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NATALIIA OSTAPENKO

Information, Business cycles and Monetary policy

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Faculty of Social Sciences, School of Economics and Business Administration, University of Tartu, Estonia.

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- Perceptions of government actions and entrepreneurship performance: an indirect effect of national culture.Comparative analysis of Ukraine and Slovak Republic, 2016, *Journal of Enterprising Communities: People and Places in the Global Economy* 10(4), 363–396.
- Determinants of entrepreneurs' views on the acceptability of tax evasion and the informal economy in Slovakia and Ukraine: an institutional asymmetry approach (with Colin C. Williams), 2016, *International Journal of Entrepreneurship and Small Business*, 28(2/3), 275–289.
- National culture, institutions and economic growth: The way of influence on productivity of entrepreneurship, 2015, *Journal of Entrepreneurship and Public Policy* 4(3), 331–351.
- Entrepreneurial Environment and Economic Growth: What Affects the Productiveness of Business Activity at Macro Level? (with Holienka M. and Pilkova A.), 2015, *The Essence and Measurement of Organizational Efficiency Springer Proceedings in Business and Economics*, 79–95.

II Conference presentations

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III Other publications

Macroeconomic Expectations: News Sentiment Analysis, 2020, Working Papers of Eesti Pank 5/2020.

List of abbreviations

AR – Autoregressive process
Fed – Federal Reserve
CES – Constant elasticity of substitution
EPU – Economic policy uncertainty
FAVAR – Factor Augmented Vector Autoregression
FOMC – Federal Open Market Committee
GDP – Gross Domestic Product
IP – Industrial Production
IST – Investment Specific Technology
LASSO – Least Absolute Shrinkage and Selection Operator
LDA – Latent Dirichlet Allocation
PCA – Principal Component Analysis
RBC – Real Business Cycle
SPF – Survey of Professional Forecasters
SVAR – Structural Vector Autoregression
SVECM – Structural Vector Error Correction Model
SVM – Support Vector Machine
TIPS – Treasury Inflation-Protected Securities
TFP – Total Factor Productivity
VAR – Vector Autoregression
VIX – Volatility Index

1 Introduction

1.1 Motivation for the research

Does the revelation of positive or negative information matter for monetary policy and real economic activity? What kind of information matters more? What are the transmission channels? Does the general public perceive the information released to them precisely? These are the main questions raised in this study. The idea of a news-driven business cycle suggests that changes in expectations may be an important driver of economic fluctuations. Expectations that future economic conditions will be better, once current fundamentals are controlled for, can be provoked by either news of high Total Factor Productivity (TFP) in the future, which is known as hard news[1], or positive confidence[2] (Levchenko and Pandalai-Nayar, 2020). This thesis sheds light on the soft news[3] channel of expectations. Since newspapers are the main transmission channel of opinions from professionals to the general public, this type of news might drive changes in household expectations.

The role of expectations is important in macroeconomics. The standard macroeconometrics methods are subject to omitted variable problems Lutkepohl (2007). One of these omitted variables is people's expectations about future macroeconomic conditions. An econometrician wanting to identify macroeconomic shocks correctly needs the same information set that decision-makers have, otherwise the identification of the shocks will be subject to omitted variable problems (Lutkepohl, 2007). One of these omitted variables might be news about future macroeconomic conditions. Identifying macroeconomic shocks from the data on expectations requires news about future economic conditions to be considered in an empirical model (Levchenko and Pandalai-Nayar, 2020).

These issues raise the popularity of studying the news and uncer-

[1]News about economic fundamentals.

[2]Confidence can be viewed as a strong belief that future economic developments will be positive, whereas sentiment is used to describe the views of economic agents about the economic conditions in the future (Nowzohour and Stracca, 2020). Sentiment in a text is a measure of the speaker's tone, attitude, or evaluation of a topic, independent of the topic's own sentiment orientation (Shapiro et al., 2020).

[3]As opposed to hard news, which means news about objective and directly quantifiable variables such as production and employment, soft news is news with subjective measures of attitudes about current and future economic conditions (Shapiro et al., 2020).

tainty shocks Beaudry and Portier (2006), Bloom (2009), Christiano et al. (2014). As stated in Feve and Guay (2018), business cycles could be driven by anticipated changes in economic conditions which almost never actually materialise or sentiment shocks that originate from information frictions and can capture waves of optimism and pessimism disconnected from any changes in economic fundamentals. Expectations of better future economic conditions, controlling for current fundamentals, can be due to either news of high future TFP, or positive confidence (Levchenko and Pandalai-Nayar, 2020).

When trying to include people's expectations, researchers mainly use the University of Michigan Survey of Consumers[4], identifying the restrictions on the contemporaneous effects for identifying news shocks (Beaudry and Portier, 2006), the estimated confidence from various Dynamic Stochastic General Equilibrium (DSGE) models (which is highly correlated with the University of Michigan Index of Consumer Sentiment[5]) or estimated news from the DSGE model (Schmitt-Grohe and Uribe, 2012). Following Barsky and Sims (2012), researchers use the following question to measure expectations: "Turning to economic conditions in the country as a whole, do you expect that over the next five years we will have mostly good times, or periods of widespread unemployment and depression, or what?". Levchenko and Pandalai-Nayar (2020) identify sentiment shocks as orthogonal to identified surprise and news TFP shocks that maximise the short-run forecast error variance of an expectational variable, or alternatively a forecast of the Gross Domestic Product (GDP) or a consumer confidence index.

Meanwhile, the use of the University of Michigan Survey of Consumers is limited for several reasons. First, it is not a perfect measure of people's expectations. Second, the usage is limited to the United States of America. Third, as stated in Levchenko and Pandalai-Nayar (2020), in order to extract a non-technology shock from data on expectations, we must control for news of future productivity; that is, to control for different types of expectations. Therefore, Levchenko and Pandalai-Nayar (2020) consider the processes for variables together with other forward-looking macroeconomic aggregates in a Vector Autoregression (VAR). In order to deal with these limitations and provide an alternative to the University of Michigan Survey of Consumers for measuring expectations, a different approach might be used, namely a sentiment text analysis, which also makes it possible to measure different types

[4] Such studies as *University of Michigan Survey of Consumers* (2019), Barsky and Sims (2012), Feve and Guay (2018).

[5] Angeletos et al. (2018)

of people's expectations.

While many studies have supported that fundamental news[6] is the main driving force behind the business cycles and subsequent economic activity, the effect of subjective information or positive/negative opinions of professionals (sentiments) have not yet been studied to the full extent. The sentiment analysis of news as a source of an expectation formation mechanism can be validated by the conclusion of Carroll (2001). It is valid for this aim since households do not follow the latest macroeconomic statistics but more probably follow news from different sources when forming their expectations about future economic development.

1.2 The aim, research questions and research tasks

The thesis aims to find out the effects of information framed (as positive or negative) by the media or by the Fed on the general public's expectations and how these effects transmit to the real economy and business cycles.

The main research questions are:

- What type of subjective information does the public react to while forming its expectations about the economy, interest rates and unemployment?
- What are the long-term effects of this subjective information on the real economy?
- What is the role of this subjective information for monetary policy?
- What is the primary transmission mechanism of sentiments to the real economy?

Therefore, this study focuses on news from the newspapers instead of news about future TFP shocks[7]. While news about future TFP shocks has received broad coverage in the literature, starting from the works of Carroll (2001) and Beaudry and Portier (2006), recent studies concentrate on the direct measures of news and uncertainty and their long-term effects[8]. The author identifies main channels of the effect of the transmission of news to the general public.

[6] Studies by Beaudry and Portier (2006), Barsky and Sims (2012), Schmitt-Grohe and Uribe (2012), Larsen and Thorsrud (2019*b*).

[7] fundamental news

[8] For instance, Shapiro et al. (2020), Larsen and Thorsrud (2019*b*), etc.

The research tasks, therefore, are as follows:

- To study the theoretical and empirical background of the effects of information and expectations on the real economy and monetary policy.
- To develop a methodological framework for measuring news sentiments as a multi-dimensional object.
- To develop a methodological framework for identifying the effect of different information types on the real economy and their role for monetary policy.
- To discuss the empirical results of the effects of different types of information.
- To figure out what types of information are crucial for the expectations of households.
- To study what types of expectations in households monetary policy reacts to.
- To study the effect of central bank sentiments during monetary policy announcements.
- To study the transmission channels of sentiments to the real economy

1.3 Research object, data and methodology

The research object includes different categories of business news from newspapers and their effect on the general public's expectations. The thesis' main task is to study the effect of this channel on the real and nominal economy.

As the main methodology, I will use suitable machine learning techniques for dealing with a sentiment analysis of news in different areas: investment, monetary and economic activity. Differentiating between the different types of expectations is validated, first, by other authors. For instance, Beaudry and Portier (2006) distinguish investment-specific news shocks from general news shocks. Second, this is known as a non-invertibility problem in Structural Vector Autoregression (SVAR), as the model is missing important variables contained in the information set of decision-makers. Current expectations about economic, investment and monetary policy are included in the information sets of different decision-makers, and will help the identification of fiscal, monetary and other types of macroeconomic shocks.

The main data source I use is the business sections of the main US newspapers. News articles are transformed into time series of topics by employing Latent Dirichlet Allocation (LDA) and Doc2Vec embedding with clustering. Afterwards, I adopt a lexical approach to assign a sentiment to each article. The lexical approach counts the proportions of positive/negative, constraining and uncertainty words in each article. Combining the topic time series derived from Doc2Vec embedding with clustering and from the LDA with the tone for each news article allows me to derive topic time series with sentiments.

These topic time series are employed to identify the types of news that are important for household expectations about unemployment, interest rates and inflation. I do this using a Least Absolute Shrinkage and Selection Operator (LASSO) regression with core macroeconomic indicators from the FRED-MD database (McCracken and Ng, 2015). I reduce the dimensionality of selected news topics using principal component analysis (PCA). The study employs the selected topic time series in Structural Vector Autoregressions (SVARs) to overcome the noninvertibility problem[9], and this allows the effects of soft news on monetary policy and real economic activity to be disentangled and the effect of different news sentiments on the macroeconomy to be studied.

To study the Federal Reserve reaction to the expectations of the public in its interest rate settings, I use the Federal Open Market Committee (FOMC) transcripts as the main data source since official economic statistics are subject to forecast revisions, and therefore might differ from the information that was available to policymakers during FOMC meetings.

This allows me to check what topics FOMC members were discussing at each FOMC meeting. Further, I employ a lexical approach to assign a sentiment (positive/negative, uncertain) to the most frequent economic phrases. These phrases with sentiments were further grouped into twelve categories: inflation expectations, consumer confidence, assets, energy, housing, demand, employment, growth, money, foreign, financial and fiscal.

These economy-related phrases from the FOMC members with the added tone (positive/negative, uncertain) are further employed to identify the types of information important for interest rate changes. Using LASSO and Elastic Net, I show that the sentiments of the FOMC members contain additional information for Taylor rule estimation even in

[9]See Beaudry and Portier (2007) for further details.

the case of controlling for the data from Greenbook official projections and forecast revisions (*Greenbook Historical and Forecast Data*, 2019).

1.4 Novelty of the study

While many studies support the idea that fundamental news[10] is the main driving force behind the business cycles and subsequent economic activity, the effect of subjective information or the positive/negative opinions of professionals (sentiments) have not been covered to the full extent. While Milani (2007), Milani (2017), Hirose and Kurozumi (2019) used data from surveys as additional information to pin down the effects of sentiments and news, there are not enough studies on the effects of emotions transmitted through newspapers on the real economy.

The thesis aims to find the effect of information framed (as positive or negative) by the media or by the Fed on the general public's expectations and how these effects are transmitted to the real economy and business cycles. The novelty of the thesis comes from the usage of sentiments measured from newspapers to identify macroeconomic effects on the real economy and for monetary policy.

Concerning *the first research question*, the main results are that the topic time series regarding the economy was found to be the most important for household expectations of interest rates, the topic time series regarding housing mattered most for unemployment expectations, and the topic time series regarding long-term loans was most relevant for inflation expectations. Moreover, the time series of these topics were obtained separately using two different text transformation approaches – LDA and Doc2Vec with k-means++ clustering. In addition, the principal component of the time series for these topics was found to have leading properties for indicators of economic activity.

Regarding *the second research question*, the study employs the topic time series mentioned above in conventional VARs with expectation variables showing that a positive soft news shock leads to a long-run increase in real economic activity and consumption, while the effects on inflation and the interest rate are also positive but transitory. Moreover, the soft news shock accounts for about 20% of the variance in the forecast error of real economic activity at longer horizons, while the effects of sentiment or expectations shocks were found to be less important. This helps to disentangle the effects of news shocks and

[10] E.g., Beaudry and Portier (2006), Barsky and Sims (2012), Schmitt-Grohe and Uribe (2012), Larsen and Thorsrud (2019*b*).

sentiment shocks empirically, so it is not necessary to impose ad hoc theoretical identifying assumptions in SVARs.

This study adds to the findings of Barsky and Sims (2012), Shapiro et al. (2020) and Larsen and Thorsrud (2019*b*) that the transitionary response of inflation to a news shock might be positive. This suggests that news shocks might not be viewed as anticipated exogenous TFP shocks, and this opens the door to alternative news shock channels, such as endogenous growth or anticipated demand shocks with endogenous propagation. This result is in line with the results of Leduc and Sill (2013), who used expectation variables from surveys in VAR and found that the anticipation of economic expansion leads to a fall in unemployment, a rise in inflation, and tighter monetary policy.

In addition, Leduc and Sill (2013) showed that expectations shocks account for a large share of the variance in real economic activity at longer horizons, while the findings from this study suggest that news shocks are more important at longer horizons for economic activity than households' expectations are. Contrary to the findings of Barsky and Sims (2012), this study shows that the news media channel is important for real economic activity and consumption [11]. The different results might be obtained because Barsky and Sims (2012) used answers regarding the news from the University of Michigan Survey, while Larsen and Thorsrud (2019*b*) and I used topic time series from actual newspaper articles and correlated those with the expectations of the general public.

Regarding *the third research question*, to my best knowledge, this is the first study examining all economic related phrases from FOMC discussions to find variables relevant to Committee decisions. In previous studies, authors ex-ante defined a list of words related to the category of interest[12]. Moreover, this is the first study that uses sentiments from newspapers as a proxy for central bank sentiments during monetary policy announcements.

The study contributes to recent literature that applies linguistic methods to the study of monetary policy. The findings are in line with previous findings in that financial variables are important to FOMC decisions[13]. However, the study expands previous findings concerning the importance of FOMC uncertainty concerning financial variables.

[11]This is also in line with the findings of Larsen and Thorsrud (2019*b*).

[12]For instance Peek et al. (2016), Cieslak and Vissing-Jorgensen (2018) among others.

[13]Peek et al. (2016), Cieslak and Vissing-Jorgensen (2018), Wischnewsky et al. (2021)

In addition, this study does not rely on a list of words but learns important economic phrases from FOMC transcripts.

First, to identify how soft news affects monetary policy, I investigate the effects of the time series for the Fed and Loans topics in an otherwise conventional VAR. It was found that the time series for the Loans topic is more important in the transmission mechanism of monetary policy than that for the Fed topic. This is because households generally do not pay much attention to monetary policy news. At the same time, monetary policy, both conventional and unconventional, can lead to a rise in long-run interest rates, and so it affects the current decisions of households and firms through this channel. The excess bond premium declines in response to a positive soft news shock, which leads to an expansion in economic activity and tighter monetary policy because of general equilibrium effects.

The results concerning the importance of consumer sentiments for the Federal Reserve objective function are in line with the findings of Hansen and McMahon (2016), who employed a narrative approach to the FOMC statements to identify what effect forward guidance had. They did not find any significant contribution from forward guidance shocks and such shocks were found to account for a small share of the forecast error variance in real variables. Neither does this study find the Fed sentiments in newspapers to have any strong effect on inflation or economic activity. One possible reason the effects are small is that the study uses data at monthly frequency.

Having said that, the findings are in line with those of Lewis et al. (2020), who employed high frequency identification and found that monetary policy news about forward guidance did not have any significant effect on household beliefs. Instead they found that news about changes in the target rate has a significant effect on the expectations of households. This is in line with the channel found in the current study, which is that monetary policy news has an effect through changes in long-term rates.

The results of this study add to the results of D'Amico and King (2017) since the study uses news about monetary policy in its analysis rather than employing survey forecasts as a proxy. D'Amico and King (2017) found that news about future monetary policy as proxied by survey forecasts has large, immediate and persistent effects on inflation and economic activity. In addition, previous findings from DSGE models show that monetary policy news shocks are generally more important than unanticipated monetary policy shocks in explaining business cycles (Milani and Treadwell, 2012; Gomes et al., 2017). The results of this study show that newspapers are not the main channel for these large effects that are observed for anticipated monetary policy.

As an alternative to changing long-run interest rates, the Fed might aim to change the inflation expectations of consumers directly, as was also pointed out by Falck et al. (2021). Changes in household inflation expectations affect the economy through the perceived real interest rate (Coibion et al., 2020), but this study did not find empirical support for the direct channel that changes households' inflation expectations as being important.

Second, the positive opinions of FOMC members about inflation expectations, consumer confidence, financial markets and fiscal policy contain additional information for interest rate changes. Whereas, FOMC member uncertainty about financial markets, monetary aggregates and inflation expectations were also found to be important. Uncertainty about financial markets, monetary aggregates and inflation expectations continue to be important for interest rates changes even while controlling for forecast revisions. Moreover, I analyse the sentiments of the FOMC Chairmen and whether these are related to changes in interest rates. The findings show that the uncertainty on the part of the Chairmen regarding monetary aggregates and financial markets are important.

As in the findings of this study, Oet and Lyytinen (2017), Boukus and Rosenberg (2006), Cecchetti (2003), Apel and Grimaldi (2012) found that themes extracted from releases of the Fed contain additional information.

The findings are also in line with Peek et al. (2016) and Cieslak and Vissing-Jorgensen (2018), who found that FOMC discussions and minutes about financial stability and stock markets contain predictive power for the federal funds rate changes. It was previously found that US monetary policy also reacts to changes in corporate credit spreads (Caldara and Herbst, 2019) and the excess equity premium measure (Cecchetti, 2003), but this study does not support these previous results.

The results also complement those of Clarida et al. (2000), who found that after 1979 the interest rate policy was much more sensitive to expected inflation. According to the results of this study, policy makers have been paying more attention to inflation expectations and financial markets since 1979.

Third, the study shows that newspapers cover FOMC announcements the next day after the announcements. Central bank communication is transmitted through the yield curve on announcement days. This finding challenges the standard identification strategies regarding monetary policy shocks, which assume that there is only one type of signal during the monetary policy announcement[14]. Furthermore, according to the standard identification, it is not essential what the central bank has actually said during the announcements[15] (Gürkaynak et al., 2005, 2020). This study shows that a central bank communication during the announcement days also moves the yield curve.

Regarding *the fourth research question*, the main transmission channel of sentiments works through increasing working hours and the number of entrants in the economy. Consumer consumption does not react in response to this shock.

1.5 Limitations of the thesis

Although the research aims to study the effects of different types of information on real economic activity and monetary policy, there are obvious limitations in the study.

First, the author uses only four major US newspapers for extracting news time series. Though this is a severe limitation due to data availability, the four selected newspapers are among the ten largest US newspapers by circulation. Moreover, these newspapers cover different parts of the USA. Nevertheless, the news concerning the economy and business should be correlated between all newspapers.

Second, the popularity of different newspapers might not be constant over time. Internet news services have gained more popularity since the 2000s. Moreover, the news and sentiments in newspapers might be biased because of political-ideological connections.

Third, the thesis uses small-scale vector autoregressions with constant coefficients and without stochastic volatility. Moreover, the models are linear in their parameters. I include the first principal component from a large macroeconomic database to capture the omitted variables effect. While non-linear models are appealing, the estimation of impulse responses in their case is complicated.

Fourth, Latent Dirichlet Allocation is a static topic model and this methodology might be unable to capture time-variation in topic distribution. To overcome this limitation, I selected a large number of topics.

These limitations will be considered in future research.

[14]See, for instance, Gertler and Karadi (2015), Jarocinski and Karadi (2020), Miranda-Agrippino and Ricco (2021)

[15]Among the exceptions is the work of Hansen and McMahon (2016).

1.6 Structure of the thesis

The second chapter discusses the theoretical foundations of the effects of expectations and news on the economy and reviews the main empirical findings on the topic.

The third chapter describes different methodologies for sentiment analysis and primary data sources.

The fourth chapter presents the main results of the decomposition of newspapers into topic time series.

The fifth chapter discusses the main effects of different types of information on the real economy and monetary policy.

The sixth chapter elaborates on the role of sentiments in monetary policy.

The seventh chapter studies the transmission mechanism of identified shocks on the real economy.

The eighth chapter concludes.

The ninth chapter discusses future research.

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Any errors that remain are my own.

2 Literature review

2.1 Review of Theoretical Literature

2.1.1 The role of information in the macroeconomy

Standard macroeconomic models are based on the rational expectations assumption based on the seminal paper by Lucas (1976). This rational expectation means that agents know the true data generating process of an underlying model and true model parameters. This assumption makes modern models not only invulnerable to Lucas' critique but also simplifies solution techniques. Therefore, it is not a straightforward task to take into account information asymmetries in standard macroeconomic models, since the common assumption is that agents have perfect foresight about the economy.

Nevertheless, in the recent few decades, there have been numerous attempts to relax this assumption favouring imperfect information models and models with learning. The early works of Lucas (1972) and Phelps and Cagan (1984) already offered some models with imperfect information, where information asymmetries were modelled as information flows between "islands" with perfect information within each of them. Similarly, Lucas (1973) assumed that suppliers are located in many markets, whereas demand is unevenly distributed across these markets. The main conclusion is that the higher the uncertainty in demand, the less favourable the terms of the Phillips curve.

There are two main stems of research on incorporating the role of information in macroeconomics. First, Mankiw and Reis (2002) proposed a sticky information model instead of sticky prices[16]. Incorporating this assumption in a model results in a more reasonable fit with observed dynamic responses about the effects of monetary policy; namely, a delayed effect on inflation, contractional disinflation and a positive correlation between inflation and the level of economic activity. Instead of assuming a fraction of firms updating their prices in each period, the model assumes a fraction of agents update information about the current state of the economy and re-optimise prices based on this information, while the rest optimise prices based on old information. Therefore, expectations matter because some agents set their prices based on old information. The model can explain the delayed effect of monetary policy on inflation and the positive correlation between economic activity and inflation.

Second, noisy information models were introduced in the works

[16] Which is the standard assumption in New Keynesian models.

of Woodford (2001) and Sims (2003). Woodford (2001) proposed an imperfect common knowledge model characterised by subjective perceptions of agents concerning aggregate demand; that is, idiosyncratic errors in processing public information. This model differs from the sticky information model proposed by Mankiw and Reis (2002). The latter assumes that suppliers obtain perfect information at random intervals. In contrast, the former assumes a noisy information channel and the Kalman filter to update agents' information in the current period. At the same time, Sims (2003) introduced a rational inattention model. He observed that a signal sent through a communication channel is quite similar to the signal extraction or adjustment cost in a model. Agents face a signal extraction problem in the rational inattention model, where noise endogenously changes with the economy. Therefore, the difference in the model by Woodford (2001) is that noise is endogenous to the state of the economy. Moreover, the author pointed out that it is costly for agents to monitor economic statistics continuously, thereby providing micro foundations for the role of the media.

The connection between expectations and the media gained popularity after the seminal works of Christopher D. Carroll, who developed several models of expectation formation in households. First, the author introduced a model where a small proportion of the population (professionals) form their expectations and spread them through media channels to the general public (Carroll, 2001). This model matches the data on inflation and unemployment expectations quite well. Using micro founded simulations, the author found substantial heterogeneity in households' attention to macroeconomic news and random mixing and social interactions in its spread between households. Therefore, he found empirical confirmation for the rational inattention model proposed by Sims (2003). In addition, Carroll (2001) argued that it is less costly to read a forecast from newspapers than to update one's own forecasting model. He found that about one-quarter of households update their inflation expectations from the news each quarter, which is similar to the assumptions in Mankiw and Reis (2002) model.

Second, Carroll (2003) suggests that people only occasionally pay attention to news reports, which, in turn, might generate stickiness in aggregate expectations. The paper provides micro foundations for Mankiw and Reis (2002) model. They also suggested that when there are more news stories, the updating speed should be faster. The author uses forecasts from the Survey of Professional Forecasters (SPF) as a proxy for news. The paper found that forecasts from the Michigan Survey of Consumers are irrational, while SPF forecasts are fairly rational.

Moreover, there is Granger causality from SPF to Michigan forecasts, but not vice versa. In the latter work, Carroll et al. (2020) proposed a model with sticky expectations, where households might have imperfect information about aggregate economic shocks and which leads to a lag in a spending response to aggregate shocks. They showed that this model could replicate the observed smoothness in consumption dynamics without introducing habit formation in a utility function of households. They also showed that their model is more plausible than models with imperfect information.

The study by Carroll (2003) also found a negative relationship between news coverage intensity and the gap between SPF and Michigan survey forecasts, meaning that people update their expectations more frequently when the news coverage is more intense. Similarly, Easaw and Ghoshray (2010) provided micro foundations for the macroeconomy's expectation formation process and found that households do not value bad news in the long run.

2.1.2 The role of information for business cycles: news and expectations shocks

Another way of incorporating the importance of information for the macroeconomy lies in the agents' expectation formation process. Roberts (1998) introduced the expectation formation mechanism into a New Keynesian model by using survey expectations, while Branch (2004) proposed a model of expectation formation where agents set their inflation forecasts based on a prediction function that might be not optimal. The forecasting models that the author considered include a VAR forecast, adaptive expectations and a naive forecast[17]. The author proposed a maximum likelihood estimator with continuous observed and latent discrete variables, where the latter represent the choice of a forecasting model. Applying this model to survey data on inflation expectations led to conclusions that agents switch predicting model as a mean squared errors change.

A first approach to studying the importance of expectations lies in incorporating news shocks into a standard model with rational expectations. The seminar paper by Beaudry and Portier (2004) assumed that agents receive imperfect information about future economic developments. This information might be news and noise. The authors pointed out that the news might be about future productivity and future policy, energy prices, etc. Subsequently, Beaudry and Portier (2007) proposed the basic framework of studying news shocks, which is the

[17] A forecast that is based on realisations from the previous period.

noisy information model where agents receive noisy signals about future technological development. In this framework, there are two ways of modelling news shocks: (a) as a signal extraction problem (a noisy signal) or (b) as an anticipated shock (which is a counterpart to an unanticipated shock). News business cycle literature views the positive anticipation of future technological development as a major driver of economic booms.

Following the popularity of news shocks, different authors started to modify the standard macroeconomic models to incorporate the effects of news shocks. The problem was in the inability of standard models to generate positive co-movement between investment and consumption in response to the anticipation of good times. Barsky and Sims (2012) incorporated information shocks into a standard New Keynesian Model as transitory innovations in the growth rate of technology. The authors assumed that agents do not observe the level of technology shocks, but they observe a noisy news signal with noise shocks, whereas firms can see level and news shocks without noise. The authors found that both technology level and information shocks are disinflationary and lead to a positive long-run impact on real activity. However, a news shock is more critical than a noise shock because the former combines aggregate demand with aggregate supply effects, while the latter only has an aggregate demand effect.

Standard models give rise to a negative co-movement between consumption and investment in anticipation of economic booms, where a popular way of changing this is to change the assumptions of the standard models. For instance, Jaimovich and Rebelo (2009) presented a theoretical model with three modifications: preferences that have fragile short-run wealth effects on labour supply; an adjustment cost for the rate of investment, which serves to produce an investment boom in response to a positive news shock as the planner wishes to minimise adjustment costs by smoothing investment over time; and adding variable capacity utilisation to the model, which allows the number of resources to be expanded in the initial periods to finance simultaneous consumption and investment booms. In contrast, Schmitt-Grohe and Uribe (2012) used an RBC model incorporating several real rigidities: internal habit formation in consumption, investment adjustment costs, variable capacity utilisation, and imperfect competition in labour markets. Both studies found that news shocks are important for business cycle fluctuations: the former study found that news shocks propagate mainly through the investments channel in firms. In contrast, the latter found that the most critical news shock is an anticipated wage markup shock.

Following the findings of Jaimovich and Rebelo (2009), several further studies exploited the importance of the investment channel for propagating news shocks. Haan and Kaltenbrunner (2009) presented a version of the RBC model with search friction in the labour market and showed that investments respond positively to a news shock, while Krusell and McKay (2010) introduced the Diamond-Mortensen-Pissarides model (Pissarides, 2000), which does not include capital, and did not find an investment response to a news shock.

Another important channel of news shocks found in the literature is through the labour market and firm creation. Fan et al. (2016) used the structural vector error correction model to show that new business formation and stock prices co-move with output under news shocks. The results presented empirical evidence of the connectedness of news about future economic conditions and firm entry. While Ravn et al. (2020) stated that labour markets might be the main channel for the propagation of sentiments shocks since agents might be uncertain about future employment and future demand conditions for firms. It follows that, conditional upon the pessimistic sunspot, monetary policy cannot impact the labour market outcomes as long as agents remain pessimistic. Similarly, Bhandari et al. (2016) found that ambiguity shocks propagate mainly through the labour market.

A popular way to measure news shocks in macroeconomic models is to use additional empirical data in the estimation, such as survey data. Bhandari et al. (2016) used survey data in a DSGE model with frictional labour markets, sticky prices and monetary policy to identify ambiguity shocks, defined as exogenous fluctuations in the worst-case model. Milani and Rajbhandari (2020) used survey expectations to identify news in a DSGE model. The authors identified the seven most popular shocks with anticipated counterparts. They found that news shocks are only weakly identified when estimating a DSGE model without additional data on expectations. The most important anticipated shocks are investment-specific technology, risk premium, wage markup and monetary policy.

In contrast to using survey data, Hirose and Kurozumi (2019) used forecast data to estimate news shocks in a business cycle DSGE model and concentrated their attention on technology shocks. They used forecast data related to inflation, output growth and interest rates from the Survey of Professional Forecasters to identify three types of anticipated shocks: technology, demand and monetary policy. Avdjiev (2016) used the data on asset prices in an RBC model. The authors checked the sensitivity of the results from a DSGE model with news shocks concerning assumptions about the structure of news shocks and advocated using a long-run news shock specification as a shock that does not affect current fundamentals but enters the information set of agents. Instead of employing Jaimovich and Rebelo (2009) preference specifications, the author used the specification of Schmitt-Grohe and Uribe (2012), namely a specification with internal habit in relation to leisure.

In contrast to the findings on the importance of news shocks, Khan and Tsoukalas (2012) estimated a DSGE model with real and nominal frictions, and the results did not confirm the importance of news shocks compared to unexpected technology shocks. The authors found that the dominant shock is the unanticipated shock to the marginal efficiency of investment. The difference from previous findings is explained by introducing nominal frictions in the model, adding endogenous countercyclical markups. Similarly, Christiano et al. (2014), investigating the significance of shocks for the cross-sectional volatility of idiosyncratic uncertainty (risk shocks), found that an unanticipated risk shock component is twice as important as an anticipated component. The authors placed news shocks on risk and noticed that a model with news shocks on transitory technology, monetary policy, equity and the marginal efficiency of investment shocks fits the data better.

A second approach to incorporating expectations is to exploit multiple equilibria. Benhabib et al. (2015) developed a Keynesian model with imperfect information concerning aggregate demand, where sentiment shocks play a crucial role under rational expectations. The mechanism is that firms face signal-extraction problems before the realisation of aggregate demand. They use a simple model, where production decisions in firms and saving and labour supply decisions in households need to occur before the realisation of demand. Under imperfect information, households form expectations about future income partly based on their sentiments, while firms receive only noisy signals about demand. Their signal extraction problem can generate equilibria, where fluctuations in output are driven by time-varying sentiment.

A third approach to incorporating expectations is to modify the rational expectations assumption. A detailed overview of the topic and stability conditions are presented in the excellent book Evans and Honkapohja (2001). Milani (2007) introduced learning into a DSGE model and found that a model with expectations and learning fits the data better than standard rational expectations models. Extending the previous work, Milani (2017) introduced sentiments in a DSGE model and relaxed the rational expectations assumption, favouring the learning process. The author identified different sentiment shocks, namely sentiments regarding consumption, investment and inflation, and found that sentiment shocks are major sources of business cycle fluctuations. These sentiments did not represent true news about future economic development but persistent waves of optimism and pessimism orthogonal to the economy's observed state. The most crucial sentiment shock is a shock to investment expectations, followed by a shock to investment-specific technology.

A fourth way of incorporating sentiments shocks in models is to introduce some frictions. Angeletos and La'O (2013) introduced sentiments into a rational expectation equilibrium by including random and decentralised trading into an RBC model, introducing shocks to expectations into a model from trading frictions. The paper finds that these sentiments shocks propagate through the communication channel because agents receive heterogeneous information about aggregate economic shocks. The study elaborates on the "island" model of Lucas (1972), where sentiments shocks arise from imperfect information regarding demand on other islands. The authors also considered an RBC model, where sentiment shocks replace standard TFP shocks.

2.1.3 The information effect of monetary policy

The information effect of monetary policy is an important question to study, considering the introduction of unconventional monetary policy measures in the recent decade. Moreover, incorporating anticipated monetary policy in a model might change impulse responses to a conventional monetary policy shock. That might help with its identification because standard identification schemes suffer from numerous drawbacks[18]. For instance, Mankiw and Reis (2002) showed that an inflationary response to a monetary policy shock has a maximum of seven quarters after the shock in a sticky-information model and immediately in a sticky-price model.

There are several ways of incorporating the importance of information in models with monetary policy. One of those is to introduce imperfect information into the model. Woodford (2001) found that the hypothesis regarding the role of imperfect information in temporal real effects of nominal disturbances based on "Island models"(Phelps and Cagan, 1984; Lucas, 1972) can be supported under two conditions, namely (1) monopolistically competitive pricing decisions depend on pricing set by others, and (2) imperfect information about monetary disturbances, which becomes public with a delay of one period. The authors concluded that monetary policy has real effects due to the public's insufficient attention to the available information. Christiano

[18]See Ramey (2016) for a complete survey.

et al. (2008) modified an RBC model with technology news shocks by introducing consumption habits and the adjustment cost to the flow of investment. The authors assumed that agents receive imperfect signals, form their expectations based on these signals, and conclude that boom-bust business cycles are generated by monetary policy. The main conclusion is that monetary policy is also essential in the transmission of expectational shocks. The models explain booms in terms of low real wages, which encourages firms to expand employment and households to supply labour at a given wage.

The second approach to studying the effect of information on monetary policy involves introducing news shocks regarding future monetary policy and working in the rational expectation paradigm. Milani and Treadwell (2012) studied the effect of news about monetary policy on the economy and found that news is more important than surprises for monetary policy[19]. The main channel of anticipated monetary policy shocks is through their impact on expectations about monetary policy and future macroeconomic developments because this information is essential for households and firms in solving their optimisation problems. Finally, the authors found that monetary policy shocks, both news and surprises, were not a major contributor to business cycles. Gomes et al. (2017) estimated a medium-scale DSGE model on US data and, like Milani and Treadwell (2012), found that monetary policy news shocks account for a substantial share of the variance of real variables at short horizons. Anticipated monetary policy shocks were found to generate expectations about future interest rates. The subsequent drop in demand is the main transmission channel of anticipated monetary policy shocks; therefore, these shocks create a contraction in the economy. The authors stated that while standard monetary policy shocks might reflect a deviation by the central bank from the systematic monetary policy rule, news shocks might indicate announcements by the central bank that market participants do not expect.

Similarly studying anticipated monetary policy shocks, Laseena and Svensson (2011) developed a linearized solution of a DSGE model with anticipated monetary policy shocks. By anticipated monetary policy shocks, they assume the central bank will make unexpected announcements or deviations from the previously announced monetary policy path. The model required that a vector of means for future anticipated shocks conditioned on current information should be given because these are the shocks with non-zero time-varying means. D'Amico and King (2017) studied the effects of anticipated and unan-

[19] News are anticipated shocks, while surprises are unanticipated.

ticipated monetary policy shocks in a VAR with sign restrictions from Arias et al. (2018) and found that anticipated monetary policy has the same directions as impulse response functions, but the magnitudes are higher. The reason is that anticipated monetary policy affects the real economy through the additional expectation channel. Therefore, all the studies on anticipated monetary policy shocks found their importance and the effect through the expectations channel. Moreover, the studies found that anticipated monetary policy shocks are more important than unanticipated.

To sum up, the theoretical literature has mainly focused on anticipated technology shocks, which should affect real variables through the investment channel and labour markets. Moreover, introducing news shocks in DSGE models with rational expectations was a more popular modelling choice than relaxing the rational expectation assumption in favour of learning models. Therefore, this monograph aims to study the effects of different sources of information asymmetries on the real and nominal economy. Moreover, I concentrate on expectations about interest rates, unemployment and inflation. Similar types of expectations were studied by Bhandari et al. (2016) and Milani and Rajbhandari (2020).

2.2 Review of Empirical Literature

2.2.1 Empirical evidence of news and expectations shocks

There are several directions in the study of news shocks. The first one uses stock prices data and identifies restrictions to study the effects of news shocks on the real economy. This stem of literature started with the pioneering work of Beaudry and Portier (2006), who noticed that short- and long-run identification schemes in vector autoregressions (VARs) consisting of TFP and stock prices obtain similar results. The authors identified a news shock as a shock to stock prices orthogonal to TFP in the short-run or that have a permanent effect on TFP in the long-run. Surprisingly, the authors found that the news shock is the main contributor to business cycle fluctuations in the long-run. Relying on a similar identification strategy, Beaudry and Lucke (2009) re-examined the results using a Structural Vector Error Correction Model (SVECM) combined with short- and long-run restrictions. Their paper aimed to estimate the relative importance of several candidate explanations of macroeconomic fluctuations: anticipated TFP shocks, unanticipated TFP shocks, investment-specific technology shocks, preference shocks, and monetary policy shocks. The authors came to the same conclusion: news shocks matter for business cycles in the long-run much more than unexpected TFP shocks.

The second direction uses the data from surveys to study the effect of news shocks. For instance, Sims (2009) identified a news shock using a VECM and a VAR with data on TFP, output, consumption, hours, stock prices, inflation, and consumer confidence. The author also identified a news shock in relation to innovations that explain future movements in TFP and found negative co-movement between consumption, output, hours, and investment in response to the news shock; therefore, good news about the future causes recessions today. Similarly Zeev and Khan (2015) found that identified news shocks are associated with nine out of eleven US recessions. The authors studied news shocks about investment-specific technology and found that those play a significant role in US business cycles. The authors employed a VAR with restrictions that maximise the forecast error variance of future Investment Specific Technology (IST) and is orthogonal to current TFP, IST, and the credit spread innovation. Bhandari et al. (2016) estimated a Factor Augmented Vector Autoregression (FAVAR) that uses household survey data and calculated the wedge between household surveys and surveys of professional forecasters.

Barsky and Sims (2012) considered another forward-looking variable as a proxy for news in a VAR: consumer confidence was measured using the Michigan Survey of Consumers. The authors did not find support for an animal spirits[20] view of confidence but instead pointed out the importance of its information channel. In addition, the authors found that both income and consumption slowly increase in response to a shock in consumer confidence with the proposed explanation that consumer confidence conveys important information about future output. In their later research Barsky and Sims (2011) identified news shocks in a VAR and VECM as shocks that are orthogonal to TFP contemporaneously but explain maximum forecast error variance in the long-run. The authors found that news shocks are positively correlated with output, consumption, stock prices and consumer confidence. Surprisingly, the authors also found a negative response in inflation. News shocks were found to be a quantitatively important driver of output at medium frequencies.

Another stream of research points out the drawbacks of VAR, such as the problems with invertibility discussed by Fernandez-Villaverde et al. (2007). Nelimarkka (2017) studies news shocks using a non-causal VAR that recovers economic shocks from both past and future variation, independent of the issue of nonfundamentalness or nonlineariti-

[20]Barsky and Sims (2012) refer to animal spirits as false news.

es. As nonfundamentalness implies non-causality, the model solves the problem of insufficient information directly.

Exploiting microeconometric evidence, Lamla et al. (2007) analysed survey data and media releases from Germany and found that news on aggregate developments affects perceptions and expectations of firms more than sectoral specific news. These expectations, in turn, have explanatory power for current and future economic developments. Benhabib and Spiegel (2019) found that sentiment shocks have a significant effect on output and consumption. The proposed mechanism is that sentiment shocks have an impact on the spending and investment decisions of households and firms, which, in turn, stimulate aggregate demand.

Benhabib and Spiegel (2019) used political partisanship at a local level as an instrument for sentiments because they were concerned about reverse causality. Similarly, Ravn et al. (2020) exploited mass shooting events as an exogenous instrument to study the causal effect of sentiment shocks. The authors found that a negative sentiment shock leads to contractions in the economy, and it has a more significant impact on the labour market than on nominal variables. The findings showed that animal spirits shocks have significant effects on the economy. They also found that news about actual technological development is not the main channel of sentiment shocks. This suggests that the identified innovations to confidence obtained using a Cholesky decomposition confounds sentiments with shocks to economic fundamentals. The authors found that a sentiment shock is more critical for the real side of the economy than the nominal, except for the short-term interest rate.

The importance of expectations is quite similar to the importance of news for real economic activity. Beaudry and Portier (2007) reviewed the literature on expectation driven business cycles and defined three major ways of studying expectations: as a psychological phenomenon, self-fulfilling fluctuations, imperfect predictions of the future based on news. Leduc and Sill (2013) used different indicators from surveys in VARs to study the role of expectations and their connection to monetary policy in explaining aggregate fluctuations. The authors found that expectations are important drivers of aggregate fluctuations: they stimulate future economic activity and inflation. However, monetary policy responded with contractionary actions to identified expectation shocks. Girardi (2014) found similar results for the euro area: expectations from surveys contain essential information for future macroeconomic development. An expectation shock accounts for 30% of the slack in about five years after the shock. Gorodnichenko et al. (2021)

used a deep learning model[21] to study the effect of FOMC Chair emotions from conferences on financial markets and found that positive sentiment leads to an increase in share prices.

2.2.2 News and expectation based indicators

Another way to study the effects of news shocks is to extract the data from newspapers directly. Fan et al. (2016) estimated a good news index measured as the difference in the frequencies of good and bad news. These frequencies, however, were taken from the Michigan Survey of Consumers. The authors found that higher frequencies of good news are highly correlated with economic booms. They also used the consumer or CEO sentiment indices in their robustness check exercise. Shapiro et al. (2020) developed a new measure of economic sentiment from economic and financial newspaper articles from 1980 to 2015. The authors compared their methodology for labelling sentiments with human judgements and used these indices in a VAR with Cholesky identification to study the effects of sentiment shocks. The paper found that positive sentiment shocks positively affect consumption, output, and interest rates, but reduce inflation. Following this line of research, Goshima et al. (2019) explored the daily Japanese newspaper articles (from Nikkei) and used them to construct business cycle indices. The authors used these indices to estimate a Phillips curve model to forecast inflation at daily frequency and found that indices that use the topics on future economic conditions are a good proxy for leading economic indicators. These indices were found to be the most important for forecasting inflation in Japan.

Yakovleva (2018) employed Latent Dirichlet Allocation (LDA) and Support Vector Machine (SVM) to construct a high-frequency indicator of economic activity in Russia. The author used news from the internet instead of newspapers as data sources for creating the index. Similarly, Larsen and Thorsrud (2019*a*) constructed a narrative index based on newspapers' news topics. Based on these narratives, the authors created indices of the business cycle at daily frequency. Moreover, the importance of these indices highlights that they contain something more than only animal spirits. In the following work, Larsen and Thorsrud (2019*b*) used LDA to decompose an influential Norwegian business newspaper into topics time series. The authors studied the importance of different topics to predict different macroeconomic outcomes and used those afterwards to derive an aggregated news index. They were able to identify what topics contain new information for

[21] A Neural Network model.

macroeconomic fluctuations. The paper found that innovations in this news index may cause persistent macroeconomic fluctuations and have a positive long-term effect on productivity.

Another popular way of using non-traditional data is to construct economic uncertainty indices, while studies on uncertainty became popular after the works of Bloom (2009) and Bloom et al. (2012). Baker et al. (2016) pioneered in developing a newspaper based index of economic policy uncertainty (EPU). This index was calculated as a frequency of newspaper articles that mention one of the following words: "economic", "uncertainty", and one word related to government. Following the previous work, Davis (2016) calculated a GDP-weighted index from national EPU indices of sixteen countries and labelled it as the Global Economic Policy Uncertainty index. Extending the previous line of work, Ahir et al. (2019) constructed the World Uncertainty Index by calculating the number of mentions of the word "uncertainty" in country reports and found that uncertainty is negatively associated with economic growth. Davis (2019) studied the causes of increasing economic uncertainty in recent years and found that trade policy and stock market volatility from 2018 are important in this regard.

However, Tobback et al. (2018) argued that EPU has a measurement error and proposed to use the support vector machine (SVM) method with a pool-based active learning algorithm to create a similar index for Belgium. This new index predicts major Belgian macroeconomic indicators better than the original EPU index. Alternatively, Yono et al. (2020) constructed uncertainty indices from news text data using the supervised Latent Dirichlet Allocation with volatility index (VIX) as the dependent variable. The authors found negative relationships between uncertainty and economic activity.

3 Methodology

3.1 Extracting sentiments from newspapers

Several studies have used newspaper articles as a data source. Cole (2010) took data from The New York Times and The Washington Post, Larsen and Thorsrud (2019*b*) used the major Norwegian newspaper, Shapiro et al. (2020) used data from 16 major US newspapers from the LexisNexis database, and Larsen and Thorsrud (2019*a*) used a large number of articles (5 million) from the Dow Jones Newswires Archive.

I use the Nexis Uni (2019) database, from which I extract daily business news from The New York Times 1980–2019, The Washington Post 1981–2019, The Los Angeles Times 1985–2019, and The Chicago Tribune 1985–2019. The New York Times is the second-largest newspaper by circulation and the largest circulating metropolitan newspaper, with a weekly circulation of 2.1 million. It is ranked 18th in the world by circulation. The Los Angeles Times is the fourth-largest US newspaper by circulation, The Chicago Tribune is the sixth-largest and The Washington Post is the seventh-largest. The total timespan is 1980:M6–2019:M7.

For comparison, Larsen and Thorsrud (2019*b*) used 25 years of news data, Cole (2010) took data from The New York Times and The Washington Post from 1980 to 2000, Larsen and Thorsrud (2019*a*) used 1990–2016, Shapiro et al. (2020) 1980–2018, and Goshima et al. (2019) 1989–2017.

Following Shapiro et al. (2020), I filtered out the news that does not contain any of the words: said, says, told, stated, wrote, or reported. Imposing this criterion meant the data pull yielded around 416,000 articles.

There are a few mainstream theories about the role news has in the expectation formation mechanism. Woodford (2001) introduced a noisy-information model, where price-setters get a noisy signal about monetary policy in every period, while Mankiw and Reis (2002) model price-setters gaining perfect information about monetary policy with the probability λ in every period, where expectations matter because some price-setters are still setting prices using old decisions and old information. In addition, some price-setters might learn about monetary policy through a limited-information channel, so it is as if they are observing monetary policy with a random error and have to solve a signal-extraction problem (Lucas, 1972). Branch (2004) pointed out that information acquisition costs may make it rational for agents to select methods other than rational expectations, so agents update their previous expectations in each period by weighing costs and benefits.

There are two main channels through which the news affects the economy. The first is reporting on actual economic data and the second is the transmission of opinions from professionals to the general public. Experts express their opinions in the news media and the more important an issue is, the more frequently it is covered by the media. The general public form their expectations from personal opinion and the news, and these expectations influence the current economic decisions of agents. Intensive news reporting improves the accuracy of household expectations because they receive more information (Doms and Morin, 2004; Carroll, 2001, 2003). The more frequently a story is covered by the news, the more probable it is that households will read it (Larsen and Thorsrud, 2019*b*). However, this effect also depends on the tone of the news (Lamla and Lein, 2014; Lei et al., 2015).

Carroll (2003) proposed the following model of the expectation formation mechanism with the media channel (1):

$$M_t(\pi_{t,t+12}) = \alpha_1 N_t(\pi_{t,t+12}) + \alpha_2 M_{t-1}(\pi_{t-1,t+11}) + \alpha_3 P_t(\pi_{t-1}) + \epsilon_t \quad (1)$$

where $\pi_{t,t+12}$ is household expectations for $t+12$ formed in time t, in this case inflation expectations over the next year; $M_t(.)$ is expectations in the current period; $M_{t-1}(.)$ is expectations from the previous period; $N_t(.)$ is news, proxied by Carroll (2003) using a survey of professional forecasters; and $P_t(.)$ is the latest statistics.

Doms and Morin (2004) stated that the news affects the perceptions of households through three channels. First, it conveys the latest economic data and the opinions of professionals to households; second, it gives them a signal about the economy through the tone and volume of news reporting; and third, the more news about the economy there is, the more likely it is that households will update their expectations about the economy. The authors found evidence that all three of these channels are important for consumer sentiment. Larsen and Thorsrud (2019*b*) tried to capture the effect of the latest economic data in the news, while Shapiro et al. (2020) focused on the opinions of professionals.

The formula quoted above (1) captures the latest economic data in $P_t(.)$ and the opinions of professionals in $N_t(.)$. Carroll (2003) used the survey of professional forecasters directly as a proxy of $N_t(.)$, while I proxy $N_t(.)$ directly using sentiments derived from newspapers. That is in line with Levchenko and Pandalai-Nayar (2020), who identified a sentiment shock as orthogonal to surprise, and news TFP shocks that maximise the short-run forecast error variance of an expectational variable, which may be a GDP forecast or a consumer confidence index.

Researchers looking at public expectations mainly use time series from the University of Michigan Survey of Consumers as proxies for expectations (*University of Michigan Survey of Consumers*, 2019; Barsky and Sims, 2012; Feve and Guay, 2018). The most commonly used surveys are the Survey of Professional Forecasters, the Lundberg Survey, the Michigan Consumers Sentiment Survey, and the Livingston Survey.

As $M_t(.)$ I employ the University of Michigan Survey of Consumers (*University of Michigan Survey of Consumers*, 2019) and I use expectations of interest rates, unemployment, and inflation over the next 12 months. These correspond to the answers to the survey questions:

- "No one can say for sure, but what do you think will happen to interest rates for borrowing money during the next 12 months – will they go up, stay the same, or go down?"
- "How about people out of work during the coming 12 months – do you think there will be more unemployment than now, about the same, or less?"
- "During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now? and By what percent do you expect prices to go up, on the average, during the next 12 months?".

The importance of expectations of this type has also been pointed out in the earlier literature. Gilbert et al. (2017) estimated a novel measure of the intrinsic value of macroeconomic announcements, which they defined as the ability of the announcement to nowcast GDP growth, inflation, and the federal funds target rate. Beechey and Wright (2009) studied the bond market response to macroeconomic news and grouped announcements into three broad categories of news about prices, news about real output, and news about monetary policy. Hirose and Kurozumi (2019) identified the anticipated and unanticipated components of shocks to technology, demand, and monetary policy using the actual and forecast data for output growth, inflation, and an interest rate.

Larsen and Thorsrud (2019*b*) ran sign adjustment on news topics to separate positive and negative news. As was pointed out by Sims (2003) though, the tone of economic reporting affects sentiment beyond the economic information contained in the reporting itself, as was explored by Shapiro et al. (2020). Therefore, I include both news frequency and news sentiments in the analysis.

To assign a sentiment to each news article I employ a combination of two dictionaries by Henry (2008) and Loughran and Mcdonald (2016) (LM) with modifications, which are discussed in Appendix A. This approach relates to Shapiro et al. (2020), who found that combining different dictionaries with a negation rule comes closer to human judgement in labelling sentiment. It is worth mentioning that Shapiro et al. (2020) also used a Vader package that was trained on general text labelled by humans from Amazon Mechanical Turk, but the performance of their modified dictionary with Vader was not statistically significantly different from that of the combination of several dictionaries with the negation rule.

Positive sentiment in an article is calculated as the sum of positive words over sentences (2):

$$Pos_i = \sum_{sentence} \frac{\#positivewords_i - \#negativewords_i}{\#totalwords_i} \tag{2}$$

Since news that is more intensively covered is more important, the monthly aggregate positive sentiment for each topic is adjusted by topic frequency within a month. The total monthly positive sentiment for a topic is calculated as the sum of daily positive sentiments minus negative sentiments multiplied by the fraction of all articles covering the topic within a month, or topic frequency (3):

$$Pos_{topic} = \sum_{i \in topic} Pos_i \times \frac{\#topic\_articles}{\#Total\_articles} \tag{3}$$

where $\#topic\_articles$ is the number of articles on one topic within a month, and $\#Total\_articles$ is the total number of articles within that month.

