The elements of Φ_i are better known as the impulse responses of the system.

$$y_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{12}$$

$$\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_j, \quad \text{for} \quad i = 1, 2, ... \tag{13}$$

However, to extract the isolated effect of policy uncertainty, in contrast to the effect of the lagged economic variables themselves, we must recover orthogonal shocks. To orthogonalize the impulse response we use a Cholesky decomposition, which assumes that a variable earlier in the ordering is unaffected by shocks to a variable later in the ordering, within the same period. To obtain the orthogonalized impulse response we choose a lower triangular matrix, P holding positive diagonal elements such that $\Sigma_u = PP'$. Then, we define $w_t = P^{-1} u_t$ and thus $\Sigma_w = E(w_t w_t') = I_K$. The rewritten MA representation is shown in (14), where $\Theta_i = \Phi_i P$ which is known as the orthogonalized impulse response.

$$y_t = \sum_{i=0}^{\infty} \Theta_i w_{t-i} \tag{14}$$

Finally, to compare the explanatory power of various policy uncertainty measures, we calculate the forecast error variance decomposition, or FEVD (see Lütkepohl (1990)). This is a measure of the amount of information contributed by each variable to all the other variables in the regression. It does so by measuring to what extent the forecast error variance of a variable can be explained by exogenous shocks to the other variables. Thus, we are interested in calculating the proportion of h-step forecast error variance of variable k, accounted for by variable j. This quantity is denoted $\omega_{kj,h}$ and the calculation is shown in (15), where e_k is the k-th column of I_K and the mean squared error is calculated as $MSE_k(h) = \sum_{i=0}^{h-1} e_k' \Phi_i \Sigma_u \Phi_i' e_k$.

$$\omega_{kj,h} = \sum_{i=0}^{h-1} (e_k' \Theta_i e_j)^2 / MSE_k(h) \tag{15}$$

2.6 Neural networks for OOS prediction

Although VAR models are useful in identifying relationships for time-series in-sample, there are other methods more appropriate for out-of-sample (OOS) prediction.[24] Due to recent advances in computational power, several machine learning techniques have gained traction. For instance, a set of models well suited to capture complex relationships between variables are known as Artificial Neural Networks (ANN). In order to assess the predictive power of the policy uncertainty indices we run multiple ANNs aiming to predict changes in stock markets, GDP and PMI for each of the Scandinavian countries. We use lagged variables of both the EPS and the economic variable (stock index, GDP or PMI) as input to the ANN models.

[24] VAR models use OLS to fit the model to the training data it is exposed to. For OOS forecasting this can result in the model being overfitted to the training data and thus less able to predict well on records from the test data.

As shown in Figure 2, an ANN consist of an input layer, one or more hidden layers and an output layer. The model aims to capture patterns from the observations it is trained on, hereby denoted the training set. The weights between the layers are adjusted through a procedure called back-propagation. Explained briefly, it calculates the gradient of the loss-function, layer by layer, and the weights are adjusted to minimize the prediction error of the model. For a full explanation, see Norvig & Russell (2009).

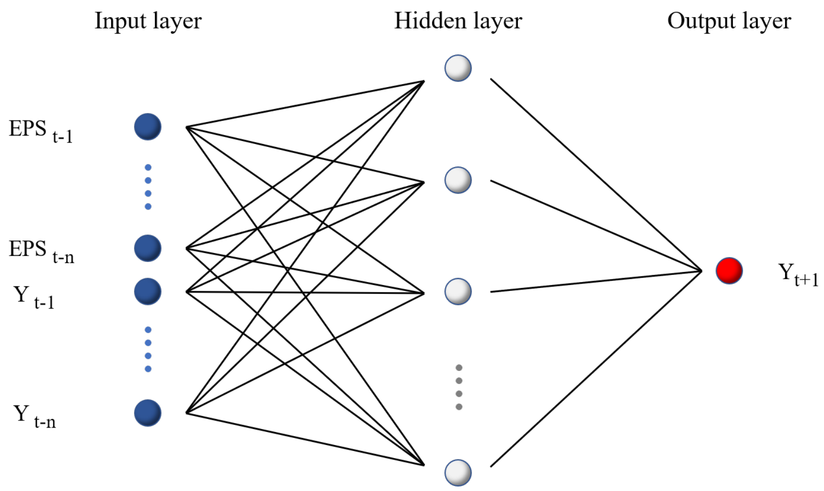


Figure 2: Illustration of the setup for an Artificial Neural Network having lagged values of the EPS and the economic variable Y as input, while predicting the economic variable one period ahead.

In order to apply an ANN model, we first need to transform the time-series into a labelled data set. We follow the approach outlined in Figure 3, where the input nodes consist of the last 4-lags[25] of the EPS (or one of the alternative policy uncertainty measures) as well as the economic variable of interest Y, while the variable to be predicted is the next period value of Y.

[25]Based on the Akaike Information Criterion (AIC) from the VAR analysis in Section 4.1.

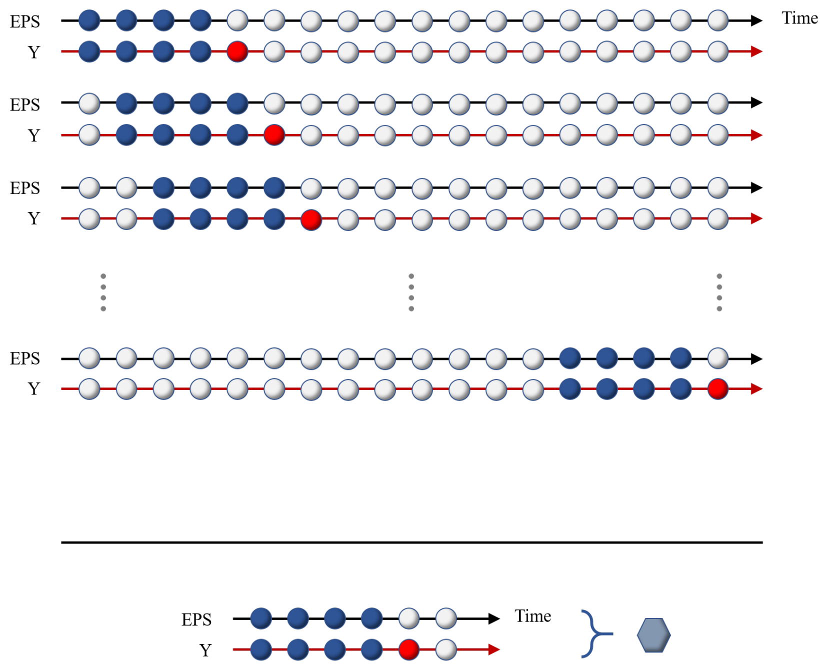


Figure 3: The conversion from two time-series into a single labelled data set. A rolling window selects the four last observations of both indices as input (blue), and well as the current observation of the economic indicator as the label (red). Together these constitute a single record for the ANN data set (gray).

As the weights in an ANN are initialized randomly, we normalize the input data to a mean of 0 and standard deviation of 1 to avoid unintended bias. Further, finding the balance between underfitting and overfitting the model leaves us to stop training before the weights have fully converged. Thus, the out-of-sample (OOS) error statistics are stochastic, even when training and testing on identical records over multiple runs. Hence, the error statistics are reported as the mean and standard deviation over a series of runs.

Further, we use cross-validation as outlined in Figure 4 to assess the accuracy of the OOS forecasts. By running several iterations and changing which data points to be included in the training and testing set, we improve the accuracy of the reported error statistics, compared to running only a single iteration.

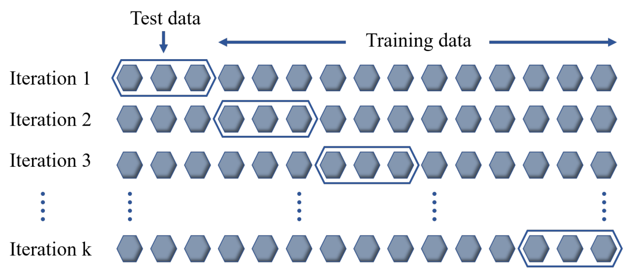


Figure 4: Illustration of cross-validation technique. We run multiple iterations and change which records are chosen as the test set. The remaining records constitute the training set.

3 Economic Policy Sentiment Index

In this chapter we present the EPS index for each of the Scandinavian countries. To ensure that the local information still dominates the final EPS index, we set $\lambda = 0.5$ and let the remaining half be the GDP-weighted average of the region as a whole.[26] First, we start with a brief narrative validation including key historical events. Then, each EPS index is compared to corresponding policy uncertainty indices using alternative methodologies, such as the original framework of Baker et al. (2016). Further, a comparison of the EPS indices to alternative measures of uncertainty, such as the VIX index of CBOE can be found in Appendix C.

3.1 Narrative validation of the EPS index

This section aims to analyze whether the EPS indices capture key historical events. Although we comment on whether the results are in line with the expectations, the key historical events for each country will not be explained in detail. For a thorough description of the key historical events and how they are expected to affect the Scandinavian countries, see Kleiven & Ifwarsson (2019). Figure 5, 6 & 7 present the EPS index of Norway, Denmark and Sweden with key global and local events highlighted. Date-specific events such as a terrorist attack, referendum or war declaration are marked with a dotted red line, while the shaded regions are major economic crises of some duration.

In the case of Norway, the EPS index in Figure 5 starts at high levels following the 1994 EU referendum where Norway, with a small margin, decided not to join the European Union. Following the referendum, as the debate cooled off and practical matters resolved, policy uncertainty declined. While the Asian crisis did not largely affect Norway, it led to the Russian crisis resulting in an all-time high for the EPS index. Again, as the Russian

[26] Alternative weighting regimes have been tested and resulted in no consistent improvements.

crisis resolved we once again see a rapid decline in the index.

Throughout the period 2000 to 2020 we see the index responding to terrorist attacks, both the 9/11 terrorist attacks and the 22nd of July attack which scarred the entire nation. Further, the index responds both to broad economic crises such as the Financial crisis and the European debt crisis. Note that while Norway is not a member of the European Union, they are highly integrated through to EEA Agreement. Further, being a major oil & gas exporting nation, the oil price plunge of 2014 to 2016 resulted in massive layoffs and largely hurt the economy. Initially, the expectations where that the OPEC countries would stabilize the oil price, however in the OPEC meeting in Vienna, 2014 it became clear that this would not be the case this time. Hence, we see an increasing trend in the Norwegian EPS index following the outcome of this meeting. This increasing policy uncertainty was further prolonged by Norway's most important trade-partner considering and eventually leaving the European Union. Lately, we also find an effect of the US-China trade war. In general, it seems like the Norwegian EPS index well captures the major historical events over the last 25 years.

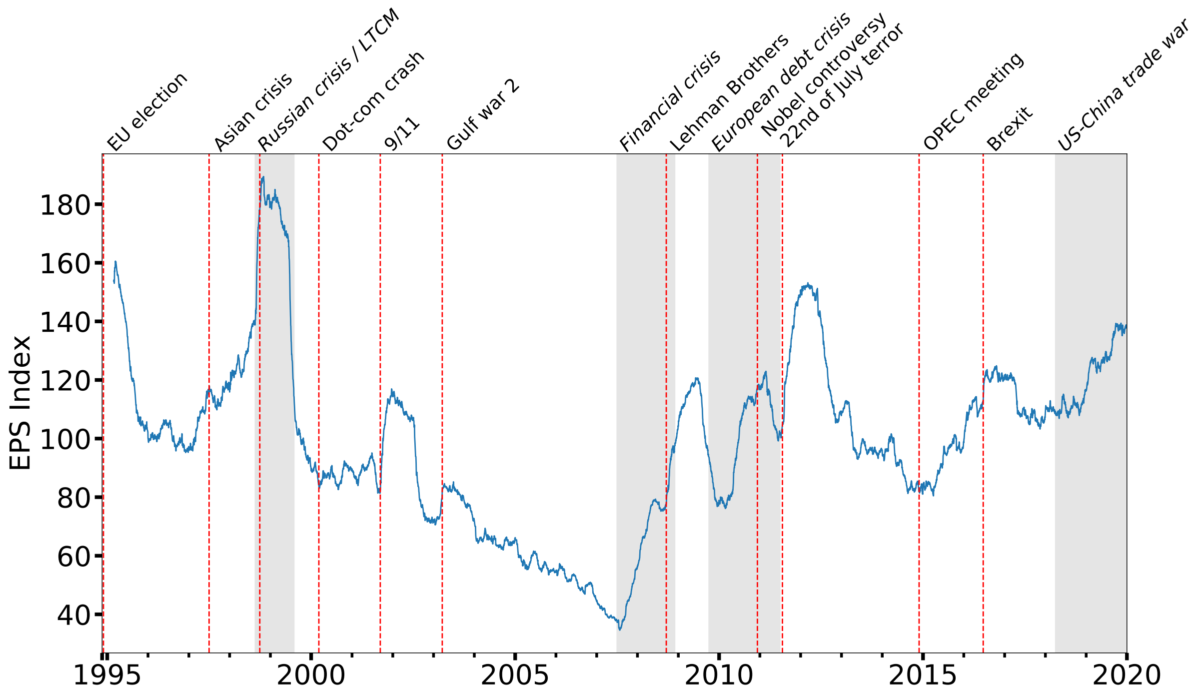


Figure 5: The Norwegian EPS index with key historical events, 300-day backward looking rolling window.

Further, the Danish EPS index is shown in Figure 6. Starting out from neutral levels, there is an increasing policy uncertainty from the Asian crisis and especially as the Russian crisis evolves. In late 2001, Denmark held their general election which resulted in an unprecedented victory for the far-right parties, calling for a drastic shift in immigration policies. Similar to Norway, we see the Danish EPS responding both to the Financial crisis and the European debt crisis. In 2011, Denmark imposed border control towards countries in the Schengen Area, violating the Schengen Agreement. As diplomatic relations are affected, and with rising fear of retaliation, the EPS rise to high levels. Note that, contrary to an oil exporting nation such as Norway, policy uncertainty in Denmark seem unaffected by the oil price plunge of 2014 to 2016.

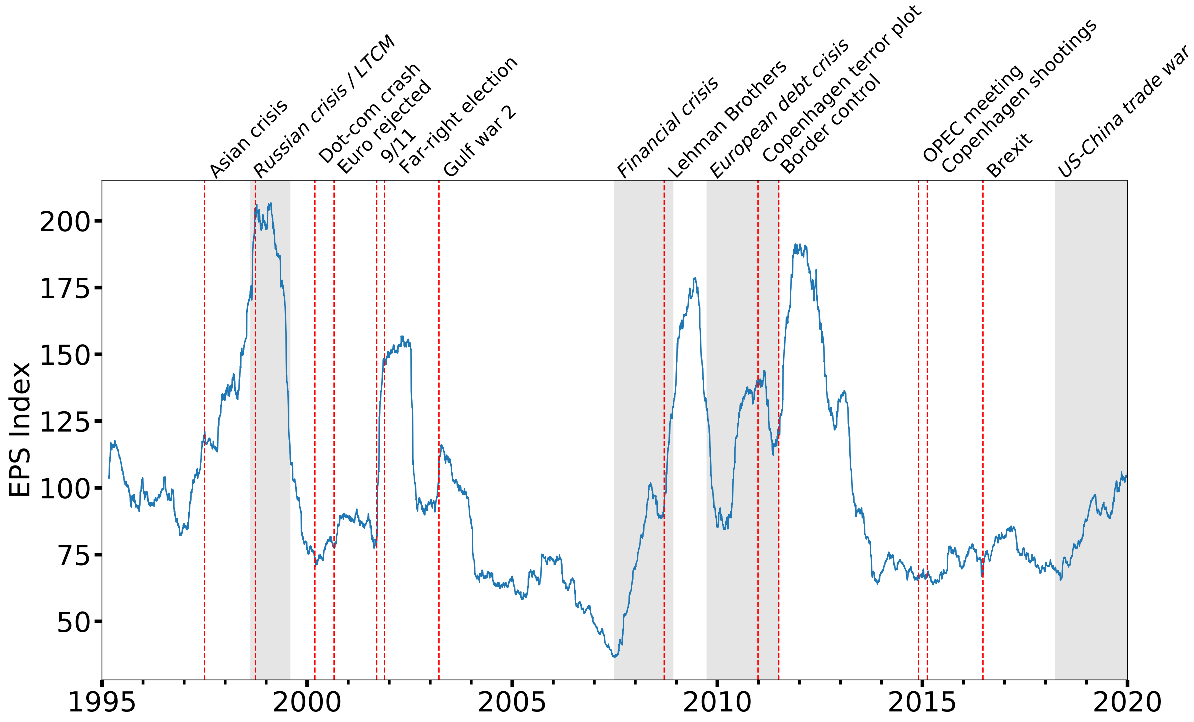


Figure 6: The Danish EPS index with key historical events, 300-day backward looking rolling window.

