

Components of Uncertainty

Vegard Høghaug Larsen

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Norges Bank

Introduction

Uncertainty and the economy

1. What is the effect of elevated uncertainty on the economy?
 - Several studies document that an increase in uncertainty is followed by worsening economic conditions, see e.g. [Bloom \(Ecma, 2009\)](#), [Jurado et al. \(AER, 2015\)](#) and [Baker et al. \(QJE, 2016\)](#)
2. Do different types of uncertainty exist? If, so, how do the different types of uncertainty affect the economy?
 - Some types of uncertainty is suggested to have a positive effect on the economy. See, e.g. [Segal et al. \(JFE, 2015\)](#) and [Kraft et al. \(2013\)](#)
 - These theories are often referred to as “growth options” theories, and have been suggested as a driver of the dot-com boom in the late 1990s.

Measuring uncertainty

Uncertainty is hard to measure, and several proxies for uncertainty have been suggested:

1. Implied stock market volatility, e.g. Bloom (Ecma, 2019)
2. Forecast disagreement, e.g. Bachmann et al. (AEJ Macro, 2013)
3. The unforecastable component of a large set of macroeconomic indicators, e.g. Jurado et al. (AER, 2015)
4. **Uncertainty terms in newspapers**, e.g. Baker et al. (QJE, 2016) and Alexopoulos and Choen (2009)

1. Measures category-specific uncertainty
 - Using machine learning techniques, I create uncertainty measures based on the frequency of uncertainty terms in various types of news.
2. Identify distinct types of uncertainty
 - Extract orthogonal components from the various category specific measures
3. Study the effect of different (orthogonal) types of uncertainty on the economy.
 - Estimate the effect of uncertainty shocks in a Structural VAR

Classifying the news

Classifying news articles

- Data: Dagens Næringsliv, Norways biggest business newspaper and the fourth largest irrespective of theme.
 - The data spans 1988–2016
 - Close to 500 000 articles
- The newspaper is decomposed according to the topics it writes about using a topic model called Latent Dirichlet Allocation (LDA) model introduced by [Blei, Jordan, and Ng \(JMLR, 2003\)](#).
- The LDA takes a set of articles as input and return two sets of distributions:
 - One set of distributions over words, one distribution for each topic j , given by θ_j
 - One set of distributions over topics, one distribution for each article i , given by φ_i

Estimating the topic model

- The researcher must select the number of topics prior to estimation:
→ # topics = 80
- There is a trade off between interpretable topics and how well the topics are at explaining the whole newspaper, see [Chang et al. \(NIPS, 2009\)](#).
- Estimation is done using MCMC

Category-specific uncertainty

Counting uncertainty terms in the newspaper

The words that are counted: *uncertain* and *uncertainty* (and also variations of these words)

Let's define

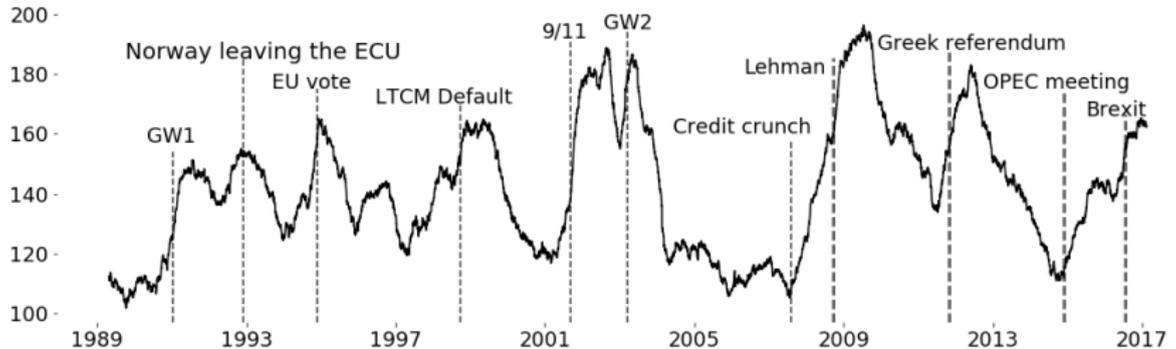
$v_i \equiv$ number of uncertainty terms in article i

