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Identification of monetary policy shocks from FOMC transcripts*

Nataliia Ostapenko †

Abstract

I propose a new approach to identifying exogenous monetary policy shocks that requires no priors on the underlying macroeconomic structure, nor any observation of monetary policy actions. My approach entails directly estimating the unexpected changes in the federal funds rate as those which cannot be predicted from the internal Federal Open Market Committee's (FOMC) discussions. I employ deep learning and basic machine learning regressors to predict the effective federal funds rate from the FOMC's discussions without imposing any time-series structure. The result of the standard three variable Structural Vector Autoregression (SVAR) with my new measure shows that economic activity and inflation decline in response to a monetary policy shock.

JEL Classification: E52, E31, E00

Keywords: monetary policy, identification, shock, deep learning, FOMC, transcripts

1 Introduction

Is it possible to identify an exogenous monetary policy shock? In economic systems almost everything depends on everything else, therefore, researchers usually try to identify exogenous variation in interest rates to describe the implications for the economy. The problem lies in the fact that a monetary policy shock might be the Federal Reserve's (the Fed's) reaction to

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changes in macroeconomic indicators. That might lead to the problem of reverse causality (Gertler & Karadi (2015)) or omitted variable bias (Romer & Romer (2004)).

The Fed should control the output gap and inflation via a monetary policy instrument. Since an output gap is a latent indicator, the Fed might use some economic indicators in deciding on monetary interventions. Inferring exogenous monetary policy changes from the usual federal funds rate in Vector Autoregression has some drawbacks. First, excluding relevant economic variables from a Vector Autoregression leads to incorrectly identified monetary policy shocks and a change in monetary policy might be the Fed's reaction to some economic events. Second, the Fed might have additional insider information (Romer & Romer (2000)) and it might react with a monetary policy instrument in response. Third, recent empirical findings have shown that the Fed reacts, unexpectedly from the theoretical point of view, to some financial market indicators (Peek et al. (2015), Cieslak & Vissing-Jorgensen (2018)). One plausible reason is that FOMC (Federal Open Market Committee) members regard these variables as good indicators of the forward trajectory of the economy (Shapiro & Wilson (2019)). Fourth, there might be some anticipation effect since monetary actions might be systematic responses to information about future developments (Romer & Romer (2004)). Employing an inappropriate measure of monetary policy may obscure an important relationship between monetary policy and other economic variables, or create the appearance of a relationship where there is no true causal link (Romer & Romer (2004)).

An exogenous monetary policy shock, therefore, is identified by employing a monetary policy instrument that is free from the anticipation and endogenous responses of the FOMC. One of the most popular methods for dealing with this is to purify the federal funds rate from anticipation and reactions to economic indicators, as was done by Romer & Romer (2004) for instance. In this paper, I propose an alternative approach to purging the monetary policy instrument from anticipation and reactions by employing a text analysis of FOMC meeting transcripts, which represent the most detailed record of discussion of interest rate change from FOMC meetings. Since these discussions in FOMC meetings contain the arguments of FOMC members about future policy changes, they may also contain more information than *Greenbook Historical and Forecast Data* (2019), which were used by Romer & Romer (2004) to purge the federal funds rate.

I purge the federal funds rate by taking the difference between the federal funds rate and the fit from an ensemble of basic regressors on the FOMC transcripts. This measure, therefore, might be considered exogenous to the Fed's expectations. I transform the FOMC transcripts to a vector representation by employing Neural Network Word2Vec (see Mikolov et al. (2013)). This Neural Network was trained on Google News. I use this Neural Network to transform words from transcripts into vectors. Transformations of these vectors were further used with an ensemble of basic regressors to predict the federal funds rate for the next month. The difference between the actual federal funds rate and the predicted one is interpreted as a measure of the monetary policy shocks, similar to the approach by Romer & Romer (2004). My findings show that by employing the ensemble of basic regressors together with the Neural Network's transformation of FOMC transcripts it is possible to accurately predict the federal fund rate for the next month (mean squared error is 0.55).

Methodologically, the paper is related to the works on identifying monetary policy shocks (Gertler & Karadi (2015), Romer & Romer (2004), Romer & Romer (2010)). My approach does not rely on any time-series information and therefore it is possible to include any additional macroeconomic variables to identify the effects of different economic shocks. My work also adds to the work of Gertler & Karadi (2015) in that the shock is a surprise not only to market participants but also to the Fed.