Finally, the Swedish EPS is shown in Figure 7. Similar to Norway, their EPS index start at high levels due to their EU referendum in 1994, resulting in a decision to join the European Union. As with Norway and Denmark we find their EPS responding to the Russian crisis, the Financial crisis and the European debt crisis in line with expectations. It is less clear, however, why Sweden responds so strongly to the 9/11 terrorist attacks compared to Norway. Further, in recent years there has been youth riots in Sweden, including arson attacks and violence towards police officers, where experts are pointing at failing integration of immigrants. Together with the uncertainty stemming from Brexit, the policy uncertainty rises throughout 2015 to 2016. The combined effect of the US-China trade war and the recent general election which resulted in no clear government constellation, leave the index at high levels to date.

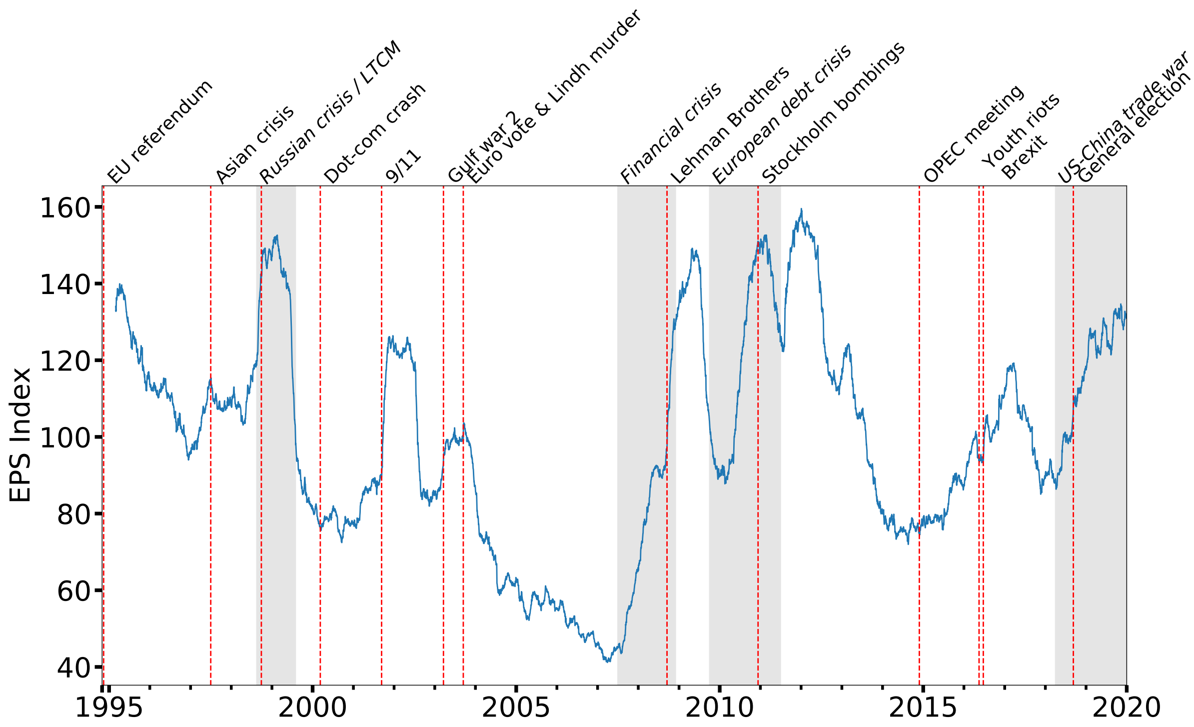


Figure 7: The Swedish EPS index with key historical events, 300-day backward looking rolling window.

To conclude across all the Scandinavian countries, the EPS indices react mostly in line with expectations when looking at key historical events. For each country we see the index responding to a mix of both global events, expected to affect small, open economies as well as local country-specific events. These results give us confidence that the methodology, including our two novel inventions, is well suited to capture policy uncertainty in small, open economies.

3.2 Alternative methodologies for measuring policy uncertainty

There are several methodologies appropriate for measuring policy uncertainty from news articles, and this section aims to compare the EPS index to some of these alternative approaches. We include two additional indices, namely the EPU and the Simple EPU index. The EPU index is calculated following the methodology outlined in Section 2.4, without weighting articles by their sentiment scores. Further, the Simple EPU index is calculated in a similar manner but includes neither sentiment scores nor the regional impact. The properties of the three methodologies are summarized in Table 5. We also construct and analyze the effect of the Simple EPS index, including news sentiment but not regional impact in Appendix D.

	Policy uncertainty	Regional impact	News sentiment
Simple EPU	✓		
EPU	✓	✓	
EPS	✓	✓	✓

Table 5: Overview of three alternative methodologies for measuring policy uncertainty.

The descriptive statistics for the monthly versions of the EPS, EPU and Simple EPU in Table 6 reveal some interesting properties. Consistently across the three countries, we find the EPU having lower volatility than the Simple EPU, while adding sentiment sharply increases volatility. All indices show positive skewness, meaning that most observations lie below the mean value. The positive skewness increases further as we add news sentiment. Further, we find excess kurtosis regardless of methodology, which means that the distributions have a higher probability in the tails than in a normal distribution. This effect increases sharply as we are adding sentiment to the index.

	Norway			Denmark			Sweden		
	Simple EPU	EPU	EPS	Simple EPU	EPU	EPS	Simple EPU	EPU	EPS
Mean	100.02	99.95	99.88	100.01	99.94	99.86	100.04	99.96	99.90
Std. dev.	43.85	35.67	42.30	49.37	37.96	57.82	37.44	33.30	41.31
Skewness	1.07	1.06	1.63	1.46	1.59	2.58	1.04	0.98	1.35
Kurtosis	2.48	2.84	5.84	3.52	4.53	10.03	1.81	1.78	3.26

Table 6: Descriptive statistics of monthly policy uncertainty indices. Kurtosis shows excess kurtosis meaning that a normal distribution would have a value of zero. Note that while the daily Simple EPU is normalized to a mean of 100, slight deviations are expected when aggregating to the monthly Simple EPU. For EPU and EPS the mean is expected to be slightly different than 100 as they include regional impact.

In the case of Norway, there are many similarities between the indices shown in Figure 8. They all start out at very high levels and follow a similar path up until 2009. However, during this period, the EPS index appears to be more volatile than the EPU and Simple EPU. Interestingly, from 2009 until now, there are considerable differences. For instance, there is an increasing trend in the Simple EPU from 2010 to 2019, which is not present in the EPS index. The EPS more clearly identifies major crisis such as the Russian crisis, Financial crisis of 2008 and European debt crisis.

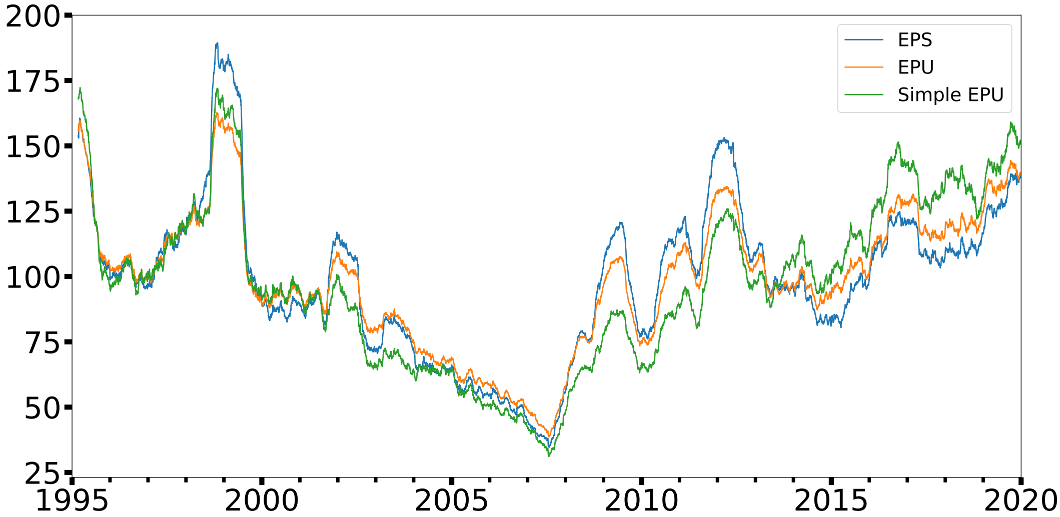


Figure 8: The Norwegian EPS, EPU and Simple EPU plotted together, 300-day backward looking rolling window.

Further, the Danish policy uncertainty indices are shown in Figure 9. Besides differences in volatility, some directional differences occur. During the decline following the European debt crisis, the EPS increase slightly around 2012:Q4 while similar movements are not evident in neither the EPU nor Simple EPU index. While no major historical events took place during this period, it is worth mentioning that in the last quarter of 2012, Denmark had a 0.16% decline in GDP following three quarters of close to zero net growth. Then, in the beginning of 2013 the economy regained speed with a 0.56% GDP growth in Q1 which coincides well with the development of the EPS index.[27] Further, in the period 2015:Q3-2016:Q3 the indices move in quite different directions. While the EPS and EPU move sideways the Simple EPU declines noticeably during the period. However, as we find no historical event taking place, it is hard to comment on which index we believe to be the most accurate during this one-year period.

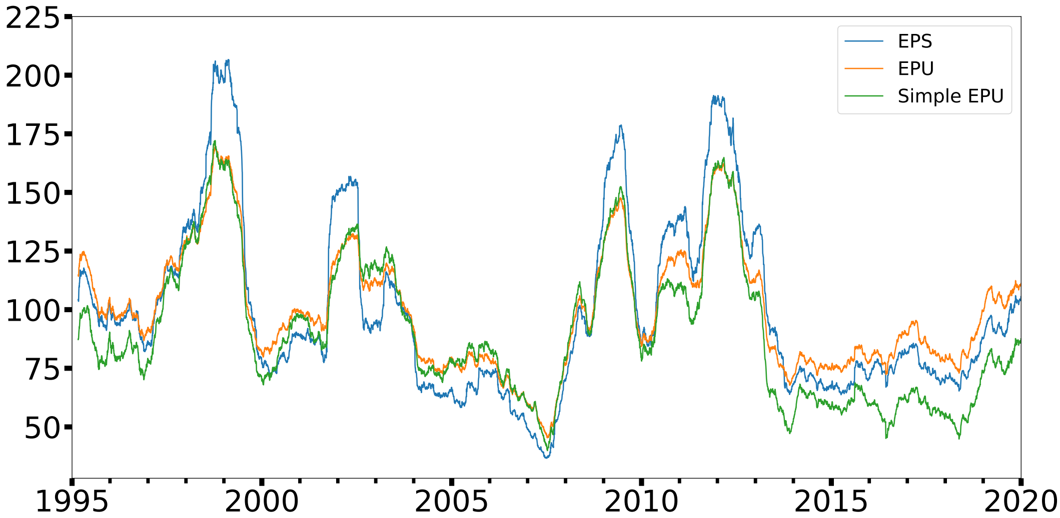


Figure 9: The Danish EPS, EPU and Simple EPU plotted together, 300-day backward looking rolling window.

The three indices for Sweden are shown in Figure 10. Already during the period 1997:Q2-1998:Q2 we see the indices moving in opposite directions. While the Simple EPU drops about 20 points, the EPS and EPU move sideways. Thus, the early warnings of the Russian crisis seem to be captured by the EPS and not the Simple EPU. Further, note the relative differences in the peaks of 2011:Q1 and 2012:Q1. In the EPS index, the 2012:Q1 peak lies about 10 points higher than the one in 2011:Q1, while for the Simple EPU 2011:Q1 peak is more than 20 points higher. This example demonstrates how adding information about regional impact and sentiment scores shift the relative importance of

[27] Denmark's quarterly GDP growth was -0.07%, 0.08%, 0.09% and -0.16% during 2012, before increasing 0.56% in Q1, 2013. Source: *statbank.dk* measuring GDP in Danish Krone, using the expenditure approach.

historical events with respect to policy uncertainty. As shown across all three countries, the EPS often exhibit clearer shifts during times of high policy uncertainty, making these spikes easier to identify.

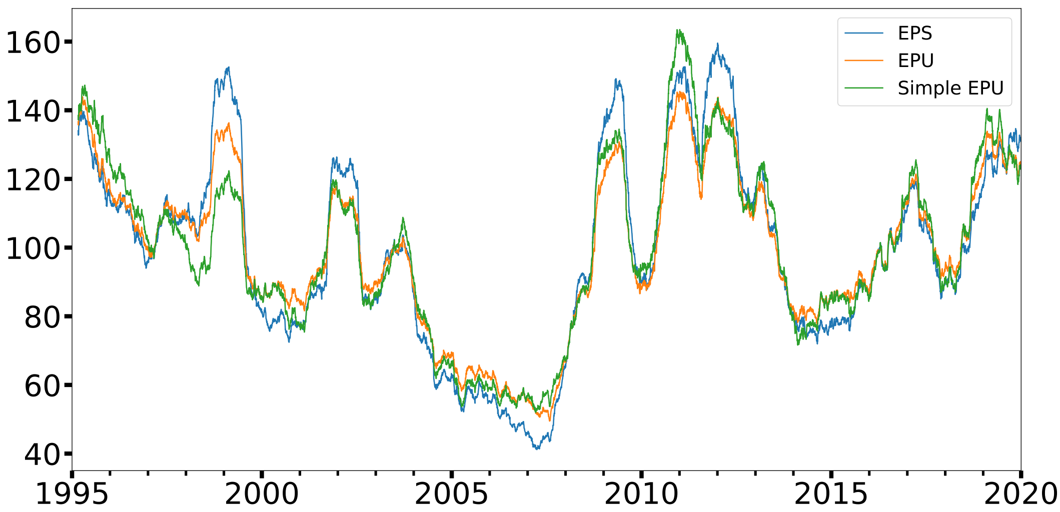


Figure 10: The Swedish EPS, EPU and Simple EPU plotted together, 300-day backward looking rolling window.

While Figure 8, 9 & 10 provide insight into how strongly the indices react to well known historical events, differences on a month-to-month basis are smoothed by the 300-day rolling window. Thus, we calculate the correlation of the monthly indices, shown in Table 7a, 7b & 7c for Norway, Denmark and Sweden, respectively. As expected, the indices are highly correlated as they are constructed to capture the same information, i.e. the level of economic policy uncertainty in a country. Comparing the EPS and Simple EPU we find correlation coefficients ranging from 0.88 to 0.91, indicating some differences between these indices. When trying to capture the same piece of information, these differences point in the direction of one index being more accurate than the others, or alternatively including different noise. This is addressed further in Section 4, through measuring the economic response to each index.

	Simple EPU	EPU	EPS
Simple EPU	1.00		
EPU	0.95	1.00	
EPS	0.88	0.96	1.00

(a) Norway

	Simple EPU	EPU	EPS
Simple EPU	1.00		
EPU	0.95	1.00	
EPS	0.91	0.94	1.00

(b) Denmark

	Simple EPU	EPU	EPS
Simple EPU	1.00		
EPU	0.96	1.00	
EPS	0.90	0.96	1.00

(c) Sweden

Table 7: Correlation matrix for the monthly EPS, EPU and Simple EPU for each country during the period 1994:09-2019:12.

4 The economic effect of policy uncertainty

This chapter presents the economic effect of the EPS, EPU and Simple EPU index for each of the Scandinavian countries. By doing so, we address whether the innovations included in the EPS index filter out noise and/or contributes with additional valuable information, and thus, results in a more distinct economic response. Our hypothesis is that for a noisy measure of policy uncertainty we will not be able to observe significant relationships between the index and the economy. In contrast, for an accurate policy uncertainty index, we should observe an economic response in line with financial theory.

4.1 Measuring economic response using VAR analysis

We aim to analyze the effect of policy uncertainty on the economy, and whether the economic response is similar across the Scandinavian countries. In line with Armelius et al. (2017), we run several bivariate vector autoregression models (VAR) to capture the effect of changes to the EPS index on economic indicators. Alternative models include Baker et al. (2016) using a multivariate VAR model to incorporate the effect of the US EPU index, the S&P 500 index, the federal funds rate and the employment rate on the US industrial production. While a multivariate model might be able to explain larger movements to the explained variable, it is less clear which portion of the response that comes directly from the policy uncertainty measure, versus indirect effects through the other explanatory variables. Hence, we find a bivariate model to be more appropriate.