$\omega_i \equiv$ number of total words in article i

I start by calculating an aggregate uncertainty measure:

$$\text{Aggregate uncertainty} = \sum_{i \in \text{day}} \frac{v_i}{\omega_i}$$

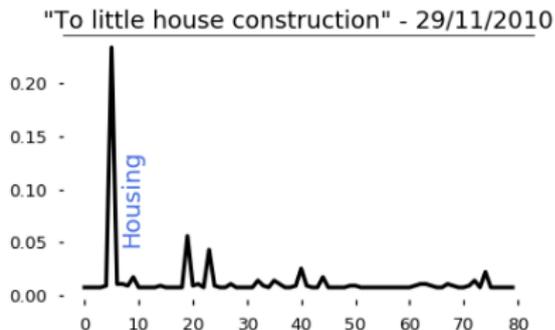
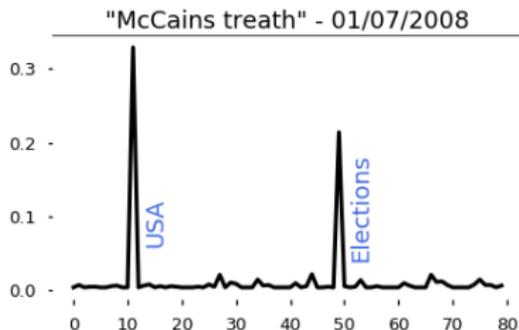
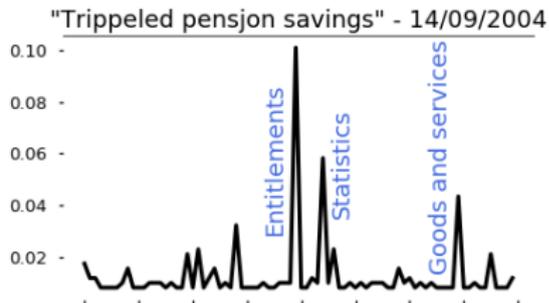
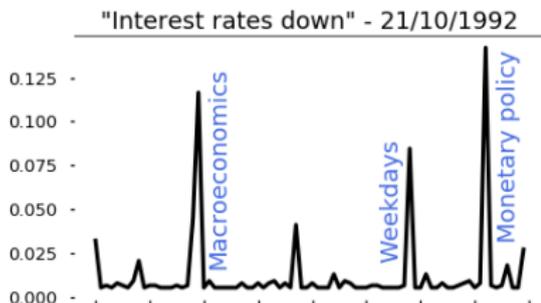
Aggregate uncertainty



Note: The 300 day backward-looking rolling mean is plotted. The series gives the share of uncertainty terms per 1 million words in the newspaper.

Classifying the news

The topic distributions are given by φ_i . Four example articles:

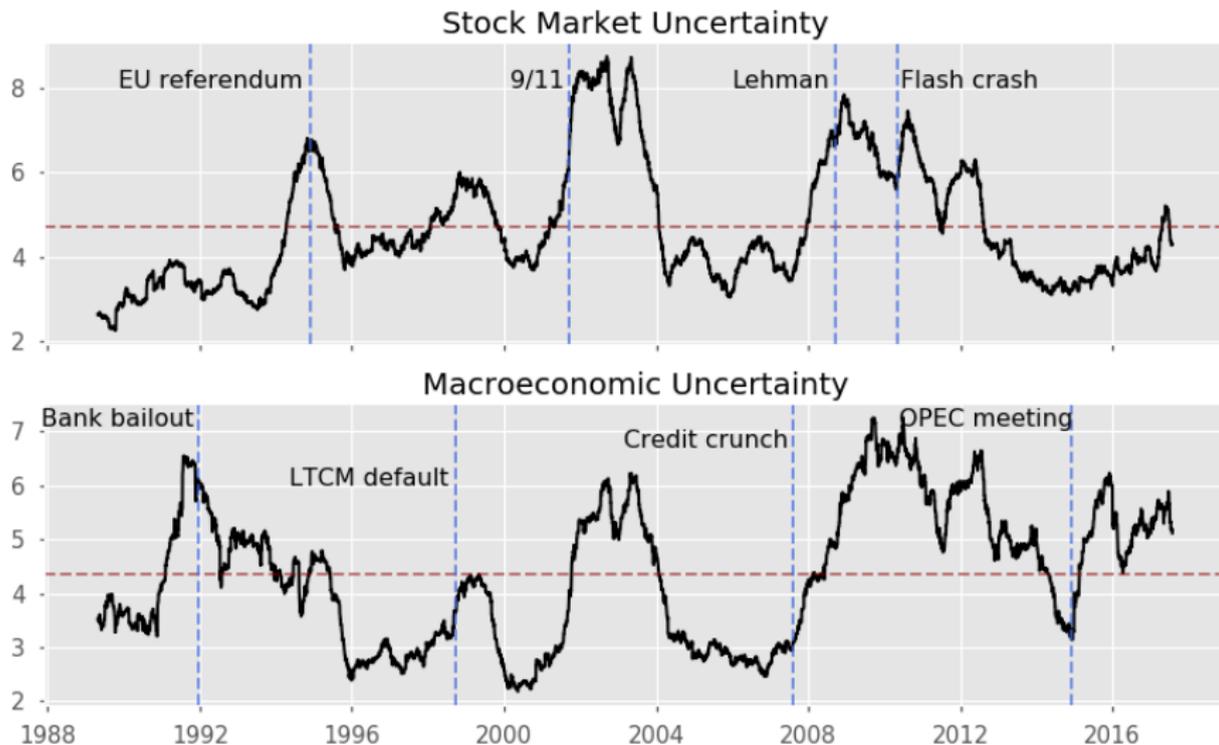


Category specific uncertainty

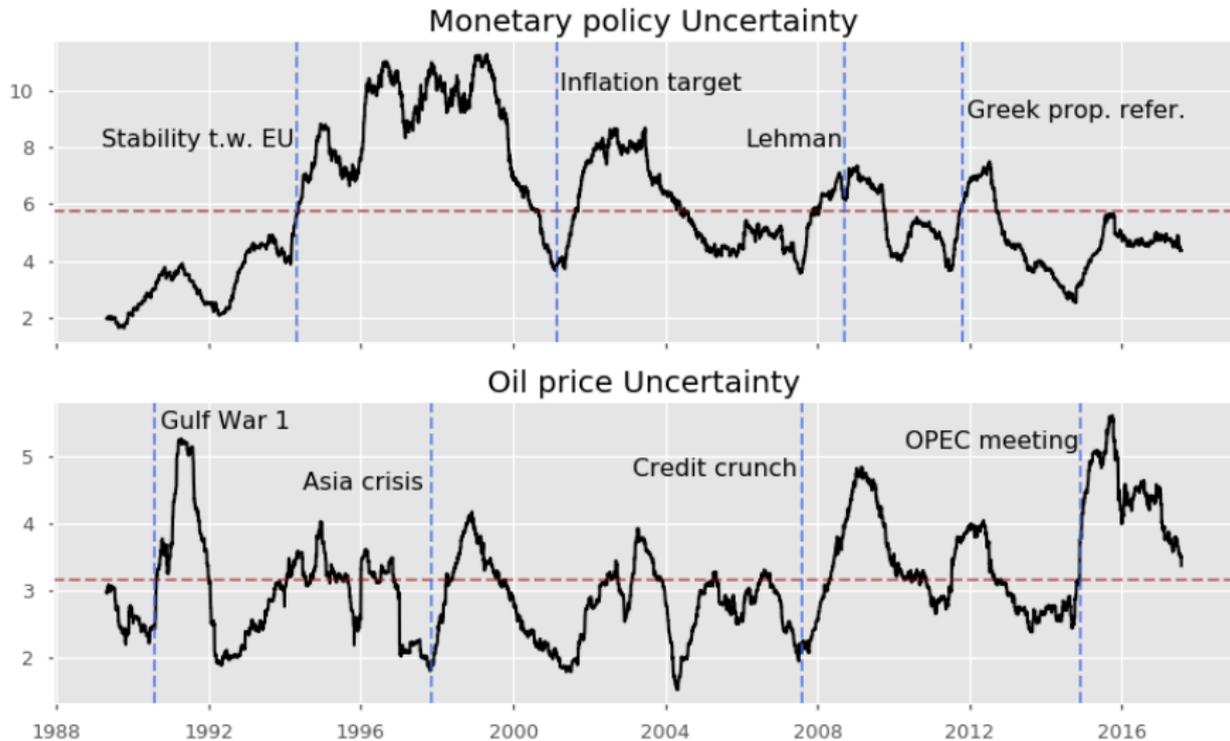
The category specific uncertainty measures are calculated for all topics j :