Similarly, I calculated uncertainty and constraining sentiments by employing (2) and (3) for uncertainty and constraining words from Loughran and Mcdonald (2016)[22]. I further use Pos_{topic}, $Uncertain_{topic}$, and $Constraining_{topic}$ as $N_t(.)$ for different news topics in (1). The methodology for extracting the news topics is discussed in the next two subsections.

3.2 Latent Dirichlet Allocation

Following Larsen and Thorsrud (2019*b*), I use the Latent Dirichlet Allocation (LDA) introduced by Blei et al. (2003) for topic extraction.

[22]The full list of words for each sentiment category is available at https://sraf.nd.edu/textual-analysis/resources/

The LDA is a probabilistic graphical model that is based on the bag-of-words assumption that word order does not matter. Mixing the words in an article and running the LDA will give the same result as not mixing. Standard text processing steps are employed to extract news topics using the Latent Dirichlet Allocation:

- Words from a stoplist are excluded. This list contains common words that contribute little meaning to the documents, such as prepositions, conjunctions and pronouns.
- Words are stemmed, or reduced to their word root form, so economy, economic, economical, economics, economise are all reduced to the root form econom.
- Rare and common words are removed.
- The vocabulary that results consists of 57,990 unique words.

The LDA is a mixed-membership directed probabilistic graphical model for a text corpus. The generative process for a document collection D under the LDA model has the following elements (Darling, 2011):

1. For each topic $k = 1, ..., K$, where K is the total number of latent topics:
   - A discrete probability distribution over a fixed vocabulary that represents the k^{th} topic distribution, $\varphi_k \sim Dirichlet(\beta)$[23]
2. For each document $d \in D$, where D is the total number of documents:
   - A document-specific distribution over the available topics (per-document topic proportion), $\theta_d \sim Dirichlet(\alpha)$[24]
   - For each word $w_n \in d$, where N is the total number of words:
     (a) Per-word topic assignment, showing which topic generated the word instance $w_{d,n}$, $z_{d,n} \sim Mult(\theta_d)$[25]
     (b) An observed word, $w_{d,n} \sim Mult(\varphi_k)$

[23] $Dirichlet(.)$ is the Dirichlet distribution (a conjugate prior for the Multinomial distribution), β is a hyper-parameter.

[24] α is a hyper-parameter.

[25] $Mult(.)$ is the Multinomial distribution.

The joint probability for the LDA takes the form (4):

$$p(w_{d,n}, z_{d,n}, \theta_d, \varphi_k|\alpha, \beta) = (\prod_{n=1}^{N} p(z_{d,n}|\theta_d)p(w_{d,n}|z_{d,n}, \varphi_{n,k}))(\prod_{k=1}^{K} p(\varphi_k|\beta))(\prod_{d=1}^{D} p(\theta_d|\alpha))$$

$$= (\prod_{n=1}^{N} Mult(z_{d,n}|\theta_d)Mult(w_{d,n}|z_{d,n}, \varphi_{d,k}))(\prod_{k=1}^{K} Dirichlet(\varphi_k|\beta))(\prod_{d=1}^{D} Dirichlet(\theta_d|\alpha)) \quad (4)$$

where, $p(w_{d,n}, z_{d,n}, \theta_d, \varphi_k|\alpha, \beta)$ is the posterior from the LDA model.

The latent variables $z_{d,n}$, θ_d, φ_k are unobserved. Inference is done using Collapsed Gibbs Sampling (Griffiths and Steyvers, 2004) with $\alpha = 50$ and $\beta = 0.01$. Since for the inference of both θ_d and φ_k it is sufficient to know just $z_{d,n}$, Collapsed Gibbs Sampling is based on integrating out the multinomial parameters and simply sampling $z_{d,n}$[26]. The outcomes of the algorithm are topic distributions θ_d and word distributions per topic φ_k.

The optimal number of topics for LDA was chosen using coherence values. The topics are considered to be coherent if all or most of the words are related, appearing for instance in the top N words for the topic. Coherence values for different numbers of topics are presented in Figure B.1. The coherence values show the optimal number of topics to be 40. All the topics from the LDA model are interpretable and are shown in Figure 1, while Table B.1 shows the word distributions for each topic.

Figure 1 presents identified topics with the most frequent words within each topic. A larger size of a word means that this word is more frequent in this topic and vice versa. All identified topics are economically meaningful and assigned labels for each topic are shown in Table B.1, these are: rates, computers, economic, food, people, media, fed, housing, credit, cars, health, trade, law, debt, loans, stocks, schools, economics, retailers, industry, cities, profits, jobs, currency, airlines, military, energy, oil/gas, international, hotels, rules, stock market, company news, services, investing, president, reports, securities, budget, deals.

[26] See Griffiths and Steyvers (2004) for the detailed treatment.

Figure 1: Topics according to the LDA model

3.3 Doc2Vec

Another way to transform articles into a numeric format is using the Neural Network (NN) Doc2Vec, which was introduced by Le and Mikolov (2014). Neural Networks take account of the word order and semantics of words and have no specific text processing requirements. Doc2Vec works with text through stochastic gradient descent and backpropagation. Each paragraph is mapped into a unique vector represented by a column in matrix D, and each word is mapped into a unique vector represented by a column in matrix W. The paragraph vector and word vectors are averaged or concatenated to predict the next word in a given context.

This Neural Network is based on the distributional hypothesis, which means that words that occur in a similar context have a similar meaning (Le and Mikolov, 2014). Doc2Vec exploits this hypothesis and transforms words that are similar semantically, as they occur in a similar context, into vectors that are similar geometrically in Euclidean space. Doc2Vec transforms articles into vector representations, and the representations for conceptually similar articles are close to each other in terms of cosine similarity. Doc2Vec does not rely on the bag-of-words assumption, so word order matters.

The objective of Doc2Vec is to maximise (5)

$$\frac{1}{T}\sum_{t=k}^{T-k}\log p(w_t|w_{t-k},...,w_{t+k}) \tag{5}$$

$$p(w_t|w_{t-k},...,w_{t+k}) = \frac{e^{y_{w_t}}}{\sum_i e^{y_i}}$$

$$y = b + Uh(w_{t-k},...,w_{t+k}|W,D)$$

where $w_{t-k},...,w_{t+k}$ is a sequence of words, $p(.)$ is a probability (softmax), y_{w_t} is the un-normalised log-probability for each output word, b and U are the softmax parameters, and $h(.)$ is constructed by concatenation or averaging of the word vectors extracted from W[27].

I normalised the vectors to have unit lengths. In this case, minimising Euclidean distance is the same as maximising cosine similarity (see Appendix C for details).

For topic clustering, I employ k-means++ (Arthur and Vassilvitskii, 2007). This algorithm selects a set of n points in Euclidean space, an integer number k, and finds a partition of these points into k subsets, each with a representative centre. This method minimises the average squared distance between points in the same cluster.

k-means++ differs from the traditional k-means clustering in the way it chooses initial clusters. After that it proceeds to standard k-means clustering. First, let me to discuss a standard k-means algorithm. Given a set of observations $(x_1, x_2, ..., x_n)$, $x \in X$, k-means clustering partitions the n observations into k sets $S = \{S_1, S_2, ..., S_k\}$ in order to minimise the within-cluster sum of squares (6):

$$L = \underset{S}{argmin}\sum_{i=1}^{k}\sum_{x\in S_i}||x-\mu_i||_2^2 \tag{6}$$

[27]For further details please consult Le and Mikolov (2014).

where μ_i is the centre of a cluster. The algorithms seek the set of centres (μ_i) that minimises the objective function stated above (6).

K-means works by repeating the following steps until convergence:

1. To assign each input point to its nearest centre given the locations of centres from step two

2. To recompute the centres given the point assignment from step one

While k-means uses a random initialisation of cluster centres as a local search, k-means++ selects only the first centre uniformly at random from the data. The probability of each subsequent centre being selected is proportional to its contribution to the overall error given the previous selection. The probability of a point being chosen to be the i^{th} centre depends on the realisation of the previous centres. An implementation of k-means++ initialisation will make k passes over the data to produce the initial centres (Bahmani et al., 2012).

K-means++ proceeds as follows (Arthur and Vassilvitskii, 2007):

1. To take one of the centres μ_0, chosen uniformly at random from X.

2. To take a new centre μ_i, choosing $x \in X$ with probability $p = \frac{D(x)^2}{\sum_{x \in X} D(x)^2}$[28]

3. To repeat Step 2 until the algorithm has taken k centres altogether.

4. To proceed as with the standard k-means algorithm (steps 1–2 from the standard k-means algorithm until convergence).

I calculated the most common words from the news headlines for each cluster. The results for 40 clusters are presented in Figure 2. Table D.1 shows the detailed descriptions of topics from Doc2Vec with k-means++ 40 clusters.

As in Figure 1, larger words are more frequent within each topic. Identified topics are also economically meaningful and their labels are as follows: new business, dow, jobs, profits, housing, reports, currency, fraud, company stocks, farm prices, retailers, energy, media, money,

[28] $D(x)$ is the shortest distance from a data point to the closest centre that has already been chosen.

international, economy, entertainment, airlines, financial markets, banking, economic, deals, services, oil/gas, real estate, loans, trading, aircraft, vehicles, financial news, health, business digest, investing, trade, fed, cities, technology, futures, online, president.

There are some similar topics to those in Figure 1, which are: housing, loans, economy, fed, jobs, oil/gas, investing, vehicles and cars, energy, media, international, airlines, cities, health, trade, president, deals, currency, stock market and company stocks, services. These similarities might be due the similarities in underlying true topics that newspapers cover.

Figure 2: Topics according to the Doc2Vec

3.4 Data and sentiment from FOMC transcripts

Does the Federal Reserve pay attention to the expectations of the public while setting its target interest rate? This is an important channel of propagation for the effects of sentiments or expectations shocks. To study this question, I take the Federal Funds Rate target provided by Federal Reserve economic data. I use the target rate seven days after each meeting to give the FOMC time to adjust its target rate based on the meeting results. As official forecasts, I use the data from

Wieland and Yang (2020), who extended the dataset from Romer and Romer (2004) to 2008. Federal Open Market Committee transcripts for 1976–2008 were downloaded from the Fed webpage[29] (*Federal Reserve Economic Data*, 2019). FOMC transcripts are released with a five-year delay and each meeting transcript contains about 200–300 pages. Total timespan is 1976–2008. I truncate the sample at 2008 since in 2008 the federal funds rate hit the zero lower bound.

The text was split into 2-grams; that is, partitioned into tuples of two words each[30]. I use the Oxford Dictionary of Economics (Black et al., 2009)[31] to filter these grams. I keep only the grams that contain all economic words. The frequency of these economic phrases are shown in Figure L.1, while Figure L.2 presents the most frequent economic phrases frequently used by Chairmen.

FOMC members usually discuss monetary policy, unemployment rate, inflation expectations, labour markets, economic growth, financial markets, GDP growth, real estate, price stability, discount rate, inflation, money markets, oil prices, stock markets and consumer spending (Figure L.1). Some of these phrases are forward-looking (inflation expectations). Moreover, these discussions might confirm that the Fed reacts to demand and supply shocks differently. For instance, a discussion of oil prices might reflect expected supply shocks, while discussions of consumer spending would do so for expected demand shocks. Chairmen usually introduce speakers, but they are also concerned with money supply and money markets (Figure L.2).

To assign a sentiment for each economic term, I employ a combination of two dictionaries of Henry (2008) and Loughran and Mcdonald (2016) (LM) with a negation rule. I employ additional modifications to assign a sentiment for inflation expectations, which are discussed in Appendix A. My approach is related to Shapiro et al. (2020), where the authors found that the combination of different dictionaries with a negation rule is closer to human judgements in labelling sentiment.

The positiveness of an economic phrase is calculated as the sum of the positiveness of this phrase in a fourteen-word window as in (2); that is, I extract seven words which precede each collocation and seven words which follow it. For all other economic collocations, I employ

[29] I am grateful to Miguel Acosta (Acosta (2015)) for providing already downloaded transcripts for 1976–2008

[30] The sentence: the quick brown fox jumped over the lazy dog. 2-grams of the sentence: "the quick", "quick brown", "brown fox", "fox jumped", "jumped over", "over the", "the lazy", "lazy dog".

[31] This approach is similar to Shapiro and Wilson (2019).

the dictionaries of Henry (2008) and Loughran and Mcdonald (2016). The details on the methodology for assiging positive/negative sentiments within each sentence can be found in Appendix A. Moreover, I use the word anchored as a positive word for inflation and inflation expectations.

Since more intensively covered economic terms are more important, I calculate the total number of positiveness for each term by each meeting. This allows me to take into account both frequency and sentiments. The frequency of the occurrence of a certain economic topic should reflect the relative importance of this topic among others. The total positiveness of a term for each meeting is calculated as the sum of the positivenesses of phrases(7):

$$Pos_{term} = \sum_{i \in term} Pos_i \tag{7}$$

Similarly, I calculated uncertain sentiments by employing (2) and (7) for uncertainty words from Loughran and Mcdonald (2016)[32].

[32]The full list of words for each sentiment category is available at https://sraf.nd.edu/textual-analysis/resources/

4 Soft news

4.1 Topic time series with sentiments

I employ two different methods for assigning topics for the LDA results, since the model offers topic distributions as an output. The first method is to assign a dominant topic for each article[33], and the second is to assign topic distributions for each article[34]. K-means++ clustering assigns one topic for each article, so I have three topic time series models in total.

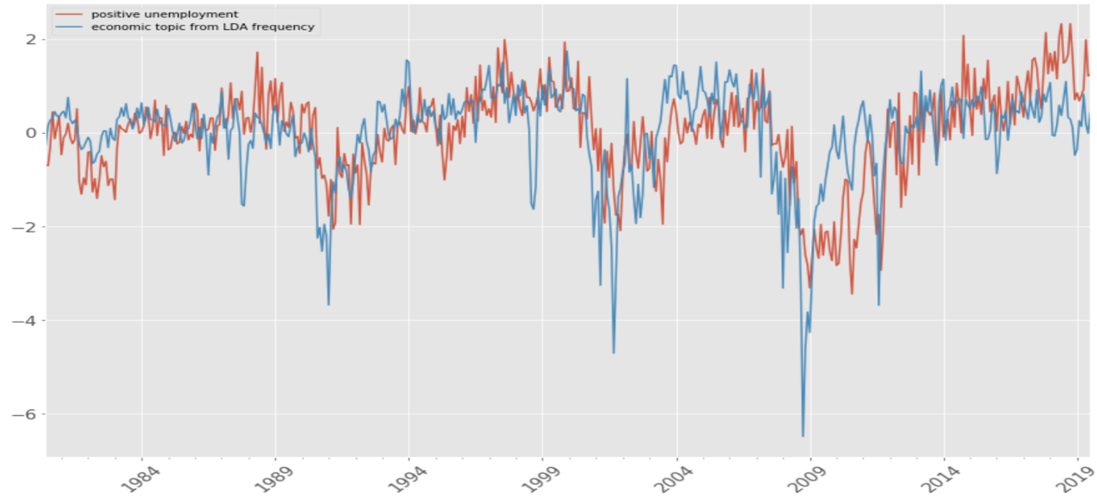
Figure E.1 shows the cross-correlations between the topic time series with the sentiments from Doc2Vec using k-means++. The topics that correlate most are Financial markets and Dow, Investment and Financial markets. The figure also includes household expectations. The highest correlations with expectations of interest rates were found for unemployment expectations, and the topics Reports, Economic, Profits, Money, Company stocks, Retailers and Jobs; for consumer unemployment expectations the correlations were with interest rates expectations, and the topics Vehicles, Economic, Housing, Financial market and Reports; and those for inflation expectations were with the time series for the topics Housing and Loans.

Figure E.2 presents the correlations between the topic time series for the sentiments from Doc2Vec with clustering and the LDA model that assigns the topic frequency for each article. Although methods employed are different, many topics are correlated between different models, such as the time series for the topics Housing, Fraud and Law, Dow and Stocks, Jobs, Profits, Currency, Company stocks and Deals, Retailers, Airlines, Economic and Reports, Loans, Oil/gas, Vehicles and Cars, Investing, President, Technology, and Computers.

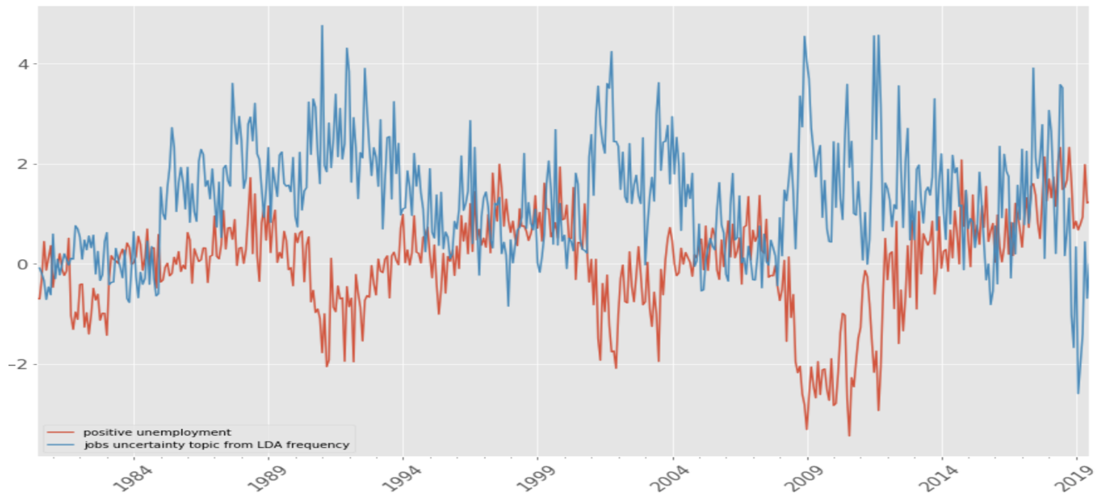
Figure E.3 discusses the correlations between the topic time series for the sentiments from Doc2Vec with clustering and the LDA model that assigns a dominant topic for each article. There are meaningful correlations between the time series for the topics Dow and Stocks, Housing, Profits, Jobs, Currency, Retailers, Energy, Airlines, Financial market and Stocks, Banking and Credit, Economic and Reports, Oil/gas, Services, Real estate and Cities, Loans, Vehicles and Cars, Health, Financial news and Securities, Investing, Fed, Technology.

[33] Which is similar to clustering, as one article is connected with the one topic that has the highest proportion among the 40 topics.

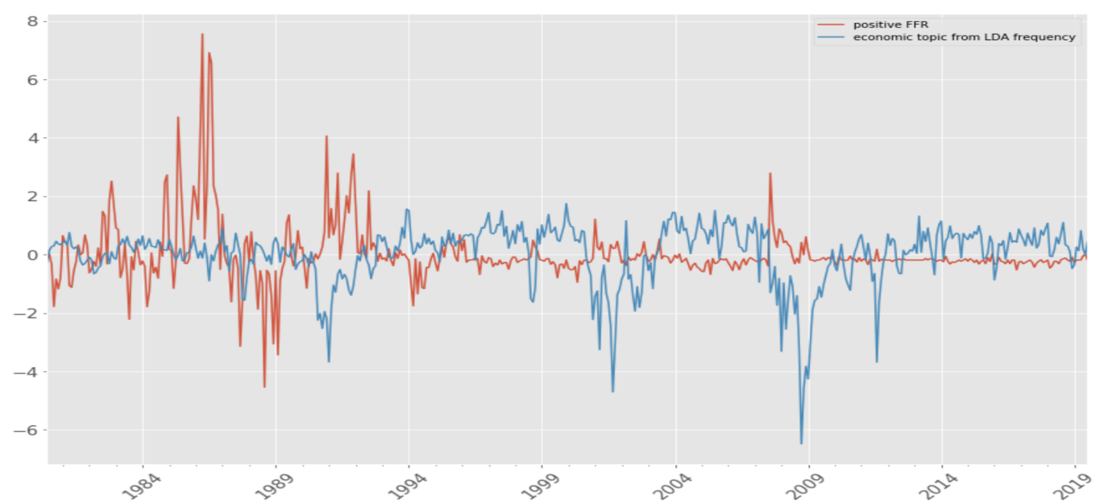
[34] One article is associated with 40 topic proportions.



(a) Unemployment positive sentiment in red and the topic Economic (positive/negative) in blue



(b) Unemployment positive sentiment in red and the Jobs (uncertain/certain) in blue



(c) FFR positive sentiment in red and the topic Economic (positive/negative) in blue

Figure 3: Comparison of the LDA topic time series with sentiment and simple sentiment frequency models. Standardised series.

Figure E.4 shows the correlations between the time series of topics for the sentiments derived from differently labelled LDA models. Almost all the time series that represent the same topic are highly correlated. Appendix E presents the dynamics of the topic time series with sentiments from different models. Even though the assumptions of the underlying models are different, the topic time series derived from the different models have quite similar dynamics and similar labels.

For comparison, I extracted sentences with keywords related to unemployment, inflation and the federal funds rate (FFR)[35], and calculated a sentiment for each keyword using the methodology described in Appendix A. After each keyword was detected, the sentiment of positive or negative was assigned to a sequence of the five words preceding it and the five words following it. The sentiment related to a specific keyword, if any, should appear in this window. I add up these sentiments for each keyword for each month. The comparisons between the sentiment models from keywords and the topic models with sentiments are shown in Figure 3.

Surprisingly, the correlation between the frequency of positive sentiments for unemployment and positive sentiments for the time series of the topic Economic from the LDA model using topic frequencies as labels is 0.57[36]. That is because the tone of the news is more negative during recessions and so the negative sentiments are more common.

The uncertainty sentiment for the time series of the topic Job is negatively correlated with the frequency of positive sentiments for the keyword unemployment (part (b) of Figure 3). During recessions there is greater uncertainty about unemployment and negative news articles about unemployment appear more frequently.

Similarly, it is seen that positive news about the federal funds rate is more common during bad times (part (c) of Figure 3). That is completely in line with the objectives of the Federal Reserve, or the Fed, as it revises rates downward to stimulate the economy during recessions. Moreover, the Fed signals more about monetary policy during recessions.

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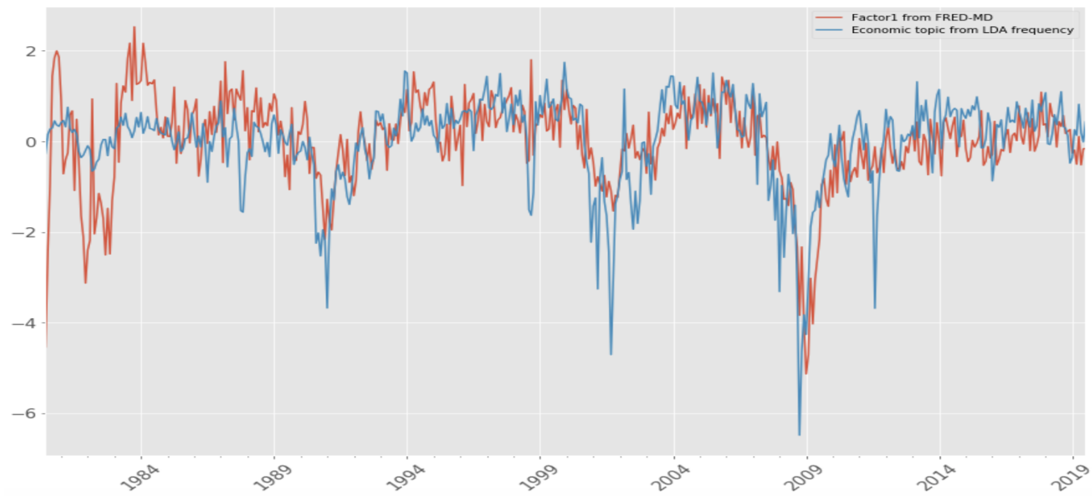
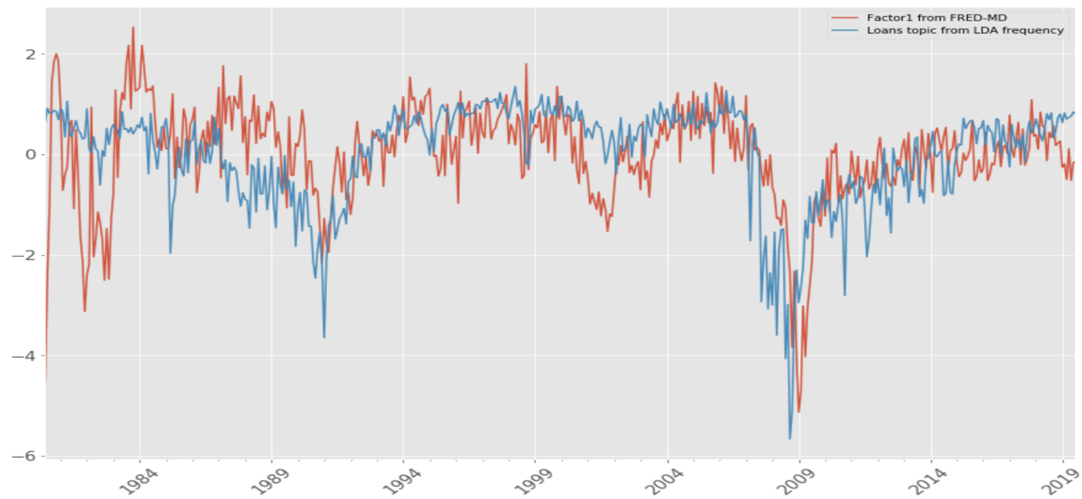
[35] The keywords for the federal funds rate are discount, rate and federal. A sentence should contain at least two of these keywords.

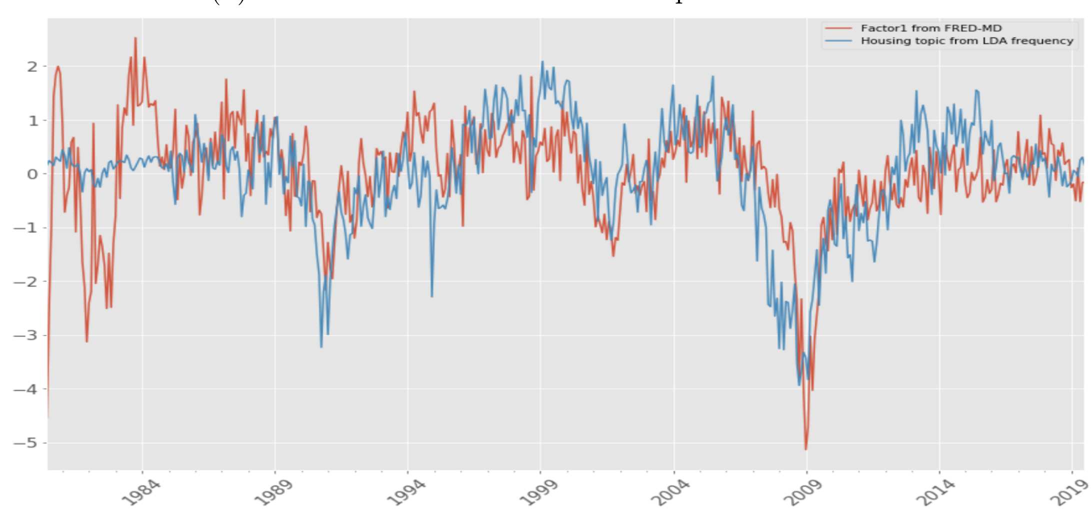
[36] All correlations in this section are presented from 1984 till 2019 because of the high level of volatility in economic variables during the Volcker disinflation.



(a) The first factor in red and the topic Economic in blue



(b) The first factor in red and the topic Loans in blue



(c) The first factor in red and the topic Housing in blue

Figure 4: LDA topic time series with positive sentiments and the first factor from the FRED-MD (McCracken and Ng, 2015). Standardised series.

Figure 4 shows the relation between the topic models and the first factor from the FRED-MD database[37] (McCracken and Ng, 2015). This factor should be a good indicator of current macroeconomic conditions (Bernanke et al., 2005) and can serve as a proxy for the cyclical position of the economy. The factor has strong correlations with the time series with positive sentiments of 0.65 with the topic Economic, 0.55 with the topic Loans, and 0.62 with the topic Housing. Since the first factor from the FRED-MD is usually used as an indicator of business cycles in the economy, these correlations between the factor and different topic time series cannot occur just by chance.

Parts (b) and (c) of Figure 4 discuss the connection between the time series with positive sentiments for the topics Housing and Loans and the first FRED-MD factor. These topic time series are correlated with business cycles since mortgage and loan rates tend to fall during recessions, as do house prices. In addition, these topics might be covered more frequently during recessions, or might be more negatively framed by experts. This then means that there is asymmetric news coverage in bad times and good times. People might also respond differently to bad news and to good news (Lamla and Lein, 2014). This is also confirmed by the results of Drager and Lamla (2017), who found that the absolute forecast error of people who hear news about higher inflation is much higher than that of people hearing news about lower inflation.

4.2 Expectations and soft news

The next question is whether the topic time series with positive sentiments that are derived contain additional information for household expectations. Larsen et al. (2021) employed the least absolute shrinkage and selection operator (LASSO) with news topics and the FRED-MD database, which contains major macroeconomic indicators for the US economy (McCracken and Ng, 2015). In line with that, I employ LASSO together with 125 stationary monthly variables from FRED-MD. The FRED-MD variables should capture the hard news channel, since hard news should contain information about economic fundamentals.

This study aims to capture the effect of the news as a transmission channel, since professionals usually follow hard economic indicators and express their opinion about current and future economic developments to the public through the media. I proceed by checking which of the

[37]This factor extracted from the FRED-MD data set is obtained using the Principal Components Analysis (PCA).

news topic time series with sentiments are important for household expectations. For the LASSO estimation I employ (1).

As $M_t(.)$ I use consumer expectations from the *University of Michigan Survey of Consumers* (2019), which gives expectations for interest rates, unemployment and inflation. In some specifications, I add consumer expectations from the previous period to capture $M_{t-1}(.)$. The FRED-MD macroeconomic indicators from the previous period should capture the latest statistics available to agents in $P_t(.)$. $N_t(.)$ are topic time series with sentiments from the previous month to avoid the problem of simultaneity. If I used N_t from the same month, it would contain information not available to agents during the surveys[38].

The regularisation parameter for LASSO is chosen using a five-fold cross-validation. All the non-stationary series were transformed into a stationary form by taking first differences. Additionally, all the variables were standardised. This is done since LASSO tends to select one variable from among highly correlated ones and from many covariates it selects those that have a large effect. Standardisation therefore makes LASSO invariant to scale.

Appendix F presents the LASSO results for expectations for interest rates, unemployment and inflation with the FRED-MD variables and the topic time series with sentiments from different models. The columns differ in how the sentiments were assigned to different topic time series. The first column shows the results for positive sentiments for different topics, the second column shows those for uncertain sentiments for topics, and the third column shows them for constraining sentiments for topics. The first three columns do not include $M_{t-1}(.)$, the expectations from the previous period. All the other columns include expectations from the previous period as a control. The seventh column presents the LASSO results for the interaction between positive and uncertain sentiments and the last column illustrates the results for the interaction of positive and constraining sentiments for each topic. All the columns include the FRED-MD variables, though outputs are omitted for the sake of brevity.

1. The LASSO results for interest rate expectations. The Fed topic time series is found to be connected to household interest rate expectations (Table F.1 columns 4,7,8, Table F.4 column 7 and Table F.7 columns 4,7,8). This topic might be important for interest rate expec-

[38]For example, some consumers were surveyed between 2 and 10 January. The news time series for a month is the sum of sentiments during the whole month, so it contains more information than was available to consumers on 10 January. A survey might also start at the end of the previous month and finish at the end of the current month.

tations, since it covers news about monetary policy and the Federal Reserve, which might give more information about monetary policy during recessions or during periods with a zero lower bound. The Federal Reserve may also signal the future path of monetary policy to the public, for instance, when it acts under commitment. It might equally use the media to transmit a signal for forward guidance, but if households were tracking and reacting to the federal funds rate hour by hour, it would not matter whether newspapers cover the topic in depth or not at all (Sims, 2003).

The results also show how important the Economic topic time series is for interest rate expectations (Table F.1 column 1, Table F.4 all columns and Table F.7 all columns). The time series for the topic Economic might be connected to household interest rate expectations since it captures general information about the economy. Negative news about the economy is more common in recessions, while the media cover more news about other topics during expansions. Interest rate expectations are also generally higher during recessions.

2. The LASSO results for unemployment expectations. The President topic time series has non-zero coefficients in LASSO regressions for household expectations about unemployment (Table F.2 columns 3,4,5,6, Table F.5 column 4, and Table F.8 columns 4,6). This topic might reflect general expectations about future economic conditions. The topic President might occur more frequently during bad times, and less often during good times. The tone of the President's statements might also be correlated with business cycles.

The Jobs topic time series with uncertain sentiment was found to be positively connected with unemployment expectations (Table F.2 column 5 and Table F.5, columns 5,7,8). This might suggest that households pay more attention to the topic when there is economic uncertainty.

The Housing topic time series is the most important for unemployment expectations (Table F.5 all columns and Table F.2 columns 1,3,4). The Housing topic time series with positive sentiment is negatively associated with unemployment expectations. This argument is supported by earlier studies that have found a negative correlation between regional labour and housing markets during the 2007–2009 recession. Previous studies also found a relationship between housing prices and unemployment, which might arise because the housing supply is inelastic (Dvorkin and Shell, 2016). An alternative explanation is that this time series is related to business cycles in the US economy. Moreover, over two-thirds of households in the US own houses and invest the majority of their portfolio in real estate (Soo, 2015). This means households are likely to pay a lot of attention to house prices. A similar argument might be given for the importance of the Loans topic time series from the LDA model using dominant topic labels (Table F.8 columns 1,3,4,6,8).

3. The LASSO results for inflation expectations. Table F.3, Table F.6, and Table F.9 show the results for inflation expectations and the topic time series from different models. Among all the models the time series for the topic Oil/gas was found to add additional information alongside economic fundamentals and the past inflation expectations of households. This result is not surprising since oil prices make up the largest part of gasoline prices. Americans generally drive cars and so must pay attention to gasoline prices. Households pay less attention to newspapers and more attention to gasoline and retail prices (Coibion et al., 2020).

The Loans topic time series from the LDA models was found to be the most important for inflation expectations (Table F.6 all columns and Table F.9 columns 1,3,4,6,8). Long-term interest rates rise during bad times, and the Federal Reserve can change long-term rates through its communication and federal funds target channel. These channels change the inflation expectations of professionals and policy-makers, and this in turn leads to changes in the long-run rates. Households might follow information about the long-run rates more closely since this information is important for their current economic decisions.

To study how the news affects business cycles, Larsen and Thorsrud (2019*b*) constructed a news index from topic time series as a weighted average of news topics with the highest predictive score. Similarly, Larsen et al. (2021) weighted selected topics by partial R^2 from OLS results based on topics selected by LASSO. The authors developed a news index as a linear combination of news topics weighted by their relative importance for expectations. Larsen and Thorsrud (2019*a*) employed principal component analysis (PCA) to reduce the dimensionality of the five least connected topics, which are more likely to be exogenous.

In line with this, I employ PCA to find how the news affects the macroeconomy. PCA is a method for extracting features and reducing dimensionality, as each component captures the direction of the maximal variance of the data and each component is orthogonal to every other component. These PCAs might be used in the same manner as factors from the FRED-MD database to augment the standard Vector Autoregressions with additional information variables[39].

Since households are unlikely to follow the latest macroeconomic

[39] See Bernanke et al. (2005) for example.

statistics but will follow the news, the first principal component from the news might help to identify the effects of anticipated macroeconomic shocks. Figure 5 shows the first principal component of positive sentiments for the time series of the topics Economic, Housing, Loans, and Oil/gas from the LDA model using topic distribution labels. As was found earlier in this study, the Economic topic time series is important for consumer expectations of the interest rate (Table F.4), the Housing topic time series is important for consumer expectations of unemployment (Table F.5), and the Loans topic time series is important for consumer expectations of inflation (Table F.6). The Oil/gas topic time series is also important for households' expectations of inflation, and as pointed out by Coibion et al. (2020) moreover, changes in gasoline prices might lead to changes in consumer expectations of inflation. Indeed oil price shocks were one of the major drivers of US inflation from 1973 (King et al., 2008).

On top of that, the previous findings of Lewis et al. (2020) can validate the choice of variables. Lewis et al. (2020) used high-frequency identification and found that surprises in jobs reports, GDP reports and housing starts releases affect consumer confidence.

The principal component extracted moves in tandem with the first factor from the FRED-MD, which suggests that it does not only capture noise. Moreover, it has leading properties with respect to the first factor from the FRED-MD. Figure F.1 presents the factor loadings and Figure F.2 compares the first principal component from the topic time series with the first factor from the FRED-MD database. The first principal component captures the most topics regarding Economic, Housing and Loans, which load more than 90% of the variation to the factor. These topics extensively co-move together. At the same time, the topic Oil/Gas loads only about 70% of the variation to the factor.

Moreover, the first PCA from the news topics time series has leading properties regarding the first factor from the FRED-MD database according to contemporaneous correlations with leads and lags (Figure F.2). Average correct predictions by experts might explain this.

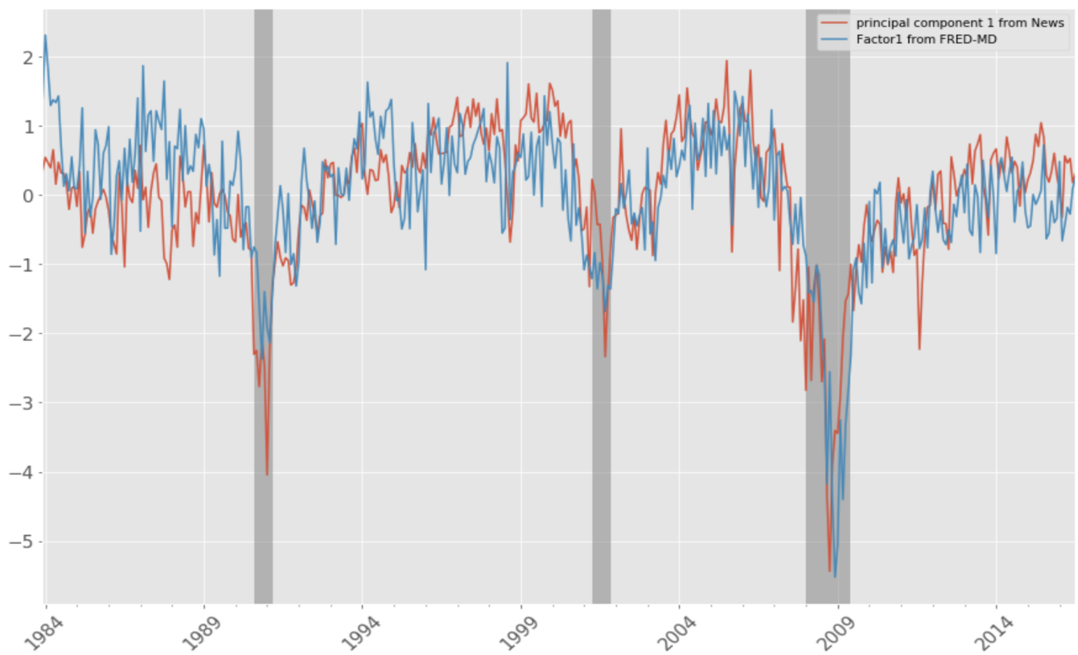


Figure 5: The first factor from the FRED-MD in blue and the principal component from news topic time series in red. All series are standardised.
The topics are Economic, Housing, Loans, Oil/gas. Positive sentiment.
Shaded areas – NBER based Recession Indicators for the United States

5 The role of news sentiments

5.1 Soft news and economic activity

To identify how soft news affects the real economy, I use the same data as Shapiro et al. (2020) for the period 1984:M1–2019:M7. These data are the logarithm of industrial production (IP), the logarithm of real personal consumption expenditures, the logarithm of the PCE price index, and the federal funds rate[40]. All the data are obtained from the *Federal Reserve Economic Data* (2019). In addition, I employ the consumer sentiment index from the *University of Michigan Survey of Consumers* (2019). I use the first factor from McCracken and Ng (2015) as a measure of hard news from current economic indicators to disentangle the effect of the soft news channel. As soft news, I use the first principal component from news defined in the previous section. The principal components were standardised. I use twelve lags because the data are at monthly frequency. Details of the estimation and priors can be found in Appendix G.

Figure 6 presents the results with two alternative ordering schemes. The first has hard news $(t-1)$, soft news $(t-1)$, output, consumption, inflation and the real rate, and the second ordering scheme has the soft news variable ordered last at time t. These alternative ordering schemes represent different assumptions about a structural news shock. In the first scheme, the structural shock affects output, consumption and the real rate on impact, whereas in the second scheme, it affects only soft news on impact.

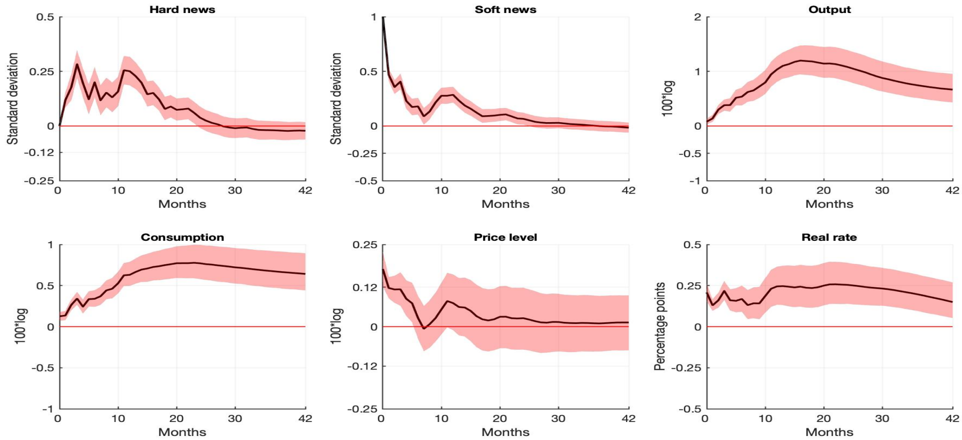
Considering that soft news should capture only news sentiments, which are the opinions of professionals rather than reports on current macroeconomic indicators, I control for the current macroeconomic indicators in VAR. To separate the effects of these two components, hard news, which is the first factor from the FRED-MD, is ordered before soft news.

The underlying mechanism of news shocks should be that when households and firms become more optimistic about future economic prospects, they start to spend more, so consumption and investment increase, driving up aggregate activity. If the optimism of the agents turns out to be justified, the economy converges to a higher long-run path; if it does not, the economy returns to its original trend because

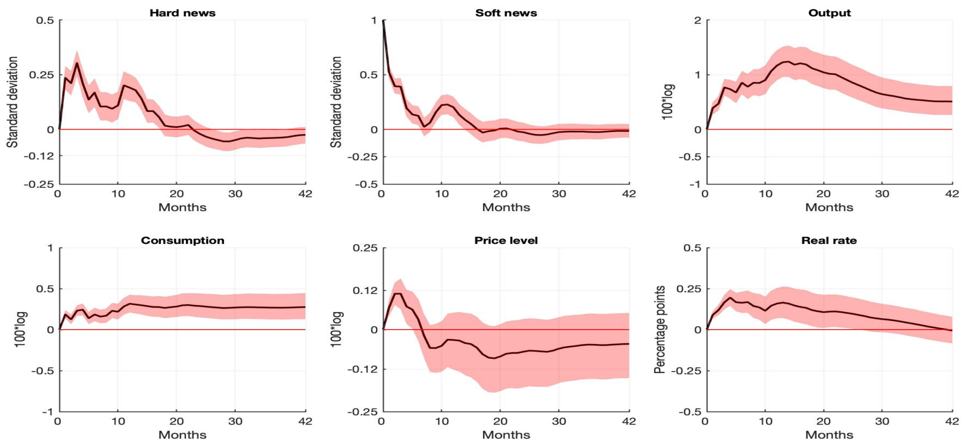
[40] Using the federal funds rate minus expected inflation from the *University of Michigan Survey of Consumers* (2019) gives similar empirical results, except that a soft news shock accounts for a larger share of the forecast error variance of the real rate (see Figure H.3).

of general equilibrium forces[41].

The findings (see Figure 6) support the expected effect of news shocks as output and consumption start to increase sluggishly in response to a one standard deviation soft news shock and converge to a new long-run equilibrium. The real interest rate starts to rise due to general equilibrium effects in response to increasing output and consumption.



(a) Soft news shock, ordered second



(b) Soft news shock, ordered last

Figure 6: Impulse responses to soft news shocks
median and 16th and 84th percentiles

[41] As stated in Lorenzoni (2011), Beaudry and Portier (2006), Barsky and Sims (2012), Larsen and Thorsrud (2019*b*). According to these authors a news shock is a shock that increases expected future productivity without affecting current productivity.

Contrary to the previous findings by Barsky and Sims (2012), Larsen and Thorsrud (2019*b*), and Shapiro et al. (2020) though, there is a transitory rise in inflation in response to a soft news shock. This effect can be explained by demand shocks with an endogenous information structure (Lorenzoni, 2009) or an endogenous growth mechanism (Barsky and Sims, 2012). At the same time, the findings of this study are in line with Leduc and Sill (2013), who found that positive expectations typically lead to a significant rise in economic activity, inflation, and the interest rate.

Since soft news is ordered after hard news, it is orthogonal to the current macroeconomic indicators and should contain only subjective information about future productivity, maybe with some noise. The forecast error variance decomposition (FEVD) (Appendix H) shows a soft news shock accounts for about 15% of the variance in output at longer horizons and up to 10% of the variance in hard news. Barsky and Sims (2012) found that the news media are not an important channel for consumer confidence, but rather that consumers aggregate information from different sources. This claim about how the actual news affects future economic developments can be tested using the data from this paper. Figure 7 presents the results with the Consumer Sentiment Index from the *University of Michigan Survey of Consumers* (2019) as an additional measure of consumer confidence. It is ordered before soft news since the topics were selected for their importance for consumer expectations at time $t + 1$, so the news should affect consumer expectations in the next period. In this case a sentiment shock[42] is a structural shock that affects consumer expectations and news on impact, whereas a news shock only affects soft news on impact. The expectation variables were standardised.

It should be noted that I employ the FRED-MD factor, ordered before soft news, to purge the soft news of any reports on hard macroeconomic indicators, so that it captures only sentiments. For contrast, Figure 7 also presents the impulse responses of variables to the first structural shock, which influences all the variables included on impact. In this case the Fed reacts more aggressively in the long-run, and that reaction restrains the positive response of inflation for a few months after the shock. There are also no prolonged responses to this shock from output or consumption.

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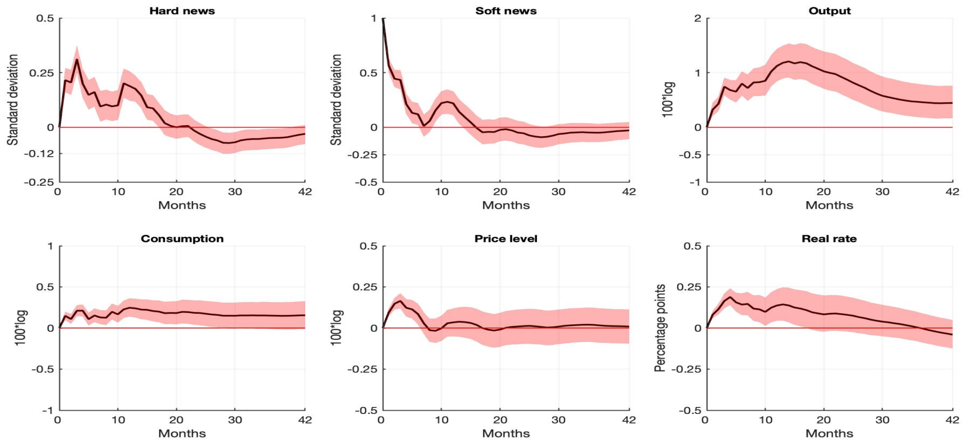
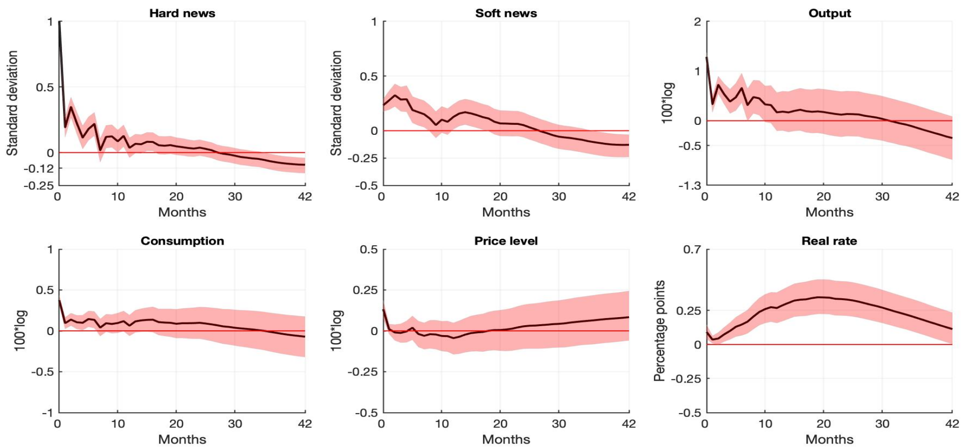
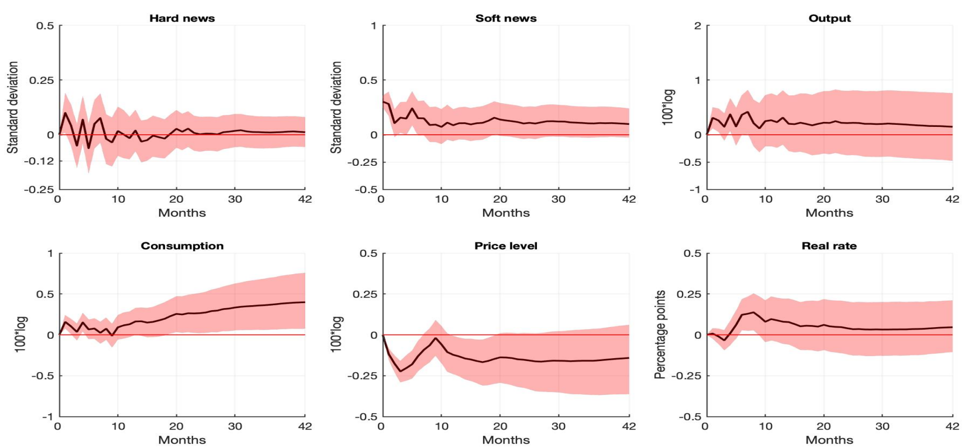
[42]A sentiment shock represents shifts in expectations about business cycles without changes in the fundamentals of the economy (Feve and Guay, 2018).



(a) Soft news shock, ordered last



(b) First shock



(c) Sentiment shock, ordered second last

Figure 7: Impulse responses to soft news and sentiment shocks
median and 16th and 84th percentiles

The impulse responses to a soft news shock are approximately the same as in Figure 6 (b) though the transitionary response of prices is somewhat larger in magnitude. The forecast error variance decomposition shows that the contributions of a soft news shock at longer horizons are also similar to the previous findings (Figure H.2 (a)).

At the same time, the impulse responses to a sentiment shock are similar to Barsky and Sims (2012), except that the response of output is more uncertain. However, according to the FEVDs, the sentiment shock does not account for a large share of the variance of output and consumption at long horizons (Figure H.2), as it only accounts for up to 10% of the variance of soft news at high frequencies. In this, the findings of this study do not support those of Barsky and Sims (2012), who argued that newspapers are unlikely to be an information channel for household confidence.

The soft news shock identified cannot be an animal spirit shock[43], since an increase in the real rate in response to a positive but false signal should dampen it. The impulse responses show, however, a persistent effect on output and consumption (Figure 6 and Figure 7) and the FEVDs confirm its importance at longer horizons (Appendix H).

The argument of Barsky and Sims (2012) relies on the assumption of exogenous growth in technology. Their findings do not indicate any causality of news, but rather the perfect foresight of future technological development. Similarly, Larsen and Thorsrud (2019*b*) considered the process of forming expectations as a signal extraction problem, where one part of the signal is the true state of future TFP. The results of this study might uncover a possible endogenous growth mechanism, as demand shocks might cause a short-run increase in real activity, which might ultimately lead to a rise in TFP through an endogenous mechanism of learning by doing or similar.

Employing consumer expectations in similar settings, Leduc and Sill (2013) also found positive co-movement between real economic activity, the real rate and inflation in response to a positive expectation shock. The authors interpreted it in the framework of an expected positive demand shock with search and matching frictions. Similarly, Benhabib and Spiegel (2019) found positive correlations between sentiment, future economic development, and consumption by households.

5.2 Heterogeneity of soft news shocks

Next I will look at the issue of whether different types of news have similar effects for the macroeconomy. Although it is unlikely, it is pos-

[43]Barsky and Sims (2012) refer to animal spirits as false news.

sible to disentangle the effects of different types of news from different types of household expectations.