When running a bivariate VAR model, as shown in (16) & (17), we let each variable depend on historical values of themselves, as well as historical values of the other variable included. To recover orthogonal shocks, we use a Cholesky decomposition, meaning that we order the variables and assume that each variable is unaffected by variables later in the ordering, within the same time period. As we are interested in measuring the effect of policy uncertainty on the economy, we put the policy uncertainty index first in the ordering. The VAR models are used to generate impulse response functions, indicating how the explained variable is affected by a standard deviation shock to the explanatory variables. Note that the nature of the impulse response function for a bivariate model is more volatile than for a model with more than two variables.

$$y_{1t} = c_1 + \sum_{i=1}^{p} \left(a_{1i} \cdot y_{1,t-i}\right) + \sum_{i=1}^{p} \left(a_{2i} \cdot y_{2,t-i}\right) + u_{1t} \tag{16}$$

$$y_{2t} = c_2 + \sum_{i=1}^{p} \left(a_{2i} \cdot y_{2,t-i}\right) + \sum_{i=1}^{p} \left(a_{1i} \cdot y_{1,t-i}\right) + u_{2t} \tag{17}$$

The number of lags to be included in a VAR model can be specified either manually by the user or calculated by an information criterion. Popular information criteria include the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Further, VAR models assume stationary variables which we assume both the EPS, EPU and Simple EPU are by construction, in line with Baker et al. (2016), Armelius et al. (2017) and Kleiven & Ifwarsson (2019).

Further, economic indicators such as the gross domestic product or the stock market are considered non-stationary as they are expected to increase over time due to inflation. Hence, we analyze the periodic change in these variables by taking log-difference which is approximately equal to the percentage change. In the following sections we analyze the effect of policy uncertainty shocks on the stock market, gross domestic product (GDP) and the Purchasing Managers' Index (PMI). The estimated coefficients of the bivariate VAR models can be found in Appendix E.

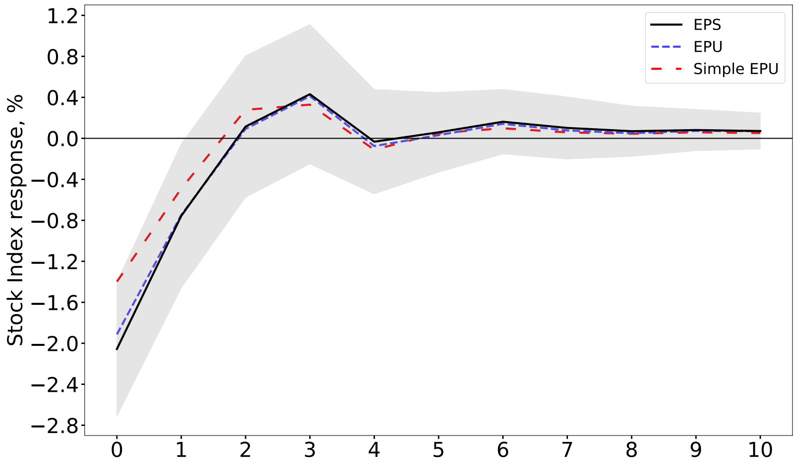
4.1.1 Effect on the stock market

In this section we measure the effect of shocks to the policy uncertainty indices on the stock markets. We use FTSE All Cap Total Return indices for Norway, Denmark and Sweden in local currencies. Further, VAR models are fitted to each policy uncertainty index and the log-difference of the corresponding stock market index for each country. The number of lags is set equal to 4 for all countries, based on the AIC.[28]

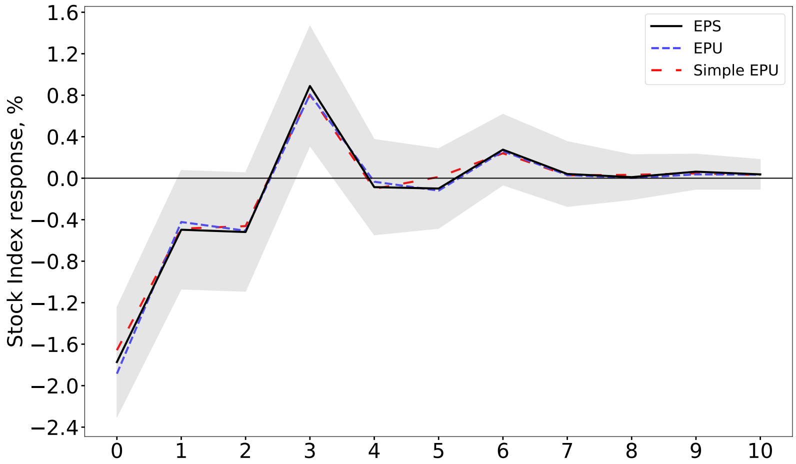
In line with Kleiven & Ifwarsson (2019), we expect the stock markets to decline as policy uncertainty rises. This is due to the real options effect as described in Dixit & Pindyck (1994) and Bernanke (1983), where increased uncertainty incentivizes deferral of irreversible investments. Repercussions of halted investments include reduced economic activity expected to depress the stock markets. Further, Veronesi (2015) shows through an empirical study that investors tend to overreact to negative news, causing the valuations to decline more than the fundamentals indicate. This effect points towards an upswing in stock markets once the policy uncertainty resolves.

Figure 11 shows how the stock markets respond to a standard deviation increase in the policy uncertainty indices. Across all countries, our results indicate that the stock markets decline sharply as policy uncertainty increases. Further, in the case of Norway and Sweden, we see a stronger response towards the EPS than to the Simple EPU index.

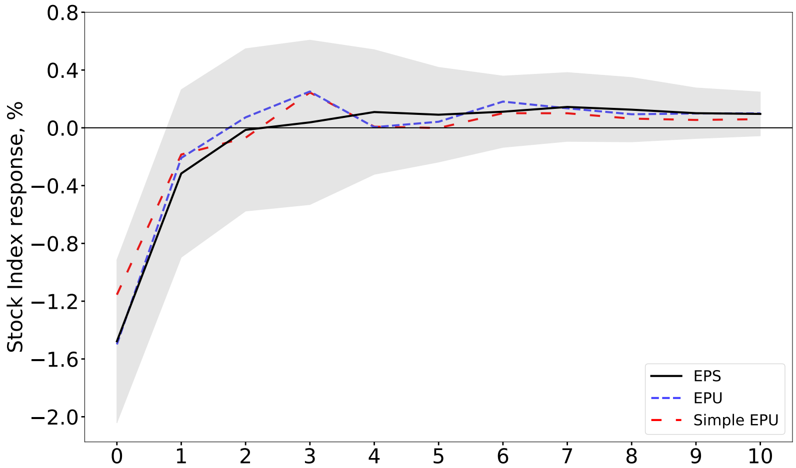
[28] AIC yields 3, 4 and 4 lags for Norway, Denmark and Sweden respectively.



(a) Norwegian EPS → Norwegian stock index



(b) Danish EPS → Danish stock index



(c) Swedish EPS → Swedish stock index

Figure 11: The impulse response functions show the effect of a one standard deviation shock in the EPS index, on the stock market index denoted in local currency. The graphs show the response in percentage points, per month following the shock. The time period analyzed is 2003:10-2019:10. The gray band indicate the 90% confidence interval for the EPS index.

4.1.2 Effect on the Gross Domestic Product

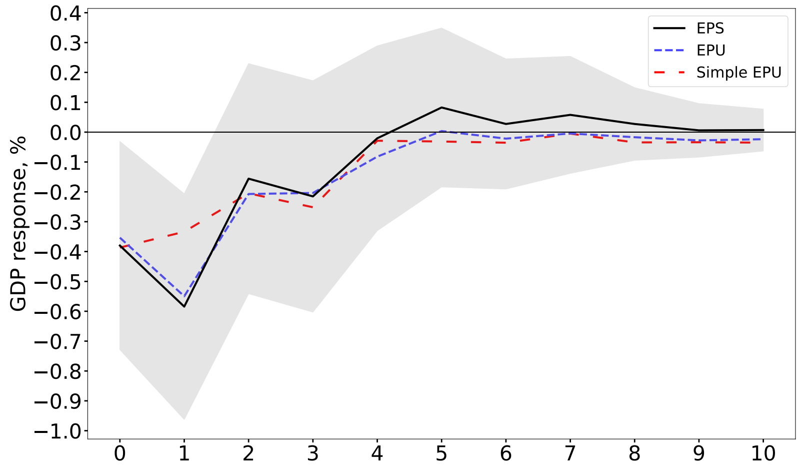
Next, we turn towards the gross domestic product (GDP) and measure the response to changes in policy uncertainty. As private domestic investments is a key component of GDP calculations[29], we expect that as investments are halted due to policy uncertainty[30], this negatively impacts the real GDP growth. However, GDP also consist of government spending which might increase to partially mitigate this effect, commonly known as counter-cyclical economic policy. We estimate bivariate VAR models including a policy uncertainty index and the percentage change in GDP for the associated country with 4 lags.[31]

Figure 12 shows the impulse response functions to a standard deviation increase in policy uncertainty. We find that the overall response to increased policy uncertainty is an instant decline in GDP, continuing for at least one quarter. Contrary to the stock markets, the response is highly similar in magnitude across all three policy uncertainty indices. Potential explanations include the fact that GDP is also largely impacted by government and consumer spending, which we have not yet discussed and might complicate the VAR analysis.

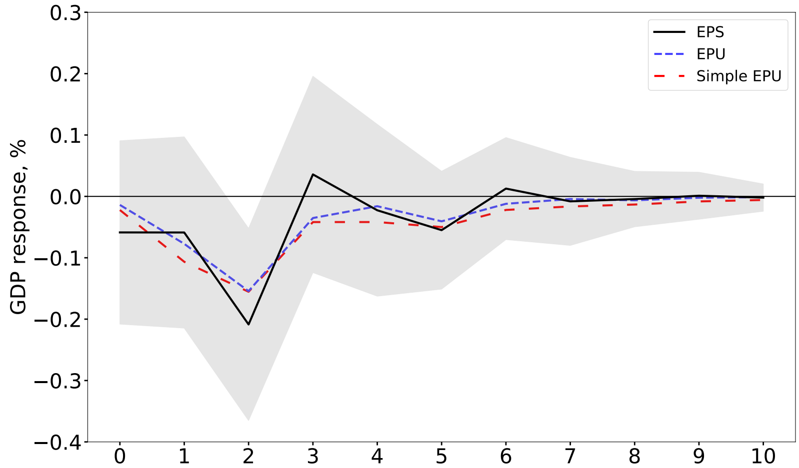
[29] The expenditure approach to calculating GDP consist of private consumption, government spending, private investments and net exports. Source: *https://www.investopedia.com/terms/g/gdp.asp*

[30] See Dixit & Pindyck (1994)

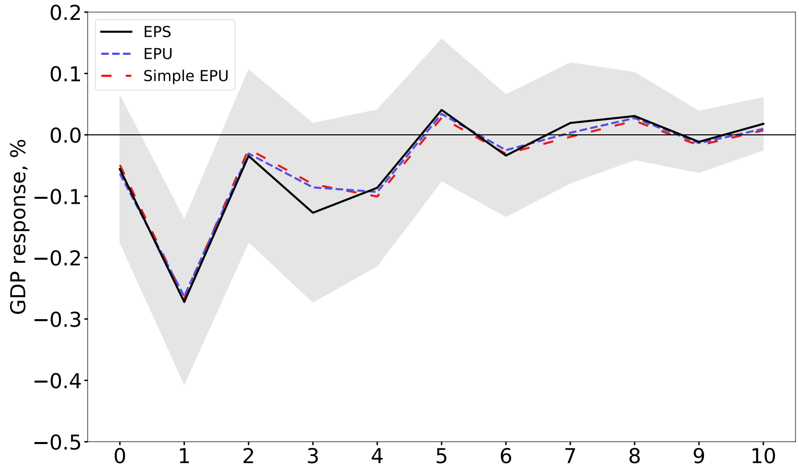
[31] AIC yields 4, 1 and 5 lags for Norway, Denmark and Sweden respectively.



(a) Norwegian EPS → Norwegian GDP



(b) Danish EPS → Danish GDP



(c) Swedish EPS → Swedish GDP

Figure 12: The impulse response functions show the effect of a one standard deviation shock in the EPS index, on the countries' GDPs. The graphs show the response in percentage points, per quarter following the shock. The time period analyzed is 1994:Q3-2019:Q2 for Norway, 1994:Q3-2019:Q2 for Denmark and 1994:Q3-2019:Q2 for Sweden. The gray band indicate the 90% confidence interval for the EPS index.

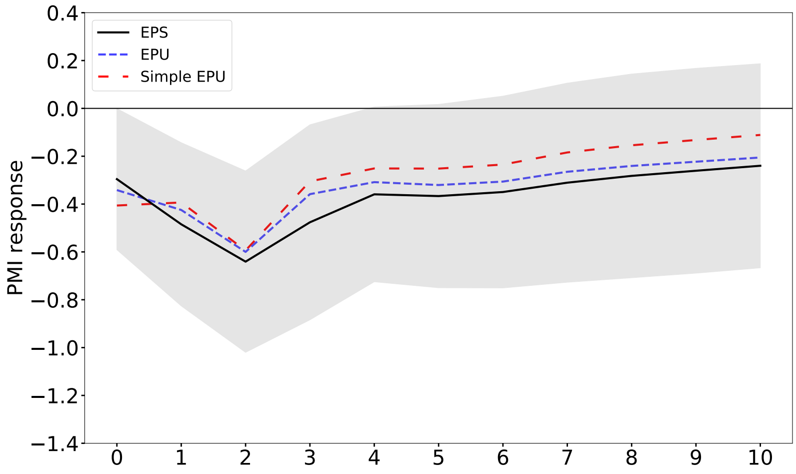
4.1.3 Effect on the Purchasing Managers' Index

Lastly, we analyze the effect of policy uncertainty on the purchasing managers' index (PMI). This is a survey-based index capturing the expectations of purchasing managers in each country on a monthly basis. Through a questionnaire, they report either improving (100), stable (50) or deteriorating (0) business outlooks. The resulting index is simply the average value in each sector, before weighting each sector by their contribution to GDP in order to create a nation-wide PMI index. Starting in the US, the original PMI was calculated by the Institute for Supply Management (2019), while the Norwegian, Danish and Swedish PMI are calculated by NIMA (2019), DILF (2019) and Swedbank (2019) respectively.

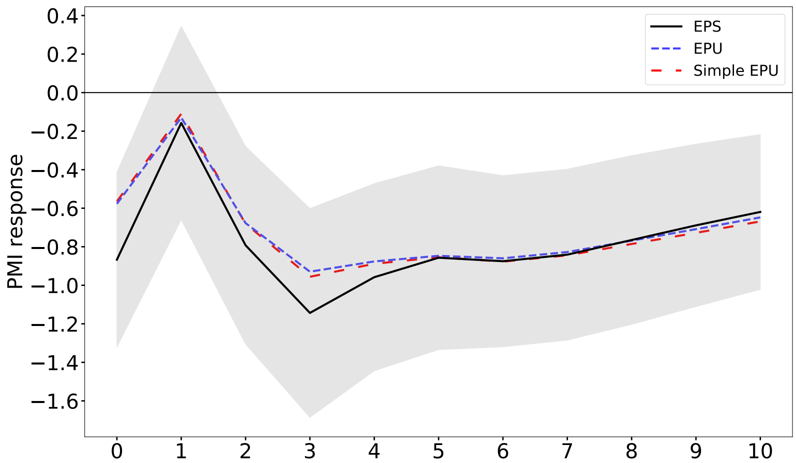
By construction the index ranges from 0 to 100, with 50 being a neutral score. Thus, the PMIs are stationary and can be applied directly in VAR analysis. We include a policy uncertainty index and the corresponding PMI index in a VAR model with 4 lags.[32]

In Figure 13 we find the response of PMI to changes in policy uncertainty. As expected, we find an instantaneous drop in PMI scores as policy uncertainty rise. This can be explained simply by irreversible investments being postponed, affecting not only the company itself but the entire supply chain. More interestingly, however is that an increase in policy uncertainty seem to depress PMI scores for at least 10 months ahead. In contrast, the response of the stock market only last for about 3 months ahead. Comparing the response towards the three policy uncertainty indices shows the potential of the EPS index. Across all three countries, the PMI responds more strongly to changes in the EPS than both the Simple EPU and EPU indices. These results indicate that by weighting news articles by their sentiment score, we are able to increase the accuracy in measuring policy uncertainty.