$$\text{Topic } j \text{ uncertainty on day } t = \frac{\sum_{i \in \text{day } t} v_i \varphi_i(\text{topic } j)}{\sum_{i \in \text{day } t} \omega_i}$$

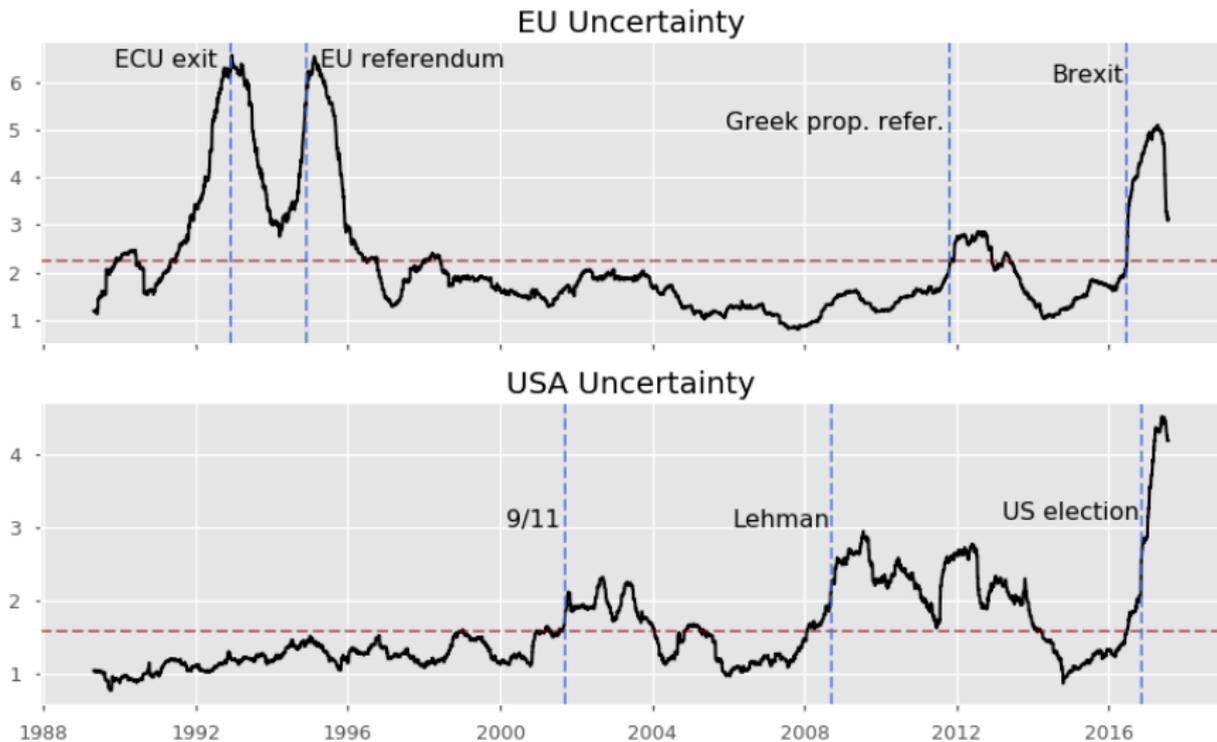
Topic specific uncertainty



Topic specific uncertainty



Topic specific uncertainty



The frequency of uncertainty terms in different types of news

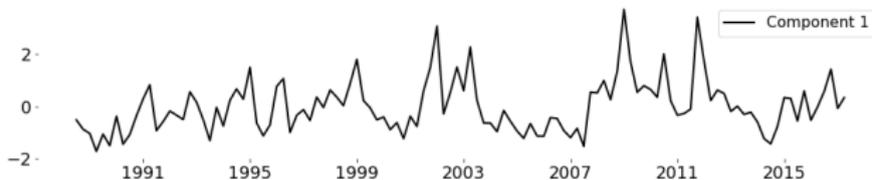
Top 10	words per 1 mil.	Bottom 10	words per 1 mil.
<i>Monetary policy</i>	5.7	<i>Drinks</i>	0.9
<i>Stock market</i>	4.7	<i>Movies/Theater</i>	0.9
<i>Macroeconomics</i>	4.4	<i>Food</i>	1.0
<i>Fear</i>	3.7	<i>Literature</i>	1.0
<i>Oil price</i>	3.2	<i>Music</i>	1.0
<i>Debate</i>	2.9	<i>Art</i>	1.0
<i>Negotiation</i>	2.4	<i>Sports</i>	1.1