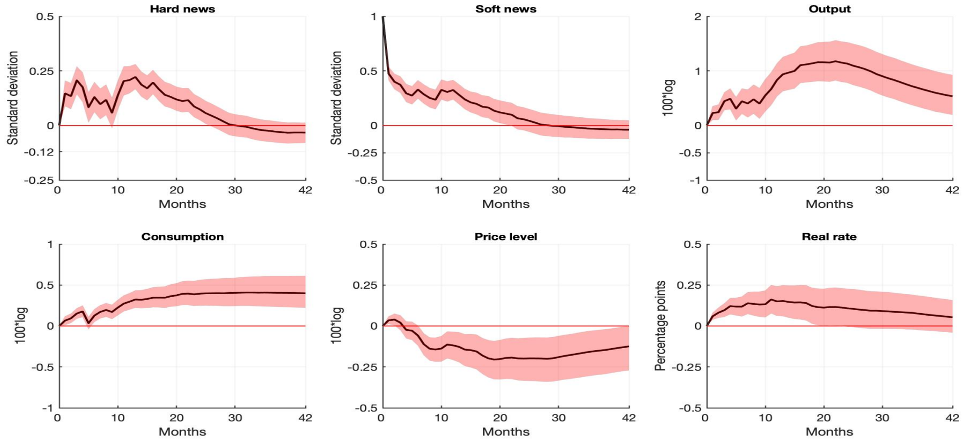
Figure 8 presents impulse responses to each type of soft news shock [44]. The impulse responses to different types of consumer sentiment shock are shown in Figure I.1. Different types of soft news are ordered last, and consumer expectations are ordered second last in each specification. I define a soft news shock as a structural shock that affects soft news on impact and a sentiment shock as a shock that affects consumer expectations and soft news on impact. The news and expectation variables were standardised.

In contrast to the results of Leduc and Sill (2013), the response of inflation to a positive sentiment shock is negative (Figure I.1 (a)). Neither do the contributions of this shock to the forecast error variances support the previous findings of Leduc and Sill (2013) (Figure I.2 (b)). The impulse responses to soft news shocks about housing and loans are quantitatively similar, but the response of inflation to a news shock about loans has a higher magnitude for a few months after the shock. The impulse responses to an economic news shock are somewhat tighter but are in the same direction.

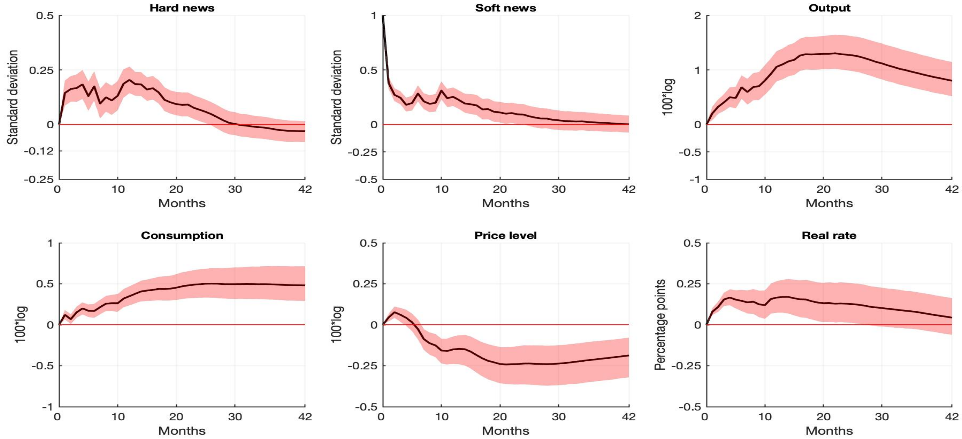
Figure I.2, Figure I.3, and Figure I.4 show the contributions of each shock to the forecast error variances of the variables. The housing news shock accounts for about 20% of the variance in output at the horizon of thirty months, while a loans news shock accounts for 37% and an economic news shock for about 7%. Housing and loans news shocks each contribute about 5% of the variance in consumption at the horizon of thirty months.

These different types of news should capture the news sentiment effects in the VARs, since none of the consumer sentiment shocks account for variances in real variables at longer horizons, except interest rate sentiment. The interest rate sentiment shock accounts for about 17% of the interest rate error variance. In this case the sentiment shock identified might be an animal spirit shock, since Barsky and Sims (2012) found that this shock has very little effect on the real variables with the exception of the real interest rate.

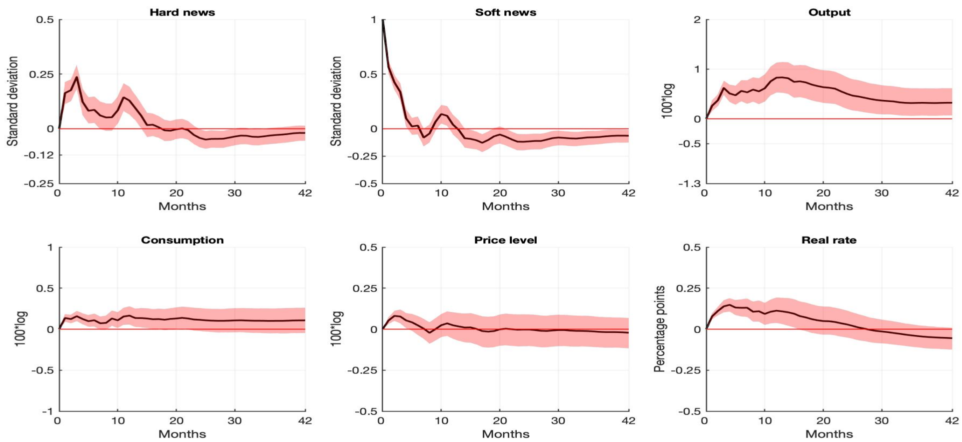
[44] From the point of view of identifying restrictions, all these shocks are soft news shocks, as each of them affects only soft news contemporaneously and reacts to all other variables. The label "... news shock" is given here for convenience.



(a) Housing news shock, ordered last



(b) Loans news shock, ordered last



(c) Economic news shock, ordered last

Figure 8: Impulse responses to soft news shocks
median and 16th and 84th percentiles

Leduc and Sill (2013) studied how unemployment expectations affect business cycles. They found positive co-movement in economic activity, inflation and the interest rate in response to expectation shocks, with the expectations variable ordered first in the VAR. The authors also found these shocks made a significant contribution to the forecast error variances of unemployment and inflation at long horizons. If the news is omitted from the VARs though, expectations might falsely account for a large share of the FEVDs of the real variables.

In line with the last argument, Figure I.5 compares the impulse responses to an oil/gas news shock and an inflation sentiment shock. The oil/gas topic time series was not found to be robust for inflation expectations in all the LASSO specifications and so its connection to expectations might be weaker. The impulse responses to an oil/gas news shock are seen to be different from the IRFs in Figure 8. In addition, a sentiment shock accounts for about 15% of the variance in output and 7% of the variance in consumption at longer horizons (Figure I.6), while the oil/gas news shock does not account for a significant part of the forecast error variances of the real variables. This finding contradicts previous findings (Figure I.3).

5.3 Soft news and monetary policy

Lastly, I employ the news time series to study how news sentiments affect monetary policy to disentangle the role of the media. The standard framework for studying monetary policy is to employ recursive identification in three variable Structural Vector Autoregressions with variables measuring economic activity, inflation and a monetary policy indicator. I use additional news variables that were found to be important for consumer expectations of the interest rate.

Recent studies have pointed out that Fed announcements might contain information on the general economic outlook[45]. The news about monetary policy does the same. To disentangle the effect of sentiments about the general economic outlook from that of sentiments about monetary policy, I also control for the Economics topic time series, since it was found to be important for consumer expectations of the interest rate, and it was also highly correlated with the first factor from the FRED-MD database that captures general economic conditions.

I use the logarithm of industrial production (IPB50001N) (alternatively the index of real economic activity (CFNAI)[46]) as a measure

[45]See Jarocinski and Karadi (2020) and Smith and Becker (2015) among others.

[46]CFNAI aggregates information from a panel of 85 macroeconomic time se-

of economic activity, the logarithm of the consumer price index (CPIAUCNS), the one-year constant-maturity Treasury yield as a monetary policy indicator (GS1)[47], and the excess bond premium as an indicator of financial conditions (EBP[48]). All the data except for the EBP are obtained from the *Federal Reserve Economic Data* (2019).

Variables are ordered in the order given above, followed by the Economic topic time series and the Fed topic time series[49]. The timing also supports the choice of ordering, as the news data are aggregated over the current month and so it is plausible that they might react to changes in economic activity or to Fed actions within the current month; moreover, the news over the current month does not affect employment and inflation contemporaneously. This assumption follows from the notion that prices and employment are slow to adjust. I employ twelve lags since the data are monthly. The timespan is 1984:M1–2016:M8. The details about estimation and priors can be found in Appendix G. The last shock is labelled as a Fed news shock[50] and identified as a shock that affects only the Fed topic time series contemporaneously.

Figure 9[51] shows that the one-year rate starts to rise in response to a positive Fed news shock one month after the shock. Real economic activity gradually increases a few months after the shock, then the speed of increase accelerates ten months after the shock and finally reaches a new long-run equilibrium about fifteen months after the

ries encompassing four types, or groups, of indicators: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. More information can be found at https://www.chicagofed.org

[47]Since it incorporates the impact of forward guidance and remains a valid measure of the monetary policy stance even when the federal funds rate is constrained by the zero lower bound (Jarocinski and Karadi, 2020).

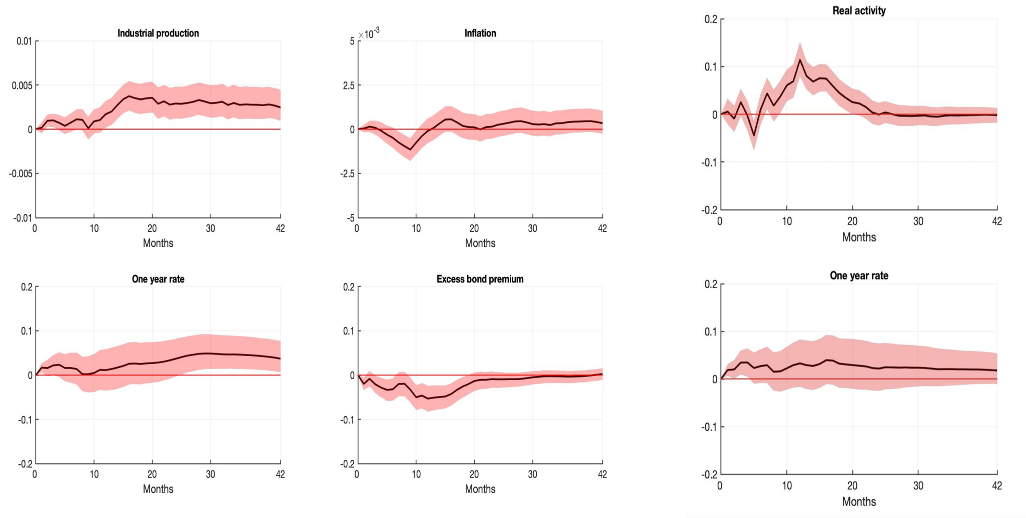
[48]This variable aggregates high-quality forward-looking information about the economy. The EBP is a component of corporate bond credit spreads that is not directly attributable to expected default risk and provides an effective measure of investor sentiment or risk appetite in the corporate bond market (Gilchrist and Zakrajsek, 2012). The excess bond premium represents credit supply conditions.

[49]In this section I use positive sentiments of the topic time series.

[50]From the point of view of theoretical restrictions this shock is still a soft news shock since it affects only soft news contemporaneously and reacts to all other variables. The label "Fed news shock" is given here for convenience.

[51]Appendix J discusses the results from additional SVAR specifications. Since 2008, the Federal Reserve has relied on unconventional monetary policy measures because the federal funds rate hit the zero lower bound. Figure J.3 shows the result for the sub-period of forward guidance.

shock. The shock has a transitory negative effect on inflation, which declines for a few months after the shock. The news shock also leads to a decline in the excess bond premium.



(a) Impulse responses to a Fed news shock with uncertainty

(b) The same as (a) with CFNAI instead of IP

Figure 9: Impulse responses to a Fed news shock (from Doc2Vec topic time series)
median and 16th and 84th percentiles

The responses are somewhat similar to those for the central bank information shock of Jarocinski and Karadi (2020), which is similar to an anticipated demand shock that the central bank partly offsets. A decline in the excess bond premium after a Fed news shock indicates an expansion in the supply of credit. This might suggest that the Fed topic time series indicates an endogenous response by the Fed to an anticipated demand shock.

Figure J.4 shows the contributions of the fifth and sixth shocks, labelled as economic news and Fed news shocks, to the forecast error variances of the macroeconomic variables. It is apparent that the economic news shock contributes substantially to the Fed topic time series from the beginning, while the Fed news shock accounts for only a 2% variation in economic activity at longer horizons.

One explanation might be found in how much attention households pay to news about monetary policy. Coibion et al. (2020) documented that households and firms do not generally follow even large policy change announcements, despite widespread news coverage. Only professionals pay attention to monetary policy announcements, while households mainly rely on their prior beliefs.

Conventional and unconventional monetary policies primarily influence the economy through their effects on long-term interest rates (Smith and Becker, 2015) and long-term interest rates are most important for households' spending decisions. In line with that, Coibion et al. (2020) also noticed that professionals closely follow the Federal Reserve announcements, and they might change contemporaneous long-term interest rates through financial markets. The finding of the connection between the loans topic time series and inflation expectations might confirm that this is a possible transmission mechanism for monetary policy.

To test this, I employ the Loans topic time series instead of the Fed topic time series in the settings described above. The impulse responses are similar to those presented in Figure 10, but are of higher magnitude. The only difference lies in the response of inflation, which increases after the shock.

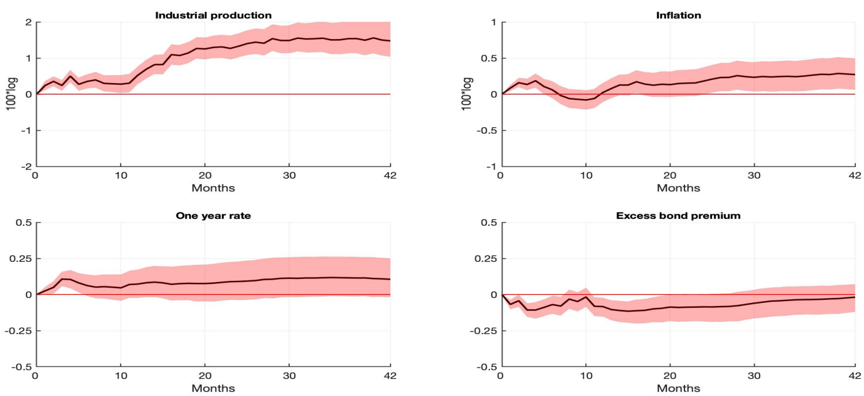


Figure 10: Impulse responses to a Loans news shock
median and 16th and 84th percentiles

Figure J.5 presents the contribution of a loans news shock to the forecast error variances of the variables. The figure reveals that the shock explains about 20% of the variance of industrial production at the horizon of thirty months and about 5% of the variance of the excess bond premium.

To investigate further how a soft news shock affects monetary policy, I added inflation expectations from the *University of Michigan Survey of Consumers* (2019) and ordered it before the Loans topic time series. The impulse responses to the soft news shock are very similar to those in Figure 9, and the FEVDs for both shocks are presented in Figure J.6. The soft news shock is quite exogenous in this setting and explains about the same share or more of the variance of industrial production at thirty months. From the tenth month, this shock explains around 10% of the variance in inflation expectations. The sixth shock, which contemporaneously impacts inflation expectations and news about loans, explains up to 7% of the variance of industrial production at all horizons.

5.4 Discussions

Causality

One concern about the causal interpretation of the results lies in possible reverse causality. Namely, soft news shocks might reflect foresight of future economic developments. To this end, these shocks can forecast future macroeconomic development. To deal with this type of endogeneity, I included and ordered before soft news those variables that should control for current[52] and future economic conditions[53]. In this case, the soft news shocks should capture professionals' expectations about the current and future economic conditions because they are orthogonal to current macroeconomic indicators and consumer expectations. These expectations are transmitted to the economy through the news channel.

An alternative interpretation is that soft news shocks might capture omitted variables from a VAR. In this case, IRF to this shock reflects the causal effect of an omitted variable. If this variable is in the decision-makers' information set, then omitting it leads to a nonfundamentalness problem and/or biased IRF from other structural shocks.

An additional robustness check of the baseline results includes S&P500[54], which is a forward-looking variable that incorporates information from many sources. According to the efficient market hypothesis, if the information is available to market participants, it should be immediately taken into account via share prices. Figure 11 presents the additional check of the results. The response of consumption to a soft news shock is transitory, and the response of output is a bit smaller in magnitude. Nevertheless, the main results are robust: a long-term

[52]I included the first principal component from a large dataset of macroeconomic indicators, which is a proxy for business cycles in the economy. This variable is very close to my proxy for news, I order it before and lag one period backwards. I also include twelve lags of all variables.

[53]I included consumer expectations from the Michigan Survey of Consumers, which is a forward-looking indicator.

[54]S&P500 data is taken from *Yahoo Finance* (2021).

effect on output, transitory and positive effect on inflation and an endogenous contractionary response of the real rate.

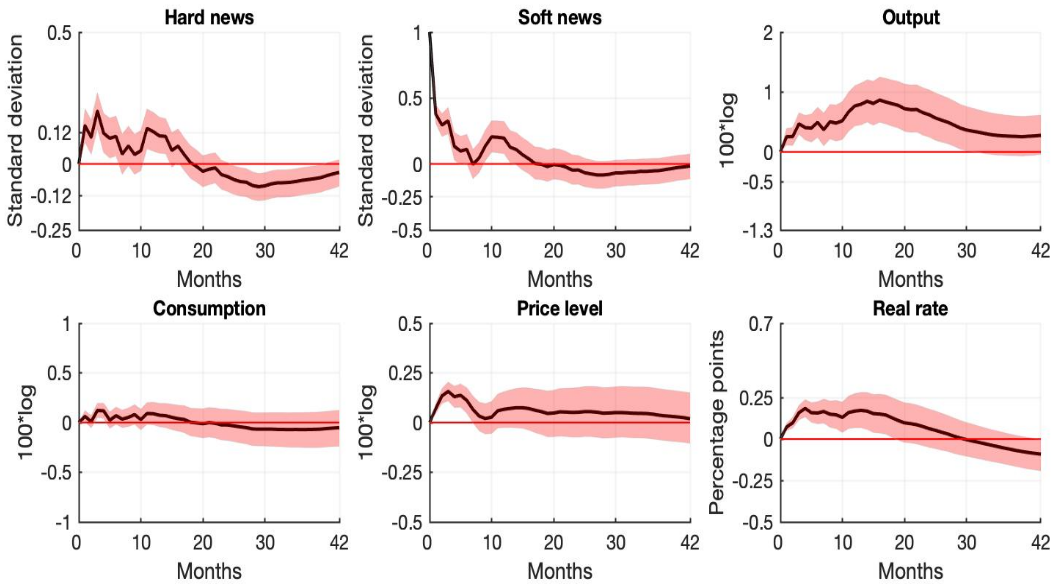


Figure 11: Baseline results with S&P500 ordered first
median and 16th and 84th percentiles

Mechanism

In terms of impulse responses, the effects of these soft news shocks are similar to animal spirits shocks that positively affect consumption, output, and inflation. According to Barsky and Sims (2012) real marginal costs[55] should increase in response to an animal spirits shock because households start to demand a higher real wage for the current employment level. That contrasts to impulse response functions that arise to the news shocks as shocks to future TFP because, in this case, the effect should be disinflationary. In their work, Barsky and Sims (2012) considered shocks to consumer confidence from the Michigan Survey of Consumers as information shocks instead of animal spirits shocks. That contrasts with the results of Leduc and Sill (2013), where the authors used expectations from the Michigan Survey of Consumers and interpreted innovations to them as sentiments shocks. Benhabib and Spiegel (2019) noted that a self-fulfilling equilibrium (that is sentiment-driven) could arise in endogenous growth, real business cycles, search or OLG models. Leduc and Liu (2016) studied a New Keynesian model with search and matching frictions and found that uncertainty shocks act as aggregate demand shocks.

[55]Real marginal costs in a New Keynesian model are the difference between real wages and technology (Barsky and Sims, 2012).

On the contrary, the main channel of the effect of news shocks is through their inter-temporal investment decisions in anticipation of future demand[56].

5.4.1 The role of sentiments regarding the economy

Economic topic time series were found to be prevalent for household expectations regarding interest rates. The reason might be that the general public does not pay attention to the Fed's statements but is observant about general economic news. Knowing that the main objective of monetary policy is to ensure price stability via controlling inflation, consumers may connect expected economic booms with contractionary monetary policy actions and vice versa. This argument can be supported by the primary finding of Lamla et al. (2007) that news on aggregate developments affects firms' perceptions and expectations more than sectoral specific news. Moreover, the authors found that these expectations, in turn, have explanatory power for current and future economic developments. This argument is also supported by the findings of Leduc and Sill (2013) that more optimistic economic expectations about the future coincide with anticipated monetary policy contraction.

5.4.2 The role of sentiments regarding housing

In theoretical models, housing affects the consumption decisions of financially constrained households because it acts as a value of collateral. Positive news about house prices increase the value of collateral and allow households to spend more today. Carroll (2003) found unemployment expectations to be a powerful predictor of household spending decisions, while Hoffmann et al. (2012) found that growth expectations explain movements in house prices, which in turn is connected to expected aggregate income.

Moreover, Leamer (2007) stated that housing starts is the best forward-looking indicator of the cycle in the economy. With this regard, unemployment expectations can also be viewed as an indicator of the cyclical position of the economy, that is in line with Leduc and Sill (2013), who used questions about future unemployment to measure expectations about business cycles and interpret a shock to the expected unemployment rate as news received by agents that leads them to reassess their beliefs regarding future prospects for the economy.

[56]See, for instance, Jaimovich and Rebelo (2009), Beaudry and Portier (2007), Milani and Rajbhandari (2020) among others.

5.4.3 The role of sentiments regarding long-term interest rates

Monetary policy might affect the real economy through long-term interest rates. Forward guidance and long-term asset purchase programmes primarily use this channel. Moreover, Milani (2017) found that inflation is largely driven by sentiment shifts, where inflation sentiment is dominant over business cycle horizons, accounting for almost 60% of the inflation forecast error variance. Similar to this study Bauer (2015) found a positive response of household inflation expectations to news. Moreover, the author found that daily changes in inflation compensation and long-term rates have a close statistical relationship. Leamer (2007) investigated primary predictors for the federal funds rate and found that the best one among them is the 10-year Treasuries, followed by unemployment and housing starts. At the same time, the influential variables for housing starts are long-term rates.

5.4.4 The role of sentiments regarding monetary policy

The results of Milani and Treadwell (2012) stated that the effect of monetary policy through announcements should be more significant than conventional surprises to a monetary policy rule. At the same time, Coibion and Gorodnichenko (2012) found that the general public usually does not pay attention to monetary policy news. The results of this study support the latter claim. In particular, it does not seem that monetary policy sentiments have some critical implications for the real economy. Moreover, these sentiments were not found to be essential for household expectations. So what is the transmission mechanism of monetary policy announcements on the real economy? One such channel might be through financial markets and long-term interest rates. Unexpected monetary policy announcements surprised financial market participants and could change longer-term interest rates regarding changed expectations. Besides that, monetary policy announcements also might change the term premium.

6 News, Information and Monetary Policy

6.1 Information set of the Federal Reserve

The reason why additional information on household expectations might be important for setting the target interest rate is that the Taylor rule assumes that policy-makers know, and can agree on, the size of the output gap. Measuring the output gap is very difficult and FOMC members typically have different judgements. It would be neither feasible nor desirable to try to force the FOMC to agree on the size of the output gap at a single point in time[57]. Discussions on households expectations might contain additional information on the future output gap. Moreover, FOMC members might be uncertain to differing degrees at any point in time about future inflation expectations or future economic conditions. In such a case, the certainty/uncertainty of the FOMC members during discussions might contain additional information.

Furthermore, the Taylor rule also assumes that the equilibrium federal funds rate (the rate when inflation is at target and the output gap is zero) is fixed. In principle, if that equilibrium rate were to change, then Taylor rule projections would have to be adjusted (Bernanke et al., 2005). The FOMC discussions also might contain information about the equilibrium federal funds rate (following this argument Shapiro and Wilson (2019) evaluate a central bank objective function from the FOMC discussions).

There are certain assumptions that went into the Greenbook forecasts, which are not reflected in the Greenbook itself (Cecchetti, 2003). FOMC members discuss these assumptions during FOMC meetings. The information from the transcripts might reveal these assumptions and the agreement of the members on these.

Table L.1 presents selected categories and the corresponding economic phrases based on the most frequent phrases. For example, any combination between columns Term 1 and Term 2 is considered a phrase related to inflation expectations. I outlined twelve categories in total. These categories are similar to those found in Oet and Lyytinen (2017) from FOMC minutes[58].

Figure L.3 shows cross-correlations between positive and uncertain sentiments for each group of economic phrases. The most positively

[57]Based on Bernanke et al. (2005).

[58]Their themes are as following: Financial stability, Output, Inflation, Employment, Money supply, Fiscal policy, Foreign activity.

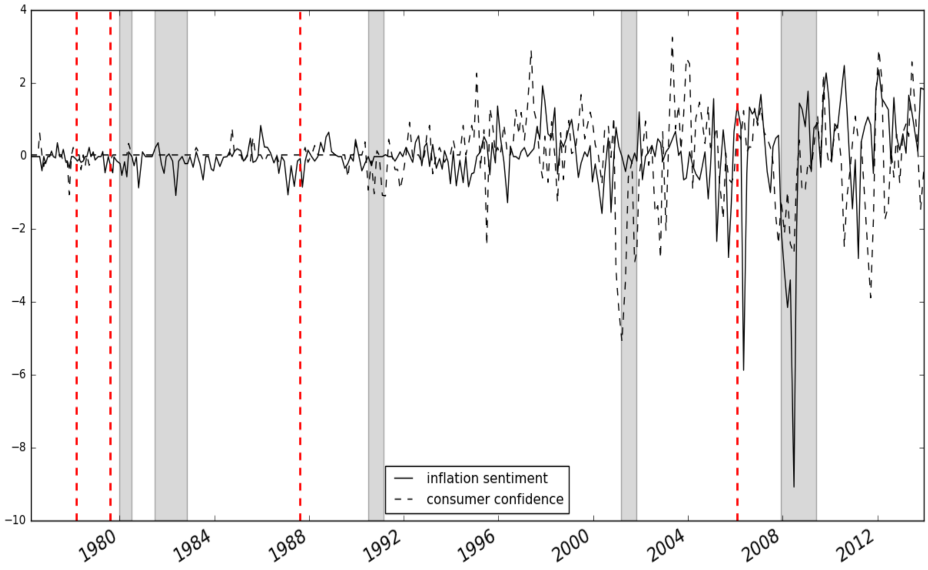
correlated are positivity and uncertainty of growth phrases, while the most negatively correlated are positivity and uncertainty of housing phrases. This suggests that when FOMC members are more positive about growth they are also generally more uncertain about it. Similarly, while FOMC members are less positive about housing they are also generally more uncertain about it.

Figure 12 shows the time series of the positivity and uncertainty of FOMC members regarding inflation expectations and consumer confidence. These two terms might indicate expectations of future inflation and consumer demand. Interestingly, the Committee members' views about consumer confidence become negative before the official recessions starting from the 1990s. Even more interestingly, FOMC members' uncertainty about consumer confidence spikes just before recession dates starting from the 1990s (part (b) of Figure 12). Inflation expectations become more negative before the 1980, 2001 and 2007–2009 recessions. But contrary to the findings of consumer confidence uncertainty, inflation expectations uncertainty is usually higher during recessions.

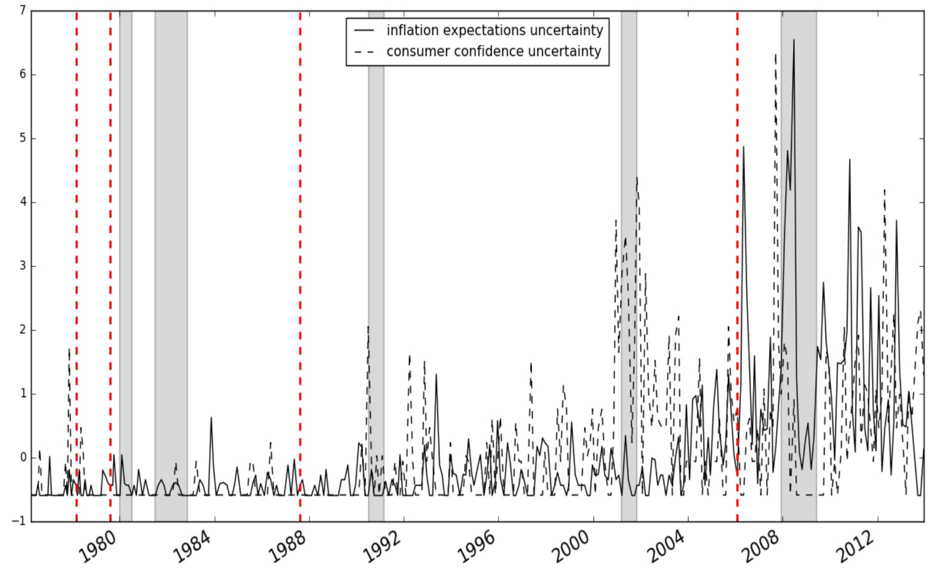
Figure 13 presents FOMC members' positivity about energy, assets and housing topics. Cieslak and Vissing-Jorgensen (2018) used stock market mentions in FOMC minutes as a forward-looking indicator. Asset positivity series are somewhat similar to those in Cieslak and Vissing-Jorgensen (2018), so these series might capture expectations about future economic development.

Asset positiveness among FOMC members declines before the 2001 and 2007–2009 recessions and it usually spikes just after the end of these recessions. Bernanke and Gertler (2001) argued that asset prices become relevant only to the extent that they may signal potential inflationary or deflationary forces. Housing positiveness drops before all the crises except the crisis 1981:M7–1982:M11. Energy positiveness declines before recessions, except the Great Recession, but it declined during the crisis.

One can see a negative spike in energy topic positiveness in 1986, which coincides with a drop in world oil prices in that year due to the surplus of crude oil in the early 1980s. FOMC members pay attention to the energy topic since global price shocks affect inflation and overall business costs, leading to higher unemployment. Energy costs might be an indicator of supply shocks.

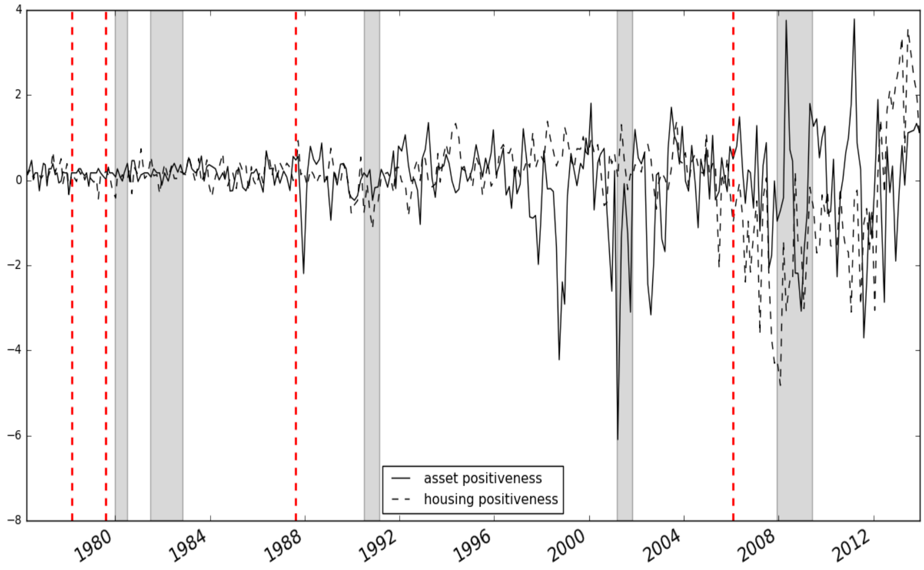


(a) Inflation expectations (solid) and consumer confidence (dashed) positiveness

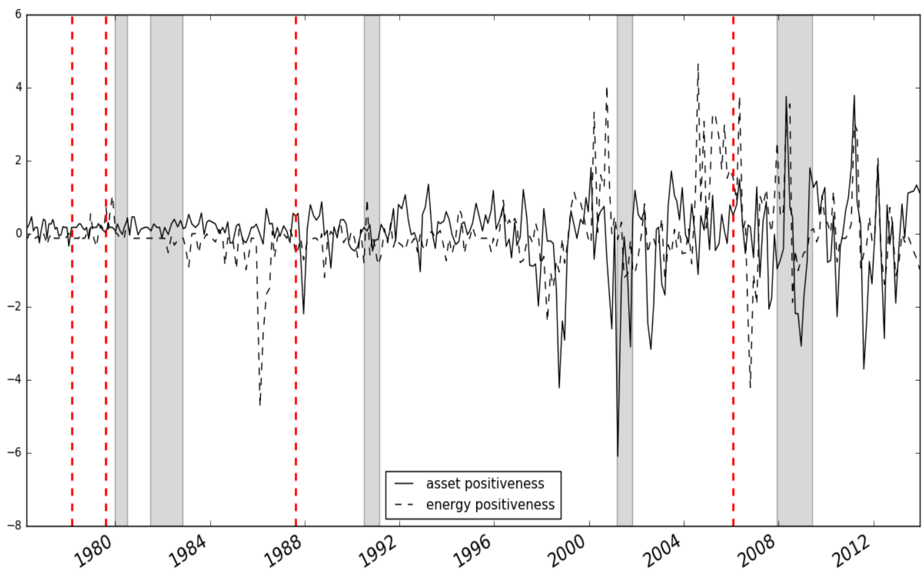


(b) Inflation expectations (solid) and consumer confidence (dashed) uncertainty

Figure 12: Comparison between inflation expectations and consumer confidence. All series are standardised.
shaded areas – NBER based recessions; red dashed – Chairman changes



(a) Asset (solid) and housing (dashed) positiveness



(b) Asset (solid) and energy (dashed) positiveness

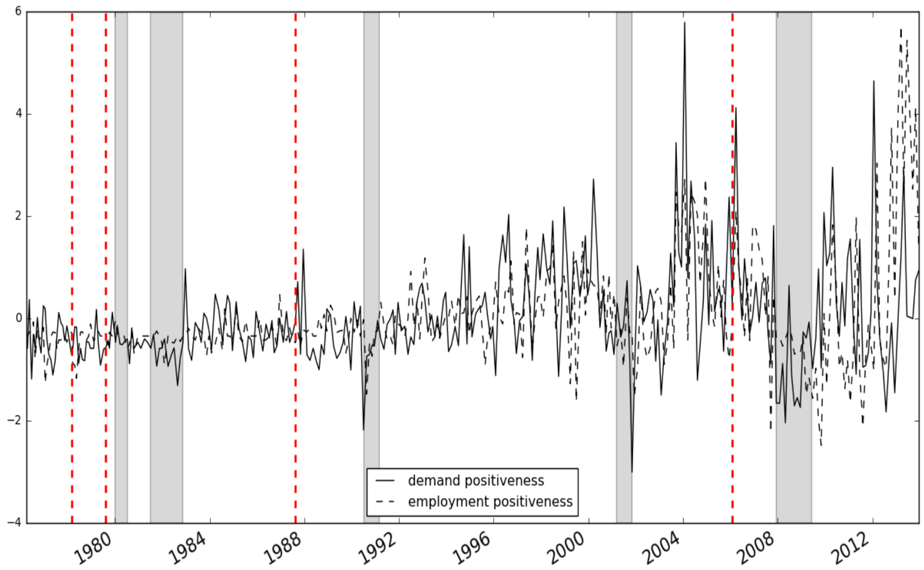
Figure 13: Comparison between energy, assets and housing terms. All series are standardised.
shaded areas – NBER based recessions; red dashed – Chairman changes

Figure 14 shows positiveness of demand, employment and growth topics. The demand positiveness of the Committee usually declines before recessions. Surprisingly, the demand positiveness also declines before the end of recessions, except in the 1981–1982 recession, although it spikes again afterwards. Employment positiveness has very similar patterns to demand positiveness. Both of these measures might be indicators of FOMC expectations of future demand and economic growth. The results are in line with the results of Wischnewsky et al. (2021), who found that in the 1990s the importance of demand factors and supply factors increased.

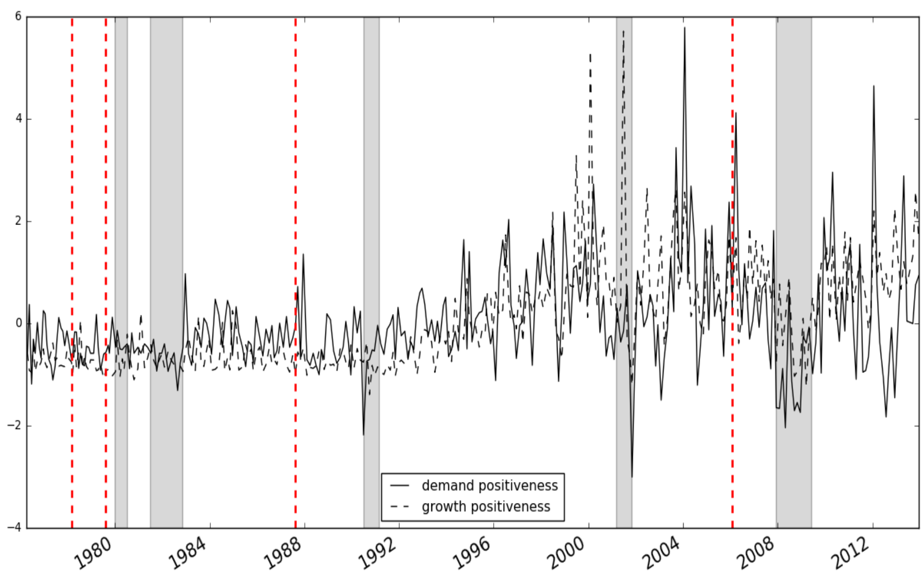
Committee member positivity about economic growth spikes in 2000 and mid-2001. This pattern should reflect the expectations of FOMC members, since US growth dropped by 0.63% in 2000 compared to 1999 and dropped by 3.1% in 2001 compared to 2000 (*U.S. GDP Growth Rate 1961-2020*, 2020).

Figure 15 discusses the positivity of FOMC members regarding monetary aggregates, foreign, financial and fiscal topics. Before the mid-2000s, monetary aggregates were an important topic in FOMC discussions, especially during the early 1980s. In 1979, the Fed began targeting the money supply to fight inflation, while in 1982, the Fed returned to targeting the federal funds rate. In February 1987, the Fed announced that it would no longer set M1 targets, and in July 1993 the Fed downgraded the use of M2 as a reliable indicator of financial conditions in the economy (Asso et al., 2010). High positivity among the members about monetary aggregates in 1998 might be explained by high M2 velocity during this period.

Peek et al. (2016) employed financial stability series to capture the expectations of the Fed. Figure 15 shows that from the 1990s positiveness towards financial markets plays a leading role in properties to economic downturns and is especially visible with respect to the Great Recession. The positivity towards financial markets moves in the opposite direction to movements in positivity towards fiscal policy. The fiscal positiveness might reflect Fed expectations regarding the US budget deficit. Negativity among the FOMC members concerning foreign markets in 1998 might be explained by the 1997 Asian financial crisis.

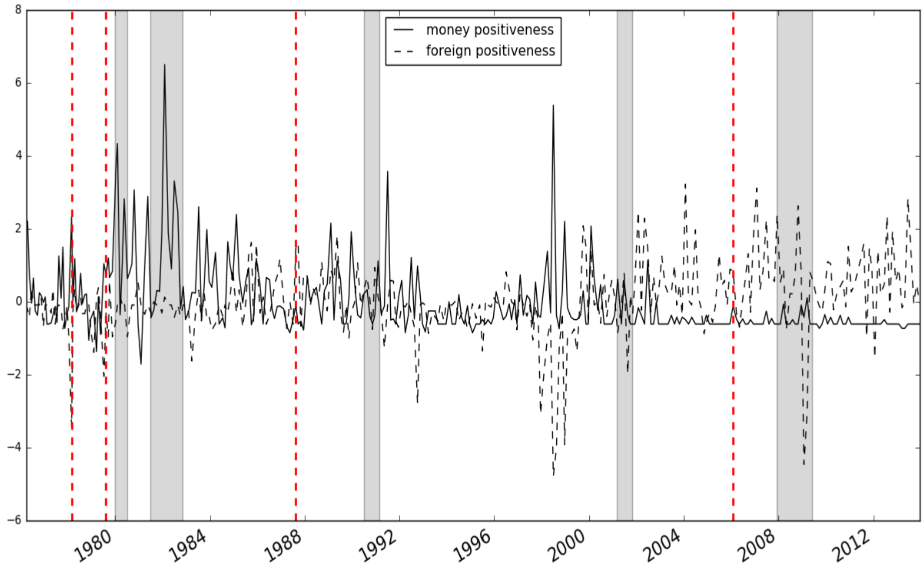


(a) Demand (solid) and employment (dashed) positiveness

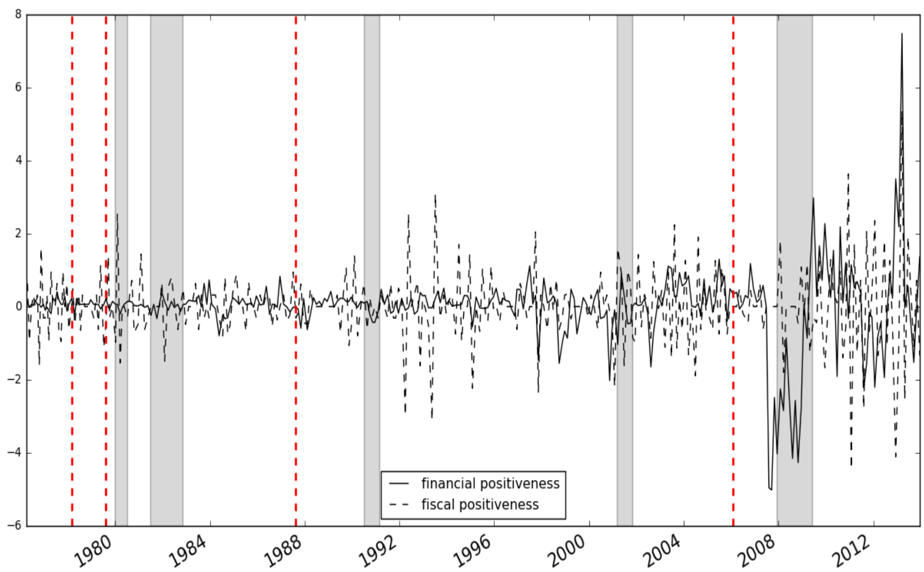


(b) Demand (solid) and growth (dashed) positiveness

Figure 14: Comparison between demand, employment and growth terms.
All series are standardised.
shaded areas – NBER based recessions; red dashed – Chairman changes



(a) Money (solid) and foreign (dashed) positiveness



(b) Financial (solid) and fiscal (dashed) positiveness

Figure 15: Comparison between money, foreign, financial and fiscal terms. All series are standardised.
shaded areas – NBER based recessions; red dashed – Chairman changes

Do the derived topic time series with sentiments contain additional information for Fed interest rate changes? Larsen et al. (2021) employed the least absolute shrinkage and selection operator (LASSO) with news topics and the FRED-MD database, which contains major macroeconomic indicators for the US economy (McCracken and Ng, 2015) for finding relevant topics for household inflation expectations.

But it is well-known that LASSO tends to select one variable from highly correlated ones. For correlated predictors, Zou and Hastie (2005) proposed a family of convex penalties called Elastic Net, which is a hybrid between LASSO and Ridge. Therefore, I employ LASSO and Elastic Net. These methods minimise their loss functions (Table 1). Additionally, there is a duality between LASSO, Elastic Net and Bayesian methods. The Lasso penalty arises as a Laplace global-local mixture, while the elastic-net regression can be recast as a global-local mixture with a mixing density belonging to the orthant-normal family of distributions (Bhadra et al., 2019).

Regularisation parameters for LASSO and Elastic Net are chosen based on 5-fold cross-validation. All non-stationary series were transformed into a stationary form by taking first differences. In addition, all variables were standardised. That is done because from the many covariates, LASSO selects covariates with large effects. Standardisation, therefore, makes LASSO invariant to scale. For Elastic Net, $\frac{\lambda_1}{\lambda_1+\lambda_2}$ is set to 0.5 and 5-fold cross-validations selects the best α parameter.

Table 1: LASSO and Elastic Net Loss functions

Regressor	LASSO	Elastic Net
Loss function	$\lVert y - X\hat{\beta}\rVert_2^2 + \lambda\lVert\hat{\beta}\rVert_1$	$\lVert y - X\hat{\beta}\rVert_2^2 + \alpha\frac{\lambda_1}{\lambda_1+\lambda_2}\lVert\hat{\beta}\rVert_1 + \alpha(1-\frac{\lambda_1}{\lambda_1+\lambda_2})\lVert\hat{\beta}\rVert_2^2$

$\alpha = \lambda_1 + \lambda_2$

The dependent variable is defined as changes in the federal funds target ΔFFR_t. Appendix M presents the detailed descriptions of baseline right-hand side variables from the Greenbook projections. Figure M.1 shows the cross-correlations between the baseline variables, twelve economic terms groups with positive sentiments (Table L.1) and the same twelve economic terms groups with uncertain sentiments. The most correlated variables are the Greenbook forecasts. Figure M.2 shows the cross-correlations between the baseline variables, twelve economic terms groups from the speeches by Chairmen during the FOMC meetings with positive and uncertain sentiments.

To select the important FOMC topic sentiments, I employ LASSO and Elastic Net to estimate the equation in the form (8).

$$\Delta FFRt_{\tau} = \alpha_0 + \beta_1 FFRt_{\tau-1} + \beta_1 \tilde{u}_{\tau,t} + \sum_{i=-1}^{2} \gamma_i \tilde{\pi}_{\tau,i} + \sum_{i=-1}^{2} \phi_i \Delta\tilde{y}_{\tau,i}$$
$$+ \sum_{i=-1}^{2} \lambda_i (\tilde{\pi}_{\tau,i} - \tilde{\pi}_{\tau-1,i}) + \sum_{i=-1}^{2} \theta_i (\Delta\tilde{y}_{\tau,i} - \Delta\tilde{y}_{\tau-1,i}) + \sum_{i=1}^{N} \gamma_i Pos^i_{\tau} + \sum_{i=1}^{N} \psi_i Un^i_{\tau} + v_{\tau} \tag{8}$$

where $FFRt_{t-1}$ is the level of the intended funds rate before any policy decision associated with meeting τ; $\tilde{u}$, $\tilde{y}$ and $\tilde{\pi}$ are the Greenbook forecasts of the unemployment rate, real output growth, and inflation, respectively, whereas i refers to the horizon of the forecasts. Pos^i_{τ} is a positive sentiment at meeting τ about topic i, whereas Un^i_{τ} is an uncertain sentiment at meeting τ about topic i.

The results of LASSO and Elastic net regressions are shown in Table 2. The positive sentiments of FOMC members regarding inflation expectations, energy, demand, money, financial and fiscal topics were found to have non-zero coefficients in all specifications. Moreover, member uncertainty concerning consumer confidence, assets, demand, growth, money and foreign topics are also found to be connected to changes in the interest rate target.

From the Greenbook projections, longer-term forecasts are less important for changes in the federal fund rate target, while short-term forecasts are more important. Unimportant forecasts include the Greenbook forecast of the percentage change in the GDP/GNP deflator two quarters ahead (GRAD2), the innovations in the Greenbook forecast for the percentage change in the GDP/GNP deflator one and two quarters ahead (IGRD1, IGRD2), and the innovation in the Greenbook forecast for the percentage change in GDP/GNP two quarters ahead (IGRY2). The Greenbook forecast of the percentage change in real GDP/GNP from the previous quarter (GRAYM) is also not important for interest rate changes.

The importance of Committee positivity towards fiscal policy is in line with the findings of Croushore and van Norden (2018), which shows that monetary policy-makers seem to respond to fiscal shocks in ways that have been quantitatively important.

Table N.10 shows the results for the sample from 1983 because of the high volatility of economic variables during Volcker disinflation. In addition to the results in Table 2, positivity in consumer confidence, housing and foreign topics are correlated with interest rate changes. Financial uncertainty is also connected to changes in interest rate targets. The previous conclusions apply to the importance of Greenbook forecasts: long-term forecasts are less important than short-term. Non-important projections include the innovation in the Greenbook forecast for the percentage change in the GDP/GNP deflator two quarters ahead (IGRD2).

Other tables from Appendix N.1 present LASSO and Elastic Net results with sentiments only from speeches by Chairmen during the FOMC meetings. Table N.9 shows that the Greenbook forecast of the percentage change in the GDP/GNP deflator two quarters ahead (GRAD2), the innovation in the Greenbook forecast for the percentage change in the GDP/GNP deflator two quarters ahead (IGRD2), and the Greenbook forecast of the percentage change in real GDP/GNP from the previous quarter (GRAYM) are found to be insignificant.

At the same time, most of the variables indicating Chairmen positiveness or uncertainty towards economic topics are significant for the federal funds rate changes (see Table N.9).

Table 3 shows the results of estimations of Equation (8) with additional factors from the *Federal Reserve Economic Data* (2019) and the Consumer Sentiment Index from *University of Michigan Survey of Consumers* (2019). One can see that FOMC member sentiment during discussions are important for interest rate changes also while taking into account observable macroeconomic indicators and consumer expectations from surveys.

Appendix N.2 presents the robustness check using the Wu and Xia (2016) shadow rate instead of the federal funds rate during the zero lower bound period and the extended sample period up to 2013.

Overall, the following variables are important for the FOMC decisions concerning interest rate changes: inflation expectations, consumer confidence, money aggregates, energy markets, financial markets and fiscal policy. The following variables are important from Chairmen sentiments: consumer confidence, money aggregates and fiscal policy.