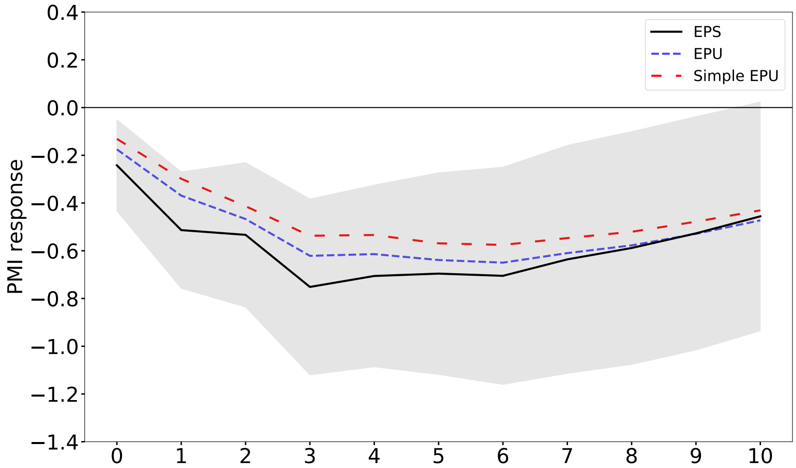
[32] AIC yields 3, 3 and 4 lags for Norway, Denmark and Sweden respectively.



(a) Norwegian EPS → Norwegian PMI



(b) Danish EPS → Danish PMI



(c) Swedish EPS → Swedish PMI

Figure 13: The impulse response functions show the effect of a one standard deviation shock in the EPS index, on the countries PMI. The graphs show the response in terms of PMI value, per month following the shock. The time period analyzed is 2004:02-2019:09 for Norway, 1994:09-2019:09 for Denmark, and 1994:11-2019:09 for Sweden. We use the Norwegian PMI of NIMA, Danish PMI of DILF and Swedish PMI of Swedbank. The gray band indicate the 90% confidence interval for the EPS index.

4.2 Predictive and explanatory power

The impulse response functions of Section 4.1 illustrate how various indicators react to changes in the policy uncertainty measures. However, this does not give a clear picture of the indices predictive power. First, we address the indices explanatory power by calculating the forecast error variance decomposition. Then, we perform out-of-sample forecasting to assess each index's predictive power using Artificial Neural Networks. In addition, an out-of-sample cross-validation analysis of the bivariate VAR models of Section 4.1 can be found in Appendix F.

4.2.1 Forecast Error Variance Decomposition

We calculate the FEVD to compare the explanatory power of the EPS, EPU and Simple EPU on the stock markets, GDP and PMI for the Scandinavian countries. From Table 8, 9 & 10 we see that the EPS in general outperforms the Simple EPU in terms of explanatory power, across all indices and all countries. For the stock markets, in Table 8, we find the EPS slightly better than the EPU for Norway and vice versa for Denmark and Sweden while both outperform the Simple EPU. These results indicate that including information from the wider region a country lies within is useful in explaining stock market movements. However, as seen in Table 9 & 10 only the EPS consistently outperforms the Simple EPU when looking at GDP and PMI. These results provide additional confidence in the EPS approach of measuring policy uncertainty.

	Norway			Denmark			Sweden		
Mo. ahead	**Simple EPU**	**EPU**	**EPS**	**Simple EPU**	**EPU**	**EPS**	**Simple EPU**	**EPU**	**EPS**
0	6.04	11.34	**13.11**	12.67	**16.48**	14.71	5.67	**9.60**	9.29
1	6.51	12.52	**14.27**	13.24	**16.65**	15.23	5.78	**9.73**	9.64
2	6.69	12.48	**14.22**	14.01	**17.55**	16.20	5.80	**9.75**	9.64
3	6.98	12.89	**14.66**	15.91	**19.21**	18.45	5.82	**9.61**	9.32
4	7.01	12.90	**14.65**	15.93	**19.19**	18.45	5.81	**9.59**	9.34

Table 8: Explanatory power of policy uncertainty on the stock markets when forecasting a fixed number of months ahead. Measured as the percentage of FEVD stemming from the policy uncertainty index as opposed to historical values of the stock market index, after orthogonalization of the impulse response.

	Norway			Denmark			Sweden		
Qr. ahead	**Simple EPU**	**EPU**	**EPS**	**Simple EPU**	**EPU**	**EPS**	**Simple EPU**	**EPU**	**EPS**
0	3.29	2.83	**3.29**	0.06	0.02	**0.43**	0.47	**0.77**	0.61
1	5.34	8.71	**9.87**	1.45	0.75	**0.87**	11.76	11.73	**12.38**
2	5.95	9.19	**9.97**	4.24	3.53	**5.95**	11.11	11.13	**11.89**
3	7.05	9.86	**10.70**	4.35	3.60	**5.97**	11.00	11.14	**12.90**
4	6.99	9.86	**10.61**	4.54	3.62	**6.02**	12.07	12.02	**13.62**

Table 9: Explanatory power of policy uncertainty on GDP when forecasting a fixed number of quarters ahead. Measured as the percentage of FEVD stemming from the policy uncertainty index as opposed to historical values of the GDP, after orthogonalization of the impulse response.

	Norway			Denmark			Sweden		
Mo. ahead	**Simple EPU**	**EPU**	**EPS**	**Simple EPU**	**EPU**	**EPS**	**Simple EPU**	**EPU**	**EPS**
0	**2.72**	1.93	1.46	1.38	1.44	**3.27**	0.42	0.75	**1.45**
1	4.05	3.77	**4.13**	1.21	1.27	**2.84**	1.62	2.55	**4.90**
2	6.76	6.60	**7.42**	2.74	2.77	**4.82**	2.72	3.79	**5.94**
3	6.83	6.99	**8.57**	5.27	5.12	**8.26**	3.75	5.13	**7.72**
4	6.58	6.96	**8.65**	7.11	6.89	**10.19**	4.56	6.16	**8.87**

Table 10: Explanatory power of policy uncertainty on PMI when forecasting a fixed number of months ahead. Measured as the percentage of FEVD stemming from the policy uncertainty index as opposed to historical values of the PMI, after orthogonalization of the impulse response.

4.2.2 Neural network prediction and cross-validation

While there is no exact blueprint of the optimal ANN specifications, the network structure should be designed according to the complexity of the relationships we are aiming to capture. As the network structure grows in terms of the number of hidden-layers and nodes per layer, an exponentially larger data set is needed for training. A larger network structure also increases the chance of overfitting if run until convergence. We try several network specifications, and report the network structure best suited for OOS prediction one period ahead on these data sets. Further, we chose the rectified linear unit function (ReLU) as the activation function for the hidden layer.[33] For the choice of optimizer we chose ADAM, which adjusts the learning rate dynamically.[34] The remaining parameters are believed to be uncontroversial and are summarized in Table 11.

Network structure (hidden-layer)	8-(4)-1
Epochs	Case specific
Learning rate	0.01 using ADAM
Cross-validation	Yes, 90/10 split between training and testing data
Number of runs	10
Hidden-layer activation function	ReLU
Output-layer activation function	Linear

Table 11: Overview of ANN parameters

We compare the policy uncertainty indices in terms of the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE), and the results are outlined in Table 12, 13 & 14.[35] We find that the EPS performs better than its peers in predicting the Swedish stock market index, the Norwegian PMI and the GDP of both Sweden and Denmark one period ahead. However, in the remaining cases, either the EPU or Simple EPU performs the best. Also note that in many cases, neither of the policy uncertainty indices perform substantially better than its peers. Thus, we have somewhat inconclusive evidence for OOS prediction of the economic response to policy uncertainty.

[33]The ReLU function returns the input value if positive, and zero otherwise. This is a popular activation function for neural networks that allows neurons to be turned off for certain input values, as opposed to a linear activation function.

[34]ADAM computes decaying learning rates, individually for each parameter depending on the moving average of the first and second momentum of the gradient. For a full explanation see Ba (2014).

[35]The RMSE penalize large deviations from the actual observations heavier than the MAE.

Stock market index

		RMSE		MAE	
Norway	Simple EPU	**5.449**	(0.075)	4.261	(0.090)
	EPU	5.459	(0.107)	**4.240**	(0.096)
	EPS	5.463	(0.107)	4.254	(0.107)
Denmark	Simple EPU	4.688	(0.046)	3.568	(0.058)
	EPU	**4.656**	(0.071)	**3.556**	(0.064)
	EPS	4.715	(0.059)	3.631	(0.055)
Sweden	Simple EPU	4.967	(0.067)	3.832	(0.048)
	EPU	4.968	(0.074)	3.840	(0.068)
	EPS	**4.897**	(0.067)	**3.818**	(0.073)

Table 12: OOS prediction for the log-difference of the stock market index per country. For each error measure, the mean is reported in the left column and standard deviation in parenthesis.

Gross Domestic Product

		RMSE		MAE	
Norway	Simple EPU	**2.123**	(0.078)	**1.707**	(0.068)
	EPU	2.140	(0.055)	1.714	(0.053)
	EPS	2.142	(0.086)	1.713	(0.069)
Denmark	Simple EPU	0.932	(0.035)	0.721	(0.034)
	EPU	0.964	(0.032)	0.750	(0.031)
	EPS	**0.928**	(0.023)	**0.719**	(0.024)
Sweden	Simple EPU	0.755	(0.019)	0.607	(0.010)
	EPU	0.768	(0.024)	0.615	(0.020)
	EPS	**0.736**	(0.024)	**0.594**	(0.019)

Table 13: OOS prediction for the percentage change in GDP per country. For each error measure, the mean is reported in the left column and standard deviation in parenthesis.

Purchasing Manager's Index

		RMSE		MAE	
Norway	Simple EPU	4.011	(0.556)	3.290	(0.491)
	EPU	4.690	(1.212)	3.870	(1.224)
	EPS	**3.733**	(0.533)	**2.924**	(0.374)
Denmark	Simple EPU	7.339	(1.290)	5.645	(1.294)
	EPU	**6.664**	(0.568)	**4.989**	(0.381)
	EPS	8.076	(1.580)	6.173	(1.440)
Sweden	Simple EPU	4.983	(1.848)	3.797	(1.845)
	EPU	**4.406**	(1.335)	**3.291**	(1.227)
	EPS	4.762	(1.937)	3.852	(1.972)

Table 14: OOS prediction for absolute change in the PMI per country. For each error measure, the mean is reported in the left column and standard deviation in parenthesis.

4.3 Predicting recessions

The results shown in Section 4.1.2 indicate that GDP reacts negatively to an increase in policy uncertainty. Hence, in this section, we aim to analyze whether policy uncertainty holds the ability to predict recessions.

In general, a recession is defined as a negative real GDP growth for two consecutive quarters, however, NBER's list of US recessions includes periods that would fall slightly outside this definition (NBER, 2010). NBER defines recessions as a significant decline in the economy, lasting for more than a few months and usually visible in not only real GDP, but also real income, employment and industrial production. To the best of our knowledge, no such list exists for the Scandinavian countries and thus we use the more stringent definition presented above. However, this results in few periods of recession.

We follow the approach of Karnizova & Li (2014) in estimating a probit model to predict recessions. Hence, we include stock market returns, the term spread and stock market volatility in the benchmark model.[36] Stock market returns are obtained from the FTSE All Cap Total Return index for each country, with data availability from 2003 until now. We calculate the term spread from government bond data, with varying availability of historical data.[37] Further, as no option-based volatility indices exist for the Scandinavian countries, with sufficient historical data, we calculate realized stock market volatility from the OBX, OMXC20 & OMXS30 stock indices for Norway, Denmark and Sweden respectively.[38]

Throughout this section we run both single factor, and multi-factor probit models to indicate whether the policy uncertainty indices hold relevant information when forecasting recession probabilities. For the single factor models we are interested in which variables

[36] Note that Karnizova & Li (2014) also include the corporate spread in their model. Due to data availability issues we do not include this variable in our model.

[37] 10-year and 3-month government bond yield are available from 2003 to 2020 for Norway and Sweden. In the case of Denmark, data is publicly available from 2003 to 2012. Source: *norges-bank.no; nationalbanken.statbank.dk; riksbank.se*

[38] Realized stock market volatility is measured as the quarterly standard deviation of percentage returns of each stock market index.

hold the most relevant information when predicting short-term (1-3 quarters ahead) and long-term (4-10 quarters ahead). Due to the fact that probit models are estimated using maximum likelihood, we report McFaddens' pseudo R^2, hereby denoted ρ^2, as opposed to standard R^2 commonly used in ordinary least-squares regression (McFadden, 1973). Further, we run a t-test on the importance of including policy uncertainty in the multi-factor probit models. The t-test holds the policy uncertainty coefficients equal to zero as the null-hypothesis, and we report P-values from these tests. A high P-value indicate that policy uncertainty does not significantly improve the multi-factor probit models, and vice versa.

We start by running the probit model for Norway during the period 2003:Q4 to 2017:Q3, where the period under consideration is limited due to data availability. During this period, Norway experienced 3 recessions.[39] In Table 15 we find, in contrast to Karnizova & Li (2014) findings for the US, that the policy uncertainty indices seem to hold the most information when predicting one quarter ahead. Note especially the single-factor model including the EPS index with $\rho^2 = 0.206$ for one quarter ahead predictions, which in the words of McFadden (1973) indicates an excellent fit.[40]

Following the findings of Wright (2006) we would also expect the term spread to contain valuable information, however, this does not seem to be the case in our setting. Further, Table 16 shows how policy uncertainty indices are able to improve a multi-factor probit model already including the term spread and equity returns. Both when predicting recessions 1-3 quarters ahead and 8-10 quarters ahead our results indicate that including policy uncertainty drastically improves the model. These results are further verified by Table 17, with P-values ranging from 0.072 to 0.324 for the Norwegian EPS when predicting 1-2 quarters ahead, and from 0.094 to 0.422 when predicting 8-10 quarters ahead.

[39]Norwegian recessions: 2009, 2010 & 2016. Source: *Statistics Norway, accessed through Refinitiv*

[40]Note that the values of ρ^2 are not directly comparable to those of the standard R^2. In the words of McFadden (1977) p.35: "values of of 0.2 to 0.4 represent an excellent fit".

	1	2	3	4	5	6	7	8	9	10
Simple EPU	0.111	0.069	0.001	0.010	0.000	0.002	0.014	0.051	0.066	0.026
EPU	0.169	0.120	0.001	0.004	0.000	0.001	0.043	0.035	0.104	0.033
EPS	0.206	0.145	0.000	0.008	0.001	0.000	0.032	0.056	0.126	0.030
Term spread	0.001	0.011	0.024	0.008	0.016	0.057	0.125	0.138	0.099	0.068
Stock market returns	0.043	0.174	0.053	0.003	0.001	0.000	0.239	0.113	0.028	0.004
Stock market volatility	0.003	0.063	0.042	0.132	0.090	0.024	0.061	0.000	0.032	0.000

Table 15: ρ^2 for Norway, using a single factor probit model to predict recessions 1-10 quarters ahead.

	1	2	3	4	5	6	7	8	9	10
Simple EPU	0.225	**0.304**	0.058	**0.026**	0.020	**0.079**	0.243	0.254	0.234	0.094
EPU	0.255	0.282	**0.067**	0.022	0.020	0.078	0.244	0.296	0.265	**0.111**
EPS	**0.266**	0.276	0.062	0.024	**0.020**	0.076	**0.248**	**0.351**	**0.293**	0.110
Benchmark	0.073	0.234	0.053	0.020	0.020	0.075	0.243	0.158	0.214	0.076

Table 16: ρ^2 for Norway, using a multi-factor probit model already including the term spread and equity returns to predict recessions 1-10 quarters ahead.

	1	2	3	4	5	6	7	8	9	10
Simple EPU	0.126	0.238	0.746	0.716	0.936	0.741	0.982	0.188	0.524	0.544
EPU	0.096	0.308	0.577	0.851	0.970	0.796	0.906	0.122	0.327	0.403
EPS	0.072	0.324	0.654	0.755	0.917	0.845	0.737	0.094	0.246	0.422

Table 17: P-values from a t-test on the significance of policy uncertainty coefficients for the Norwegian multi-factor probit models. The t-test holds the coefficients equal to zero as the null hypothesis. A P-value of 1.000 indicates full support to the null hypothesis and vice versa. NaN values indicate perfect multicollinearity.

Next, we run the probit model for Denmark during the period 2003:Q4 to 2012:Q4, limited due to data availability. In this period, Denmark experienced 6 quarters in recession.[41] For the single factor model shown in Table 18, we find that both the term spread and stock market returns are good models in the short-term while the policy uncertainty indices are more informative when predicting 7-10 quarters ahead. These results differ substantially

[41] Danish recessions (# of quarters): 2006 (1) & 2008 (5). Source: *Statistics Denmark, accessed through Refinitiv*

from those presented for Norway, where neither the stock market returns nor the term spread seem to hold any predictive power for future recessions. Turning to the multi-factor model shown in Table 19, our results are as expected based on the single-factor models. Although policy uncertainty indices do not improve the benchmark substantially in the short-term, they offer considerable improvements when predicting 7-10 quarters ahead, also verified by Table 20, where we find P-values ranging from 0.033 to 0.196. Note that the EPS almost consistently outperforms the alternative indices.