<i>Results</i>	2.4	<i>Family business</i>	1.1
<i>Oil production</i>	2.3	<i>Watercraft</i>	1.1
<i>Elections</i>	2.3	<i>Tourism</i>	1.1

Components of uncertainty

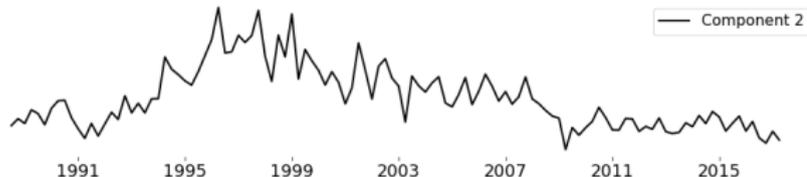
Finding orthogonal components

- The 80 uncertainty measures often capture similar types of uncertainty.
- I extract orthogonal components of uncertainty by principal component analysis (PCA)
- Keep the components that explain 5 percent or more of the topic-based measures
- Normalize the components according to the topic-based measure with the highest correlation

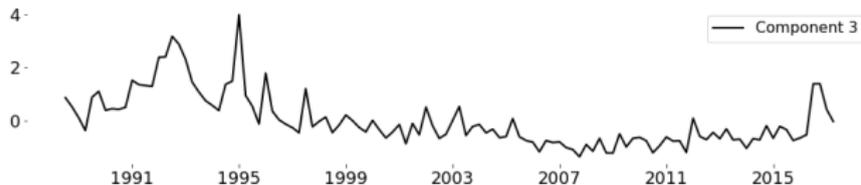
The component measures



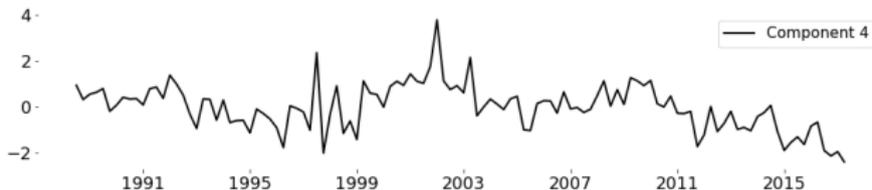
EV: 35% (35%)



EV: 15% (49%)



EV: 9% (58%)



EV: 6% (64%)