Table 2: LASSO and Elastic Net results with sentiments, 1976–2008

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.07	-0.07	-0.07	-0.07	-0.08	-0.08	-0.07	-0.07
GRADM	0.12	0.11	0.1	0.1	0.13	0.13	0.11	0.1
GRAD0	-0.08	-0.07	-0.08	-0.08	-0.11	-0.1	-0.09	-0.08
GRAD1	0.06	0.05	0.06	0.06	0.07	0.06	0.05	0.04
GRAD2	-	-	-	-	-	-	-	-
IGRDM	0.01	0.01	0.01	0.01	-	-	-	-
IGRD0	-0.03	-0.03	-0.03	-0.03	-0.01	-0.01	-0.02	-0.02
IGRD1	-	0.01	-	-	-	-	-	-
IGRD2	-	-	-	-	-	-	-	-
GRAYM	-	-	-	-0.01	-	-	-	-
GRAY0	0.02	0.02	0.02	0.03	-	0.01	0.01	0.01
GRAY1	0.07	0.07	0.06	0.05	0.06	0.06	0.05	0.04
GRAY2	0.01	0.01	0.02	0.02	0.03	0.03	0.03	0.04
IGRYM	0.03	0.03	0.03	0.03	0.05	0.05	0.04	0.04
IGRY0	0.13	0.13	0.14	0.14	0.14	0.14	0.14	0.14
IGRY1	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.03
IGRY2	-	-	-	-	-	-	-	-
GRAU0	-0.06	-0.06	-0.06	-0.06	-0.07	-0.07	-0.06	-0.06
positiveness								
inflation expectations			-	-0.01			-0.01	-0.01
consumer confidence			0.02	0.02			-	-
assets			-	-			-	-
energy			0.04	0.04			0.04	0.04
housing			-	-			-	-
demand			-0.01	-0.01			-0.01	-0.01
employment			-	-			-	-
growth			-0.01	-0.01			-	-
money			0.01	0.01			0.01	0.01
foreign			-	-			-	-
financial			0.03	0.03			0.02	0.02
fiscal			-0.04	-0.04			-0.04	-0.04
uncertainty								
inflation expectations					-	-	-0.02	-0.02
consumer confidence					-0.05	-0.04	-0.04	-0.04
assets					0.01	0.01	0.01	0.01
energy					0.02	0.02	-	-
housing					-	-	-	-
demand					-0.02	-0.02	-0.01	-0.01
employment					-	-	-	-
growth					-0.01	-0.01	-0.01	-0.01
money					-0.04	-0.04	-0.03	-0.03
foreign					0.02	0.02	0.02	0.02
financial					0.01	0.01	-	-
fiscal					0.01	0.01	-	-

Table 3: LASSO and Elastic Net results with sentiments, FRED-MD factors and Consumer Sentiment Index, 1978–2008

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.011	-0.012	-	-	-0.003	-0.005	-	-
GRADM	0.094	0.095	0.08	0.078	0.091	0.092	0.069	0.069
GRAD0	-	-	-	-	-	-	-	-
GRAD1	-	-	-	-	-	-	-	-
GRAD2	-	-	-	-	-	-	-	-
IGRDM	0.021	0.021	0.021	0.022	0.013	0.013	0.016	0.016
IGRD0	-0.054	-0.055	-0.056	-0.055	-0.037	-0.037	-0.034	-0.034
IGRD1	0.003	0.004	-	-	-	-	-0.002	-0.002
IGRD2	-0.004	-0.004	-0.005	-0.004	-0.001	-0.001	-0.003	-0.003
GRAYM	0.013	0.013	0.002	0.002	0.015	0.015	0.005	0.005
GRAY0	0.004	0.004	0.015	0.014	-	-	-	-
GRAY1	0.023	0.023	0.007	0.007	0.001	0.002	-	-
GRAY2	-	-	0.001	0.002	0.022	0.021	0.019	0.02
IGRYM	0.009	0.009	0.009	0.009	0.025	0.026	0.022	0.022
IGRY0	0.04	0.041	0.042	0.042	0.04	0.04	0.041	0.042
IGRY1	-	-	-	-	-	-0.001	-	-
IGRY2	0.015	0.015	0.019	0.019	0.015	0.016	0.02	0.02
GRAU0	-0.059	-0.059	-0.053	-0.052	-0.063	-0.063	-0.056	-0.057
Factor 1	-0.128	-0.127	-0.132	-0.132	-0.126	-0.125	-0.134	-0.133
Factor 2	0.016	0.016	0.015	0.014	0.005	0.005	-	-
Factor 3	-0.075	-0.075	-0.068	-0.066	-0.091	-0.09	-0.073	-0.074
Factor 4	-0.11	-0.11	-0.104	-0.104	-0.117	-0.117	-0.115	-0.115
Factor 5	0.117	0.116	0.124	0.123	0.123	0.123	0.124	0.124
Factor 6	-0.006	-0.006	-0.005	-0.005	-0.002	-0.002	-0.002	-0.002
Factor 7	-0.03	-0.03	-0.016	-0.016	-0.037	-0.038	-0.021	-0.022
Consumer Sentiment	-0.038	-0.038	-0.031	-0.03	-0.048	-0.049	-0.037	-0.037
positiveness								
inflation expectations			-0.004	-0.004			-0.012	-0.013
consumer confidence			0.016	0.016			-	-
assets			-0.002	-0.002			-0.003	-0.004
energy			0.021	0.021			0.007	0.007
housing			-0.018	-0.018			-0.015	-0.015
demand			-0.001	-0.001			-	-0.001
employment			-	-			-	-
growth			-0.015	-0.015			-	-
money			0.017	0.017			0.036	0.036
foreign			-	-			-	-
financial			0.005	0.005			-	-
fiscal			-0.039	-0.038			-0.038	-0.039
uncertainty								
inflation expectations					-0.016	-0.016	-0.021	-0.021
consumer confidence					-0.035	-0.035	-0.042	-0.043
assets					0.018	0.018	0.009	0.009
energy					0.036	0.036	0.026	0.026
housing					-	-	-	-
demand					-	-	-	-
employment					0.002	0.003	0.002	0.003
growth					-0.013	-0.013	-0.013	-0.014
money					-0.066	-0.066	-0.071	-0.07
foreign					0.008	0.008	-	-
financial					0.006	0.007	-	0.001
fiscal					0.002	0.002	-	-

6.2 Central bank communication

The central bank has relied heavily on the communication channel since the interest rate hit the zero lower bound. As was noted in Milani and Treadwell (2012), a central bank's anticipated actions through the communication channel might invalidate identification in a VAR because of the invertibility problem[59]. In this case, the information set from agents differs from that of the the econometrician. As a result, the identified shocks from the values for past and current observed variables would not be true structural shocks. The most suitable solution to the above-mentioned problems is to add additional information or forward-looking variables to the VAR.

It is essential to investigate how the news channel covers monetary policy announcements. Figure 16 presents differences in frequencies of news topics on the next day after the monetary policy announcement and all other days. One can see that the topic about the Fed prevails on the next day after the announcements. Moreover, there are no signs of Odyssean forward guidance[60] being transmitted through the news channel, namely economic news are not more frequent on the next day after the Fed announcement.

The topic frequency augmented with sentiments (negative, positive, uncertain) from the next day after the announcements can serve as a good proxy for what the newspaper's writers and editors heard. Is it the same as what the central bank said or intended to say? Not necessarily. The news sentiments might be a good proxy for what the markets heard. Because central bank communication is transmitted mainly through the yield curve, Table 4 and Table 5 show the regression results for the dependencies of the yield curve and forward rates from the news topic time series[61]. The dependent variables are daily differences in yields and forward rates of different maturities, whereas the right-hand side variables are the sentiment topic time series from the daily newspapers.

[59]This invertibility or nonfundamentalness problem is usually studied with respect to fiscal shocks, as in Leeper et al. (2013), Ramey (2016), Romer and Romer (2010).

[60]Odyssean forward guidance is a revelation of new information about the future economic conditions by the central bank during policy announcements (Campbell et al., 2012).

[61]Daily yields, Treasury Inflation-Protected Securities (TIPS) and break-even inflation rates are taken from Gürkaynak et al. (2007) and Gürkaynak et al. (2010). Inflation compensation incorporates inflation risk premiums and the effects of the differential liquidity of TIPS and nominal securities.

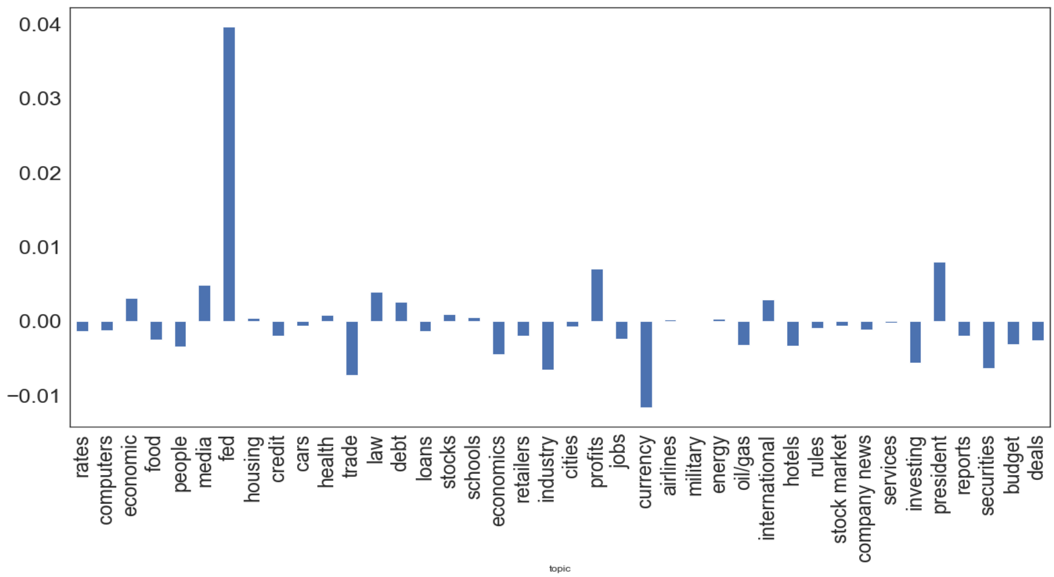


Figure 16: Difference between frequencies of topics between the news on the next day after monetary policy announcements and on other days

The yield curve topic time series does not seem to be significant, while the forward rates news coverage concerning economic, international, securities and reports topics are somewhat important. R^2 from all regressions are tiny, whereas adjusted R^2 are negative, meaning that regressions fit the data poorly.

The main argument against the above-mentioned analysis is that the central bank announcements had taken place one day before their coverage by newspapers. Moreover, markets are forward-looking and might possess the information regarding important economic events also before its official coverage by newspapers. To take these arguments into account, I adjusted the publication date one day back. Table 6 and Table 7 present the regressions at daily frequency for the same dependent variables, but the results are quite different from those of Table 4 and Table 5.

The sentiments from newspapers regarding the Fed are statistically significant in both Table 6 and Table 7. Moreover, these sentiments are important for yields at different maturities. These observations pose alternative insights into the standard identification of monetary policy shocks. These shocks are identified from the yield reactions within a window of announcements or within a daily window. The standard assumption is that there are no other things in the selected window. Nevertheless, the results show that the central bank's information is also essential during these days.

Table 4: Yields, one day difference

	Dependent variable:							
	1 Year	2 Year	5 Year	10 Year	15 Year	20 Year	25 Year	30 Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rates	−0.053	−0.031	0.015	0.014	0.017	0.011	−0.014	−0.056
computers	0.024	0.061	0.073	0.077	0.085	0.079	0.061	0.035
economic	0.118	0.076	−0.012	−0.069	−0.086	−0.098	−0.122	−0.164
food	0.068	0.080	0.124	0.095	0.071	0.078	0.096	0.112
people	−0.122	−0.130	−0.118	−0.117	−0.116	−0.111	−0.101	−0.082
media	−0.009	0.004	0.038	0.045	0.048	0.053	0.055	0.052
fed	0.032	0.041	0.079	0.113	0.118	0.113	0.102	0.088
housing	0.037	0.020	0.016	−0.009	−0.041	−0.067	−0.086	−0.100
credit	0.031	0.060	0.029	0.010	0.011	0.003	−0.015	−0.039
cars	0.027	0.043	0.087	0.084	0.062	0.044	0.029	0.018
health	0.057	0.043	−0.024	−0.061	−0.071	−0.075	−0.076	−0.076
trade	0.071	0.077	0.051	0.043	0.039	0.048	0.069	0.097
law	−0.030	0.002	0.019	0.003	−0.003	−0.003	−0.003	−0.004
debt	0.143*	0.162*	0.119	0.074	0.066	0.073	0.074	0.063
loans	−0.016	−0.082	−0.140	−0.158	−0.132	−0.113	−0.103	−0.098
stocks	−0.053*	−0.041	−0.032	−0.025	−0.020	−0.016	−0.008	0.003
schools	−0.037	−0.058	−0.120	−0.133	−0.122	−0.103	−0.070	−0.026
economics	0.013	−0.021	−0.018	0.023	0.022	0.014	0.015	0.023
retailers	0.020	−0.020	−0.045	−0.051	−0.059	−0.068	−0.071	−0.065
industry	0.009	−0.054	−0.148	−0.127	−0.110	−0.146	−0.214	−0.289*
cities	−0.005	0.045	0.050	0.058	0.058	0.053	0.050	0.051
profits	−0.012	−0.030	−0.045	−0.035	−0.033	−0.030	−0.024	−0.012
jobs	−0.031	−0.118	−0.150*	−0.112	−0.089	−0.065	−0.034	0.004
currency	−0.028	−0.047	−0.065	−0.104	−0.126	−0.135	−0.140	−0.143
airlines	0.065	0.029	−0.018	−0.072	−0.118	−0.131	−0.111	−0.066
military	0.036	0.009	−0.045	−0.069	−0.072	−0.074	−0.077	−0.080
energy	0.051	0.044	0.074	0.048	0.034	0.040	0.051	0.060
oil/gas	0.048	0.085	0.083	0.032	0.021	0.016	−0.002	−0.034
international	−0.031	−0.021	−0.002	0.031	0.064	0.095	0.124	0.149*
hotels	−0.013	−0.046	−0.045	−0.027	−0.015	−0.0002	0.012	0.021
rules	−0.048	−0.015	−0.026	0.005	0.032	0.020	−0.021	−0.073
stock market	0.091	0.077	0.128	0.112	0.046	0.016	0.025	0.059
company news	−0.076	−0.092	−0.053	0.004	0.032	0.033	0.016	−0.008
services	0.020	0.016	−0.002	−0.080	−0.100	−0.093	−0.075	−0.055
investing	−0.037	−0.021	0.035	0.033	0.034	0.038	0.042	0.046
president	−0.026	−0.014	0.056	0.090	0.088	0.082	0.075	0.065
reports	0.049	0.062	0.055	0.049	0.035	0.043	0.076	0.127**
securities	−0.017	0.032	0.129	0.156	0.185	0.214	0.238*	0.259*
budget	−0.039	0.027	0.103	0.149	0.131	0.099	0.076	0.069
deals	0.096	0.068	−0.020	−0.012	−0.005	0.002	0.021	0.052
Constant	0.0003	0.001	0.0004	−0.0001	−0.0001	−0.0002	−0.0003	−0.001
Observations	6,384	6,384	6,384	6,384	6,384	6,384	6,384	6,384
R^2	0.006	0.004	0.004	0.004	0.004	0.005	0.005	0.006
Adjusted R^2	-0.0002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001

Note: Newey-West standard errors; *p<0.1; **p<0.05; ***p<0.01

Table 5: Forward Rates, one day difference

	Dependent variable:							
	2 Year	5 Year	10 Year	15 Year	20 Year	25 Year	30 Year	1 Year Forward 4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rates	0.022	0.032	0.016	0.022	−0.051	−0.188	−0.344	0.043
computers	0.113	0.060	0.103	0.088	0.026	−0.051	−0.129	0.063
economic	0.001	−0.112	−0.128	−0.119	−0.163	−0.285*	−0.462**	−0.106
food	0.115	0.146	0.011	0.054	0.140	0.188	0.186	0.161
people	−0.132	−0.106	−0.120	−0.104	−0.086	−0.034	0.071	−0.107
media	0.042	0.063	0.047	0.063	0.067	0.051	0.021	0.067
fed	0.062	0.135	0.144	0.113	0.078	0.039	−0.002	0.129
housing	0.004	0.008	−0.076	−0.129	−0.155*	−0.169	−0.171	0.015
credit	0.066	−0.020	0.009	0.006	−0.052	−0.126	−0.182	−0.016
cars	0.083	0.121	0.043	0.00004	−0.021	−0.036	−0.044	0.128
health	−0.004	−0.099	−0.093	−0.088	−0.085	−0.079	−0.073	−0.096
trade	0.052	0.035	0.029	0.044	0.111	0.196	0.276	0.034
law	0.047	0.007	−0.020	−0.008	−0.0001	−0.005	−0.019	0.016
debt	0.163	0.043	0.030	0.077	0.097	0.051	−0.046	0.054
loans	−0.160	−0.200*	−0.124	−0.056	−0.058	−0.070	−0.073	−0.198
stocks	−0.026	−0.025	−0.012	−0.009	0.007	0.039	0.079	−0.027
schools	−0.112	−0.174*	−0.120	−0.081	0.001	0.125	0.258	−0.180*
economics	−0.056	0.033	0.057	−0.006	−0.002	0.042	0.079	0.017
retailers	−0.066	−0.062	−0.059	−0.089	−0.095	−0.063	−0.007	−0.063
industry	−0.175	−0.189	−0.048	−0.145	−0.371**	−0.585*	−0.739	−0.209
cities	0.091	0.047	0.070	0.044	0.036	0.045	0.062	0.044
profits	−0.067	−0.033	−0.026	−0.030	−0.014	0.022	0.072	−0.041
jobs	−0.233**	−0.112	−0.055	−0.025	0.042	0.140	0.248	−0.131
currency	−0.064	−0.103	−0.168	−0.165	−0.158	−0.159	−0.160	−0.094
airlines	−0.023	−0.072	−0.183*	−0.212**	−0.115	0.060	0.270	−0.066
military	−0.040	−0.103	−0.079	−0.077	−0.086	−0.092	−0.102	−0.102
energy	0.062	0.081	−0.009	0.029	0.081	0.104	0.097	0.095
oil/gas	0.140	0.014	−0.018	0.011	−0.024	−0.126	−0.272	0.034
international	−0.008	0.029	0.098	0.161*	0.216**	0.259**	0.287*	0.023
hotels	−0.087	−0.012	−0.005	0.027	0.056	0.066	0.058	−0.018
rules	0.005	−0.034	0.092	0.053	−0.097	−0.264	−0.400	−0.043
stock market	0.070	0.202	−0.025	−0.109	−0.017	0.144	0.311	0.207
company news	−0.075	0.012	0.093	0.069	−0.005	−0.090	−0.175	0.001
services	0.040	−0.098	−0.169	−0.106	−0.036	0.023	0.063	−0.073
investing	0.049	0.055	0.027	0.044	0.055	0.063	0.063	0.065
president	0.030	0.138*	0.101	0.071	0.056	0.034	0.0002	0.135
reports	0.056	0.062	0.014	0.020	0.129**	0.291***	0.464***	0.059
securities	0.140	0.192	0.205	0.275*	0.318**	0.351	0.377	0.205
budget	0.111	0.194	0.158	0.036	−0.017	0.001	0.067	0.185
deals	−0.031	−0.055	0.015	0.006	0.052	0.147	0.266	−0.071
Constant	0.001	−0.001	−0.0004	−0.0001	−0.001	−0.002	−0.003	−0.0003
Observations	6,384	6,384	6,384	6,384	6,384	6,384	6,384	6,384
R^2	0.004	0.005	0.005	0.006	0.007	0.006	0.006	0.005
Adjusted R^2	-0.002	-0.001	-0.001	-0.0003	0.0004	0.0001	-0.0002	-0.001

Note: Newey-West standard errors; *p<0.1; **p<0.05; ***p<0.01

Table 6: Yields, one day difference news lagged one day backwards

	Dependent variable:							
	1 Year	2 Year	5 Year	10 Year	15 Year	20 Year	25 Year	30 Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rates	−0.109	−0.046	0.095	0.201	0.252*	0.300**	0.356***	0.419***
computers	0.006	0.002	−0.030	−0.066	−0.081	−0.071	−0.037	0.015
economic	0.726***	0.843***	0.872***	0.694***	0.578***	0.532***	0.517***	0.512***
food	0.102	0.147*	0.151	0.147	0.143	0.115	0.067	0.010
people	−0.002	0.034	0.038	0.026	0.004	−0.001	0.016	0.057
media	0.105*	0.087	0.072	0.081	0.077	0.064	0.050	0.035
fed	−0.259***	−0.388***	−0.460***	−0.435***	−0.395***	−0.348***	−0.305***	−0.272***
housing	−0.096	−0.090	−0.093	−0.085	−0.057	−0.032	−0.016	−0.010
credit	−0.001	0.020	0.008	0.012	0.017	0.013	−0.001	−0.020
cars	0.010	−0.027	−0.029	−0.008	−0.014	−0.030	−0.043	−0.053
health	−0.008	0.022	0.020	0.023	0.049	0.073	0.098	0.128
trade	0.008	0.024	−0.052	−0.102	−0.104	−0.090	−0.067	−0.040
law	0.014	0.052	0.082*	0.077*	0.078*	0.076**	0.067*	0.051
debt	0.090	0.109	0.141	0.150	0.171	0.182	0.180*	0.170
loans	0.161**	0.105	−0.051	−0.118	−0.123	−0.129	−0.145	−0.170*
stocks	0.059**	0.086***	0.082***	0.062**	0.049*	0.034	0.017	−0.001
schools	−0.020	−0.022	−0.023	0.005	0.005	−0.006	−0.016	−0.023
economics	−0.149	−0.235*	−0.342**	−0.389***	−0.374***	−0.358***	−0.357***	−0.368***
retailers	−0.040	−0.072	−0.069	−0.070	−0.075	−0.069	−0.051	−0.025
industry	−0.034	−0.111	−0.136	−0.150	−0.091	−0.048	−0.062	−0.134
cities	0.001	0.007	0.017	0.042	0.069	0.074	0.058	0.030
profits	−0.062	−0.079*	−0.095*	−0.105**	−0.103**	−0.100**	−0.098**	−0.095**
jobs	−0.051	−0.058	−0.083	−0.064	−0.060	−0.069	−0.072	−0.067
currency	−0.156*	−0.191*	−0.242**	−0.227**	−0.226**	−0.225**	−0.213**	−0.189*
airlines	0.060	0.062	0.006	0.016	0.004	−0.036	−0.078	−0.112
military	0.040	0.001	−0.079	−0.122	−0.127	−0.115	−0.097	−0.080
energy	−0.049	−0.131	−0.195*	−0.207**	−0.218**	−0.225**	−0.221***	−0.206**
oil/gas	0.065	0.124*	0.220***	0.237***	0.241***	0.237***	0.222***	0.195***
international	−0.056	0.058	0.200**	0.316***	0.368***	0.372***	0.351***	0.321***
hotels	−0.050	−0.086	−0.082	−0.031	−0.004	−0.001	−0.016	−0.042
rules	−0.030	0.024	0.098	0.116	0.084	0.066	0.083	0.130
stock market	0.283**	0.298*	0.260*	0.173	0.137	0.123	0.110	0.091
company news	−0.108	−0.154	−0.032	0.026	0.011	0.016	0.047	0.090
services	−0.055	−0.051	−0.081	−0.100	−0.099	−0.094	−0.092	−0.096
investing	−0.138	−0.148	−0.172	−0.224*	−0.224*	−0.198*	−0.173*	−0.157
president	−0.025	−0.016	0.043	0.059	0.052	0.047	0.039	0.023
reports	0.136***	0.161***	0.139***	0.122**	0.096*	0.062	0.027	−0.005
securities	−0.192	−0.215	−0.191	−0.199	−0.207	−0.196	−0.168	−0.129
budget	−0.040	−0.070	0.004	0.099	0.108	0.097	0.095	0.106
deals	−0.080	−0.153	−0.228*	−0.209	−0.206*	−0.222*	−0.238**	−0.246**
Constant	0.001	0.002	0.002	0.001	0.001	0.001	0.001	0.001
Observations	6,384	6,384	6,384	6,384	6,384	6,384	6,384	6,384
R^2	0.055	0.052	0.044	0.036	0.032	0.031	0.029	0.025
Adjusted R^2	0.049	0.046	0.038	0.030	0.026	0.025	0.023	0.019
Note:	Newey-West standard errors; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$							

Table 7: Forward Rates, one day difference news lagged one day backwards

	Dependent variable:							
	2 Year	5 Year	10 Year	15 Year	20 Year	25 Year	30 Year	1 Year Forward 4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rates	0.082	0.267	0.327*	0.390***	0.506***	0.655***	0.819**	0.253
computers	−0.018	−0.078	−0.117	−0.091	0.020	0.185	0.370*	−0.072
economic	0.982***	0.743***	0.369***	0.357***	0.429***	0.479***	0.495**	0.818***
food	0.188	0.132	0.155	0.098	−0.043	−0.205	−0.345	0.138
people	0.048	0.044	−0.022	−0.044	0.022	0.165	0.366	0.043
medi	0.062	0.073	0.090	0.047	0.007	−0.023	−0.048	0.070
fed	−0.542***	−0.461***	−0.366***	−0.259***	−0.160*	−0.112	−0.118	−0.489***
housing	−0.079	−0.105	−0.036	0.029	0.050	0.037	0.003	−0.107
credit	0.029	−0.004	0.030	0.019	−0.026	−0.086	−0.147	−0.006
cars	−0.077	0.009	0.0003	−0.055	−0.090	−0.100	−0.100	−0.001
health	0.043	0.002	0.066	0.126	0.169*	0.231**	0.321*	0.005
trade	−0.003	−0.157	−0.132	−0.081	−0.013	0.061	0.127	−0.153
law	0.107**	0.088*	0.071	0.081*	0.056	0.002	−0.060	0.095*
debt	0.155	0.151	0.186	0.225*	0.197*	0.146	0.102	0.158
loans	−0.032	−0.208*	−0.151	−0.131	−0.172	−0.250	−0.343	−0.205*
stocks	0.108***	0.054	0.034	0.010	−0.030	−0.072*	−0.107	0.061*
schools	−0.039	0.009	0.030	−0.021	−0.052	−0.057	−0.052	−0.004
economics	−0.354**	−0.456***	−0.389**	−0.312**	−0.321**	−0.385*	−0.467	−0.453**
retailers	−0.101	−0.052	−0.088	−0.074	−0.018	0.061	0.148	−0.054
industry	−0.151	−0.194	−0.074	0.098	0.018	−0.285	−0.717	−0.184
cities	0.013	0.035	0.105	0.121	0.046	−0.058	−0.151	0.031
profits	−0.097	−0.114*	−0.107*	−0.093*	−0.091*	−0.086	−0.074	−0.114*
jobs	−0.080	−0.090	−0.028	−0.081	−0.099	−0.065	−0.012	−0.104
currency	−0.270**	−0.243*	−0.210*	−0.230**	−0.203*	−0.125	−0.014	−0.263*
airlines	0.030	−0.030	0.037	−0.090	−0.211**	−0.273*	−0.285	−0.042
military	−0.074	−0.162*	−0.158*	−0.112	−0.047	−0.003	−0.001	−0.159*
energy	−0.250**	−0.220*	−0.226**	−0.250***	−0.232**	−0.172	−0.096	−0.227*
oil/gas	0.243**	0.279***	0.246**	0.244***	0.202***	0.115	0.002	0.291***
international	0.227**	0.351***	0.483***	0.438***	0.326***	0.217*	0.129	0.337***
hotels	−0.123	−0.030	0.050	0.038	−0.028	−0.123	−0.221	−0.047
rules	0.107	0.169	0.073	−0.012	0.064	0.250	0.474*	0.168
stock market	0.318*	0.150	0.056	0.077	0.078	0.030	−0.043	0.181
company news	−0.130	0.137	0.010	−0.018	0.094	0.243	0.368	0.129
services	−0.060	−0.122	−0.109	−0.086	−0.076	−0.094	−0.144	−0.120
investing	−0.162	−0.231	−0.276**	−0.167	−0.087	−0.066	−0.095	−0.220
president	0.022	0.106	0.048	0.036	0.023	−0.022	−0.094	0.106
reports	0.164***	0.111*	0.085	0.0004	−0.081	−0.141*	−0.179	0.115*
securities	−0.207	−0.178	−0.229	−0.203	−0.115	0.006	0.131	−0.181
budget	−0.068	0.154	0.178	0.079	0.064	0.120	0.201	0.132
deals	−0.266*	−0.243*	−0.172	−0.238*	−0.295**	−0.301	−0.258	−0.265*
Constant	0.003	0.001	−0.0001	0.001	0.001	0.002	0.002	0.001
Observations	6,384	6,384	6,384	6,384	6,384	6,384	6,384	6,384
R^2	0.043	0.030	0.022	0.021	0.018	0.010	0.006	0.032
Adjusted R^2	0.037	0.024	0.016	0.015	0.012	0.003	-0.0001	0.025
Note:								Newey-West standard errors; *p<0.1; **p<0.05; ***p<0.01

Sentiments regarding the Fed topic are significant for the whole yield curve, but the effect is larger for yields with maturities of five and ten years. The higher economic effect of these sentiments is also observed for two and five years forward. This might capture the impact of forward guidance because this type of shock affects the medium-term yields.

The contrasting conclusions between Table 4 and Table 5, and Table 6 and Table 7 regarding the overall fit of the regressions and statistical significance of coefficients support the claim that markets incorporate in prices all forward-looking information immediately. If some information is available to newspaper reporters, the same information also should be available to the market participants on the same day before official newspaper reports, which are created mainly for the public.

Sentiments regarding interest rates are essential for the longer tail of the yield curve. In contrast, sentiments regarding the economic topic are important for yields with different maturities, but the economic significance is higher for the shorter tail. Beliefs regarding the economics topic also impact the whole yield curve and forward rates with different maturities.

Sentiments regarding the profits, currency, oil/gas, international and energy topics are connected to the longer tail of the yield curve, whereas these sentiments have an effect on the forward rates with shorter maturities. In contrast, sentiments regarding stocks, stock market, and reports are connected to the curve's shorter tail.

These results indicate how the state of the different aspects of economic developments are connected to the yields and forward rates. Taking into account these results, it is possible to develop an effective central bank communication strategy. Different aspects of central bank communication might affect different tails of the yield curve. Currently, only Delphic forward guidance[62] is seen to have an effect on the medium-term yields and forward rates. Newspapers do not seem to cover the economic aspect of the central bank announcements, and therefore a different proxy is needed to study the effect of Odyssean forward guidance. Still, generally, economic sentiments can move the yield curve and forward rates.

[62]Delphic forward guidance is a revelation of new information about the future actions of the central bank during policy announcements (Campbell et al., 2012).

7 The mechanism of soft news shocks

One possible modification of a DSGE model that introduces positive co-movements of expectations and business cycle booms involves using an RBC model and include labour market frictions in the fashion of Pissarides (2000). In this framework, expectations of good times increase the benefit of a match and lead to a fall in current unemployment and more posted vacancies. Studying the effects of an anticipated increase in productivity in a labour search model, Haan and Kaltenbrunner (2009) find that it stimulates entrepreneurs to increase investment and post more vacancies, and therefore induce economic expansion. Ravenna and Walsh (2008) introduced search and matching frictions into a New Keynesian model to take into account an extensive margin.

A second possibility is to introduce nominal rigidities into an RBC model, as was done by Barsky and Sims (2012), for instance. These rigidities are essential because they raise the inter-temporal nature of a firm problem. Angeletos and La'O (2013) introduced sentiments into a rational expectation equilibrium by including random and decentralised trading into an RBC model, which introduces shocks to expectations because of trading frictions. The paper finds that these sentiments shocks propagate through the communication channel because agents receive heterogeneous information about the aggregate economic shocks[63].

A third way is to introduce the learning process. For example, Milani (2017) introduced sentiments shocks in a DSGE model, where these sentiments capture persistent waves of optimism and pessimism orthogonal to the economy's observed state. Milani and Rajbhandari (2020) developed a learning model for expectations and news shocks under the rational expectation assumption. Moreover, as Lorenzoni (2009) stated, dispersed information slows down the capacity of agents to learn the true state of the economy, which allows noise shocks to have long-lasting effects on economic activity.

Bhandari et al. (2019) introduced a model with endogenous subjective beliefs and applied it to a New-Keynesian model with frictional labour markets. The authors used additional data from surveys because agents use a set of plausible models.

To study the mechanism behind different types of sentiment shocks, I change the frequency to quarterly and add additional variables that are usually used in DSGE models. There are several potential mecha-

[63]Sentiments shocks are aggregate shocks in information flows in their model or shocks to first order beliefs about endogenous economic outcomes.

nisms of the effects of sentiment shocks: (1) through the consumption smoothing channel, (2) through increasing productivity in anticipation of higher demand[64], (3) through increasing working hours because of the income-substitution channel, (4) through labour markets since it might affect the future value of a firm match, (5) through increasing entrepreneurship birth rate. I use additional variables in SVAR to investigate the importance of these channels.

The baseline variables are the *Interest rate*[65], *TFP*, *Output*, *Hours*, *Establishment birth*, *Inflation*[66] and *Sentiments*[67]. The full data description is presented in Appendix O and the construction of the *Establishment birth* series. Figure 17 presents the results of the SVAR with variables that are ordered as mentioned above for 1985:Q1–2008:Q4.

Figure 17 shows that the identified shocks, even aggregated at quarterly frequency, are close to exogenous (IRFs, when soft news variable is ordered first, are similar to those when soft news is ordered last in the system). The positive shock temporarily drives up inflation. In this case, it is similar to a positive demand shock. Moreover, the shock leads to temporal increases in working hours and establishment birth rates for ten months after the shock. Entrepreneurs see new opportunities in anticipation of good times and decide to start new businesses. Workers in existing firms start to work more. Increased working hours and the number of new businesses lead to a gradual increase in the long run in response to a positive soft news shock. In this case, the shock has a similar effect to a news shock when agents observe a true future state.

The central bank reacts to the expansionary supply side of the economy by increasing the interest rate in the short run to dampen increasing inflation. Nevertheless, the increase in output is permanent, which is in line with the empirical findings from the previous chapters.

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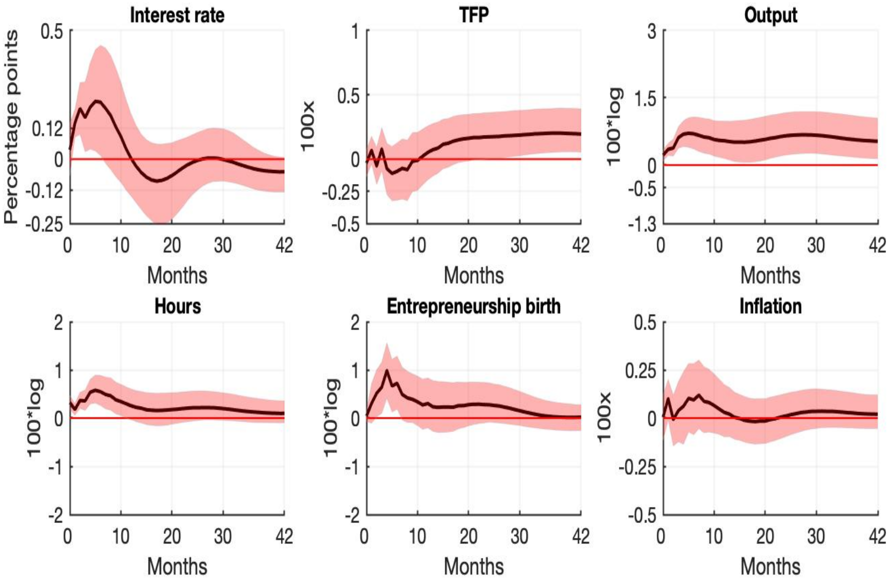
[64]The main channel of news shocks.

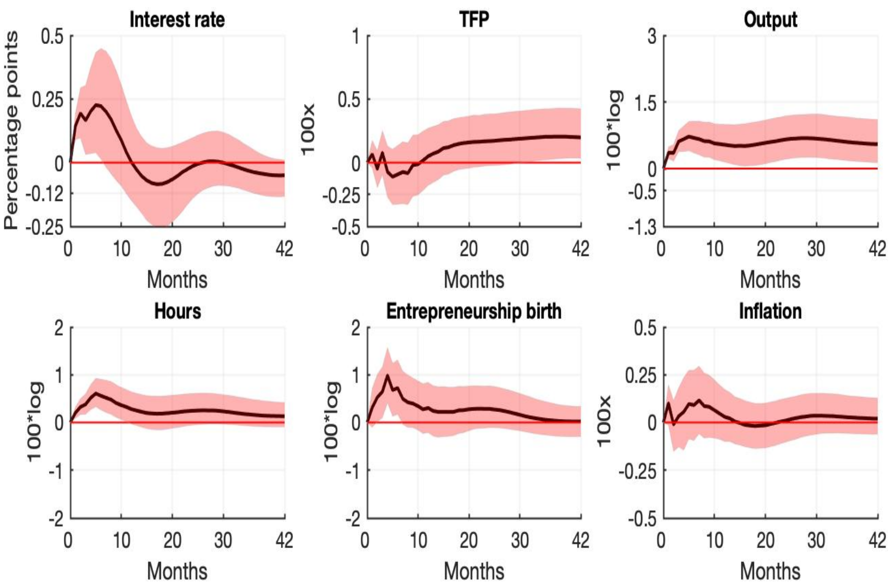
[65]The federal funds rate.

[66]$\Delta CPI_t * 100$, where CPI_t is the logarithm of CPI index.

[67]Shocks identified as in Figure 6 and aggregated at quarterly frequency.



(a) Impulse responses to a soft news shock, ordered first



(b) Impulse responses to a soft news shock, ordered last

Figure 17: Impulse responses in a quarterly VAR without the ZLB period
median and 16th and 84th percentiles

8 Conclusions

The study combines the techniques of Doc2Vec with clustering, LDA, and lexical methods to transform the data from newspapers into topic time series with sentiments. The findings show that the Economic topic time series is connected to household expectations for the interest rate, the Loans topic time series is connected to inflation expectations, and the Housing topic time series is connected to unemployment expectations. By combining these topic time series with the Oil/gas topic and reducing the dimensionality, the study derives an indicator of news sentiments about business cycles. This indicator has leading properties for the business cycle indicator based on official statistics.

The first principal component from the positive sentiments of the Loans, Housing, Economic, and Oil/gas topic time series is employed in Structural Vector Autoregressions to identify the role of soft news, which means the news that presents the subjective opinions of experts about the future development of the economy. The study finds that a soft news shock accounts for about 20% of the forecast error variance of output at long horizons. Decomposing the principal component by soft news shocks to separate topics accounts for about 7–27% of the forecast error variance of output and about 5% of the variance in consumption at long horizons in different models. Moreover, the inclusion of news variables leads consumer sentiment and expectation shocks to play a smaller role in SVARs. The effect of a positive soft news shock is in line with an expected positive demand shock with an endogenous propagation mechanism.

On top of that, the study finds empirical support that the transmission mechanism for monetary policy lies in the effect on the long-run interest rates. Households do not pay much attention to news about monetary policy, whereas the topic time series about loans is important for their inflation expectations.

In addition, while previous studies used pre-defined lists of words connected to a certain topic, this study investigates all economic phrases by FOMC members during their meetings. The most frequent phrases were grouped into twelve categories and assigned a sentiment (positive/negative, uncertain). These topic time series were employed further for testing for omitted variables in standard Taylor rule specifications. The study supports the importance of consumer and inflation expectations of consumers for FOMC interest rate decisions.

The study finds that newspapers cover the Federal board announcements quite accurately, reporting it on the next day after announcements. Central bank communication, measured by news sentiments from the Fed topic, was transmitted through the yield curve on the announcement days. The study poses a question regarding the information being important during FOMC announcements. The current identification strategies regarding monetary policy shocks assume that there is only one type of signal during the announcement, namely a monetary policy shock, the information unexpected by markets. This study's results find that central bank communications during the announcement days also moves the yield curve.

Moreover, markets are forward-looking, and they obtain the current information before its publication in newspapers. According to the results from regressions at daily frequency, news regarding economic, international, securities, stock market, company reports, energy, currency, oil/gas, and profits are also connected to the movements in the yield curve.

Soft news shocks were found to have a long-run effect on output through both intensive (increasing hours worked) and extensive (more new businesses) margins in the medium term and through a long-run increase in TFP. In this regard, the identified shocks are similar to news shocks identified earlier in the literature.

9 Future research

An interesting extension would be to employ non-linear VAR and study the non-linear effects of the news on economic activity. A smooth transition conventional VAR might be employed with the transition function derived from the news topics. In this case, it will be possible to distinguish the public's reaction to certain shocks in times of high or low news coverage of a certain topic, or in times of positive sentiments versus negative sentiments.Therefore, standard macroeconomic shocks might have a non-linear effect, and news data makes it possible to disentangle these effects since it covers the whole population instead of specific categories of households. Moreover, the news here is not the news about true future TFP shocks, but it also touches households' signal-extraction problem. In times of frequent news coverage, signal-extraction might be more comfortable than in times of infrequent news coverage. That is an interesting idea for future research.

Furthermore, news data might help to derive an uncertainty index, which can make it possible to study the propagation of the monetary policy during uncertain times. The studies of Christiano et al. (2014), Fernández-Villaverde and Guerrón-Quintana (2020), Colombo and Paccagnini (2020) among others, confirm the interest in these types of questions. It is possible to derive uncertainty indicators relevant to each type of news topic time series and study the effects of the second moments shocks.

It would be interesting to employ new methods to decompose text data into topics time series and compare the results from the methodological perspective. New developments in the area of textual analysis make it possible to employ dynamic topic models, correlated topic models or structural topic models, among others. The dynamic topic model can bring new insights because the tone of newspapers might change from the 1980s to the 2020s.

Besides, it would also be interesting to combine news data with other non-standard data, such as Google Trends, Twitter data, Facebook, etc., to study the public's reaction to different news types. Analysing these reactions will offer new insights into the expectation formation mechanism of households.

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Appendix A News sentiments

Souleles (2004) noted that for inflation and unemployment "an increase" denotes the bad state. The same intuition applies for the federal funds rate, the discount rate, and interest rates, which are here denoted as keywords together with inflation and unemployment. Therefore, if the following words appear near to the keywords they are labelled as negative, further to LM dictionary: Therefore, if the following words[68] appear near to the inflation expectations they are labelled as negative[69]:

negative, negatively, negatives, difficult, difficulty, hurdle, hurdles, obstacle, obstacles, uncertain, uncertainty, unsettled, unfavorable, depressed, disappoint, disappoints, disappointing, disappointed, disappointment, risk, risks, risky, threat, threats, penalty, penalties, deteriorate, deteriorates, deteriorating, deteriorated, worsen, worsens, worsening, worse, worst, challenge, challenges, challenging, challenged, up, increase, increases, increasing, increased, rise, rises, rising, rose, risen, exceed, exceeds, exceeded, exceeding, growth, up, high, higher, pessimism, more, above, high, higher, highest, greater, greatest, larger, largest, grow, grows, growing, grew, grown, growth, climbed.

The following words are labelled as positive if they appear near to the keywords: cut, cutback, cutbacks, deceased, decline, declined, declines, declining, diminish, diminished, diminishes, diminishing, downtime, downtimes, downturn, downturns, downward, downwards, dropped, neglect, neglected, neglectful, neglecting, neglects, negligence, negligences, negligent, negligently, shut, shutdown, shutdowns, shuts, shutting, slow, slowdown, slowdowns, slowed, slower, slowest, slowing, slowly, slowness, sluggish, sluggishly, sluggishness, weak, weaken, weakened, weakening, weakens, weaker, weakest, weakly, weakness, weaknesses, undercut, undercuts, undercutting, against, positive, positives, success, successes, successful, succeed, succeeds, succeeding, succeeded, accomplish, accomplishes, accomplishing, accomplished, accomplishment, accomplishments, strong, strength, strengths, certain, certainty, definite, solid, excellent, good, leading, achieve, achieves, achieved, achieving, achievement, achievements, progress, progressing, deliver, delivers, delivered, delivering, leader, leading, pleased, reward, rewards, rewarding, rewarded, opportunity, opportunities, enjoy, en-

[68] These words are taken from Henry (2008) dictionary, but meaning of some of them is reversed. For example, high in Henry (2008) dictionary is a positive word, in case for inflation expectations it has a negative meaning.

[69] Additionally to Loughran and Mcdonald (2016) dictionary.

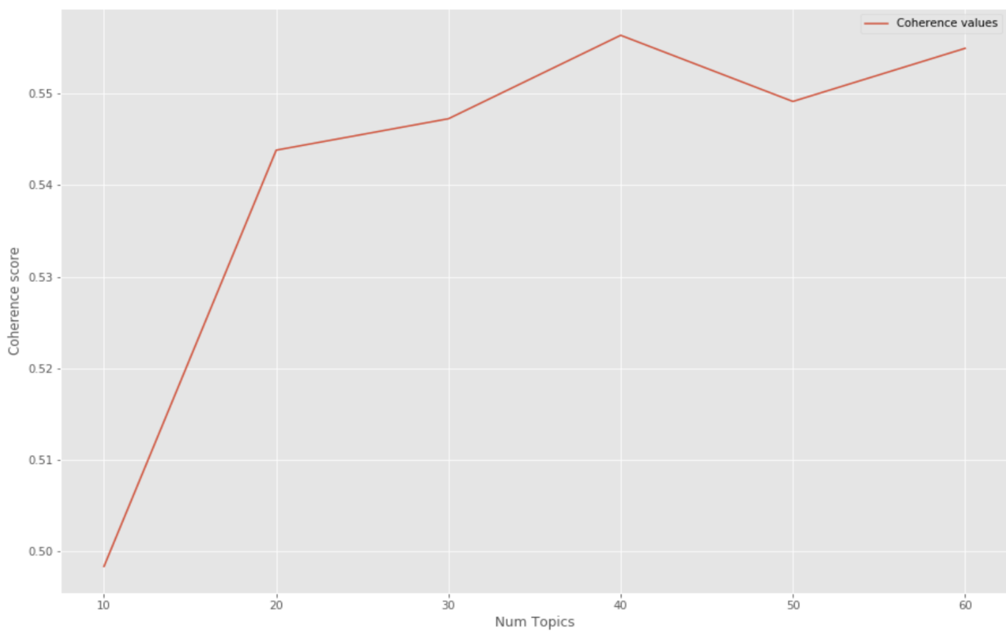
joys, enjoying, enjoyed, encouraged, encouraging, improve, improves, improving, improved, improvement, improvements, strengthen, strengthens, strengthening, strengthened, stronger, strongest, better, best, expand, expands, expanding, expanded, expansion, beat, beats, beating, fail, fails, failing, failure, weak, weakness, weaknesses, slump, slumps, slumping, slumped, downturn, down, decrease, decreases, decreasing, decreased, decline, declines, declining, declined, fall, falls, falling, fell, fallen, drop, drops, dropping, dropped, weaken, weakens, weakening, weakened, low, lower, lowest, less, least, cut, smaller, smallest, shrink, shrinks, shrinking, shrunk, below, under, deal, moderation, moderate, down, stop, stopping, deal, cool, optimism, stoppage, stoppages, stopped, stopping, stops, decline, lower, drop, decrease, slide.

I extract the five words that precede a keyword and the five words that follow it. If a sentence starts with a keyword I extract the seven following words, if a sentence ends with a keyword I extract the seven preceding words; in a short sentence I extract the words from the beginning of the sentence or the end of the sentence. After extracting words near a keyword I apply a lexical-based approach to label the sentiment of the keyword.

Additionally, I use a negation dictionary[70]. If the following words precede a sentiment of keywords in the three-word window, then they are labelled as the opposite sentiment. The negation dictionary consists of the following words: aint, arent, cannot, cant, couldnt, darent, didnt, doesnt, ain't, aren't, can't, couldn't, daren't, didn't, doesn't, dont, hadnt, hasnt, havent, isnt, mightnt, mustnt, neither, don't, hadn't, hasn't, haven't, isn't, mightn't, mustn't, neednt, needn't, never, none, nope, nor, not, nothing, nowhere, oughtnt, shant, shouldnt, wasnt, werent, oughtn't, shan't, shouldn't, wasn't, weren't, without, wont, wouldnt, won't, wouldn't, rarely, seldom, despite, no, nobody.

[70] As in Shapiro et al. (2020) for instance.