	1	2	3	4	5	6	7	8	9	10
Simple EPU	0.044	0.028	0.002	0.032	0.047	0.102	0.294	0.438	0.431	0.270
EPU	0.036	0.021	0.006	0.055	0.080	0.155	0.397	0.484	0.480	0.315
EPS	0.036	0.008	0.014	0.077	0.103	0.158	0.372	0.650	0.452	0.359
Term spread	0.511	0.531	0.419	0.323	0.282	0.219	0.129	0.059	0.023	0.006
Stock market returns	0.304	0.455	0.112	0.025	0.008	0.007	0.046	0.009	0.014	0.019
Stock market volatility	0.001	0.000	0.030	0.030	0.035	0.045	0.039	0.058	0.054	0.045

Table 18: ρ^2 for Denmark, using a single factor probit model to predict recessions 1-10 quarters ahead.

	1	2	3	4	5	6	7	8	9	10
Simple EPU	0.545	NaN	0.464	0.426	0.411	0.482	0.546	0.465	0.436	0.271
EPU	0.545	NaN	0.467	0.438	0.424	0.493	0.609	0.517	**0.490**	0.317
EPS	**0.546**	NaN	**0.489**	**0.465**	**0.445**	**0.503**	**0.658**	**0.753**	0.460	**0.359**
Benchmark	0.545	0.682	0.437	0.409	0.398	0.474	0.403	0.117	0.068	0.044

Table 19: ρ^2 for Denmark, using a multi-factor probit model already including the term spread and equity returns to predict recessions 1-10 quarters ahead. NaN values indicate perfect multicollinearity.

	1	2	3	4	5	6	7	8	9	10
Simple EPU	0.912	NaN	0.387	0.485	0.533	0.625	0.076	0.022	0.018	0.036
EPU	0.940	NaN	0.377	0.386	0.400	0.468	0.046	0.026	0.024	0.027
EPS	0.884	NaN	0.243	0.244	0.277	0.389	0.043	0.196	0.031	0.033

Table 20: P-values from a t-test on the significance of policy uncertainty coefficients for the Danish multi-factor probit models. The t-test holds the coefficients equal to zero as the null hypothesis. A P-value of 1.000 indicates full support to the null hypothesis and vice versa. NaN values indicate perfect multicollinearity.

Finally, we run the probit model for Sweden during the period 2003:Q4 to 2017:Q3, limited by data availability. Sweden experienced 3 quarters in recession during this period.[42] The results presented in Table 21 are in contrast to those of both Table 15 for Norway and Table 18 for Denmark. In the case of Sweden, the term spread, stock market returns and policy uncertainty indices are a good fit for one quarter ahead prediction. However, predicting three quarters ahead, or more, the policy uncertainty indices holds little information. When combining several variables in the multi-factor probit models of Table 22 we find some additional improvement of adding a policy uncertainty index both short- and long-term. From Table 23 it seems like policy uncertainty holds less predictive value in the case of Sweden than the other Scandinavian countries. However, predicting only one quarter ahead we find a P-value of 0.242 indicating a 75.8% probability of the index improving the benchmark model.[43]

	1	2	3	4	5	6	7	8	9	10
Simple EPU	0.197	0.050	0.000	0.002	0.038	0.044	0.035	0.005	0.008	0.001
EPU	0.200	0.039	0.000	0.020	0.054	0.059	0.060	0.028	0.000	0.001
EPS	0.211	0.049	0.001	0.019	0.081	0.032	0.038	0.036	0.003	0.006
Term spread	0.452	0.577	0.505	0.408	0.168	0.043	0.020	0.015	0.001	0.060
Stock market returns	0.173	0.291	0.084	0.082	0.363	0.018	0.001	0.099	0.140	0.023
Stock market volatility	0.000	0.062	0.063	0.000	0.029	0.062	0.262	0.104	0.016	0.002

Table 21: ρ^2 for Sweden, using a single factor probit model to predict recessions 1-10 quarters ahead.

	1	2	3	4	5	6	7	8	9	10
Simple EPU	**0.633**	0.589	NaN	**0.446**	**0.400**	0.138	0.062	0.185	**0.197**	0.178
EPU	0.576	0.590	0.664	0.414	0.390	**0.159**	**0.086**	0.187	0.170	0.180
EPS	0.558	**0.593**	**0.665**	0.417	0.382	0.122	0.064	**0.188**	0.162	**0.202**
Benchmark	0.456	0.589	0.525	0.413	0.368	0.044	0.031	0.183	0.157	0.147

Table 22: ρ^2 for Sweden, using a multi-factor probit model already including the term spread and equity returns to predict recessions 1-10 quarters ahead. NaN values indicate perfect multicollinearity.

[42] Swedish recessions (# of quarters): 2008 (2) & 2013 (1). Source: *Statistics Sweden, accessed through Refinitiv*

[43] A P-value of 0.242 indicates a 24.2% probability of the policy uncertainty index not improving the benchmark model.

	1	2	3	4	5	6	7	8	9	10
Simple EPU	0.212	0.957	NaN	0.449	0.406	0.215	0.436	0.832	0.352	0.441
EPU	0.211	0.883	0.303	0.907	0.487	0.178	0.306	0.769	0.586	0.420
EPS	0.242	0.765	0.283	0.759	0.577	0.248	0.412	0.723	0.741	0.311

Table 23: P-values from a t-test on the significance of policy uncertainty coefficients for the Swedish multi-factor probit models. The t-test holds the coefficients equal to zero as the null hypothesis. A P-value of 1.000 indicates full support to the null hypothesis and vice versa. NaN values indicate perfect multicollinearity.

5 Conclusions and further research

We present the Economic Policy Sentiment index (EPS) as a measure of economic policy uncertainty. Although the methodology can be applied worldwide, we exploit our domain knowledge and focus on the Scandinavian countries; Norway, Denmark and Sweden. Our EPS index extends the existing framework for measuring economic policy uncertainty, introduced by Baker et al. (2016), through two novel innovations. Firstly, we include information from the wider region a country lies within, which is especially relevant in the case of small, open economies. More specifically, to measure economic policy uncertainty we analyze newspaper articles and obtain the frequency of news relevant for this topic. In contrast to the existing methodology, we also include newspapers from neighboring countries. Secondly, we utilize advanced sentiment analysis techniques to capture the tone of writing, and weight the importance of each article accordingly. Thus, articles describing intensified policy uncertainty will be given a higher weight than articles describing decreasing policy uncertainty.

We compare the EPS index to alternative policy uncertainty indices including only one, or none of our two innovations. We are interested in measuring the economic response to changes in the policy uncertainty indices, and utilize a series of bivariate VAR models to do so. Our results indicate that the stock markets, both in Norway and Sweden react stronger to the EPS index than the existing alternatives. Similarly, the Purchasing Manager's Index (PMI) responds more strongly to changes in the EPS, consistently across all three countries. Furthermore, we calculate and compare the Forecast Error Variance Decomposition (FEVD) of the bivariate VAR models, and find that the EPS holds a higher explanatory power for the GDP, PMI and partially for the stock markets, than the alternative policy uncertainty indices. These results provide confidence that the innovations included in the EPS index increase its accuracy for measuring economic policy uncertainty. Further, we incorporate policy uncertainty in a probit model for predicting future recessions. We find the importance of policy uncertainty relative to other economic variables to vary substantially across the Scandinavian countries. However, including the EPS index consistently improves the prediction models for future recessions illustrating the importance of an accurate policy uncertainty measure.

Extensions to this paper may include implementing the EPS index for other countries and regions. Alternatively, the effect of political slant to the index has not been subject to research in this paper, but could be an interesting topic to address for newspaper based indices worldwide. Finally, we propose including the EPS index in wider economic prediction models to improve forecasts and shed light on the importance of policy uncertainty.

A Translated EPU search words

In line with Kleiven & Ifwarsson (2019), we translate the search words of Baker et al. (2016) to the three Scandinavian languages. We apply the official academic dictionary for each country and verify these translations by consulting native speakers. Further, we include the country-specific names on parliament, government and central banks, aiming to further improve the accuracy. An overview of the search words is found in Table 24, 25 & 26 for Norway, Denmark and Sweden, respectively.

Word type	Root of keyword	Full list of keywords
Economic	Økonomi	økonomi, økonomien, økonomier, økonomiene
	Økonomisk	økonomisk, økonomiske
Policy	Norges Bank	Norges Bank
	Sentralbank	sentralbank, sentralbanken, sentralbanker, sentralbankene
	Regjering	regjering, regjeringen, regjeringer, regjeringene
	Departement	departement, departementet, departementene
	Regulering	regulering, reguleringen, reguleringer, reguleringene
	Minister	minister, ministeren, ministere, ministerene
	Direktiv	direktiv, direktivet, direktivene
	Storting	storting, stortinget, stortingene
Uncertainty	Usikker	usikker, usikkert, usikre
	Usikkerhet	usikkerhet, usikkerheten, usikkerheter, usikkerhetene
	Uro	uro, uroen, uroer

Table 24: Norwegian policy uncertainty keywords. Source: Den Norske Akademis Ordbok.

Word type	**Root of keyword**	**Full list of keywords**
Economic	Økonomi	økonomi, økonomien, økonomier, økonomierne
	Økonomisk	økonomisk, økonomiske
Policy	Nationalbank	nationalbank, nationalbanken, nationalbanker, nationalbankerne
	Centralbank	centralbank, centralbanken, centralbanker, centralbankerne
	Regering	regering, regeringen, regeringer, regeringerne
	Departement	departement, departementet, departementerne
	Regulering	regulering, reguleringen, reguleringer, reguleringerne
	Minister	minister, ministeren, ministre, ministrene
	Direktiv	direktiv, direktivet, direktiver, direktiverne
	Folketing	folketing, folketinget, folketingene
Uncertainty	Usikker	usiker, usikkert, usikre, usikrere, usikrest
	Usikkerhed	usikkerhed, usikkerheden, usikkerheder, usikkerhederne
	Uro	uro, uroen, uroer, uroene

Table 25: Danish policy uncertainty keywords. Source: Den Danske Ordbog.

Word type	**Root of keyword**	**Full list of keywords**
Economic	Ekonomi	ekonomi, ekonomin, ekonomier
	Ekonomisk	ekonomisk, ekonomiskt, ekonomiska
Policy	Riksbank	riksbank, riksbanken, riksbanker
	Centralbank	centralbank, centralbanken, centralbanker
	Regering	regering, regeringen, regeringar
	Departement	departement, departementet, departementen
	Reglering	reglering, regleringen, regleringar
	Minister	minister, ministern, ministrar
	Direktiv	direktiv, direktivet
	Riksdag	riksdag, riksdagen, riksdan, riksdagar
Uncertainty	Osäker	osäker, osäkert
	Osäkerhet	osäkerhet, osäkerheter, osäkerheten
	Oro	oro, oron

Table 26: Swedish policy uncertainty keywords. Source: Svenska Akademiens Ordböcker.

B Understanding Vader

To understand how the sentiment analysis engine Vader by Hutto & Gilbert (2015) works, a brief introduction to sentiment analysis is appropriate.

For the purpose of sentiment analysis, the starting point for any model is the underlying lexicon. The lexicon labels words according to their emotions, i.e. positive and negative words. Popular lexicons include the General Inquirer (GI)[44], Hu-Liu04[45], and Linguistic Inquiry and Word Count (LIWC)[46], which categorize words as positive (+1), neutral (0) and negative (-1). These lexicons are widely used, and contain about 11,000, 6.800 and 4,500 words respectively (Hutto & Gilbert, 2015). While these are a good starting point, neither are able to account for the intensity of a positive or negative word. For instance, "*excellent*" is considered a more intense word than "*okay*". Similarly, "terrible" is a more intense word than "*mediocre*". The Affective Norms for English Words (ANEW)[47] library account for valence, i.e. the intensity of the positive and negative words. ANEW use a scoring regime of 1-9 with a score of 5 indicating neutrality, and the lexicon holds about 1,000 words (Hutto & Gilbert, 2015).

Vader was initially created to analyze sentiment in social media, and hence Hutto & Gilbert (2015) created their own lexicon based on GI, LIWC and ANEW. In addition, common slang, abbreviations and western emoticons were added to the lexicon. Using Amazon Mechanical Turk[48] they obtain a total of ten human classifications per word, in total 90,000 classifications for their lexicon. The scoring regime ranges from extremely negative (-4) to extremely positive (+4) with neutrality (0) as an option, hence 9 possible classifications. Words holding a non-zero mean and standard deviation less than 2.5 are

[44] *http://www.wjh.harvard.edu/ inquirer/*
[45] *https://www.cs.uic.edu/ liub/FBS/sentiment-analysis.html*
[46] *http://liwc.wpengine.com/*
[47] See Bradley & Lang (1999) for instruction manual and complete list of words
[48] Amazon Mechanical Turk is a platform to outsource manual labor, such as the labelling of words in a lexicon. See *https://www.mturk.com/ for more information.*

included in the final lexicon. Note that the Vader sentiment engine returns an overall score of entire sentences scaled to a [-1, 1] scoring regime.

Once a lexicon is in place, the simplest bag-of-words methods return the average score of all non-zero words scaled to a scoring regime ranging from -1 to 1. There are several drawbacks to this method, most prominently the case of negation and intensity adjustments, as illustrated by the examples in Table 27 & 28.

Statement	Sentiment (-4 to 4)	Bag-of-words (-1 to 1)	Vader (-1 to 1)	Reality
The food was not bad	[0.0, 0.0, 0.0, 0.0, -2.5]	Negative **-0.63**	Positive **0.43**	Positive
The book was neither interesting enlightening nor well written	[0.0, 0.0, 0.0, 0.0, 1.7] [2.3, 0.0, 1.1, 0.0]	Positive **0.43**	Negative **-0.70**	Negative

Table 27: Examples of statements containing intensifying words. The sentiment column shows the value of each word as expressed in the Vader lexicon. The bag-of-words classification is based on the average score of the sentiment column, scaled to a -1 to 1 scoring regime. Reality is the authors subjective opinion, however believed to be uncontroversial.

Statement	Sentiment (-4 to 4)	Bag-of-words (-1 to 1)	Vader (-1 to 1)	Reality
This paper is somewhat well written	[0.0, 0.0, 0.0, 0.0, 1.1, 0.0]	Positive **0.28**	Positive **0.20**	Positive +
This paper is well written	[0.0, 0.0, 0.0, 1.1, 0.0]	Positive **0.28**	Positive **0.27**	Positive ++
This paper is very well written	[0.0, 0.0, 0.0, 0.0, 1.1, 0.0]	Positive **0.28**	Positive **0.33**	Positive +++

Table 28: Examples of statements containing intensifying words. The sentiment column shows the value of each word as expressed in the Vader lexicon. The bag-of-words classification is based on the average score of the sentiment column, scaled to a -1 to 1 scoring regime. Reality is the authors subjective opinion where the number of plus-signs indicate the degree of positiveness in the statements.

As seen in Table 27, Vader is able to handle negation through some of its heuristics. If a word is signaling negation, the sign of each word is flipped, and the intensity adjusted. From Table 28 we also see Vader being able to handle intensifying words in both directions, scaling up or down the sentiment score of the associated words. These heuristics goes a long way in distancing Vader from simple bag-of-words methods.

C Alternative measures of uncertainty

In this section, we compare the EPS index to measures of interrelated types of uncertainty, such as the US EPU of Baker et al. (2016) and the VIX index by CBOE. Further, Jurado et al. (2015) and Caldara & Iacoviello (2018) introduce global measures of macroeconomic, financial and geopolitical risk. Details on how the various types of uncertainty are interrelated are further described in Kleiven & Ifwarsson (2019).

Table 29 shows the correlation between the EPS indices and the alternative measures of uncertainty. First, we find a very low correlation between the EPS and both geopolitical and macroeconomic risk. This is somewhat expected as these indices measure different types of uncertainty, and secondly that the geopolitical and macroeconomic measures are global indices, while the EPS indices are country-specific. Further, note that the correlation between the EPS and both the financial uncertainty index of Jurado et al. (2015) and the VIX, are substantially higher than for macroeconomic uncertainty. Possible explanations include that the global financial markets might be more tightly coupled than the general economies. Hence, there is a higher spillover effect of financial uncertainty than general economic uncertainty.

Comparing the EPS indices towards the US EPU we find some similarities as policy uncertainty rise around key global events. However, correlation coefficients ranging from 0.47 to 0.61 also indicate clear differences between economic policy uncertainty in the US and in the Scandinavian countries. Thus, we conclude that the country-specific EPS indices indeed capture new information, not already available in existing uncertainty measures.