Labeling the components – highest correlated topics

	Component 1		Component 2	
		<u>Correlation</u>		<u>Correlation</u>
1st	Narrative	0.87	Monetary policy	0.75
2nd	Fear	0.83	Employment	-0.56
3rd	Stock Market	0.81	Organizations	-0.56
4th	Statistics	0.81	<i>Macroeconomics</i>	-0.46
5th	Unknown	0.81	<i>Weekdays</i>	0.46
	Component 3		Component 4	
		<u>Correlation</u>		<u>Correlation</u>
1st	EU	0.85	Mergers & Acquis.	0.55
2nd	Europe	0.72	Stock listings	0.55
3rd	Agriculture	0.68	IT systems	0.50
4th	Argumentation	0.59	<i>Engineering</i>	0.47
5th	Fiscal policy	0.55	<i>Telecommunication</i>	0.43

Labeling the components – highest correlated topics

	economic and financial distress		institut. framework of mon. pol.	
		<u>Correlation</u>		<u>Correlation</u>
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Component correlations with alternative measures

Norway EPU	0.69	-0.16	0.25	-0.2
US VIX	0.66	-0.033	-0.24	0.33
US EPU	0.55	-0.59	-0.094	0.0053
JLN Finance	0.52	-0.06	-0.29	0.37
EU EPU	0.48	-0.41	-0.11	-0.4
JLN Macro	0.42	-0.28	-0.41	0.34
China EPU	0.41	-0.52	0.24	-0.32
RSMV	0.38	-0.33	-0.56	-0.19
UK EPU	0.27	-0.62	0.34	-0.49
	Component 1	Component 2	Component 3	Component 4

Uncertainty and the economy

A Structural VAR

I follow [Baker et al. \(QJE, 2016\)](#) and specify a structural VAR model where the identification is achieved using a Cholesky decomposition:

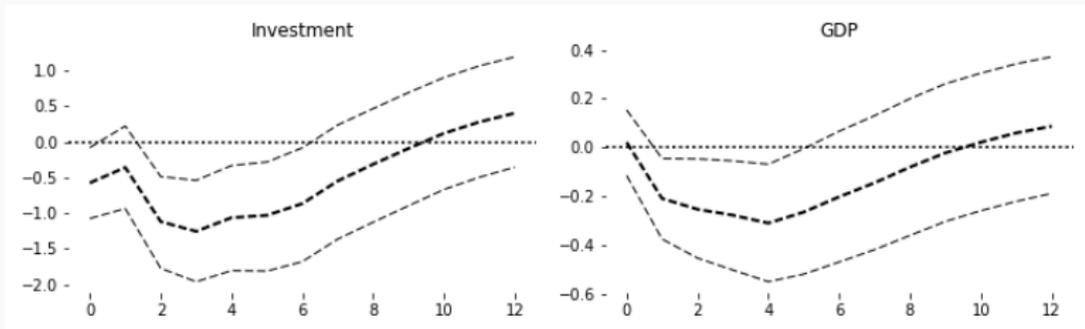
$$\mathbf{A}_0 \mathbf{y}_t = \sum_{j=1}^3 \mathbf{A}_j \mathbf{y}_{t-j} + \mathbf{B} \boldsymbol{\varepsilon}_t$$

$$\text{where } \mathbf{y}_t \equiv \begin{bmatrix} \text{Uncertainty} \\ \log(\text{OSEBX}) \\ \text{Interest rate} \\ \log(\text{Investments}) \\ \log(\text{GDP}) \end{bmatrix}$$