Appendix B Latent Dirichlet Allocation




```
Num Topics = 10  has Coherence Value of 0.4984
Num Topics = 20  has Coherence Value of 0.5438
Num Topics = 30  has Coherence Value of 0.5473
Num Topics = 40  has Coherence Value of 0.5564
Num Topics = 50  has Coherence Value of 0.5491
Num Topics = 60  has Coherence Value of 0.5549
```

Figure B.1: Coherence values for the number of topics

Table B.1: Topic labelling for the LDA model

Topic	Words
rates	percent, year, increas, rate, averag, price, declin, rise, month, drop
computers	comput, technolog, compani, system, softwar, product, appl, microsoft, electron, market
economic	year, economi, growth, market, recess, expect, econom, mani, continu, industri
food	food, year, product, price, farm, market, farmer, restaur, agricultur, produc
people	peopl, time, make, thing, day, good, lot, work, back, tri
media	advertis, onlin, ad, site, internet, web, time, media, googl, publish
fed	rate, fed, interest, inflat, feder, reserv, economi, econom, polici, economist
housing	home, hous, california, lo, angel, year, price, counti, sale, san
credit	credit, consum, card, pay, custom, fee, account, servic, charg, check
cars	car, sale, auto, vehicl, ford, year, motor, chrysler, truck, model
health	insur, health, drug, care, compani, cost, medic, hospit, plan, year
trade	trade, state, unit, american, countri, foreign, import, world, mexico, export
law	case, court, investig, file, law, feder, charg, lawyer, attorney, judg
debt	debt, financi, billion, govern, bankruptci, crisi, plan, financ, money, problem
loans	bank, loan, mortgag, financi, feder, save, institut, borrow, lender, lend
stocks	stock, market, index, point, dow, rose, fell, gain, close, share
schools	chicago, school, photo, student, illinoi, famili, univers, colleg, program, tribun
economics	studi, econom, research, chang, univers, professor, differ, mani, exampl, problem
retailers	store, retail, sale, shop, year, chain, custom, buy, consum, holiday
industry	compani, industri, product, manufactur, steel, million, busi, produc, equip, oper
cities	citi, build, develop, offic, area, project, project, real, properti, million
profits	million, quarter, share, billion, earn, year, profit, compani, cent, sale
jobs	job, worker, work, employ, labor, employe, union, wage, unemploy, peopl
currency	dollar, york, cent, price, gold, trade, late, exchang, futur, currenc
airlines	airlin, travel, unit, air, fare, american, flight, carrier, boe, airport
military	war, govern, nation, countri, offici, attack, militari, soviet, world, defens
energy	power, energi, electr, state, util, plant, ga, water, cost, project
oil/gas	price, oil, energi, barrel, ga, product, gasolin, crude, day, produc
international	global, european, world, unit, europ, china, countri, british, intern, bank
hotels	hotel, photo, room, year, park, show, game, open, peopl, time
rules	propos, rule, regul, agenc, offici, feder, requir, law, member, committe
stock market	trade, market, stock, exchang, firm, secur, street, wall, futur, option
company news	compani, busi, execut, chief, firm, manag, presid, corpor, offic, year
services	servic, compani, commun, phone, network, custom, provid, busi, cabl, telephon
investing	fund, invest, stock, investor, market, manag, money, return, year, valu
president	presid, hous, republican, democrat, obama, trump, senat, white, polit, administr
reports	report, month, consum, economist, depart, increas, rose, declin, good, show
securities	bond, rate, treasuri, market, yield, price, issu, interest, note, secur
budget	tax, incom, year, budget, cut, plan, spend, save, pay, benefit
deals	compani, share, deal, million, offer, stock, billion, sharehold, merger, bid

Appendix C Cosine similarity and Euclidian distance

Cosine similarity between two vectors $\vec{A}$ and $\vec{B}$ is:

$$cos(\angle(\vec{A},\vec{B})) = \frac{\vec{A}\cdot\vec{B}}{||\vec{A}||_2||\vec{B}||_2}$$

where $\vec{A}\cdot\vec{B}$ is an inner product (a dot product in the Euclidean space) between two vectors and $||\vec{A}||_2||\vec{B}||_2$ is a product of their Euclidean lengths (L^2 norms).

$$||\vec{A}||_2 = \sqrt{\sum_i \vec{A_i}^2}$$

For unit-length vectors, cosine similarity is:

$$cos(\theta) = \vec{A}\cdot\vec{B}$$

since $||\vec{A}||_2 = ||\vec{B}||_2 = 1$. In this case minimisation of Euclidian distance (squared) is the same as maximisation of cosine similarity since:

$$Euclidian\_distance^2 = ||\vec{A}-\vec{B}||_2^2 = ||\vec{A}||_2^2 - 2\vec{A}\cdot\vec{B} + ||\vec{B}||_2^2 = 2 - 2cos(\angle(\vec{A},\vec{B}))$$

For an n-dimensional space the Euclidean distance is:

$$Euclidian\_distance = \sqrt{(a_1-b_1)^2 + (a_2-b_3)^2 + ... + (a_n-b_n)^2} =$$

$$= \sqrt{\sum_n (a_i-b_i)^2} = ||\vec{A}-\vec{B}||_2 = \sqrt{||\vec{A}||_2^2 + ||\vec{B}||_2^2 - 2\vec{A}\cdot\vec{B}}$$

Appendix D Doc2Vec with k-means++

Table D.1: Topic labelling for Doc2Vec with kmeans++ 40 clusters

Topic	Words
new business	new, business, small, big, business, home, firm, sales, u.s., correction, appended, market, firms, industry, get, many, still
dow	dow, stocks, shares, markets, bonds, market, rally, markets, trading, gains, prices, rise, wall, nasdaq, day, fall, investors, stock
jobs	job, workers, jobs, new, pay, firms, work, u.s., business, jobless, labor, rate, companies, may, economy, study, many, says
profits	profit, earnings, company, quarter, loss, sales, reports, net, profits, posts, news, million, cut, business, rise, earnings, says, stock,
housing	home, sales, housing, prices, real, mortgage, homes, rates, new, rise, market, price, starts, drop, newhome, fall, rate, u.s., may,
reports	company, news, business, brief, rates, prices, earnings, profit, economy, rise, sales, briefing, reports, mortgage, u.s., briefing, rate
currency	dollar, currency, markets, gold, u.s., prices, yen, mixed, trading, markets, falls, gains, stocks, rises, mark, higher, new, lower
fraud	case, fraud, says, million, sec, u.s., firm, suit, pay, former, court, stock, probe, accused, charges, judge, bank, new, may, firms
company stocks	stock, bid, company, buy, deal, firm, billion, offer, million, may, stake, news, shares, merger, new, sell, takeover, sale, business
farm prices	prices, food, u.s., farmers, farm, new, may, crop, industry, price, market, growers, sales, california, business, could, big, corn
retailers	sales, retailers, stores, retail, new, holiday, walmart, online, shoppers, profit, chain, sears, retailer, store, may, big, company
energy	power, energy, gas, utility, new, u.s., california, electricity, utilities, state, plan, may, solar, natural, coal, plant, nuclear
media	media, advertising, business, new, ad, advertising, ads, business, appended, correction, times, online, web, magazine, campaign
money	tax, money, personal, new, home, financial, money, may, retirement, loan, finance, mortgage, debt, college, savings, credit, loans
international	world, u.s., debt, mexico, bank, new, economic, international, global, plan, latin, nations, aid, crisis, business, imf, economy
economy	economic scene, tax, u.s., new, business, economy, market, correction, appended, may, economists, deficit, plan, budget, growth,
entertainment	company, town, tv, new, media, disney, sales, video, film, music, movie, may, deal, profit, hollywood, big, online, cable, digital
airlines	airlines, airline, air, travel, united, fares, business, fare, american, new, delta, cuts, u.s., fuel, company, may, cut, flights, loss
financial markets	stocks, dow, market, markets, financial, rally, roundup, stock, investors, bond, wall, prices, nasdaq, oil, yields, gains, rise, tech
banking	credit, card, bank, new, banks, cards, fees, consumer, personal, rates, consumers, online, may, money, pay, get, data, banking
economic	consumer, growth, u.s., sales, orders, economy, rise, rate, prices, spending, jobless, retail, economic, index, factory, inflation
deals	market, business, new, place, chief, correction, appended, people, wall, big, bank, company, u.s., stock, deal, executive, s.e.c.
services	phone, at&t, cable, fcc, new, wireless, company, service, tv, deal, internet, may, telecom, firm, plan, firms, mci, rates, bell
oil/gas	oil, prices, gas, opec, price, u.s., gasoline, crude, output, rise, may, energy, cut, production, exxon, profit, company, new, pump
real estate	real, estate, new, office, commercial, building, market, estate, city, downtown, may, housing, project, space, hotel, center, million
loans	bank, banks, new, u.s., fed, loans, loan, mortgage, banking, big, profit, billion, financial, plan, says, s&l, credit, first, million
trading	trading, market, stock, futures, new, exchange, sec, nasdaq, wall, big, cbot, merc, nyse, board, options, markets, trade, chicago
aircrafts	boeing, new, airbus, company, defense, u.s., air, orders, jet, deal, may, aircraft, business, says, billion, firm, lockheed, aerospace
vehicles	sales, auto, ford, car, gm, chrysler, u.s., new, g.m., company, cars, big, toyota, prices, profit, may, news, vehicle, says, plant
financial news	credit, markets, bond, prices, treasury, bonds, rates, yields, u.s., rise, issues, financenew, market, issues, treasuries, interest, new
health	drug, health, insurance, care, new, costs, price, may, medical, healthcare, business, u.s., says, insurers, prices, company, drugs
business digest	business, digest, digest, week, economy, saturday, business, thursday, wednesday, friday, tuesday, monday, july, may, august
investing	market, funds, stocks, investors, mutual, stock, fund, place, wall, may, investing, new, beat, tom, money, bond, investing
trade	trade, u.s., deficit, steel, talks, pact, imports, new, exports, may, says, global, gap, tariffs, world, mexico, foreign, trump, deal
fed	fed, rate, rates, interest, greenspan, inflation, says, economy, growth, economic, may, chief, fed's, cut, market, u.s., policy, money
cities	city, state, new, tax, chicago, plan, business, says, may, illinois, would, county, budget, could, d.c., economic, million, mayor, jobs
technology	new, apple, computer, company, sales, profit, technology, microsoft, market, chip, intel, pc, i.b.m., software, earnings, technology
futures	prices, futures, futuresoptions, commodities, markets, oil, soybeans, grain, rise, corn, fall, wheat, coffee, gold, price, cattle, soybean
online	online, web, internet, new, google, technology, yahoo, business, firm, amazon, ad, company, microsoft, site, aol, tech, deal, firms
president	tax, obama, gop, house, plan, senate, bill, budget, new, bush, democrats, trump, u.s., president, says, debt, economic, may, deficit

Appendix E Topic time series. Positive sentiments

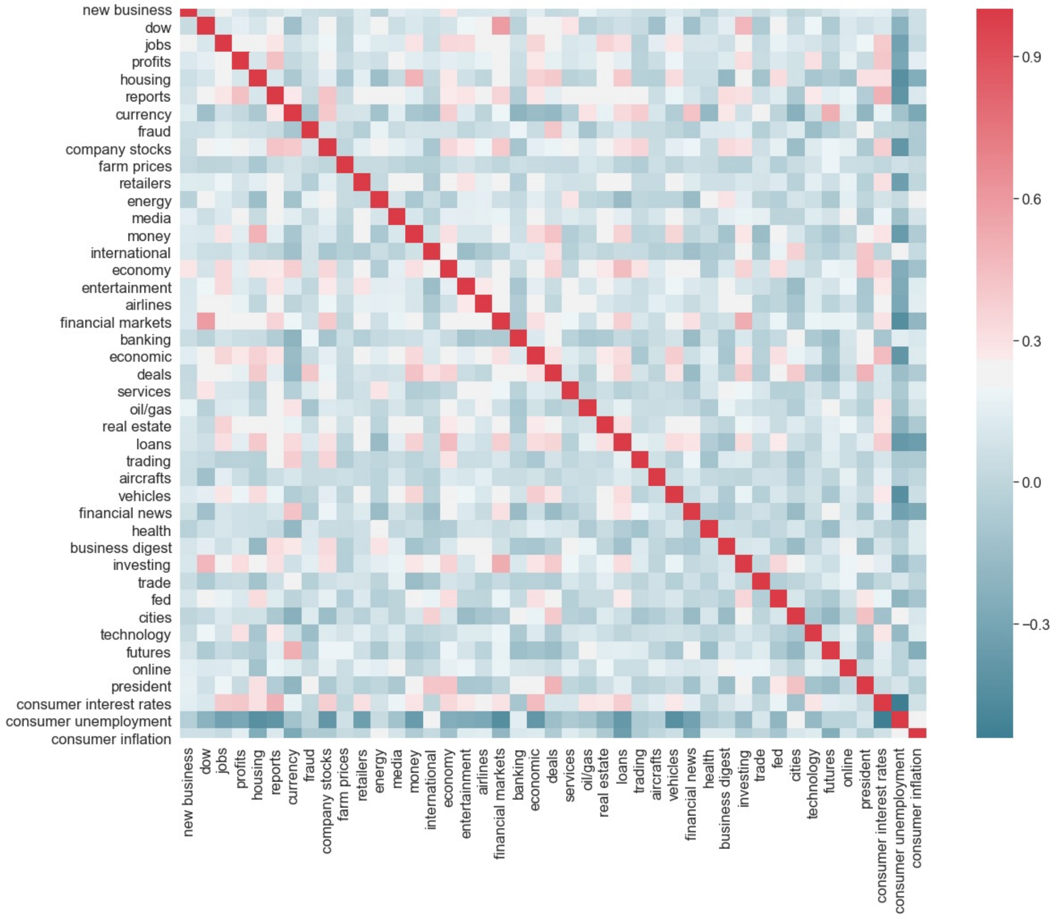


Figure E.1: Cross-correlations between topic time series from the Doc2Vec model with k-means++

Consumer inflation, consumer interest and consumer unemployment are the expectations from the *University of Michigan Survey of Consumers* (2019)

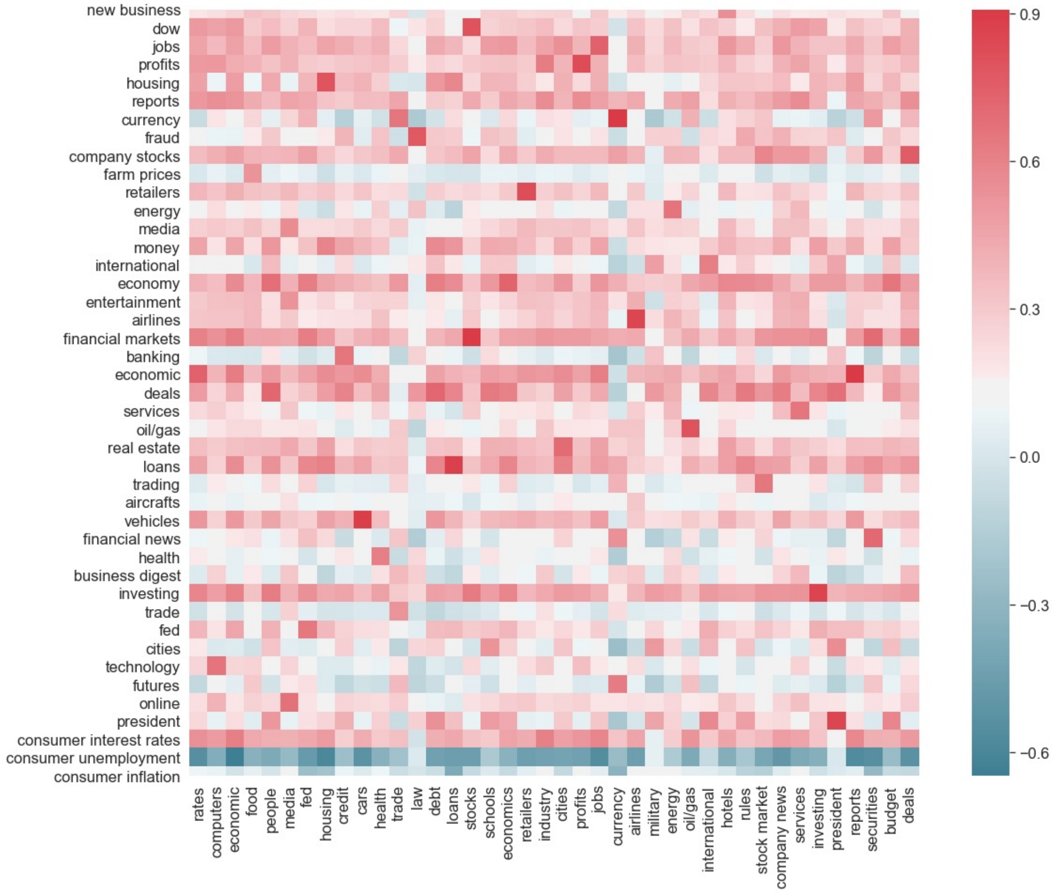


Figure E.2: Correlations between topic time series from the Doc2Vec model with k-means++ (y axis) and LDA using topic frequency labels (x axis)

Consumer inflation, consumer interest and consumer unemployment are expectations from the *University of Michigan Survey of Consumers* (2019)

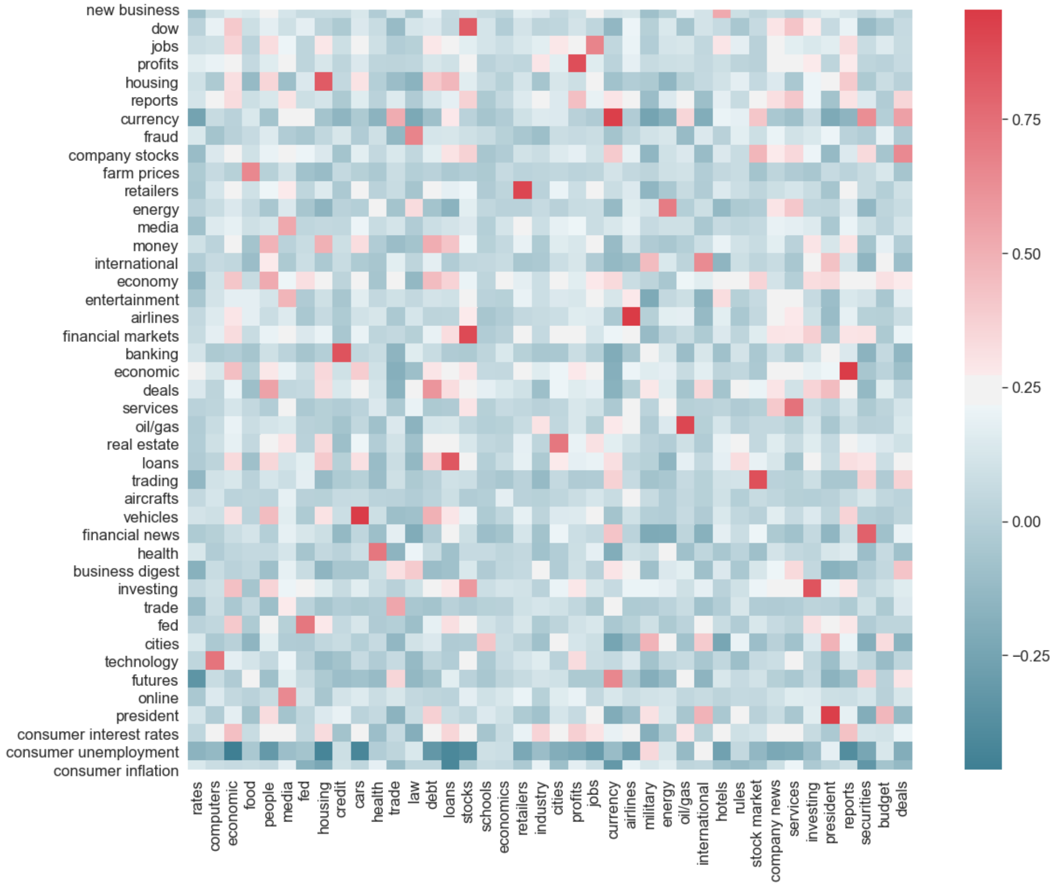


Figure E.3: Correlations between topic time series from the Doc2Vec model with k-means++ (y axis) and LDA using dominant topic labels (x axis)

Consumer inflation, consumer interest and consumer unemployment are expectations from the *University of Michigan Survey of Consumers* (2019)

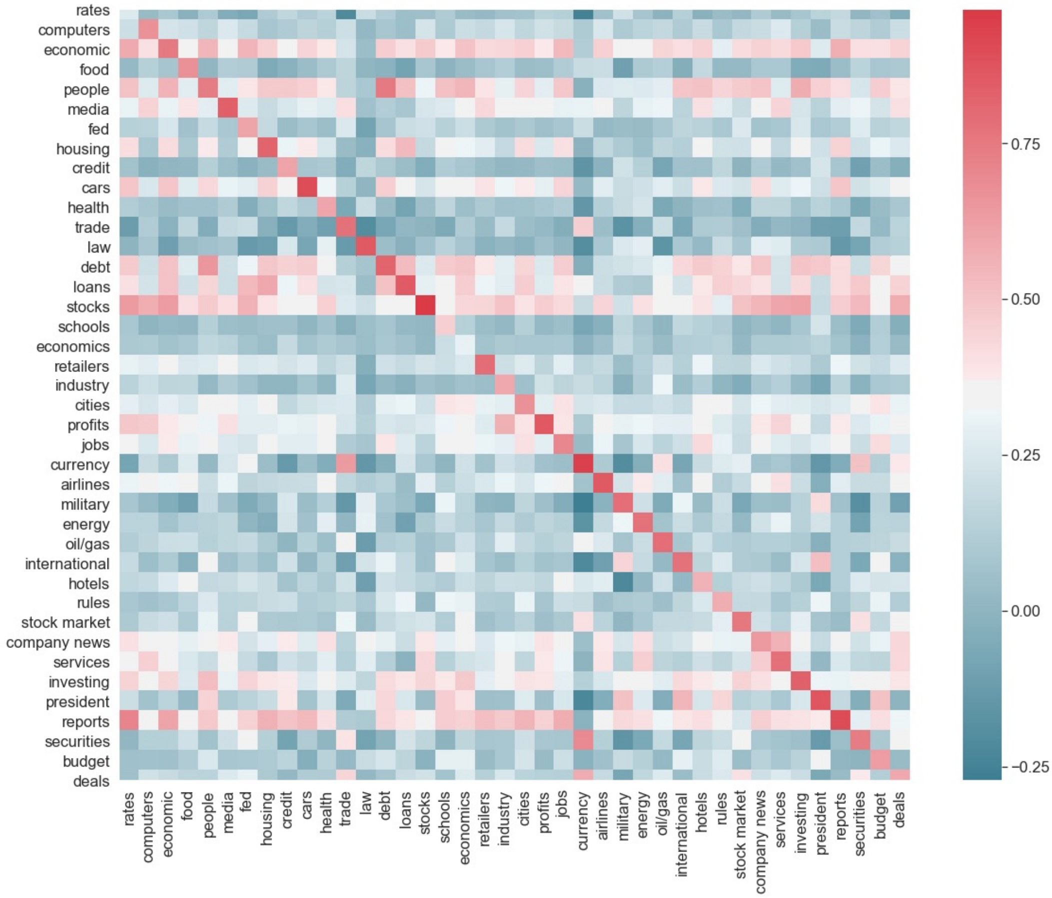
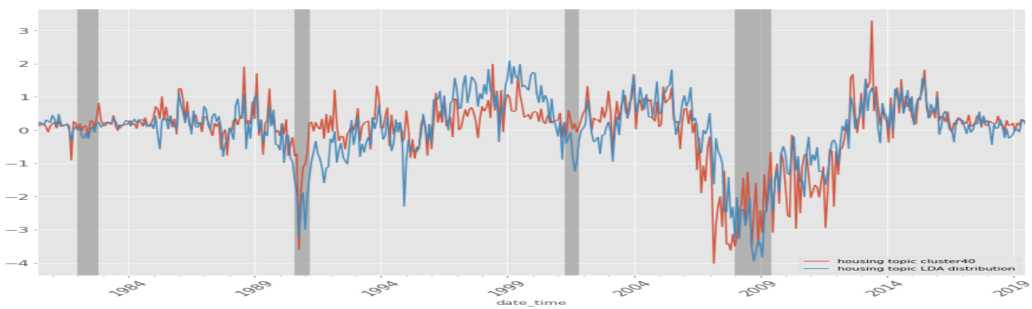


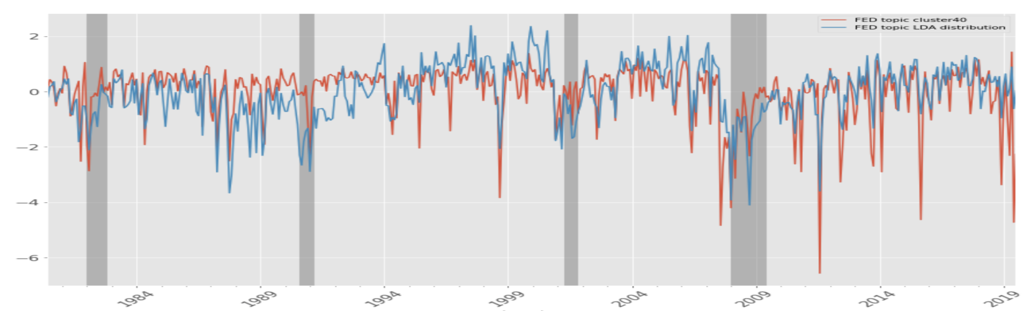
Figure E.4: Correlations between topic time series from LDA using dominant topic labels (y axis) and LDA using topic frequency labels (x axis)

(a) Housing topics from Doc2Vec (red) and LDA (blue) using dominant topic labels



(b) Housing topics from Doc2Vec (red) and LDA (blue) using topic distributions labels

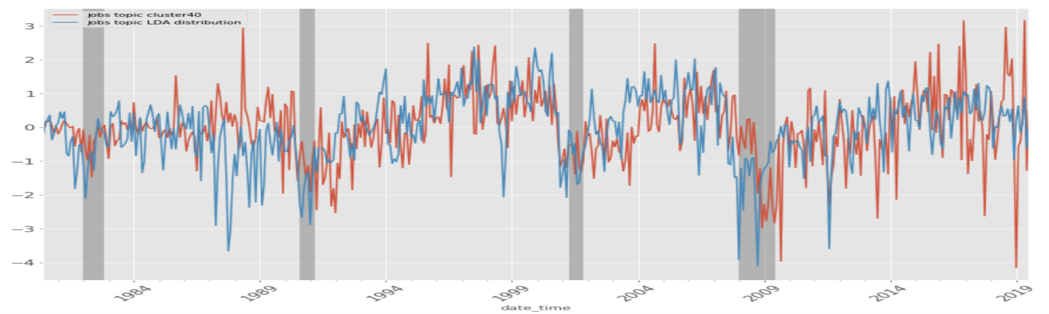
(c) FED topics from Doc2Vec (red) and LDA (blue) using dominant topic labels



(d) FED topics from Doc2Vec (red) and LDA (blue) using topic distributions labels

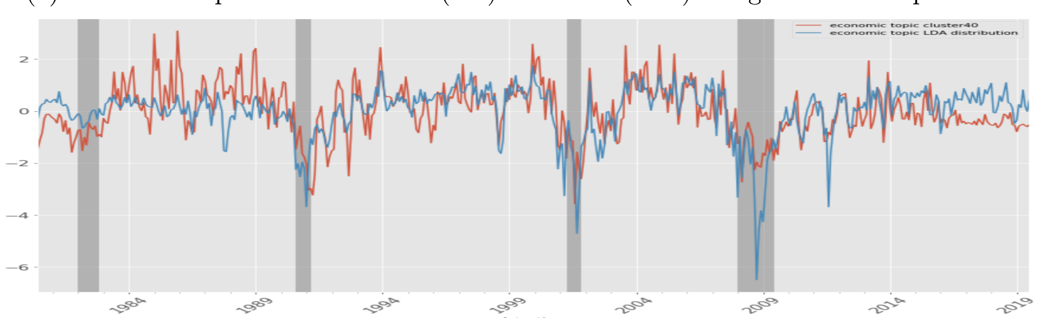
Figure E.5: Topics about Housing and Fed. All series are standardised.
Shaded areas – NBER based Recession Indicators for the United States

(a) Jobs topics from Doc2Vec (red) and LDA (blue) using dominant topic labels



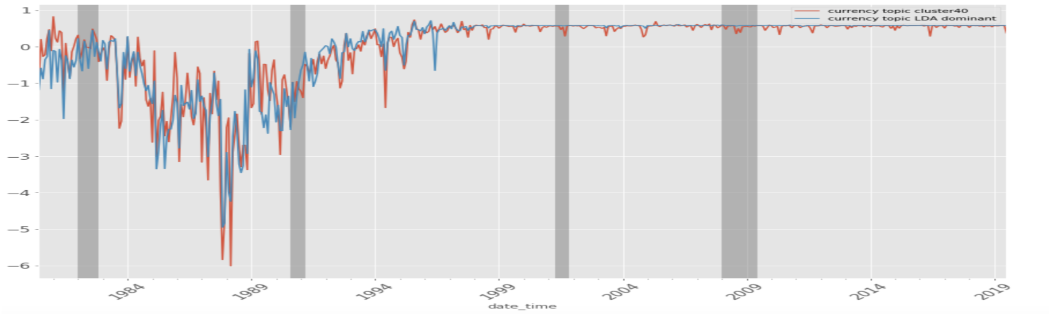
(b) Jobs topics from Doc2Vec (red) and LDA (blue) using topic distributions labels

(c) Economic topics from Doc2Vec (red) and LDA (blue) using dominant topic labels

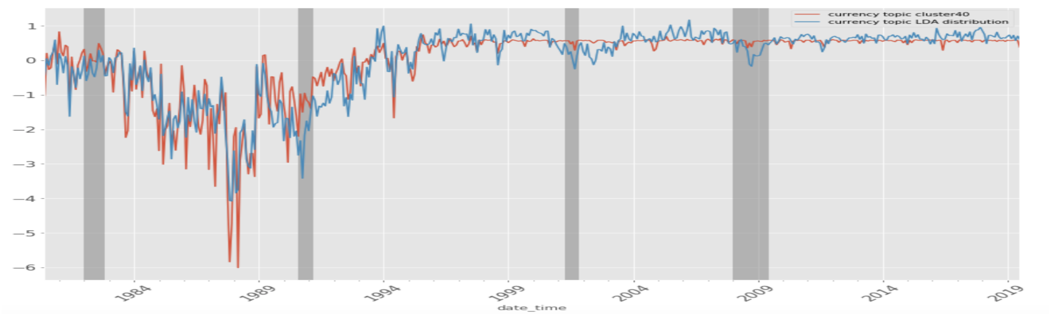


(d) Economic topics from Doc2Vec (red) and LDA (blue) using topic distributions labels

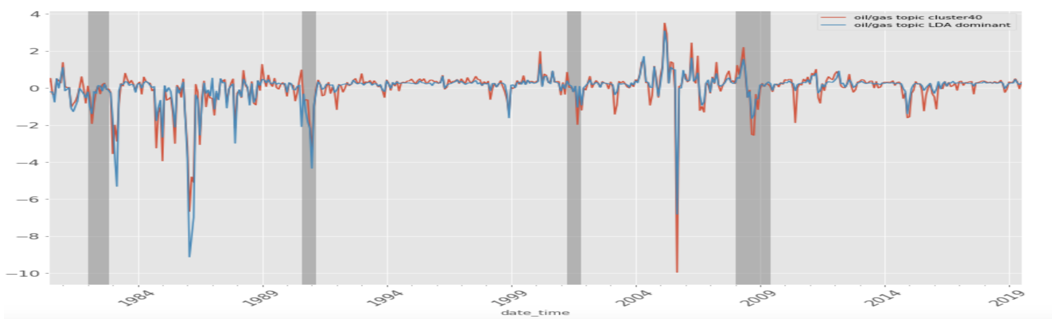
Figure E.6: Topics about Jobs and Economy. All series are standardised.
Shaded areas – NBER based Recession Indicators for the United States



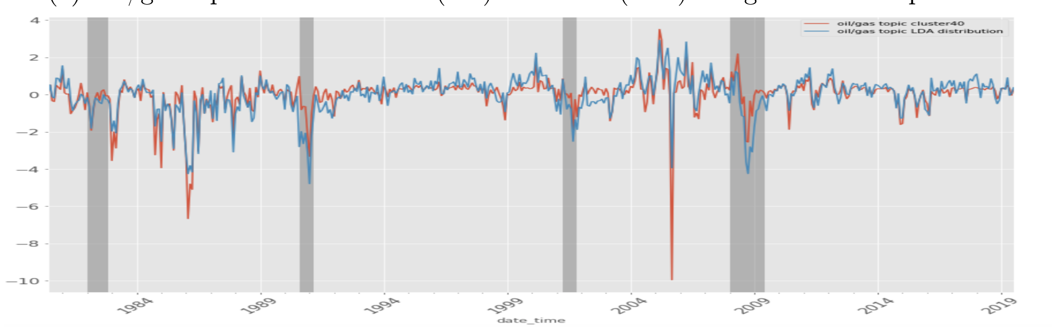
(a) Currency topics from Doc2Vec (red) and LDA (blue) using dominant topic labels



(b) Currency topics from Doc2Vec (red) and LDA (blue) using topic distributions labels

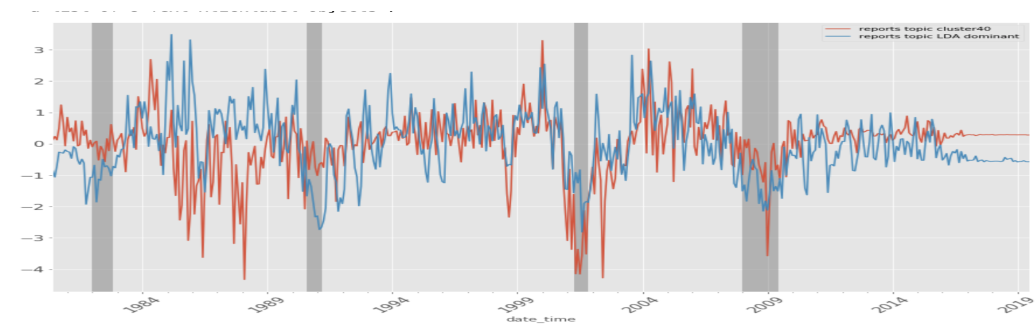


(c) Oil/gas topics from Doc2Vec (red) and LDA (blue) using dominant topic labels

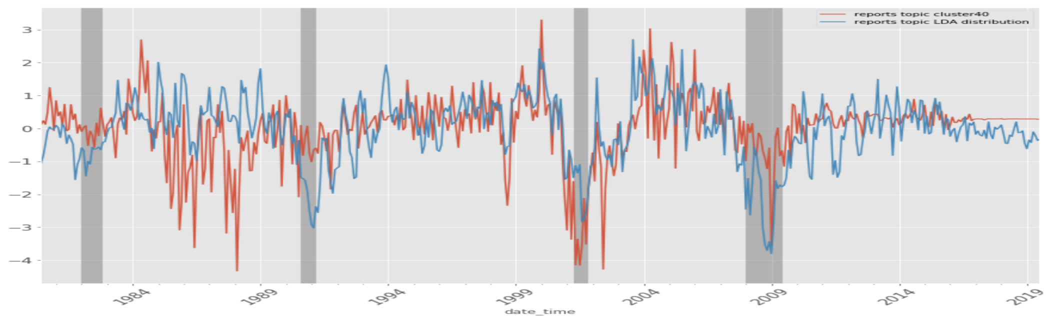


(d) Oil/gas topics from Doc2Vec (red) and LDA (blue) using topic distributions labels

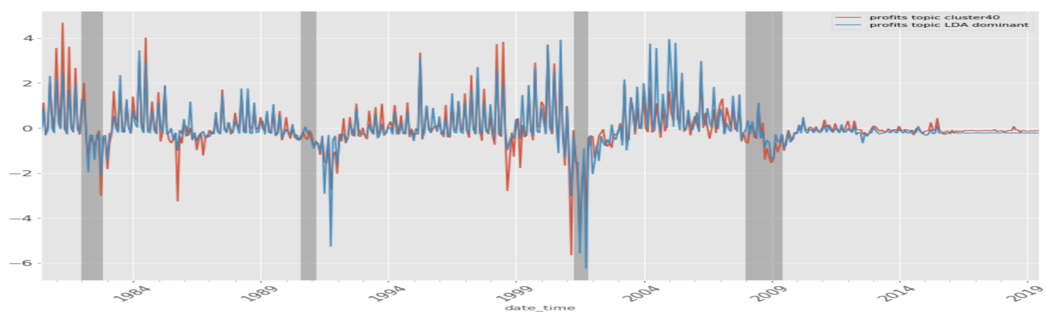
Figure E.7: Topics about Currency and Oil/gas. All series are standardised.
Shaded areas – NBER based Recession Indicators for the United States



(a) Reports topics from Doc2Vec (red) and LDA (blue) using dominant topic labels



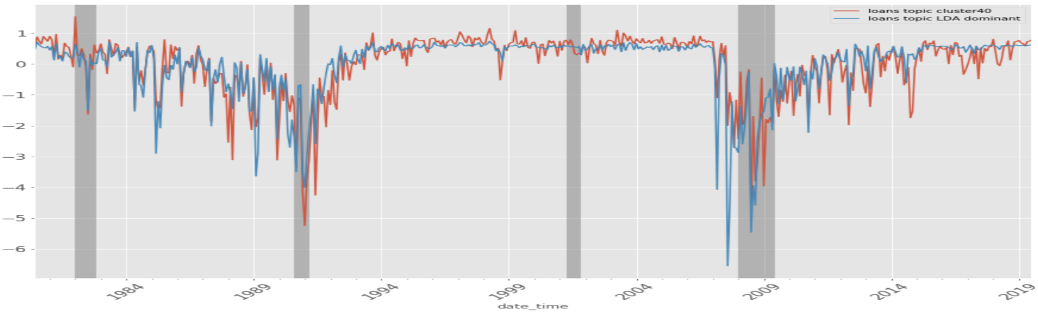
(b) Reports topics from Doc2Vec (red) and LDA (blue) using topic distributions labels



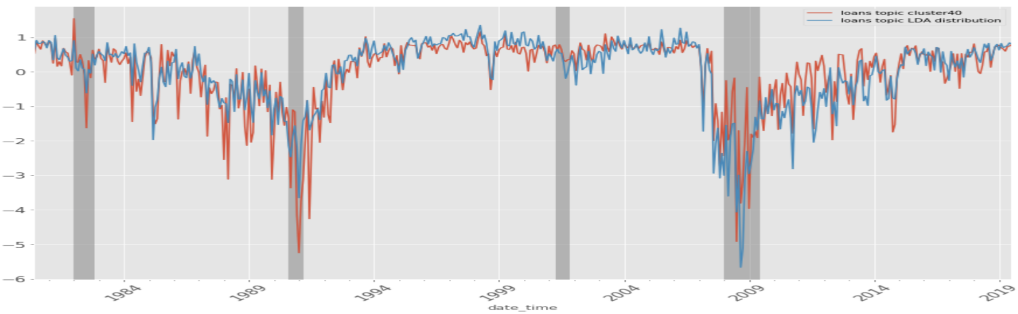
(c) Profits topics from Doc2Vec (red) and LDA (blue) using dominant topic labels

(d) Profits topics from Doc2Vec (red) and LDA (blue) using topic distributions labels

Figure E.8: about Reports and Profits. All series are standardised.
Shaded areas – NBER based Recession Indicators for the United States



(a) Loans topics from Doc2Vec (red) and LDA (blue) using dominant topic labels



(b) Loans topics from Doc2Vec (red) and LDA (blue) using topic distributions labels

Figure E.9: Topics about Loans. All series are standardised.
Shaded areas – NBER based Recession Indicators for the United States

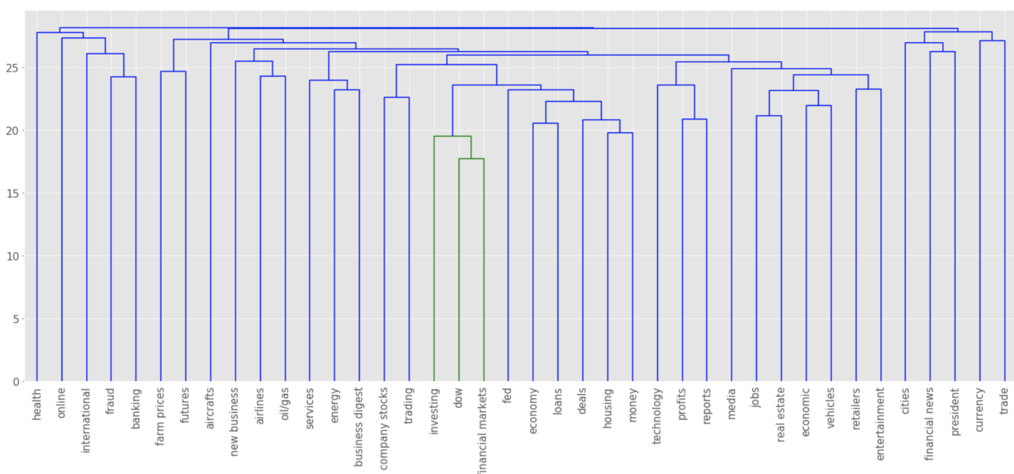


Figure E.10: Hierarchical clustering of Doc2Vec topic time series using weighted linkage

Appendix F LASSO results

Table F.1: Doc2Vec: LASSO results for interest rates

	positive	uncertainty	constraining	positive +AR(1) +AR(1)	uncertainty +AR(1) +AR(1)	constraining +AR(1) +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
new business								
dow								0.009
jobs	0.017			0.001				
profits	0.091			0.02			0.004	
housing				0.006				
reports	0.092			0.027				
currency								
fraud								
company stocks	0.01			0.002				
farm prices								
retailers								
energy								
media						-0.014		
money	0.01							
international							0.006	
economy								0.001
entertainment								
airlines								
financial markets				0.011				
banking								
economic	0.014							
deals								
services								
oil/gas								
real estate								
loans								0.002
trading							0.006	
aircrafts								
vehicles								
financial news								
health								
business digest								
investing				0.001				
trade								
fed				0.014			0.006	0.002
cities								
technology	0.028			0.006				0.001
futures								
online				0.002				
president								

Table F.2: Doc2Vec: LASSO results for unemployment

	positive	uncertainty	constraining	positive +AR(1) +AR(1)	uncertainty +AR(1) +AR(1)	constraining +AR(1) +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
new business								
dow			0.005					-0.024
jobs			0.002		0.004			
profits			-0.013					
housing	-0.104		0.012	-0.005				
reports								
currency			0.002					
fraud			-0.01					
company stocks			0.038		0.012			
farm prices			-0.009					
retailers								
energy								
media			0.063					
money		0.089	0.137		0.002			
international			-0.065					
economy								
entertainment			-0.004					
airlines			0.068					
financial markets	-0.157		-0.034	-0.056				
banking			-0.001					
economic			-0.013					
deals			-0.035					
services							0.003	0.007
oil/gas								
real estate			-0.013					
loans								
trading								
aircrafts								
vehicles		0.004						
financial news			-0.028			-0.005	-0.016	
health			0.014					
business digest			-0.078					
investing								
trade								
fed								
cities		-0.149			-0.029			
technology			-0.008					
futures			0.009					
online				-0.015				
president			0.027	-0.002	0.006	0.002		

Table F.3: Doc2Vec: LASSO results for inflation

	positive	uncertainty	constraining	positive +AR(1) +AR(1)	uncertainty +AR(1) +AR(1)	constraining +AR(1) +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
new business		0.015	0.016	0.007				
dow		-0.033	0.034		-0.008		0.002	
jobs		0.04			0.006		-0.022	
profits		-0.013	-0.046					
housing	-0.07			-0.009				
reports	0.001	0.019	0.03					-0.011
currency		0.029	0.007					
fraud			0.011					
company stocks		0.017						
farm prices		0.005			0.001			
retailers		-0.044	-0.075			-0.002		
energy	0.005		-0.016					
media								
money			0.027					-0.001
international		0.002						
economy		-0.017	-0.076					
entertainment								
airlines		0.071	0.056	0.011			0.012	0.015
financial markets	-0.029							
banking		-0.094	-0.071	0.002				
economic		0.01	0.001					
deals			-0.018					
services			0.008					
oil/gas		0.19	0.161	0.003	0.009	0.003		
real estate			-0.003	-0.002			-0.002	
loans	-0.217	-0.013	0.046	-0.016		0.001		
trading		-0.075	-0.02					
aircrafts		-0.008	0.019					
vehicles		0.032						
financial news			-0.021					
health				0.001	-0.001		0.002	
business digest		-0.076	-0.104					
investing		-0.011						
trade								
fed		-0.038						
cities		-0.199	-0.02					
technology		-0.006	-0.083			-0.001		
futures	-0.056		0.116		0.012	0.02		-0.015
online		-0.003						
president		-0.009						

Table F.4: LDA using topic frequency labels: LASSO results for interest rates

	positive	uncertainty	constraining	positive +AR(1) +AR(1)	uncertainty +AR(1) +AR(1)	constraining +AR(1) +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
rates								
computers	0.012			0.005			0.007	
economic	0.002	-0.188	-0.107	0.076	-0.06	-0.017	0.069	0.066
food								
people								
media								
fed							0.003	
housing								
credit								
cars								
health								
trade								
law								
debt								
loans								
stocks								0.005
schools								
economics					0.001			
retailers								
industry	0.095			0.007				
cities								
profits	0.072			0.018				
jobs	0.129							
currency								
airlines								
military								
energy								
oil/gas	0.043	0.011						
international								
hotels								
rules								
stock market								
company news								
services								
investing								
president								
reports								
securities								
budget								
deals							0.004	

Table F.5: LDA using topic frequency labels: LASSO results for unemployment

	positive	uncertainty	constraining	positive +AR(1) +AR(1)	uncertainty +AR(1) +AR(1)	constraining +AR(1) +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
rates					-0.001			
computers								
economic	-0.234	0.13						
food								
people								
media								
fed							-0.008	
housing	-0.157	0.27	0.028	-0.026	0.07		-0.038	-0.051
credit								
cars								
health								
trade								
law								
debt								
loans								
stocks				-0.059				
schools								
economics								
retailers					0.004			
industry								
cities								
profits					-0.005			
jobs					0.014		-0.024	-0.001
currency								
airlines								
military					-0.019			
energy								
oil/gas		0.016						
international								
hotels								
rules					0.007		-0.015	-0.004
stock market		0.008					-0.001	
company news								
services								
investing								-0.01
president				-0.016				
reports								
securities								
budget								
deals					0.003			

Table F.6: LDA using topic frequency labels: LASSO results for inflation

	positive	uncertainty	constraining	positive +AR(1) +AR(1)	uncertainty +AR(1) +AR(1)	constraining +AR(1) +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
rates					-0.001			0.017
computers								
economic		-0.037	-0.007					0.034
food		0.178	0.124		0.04	0.02		
people								
media								
fed	-0.002	-0.029			-0.007			
housing	-0.006	0.029					-0.011	-0.023
credit	0.087	-0.044	-0.021	0.03			0.005	0.026
cars		-0.031			-0.009			
health			-0.01	0.002	-0.013	-0.023	0.02	0.025
trade		0.014			0.006			
law				-0.007		0.003		-0.005
debt								
loans	-0.452	0.148	0.228	-0.078	0.021	0.038	-0.004	-0.058
stocks	-0.002	-0.019			-0.003			0.018
schools					0.003			0.005
economics			-0.025					
retailers		-0.037	-0.009					
industry	0.03	-0.005						
cities		-0.035	-0.072			-0.01		
profits	0.027	-0.015						
jobs			-0.008		0.007			-0.005
currency					0.009	0.024		0.003
airlines	0.028			0.019	-0.012	-0.011	0.05	0.038
military		-0.184	-0.145	0.012	-0.046	-0.025		0.007
energy								
oil/gas		0.322	0.207	0.019	0.033	0.01		
international					0.001	0.008		
hotels		0.007				0.004		
rules								
stock market								
company news								
services		-0.007			-0.006			-0.002
investing								
president		-0.035			-0.014	-0.004		
reports								0.001
securities						0.001		
budget			0.004			0.01		-0.013
deals								-0.005

Table F.7: LDA using dominant topic labels: LASSO results for interest rates

	positive	uncertainty	constraining	positive +AR(1) +AR(1)	uncertainty +AR(1) +AR(1)	constraining +AR(1) +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
rates								
computers								
economic	0.052	-0.067	-0.053	0.053	-0.041	-0.035	0.039	0.047
food								
people								
media	0.008							
fed				0.009			0.009	0.012
housing								
credit								
cars								
health								
trade								
law								
debt								
loans						-0.005		0.007
stocks	0.004			0.011				
schools								
economics								
retailers								
industry	0.048							
cities								
profits	0.123			0.037			0.023	0.027
jobs	0.007							
currency								
airlines								
military								
energy								
oil/gas								
international								
hotels								
rules								
stock market								
company news				0.015				
services								
investing								0.001
president								
reports								
securities							0.001	
budget								
deals				0.002				

Table F.8: LDA using dominant topic labels: LASSO results for unemployment

	positive	uncertainty	constraining	positive +AR(1) +AR(1)	uncertainty +AR(1) +AR(1)	constraining +AR(1) +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
rates								
computers								
economic	-0.109		0.009					
food								
people								
media								
fed								
housing			0.006			0.012		
credit						-0.001		
cars	-0.007							
health								
trade								
law								
debt								
loans	-0.049		0.012	-0.005		0.004		-0.009
stocks	-0.039			-0.048				
schools								
economics								
retailers						0.002		
industry								
cities								
profits								
jobs								
currency								
airlines								
military							0.021	0.023
energy								
oil/gas								
international			-0.027			-0.015		
hotels						-0.011		
rules								
stock market								
company news								
services								
investing								
president				-0.012		0.013		
reports								
securities					-0.003	-0.031	-0.017	
budget								
deals								

Table F.9: LDA using dominant topic labels: LASSO results for inflation

	positive	uncertainty	constraining	positive +AR(1)	uncertainty +AR(1)	constraining +AR(1)	positive× uncertainty +AR(1)	positive× constraining +AR(1)
rates								
computers							0.003	
economic		-0.03		0.008			0.027	0.01
food		0.129	0.098		0.009	0.009		
people								
media								
fed							0.005	
housing			0.043			0.001	-0.002	
credit		-0.009		0.003			0.012	
cars							0.008	0.007
health				0.005		-0.007	0.008	
trade								
law							-0.003	
debt								
loans	-0.282		0.207	-0.036		0.032		-0.01
stocks								
schools								
economics			-0.01					
retailers								
industry	0.006							
cities				-0.002				
profits								
jobs								
currency			0.067			0.019		-0.01
airlines	0.031			0.022			0.028	0.037
military							0.003	
energy								
oil/gas		0.189	0.11					
international								
hotels			-0.054					
rules								
stock market								
company news								
services								
investing							-0.008	
president								
reports								
securities								
budget								
deals								

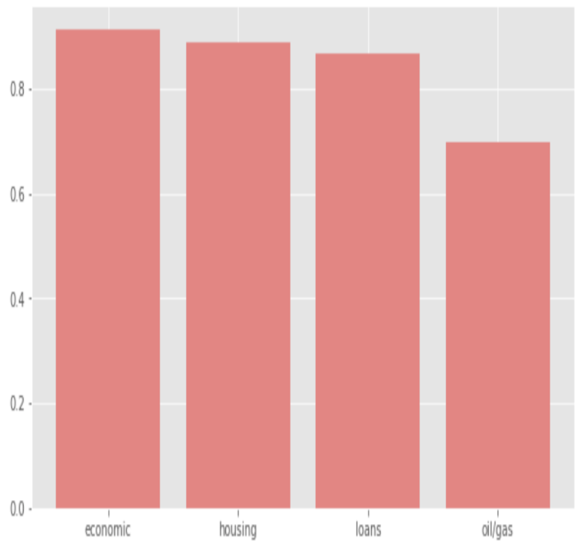


Figure F.1: Factor loadings

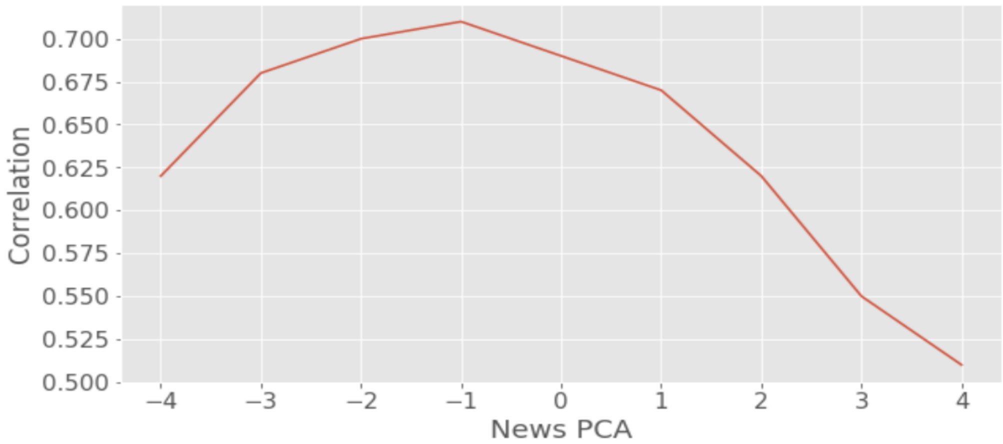


Figure F.2: Correlations between the first principal component from news and the first factor from the FRED-MD (McCracken and Ng, 2015) at leads and lags

Negative numbers are lags, positive numbers are leads

Appendix G The Bayesian Vector Autoregression

I use Bayesian Vector Autoregression (BVAR) with an independent normal-inverted Wishart prior for the reduced form coefficients[71]:

$$p(\beta, Q) = p(\beta)p(Q)$$
$$p(\beta) \sim f_N(\beta|\underline{\beta}, \underline{V_\beta})$$
$$p(Q) \sim f_{IW}(Q|\underline{Q}, \underline{v_Q})$$

To deal with overfitting I entertain a prior in Minnesota fashion. Prior for β is set at its univariate AR(p) estimate, and zero everywhere else. $\underline{V_\beta}$ is a diagonal matrix implying that the standard deviation of lag l of variable j in equation i is $\dfrac{\lambda_1\lambda_2\sigma_i}{\sigma_j l^{\lambda_3}}$ for $j \neq i$, $\dfrac{\lambda_1}{l^{\lambda_3}}$ for $j = i$ and $\lambda_4\sigma_i$ for a constant. I use standard hyperparameters from the literature: $\lambda_1 = 0.2$, $\lambda_2 = 0.5$, $\lambda_3 = 1$, $\lambda_4 = 100$. σ_i, σ_j are scaled measures of the variance associated with the AR(p) equation estimate. $\underline{Q}$ is a diagonal matrix with diagonal elements equal to its initial OLS estimate. Lastly, I set $\underline{v_Q} = 30$. Based on the priors the conditional posterior for β is:

$$\beta|y, Q^{-1} \sim N(\overline{\beta}, \overline{V_b})_{I_{s(\beta)}}$$
$$\overline{V_\beta} = (\underline{V_\beta}^{-1} + \sum_{t=1}^{T} X_t' Q^{-1} X_t)^{-1}$$
$$\overline{V_b} = \overline{V_\beta}(\underline{V_\beta}^{-1}\underline{\beta} + \sum_{t=1}^{T} X_t' Q^{-1} y_t)$$

$I_{s(\beta)}$ is an indicator function used to denote that the roots of β lie outside the unit circle.

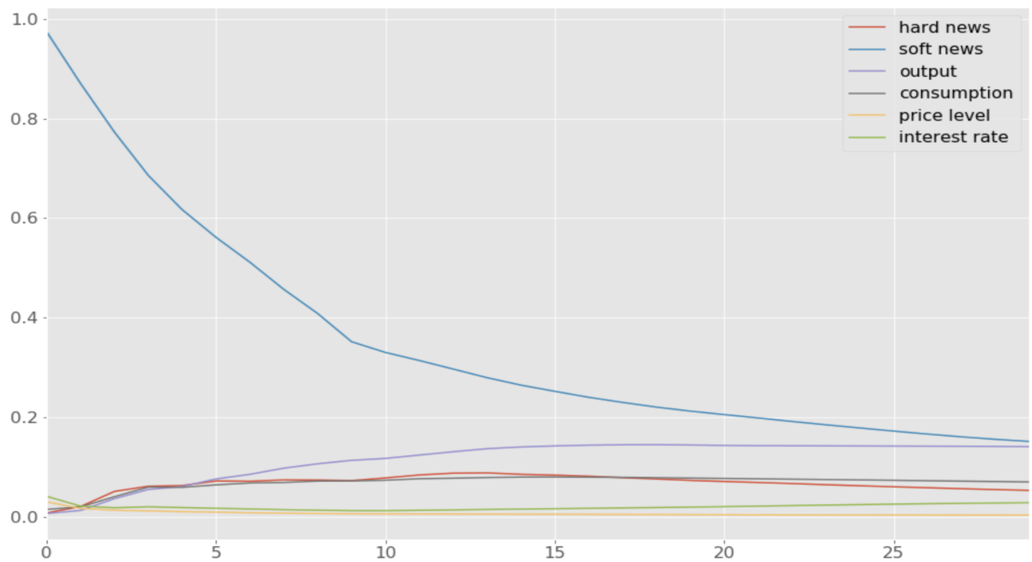
The conditional posterior of Q is:

$$Q|y, \beta \sim IW(\overline{Q}, \overline{v_Q})$$
$$\overline{v_Q} = \underline{v_Q} + T$$
$$\overline{Q} = \underline{Q} + \sum_{t=1}^{T}(y_t - X_t'\beta)(y_t - X_t'\beta)'$$

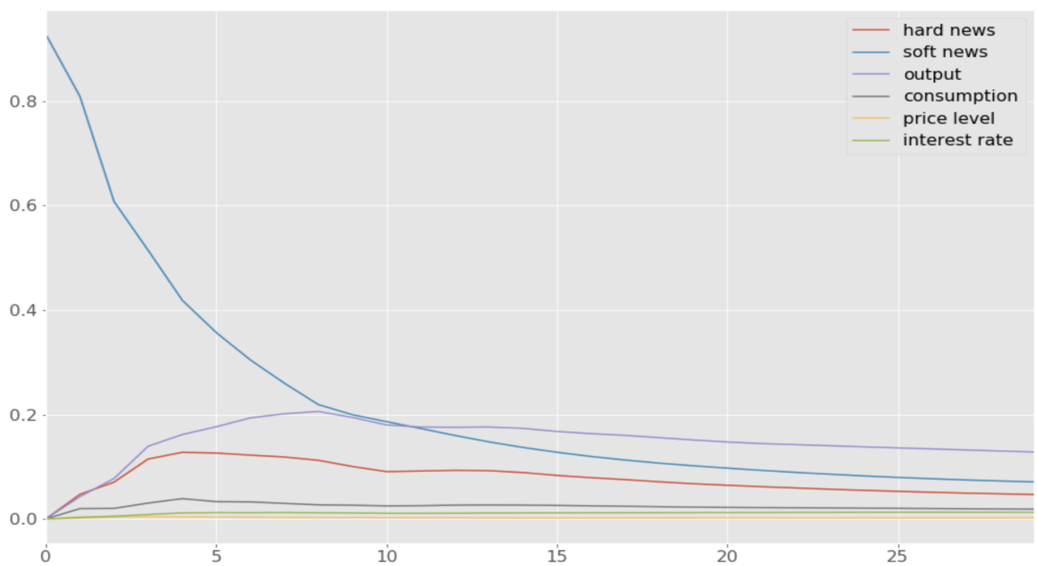
12,000 Gibbs sampler draws were taken in total and 2,000 were discarded after burn-in.

[71]See Koop and Korobilis (2010) for more details.