	US EPU	VIX	GPR	Macro	Financial
Norway EPS	0.51	0.35	0.04	-0.08	0.27
Sweden EPS	0.61	0.45	0.07	0.09	0.37
Denmark EPS	0.47	0.58	0.04	0.21	0.43

Table 29: Correlation coefficients between EPS indices and alternative uncertainty measures. We use the US EPU of Baker et al. (2016), VIX index of CBOE, GPR index of Caldara & Iacoviello (2018) as well as the Macroeconomic and Financial uncertainty indices of Jurado et al. (2015), for the period 1994:09-2019:12. Source: *policyuncertainty.com, CBOE.com, matteoiacoviello.com, www.sydneyludvigson.com.*

D Introducing the Simple EPS index

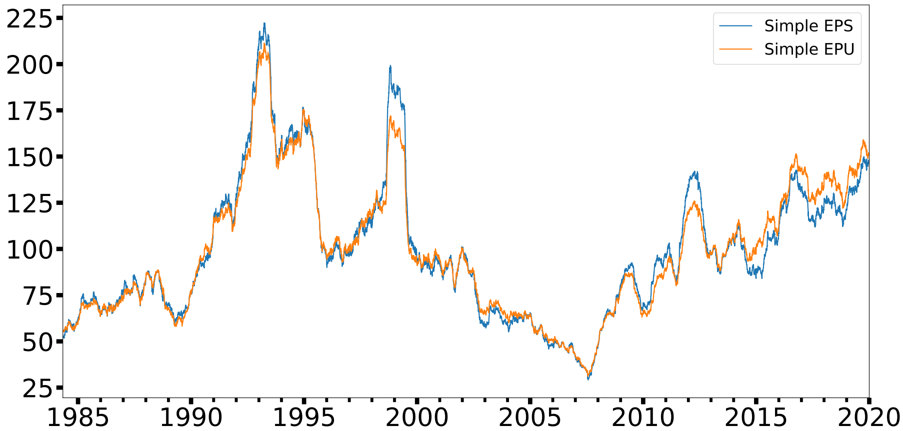
In this appendix we analyze whether incorporating sentiment analysis in the Simple EPU framework is a significant improvement. Our hypothesis is that articles regarding policy uncertainty might be addressing increasing, declining or the absence of policy uncertainty and should be weighted accordingly. In contrast, the Simple EPU weights each article equally if relevant to policy uncertainty.

D.1 Creating the index

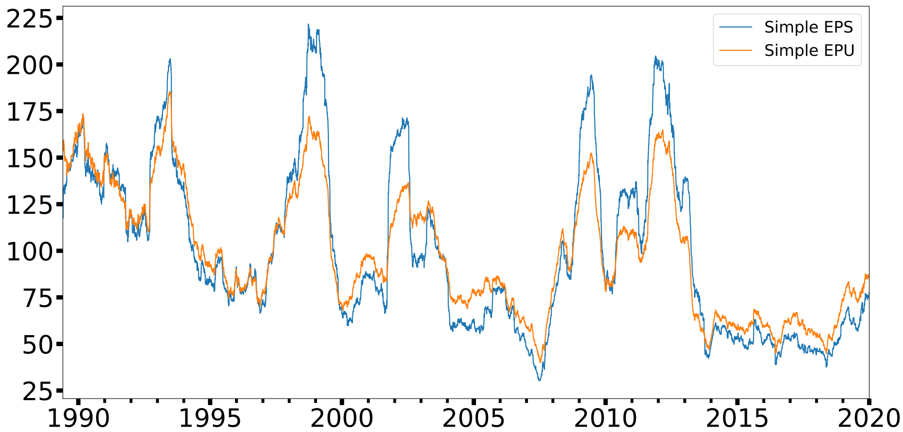
To create the Simple EPS we follow the methodology presented in Section 2.4, and set the parameter $\lambda = 1$. Thus, we focus only on information from the country itself, and no component from the overall region the country lies within. We modify (9) as shown in (18).

$$EPS_{ct} = w_{ct} \tag{18}$$

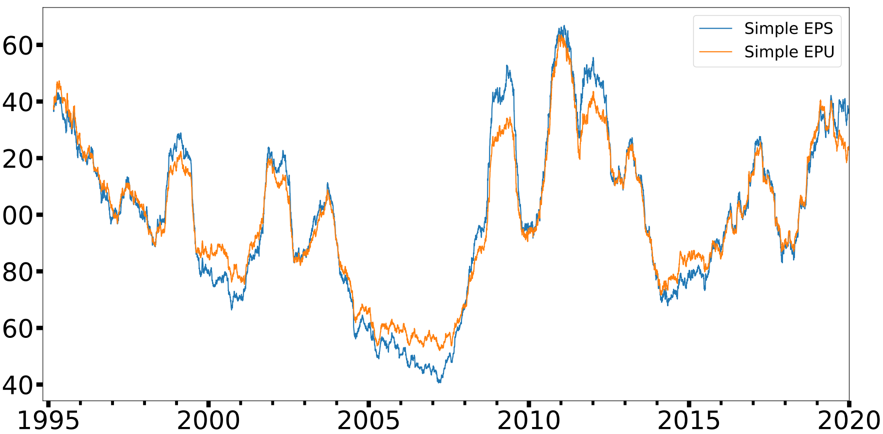
Figure 14 shows the resulting indices for Norway, Denmark and Sweden using 300-day rolling backward-looking window to reduce month-to-month fluctuations. As seen in Figure 14 the indices are highly similar, though the sentiment-weighted Simple EPU, hereby denoted the Simple EPS, seem to be more volatile.



(a) Norwegian Simple EPS and Simple EPU



(b) Danish Simple EPS and Simple EPU



(c) Swedish Simple EPS and Simple EPU

Figure 14: Comparing the Simple EPS and Simple EPU indices for the Scandinavian countries using a 300-day backward looking rolling window.

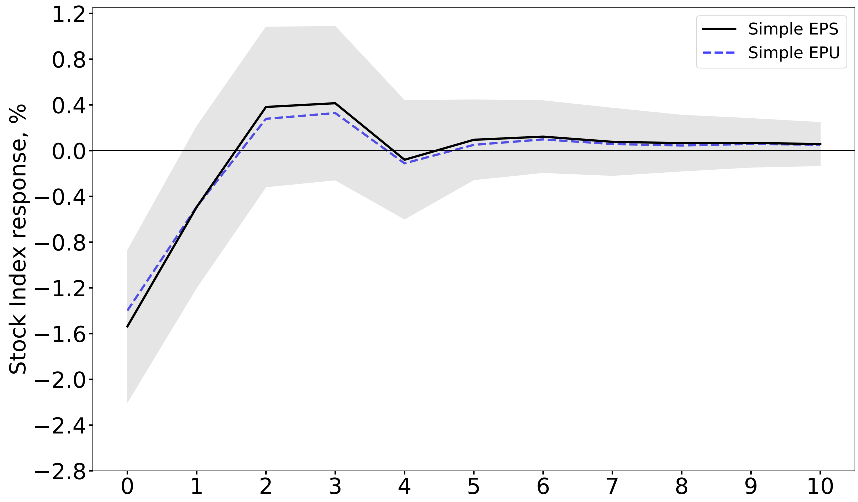
D.2 Bivariate VAR

Once the indices are created, we run multiple bivariate VAR models to analyze the effect of the sentiment-weighted and plain policy uncertainty indices. We estimate the regressions of Section 4.1 using the Simple EPS and Simple EPU as measures of policy uncertainty, on the stock market, GDP and PMI for each country.

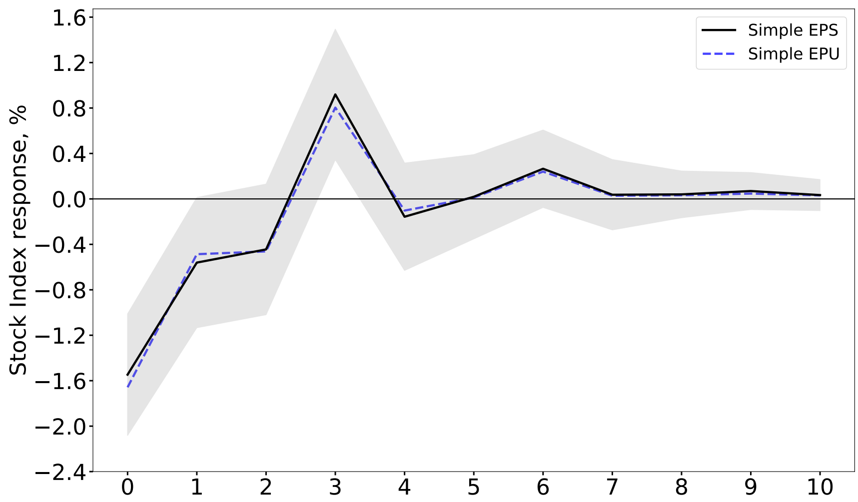
Figure 15 shows the resulting impulse response functions for the stock market. The stock market reacts stronger to the Norwegian Simple EPS than to the Simple EPU, while we find opposite results for both Denmark and Sweden.

Further, Figure 16 shows the impulse response functions for each nations' GDP. For Norway, we find that the GDP reacts slightly stronger to the Simple EPS than to the Simple EPU. However, both for Sweden and Denmark the results are close to identical.

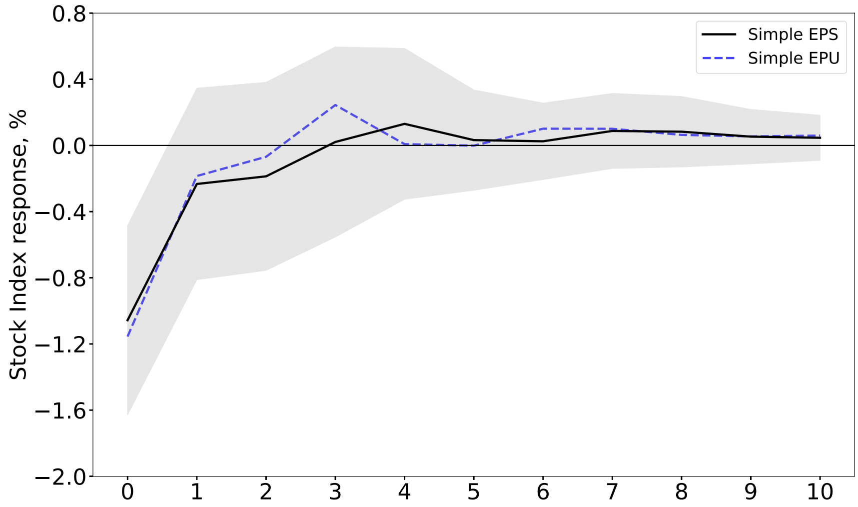
Lastly, Figure 17 shows the impulse response functions for the PMI indices. Note that the PMI responds more strongly to the Simple EPS than towards the Simple EPU, looking 0-4 months ahead, with the sole exception of the instant response in Norway. We find the most distinct difference in the case of Denmark with an instantaneous response of -0.9 to the Simple EPS, while only a -0.6 response to the Simple EPU, as shown in Figure 17b.



(a) Norwegian Simple EPS and Simple EPU on the Norwegian stock index

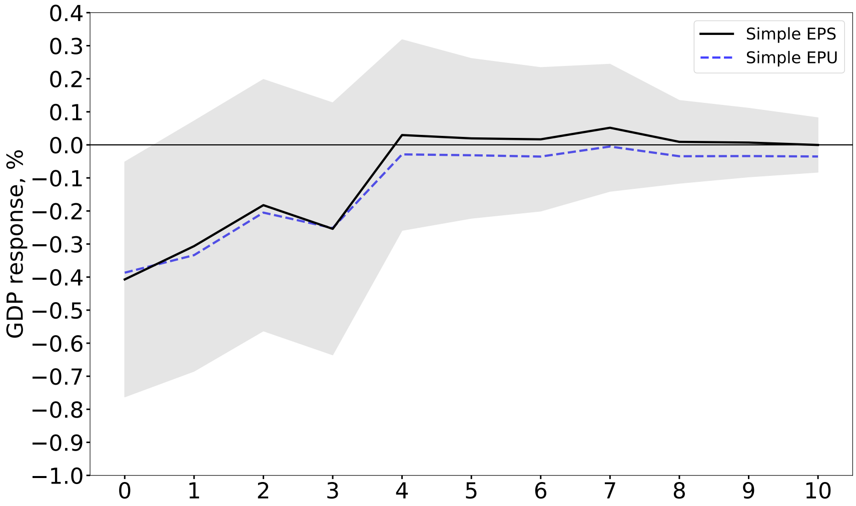


(b) Danish Simple EPS and Simple EPU on the Danish stock index

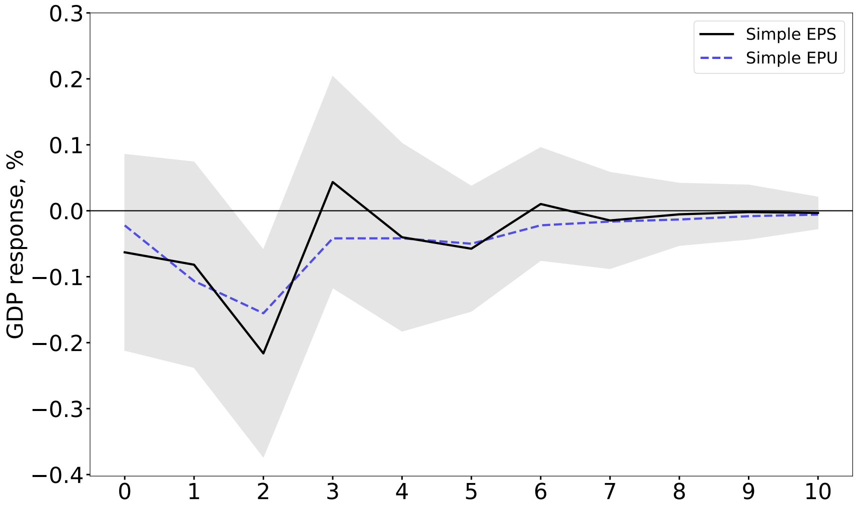


(c) Swedish Simple EPS and Simple EPU on the Swedish stock index

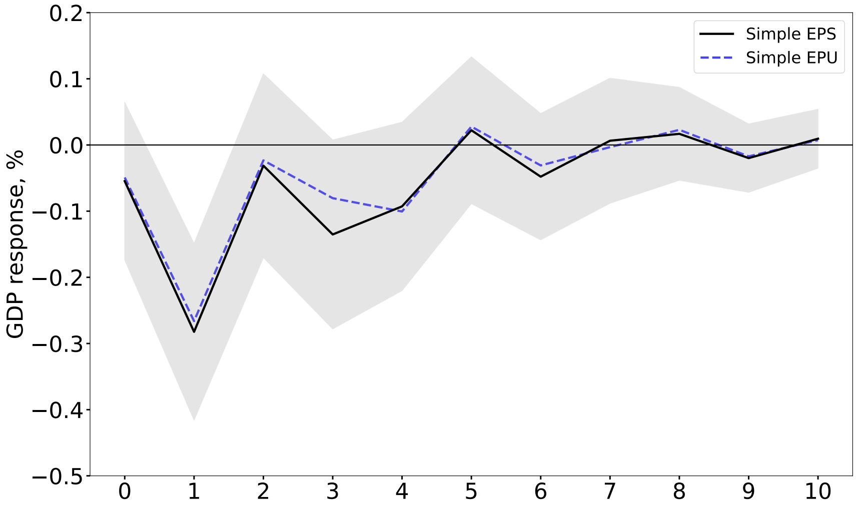
Figure 15: The impulse response functions show the effect of a one standard deviation shock in a policy uncertainty index, on the stock market index denoted in local currency. The graphs show the response in percentage points, per month following the shock. The time period analyzed is 2003:10-2019:10.