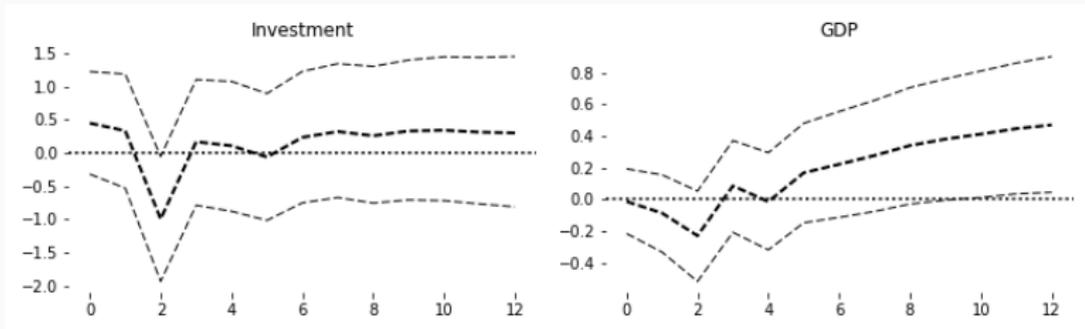
the data sample is 1988Q2 – 2016Q4

Impulse responses from Comp. 1 and Comp. 2 shock

economic and financial distress

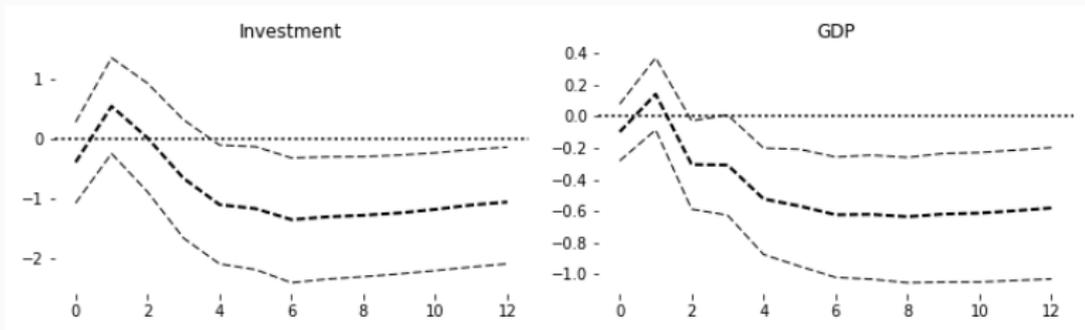


instit. framework of monetary policy

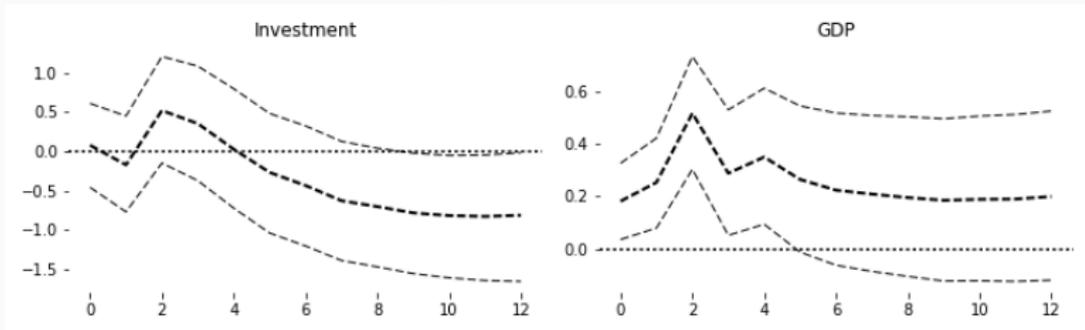


Impulse responses from Comp. 3 and Comp. 4 shock

relationship with the EU



technology and firm expansion



Conclusion

Summary

1. I have proposed a new method for constructing topic specific newspaper uncertainty
2. I have created 80 category specific measures of uncertainty for Norway based on the DN newspaper
3. Most topics have a clear interpretation
4. I extract four orthogonal components from the 80 topic-based measures
5. The effect of an uncertainty shock depends on the type of uncertainty
 - 5.1 A shock to Component 1, labeled as uncertainty related to economic and financial distress, yield an economic contraction in line with the uncertainty literature
 - 5.2 A shock to Component 4, labeled as uncertainty related to technology and firm expansion, yield a boom in GDP