Appendix H Soft news and real activity

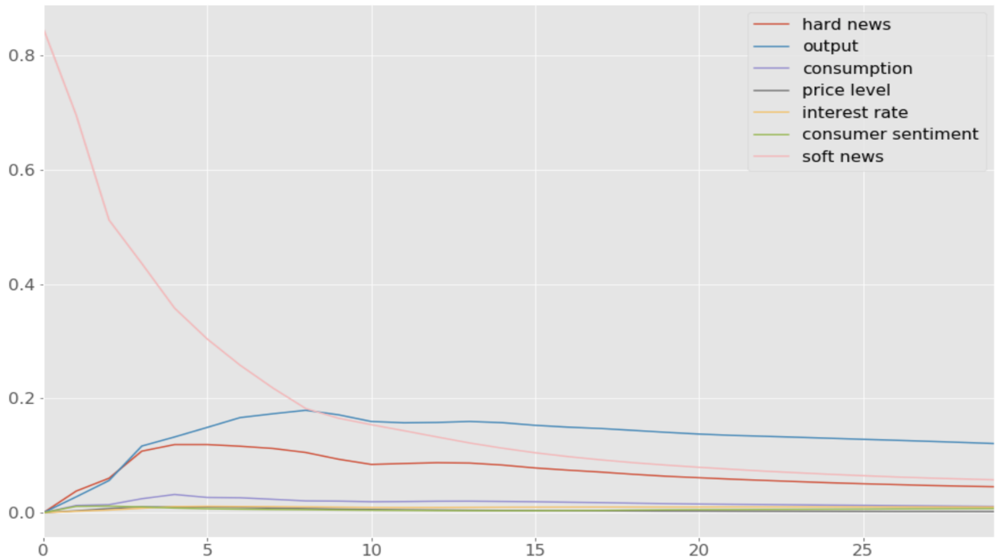


(a) Soft news shock. Ordered first

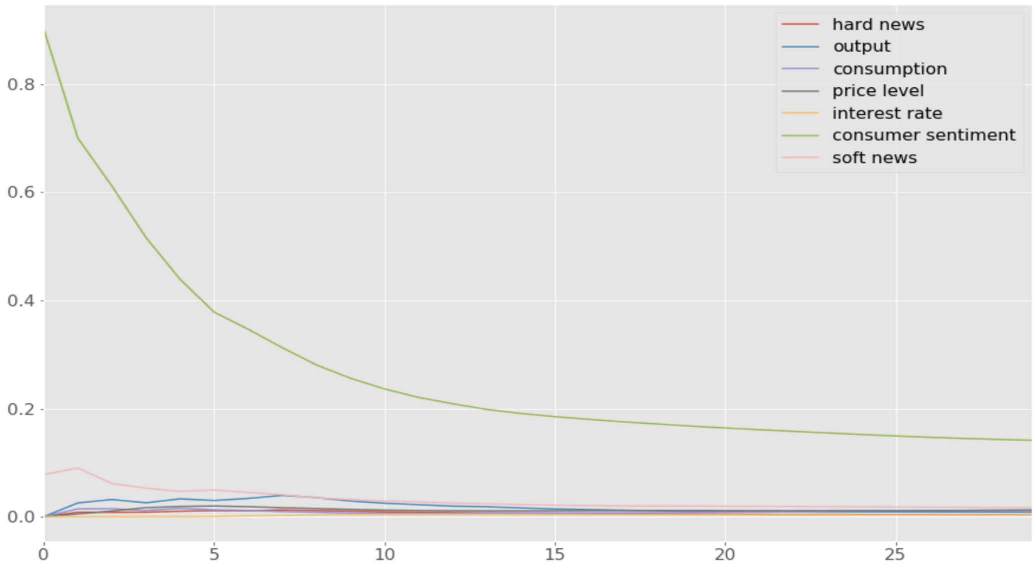


(b) Soft news shock. Ordered last

Figure H.1: Contributions of shocks to forecast error variances.
SVAR using the principal component from news
(Without the consumer sentiment index)
The numbers are based on the median impulse response functions

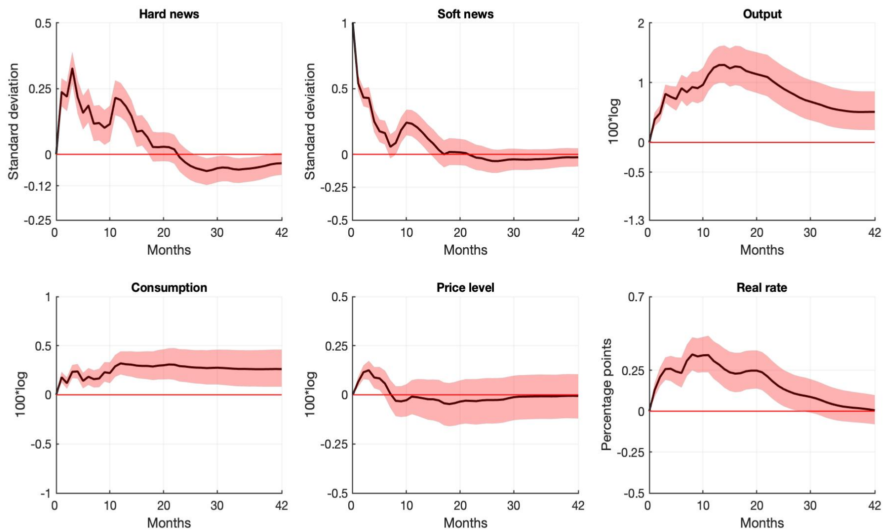


(a) Soft news shock. Ordered last

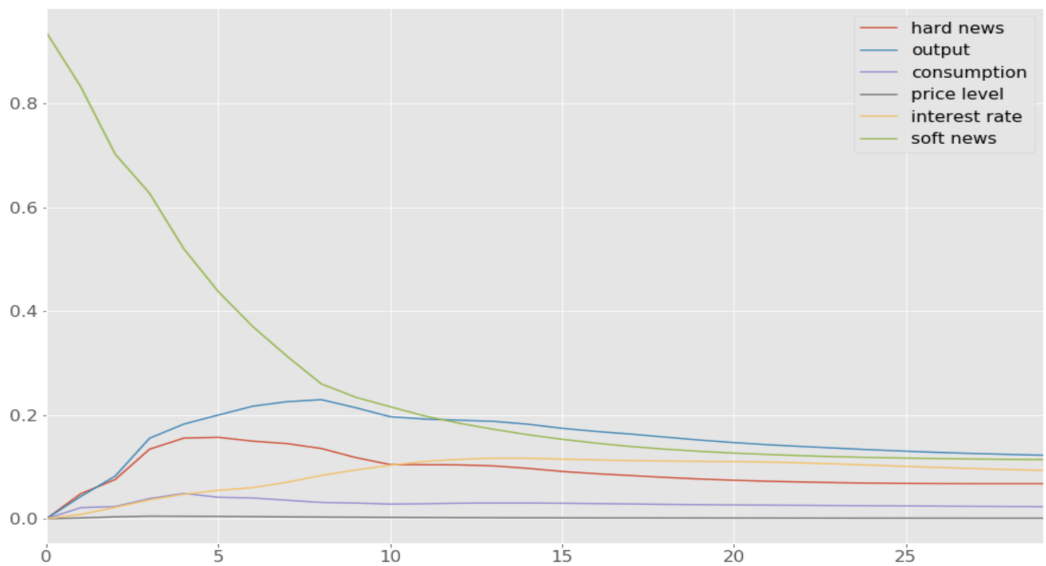


(b) Consumer sentiment shock. Ordered second last

Figure H.2: Contributions of shocks to forecast error variances. SVAR using the principal component from news and consumer sentiments (With the consumer sentiment index)
The numbers are based on the median impulse response functions



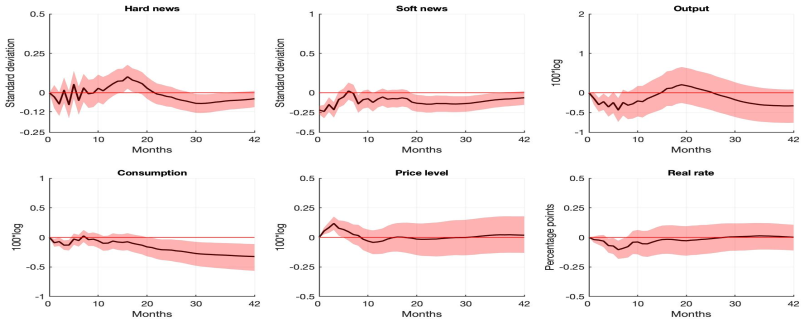
(a) IRFs to a soft news shock. Ordered last



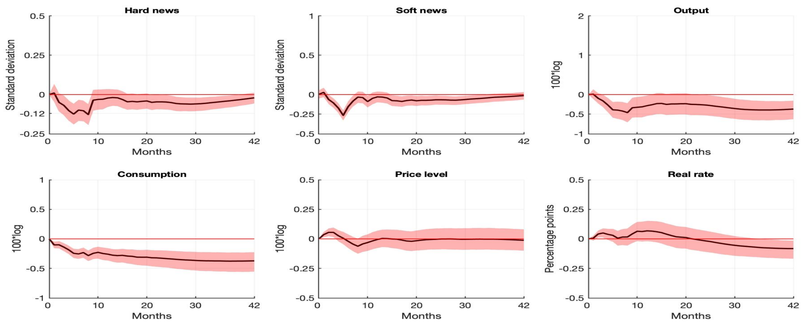
(b) Soft news shock for forecast error variances

Figure H.3: Soft news shock. SVAR using the principal component from news
The real rate is the FFR less expected inflation

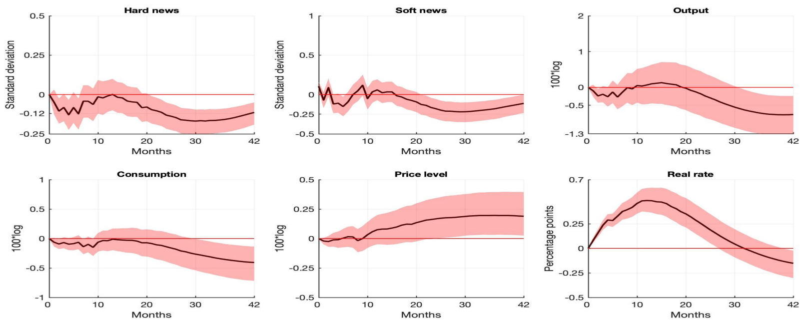
Appendix I Heterogeneity of shocks



(a) Unemployment sentiment shock, ordered second last

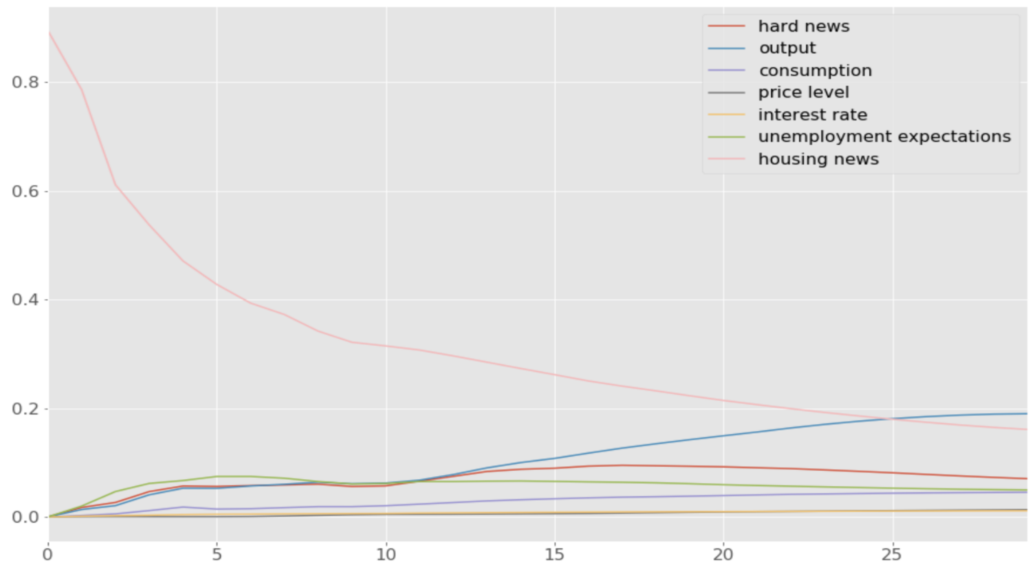


(b) Inflation sentiment shock with loans, ordered second last

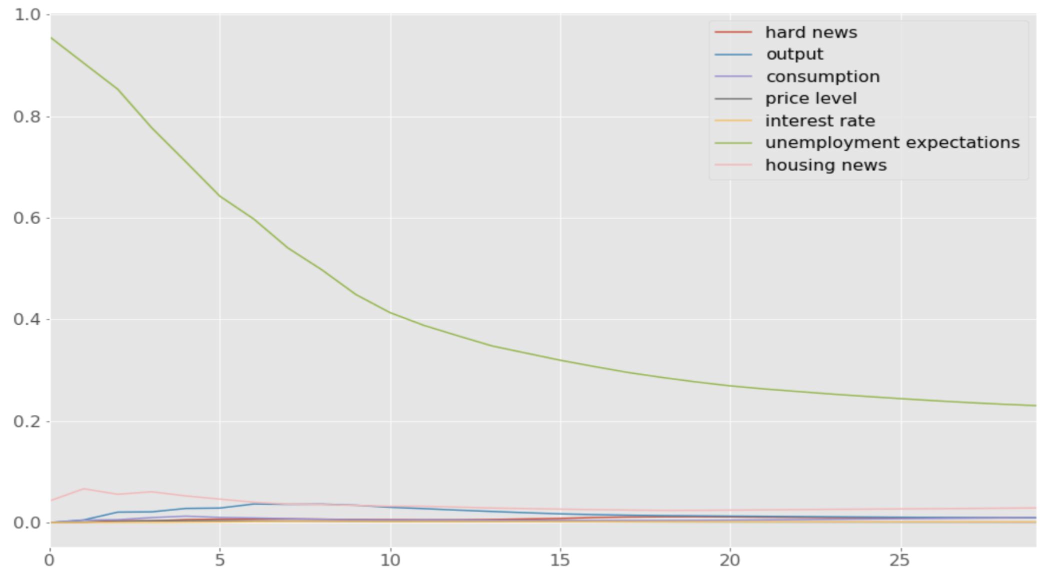


(c) Interest rate sentiment shock with economic topic, ordered second last

Figure I.1: Sentiment shocks. SVARs using news topics and expectations
median and 16th and 84th percentiles

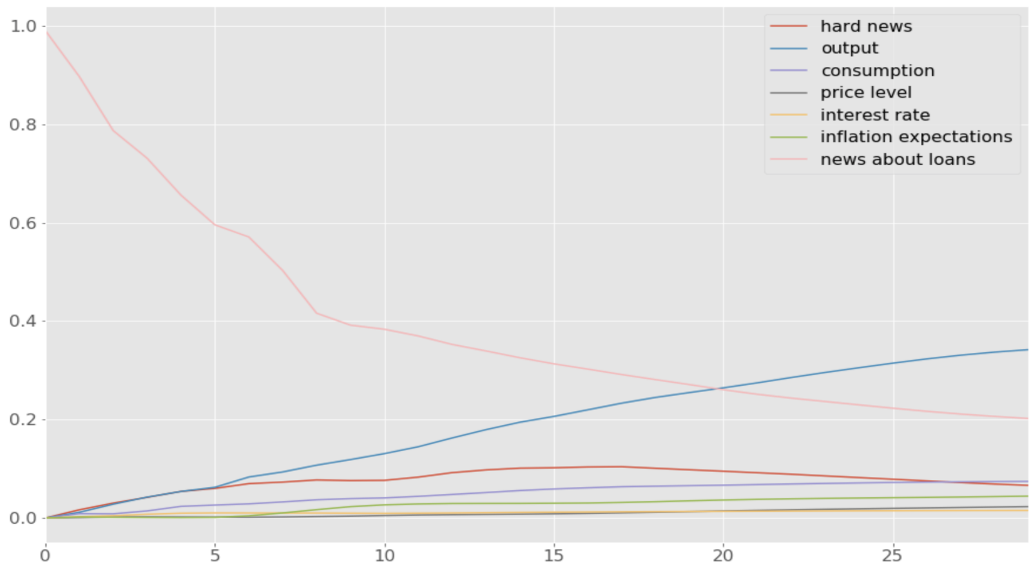


(a) Housing news shock

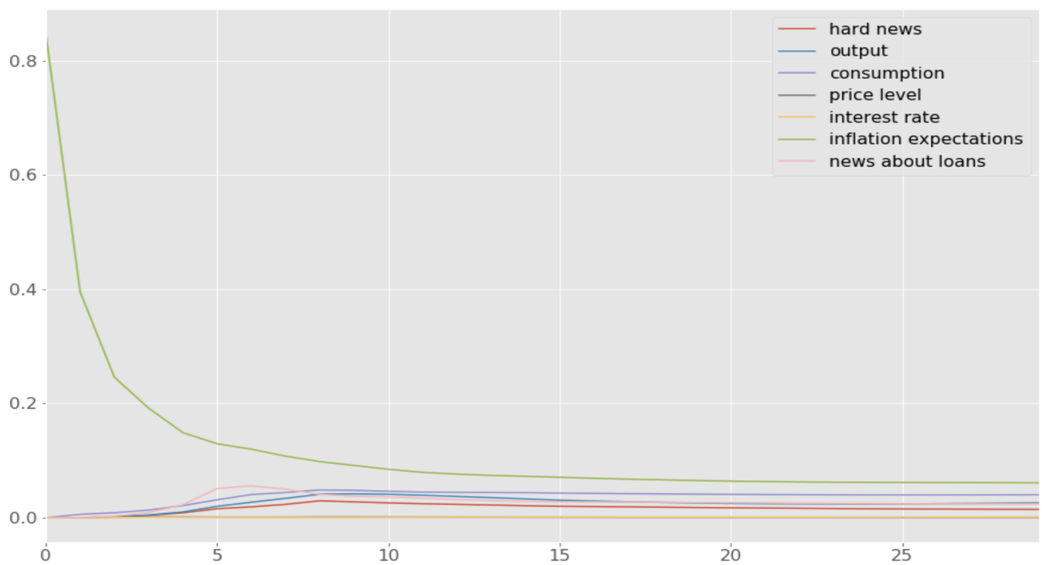


(b) Unemployment sentiment shock

Figure I.2: Contributions of shocks to forecast error variances. SVAR using unemployment expectations and the Housing topic
The numbers are based on the median impulse response functions

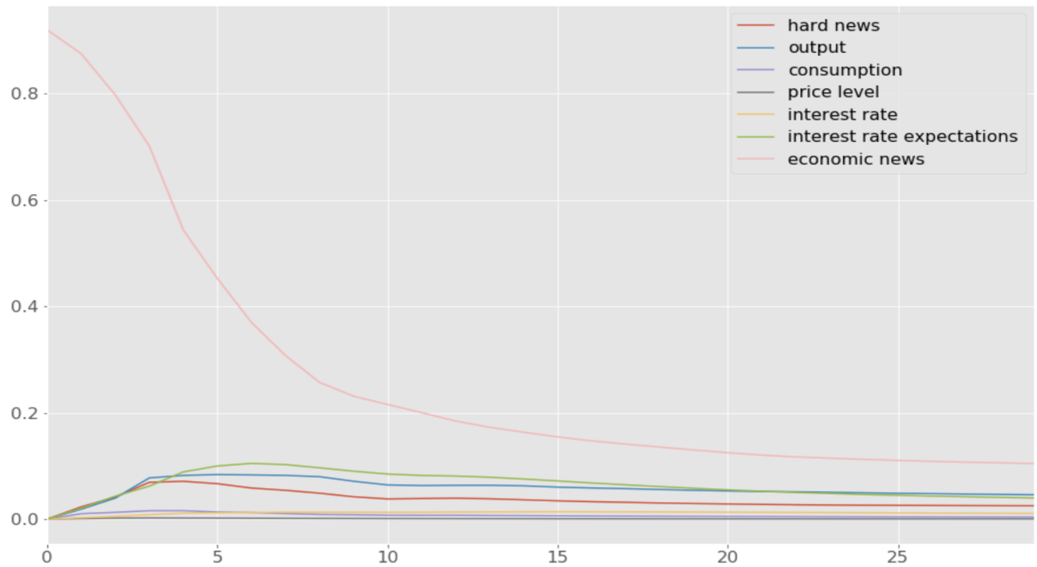


(a) Loans news shock

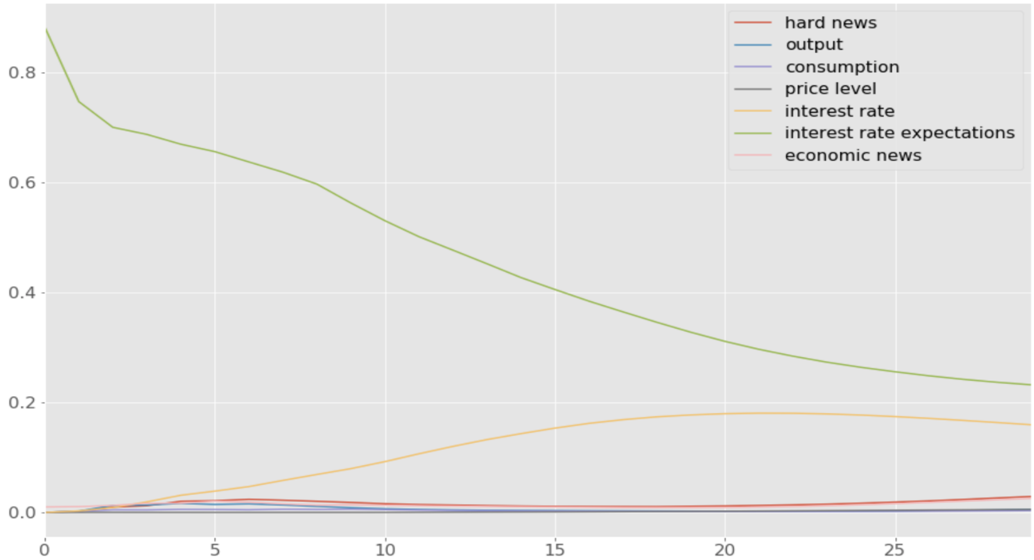


(b) Inflation sentiment shock

Figure I.3: Contributions of shocks to forecast error variances. SVAR using inflation expectations and the Loans topic
The numbers are based on the median impulse response functions

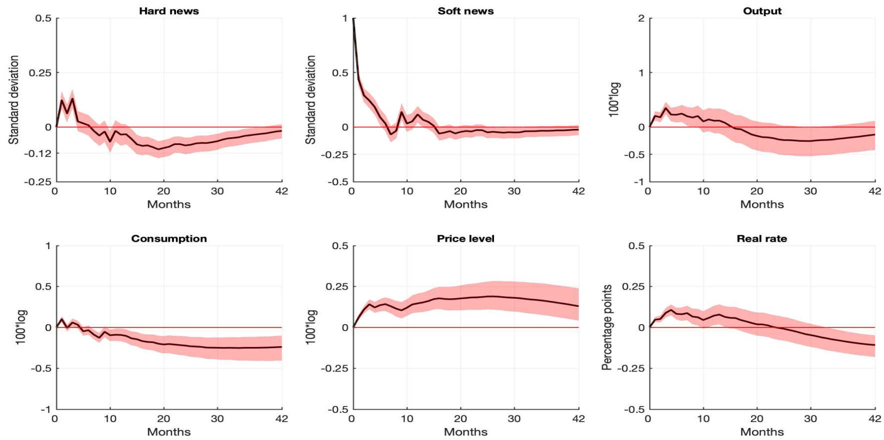


(a) Economic news shock

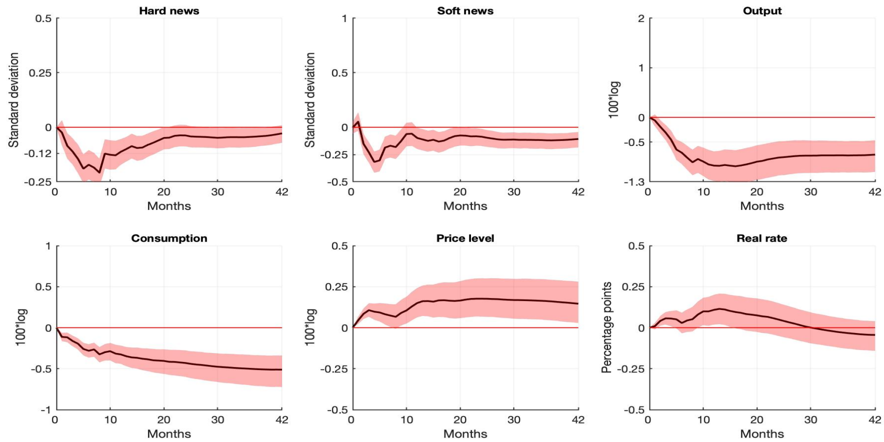


(b) Interest rate sentiment shock

Figure I.4: Contributions of shocks to forecast error variances. SVAR using interest rate expectations and the Economic topic
The numbers are based on the median impulse response functions

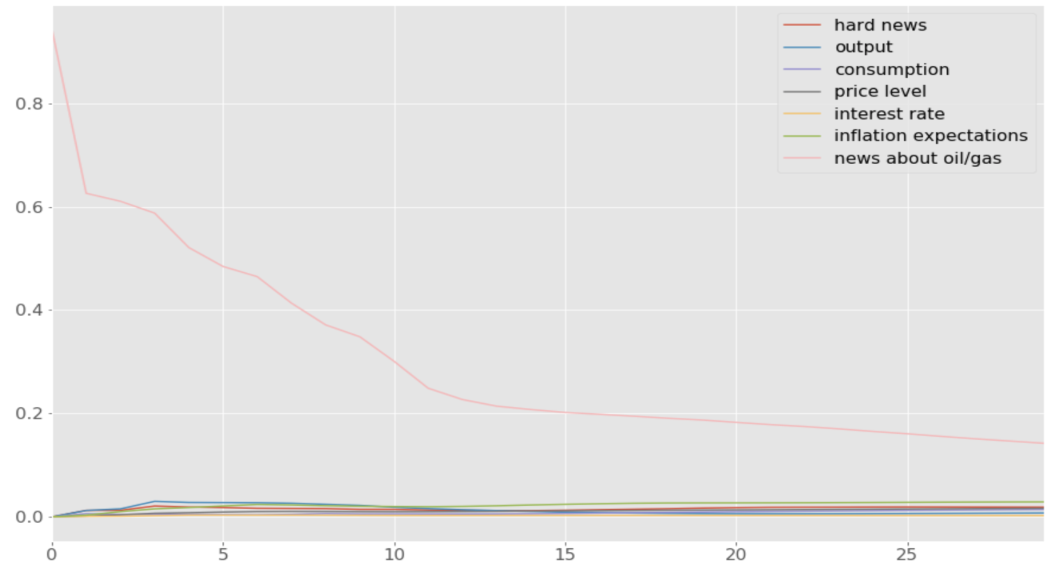


(a) Oil/gas news shock, ordered last

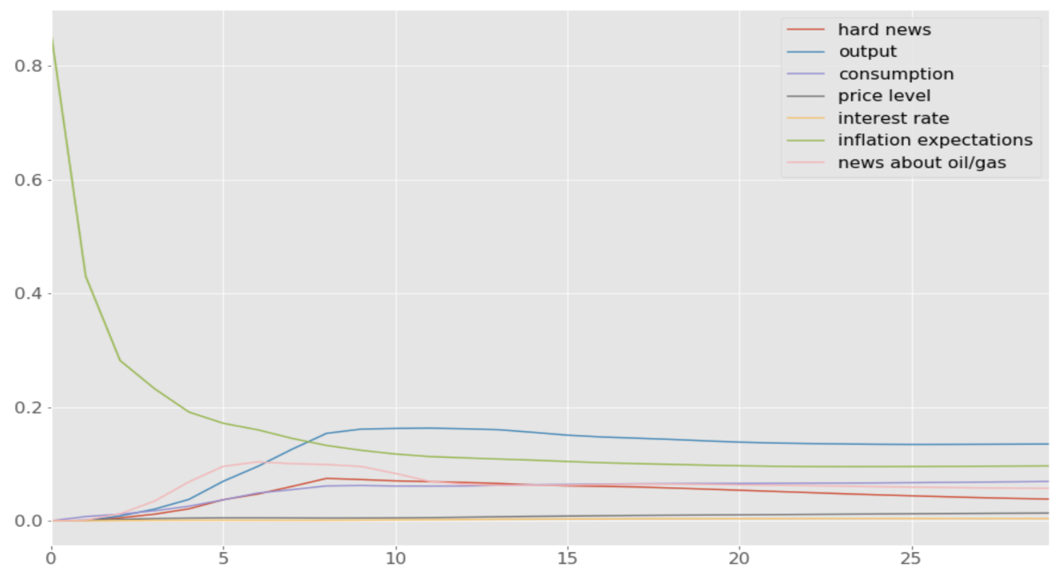


(b) Inflation sentiment shock, ordered second last

Figure I.5: Soft news and sentiment shocks. SVAR using inflation expectations and the Oil/gas topic
median and 16th and 84th percentiles



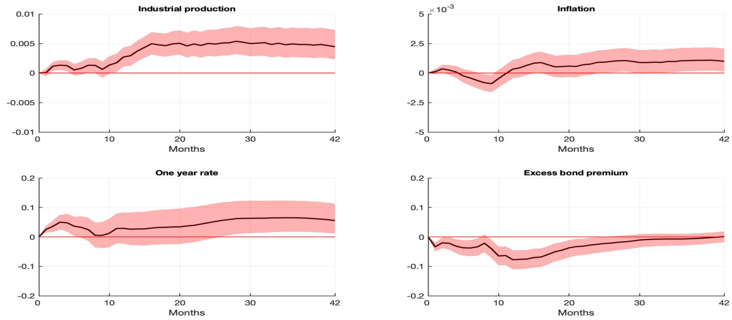
(a) Oil/gas news shock



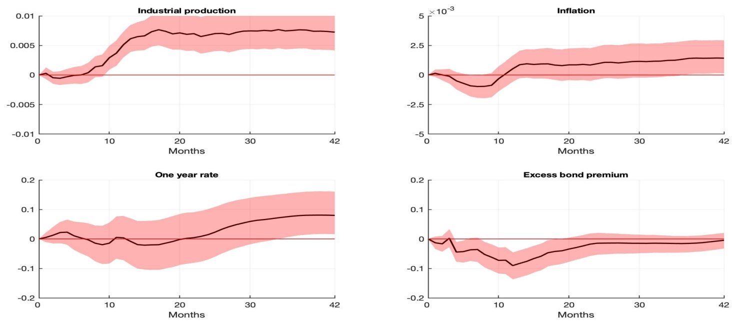
(b) Inflation sentiment shock

Figure I.6: Contributions of shocks to forecast error variances. SVAR using inflation expectations and the Oil/gas topic
The numbers are based on the median impulse response functions

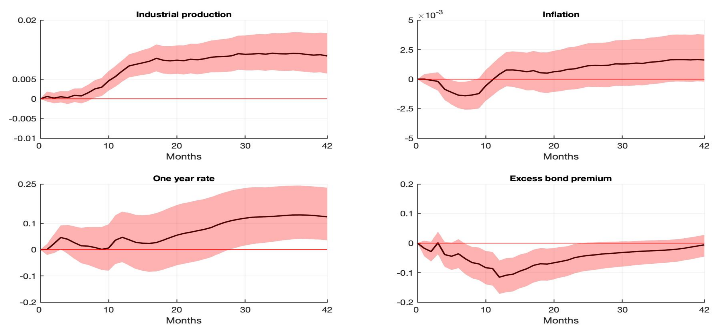
Appendix J Soft news and monetary policy



(a) Impulse responses to a Fed news shock (from Doc2Vec)

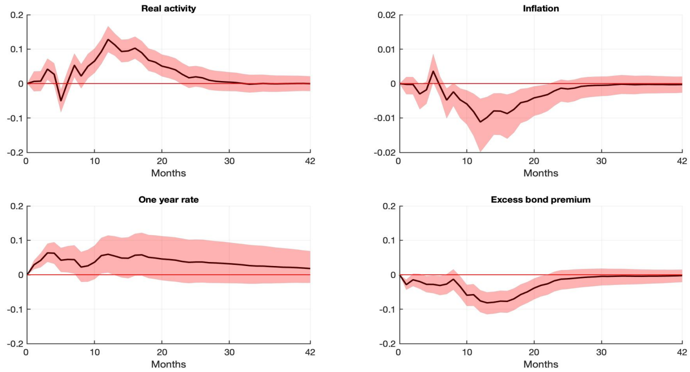


(b) Impulse responses to a Fed news shock (sentiment uncertainty)

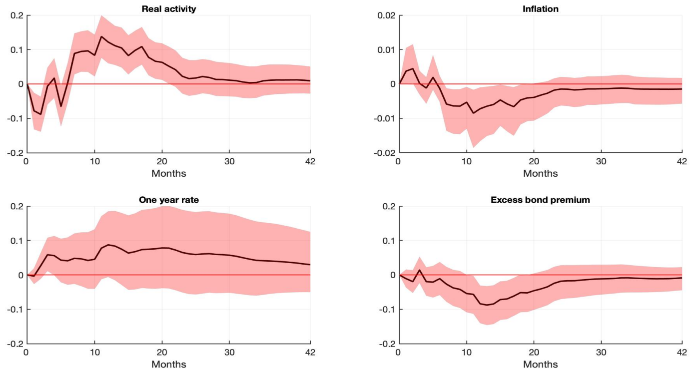


(c) Impulse responses to Fed news shocks

Figure J.1: Impulse responses to Fed news shocks from the LDA model using topic frequency labels
median and 16th and 84th percentiles



(a) Impulse responses using CFNAI instead of industrial production



(b) Impulse responses using CFNAI (from the LDA frequency model)

Figure J.2: Impulse responses to a Fed news shock using sentiment uncertainty
median and 16th and 84th percentiles

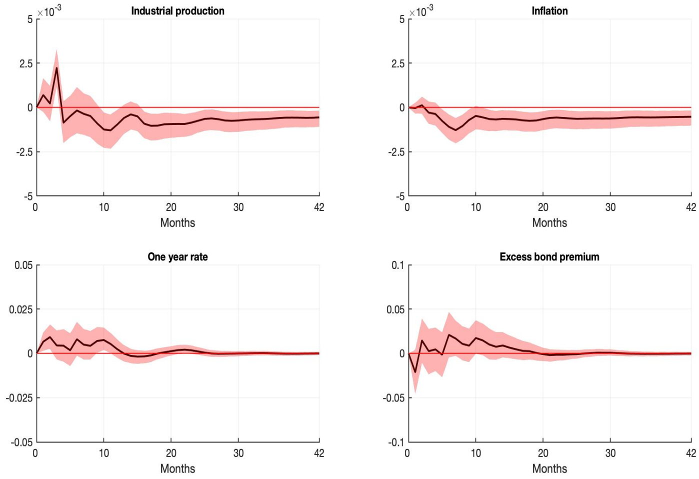
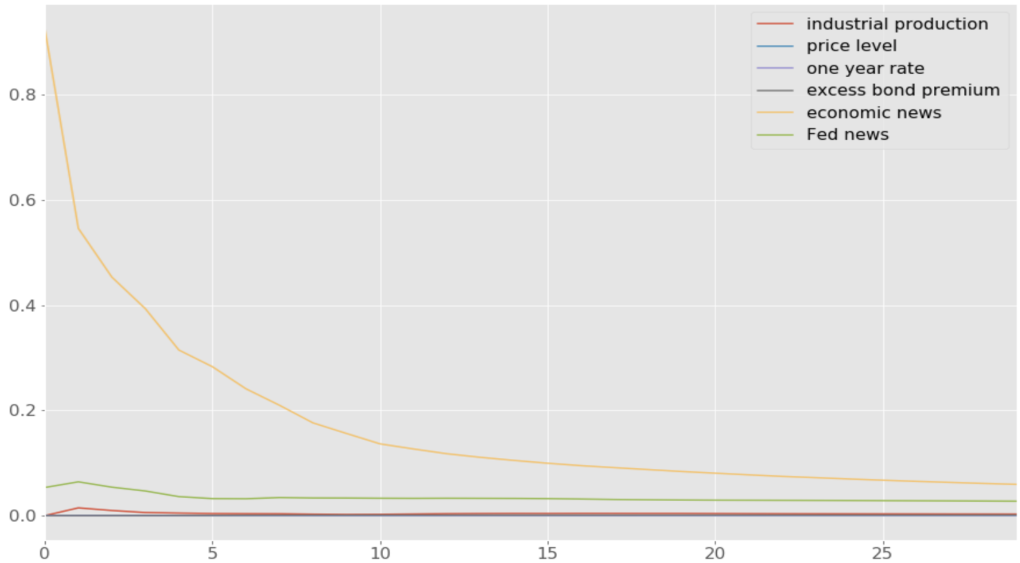
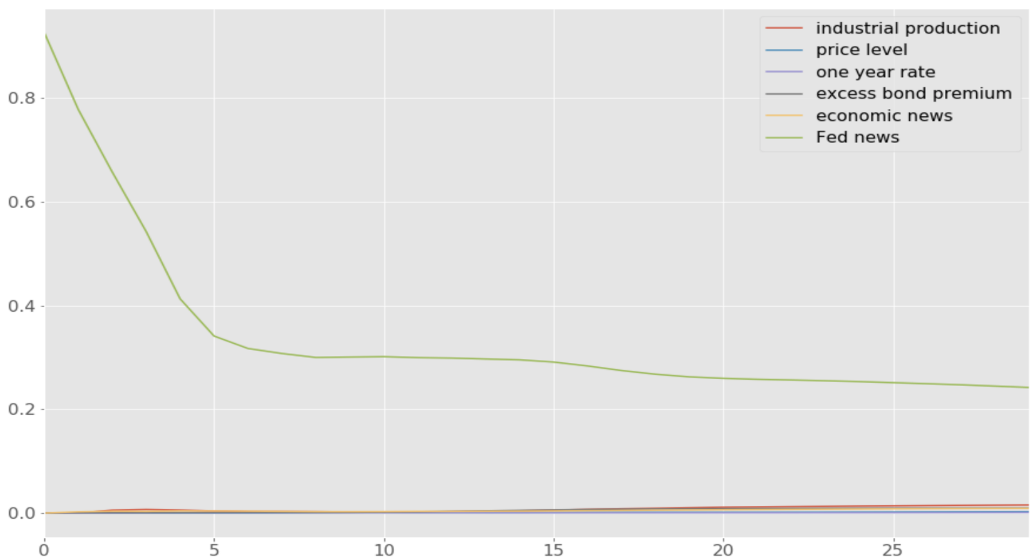


Figure J.3: Impulse responses to a Fed news shock, 2008:M1–2014:M12, 6 lags
median and 16th and 84th percentiles



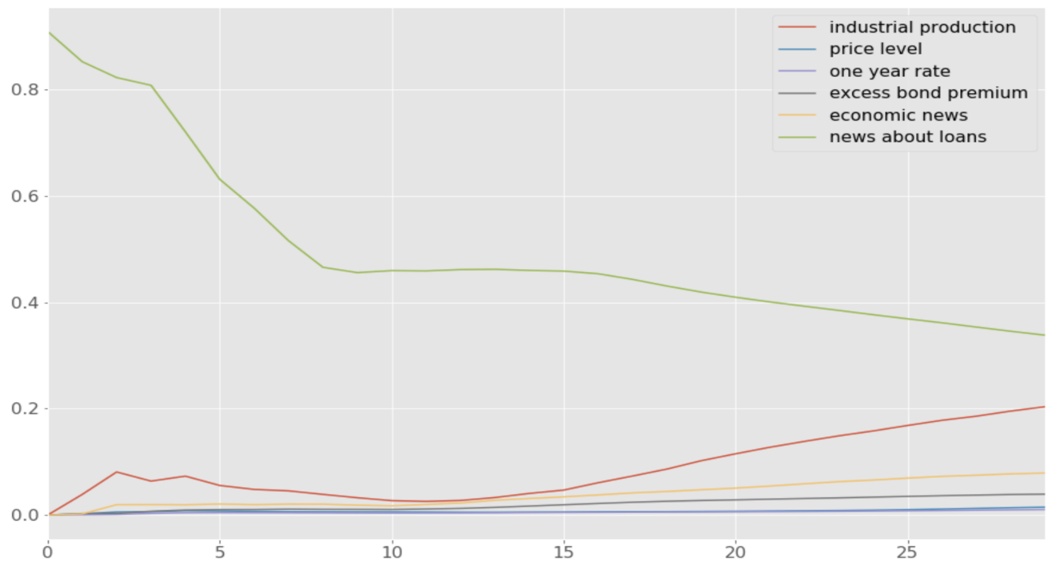
(a) Economic news shock



(b) Fed news shock

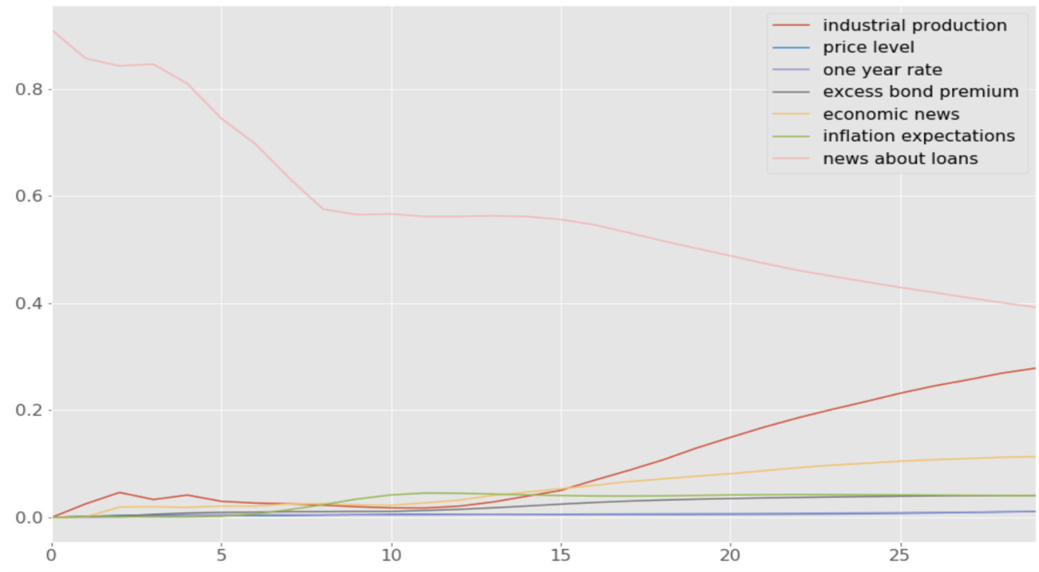
Figure J.4: Contributions of shocks to forecast error variances. SVAR using the Economic and the Fed topics

The numbers are based on the median impulse response functions

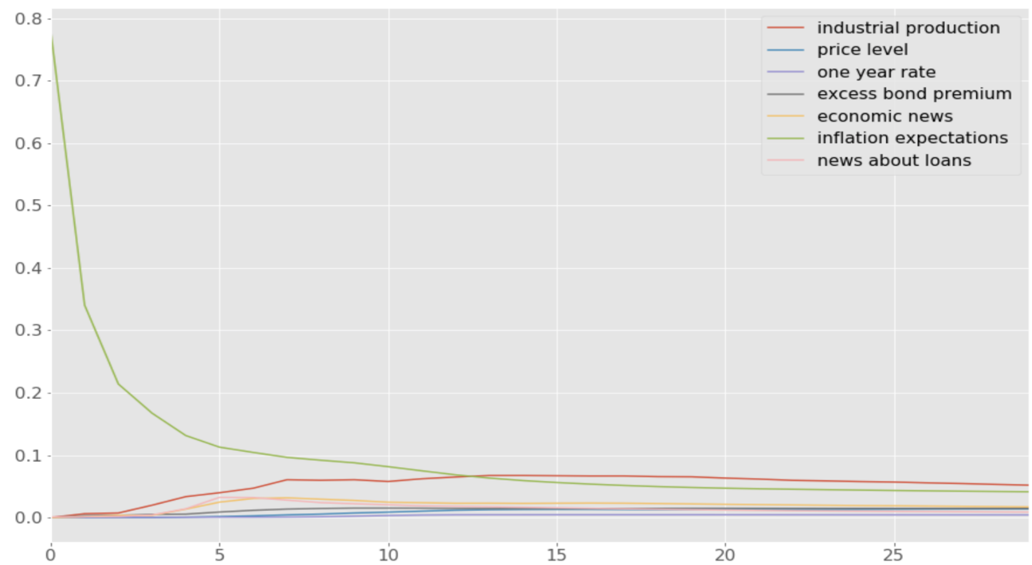


(a) Loans news shock

Figure J.5: Contributions of shocks to forecast error variances. SVAR using the Economic and the Loans topics
The numbers are based on the median impulse response functions



(a) Loans news shock



(b) Sixth shock

Figure J.6: Contributions of shocks to forecast error variances. SVAR using the Economic, the Loans topics and inflation expectations
The numbers are based on the median impulse response functions

Appendix K Information augmentation for conventional monetary policy shocks

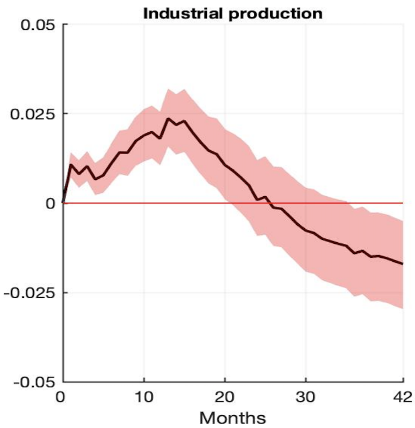
A conventional problem in identifying monetary policy shocks is that the information set of a decision-maker, the Federal Reserve in this case, is larger than the information set of the econometrician, which is the variables included in an econometric model. In this case a shock from the econometric model is not correctly identified, which is the well-known problem of nonfundamentalness[72].

Given this, Bernanke et al. (2005) augmented the standard monetary VAR with the first principal component from the FRED-MD database to take unobservables about economic conditions into account. Therefore, I additionally augment the model with the first principal component from the news topic time series to take the information set of private agents into account as well. Besides sentiment, the news media might capture unobserved fundamentals or unobserved information.

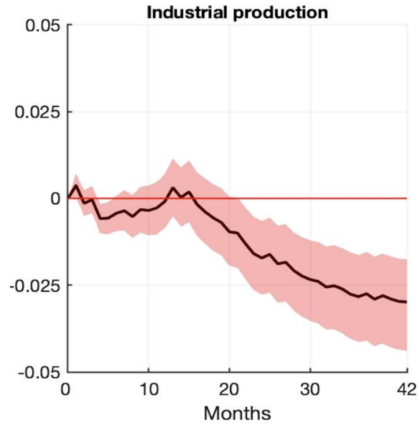
The variables in the VAR are the logarithm of industrial production (IPB50001N), the logarithm of the consumer price index (CPIAUCNS), and the federal funds rate (FEDFUNDS). All the variables are taken from the *Federal Reserve Economic Data* (2019) and the period studied is 1984:M1–2019:M7. The impulse responses of real economic activity to a monetary policy shock are presented in Figure K.1[73]. The VAR estimation details are presented in Appendix G. Identification is achieved via standard recursive ordering: industrial production, inflation, the federal funds rate, the first factor from the FRED-MD, and the first principal component from the topic time series. The results are robust to re-ordering of the informational variables.

[72] This problem was pointed out by Bernanke et al. (2005), Christiano et al. (1999), Rudebusch (1998), and Leeper et al. (2013) among others.

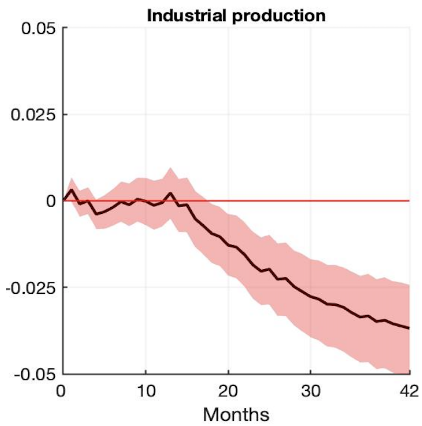
[73] The impulse responses of inflation show a price puzzle of similar magnitude in all specifications.