(a) Norwegian Simple EPS and Simple EPU on the Norwegian GDP

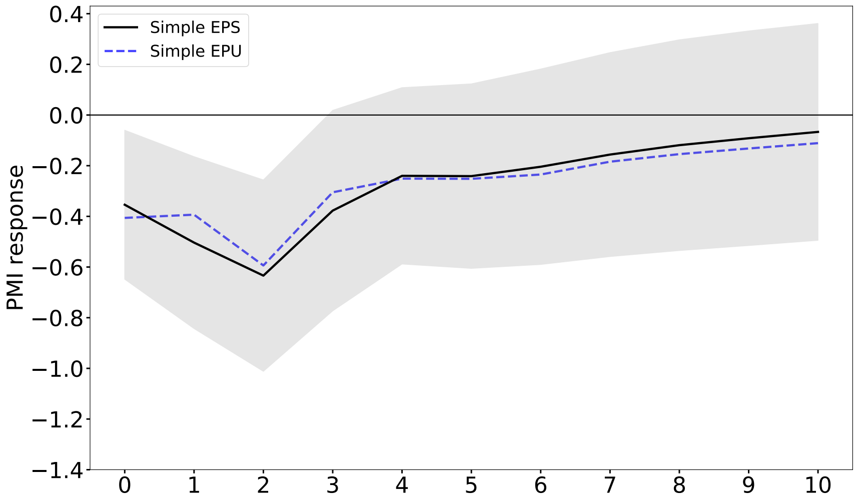


(b) Danish Simple EPS and Simple EPU on the Danish GDP

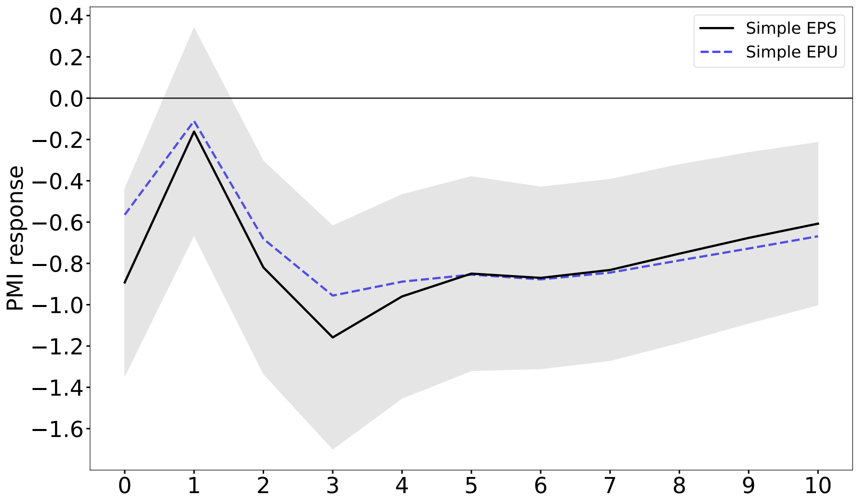


(c) Swedish Simple EPS and Simple EPU on the Swedish GDP

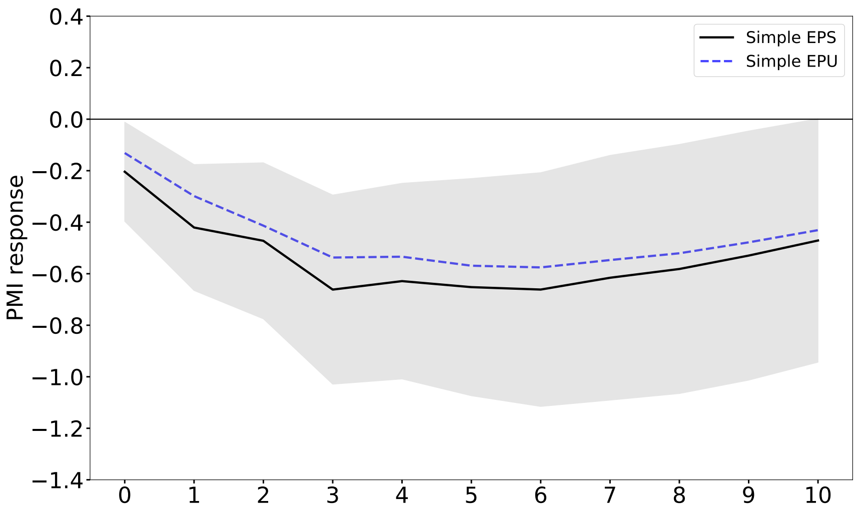
Figure 16: The impulse response functions show the effect of a one standard deviation shock in a policy uncertainty index, on the countries' GDP. The graphs show the response in percentage points, per quarter following the shock. The time period analyzed is 1994:Q3-2019:Q2 for Norway, 1994:Q3-2019:Q2 for Denmark and 1994:Q3-2019:Q2 for Sweden.



(a) Norwegian Simple EPS and Simple EPU on the Norwegian PMI



(b) Danish Simple EPS and Simple EPU on the Danish PMI



(c) Swedish Simple EPS and Simple EPU on the Swedish PMI

Figure 17: The impulse response functions show the effect of a one standard deviation shock in a policy uncertainty index, on the countries' PMI. The graphs show the response in terms of PMI value, per month following the shock. The time period analyzed is 2004:02-2019:09 for Norway, 1994:09-2019:09 for Denmark, and 1994:11-2019:09 for Sweden. We use the Norwegian PMI of NIMA, Danish PMI of DILF and Swedish PMI og Swedbank.

We find that while the stock markets and GDP respond highly similar to the Simple EPS and Simple EPU, the PMI respond stronger to the Simple EPS across the Scandinavian countries. These results indicate that the Simple EPS captures information relevant to purchasing managers, thereby making the index slightly more relevant to economists than the Simple EPU. These results are in line with the findings presented in Section 4.1.

E VAR coefficients

This section presents the coefficients of the VAR analysis in Section 4.1. Table 30, 31 & 32 presents the VAR coefficients for the EPS and Simple EPU, estimated in Section 4.1.1, 4.1.2 & 4.1.3 respectively.

	coefficient	std. error	t-stat	prob
const	-0.413	1.421	-0.291	0.771
L1.EPS	-0.015	0.016	-0.892	0.373
L1.Norway Stock Index	0.173	0.079	2.186	0.029
L2.EPS	0.020	0.018	1.126	0.260
L2.Norway Stock Index	0.037	0.080	0.456	0.648
L3.EPS	0.013	0.018	0.705	0.481
L3.Norway Stock Index	0.037	0.079	0.463	0.643
L4.EPS	-0.009	0.016	-0.570	0.568
L4.Norway Stock Index	0.025	0.077	0.327	0.743

(a) EPS on Norway Stock Index

	coefficient	std. error	t-stat	prob
const	-0.123	1.200	-0.102	0.918
L1.Simple EPU	-0.008	0.015	-0.522	0.602
L1.Norway Stock Index	0.189	0.076	2.483	0.013
L2.Simple EPU	0.018	0.016	1.136	0.256
L2.Norway Stock Index	0.035	0.078	0.457	0.648
L3.Simple EPU	0.007	0.016	0.433	0.665
L3.Norway Stock Index	0.023	0.076	0.302	0.763
L4.Simple EPU	-0.012	0.015	-0.759	0.448
L4.Norway Stock Index	0.015	0.074	0.196	0.845

(b) Simple EPU on Norway Stock Index

	coefficient	std. error	t-stat	prob
const	-0.018	0.947	-0.019	0.985
L1.EPS	-0.004	0.009	-0.445	0.657
L1.Denmark Stock Index	0.187	0.079	2.376	0.017
L2.EPS	-0.008	0.010	-0.750	0.453
L2.Denmark Stock Index	0.020	0.077	0.261	0.794
L3.EPS	0.039	0.010	3.799	0.000
L3.Denmark Stock Index	0.171	0.077	2.219	0.026
L4.EPS	-0.021	0.009	-2.224	0.026
L4.Denmark Stock Index	-0.002	0.076	-0.032	0.975

(c) EPS on Denmark Stock Index

	coefficient	std. error	t-stat	prob
const	0.008	1.000	0.008	0.994
L1.Simple EPU	-0.005	0.010	-0.506	0.613
L1.Denmark Stock Index	0.181	0.078	2.313	0.021
L2.Simple EPU	-0.007	0.011	-0.587	0.557
L2.Denmark Stock Index	0.026	0.077	0.332	0.740
L3.Simple EPU	0.038	0.011	3.400	0.001
L3.Denmark Stock Index	0.163	0.077	2.113	0.035
L4.Simple EPU	-0.020	0.010	-1.951	0.051
L4.Denmark Stock Index	-0.016	0.076	-0.215	0.829

(d) Simple EPU on Denmark Stock Index

	coefficient	std. error	t-stat	prob
const	-0.455	1.136	-0.400	0.689
L1.EPS	-0.008	0.012	-0.649	0.517
L1.Sweden Stock Index	0.053	0.077	0.681	0.496
L2.EPS	0.005	0.013	0.361	0.718
L2.Sweden Stock Index	-0.002	0.077	-0.032	0.975
L3.EPS	0.010	0.013	0.753	0.451
L3.Sweden Stock Index	0.197	0.077	2.556	0.011
L4.EPS	0.002	0.011	0.206	0.837
L4.Sweden Stock Index	0.043	0.078	0.553	0.580

(e) EPS on Sweden Stock Index

	coefficient	std. error	t-stat	prob
const	-0.262	1.183	-0.221	0.825
L1.Simple EPU	-0.003	0.011	-0.296	0.767
L1.Sweden Stock Index	0.067	0.076	0.876	0.381
L2.Simple EPU	-0.000	0.012	-0.009	0.993
L2.Sweden Stock Index	-0.002	0.076	-0.021	0.983
L3.Simple EPU	0.016	0.012	1.293	0.196
L3.Sweden Stock Index	0.198	0.076	2.615	0.009
L4.Simple EPU	-0.005	0.011	-0.465	0.642
L4.Sweden Stock Index	0.033	0.076	0.426	0.670

(f) Simple EPU on Sweden Stock Index

Table 30: Panel of VAR coefficients from the regressions estimated in Section 4.1.1 for the EPS and Simple EPU indices.

	coefficient	std. error	t-stat	prob
const	1.481	0.899	1.647	0.099
L1.EPS	-0.018	0.008	-2.241	0.025
L1.Norway GDP	0.216	0.108	2.006	0.045
L2.EPS	0.012	0.009	1.257	0.209
L2.Norway GDP	0.156	0.110	1.415	0.157
L3.EPS	-0.004	0.009	-0.447	0.655
L3.Norway GDP	0.008	0.108	0.070	0.944
L4.EPS	0.006	0.008	0.753	0.451
L4.Norway GDP	-0.114	0.108	-1.060	0.289

(a) EPS on Norway GDP

	coefficient	std. error	t-stat	prob
const	1.622	0.822	1.972	0.049
L1.Simple EPU	-0.010	0.009	-1.111	0.266
L1.Norway GDP	0.224	0.107	2.099	0.036
L2.Simple EPU	0.002	0.010	0.200	0.842
L2.Norway GDP	0.151	0.110	1.371	0.170
L3.Simple EPU	-0.004	0.010	-0.366	0.714
L3.Norway GDP	0.006	0.110	0.052	0.958
L4.Simple EPU	0.006	0.008	0.694	0.487
L4.Norway GDP	-0.146	0.109	-1.349	0.177

(b) Simple EPU on Norway GDP

	coefficient	std. error	t-stat	prob
const	0.509	0.316	1.612	0.107
L1.EPS	-0.001	0.002	-0.605	0.545
L1.Denmark GDP	0.025	0.107	0.233	0.816
L2.EPS	-0.004	0.002	-1.680	0.093
L2.Denmark GDP	0.087	0.105	0.832	0.406
L3.EPS	0.004	0.003	1.472	0.141
L3.Denmark GDP	0.125	0.103	1.213	0.225
L4.EPS	-0.000	0.002	-0.131	0.896
L4.Denmark GDP	0.022	0.104	0.210	0.834

(c) EPS on Denmark GDP

	coefficient	std. error	t-stat	prob
const	0.675	0.349	1.933	0.053
L1.Simple EPU	-0.003	0.003	-1.109	0.267
L1.Denmark GDP	0.002	0.107	0.019	0.985
L2.Simple EPU	-0.003	0.003	-0.885	0.376
L2.Denmark GDP	0.083	0.106	0.783	0.433
L3.Simple EPU	0.002	0.003	0.507	0.612
L3.Denmark GDP	0.135	0.104	1.290	0.197
L4.Simple EPU	0.001	0.003	0.188	0.851
L4.Denmark GDP	0.008	0.105	0.076	0.939

(d) Simple EPU on Denmark GDP

	coefficient	std. error	t-stat	prob
const	0.682	0.329	2.076	0.038
L1.EPS	-0.009	0.003	-3.356	0.001
L1.Sweden GDP	0.274	0.101	2.706	0.007
L2.EPS	0.007	0.003	2.102	0.036
L2.Sweden GDP	0.172	0.103	1.675	0.094
L3.EPS	-0.003	0.003	-0.955	0.340
L3.Sweden GDP	0.226	0.101	2.241	0.025
L4.EPS	0.003	0.003	0.908	0.364
L4.Sweden GDP	-0.298	0.097	-3.059	0.002

(e) EPS on Sweden GDP

	coefficient	std. error	t-stat	prob
const	0.756	0.356	2.123	0.034
L1.Simple EPU	-0.010	0.003	-3.294	0.001
L1.Sweden GDP	0.270	0.100	2.699	0.007
L2.Simple EPU	0.007	0.003	2.143	0.032
L2.Sweden GDP	0.192	0.101	1.896	0.058
L3.Simple EPU	-0.002	0.003	-0.617	0.537
L3.Sweden GDP	0.248	0.101	2.451	0.014
L4.Simple EPU	0.001	0.003	0.350	0.726
L4.Sweden GDP	-0.347	0.097	-3.563	0.000

(f) Simple EPU on Sweden GDP

Table 31: Panel of VAR coefficients from the regressions estimated in Section 4.1.2 for the EPS and Simple EPU indices.

	coefficient	std. error	t-stat	prob
const	6.391	2.808	2.276	0.023
L1.EPS	-0.012	0.007	-1.791	0.073
L1.Norway PMI	0.516	0.076	6.830	0.000
L2.EPS	-0.004	0.007	-0.571	0.568
L2.Norway PMI	0.259	0.084	3.077	0.002
L3.EPS	0.006	0.008	0.824	0.410
L3.Norway PMI	0.021	0.085	0.248	0.804
L4.EPS	0.006	0.007	0.840	0.401
L4.Norway PMI	0.089	0.075	1.177	0.239

(a) EPS on Norway PMI

	coefficient	std. error	t-stat	prob
const	5.308	2.551	2.081	0.037
L1.Simple EPU	-0.006	0.006	-0.954	0.340
L1.Norway PMI	0.532	0.076	7.016	0.000
L2.Simple EPU	-0.007	0.007	-1.042	0.298
L2.Norway PMI	0.253	0.085	2.976	0.003
L3.Simple EPU	0.009	0.007	1.362	0.173
L3.Norway PMI	0.022	0.086	0.260	0.795
L4.Simple EPU	0.005	0.007	0.729	0.466
L4.Norway PMI	0.090	0.076	1.182	0.237

(b) Simple EPU on Norway PMI

	coefficient	std. error	t-stat	prob
const	16.214	3.324	4.877	0.000
L1.EPS	0.005	0.006	0.792	0.428
L1.Denmark PMI	0.441	0.060	7.401	0.000
L2.EPS	-0.018	0.007	-2.497	0.013
L2.Denmark PMI	0.033	0.064	0.511	0.609
L3.EPS	-0.004	0.007	-0.626	0.531
L3.Denmark PMI	0.218	0.063	3.435	0.001
L4.EPS	-0.000	0.006	-0.064	0.949
L4.Denmark PMI	0.045	0.058	0.772	0.440

(c) EPS on Denmark PMI

	coefficient	std. error	t-stat	prob
const	16.815	3.367	4.994	0.000
L1.Simple EPU	0.003	0.007	0.473	0.636
L1.Denmark PMI	0.433	0.059	7.329	0.000
L2.Simple EPU	-0.017	0.008	-2.139	0.032
L2.Denmark PMI	0.042	0.063	0.665	0.506
L3.Simple EPU	-0.007	0.008	-0.831	0.406
L3.Denmark PMI	0.213	0.063	3.396	0.001
L4.Simple EPU	-0.001	0.007	-0.181	0.856
L4.Denmark PMI	0.045	0.058	0.778	0.437

(d) Simple EPU on Denmark PMI

	coefficient	std. error	t-stat	prob
const	6.609	1.496	4.417	0.000
L1.EPS	-0.011	0.004	-2.783	0.005
L1.Sweden PMI	0.754	0.057	13.327	0.000
L2.EPS	0.004	0.004	1.006	0.315
L2.Sweden PMI	0.333	0.072	4.652	0.000
L3.EPS	-0.004	0.005	-0.980	0.327
L3.Sweden PMI	0.088	0.072	1.218	0.223
L4.EPS	0.005	0.004	1.169	0.243
L4.Sweden PMI	-0.286	0.056	-5.138	0.000

(e) EPS on Sweden PMI

	coefficient	std. error	t-stat	prob
const	6.531	1.434	4.555	0.000
L1.Simple EPU	-0.007	0.004	-1.671	0.095
L1.Sweden PMI	0.760	0.056	13.495	0.000
L2.Simple EPU	-0.001	0.004	-0.343	0.732
L2.Sweden PMI	0.340	0.072	4.737	0.000
L3.Simple EPU	-0.001	0.004	-0.237	0.813
L3.Sweden PMI	0.085	0.073	1.169	0.242
L4.Simple EPU	0.003	0.004	0.661	0.509
L4.Sweden PMI	-0.294	0.056	-5.248	0.000

(f) Simple EPU on Sweden PMI

Table 32: Panel of VAR coefficients from the regressions estimated in Section 4.1.3 for the EPS and Simple EPU indices.