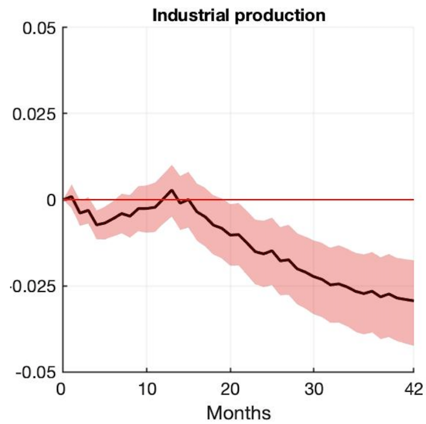
(a) 3 variable SVAR



(b) 3 variable SVAR using FRED-MD



(c) 3 variable SVAR using news sentiments



(d) 3 variable SVAR using FRED-MD and news sentiments

Figure K.1: Impulse responses of industrial production to a monetary policy shock using additional information variables
median and 16th and 84th percentiles

Appendix L Economic collocations

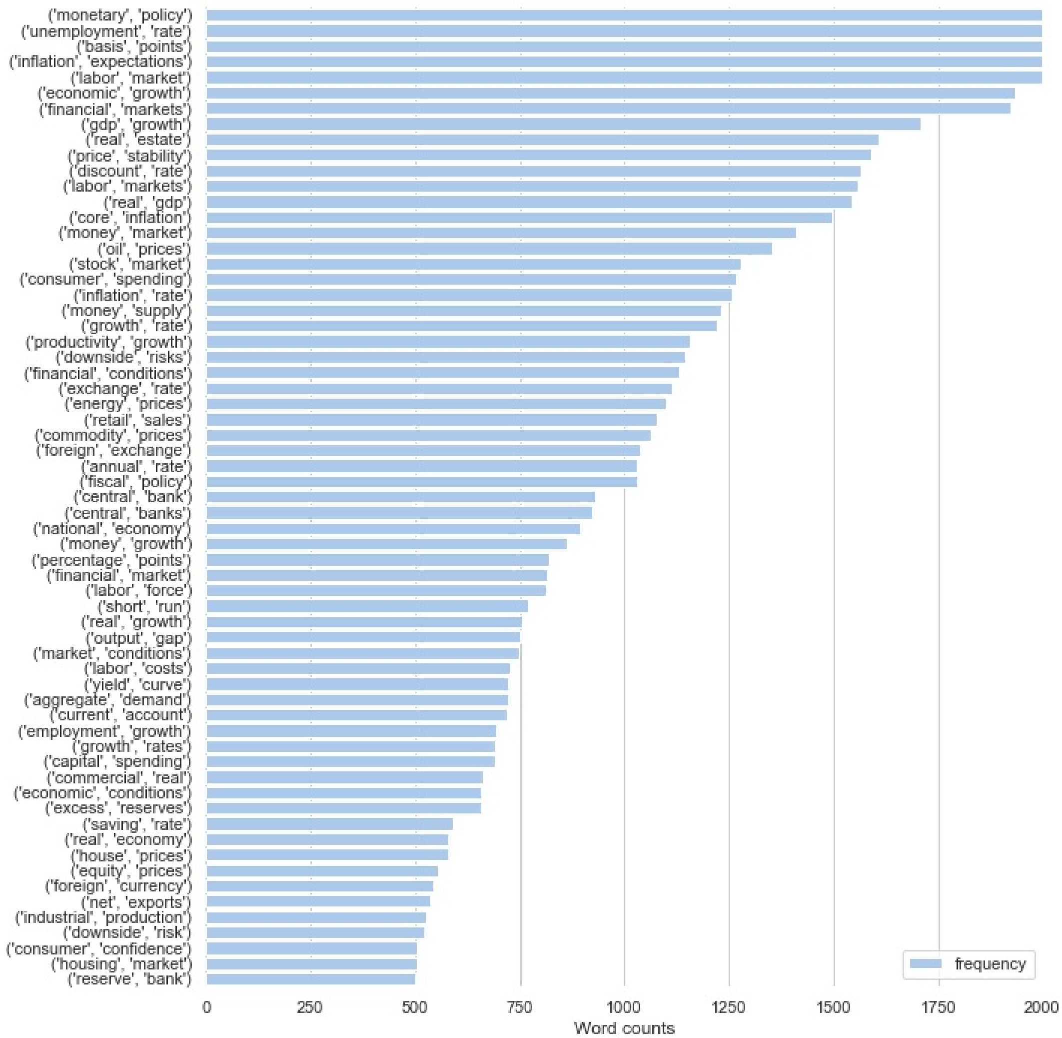


Figure L.1: Total frequency of economic collocations

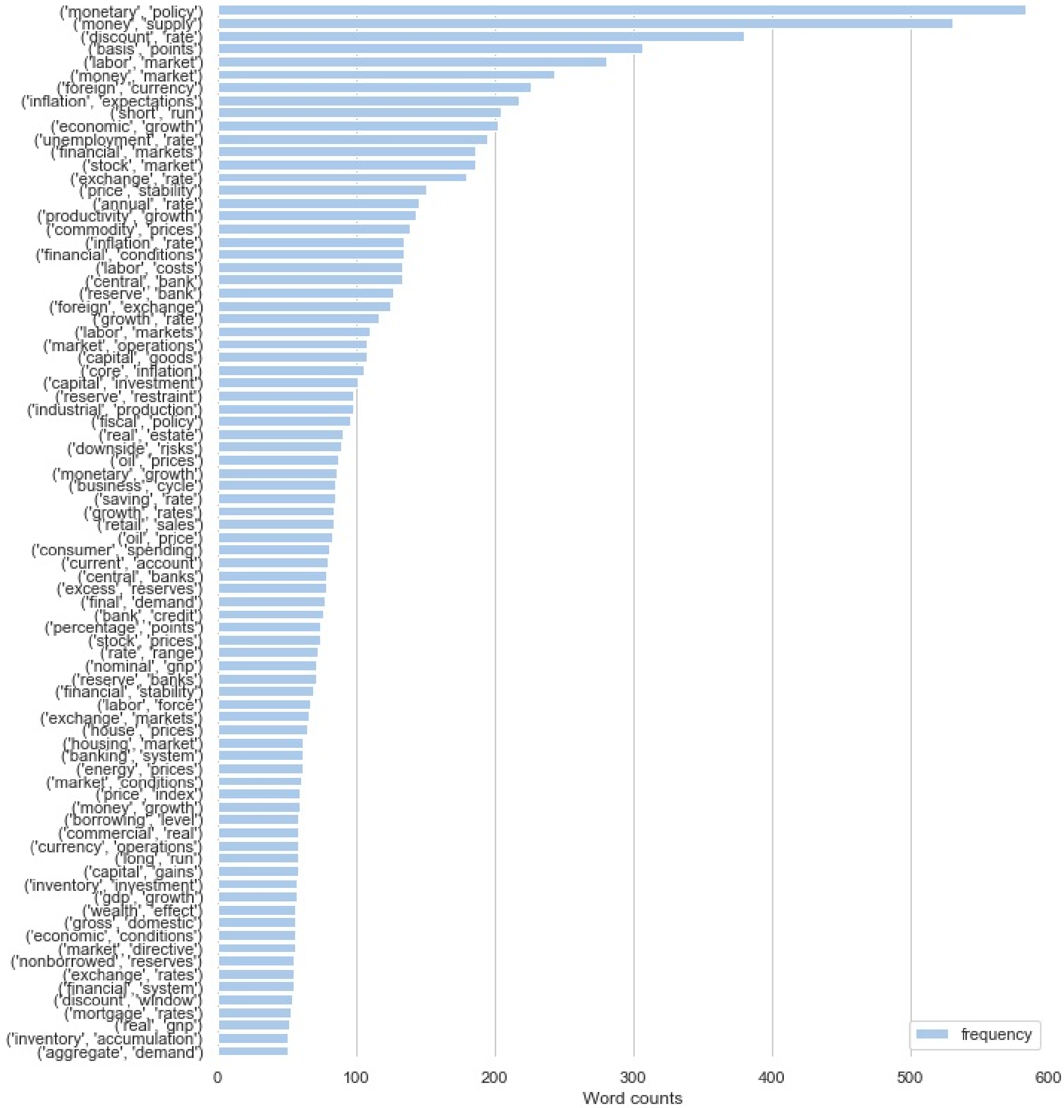


Figure L.2: Total frequency of Chairmen's economic collocations

Table L.1: Selected collocations

Terms	Terms 1	Terms 2
Inflation expectations	inflationary, inflation, price	expectations, expectation
Consumer sentiments	confidence, sentiment, expectations, expectation, sentiments	consumer, business, household, investor, public
Assets	securities, market, markets, security, yield	forward, asset, equity, stock, yield
	bill, rate, rates, purchase, issues	commercial, treasury, commodity
	coupon, coupons, bond, bonds, futures	
	account, paper, papers, options, curve	
	sales, sale, banking, debt, lending	
	loans, finance, payments, spreads, payment	
	sector, price, prices, rates, estate, curve	
Energy	securities, market, markets, security, yield	energy, oil
	bill, rate, rates, purchase, issues	
	coupon, coupons, bond, bonds, futures	
	account, paper, papers, options, curve	
	sales, sale, banking, debt, lending	
	loans, finance, payments, spreads, payment	
	sector, price, prices, rates, estate, curve	
Housing	securities, market, markets, security, yield	house, housing, mortgage, real
	bill, rate, rates, purchase, issues	
	coupon, coupons, bond, bonds, futures	
	account, paper, papers, options, curve	
	sales, sale, banking, debt, lending	
	loans, finance, payments, spreads, payment	
	sector, price, prices, rates, estate, curve	
Demand	spending, demand, spendings, sales, loans	consumer, capital, aggregate, retail, growth
	loan, credit, sector, consumption	average, expected, annual, future, potential
Growth	growth, real, nominal, gap, economy	gdp, gnp, output, economic, productivity
	condition, industrial, potential, national	production, economy, income
Employment	growth, market, markets, force, costs	labor, employment, job, wage
Money	growth, supply, demand, aggregate	m1, m2, m3, money, monetary
Foreign	exchange, currency, exports, export, import	foreign, net
	imports, economy, economies, demand	
	gdp, market, markets, growth	
Financial	markets, market, conditions, condition, indicators	financial
	indicator, stability, sector, system, assets, asset	
	institutions, institution, services, service, innovation	
	innovations, structure, health, sectors, corporations	
Fiscal	policy, policies, effect, effects, restraint	fiscal, tax
	package, rate	

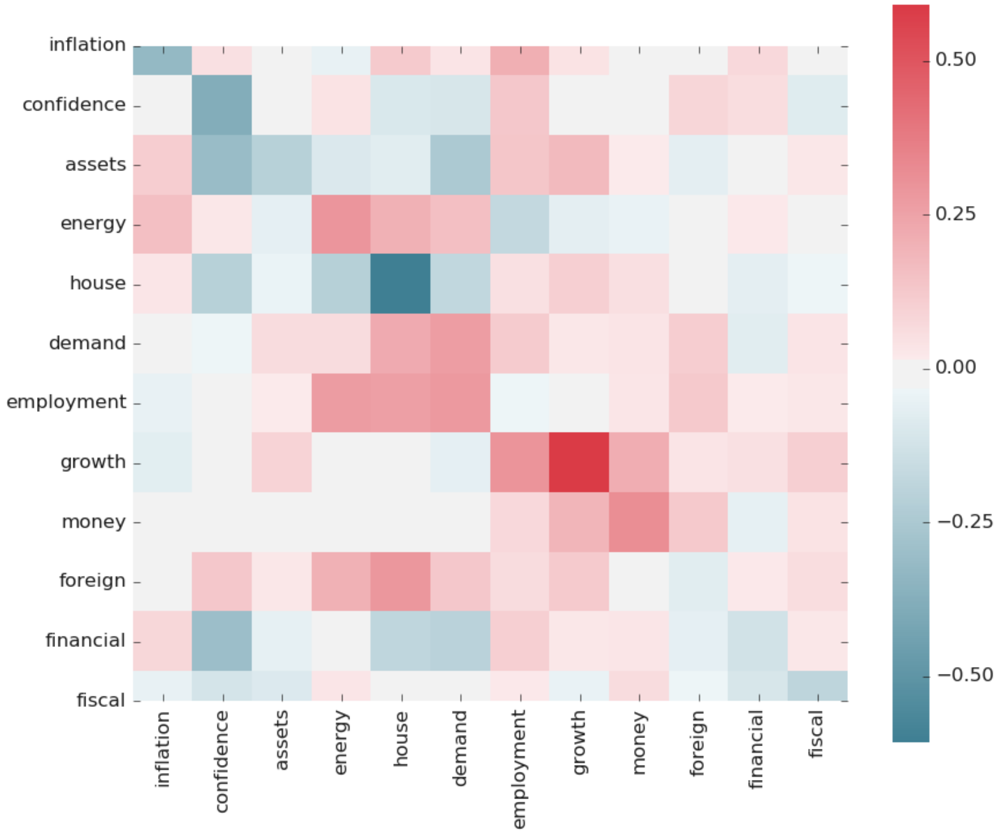
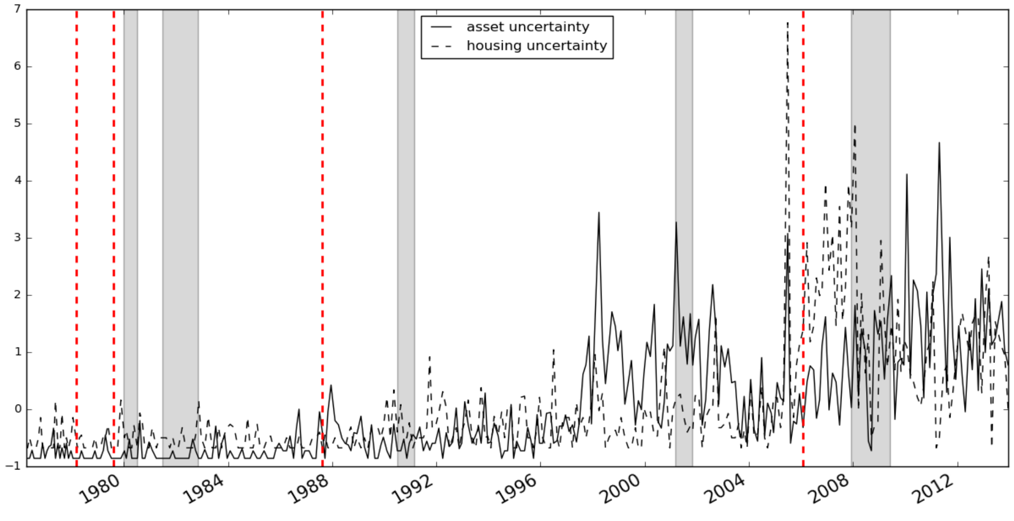
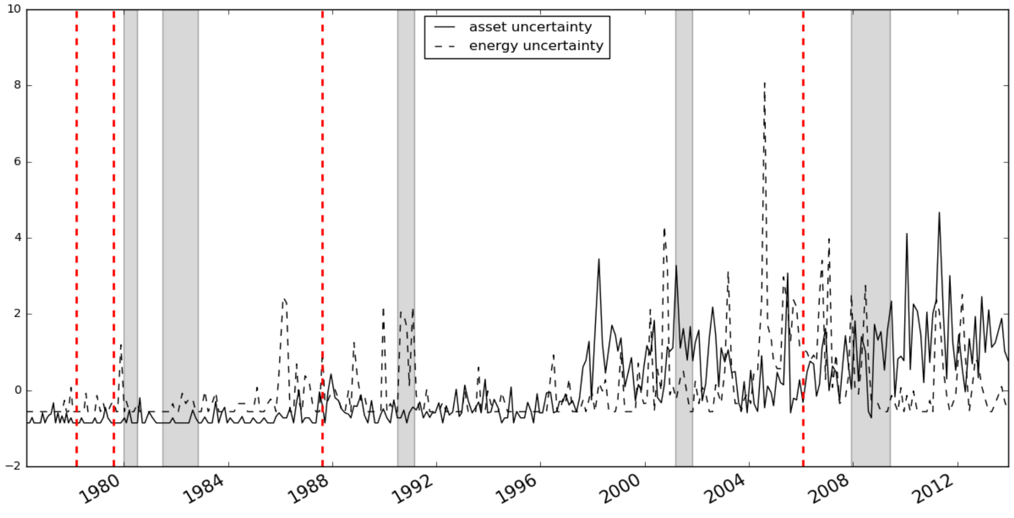


Figure L.3: Cross-correlations between positive (y-axis) and uncertain (x-axis) sentiment economic terms time series

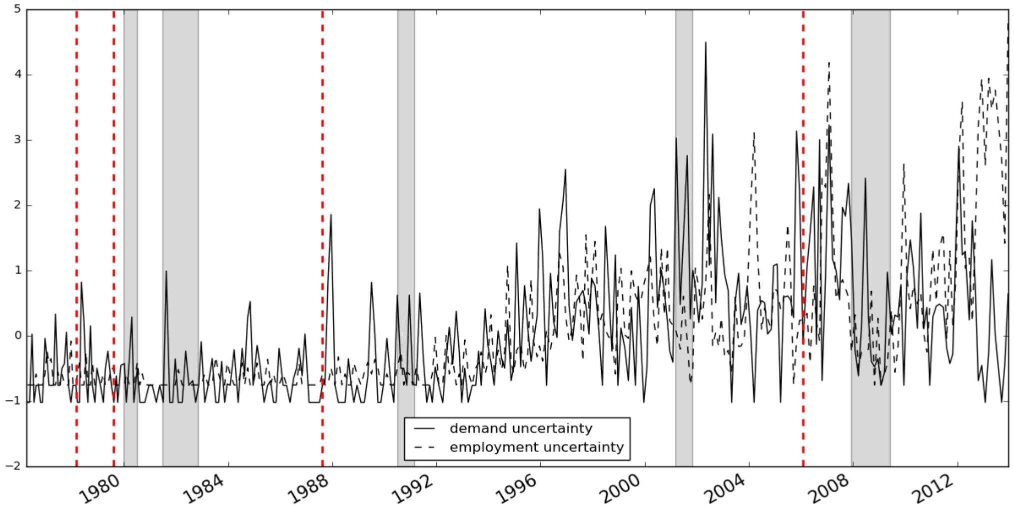


(a) Asset (solid) and housing (dashed) uncertainty

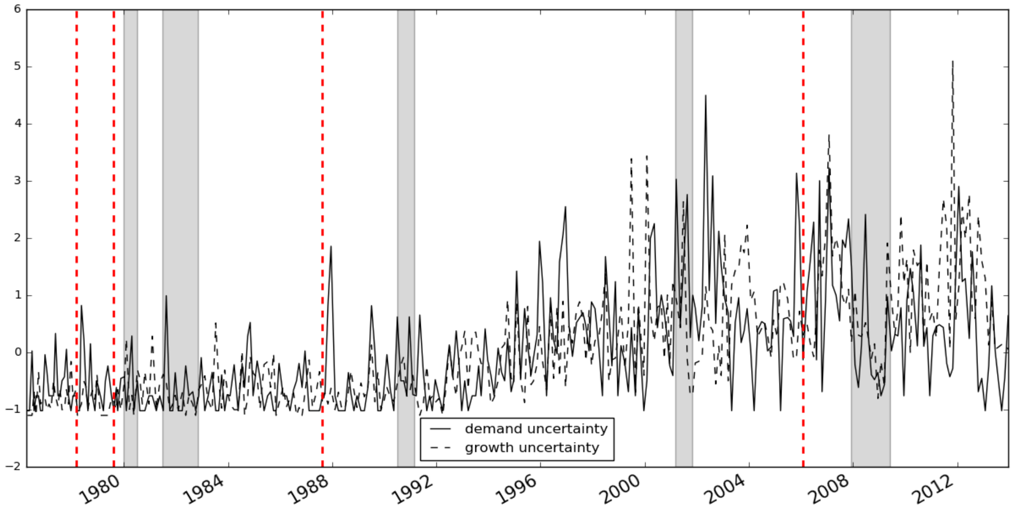


(b) Asset (solid) and energy (dashed) uncertainty

Figure L.4: Comparison between energy, assets and housing terms uncertainty. All series are standardised.
shaded areas – NBER based recessions; red dashed – Chairman changes

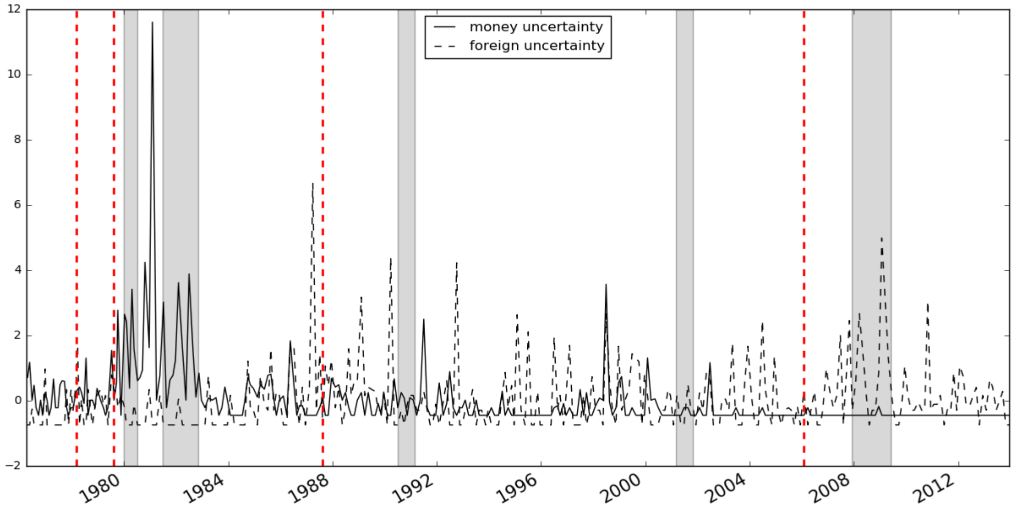


(a) Demand (solid) and employment (dashed) uncertainty

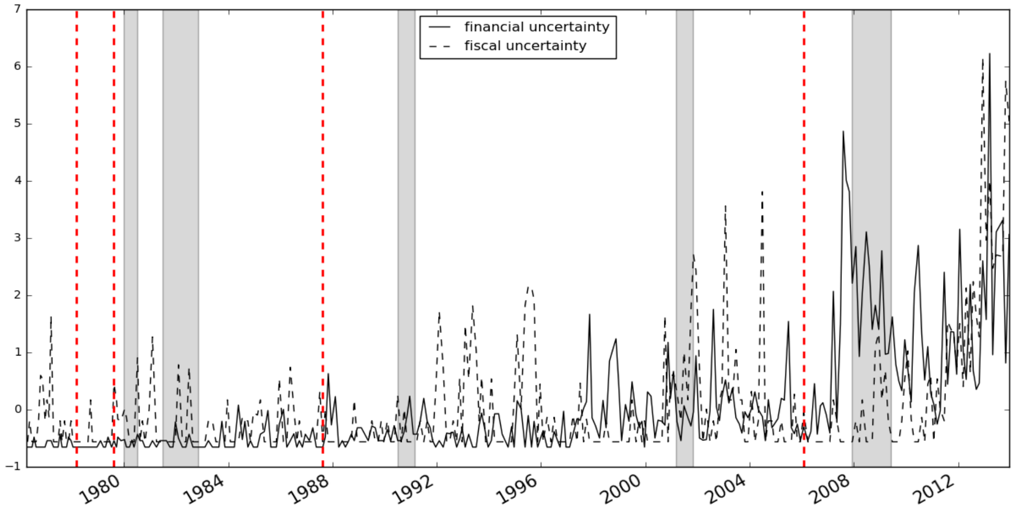


(b) Demand (solid) and growth (dashed) uncertainty

Figure L.5: Comparison between demand, employment and growth terms uncertainty. All series are standardised.
shaded areas – NBER based recessions; red dashed – Chairman changes



(a) Money (solid) and foreign (dashed) uncertainty



(b) Financial (solid) and fiscal (dashed) uncertainty

Figure L.6: Comparison between money, foreign, financial and fiscal terms uncertainty. All series are standardised.
shaded areas – NBER based recessions; red dashed – Chairman changes

Appendix M Description of variables

I use Romer and Romer (2004) series expanded till year 2008 from Wieland and Yang (2020).

- OLDTARG is the target Federal Funds rate before the meeting
- GRAD is the Greenbook forecast of the percentage change in the GDP/GNP deflator
- IGRD is the innovation in the Greenbook forecast for the percentage change in the GDP/GNP deflator
- GRAY is the Greenbook forecast of the percentage change in real GDP/GNP
- IGRY is the innovation in the Greenbook forecast for the percentage change in GDP/GNP
- GRAU is the Greenbook forecast for the unemployment rate
  - M means the previous quarter
  - 0 means the current quarter
  - 1 means one quarter ahead
  - 2 means two quarters ahead

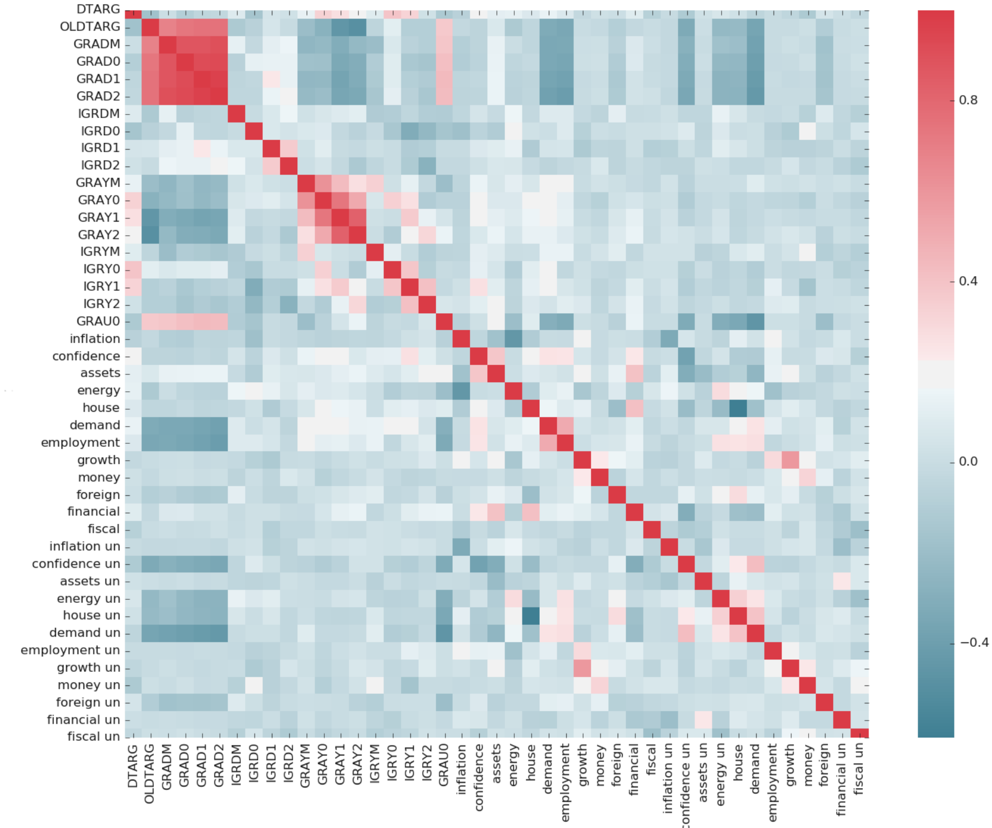


Figure M.1: Cross-correlations between variables
un means uncertainty, without un - positiveness

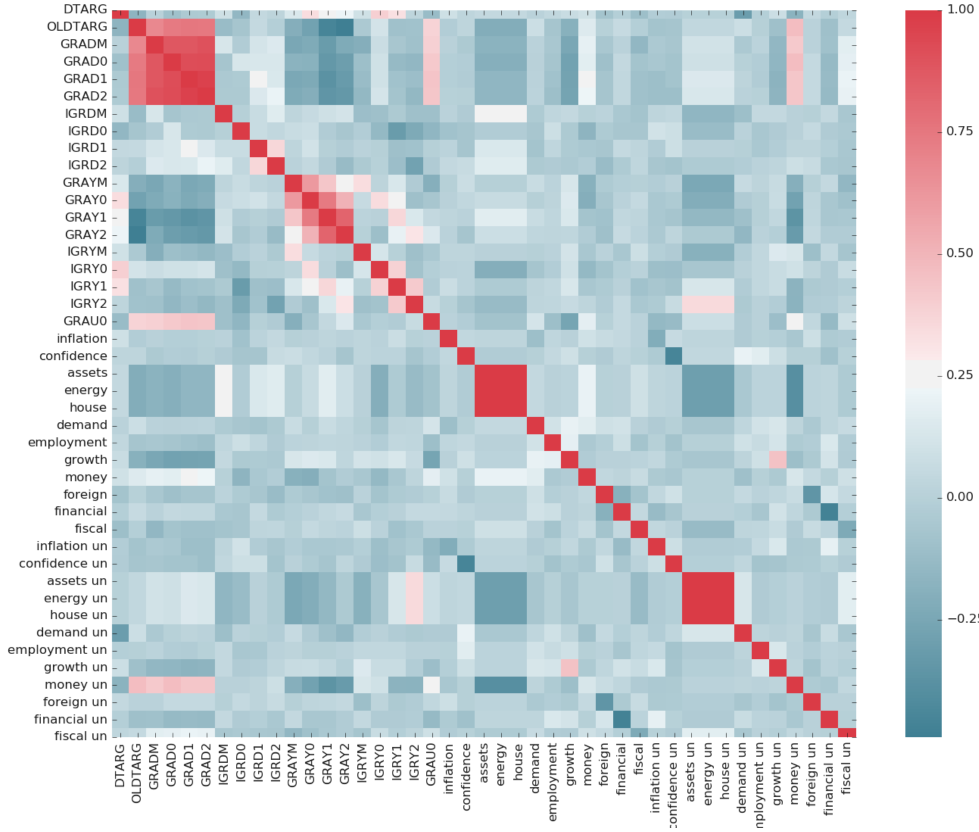


Figure M.2: Cross-correlations between variables with Chairmen's economic terms
un means uncertainty, without un - positiveness

Appendix N Additional results

Table N.1: LASSO and Elastic Net results with sentiments with FRED-MD factors, 1976–2008

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
oldtar_my	-	-	-	-	-	-	-	-
GRADM	0.041	0.042	0.019	0.018	0.028	0.026	0.02	0.019
GRAD0	-	-	-	-	-	-	-	-
GRAD1	-	-	-	-	-	-	-	-
GRAD2	-	-	-	-	-	-	-	-
IGRDM	0.031	0.031	0.026	0.026	0.023	0.023	0.023	0.023
IGRD0	-0.042	-0.042	-0.04	-0.039	-0.026	-0.026	-0.026	-0.026
IGRD1	-	-	-	-	-	-	-	-
IGRD2	-	-	-	-	-	-	-	-
GRAYM	0.006	0.006	-	-	0.001	0.001	-	-
GRAY0	0.003	0.006	-	-	-	-	-	-
GRAY1	-	-	-	-	-	-	-	-
GRAY2	-	-	-	-	-	-	-	-
IGRYM	0.001	0.001	-	-	0.006	0.006	0.004	0.004
IGRY0	0.04	0.04	0.042	0.042	0.037	0.037	0.039	0.039
IGRY1	-	0.001	0.001	0.003	-	-	-	-
IGRY2	0.013	0.013	0.008	0.007	0.01	0.01	0.011	0.011
GRAU0	-0.043	-0.044	-0.024	-0.023	-0.033	-0.032	-0.027	-0.026
Factor 1	-0.133	-0.131	-0.135	-0.133	-0.133	-0.132	-0.134	-0.133
Factor 2	-	-	-	-	-	-	-	-
Factor 3	-0.051	-0.052	-0.031	-0.031	-0.046	-0.045	-0.04	-0.039
Factor 4	-0.103	-0.103	-0.096	-0.095	-0.105	-0.104	-0.106	-0.105
Factor 5	0.1	0.1	0.096	0.094	0.098	0.097	0.096	0.095
Factor 6	-0.002	-0.002	-	-	-	-	-	-
Factor 7	-0.014	-0.015	-0.005	-0.005	-0.009	-0.009	-0.004	-0.004
positiveness								
inflation expectations			-	-			-0.001	-
consumer confidence			0.011	0.011			0.003	0.003
assets			-	-			-	-
energy			0.021	0.021			0.012	0.013
housing			-	-			-	-
demand			-	-			-	-
employment			-	-			-	-
growth			-0.003	-0.003			-	-
money			0.006	0.006			0.022	0.021
foreign			-	-			-	-
financial			-	-			-	-
fiscal			-0.024	-0.024			-0.023	-0.023
uncertainty								
inflation expectations					-0.001	-0.001	-0.003	-0.003
consumer confidence					-0.02	-0.019	-0.019	-0.019
assets					0.003	0.003	-	-
energy					0.02	0.02	0.016	0.016
housing					-	-	-	-
demand					-	-	-	-
employment					-	-	-	-
growth					-	-	-	-
money					-0.05	-0.049	-0.053	-0.052
foreign					-	-	-	-
financial					-	-	-	-
fiscal					-	-	-	-

Table N.2: LASSO and Elastic Net results with sentiments residual from AR(1) with FRED-MD factors and Consumer Sentiment Index, 1978–2008

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.013	-0.015	-0.014	-0.015	-0.008	-0.009	-0.017	-0.018
GRADM	0.099	0.099	0.086	0.087	0.102	0.1	0.088	0.086
GRAD0	-	-	-	-	-	-	-	-
GRAD1	-	-	-	-	-	-	-	-
GRAD2	-	-	-	-	-	-	-	-
IGRDM	0.021	0.021	0.02	0.02	0.016	0.017	0.018	0.018
IGRD0	-0.054	-0.054	-0.053	-0.053	-0.038	-0.038	-0.031	-0.031
IGRD1	0.004	0.005	-	-	-	-	-	-
IGRD2	-0.005	-0.005	-0.006	-0.007	-	-	-0.008	-0.007
GRAYM	0.013	0.013	0.001	0.001	0.01	0.01	-	-
GRAY0	0.002	0.002	0.018	0.019	-	-	-	-
GRAY1	0.026	0.026	0.018	0.018	0.009	0.009	0.016	0.016
GRAY2	-	-	-	-	0.02	0.02	0.017	0.018
IGRYM	0.009	0.01	0.009	0.009	0.024	0.024	0.022	0.022
IGRY0	0.04	0.04	0.039	0.039	0.043	0.043	0.047	0.047
IGRY1	-	-	-	-	-	-	-	-
IGRY2	0.016	0.016	0.024	0.024	0.013	0.013	0.018	0.018
GRAU0	-0.06	-0.06	-0.049	-0.049	-0.068	-0.066	-0.059	-0.058
Factor 1	-0.13	-0.129	-0.13	-0.129	-0.129	-0.129	-0.131	-0.131
Factor 2	0.017	0.017	0.01	0.01	0.011	0.01	0.002	0.001
Factor 3	-0.076	-0.076	-0.062	-0.062	-0.089	-0.087	-0.072	-0.071
Factor 4	-0.109	-0.11	-0.113	-0.114	-0.108	-0.109	-0.116	-0.116
Factor 5	0.116	0.115	0.118	0.117	0.12	0.119	0.116	0.115
Factor 6	-0.006	-0.006	-0.008	-0.008	-0.008	-0.008	-0.015	-0.014
Factor 7	-0.029	-0.03	-0.022	-0.023	-0.039	-0.038	-0.034	-0.034
Consumer Sentiment	-0.039	-0.04	-0.034	-0.034	-0.049	-0.049	-0.047	-0.046
positiveness								
inflation expectations			-	-0.001			-0.009	-0.009
consumer confidence			0.006	0.006			-	-
assets			-	-			-0.007	-0.007
energy			0.006	0.006			-	-
housing			-0.021	-0.022			-0.014	-0.013
demand			-	-0.001			-0.004	-0.004
employment			-	-			-0.006	-0.006
growth			-0.025	-0.025			-0.016	-0.016
money			0.04	0.04			0.062	0.062
foreign			-	-			-	-
financial			-0.004	-0.004			-	-
fiscal			-0.009	-0.01			-0.01	-0.01
uncertainty								
inflation expectations					-0.007	-0.007	-0.014	-0.013
consumer confidence					-0.029	-0.029	-0.036	-0.035
assets					0.003	0.003	-	-
energy					0.016	0.015	0.008	0.008
housing					-0.003	-0.003	-	-
demand					-	-	-	-
employment					0.003	0.003	0.005	0.005
growth					-0.006	-0.006	-	-
money					-0.078	-0.077	-0.09	-0.09
foreign					0.01	0.01	-	-
financial					0.017	0.017	0.012	0.012
fiscal					-	-	-	-

Table N.3: LASSO and Elastic Net results with sentiments
Sample from 1983

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.14	-0.14	-0.1	-0.1	-0.12	-0.12	-0.09	-0.09
GRADM	0.02	0.02	0.01	0.01	0.03	0.03	0.02	0.02
GRAD0	0.06	0.06	0.06	0.06	0.05	0.05	0.04	0.04
GRAD1	0.03	0.03	0.01	0.01	0.02	0.02	0.02	0.02
GRAD2	0.04	0.04	0.04	0.03	0.01	0.01	0.01	0.01
IGRDM	0.01	0.01	0.01	0.01	-	-	-	-
IGRD0	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03	-0.03	-0.03
IGRD1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
IGRD2	-	-	-	-	0.01	0.01	-	-
GRAYM	0.01	0.01	-	-	-	-	-	-
GRAY0	0.1	0.1	0.09	0.09	0.09	0.09	0.09	0.09
GRAY1	0.03	0.03	-	-	-	0.01	-	-
GRAY2	-0.02	-0.02	-	-	-	-	-	-
IGRYM	-	-	-	0.01	0.01	0.01	0.01	0.01
IGRY0	0.03	0.03	0.04	0.04	0.03	0.03	0.04	0.04
IGRY1	0.02	0.02	0.01	0.01	0.03	0.02	0.02	0.02
IGRY2	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01
GRAU0	-0.07	-0.07	-0.06	-0.06	-0.07	-0.07	-0.06	-0.06
positiveness								
inflation expectations			-0.01	-0.01			-0.02	-0.02
consumer confidence			0.04	0.04			0.02	0.02
assets			-	-			-	-
energy			0.04	0.04			0.03	0.03
housing			0.01	0.01			0.01	0.01
demand			-0.02	-0.02			-0.02	-0.02
employment			-	-			-0.01	-0.01
growth			-	-			0.01	0.01
money			-	-			-0.01	-0.01
foreign			-0.01	-0.01			-	-
financial			0.02	0.02			0.01	0.01
fiscal			-0.01	-0.01			-0.02	-0.02
uncertainty								
inflation expectations					-	-	-0.02	-0.02
consumer confidence					-0.05	-0.04	-0.04	-0.04
assets					0.01	0.01	0.01	0.01
energy					0.01	0.01	-	-
housing					-	-	0.01	0.01
demand					-0.01	-0.01	-	-
employment					-	-	-	-
growth					-0.01	-0.02	-0.02	-0.02
money					0.01	0.01	0.02	0.02
foreign					0.01	0.01	0.01	0.01
financial					0.02	0.02	0.01	0.01
fiscal					0.01	0.01	-	-

Table N.4: LASSO and Elastic Net results with sentiments and FRED-MD factors
Sample from 1983

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.121	-0.121	-0.113	-0.111	-0.113	-0.113	-0.111	-0.111
GRADM	0.021	0.021	0.017	0.017	0.024	0.024	0.016	0.016
GRAD0	0.051	0.051	0.054	0.054	0.044	0.044	0.045	0.045
GRAD1	0.018	0.018	0.007	0.007	0.023	0.023	0.022	0.022
GRAD2	0.028	0.029	0.03	0.029	0.005	0.005	0.007	0.007
IGRDM	0.001	0.001	0.001	0.001	-	-	0.002	0.002
IGRD0	-0.042	-0.042	-0.048	-0.048	-0.039	-0.039	-0.044	-0.044
IGRD1	0.005	0.006	0.006	0.006	0.005	0.005	0.004	0.004
IGRD2	-0.003	-0.003	-0.002	-0.002	-	-	-	-
GRAYM	0.003	0.004	-	-	0.003	0.003	-	-
GRAY0	0.054	0.053	0.054	0.054	0.061	0.061	0.062	0.062
GRAY1	0.014	0.014	-	-	-	-	-	-
GRAY2	0.002	0.002	0.004	0.004	0.004	0.004	0.003	0.003
IGRYM	-0.001	-0.002	-	-	0.001	0.001	0.003	0.003
IGRY0	0.021	0.021	0.025	0.025	0.017	0.018	0.023	0.024
IGRY1	0.006	0.006	-	-	0.011	0.011	0.003	0.003
IGRY2	0.009	0.009	0.008	0.008	0.005	0.005	0.007	0.007
GRAU0	-0.044	-0.044	-0.036	-0.036	-0.043	-0.043	-0.043	-0.043
Factor 1	-0.064	-0.064	-0.055	-0.055	-0.052	-0.052	-0.048	-0.048
Factor 2	-0.022	-0.022	-0.027	-0.026	-0.03	-0.03	-0.03	-0.03
Factor 3	0.024	0.024	0.034	0.033	0.018	0.019	0.026	0.026
Factor 4	-0.053	-0.053	-0.051	-0.051	-0.057	-0.057	-0.05	-0.05
Factor 5	0.014	0.014	0.007	0.007	0.014	0.014	0.008	0.008
Factor 6	-0.012	-0.012	-0.008	-0.008	-0.003	-0.003	-0.001	-0.001
Factor 7	-0.033	-0.033	-0.027	-0.027	-0.033	-0.033	-0.031	-0.032
Consumer Sentiment	-0.019	-0.019	-0.007	-0.007	-0.018	-0.018	-0.011	-0.011
positiveness								
inflation expectations			-0.006	-0.006			-0.016	-0.017
consumer confidence			0.04	0.04			0.025	0.025
assets			-0.005	-0.004			-	-
energy			0.027	0.027			0.023	0.023
housing			0.013	0.013			0.012	0.012
demand			-0.015	-0.015			-0.02	-0.02
employment			-0.001	-0.001			-0.011	-0.011
growth			0.001	0.001			0.006	0.006
money			0.003	0.003			-0.005	-0.005
foreign			-0.008	-0.008			-0.005	-0.005
financial			0.009	0.009			0.007	0.007
fiscal			-0.009	-0.009			-0.016	-0.016
uncertainty								
inflation expectations					-0.013	-0.013	-0.024	-0.024
consumer confidence					-0.039	-0.039	-0.033	-0.033
assets					0.012	0.012	0.011	0.011
energy					0.016	0.016	0.008	0.008
housing					-0.012	-0.012	-	-
demand					-	-	-	-
employment					0.001	0.001	0.004	0.004
growth					-0.015	-0.015	-0.018	-0.018
money					0.006	0.006	0.015	0.015
foreign					0.005	0.005	0.003	0.003
financial					0.014	0.014	0.009	0.009
fiscal					0.002	0.002	0.001	0.001

Table N.5: LASSO and Elastic Net results with sentiments residual from AR(1)
Sample from 1983

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.127	-0.127	-0.126	-0.126	-0.121	-0.12	-0.123	-0.123
GRADM	0.02	0.02	0.019	0.019	0.021	0.021	0.013	0.013
GRAD0	0.052	0.052	0.058	0.058	0.051	0.05	0.051	0.051
GRAD1	0.018	0.018	0.009	0.009	0.024	0.023	0.019	0.019
GRAD2	0.035	0.035	0.039	0.04	0.018	0.018	0.025	0.026
IGRDM	0.004	0.004	0.004	0.004	0.004	0.004	0.008	0.008
IGRD0	-0.043	-0.043	-0.048	-0.048	-0.039	-0.038	-0.041	-0.041
IGRD1	0.007	0.007	0.006	0.006	0.007	0.007	0.007	0.007
IGRD2	-0.005	-0.005	-0.004	-0.005	-	-	-0.002	-0.002
GRAYM	0.006	0.007	0.002	0.003	0.004	0.004	-	-
GRAY0	0.051	0.051	0.059	0.059	0.06	0.06	0.07	0.069
GRAY1	0.016	0.016	0.009	0.009	0.008	0.008	0.007	0.008
GRAY2	0.002	0.002	0.003	0.003	0.001	0.001	0.002	0.002
IGRYM	-0.002	-0.002	-	-	-	-	0.002	0.002
IGRY0	0.021	0.021	0.018	0.018	0.017	0.017	0.019	0.019
IGRY1	0.005	0.005	-	-	0.008	0.008	0.002	0.002
IGRY2	0.01	0.01	0.013	0.013	0.011	0.011	0.014	0.013
GRAU0	-0.047	-0.047	-0.049	-0.049	-0.045	-0.045	-0.051	-0.051
Factor 1	-0.065	-0.065	-0.064	-0.064	-0.056	-0.056	-0.052	-0.053
Factor 2	-0.022	-0.022	-0.023	-0.023	-0.029	-0.028	-0.029	-0.029
Factor 3	0.023	0.023	0.025	0.025	0.021	0.021	0.022	0.022
Factor 4	-0.052	-0.052	-0.05	-0.05	-0.054	-0.054	-0.051	-0.051
Factor 5	0.014	0.014	0.013	0.013	0.018	0.018	0.012	0.012
Factor 6	-0.011	-0.011	-0.009	-0.009	-0.003	-0.003	-0.001	-0.001
Factor 7	-0.032	-0.032	-0.033	-0.033	-0.036	-0.036	-0.037	-0.038
Consumer Sentiment	-0.02	-0.02	-0.015	-0.015	-0.022	-0.022	-0.018	-0.018
positiveness								
inflation expectations			-0.007	-0.007			-0.022	-0.022
consumer confidence			0.026	0.026			0.018	0.018
assets			-0.008	-0.009			-0.007	-0.007
energy			0.007	0.007			0.007	0.007
housing			-	-			0.005	0.005
demand			-0.008	-0.008			-0.018	-0.018
employment			-0.004	-0.004			-0.011	-0.011
growth			-	-			-	-
money			-	-			-0.001	-0.001
foreign			-0.007	-0.007			-0.003	-0.004
financial			0.004	0.004			0.012	0.012
fiscal			-0.004	-0.004			-0.01	-0.01
uncertainty								
inflation expectations					-0.009	-0.009	-0.023	-0.023
consumer confidence					-0.032	-0.032	-0.032	-0.032
assets					0.007	0.007	0.004	0.004
energy					-	-	-0.006	-0.006
housing					-0.006	-0.006	-	-
demand					-	-	0.004	0.005
employment					0.004	0.004	0.011	0.011
growth					-0.012	-0.012	-0.011	-0.011
money					0.002	0.002	0.008	0.008
foreign					0.006	0.006	0.004	0.004
financial					0.02	0.02	0.022	0.022
fiscal					0.002	0.002	0.002	0.003

N.1 Additional results with Chairmen's sentiments

Table N.6: LASSO and Elastic Net results with Chairmen's economic sentiments

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.07	-0.07	-0.07	-0.06	-0.05	-0.05	-0.05	-0.05
GRADM	0.12	0.11	0.11	0.1	0.1	0.1	0.09	0.09
GRAD0	-0.08	-0.07	-0.06	-0.06	-0.08	-0.07	-0.07	-0.07
GRAD1	0.06	0.05	0.01	0.01	0.07	0.06	0.05	0.05
GRAD2	-	-	-	-	-	-	-	-
IGRDM	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
IGRD0	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
IGRD1	-	0.01	0.01	0.01	-	-	0.01	0.01
IGRD2	-	-	-	-	-	-	-	-
GRAYM	-	-	-	-	-	-	-	-
GRAY0	0.02	0.02	0.04	0.04	0.02	0.02	0.03	0.03
GRAY1	0.07	0.07	0.05	0.05	0.07	0.07	0.07	0.07
GRAY2	0.01	0.01	0.02	0.02	-	-	-	-
IGRYM	0.03	0.03	0.04	0.03	0.04	0.04	0.04	0.05
IGRY0	0.13	0.13	0.14	0.14	0.14	0.14	0.16	0.16
IGRY1	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02
IGRY2	-	-	-	-	-0.01	-0.01	-0.01	-0.01
GRAU0	-0.06	-0.06	-0.06	-0.06	-0.05	-0.05	-0.06	-0.06
positiveness								
inflation expectations			0.01	0.01			0.01	0.01
consumer confidence			0.01	0.01			0.04	0.04
assets			0.01	-			-	-
energy			-	-			-	-
housing			-	-			-	-
demand			0.01	0.01			0.02	0.02
employment			-	-			0.02	0.02
growth			-0.02	-0.02			-0.03	-0.03
money			0.07	0.07			0.07	0.07
foreign			-0.01	-0.01			-	-
financial			-	-			-	-
fiscal			-0.04	-0.04			-0.03	-0.03
uncertainty								
inflation expectations					-	-	0.01	0.01
consumer confidence					0.01	0.01	0.03	0.03
assets					0.04	0.01	0.04	0.01
energy					-	0.01	0.01	
housing					-	0.01	-	0.01
demand					-0.11	-0.11	-0.11	-0.11
employment					-0.01	-0.01	-0.01	-0.01
growth					0.01	0.01	0.02	0.02
money					-0.05	-0.05	-0.05	-0.05
foreign					0.01	0.01	0.01	0.01
financial					-	-	-	-
fiscal					-	-	-0.01	-0.01

Table N.7: LASSO and Elastic Net results with Chairmen's economic sentiments, with FRED-MD factors

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-	-	-	-	-	-	-	-
GRADM	0.041	0.042	-	-	0.042	0.043	0.026	0.025
GRAD0	-	-	-	-	-	-	-	-
GRAD1	-	-	-	-	-	-	-	-
GRAD2	-	-	-	-	-	-	-	-
IGRDM	0.031	0.031	0.017	0.018	0.025	0.026	0.026	0.025
IGRD0	-0.042	-0.042	-0.021	-0.021	-0.04	-0.04	-0.033	-0.032
IGRD1	-	-	-	-	-	-	-	-
IGRD2	-	-	-	-	-	-	-	-
GRAYM	0.006	0.006	-	-	0.018	0.019	0.023	0.022
GRAY0	0.003	0.006	-	-	-	-	-	-
GRAY1	-	-	-	-	-	-	-	-
GRAY2	-	-	-	-	-	-	-	-
IGRYM	0.001	0.001	-	-	-	-	-	-
IGRY0	0.04	0.04	0.034	0.037	0.05	0.051	0.067	0.066
IGRY1	-	0.001	0.008	0.01	-	-	-	-
IGRY2	0.013	0.013	-	-	0.003	0.003	0.003	0.003
GRAU0	-0.043	-0.044	-0.004	-0.007	-0.037	-0.038	-0.036	-0.036
Factor 1	-0.133	-0.131	-0.135	-0.132	-0.119	-0.119	-0.121	-0.121
Factor 2	-	-	-	-	-	-	-	-
Factor 3	-0.051	-0.052	-0.006	-0.009	-0.049	-0.05	-0.047	-0.046
Factor 4	-0.103	-0.103	-0.085	-0.085	-0.113	-0.113	-0.115	-0.115
Factor 5	0.1	0.1	0.086	0.084	0.077	0.077	0.066	0.066
Factor 6	-0.002	-0.002	-	-	-0.001	-0.001	-0.003	-0.003
Factor 7	-0.014	-0.015	-	-	-0.017	-0.017	-0.011	-0.011
positiveness								
inflation expectations			-	-			-	-
consumer confidence			-	-			0.019	0.018
assets			-	-			-	-
energy			-	-			-	-
housing			-	-			-	-
demand			-	-			-	-
employment			-	-			0.021	0.021
growth			-	-			-0.021	-0.02
money			0.027	0.029			0.054	0.054
foreign			-	-			-	-
financial			-	-			-	-
fiscal			-0.001	-0.004			-0.026	-0.025
uncertainty								
inflation expectations					-	-	-	-
consumer confidence					0.005	0.006	0.019	0.018
assets					0.008	0.003	0.011	0.004
energy					-	0.003	-	0.004
housing					-	0.002	-	0.003
demand					-0.091	-0.091	-0.094	-0.094
employment					-	-	-	-
growth					0.002	0.003	0.01	0.009
money					-0.036	-0.037	-0.042	-0.042
foreign					0.004	0.004	0.002	0.002
financial					-	-	-	-
fiscal		-			-0.011	-0.011	-0.018	-0.018

Table N.8: LASSO and Elastic Net results with Chairmen's economic sentiments
Sample from 1983

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.14	-0.14	-0.12	-0.12	-0.15	-0.15	-0.13	-0.13
GRADM	0.02	0.02	0.02	0.02	0.03	0.03	0.02	0.02
GRAD0	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
GRAD1	0.03	0.03	0.02	0.02	0.04	0.04	0.04	0.04
GRAD2	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03
IGRDM	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
IGRD0	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
IGRD1	0.01	0.01	0.01	0.01	-	-	0.01	0.01
IGRD2	-	-	-	-	-	-	-	-
GRAYM	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01
GRAY0	0.1	0.1	0.09	0.09	0.1	0.1	0.1	0.1
GRAY1	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02
GRAY2	-0.02	-0.02	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01
IGRYM	-	-	-	-	0.01	0.01	0.01	0.01
IGRY0	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
IGRY1	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
IGRY2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
GRAU0	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07
positiveness								
inflation expectations			-	-			-	-
consumer confidence			0.01	0.01			0.01	0.01
assets			-0.01	-0.01			-0.01	-0.01
energy			-	-			-	-
housing			-	-			-	-
demand			-	-			-	-
employment			-	-			-	-
growth			-	-			0.01	0.01
money			-0.02	-0.02			-0.03	-0.03
foreign			-0.01	-0.01			-	-0.01
financial			-	-			-	-
fiscal			-0.02	-0.02			-0.02	-0.02
uncertainty								
inflation expectations					0.01	0.01	0.01	0.01
consumer confidence					-	-	-	-
assets					0.01	0.01	-	-
energy					-	-	-	-
housing					-	-	-	-
demand					-0.02	-0.02	-0.02	-0.02
employment					-0.01	-0.01	-0.01	-0.01
growth					-	-	-	-
money					0.02	0.02	0.03	0.03
foreign					0.02	0.02	0.01	0.01
financial					-	-	-	-
fiscal					-	-	-	-

Table N.9: LASSO and Elastic Net results with Chairmen's economic sentiments and dummies

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.07	-0.07	-0.06	-0.06	-0.05	-0.05	-0.04	-0.04
GRADM	0.11	0.11	0.12	0.11	0.1	0.1	0.11	0.11
GRAD0	-0.07	-0.06	-0.07	-0.06	-0.08	-0.07	-0.1	-0.09
GRAD1	0.05	0.05	0.03	0.03	0.07	0.06	0.08	0.08
GRAD2	-	-	-	-	-	-	-	-
IGRDM	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
IGRD0	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
IGRD1	0.01	0.01	0.01	0.01	-	-	-	-
IGRD2	-	-	-	-	-	-	-	-
GRAYM	-	-	-	-	-	-	-	-
GRAY0	0.02	0.02	0.05	0.05	0.02	0.02	0.03	0.03
GRAY1	0.07	0.07	0.05	0.05	0.07	0.07	0.08	0.07
GRAY2	0.01	0.01	0.02	0.02	-	-	-	-
IGRYM	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.05
IGRY0	0.13	0.13	0.14	0.14	0.14	0.14	0.16	0.16
IGRY1	0.03	0.03	0.03	0.03	0.02	0.02	0.01	0.02
IGRY2	-	-	-	-	-0.01	-0.01	-0.01	-0.01
GRAU0	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
positiveness								
inflation expectations			0.01	0.01			0.01	0.01
consumer confidence			0.01	0.01			0.04	0.04
assets			0.01	-			-	-
energy			-	-			-	-
housing			-	-			-	-
demand			0.01	0.01			0.02	0.02
employment			0.01	0.01			0.02	0.02
growth			-0.02	-0.02			-0.03	-0.03
money			0.08	0.08			0.07	0.07
foreign			-0.01	-0.01			-	-
financial			-	-			-	-
fiscal			-0.04	-0.04			-0.04	-0.04
uncertainty								
inflation expectations			-	-	-	-	0.01	0.01
consumer confidence			-	-	0.01	0.01	0.04	0.03
assets					0.04	0.01	0.04	0.01
energy					-	0.01	-	0.02
housing					-	0.01	-	0.01
demand					-0.11	-0.11	-0.11	-0.11
employment					-0.01	-0.01	-0.01	-0.01
growth					0.01	0.01	0.03	0.02
money					-0.05	-0.05	-0.05	-0.05
foreign					0.01	0.01	0.01	0.01
financial					-	-	0.01	0.01
fiscal					-	-	-0.02	-0.02
dummy Miller	-	-	-	-	-	-	-	-
dummy Volcker	-	-	-	-	-	-	-	-
dummy Greepspan	0.02	0.02	0.07	0.06	-	-	0.08	0.07
dummy Bernanke	-	-	-	-	-	-	-	-

Table N.10: LASSO and Elastic Net results with Chairmen's economic sentiments and dummies
Sample from 1983