F Time series cross-validation

In order to assess the predictive power of the policy uncertainty indices we use out-of-sample forecasting. We apply the time series cross-validation technique, as described by Hyndman & Athanasopoulos (2018) and illustrated in Figure 18. In each iteration, we aim to forecast the records illustrated as red circles, which constitute the testing set. In order to do so, we use all prior observations to fit the bivariate VAR model, hereby referred to as the training set.

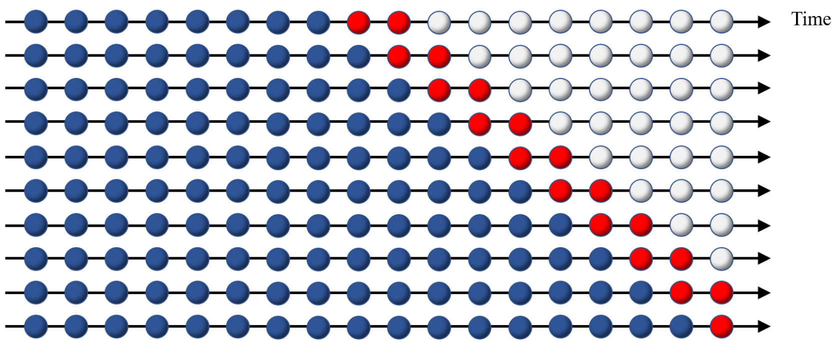


Figure 18: Illustration of the cross-validation technique. The blue points constitute the training set, the red points denote the testing set while white points are unused. Each line is a separate iteration.

The forecasts are compared to the actual observations, and error measures for each index are reported in Table 34, 33 & 35. The accuracy of each model is reported as Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE). The RMSE penalize large deviations from the actual observations heavier than the MAE.

In general, we find no consistent results across the three countries and alternative indices. Also note that in several cases, the RMSE and MAE disagree on which model holds the highest accuracy. We find no consistent results of which policy uncertainty index performs the best, neither with respect to country nor economic indicator. The results indicate one of two things: The policy uncertainty indices are equally suitable for OSS prediction, or alternatively, that the VAR models are unfit for OOS prediction.

Error	Mo.	**Norway**			**Denmark**			**Sweden**		
measure	ahead	Simple EPU	EPU	EPS	Simple EPU	EPU	EPS	Simple EPU	EPU	EPS
RMSE	1	3.755	3.756	**3.638**	**3.805**	3.822	3.893	**4.206**	4.228	4.223
	2	3.557	**3.526**	3.542	**3.667**	3.680	3.764	**4.043**	4.063	4.050
	3	**3.385**	3.407	3.413	**3.612**	3.655	3.704	4.024	**4.021**	4.033
	4	3.272	3.269	**3.240**	**3.626**	3.662	3.629	3.941	3.953	**3.930**
MAE	1	2.969	3.044	**2.928**	3.050	**2.992**	3.107	3.319	**3.315**	3.352
	2	**2.710**	2.725	2.730	2.933	**2.921**	2.988	3.206	**3.185**	3.215
	3	**2.532**	2.581	2.562	**2.859**	2.869	2.896	3.201	**3.188**	3.210
	4	2.418	2.401	**2.386**	**2.875**	2.898	2.885	3.071	3.066	**3.045**

Table 33: Error statistics for OOS forecasting when using a VAR model to predict the monthly change (log-difference) for the stock markets.

Error	Qr.	**Norway**			**Denmark**			**Sweden**		
measure	ahead	Simple EPU	EPU	EPS	Simple EPU	EPU	EPS	Simple EPU	EPU	EPS
RMSE	1	**1.924**	2.013	1.985	0.771	0.772	**0.760**	0.567	**0.557**	0.568
	2	**1.778**	1.823	1.823	0.771	0.767	**0.749**	**0.500**	0.505	0.513
	3	**1.681**	1.696	1.705	0.723	0.732	**0.719**	**0.513**	0.526	0.534
	4	**1.684**	1.701	1.713	**0.718**	0.722	0.722	**0.567**	0.568	0.593
MAE	1	**1.516**	1.597	1.582	0.518	0.525	**0.508**	0.452	**0.425**	0.427
	2	**1.466**	1.481	1.483	0.506	0.516	**0.484**	0.415	0.414	**0.403**
	3	**1.423**	1.425	1.436	0.508	0.521	**0.497**	**0.406**	0.415	0.417
	4	**1.389**	1.401	1.416	**0.494**	0.500	0.495	0.455	**0.448**	0.456

Table 34: Error statistics for OOS forecasting when using a VAR model to predict the quarterly percentage change in GDP.

Error measure	Mo. ahead	Norway Simple EPU	Norway EPU	Norway EPS	Denmark Simple EPU	Denmark EPU	Denmark EPS	Sweden Simple EPU	Sweden EPU	Sweden EPS
RMSE	1	**2.474**	2.518	2.496	5.292	5.273	**5.237**	2.041	2.036	**2.025**
	2	2.876	2.904	**2.864**	5.665	5.642	**5.607**	2.263	**2.263**	2.273
	3	**3.015**	3.083	3.083	**5.826**	5.845	5.838	**2.411**	2.413	2.416
	4	3.119	3.140	**3.096**	**5.435**	5.457	5.464	3.084	3.077	**3.059**
MAE	1	2.018	2.038	**2.010**	4.221	4.203	**4.171**	1.638	1.635	**1.619**
	2	**2.155**	2.219	2.175	4.433	4.436	**4.393**	1.782	1.775	**1.763**
	3	**2.443**	2.503	2.506	**4.643**	4.696	4.657	**1.855**	1.872	1.864
	4	2.396	2.434	**2.384**	**4.363**	4.367	4.386	2.388	2.375	**2.342**

Table 35: Error statistics for OOS forecasting when using a VAR model to predict monthly change in the PMIs.

References

Armelius, H., Hull, I., & Stenbacka Köhler, H. (2017, June). The timing of uncertainty shocks in a small open economy. *Economics Letters*, *155*, 31–34. doi: 10.1016/j.econlet.2017.03.016

Ba, J. (2014, December). ADAM: A method for stochastic optimization. San Diego, CA: 3rd International Conference for Learning Representations.

Baker, S. R., Bloom, N., & Davis, S. J. (2016, July). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636. (Publisher: Oxford University Press (OUP)) doi: 10.1093/qje/qjw024

Bautin, M., Vijayarenu, L., & Skiena, S. (2008, January). International Sentiment Analysis for News and Blogs. Seattle, WA.

BBC. (2019, August). Asian stocks drop as US-China trade war escalates. *BBC News*.

Bernanke, B. S. (1983, February). Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics*, *98*(1), 85. (Publisher: Oxford University Press (OUP)) doi: 10.2307/1885568

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003, January). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*, 993–1022.

Boomsma, T. K., & Linnerud, K. (2015, September). Market and policy risk under different renewable electricity support schemes. *Energy*, *89*, 435–448. doi: 10.1016/j.energy.2015.05.114

Boomsma, T. K., Meade, N., & Fleten, S.-E. (2012, July). Renewable energy investments under different support schemes: A real options approach. *European Journal of Operational Research*, *220*(1), 225–237. doi: 10.1016/j.ejor.2012.01.017

Boudoukh, J., Feldman, R., Kogan, S., & Richardson, M. (2013). Which News Moves Stock Prices? A Textual Analysis. *National Bureau of Economic Research Working Paper Series*, *No. 18725*. doi: 10.3386/w18725

Bradley, M., & Lang, P. (1999). *Affective Norms for English Words (ANEW): Instruction Manual and Affective Ratings.* NIMH Center for the Study of Emotion and Attention.

Bremmer, I. A. (2005). Managing risk in an unstable world. *Harvard business review*, 51–4, 56, 58–60 passim.

Brogaard, J., & Detzel, A. (2015, January). The Asset-Pricing Implications of Government Economic Policy Uncertainty. *Management Science*, *61*(1), 3–18. (Publisher: Institute for Operations Research and the Management Sciences (INFORMS)) doi: 10.1287/mnsc.2014.2044

Business Insider. (2019, August). The Dow plummets more than 600 points after Trump vows to retaliate against China's latest tariffs. *Market Insider*.

Caldara, D., & Iacoviello, M. (2018, February). Measuring Geopolitical Risk. *International Finance Discussion Paper*, *2018*(1222), 1–66. (Publisher: Board of Governors of the Federal Reserve System) doi: 10.17016/ifdp.2018.1222

Colombo, V. (2013, October). Economic policy uncertainty in the US: Does it matter for the Euro area? *Economics Letters*, *121*(1), 39–42. doi: 10.1016/j.econlet.2013.06.024

Deutsche Bank. (2018, January). *Economic policy uncertainty in Europe* (Tech. Rep.). Frankfurt, Germany.

de Vries, E., Schoonvelde, M., & Schumacher, G. (2018). No Longer Lost in Translation: Evidence that Google Translate Works for Comparative Bag-of-Words Text Applications. *Political Analysis*, *26*(4), 417–430. doi: 10.1017/pan.2018.26

DILF. (2019, December). *Øget vækst i industriaktivitet i november* (Monthly). Copenhagen, Denmark: Danish Purchasing and Logistics Forum.

Dixit, A., & Pindyck, R. (1994). *Investment Under Uncertainty.* Princeton, NJ: Princeton University Press.

Estrella, A., & Mishkin, F. S. (1998, February). Predicting U.S. Recessions: Financial Variables as Leading Indicators. *The Review of Economics and Statistics*, *80*(1), 45–61. doi: 10.1162/003465398557320

Financial Times. (2019a, January). Global policy uncertainty at record levels, Deutsche Bank says.

Financial Times. (2019b, December). UK services activity 'back in decline' as political uncertainty lingers. *Financial Times*.

Financial Times. (2020, January). Is the UK set for a Brexit bounce? *Financial Times*.

Forbes. (2020a, January). GDP Dropped For China And U.S. Amid Trade War, While Consumer Spending Remained Solid. *Forbes*.

Forbes. (2020b, January). Stocks Hit Record Highs As U.S. Signs Phase One Trade Deal With China. *Forbes*.

Fountas, S., Karatasi, P., & Tzika, P. (2018). Economic policy uncertainty in Greece: measuring uncertainty for the greek macroeconomy. *South-Eastern Europe Journal of Economics*, *16*(1), 80–92.

Godbole, N., Srinivasaiah, M., & Skiena, S. (2007, January). Large-Scale Sentiment Analysis for News and Blogs..

Goldman Sachs. (2012, October). *Policy Uncertainty: Is Now the Time?* (Tech. Rep.).

Gulen, H., & Ion, M. (2015, September). Policy Uncertainty and Corporate Investment. *The Review of Financial Studies*, *29*(3), 523–564. doi: 10.1093/rfs/hhv050

Hutto, C., & Gilbert, E. (2015, January). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text..

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: principles and practice.* Melbourne, Australia: OTexts.

Institute for Supply Management. (2019, May). *Economic growth to continue throughout 2019* (Semi-annual). Tempe, AZ: Institute for Supply Management.

Jurado, K., Ludvigson, S. C., & Ng, S. (2015, March). Measuring Uncertainty. *American Economic Review*, *105*(3), 1177–1216. (Publisher: American Economic Association) doi: 10.1257/aer.20131193

Karnizova, L., & Li, J. C. (2014, November). Economic policy uncertainty, financial markets and probability of US recessions. *Economics Letters*, *125*(2), 261–265. doi: 10.1016/j.econlet.2014.09.018

Kleiven, L. E., & Ifwarsson, E. J. V. (2019). Policy Uncertainty in the Scandinavian Countries. *SSRN Electronic Journal*. (Publisher: Elsevier BV) doi: 10.2139/ssrn.3515202

Loughran, T., & McDonald, B. (2011, February). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35–65. doi: 10.1111/j.1540-6261.2010.01625.x

Lütkepohl, H. (1990). Asymptotic Distributions of Impulse Response Functions and Forecast Error Variance Decompositions of Vector Autoregressive Models. *The Review of Economics and Statistics*, *72*(1), 116–125. doi: 10.2307/2109746

McDonald, R., & Siegel, D. (1986, November). The Value of Waiting to Invest. *The Quarterly Journal of Economics*, *101*(4), 707–727. doi: 10.2307/1884175

McFadden, D. (1973). Conditional logit analysis of Qualitative choice behavior. Berkeley, CA: University of California at Berkeley.

McFadden, D. (1977). *Quantitative Methods for Analyzing Travel Behaviour of Individuals: Some Recent Developments* (Tech. Rep. No. 474). Cowles Foundation for Research in Economics, Yale University.

NBER. (2010, September). *US Business Cycle Expansions and Contractions* (Tech. Rep.). Cambridge, MA: the National Bureau of Economic Research.

NIMA. (2019, December). *DNB PMI ned i november* (Monthly). Oslo, Norway: Norwegian Association of Purchasing and Logistics (NIMA).

Norvig, P., & Russell, S. (2009). *Artificial Intelligence: A Modern Approach* (3rd edition ed.). Hoboken, NJ: Pearson Education.

OECD. (2016, April). *The Economic Consequences of Brexit* (Tech. Rep. No. 2226-583X). Organisation for Economic Co-Operation and Development (OECD). doi: 10.1787/5jm0lsvdkf6k-en

Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment Classification Using Machine Learning Techniques. In *Proceedings of the ACL-02 Conference on Empirical Methods in Natural Language Processing* (Vol. 10, pp. 79–86). Stroudsburg, PA: Association for Computational Linguistics. doi: 10.3115/1118693.1118704

Pástor, L., & Veronesi, P. (2013, December). Political uncertainty and risk premia. *Journal of Financial Economics*, *110*(3), 520–545. doi: 10.1016/j.jfineco.2013.08.007

Ritzenhofen, I., & Spinler, S. (2016, January). Optimal design of feed-in-tariffs to stimulate renewable energy investments under regulatory uncertainty — A real options analysis. *Energy Markets*, *53*, 76–89. doi: 10.1016/j.eneco.2014.12.008

Rodrik, D. (1989). Policy Uncertainty and Private Investment in Developing Countries. *National Bureau of Economic Research Working Paper Series*, *No. 2999*. doi: 10.3386/w2999

Soric, P., & Lolic, I. (2017). Economic uncertainty and its impact on the Croatian economy. *Public Sector Economics*. doi: 10.3326/pse.41.4.3

Stockhammar, P., & Österholm, P. (2016, March). Effects of US policy uncertainty on Swedish GDP growth. *Empirical Economics*, *50*(2), 443–462. doi: 10.1007/s00181-015-0934-y

Swedbank. (2019, December). *PMI dropped to 45.4 in November: Manufacturing continues to slide* (Monthly). Stockholm, Sweden: Author.

Tarassow, A. (2019, April). Forecasting U.S. money growth using economic uncertainty measures and regularisation techniques. *International Journal of Forecasting*, *35*(2), 443–457. doi: 10.1016/j.ijforecast.2018.09.012

Tetlock, P. C. (2007, June). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *The Journal of Finance*, *62*(3), 1139–1168. doi: 10.1111/j.1540-6261.2007.01232.x

The Economist Intelligence Unit. (2019, January). *Democracy Index 2018: Me too? Political participation, protest and democracy* (Whitepaper No. 11). London, UK: The Economist Intelligence Unit.

The Wall Street Journal. (2019, October). Trade Uncertainty Clouds Global Growth Prospects.

Thorsrud, L. A. (2018, August). Words are the New Numbers: A Newsy Coincident Index of the Business Cycle. *Journal of Business & Economic Statistics*, 1–17. doi: 10.1080/07350015.2018.1506344

Veronesi, P. (2015, June). Stock Market Overreactions to Bad News in Good Times: A Rational Expectations Equilibrium Model. *The Review of Financial Studies*, *12*(5), 975–1007. doi: 10.1093/rfs/12.5.975

World Bank Development Research Group. (2020, March). *GINI index (World Bank estimate)* (Tech. Rep.). Washington, DC: World Bank, Development Research Group.

World Trade Organization. (2019, April). Global trade growth loses momentum as trade tensions persist. *WTO - Trade statistics and outlook*, 1–14.

Wright, J. H. (2006, May). The Yield Curve and Predicting Recessions. *FEDs Working Paper No. 2006-7*. doi: 10.2139/ssrn.899538

Zalla, R. (2017, June). Economic Policy Uncertainty in Ireland. *Atlantic Economic Journal*, *45*(2), 269–271. doi: 10.1007/s11293-017-9536-8

NTNU

Norwegian University of
Science and Technology