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
OLDTARG	-0.13	-0.13	-0.12	-0.12	-0.13	-0.13	-0.12	-0.12
GRADM	0.02	0.02	0.02	0.02	0.03	0.03	0.02	0.02
GRAD0	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05
GRAD1	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.03
GRAD2	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03
IGRDM	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
IGRD0	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
IGRD1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
IGRD2	-	-	-	-	-	-	-	-
GRAYM	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01
GRAY0	0.1	0.1	0.09	0.09	0.1	0.1	0.1	0.1
GRAY1	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02
GRAY2	-0.02	-0.02	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01
IGRYM	-	-	-	-	0.01	0.01	0.01	0.01
IGRY0	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
IGRY1	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
IGRY2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
GRAU0	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.06	-0.06
positiveness								
inflation expectations			-	-			-	-
consumer confidence			0.01	0.01			0.01	0.01
assets			-0.01	-0.01			-0.01	-0.01
energy			-	-			-	-
housing			-	-			-	-
demand			-	-			-	-
employment			-	-			0.01	0.01
growth			-	-			0.01	0.01
money			-0.02	-0.02			-0.03	-0.03
foreign			-0.01	-0.01			-	-
financial			-	-			-	-
fiscal			-0.02	-0.02			-0.02	-0.02
uncertainty								
inflation expectations					0.01	0.01	0.01	0.01
consumer confidence					-	-	-	-
assets					0.01	0.01	-	-
energy					-	-	-	-
housing					-	-	-	-
demand					-0.02	-0.02	-0.02	-0.02
employment					-0.01	-0.01	-0.01	-0.01
growth					-	-	-	-
money					0.02	0.02	0.03	0.03
foreign					0.02	0.02	0.02	0.02
financial					-	-	-	-
fiscal					-	-	-	-
dummy Miller	-	-	-	-	-	-	-	-
dummy Volcker	-	-	-	-	-	-	-	-
dummy Greenspan	-0.03	-0.03	-	0.01	0.02	0.02	0.02	0.02
dummy Bernanke	-	-	-0.02	-0.02	-	-	-	-

N.2 Additional results using Wu and Xia (2016) shadow rate

Table N.11: LASSO and Elastic Net results with sentiments using Wu and Xia (2016) shadow rate, 1976–2013

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
Rate $(t-1)$	0.946	0.943	0.942	0.936	0.937	0.934	0.937	0.93
GRADM	0.06	0.059	0.056	0.056	0.064	0.067	0.06	0.06
GRAD0	-0.027	-0.025	-	-0.003	-0.022	-0.028	-0.007	-0.008
GRAD1	0.031	0.032	0.007	0.014	0.022	0.029	0.01	0.015
GRAD2	-	-	-	-	-	-	-	-
IGRDM	-	-	-	-	-0.002	-0.003	-	-
IGRD0	-0.02	-0.021	-0.025	-0.024	-0.017	-0.016	-0.019	-0.019
IGRD1	-0.006	-0.006	-0.002	-0.003	-0.004	-0.005	-0.002	-0.003
IGRD2	0.005	0.005	0.002	0.002	0.003	0.004	0.002	0.002
GRAYM	-0.007	-0.006	-0.004	-0.004	-0.007	-0.007	-0.005	-0.005
GRAY0	-	-	-	-	-	-	-	-
GRAY1	-	-	-	-	-	-	-	-
GRAY2	0.026	0.025	0.021	0.021	0.024	0.025	0.022	0.021
IGRYM	0.02	0.02	0.018	0.018	0.026	0.028	0.025	0.026
IGRY0	0.028	0.028	0.028	0.029	0.029	0.029	0.03	0.03
IGRY1	0.021	0.021	0.017	0.017	0.016	0.016	0.013	0.013
IGRY2	-0.027	-0.027	-0.023	-0.023	-0.023	-0.024	-0.02	-0.02
GRAU0	-0.021	-0.022	-0.02	-0.021	-0.021	-0.023	-0.022	-0.023
positiveness								
inflation expectations			0.002	0.002			0.006	0.006
consumer confidence			0.003	0.003			-	-
assets			-	-			-	-
energy			0.004	0.005			0.005	0.005
housing			0.001	0.001			-	-
demand			-	-			-	-
employment			-0.003	-0.005			-0.003	-0.004
growth			-	-			-	0.001
money			-	-			0.002	0.002
foreign			-0.008	-0.008			-0.004	-0.004
financial			0.002	0.002			0.001	0.001
fiscal			-	-			0.001	0.001
uncertainty								
inflation expectations					-	-	-	-
consumer confidence					-0.01	-0.01	-0.009	-0.01
assets					-	-	-	-
energy					0.005	0.007	0.004	0.005
housing					-0.008	-0.009	-0.007	-0.008
demand					-0.008	-0.008	-0.008	-0.009
employment					-	-0.001	- -0.001	-0.001
growth					-	-	-	-
money					-0.022	-0.022	-0.021	-0.022
foreign					0.013	0.014	0.012	0.012
financial					-0.002	-0.002	-0.001	-0.001
fiscal					-	0.001	-	-

Table N.12: LASSO and Elastic Net results with sentiments using Wu and Xia (2016) shadow rate, 1976–2013, with FRED factors

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
Rate $(t-1)$	0.961	0.955	0.961	0.954	0.962	0.955	0.961	0.953
GRADM	0.049	0.055	0.049	0.055	0.052	0.057	0.052	0.057
GRAD0	-	-	-	-	-	-	-	-
GRAD1	-	-	-	-	-	-	-	-
GRAD2	-	-	-	-	-	-	-	-
IGRDM	0.002	0.002	0.002	0.002	-	-	-	-
IGRD0	-0.022	-0.023	-0.022	-0.023	-0.016	-0.017	-0.016	-0.017
IGRD1	-	-0.002	-	-0.002	-0.002	-0.004	-0.002	-0.004
IGRD2	-	-	-	-	-	-	-	-
GRAYM	-	-	-	-	-	-	-	-
GRAY0	-	-	-	-	-0.004	-0.007	-0.004	-0.007
GRAY1	-0.018	-0.02	-0.018	-0.021	-0.017	-0.018	-0.017	-0.018
GRAY2	-	-	-	-	-	-	-	-
IGRYM	0.007	0.009	0.008	0.009	0.013	0.015	0.014	0.016
IGRY0	0.002	0.001	0.002	0.002	0.001	0.002	0.001	0.002
IGRY1	-	0.002	-	0.002	-	-	-	-
IGRY2	-0.009	-0.011	-0.008	-0.009	-0.009	-0.01	-0.007	-0.008
GRAU0	-0.002	-0.004	-0.001	-0.003	-0.002	-0.005	-0.002	-0.004
Factor 1	-0.057	-0.059	-0.059	-0.061	-0.061	-0.063	-0.062	-0.065
Factor 2	-	-	-	-	-	-	-	-
Factor 3	-0.024	-0.025	-0.023	-0.023	-0.027	-0.028	-0.026	-0.026
Factor 4	-0.02	-0.02	-0.02	-0.019	-0.022	-0.021	-0.022	-0.022
Factor 5	0.045	0.046	0.046	0.047	0.046	0.046	0.047	0.046
Factor 6	-	-	-	-	-	-	-	-0.001
Factor 7	-0.01	-0.01	-0.01	-0.011	-0.01	-0.011	-0.01	-0.012
positiveness								
inflation expectations			-	-		-	-	-
consumer confidence			-	-			-	-
assets			-0.003	-0.003			-0.004	-0.005
energy			-	-			-	-
housing			-0.005	-0.005			-0.003	-0.003
demand			-	-			-	-
employment			-0.001	-0.002			-0.002	-0.004
growth			-	-			-	-
money			-	-			0.003	0.004
foreign			-0.001	-0.003			-0.001	-0.002
financial			-	-			-	-
fiscal			-	-			-	-
uncertainty								
inflation expectations					-	-	-	-
consumer confidence					-0.001	-0.003	-0.001	-0.003
assets					-	-	-	-
energy					0.006	0.007	0.006	0.007
housing					-	-	-	-
demand					-0.003	-0.004	-0.004	-0.006
employment					-	-	-	-
growth					-	-	-	-
money					-0.026	-0.028	-0.027	-0.029
foreign					0.006	0.007	0.005	0.006
financial					-	-0.001	-	-0.001
fiscal				-	-	-	-	-

Table N.13: LASSO and Elastic Net results with sentiments using Wu and Xia (2016) shadow rate, 1978–2013, with FRED factors and consumer sentiment index

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
Rate $(t-1)$	0.955	0.943	0.952	0.94	0.953	0.946	0.955	0.943
GRADM	0.055	0.052	0.055	0.052	0.057	0.056	0.058	0.056
GRAD0	-	0.005	-	0.006	-	0.003	-	0.004
GRAD1	0.004	0.012	0.005	0.013	-	0.005	-	0.007
GRAD2	0.004	0.005	0.004	0.005	0.003	0.006	0.002	0.004
IGRDM	-	-	-	-	-	-	-	-
IGRD0	-0.025	-0.027	-0.025	-0.028	-0.018	-0.019	-0.018	-0.02
IGRD1	-0.001	-0.004	-0.002	-0.005	-	-0.004	-0.003	-0.005
IGRD2	-	-	-	-	-	-	-	-
GRAYM	-	-	-	-	-	-	-	-
GRAY0	-0.001	-0.001	-	-0.001	-0.006	-0.009	-0.009	-0.01
GRAY1	-0.006	-0.004	-0.005	-0.002	-0.004	-0.005	-0.005	-0.003
GRAY2	-	-	-	-	-	-	-	-
IGRYM	0.009	0.01	0.01	0.011	0.014	0.017	0.017	0.018
IGRY0	-	-	-	-	-	-	-	-
IGRY1	-	0.001	-	-	-	-	-	-
IGRY2	-0.011	-0.012	-0.009	-0.009	-0.008	-0.01	-0.008	-0.007
GRAU0	-0.003	-0.006	-0.001	-0.005	-	-0.004	-0.002	-0.004
Factor 1	-0.054	-0.055	-0.056	-0.057	-0.057	-0.06	-0.062	-0.063
Factor 2	-	-	-	-	-	-	-	-
Factor 3	-0.025	-0.025	-0.023	-0.024	-0.02	-0.026	-0.026	-0.025
Factor 4	-0.02	-0.02	-0.019	-0.019	-0.021	-0.022	-0.022	-0.022
Factor 5	0.047	0.048	0.049	0.05	0.046	0.048	0.05	0.05
Factor 6	-	-	-	-	-	-	-0.001	-0.001
Factor 7	-0.01	-0.011	-0.012	-0.014	-0.008	-0.012	-0.014	-0.015
Consumer Sentiment	-0.003	-0.006	-0.005	-0.008	-0.002	-0.007	-0.007	-0.01
positiveness								
inflation expectations			-	-			-	0.001
consumer confidence			-	-			-	-
assets			-0.005	-0.006			-0.006	-0.008
energy			-	-			-	-
housing			-0.006	-0.007			-0.004	-0.005
demand			-	-0.001			-	-
employment			-0.003	-0.004			-0.004	-0.006
growth			-	-	-			0.001
money			-	-			0.005	0.006
foreign			-0.004	-0.005			-0.002	-0.003
financial			-	-			-	-
fiscal			-	-			0.001	0.002
uncertainty								
inflation expectations					-	-	-	-
consumer confidence					-0.001	-0.003	-0.003	-0.004
assets					-	-	-	-
energy					0.001	0.004	0.004	0.005
housing					-	-	-	-
demand					-0.003	-0.004	-0.004	-0.005
employment					-	-	-	-
growth					-	-	-	-
money					-0.026	-0.029	-0.031	-0.032
foreign					0.005	0.007	0.005	0.005
financial					-	-0.002	-0.001	-0.002
fiscal					-	-	-	-

Table N.14: LASSO and Elastic Net results with sentiments using Wu and Xia (2016) shadow rate, 1983–2013, with FRED factors and consumer sentiment index.
Sentiments are residuals from AR(1)

	Baseline		Extended		Uncertainty		All	
	lasso	elastic net	lasso	elastic net	lasso	elastic net	lasso	elastic net
Rate $(t-1)$	0.978	0.969	0.974	0.964	0.977	0.968	0.974	0.961
GRADM	0.01	0.012	0.01	0.014	0.011	0.013	0.011	0.015
GRAD0	0.005	0.009	0.005	0.01	0.006	0.01	0.005	0.009
GRAD1	-	0.001	-	0.002	-	0.001	-	0.005
GRAD2	0.001	0.004	0.002	0.004	-	0.003	0.001	0.002
IGRDM	-	-0.001	-	-0.002	-0.001	-0.002	-0.001	-0.003
IGRD0	-0.007	-0.009	-0.007	-0.01	-0.007	-0.009	-0.006	-0.009
IGRD1	0.006	0.006	0.005	0.004	0.006	0.005	0.005	0.003
IGRD2	-	-	-	-	-	-	-	-
GRAYM	0.002	0.003	0.001	0.003	0.003	0.005	0.003	0.005
GRAY0	0.004	0.007	0.005	0.01	0.005	0.009	0.005	0.01
GRAY1	-	-	-	-	-	-	-	-
GRAY2	-0.003	-0.005	-0.002	-0.005	-0.003	-0.005	-0.002	-0.004
IGRYM	-	-	-	-	-	-	-	-
IGRY0	-	-	-	-	-	-0.001	-	-
IGRY1	-	-	-	-0.001	-	-	-	-
IGRY2	-	-	-	-	-	-	-	-
GRAU0	-	-0.007	-	-0.008	-0.003	-0.009	-0.001	-0.009
Factor 1	-0.029	-0.03	-0.029	-0.03	-0.029	-0.03	-0.029	-0.03
Factor 2	-0.005	-0.004	-0.006	-0.004	-0.004	-0.003	-0.005	-0.004
Factor 3	-0.005	-0.01	-0.001	-0.007	-0.008	-0.013	-0.003	-0.009
Factor 4	-0.012	-0.012	-0.011	-0.012	-0.011	-0.012	-0.011	-0.012
Factor 5	0.016	0.019	0.015	0.019	0.016	0.017	0.015	0.018
Factor 6	-	-	-	-	-	0.001	-	0.001
Factor 7	-0.006	-0.008	-0.006	-0.01	-0.006	-0.008	-0.006	-0.009
Consumer Sentiment	-	-0.003	-	-0.004	-	-0.002	-	-0.003
positiveness								
inflation expectations			0.002	0.004			0.002	0.006
consumer confidence			0.002	0.003			-	0.001
assets			-	-0.001			-	-
energy			0.002	0.004			0.001	0.002
housing			-	-			-	-
demand			-	-			-	-
employment			-0.004	-0.007			-0.005	-0.008
growth			0.003	0.003			0.002	0.002
money			0.001	0.003			-	0.001
foreign			-0.004	-0.006			-0.003	-0.004
financial			-	-			-	-
fiscal			0.001	0.003			0.002	0.003
uncertainty								
inflation expectations					-	-	-	-
consumer confidence					-0.003	-0.003	-0.003	-0.004
assets					-	-	-	-
energy					0.004	0.005	0.003	0.005
housing					-0.002	-0.003	-0.001	-0.002
demand					-	-	-	-
employment					-	-	-	-0.001
growth					-	0.001	-	-
money					-	-	-	-
foreign					0.008	0.009	0.007	0.009
financial					0.002	0.003	0.001	0.002
fiscal					-	-	-	-

Appendix O Data description

All variables are in logarithms.

- Utilisation-adjusted TFP, cumulative. In natural logarithm. 1947:Q1–2017:Q4. Source: (Fernald, 2014).
- Business Sector: Average Weekly Hours, Seasonally Adjusted, Quarterly Index. Index 2009=100. In natural logarithm. 1947:Q1–2018:Q. Source: Federal Reserve Bank of St. Louis.
- Business Sector: Real Output, Seasonally Adjusted, Quarterly. Index 2009=100. In natural logarithm.1947:Q1–2018:Q1 (o). Source: Federal Reserve Bank of St. Louis.
- Working age population; Aged 15 and over; All persons. Not Seasonally Adjusted. 1955:Q1–2018:Q1. Source: Organisation for Economic Co-operation and Development.
- Private sector establishment births in thousands, divided by 1000 of population. Seasonally Adjusted. In natural logarithm. 1993:Q1–2017:Q3. Source: Bureau of Labor Statistics.
- Historical data New Business Incorporations in thousands, divided by 1000 of population. Not Seasonally Adjusted. In natural logarithm. 1948:M1–1994:M12. Source: Survey of Current Business, January/February 1996.

I construct establishment birth series similar to Brand et al. (2017).

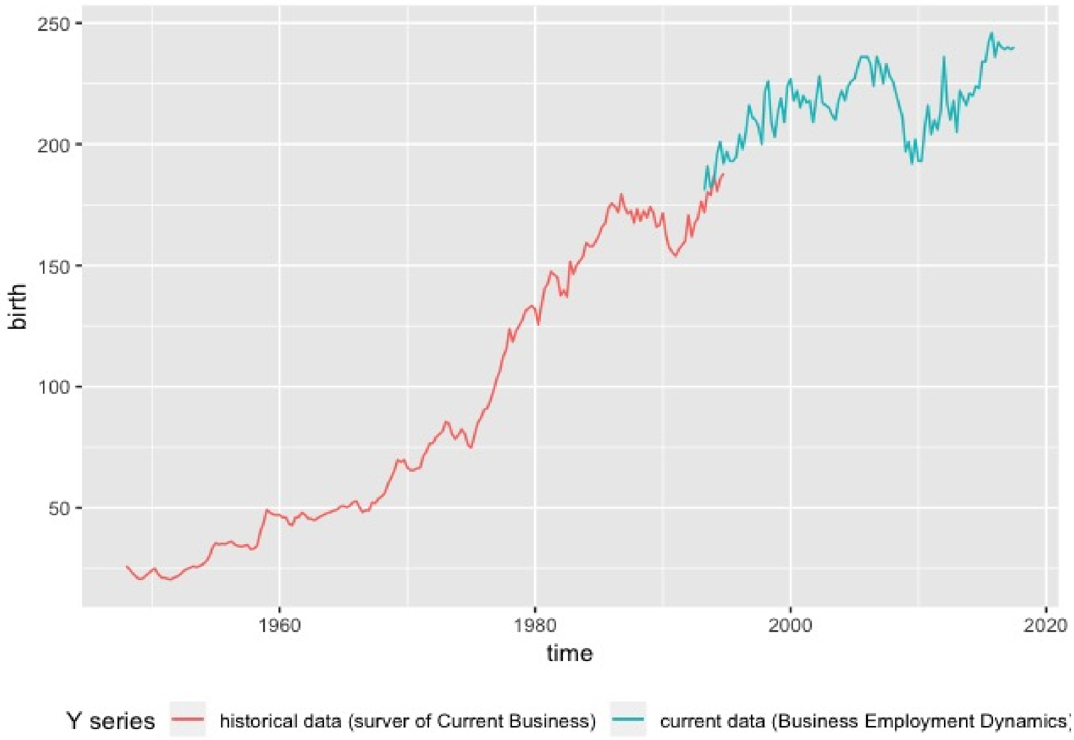


Figure O.1: Entrepreneurship birth data

Summary in Estonian

Teave, majandustsüklid ja rahapoliitika

Motivatsioon uurimistööks

Kas positiivse või negatiivse teabe avaldamine on rahapoliitika ja reaalse majandusaktiivsuse seisukohalt oluline? Missugune teave on olulisem? Millised on edastuskanalid? Kas üldsus tajub neile avaldatud teavet täpselt? Need on peamised uuringus tõstatatud küsimused. Uudistepõhise majandustsükli idee osutab sellele, et muutused ootustes võivad olla olulised majanduskõikumiste põhjustajad. Ootusi, et majandustingimused on tulevikus paremad – võttes arvesse olemasolevaid põhinäitajaid –, võivad esile kutsuda kas uudised tootmistegurite kõrgest kogutootlikkusest (TFP) tulevikus, mida peetakse n-ö kõvadeks uudisteks[74], või tugev kindlustunne[75] (Levchenko and Pandalai-Nayar, 2015). Käesolev töö heidab valgust n-ö pehmete uudiste[76] ootustekanalile. Et ajalehed on peamine kanal, mille kaudu eksperdid edastavad oma arvamusi laiemale avalikkusele, võivad seda laadi uudised suunata leibkondade ootusi.

Ootustel on makromajanduses väga oluline roll. Tavaliselt rakendatavate makroökonomeetriliste meetoditega kaasnevad väljajäetud muutujate probleemid (Lutkepohl, 2007). Üks neist väljajäetud muutujatest on inimeste ootused tulevase makromajandusliku keskkonna suhtes. Ökonomeetrikul, kes soovib õigesti kindlaks teha makromajanduslikke šokke, on väljajäetud muutujate probleemi ennetamiseks vaja sama teabekogumit, mis on olemas otsustajatel (vt nt Lutkepohl, 2007). Tulevast makromajanduslikku keskkonda käsitlevad uudised võivad olla üks neist väljajäetud muutujatest. Et tuvastada ootusi käsitleva-

[74] Uudised majanduse põhinäitajate kohta.

[75] Kindlustunnet võib käsitleda tugeva veendumusena, et tulevane majandusareng on positiivne, samas kui majandussubjektide vaateid tulevastele majandusoludele kirjeldatakse meeleolu kaudu (Nowzohour and Stracca, 2017). Teksti meeleolu ehk tonaalsuse määrab autori toon, hoiak või teemale antud hinnang, see ei sõltu teema enda tundesuunitlusest (Shapiro jt, 2017).

[76] Vastupidiselt kõvadele uudistele, s.o uudistele objektiivsete ja otseselt kvantifitseeritavate muutujate kohta nagu tootmine ja tööhõive, iseloomustab pehmeid uudiseid subjektiivne hinnang praegustele ja tulevastele majandusoludele (Shapiro, 2017).

test andmest makromajanduslikke šokke, tuleb empiirilises mudelis arvesse võtta uudiseid tulevaste majandusolude kohta (Levchenko and Pandalai-Nayar, 2015).

Need küsimused suurendavad uudiste- ja ebakindlusšokke käsitlevate uuringute populaarsust (Beaudry and Portier, 2006a; Bloom, 2009; Christiano et al., 2014). Nagu väidavad Feve ja Guay (2016), võivad majandustsükleid suunata oodatavad muutused tulevastes majandustingimustes, mis peaaegu kunagi tegelikult ei realiseeru, või meeleolušokid, mis tulenevad teabe vastuolulisusest ning võivad kaasa tuua optimismi- ja pessimismilaineid, mis ei ole majanduse põhinäitajate muutumisega üldse seotud. Paremate tulevaste majandusolude ootus, võttes arvesse olemasolevaid põhinäitajaid, võib tuleneda kas uudistest tootmistegurite kõrge tulevase kogutootlikkuse kohta või tugevast kindlustundest (Levchenko and Pandalai-Nayar, 2015).

Teadlased, kes püüavad arvesse võtta inimeste ootusi, kasutavad peamiselt Michigani Ülikooli tarbijauuringut (University of Michigan Survey of Consumers, 2019; Barsky and Sims, 2008; Feve and Guay, 2016), tuvastades samaaegsete mõjude piiranguid, et teha kindlaks uudistešokid (Beaudry and Portier, 2006a), hinnanguline kindlustunne erinevate stohhastilis-dünaamiliste tasakaalumudelite (DSGE) järgi (mis on tugevas korrelatsioonis Michigani Ülikooli tarbijameeleolu indeksiga (Angeletos et al., 2015) või hinnangulised uudised DSGE mudeli järgi (Schmitt-Grohe and Uribe, 2012). Lähtudes Barsky ja Simsi (2008) uuringust, kasutavad teadlased ootuste mõõtmiseks järgmist küsimust: kui rääkida riigis valitsevatest majandustingimustest tervikuna, siis kas teie arvates on meil järgmise viie aasta jooksul peamiselt head ajad või on suur tööpuudus ja majandussurutis või midagi muud? Levchenko ja Pandalai-Nayar (2015) määratlevad meeleolušokke ortogonaalsetena üllatusšokkide ja uudistega seotud TFP-šokkide suhtes, mis maksimeerivad oodatavusmuutuja lühiajalise prognoosivea dispersiooni või alternatiivina sisemajanduse koguprodukti (SKP) prognoosi või tarbijate kindlustunde indeksi.

Samas on Michigani Ülikooli tarbijauuringu kasutatavus mitmel põhjusel piiratud. Esiteks ei mõõda see inimeste ootusi täiuslikult. Teiseks kasutatakse seda üksnes Ameerika Ühendriikides. Kolmandaks, nagu väidavad Levchenko ja Pandalai-Nayar (2015), peame mittetehnoloogilise šoki eraldamiseks ootuseandmetest võtma arvesse tuleviku tootlikkuse uudiseid (st võtma arvesse erinevaid ootusi). Seetõttu käsitlevad Levchenko ja Pandalai-Nayar (2015) muutujate protsesse koos teiste ettevaatavate makromajanduslike agregaatidega vektorautoregressioonis (VAR). Et neid piiranguid lahendada ja pakkuda ootuste mõõtmisel alternatiivi Michigani Ülikooli tarbijauuringule, võib kasutada teistsugust lähenemisviisi, nimelt teksti tundmusanalüüsi, mis võimaldab ühtlasi mõõta inimeste erinevat tüüpi ootusi.

Kuigi paljud uuringud on kinnitanud, et põhiuudised (Beaudry and Portier, 2006a; Barsky and Sims, 2008; Schmitt-Grohe and Uribe, 2012; Larsen and Thorsrud, 2019b) on majandustsüklite ja majandusaktiivsuse peamine liikumapanev jõud, ei ole subjektiivse teabe või ekspertide positiivsete/negatiivsete arvamuste (tonaalsuse) mõju veel täies ulatuses uuritud. Uudiste tundmusanalüüsi kui ootuste kujunemise mehhanismi allikat saab kontrollida Carrolli (2001) järelduse abil – see sobib antud eesmärgiga, sest kodumajapidamised ei jälgi uusimat makromajanduslikku statistikat, vaid tõenäolisemalt jälgivad nad eri allikatest pärit uudiseid, kujundades oma ootusi tuleviku majandusarengu suhtes.

Eesmärk, uurimisküsimused ja -ülesanded

Lõputöö eesmärk on välja selgitada meedia või
Föderaalreservi (positiivse või negatiivsena) esitatud teabe mõju üldsuse ootustele ning selle mõju ülekandumine reaalmajandusse ja majandustsüklitesse.

Peamised uurimisküsimused on järgmised:

Missugusele subjektiivsele teabele avalikkus reageerib, kui ta kujundab oma ootusi majanduse, intressimäärade ja töötuse suhtes?

Milline on selle subjektiivse teabe pikaajaline mõju reaalmajandusele?

Milline on selle subjektiivse teabe roll rahapoliitikas?

Mis on meeleolude reaalmajandusse ülekandumise peamine mehhanism?

Seetõttu keskendub käesolev uuring ajaleheuudistele, mitte uudistele tulevastest TFP-šokkidest[77]. Tulevasi TFP-šokke käsitlevaid uudiseid on teaduskirjanduses ulatuslikult kajastatud, alates Carrolli (2001) ning Beaudry ja Portier' (2006a) uurimustest, samas kui uusimad uuringud keskenduvad uudiste ja ebakindluse ning nende pikaajalise mõju otsesele mõõtmisele (nt Shapiro et al., 2017; Larsen and Thorsrud, 2019b jne). Autor määrab kindlaks peamised avalikkusele uudiste edastamise mõju kanalid.

Sellest tulenevalt on uurimisülesanded järgmised:

Uurida teabe ja ootuste reaalmajandusele ja rahapoliitikale avaldatava mõju teoreetilist ja empiirilist tausta.

Töötada välja metoodiline raamistik uudiste tonaalsuse mõõt-

[77]põhiuudised

miseks mitmemõõtmelise objektina.

Töötada välja metoodiline raamistik, mille abil teha kindlaks eri tüüpi teabe mõju reaalmajandusele ja roll rahapoliitikas.

Käsitleda eri tüüpi teabe mõju empiirilisi tulemusi.

Selgitada välja, mis tüüpi teave on leibkondade ootuste seisukohalt kõige olulisem.

Uurida, millistele leibkondade ootustele rahapoliitika reageerib.

Uurida keskpanga meeleolude mõju rahapoliitilistes teadaannetes.

Uurida meeleolude reaalmajandusse edasikandumise kanaleid.

Uurimisobjekt, andmed ja metoodika

Uurimisobjekt hõlmab ajalehtede äriuudiste erinevaid kategooriaid ja nende mõju üldsuse ootustele. Uurimistöö peamine ülesanne on selgitada välja selle kanali mõju reaal- ja nominaalmajandusele.

Peamise metoodikana kasutan eri valdkondade – investeerimine, rahapoliitika ja majandusaktiivsus – uudiste tonaalsuse analüüsimiseks sobivaid masinõppe meetodeid. Eri tüüpi ootuste eristamist valideerivad esmalt teised autorid. Näiteks eristavad Beaudry ja Portier (2006a) investeerimisega seotud uudistešokke üldistest uudistešokkidest. Teiseks on see tuntud kui struktuurse vektorautoregressiooni (SVAR) pöördumatuse probleem, samas kui mudelist puuduvad olulised muutujad, mis leiduvad otsustajate teabekogumis. Praegused ootused majandus-, investeerimis- ja rahapoliitika suhtes sisalduvad eri otsustajate käsutuses olevas teabes ning aitavad tuvastada eelarve-, raha- ja muud tüüpi makromajanduslikke šokke.

Peamise andmeallikana kasutan USA tähtsamate ajalehtede ärirubriike. Uudisteartiklid muudetakse teemade aegridadeks, kasutades latentset Dirichleti jaotust (LDA) ja Doc2Vec manustust koos klasterdamisega. Seejärel kasutan leksikaalset lähenemisviisi, et määrata iga artikli tonaalsus. Leksikaalse lähenemisviisiga tehakse kindlaks positiivse/negatiivse, vaoshoitud ja ebamäärase tonaalsusega sõnade osatähtsus igas artiklis. Doc2Vec manustusest koos klasterdamisega ja LDA-st saadud teemade aegridade kombineerimine iga uudisteartikli tooniga võimaldab tuletada teemade aegread koos tonaalsusega.

Nende teemade aegridade abil tehakse kindlaks uudiste tüübid, mis oluliselt mõjutavad leibkondade ootusi tööpuuduse, intressimäärade ja inflatsiooni suhtes. Selleks kasutan lassoregressiooni koos FRED-MD andmebaasist pärit peamiste makromajanduslike näitajatega (McCracken and Ng, 2015). Valitud uudiseteemade dimensionaalsust vähendan põhikomponentide analüüsi (PCA) teel. Uuringus kasutatakse valitud teemade aegridasid struktuursetes vektorautoregressioonides

(SVAR), et ületada pöördumatuse probleem (vt täpsemalt Beaudry and Portier, 2006b), mis võimaldab eristada pehmete uudiste mõju rahapoliitikale ja tegelikule majandustegevusele ning uurida uudiste tonaalsuse mõju makromajandusele.

Et uurida Föderaalreservi reaktsiooni avalikkuse ootustele intressimäärade kehtestamisel, kasutan peamise andmeallikana avaturukomitee (FOMC) ärakirju, sest ametliku majandusstatistika prognoose korrigeeritakse ja see võib seetõttu erineda teabest, mis oli poliitikakujundajatele kättesaadav FOMC koosolekutel.

See võimaldab mul kontrollida teemasid, mida FOMC liikmed igal FOMC koosolekul arutasid. Peale selle kasutan leksikaalset lähenemisviisi, et määrata kõige sagedamini esinevate majandusfraaside tonaalsus (positiivne/negatiivne, ebamäärane). Need meeleolu kandvad fraasid on seejärel rühmitatud kaheteistkümnesse kategooriasse: inflatsiooniootused, tarbijate kindlustunne, varad, energia, eluase, nõudlus, tööhõive, majanduskasv, raha, välismaa, finantsturud ja eelarvepoliitika.

FOMC liikmete kasutatud majandusteemalisi fraase koos neile omistatud tonaalsusega (positiivne/negatiivne, ebamäärane) kasutatakse seejärel nende teabeliikide kindlakstegemiseks, mis on olulised intressimäärade muutuste seisukohalt. Rakendades lasso- ja elastvõrguregressiooni, näitan, et FOMC liikmete kasutatud tonaalsus sisaldab lisateavet Taylori reegli hindamiseks isegi juhul, kui võetakse arvesse Greenbooki ametlike prognooside ja prognooside korrigeerimise andmeid (Greenbook Historical and Forecast Data, 2019).

Uuringu uudsus

Kuigi paljud uuringud on kinnitanud, et põhiuudised (esimesed uuringud olid Beaudry and Portier, 2006a; Barsky and Sims, 2008; Schmitt-Grohe and Uribe, 2012; Larsen and Thorsrud, 2019b) on majandustsüklite ja majandusaktiivsuse peamine liikumapanev jõud, ei ole subjektiivse teabe või ekspertide positiivsete/negatiivsete arvamuste (tonaalsuse) mõju veel täies ulatuses uuritud. Kui Milani (2006 ja 2017) ning Hirose ja Kurozumi (2012) kasutasid küsitluste andmeid lisateabena, et selgitada välja meeleolude ja uudiste mõju, siis ajalehtede kaudu edastatavate emotsioonide mõju reaalmajandusele ei ole piisavalt uuritud.

Käesoleva uurimuse eesmärk on välja selgitada meedia või Föderaalreservi (positiivse või negatiivsena) esitatud teabe mõju üldsuse ootustele ning selle mõju ülekandumine reaalmajandusse ja majandustsüklitesse. Uurimuse uudsus seisneb ajalehtede põhjal mõõdetud meeleolude kasutamises reaalmajandusele ja rahapoliitikale avalduva makromajandusliku mõju tuvastamisel.

Esimese uurimisküsimuse osas selgus, et majandusega seotud teemade aegrida osutus kõige olulisemaks leibkondade intressimääraootuste seisukohalt, eluasemega seotud teemade aegrida oli kõige olulisem töötusega seotud ootuste seisukohalt ja pikaajalisi laene käsitlevate teemade aegrida oli kõige olulisem inflatsiooniootuste seisukohalt. Peale selle saadi ka nende teemade aegread eraldi, kasutades kaht erinevat lähenemisviisi teksti teisendamisele: LDA ja Doc2Vec k-keskmiste++ klasterdamise teel. Lisaks leiti, et nende teemade aegridade põhikomponendil on majandusaktiivsuse näitajate suhtes juhtivad omadused.

Mis puudutab teist uurimisküsimust, siis kasutatakse uuringus eespool mainitud teemade aegridu tavapärastes VAR-ides koos ootusmuutujatega, mis näitavad, et positiivne pehmete uudiste šokk viib reaalse majandusaktiivsuse ja tarbimise pikaajalise suurenemiseni, samas kui mõju inflatsioonile ja intressimäärale on samuti positiivne, kuid ajutine. Pealegi moodustab pehmete uudiste šokk umbes 20% reaalse majandusaktiivsuse prognoosivea dispersioonist pikematel perioodidel, samas kui meeleolu- või ootusešokkide mõju on vähem oluline. See aitab empiiriliselt lahutada uudistešokkide ja meeleolušokkide mõju, mistõttu ei ole vaja kasutada SVAR-ides ad hoc teoreetilise tuvastamise eeldusi.

Käesolev uuring täiendab Barsky ja Simsi (2008), Shapiro jt (2017) ning Larseni ja Thorsrudi (2019b) järeldusi, et inflatsiooni üleminekureaktsioon uudistešokile võib olla positiivne. See viitab asjaolule, et uudistešokke ei pruugita käsitleda oodatavate eksogeensete TFP-šokkidena, mis avab ukse alternatiivsetele uudistešokikanalitele, nagu endogeenne majanduskasv või endogeense levikuga oodatavad nõudlusšokid. Niisugune järeldus on kooskõlas Leduci ja Silli (2013) tulemustega, kes kasutasid VAR-i küsitlustest saadud ootusemuutujaid ja leidsid, et majanduskasvu ootus toob kaasa töötuse vähenemise, inflatsiooni tõusu ja rangema rahapoliitika.

Peale selle järeldasid Leduc ja Sill (2013), et ootusšokid moodustavad suure osa reaalse majandusaktiivsuse dispersioonist pikematel perioodidel, samas kui selle uuringu tulemused näitavad, et uudistešokid on majandusaktiivsuse seisukohalt pikemas perspektiivis olulisemad kui kodumajapidamiste ootused. Vastupidiselt Barsky ja Simsi (2008) järeldustele näitab käesolev uuring, et uudiste meediakanal on oluline reaalse majandusaktiivsuse ja tarbimise seisukohalt (see on kooskõlas ka Larseni ja Thorsrudi (2019b) seisukohtadega). Tulemused võivad erineda seetõttu, et Barsky ja Sims (2008) kasutasid Michigani Ülikooli küsitluse vastuseid uudiste kohta, kuid Larsen ja Thorsrud (2019b) ning mina kasutame ajaleheartiklite teemade aegridu ja korreleerime neid üldsuse ootustega.

Mis puudutab kolmandat uurimisküsimust, siis minu teada on see esimene uuring, milles käsitletakse kõiki FOMC arutelude majandusega seotud väljendeid, et leida komitee otsustega seotud muutujaid. Varasemates uuringutes koostasid autorid eelnevalt huvipakkuva kategooriaga seotud sõnade loendi (seda tegid teiste seas ka Peek et al. (2016) ning Cieslak and Vissing-Jorgensen (2018)). Pealegi on see esimene uuring, mis kasutab ajalehtede meeoleolusid keskpanga meeleolude asendajana rahapoliitilistes teadaannetes.

Uuring täiendab hiljuti avaldatud töid, milles rahapoliitikat uuritakse lingvistiliste meetodite abil. Tulemused on kooskõlas varasemate järeldustega, mille kohaselt finantsmuutujad on FOMC otsuste seisukohalt olulised (Peek et al., 2016; Cieslak and Vissing-Jorgensen, 2018; Wischnewsky et al., 2019). Samas laiendab uuring varasemaid järeldusi seoses FOMC ebamäärase tonaalsusega finantsmuutujate käsitlemisel. Lisaks sellele ei tugine see uuring sõnade loendile, vaid otsib FOMC ärakirjadest olulisi majandusalaseid väljendeid.

Esiteks, et teha kindlaks, kuidas pehmed uudised rahapoliitikat mõjutavad, uurin muidu tavapärases VAR-is Föderaalreservi ja laenude teema aegridade mõju. Leian, et laenuteema aegrida on rahapoliitika ülekandemehhanismis olulisem kui Föderaalreservi teema. Seda seetõttu, et leibkonnad ei pööra rahapoliitikat käsitlevatele uudistele kuigi suurt tähelepanu. Samas võib nii tavapärane kui ka ebatraditsiooniline rahapoliitika kaasa tuua pikaajaliste intressimäärade tõusu ja mõjutab seega selle kanali kaudu kodumajapidamiste ja ettevõtete otsuseid. Võlakirjade ülekurss väheneb vastusena pehmete uudiste positiivsele šokile, mis üldise tasakaalu mõju tõttu toob kaasa majandusaktiivsuse suurenemise ja rahapoliitika karmistumise.

Tulemused, mis puudutavad tarbijate meeleolude tähtsust Föderaalreservi eesmärgi seisukohalt, on kooskõlas Hanseni ja McMahoni (2016) järeldustega, kes kasutasid narratiivset lähenemisviisi FOMC avaldustele, et teha kindlaks eelkommunikatsiooni mõju. Nad ei tuvastanud eelkommunikatsioonišokkide olulist panust ja leidsid, et niisugused šokid moodustavad väikese osa prognoosivigade dispersioonist reaalmuutujates. Ka käesolevas uuringus ei leita, et ajalehtedes kajastatud Föderaalreservi meeleoludel oleks suur mõju inflatsioonile või majandusaktiivsusele. Üks võimalik põhjus, miks mõju on väike, on see, et uuringus kasutatakse igakuiseid andmeid.

Siiski on tulemused kooskõlas Lewise jt (2020) järeldustega, kes kasutasid kiirtuvastamist ja leidsid, et rahapoliitilised uudised eelkommunikatsiooni kohta ei avaldanud olulist mõju leibkondade veendumustele. Selle asemel avastasid nad, et kodumajapidamiste ootusi mõjutavad oluliselt uudised sihtintressimäära muutustest. See on kooskõlas praeguses uuringus leitud kanaliga, mille kohaselt rahapoliitilised uudised avaldavad mõju pikaajaliste intressimäärade muutuste kaudu.

Selle uuringu tulemused täiendavad D'Amico ja Kingi (2017) tulemusi, sest kasutan oma analüüsis rahapoliitilisi uudiseid, mitte küsitlusprognoose. D'Amico ja King (2017) märkisid, et uudistel tulevase rahapoliitika kohta, mille asendajaks olid küsitlusprognoosid, on suur, vahetu ja püsiv mõju inflatsioonile ja majandusaktiivsusele. Lisaks näitavad varasemad DSGE mudelite tulemused, et rahapoliitika uudistešokid on majandustsüklite seletamisel enamasti olulisemad kui ootamatud rahapoliitilised šokid (Milani and Treadwell, 2012; Gomes et al., 2017). Selle uuringu tulemused näitavad, et ajalehed ei ole oodatava rahapoliitika suhtes täheldatava suure mõju peamine kanal.

Pikaajaliste intressimäärade muutmise alternatiivina võib Föderaalreservi eesmärk olla muuta tarbijate inflatsiooniootusi otse, nagu osutasid ka Flack jt (2019). Muutused leibkondade inflatsiooniootustes mõjutavad majandust tajutava reaalintressimäära kaudu (Coibion et al., 2020), kuid selles uuringus ei leitud empiirilist kinnitust, et majapidamiste inflatsiooniootusi muutev otsekanal oleks oluline.

Teiseks sisaldavad FOMC liikmete positiivsed arvamused inflatsiooniootuste, tarbijate kindlustunde, finantsturgude ja eelarvepoliitika suhtes lisateavet intressimäärade muutuste kohta. Oluliseks osutus ka FOMC liikmete ebakindlus finantsturgude, rahaagregaatide ja inflatsiooniootuste suhtes. Ebakindlus finantsturgude, rahaagregaatide ja inflatsiooniootuste suhtes on jätkuvalt oluline intressimäärade muutuste seisukohalt, isegi kui võtta arvesse prognooside korrigeerimist. Peale selle analüüsin ma FOMC esimeeste kasutatud tonaalsust ja selle võimalikku seost intressimäärade muutustega. Tulemused näitavad, et esimeeste kasutatud ebamäärane toon rahaagregaatide ja finantsturgude kirjeldamisel on oluline.

Sarnaselt käesoleva uuringu tulemustega leidsid Oet ja Lyytinen (2017), Boukus ja Rosenberg (2006), Cecchetti (2003) ning Apel ja Grimaldi (2012), et Föderaalreservi teadetest eraldatud teemad sisaldavad lisateavet.

Tulemused on kooskõlas ka Peeki jt (2016) ning Cieslaki ja Vissing-Jorgenseni (2018) omadega, kes leidsid, et FOMC arutelud ja protokollid finantsstabiilsuse ja aktsiaturgude kohta võimaldavad ennustada Föderaalreservi intressimäärade muutusi. Varem on leitud, et USA rahapoliitika reageerib ka muutustele ettevõtete krediidiriski marginaalides (Caldara and Herbst, 2019) ja aktsiate ülekursis (Cecchetti, 2003), kuid see uuring ei toeta varasemaid tulemusi.

Tulemused täiendavad ka Clarida jt (2000) järeldusi, kes leidsid, et pärast 1979. aastat on intressimäärapoliitika oodatava inflatsiooni suhtes palju tundlikum. Selle uuringu tulemuste kohaselt on poliitikakujundajad alates 1979. aastast pööranud suuremat tähelepanu inflatsiooniootustele ja finantsturgudele.

Kolmandaks näitab uuring, et ajalehed kajastavad FOMC teadaandeid järgmisel päeval. Keskpanga teave kandub tootluskõvera kaudu edasi selle avaldamise päeval. See leid seab kahtluse alla tavapärased rahapoliitiliste šokkide tuvastamise strateegiad, mis eeldavad, et rahapoliitika väljakuulutamise ajal on tegemist vaid üht tüüpi signaaliga (vt nt Gertler and Karadi, 2015; Jarocinski and Karadi, 2020; Miranda-Agrippino and Ricco (avaldamisel)). Peale selle ei ole tavapärase tuvastamise kohaselt oluline, mida keskpank oma teadaandes tegelikult ütles5 (Gürkaynak et al., 2005; Gürkaynak et al., 2020). See uuring näitab, et keskpanga teade mõjutab oma avaldamispäeval ka tootluskõverat.

Mis puudutab neljandat uurimisküsimust, siis meeleolude peamine edastuskanal toimib töötundide kasvu ja majandusse sisenejate arvu suurenemise kaudu. Tarbijate tarbimiskäitumine ei reageeri sellele šokile.

Uurimuse struktuur ja peamised tulemused

Teises peatükis käsitletakse ootuste ja uudiste majandusliku mõju teoreetilisi aluseid ning vaadatakse läbi selle teema peamised empiirilised järeldused.

Lucase (1976) põhjaliku töö kohaselt eeldavad tavapärased makromajanduslikud mudelid, et otsustaja on mudeli struktuurist, selle parameetritest ja šokkide jaotusest täielikult informeeritud (ratsionaalsete ootuste eeldus). Teabe mõju väljaselgitamiseks tuleks seda eeldust leevendada. Selleks on mitu võimalust.

Esimene on n-ö kleepuvuse sisseviimine mudelitesse. Mankiw ja Reis (2002) võtsid kasutusele kleepuva teabe mudeli, Woodford (2001) ja Sims (2003) aga pakkusid samal ajal välja n-ö mürarikka teabe mudelid. Uudiste rollile ootuste kleepuvuses juhtis tähelepanu Carroll (2001 ja 2003).

Teine lähenemisviis on majandussubjektide ootuste otsene modelleerimine. Roberts (1998) ja Branch (2004) pakkusid välja uusi ootuste kaasamise mudeleid, samas kui teised teadlased hakkasid arvestama uudiste olulisusega (Beaudry and Portier, 2004; Beaudry and Portier, 2006b) ja muutma teoreetilisi mudeleid, et need suudaksid jälgida uudiste (Barsky and Sims, 2008; Jaimovich and Rebelo, 2009; Schmitt-Grohe and Uribe, 2012; Haan and Kaltenbrunner, 2009; Khan and Tsoukalas, 2012), meeleolude (Benhabib et al., 2012; Angeletos and

La'O, 2013) ja ootusšokkide mõju (Evans and Honkapohja, 2001; Milani, 2006; Milani, 2017).

Rahapoliitika teabemõjusid uuriti samamoodi, lisades teabemõjud teoreetilistesse mudelitesse (Christiano et al., 2007; Milani and Treadwell, 2012; Laseena and Svensson, 2011; Gomes et al., 2017).

Teabe rolli empiirilisi mõjusid makromajandusele uuriti, tuvastades uudiste- ja ootusšokke vektorautoregressioonides. Beaudry ja Portieri (2006a) põhjalik uurimus muutis selle uurimisteema populaarseks. Tuginedes lühi- ja pikaajaliste piirangutega vektorautoregressioonidele, leidsid autorid, et uudistešokid on majandustsükli kõikumistes olulised tegurid. Edasistes sama valdkonna uurimustes kasutati vektorautoregressioonides erinevaid identifitseerimismeetodeid ja üldjuhul kinnitati uudistešokkide tähtsust majandustsüklites (Barsky and Sims, 2008; Beaudry and Lucke, 2009; Sims, 2009; Zeev and Khan, 2015). Sarnastes ootusšokkide uuringutes (Leduc and Sill, 2013) leiti, et ootused on majandustsükli kõikumiste olulised suunajad.

Viimasel ajal on uudiste- ja ootusšokkide majandusliku mõju uurimisel populaarseks muutunud masinõppemeetodid, mis on peamiselt abiks ajaleheartiklite põhjal uudiste ja ootuste indeksite koostamisel (Fan et al., 2016; Shapiro et al., 2017; Goshima et al., 2019; Larsen and Thorsrud, 2019a; Larsen and Thorsrud, 2019b et al.) ning uudiste- ja ootusšokkide mõju uurimisel uute väljatöötatud näitajate põhjal.

Kolmandas peatükis kirjeldatakse meeleolude analüüsimise erinevaid metoodikaid ja esmaseid andmeallikaid. Esiteks kasutasin nelja tähtsama USA ajalehe andmeid: The New York Times 1980–2019, The Washington Post 1981–2019, The Los Angeles Times 1985–2019 ja The Chicago Tribune 1985–2019. Töötasin artiklid eelnevalt läbi, et need sisaldaksid statistiliste andmete asemel ainult ekspertide subjektiivseid arvamusi, ning arvutasin välja iga lause positiivsuse. Seejärel rakendasin artiklite teemadeks teisendamisel kaht erinevat meetodit: latentne Dirichleti jaotus (LDA) ja Doc2Vec. Lõpuks, ühendades tonaalsuse (positiivsuse) teemadega, sain 40 erineva teema aegread, mida kasutasin edasises analüüsis.

Lisaks kasutasin andmeallikana föderaalse avaturukomitee (FOMC) ärakirju, et uurida erinevate teemade olulisust FOMC liikmete jaoks nende rahapoliitiliste otsuste tegemisel. Tegin kindlaks majandusega seotud sõnade kombinatsioonid ja omistasin igale majandusalasele fraasile tonaalsuse (positiivsuse).

Neljandas peatükis on esitatud ajalehteartiklite teemade aegridadeks jaotamise peamised tulemused. Mõned teemade aegread, mis on saadud erinevate metoodikate abil (LDA ja Doc2Vec), on sarnased ja pealegi tugevas korrelatsioonis. Need on aegread, mis käsitlevad majandust, eluasemeturgu, pikaajalisi laene, finantsturge, ettevõtete kasumeid, tööturgu, rahapoliitikat jne. Lisaks on mõned aegread tugevas korrelatsioonis USA majandustsüklitega.

Uurin ka, millised teemade aegread on seotud tarbijate ootustega töötuse, intressimäärade ja inflatsiooni suhtes vastavalt Michigani Ülikooli tarbijauuringule (2019). Selleks kasutasin lassoregressiooni. Sõltuvad muutujad on tarbijate ootused, parempoolse külje muutujad aga minu poolt välja töötatud teemade aegread ja ametlikud statistilised andmed. Tulemused näitavad, et majandusteema aegrida on oluline intressimäära ootuste seisukohalt, eluasemeteema aegrida tööpuuduse ootuste seisukohalt ning pikaajaliste laenude teema aegrida on oluline tarbijate intressimääraootuste seisukohalt. Veelgi enam, eespool nimetatud teemade aegridade esimene põhikomponent on tugevas korrelatsioonis USA suure makromajandusliku andmebaasi esimese teguriga.

Viiendas peatükis võetakse vaatluse alla eri tüüpi teabe mõju reaalmajandusele ja rahapoliitikale ning esitatakse selle käsitluse peamised tulemused. Kasutan tarbijate ootuste seisukohalt olulisi teemade aegridu ja nende esimest põhikomponenti, et uurida ajalehtedes avaldatud eksperdiarvamuste mõju reaalmajandusele. Kasutan Bayesi vektorautoregressiooni toodangu, tarbimise, inflatsiooni, intressimäära, kõvade uudiste asendaja (uudised makromajanduse põhinäitajate kohta), pehmete uudiste asendaja (ajalehtedes avaldatud eksperdiarvamused) ja tarbijate ootustega seoses. Tulemused näitavad, et pehmed uudised on majanduse kogutoodangu oluline pikaajaline suunaja.

Sellele vaatamata ei mõjuta ajalehtede rahapoliitikaga seonduv meeleolu reaalmajandust. Seda seetõttu, et üldsus ei pööra seda laadi uudistele oma ootuste ja tulevase majanduskäitumise kujundamisel kuigi suurt tähelepanu.

Kuuendas peatükis käsitletakse meeleolude rolli rahapoliitikas. Kasutan lasso- ja elastvõrguregressiooni koos majandusega seotud tonaalsusega FOMC ärakirjades ja ametlikes prognoosides ning leian, et FOMC liikmed jälgivad rahapoliitiliste otsuste tegemisel mitte ainult SKP lõhet ja inflatsiooni, vaid ka muid tulevikku suunatud näitajaid, nagu tarbijate kindlustunne, inflatsiooniootused, finantsvarad ja energiahinnad.

Lisaks leian, et ajaleheartiklid järgivad rahapoliitilisi teadaandeid täpselt ja kajastavad neid järgmisel päeval. Samal ajal edastatakse rahapoliitikat finantsturgude kaudu, kus teadaanded mõjutavad tootlust ja intressimäärasid samal päeval. Lisaks reageerivad turuosalised mitte ainult rahapoliitikat käsitlevatele uudistele, vaid ka finantsturgudele, energiahindadele, rahvusvahelistele uudistele ja vahetuskurssidele. Seetõttu kanduvad rahapoliitika tegelikud mõjud edasi pikaajaliste intressimäärade muutuste kaudu.

Seitsmendas peatükis uuritakse tuvastatud šokkide reaalmajandusse ülekandumise mehhanismi. Pehmete uudiste šokid mõjutavad pikaajalises plaanis kogutoodangut uute ettevõtete loomise ja tööjõu tööaja pikenemise kaudu.

Kaheksandas peatükis esitatakse järeldused ja üheksas peatükk käsitleb tulevast uurimistööd.

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