Structural Vector Autoregression (SVAR) results with my new measure of exogenous monetary policy changes show impulse responses of economic activity and inflation that are completely compatible with the macroeconomic theory. In comparison with Romer & Romer (2004), the results with the new measure presented here are more robust to period truncation and different lag lengths. This suggests that the new measure of unexpected interest rate changes is potentially free from endogenous responses and anticipatory movements.

SVAR results using the new measure of monetary policy shocks used in the framework of Gertler & Karadi (2015) also confirm the monetary policy transmission mechanism: excess bond premium, mortgage spread and commercial paper spread increase in response to a monetary policy shock identified using the new measure. The sign and persistence of the effect are in line with the results of Gertler & Karadi (2015) in a setting with external instruments. This result might also confirm that this new measure of monetary policy shocks is free from anticipation and responses of monetary authority to financial variables.

The paper also adds to the literature on processing information from the FOMC meetings addressing economic questions. To the author's best knowledge, this is the first paper that employs a vector representation of words from a Neural Network in this context. Shapiro & Wilson (2019) directly estimated the FOMC objective function from the sentiment expressed by participants at internal meetings. Boukus & Rosenberg (2006) employed Latent Semantic

Analysis (LSA) to analyse the information of FOMC minutes from 1987–2005, and showed that these themes are correlated with current and future economic conditions, as well as treasury yield changes around the time of the release of the minutes. Moniz & de Jong (2014) designed an automated system that predicts the impact of central bank communications on investor interest rate expectations using the Bank of England's Monetary Policy Committee Minutes.

Rybinski (2019) used a supervised machine learning framework based on the dictionary and Wordscores models that makes it possible to analyse interactions between the official central bank communication (policy statements) and media discourse (newspaper articles). Cieslak & Vissing-Jorgensen (2018) employed a textual analysis of FOMC minutes and transcripts. The authors found that FOMC participants are more likely to mention the stock market after market declines and the frequency of negative stock market mentions in FOMC documents predicts target rate cuts. Peek et al. (2015) used word counts of terms related to financial instability appearing in FOMC meeting transcripts and showed that the word counts of terms related to financial instability do influence monetary policy decisions. Lima et al. (2019) utilised machine learning to identify the most predictive words of a given Fed minute and used them to derive new predictors, which improve real-time forecasts of output growth by a statistically significant margin.

The remainder of the paper proceeds as follows. Section 2 describes a processing technique for FOMC transcripts. Section 3 presents the core results of the paper. Section 4 shows the applications of exogenous interest rate changes for identifying monetary policy shocks. Section 5 concludes.

2 Data

2.1 FOMC transcripts

The Federal Open Market Committee (FOMC) holds eight scheduled meetings during the year and additional meetings as needed. At these meetings the FOMC decides on interest rate changes to adjust inflation. Beginning with the 1994 meetings, the FOMC Secretariat has produced transcripts shortly after each meeting from an audio recording of the proceedings, lightly editing the speakers' original words where necessary to facilitate the reader's understanding (*Federal Open Market Committee: Transcripts and other historical materials* (2019)).

The traditional policy tool of the Federal Reserve is to target the federal funds rate: the Fed sets the target and then conducts open market operations so that the overnight interest rate on funds deposited by banks at the Fed reaches that target. Obviously, reaching the target is sometimes harder, especially in times when there is a lot of uncertainty in the markets. Deviations between the federal funds rate and its target are short-lived, which shows that the open market operations do have the desired effect (*The FRED Blog* (2019)).

The Federal Funds Rate (FFR) is provided by Federal Reserve economic data. FOMC transcripts for 2008–2013 were downloaded from the Fed webpage[1] (*Federal Open Market Committee* (2019)). Total timespan is 1976–2013 and, therefore, I have 316 observations.

After each meeting, the FOMC releases to the public a statement regarding its policy decision. FOMC statements about the policy and economic outlook typically require time to digest and are subject to a great deal of uncertainty with respect to how they are interpreted by other financial market participants, so that the process of assimilating the information contained in the statements is not instantaneous. The FOMC might use it as a signalling device since FOMC statements likely exert effects on financial markets through their influence on the expectations of financial market participants in regard to future policy actions (Gurkaynak et al. (2005)). In particular, the fact that FOMC statements have such significant effects on long-term yields suggests that the FOMC may be able to credibly commit to future plans for the federal funds rate. FOMC minutes are released three weeks after the FOMC meeting (Figure 1).

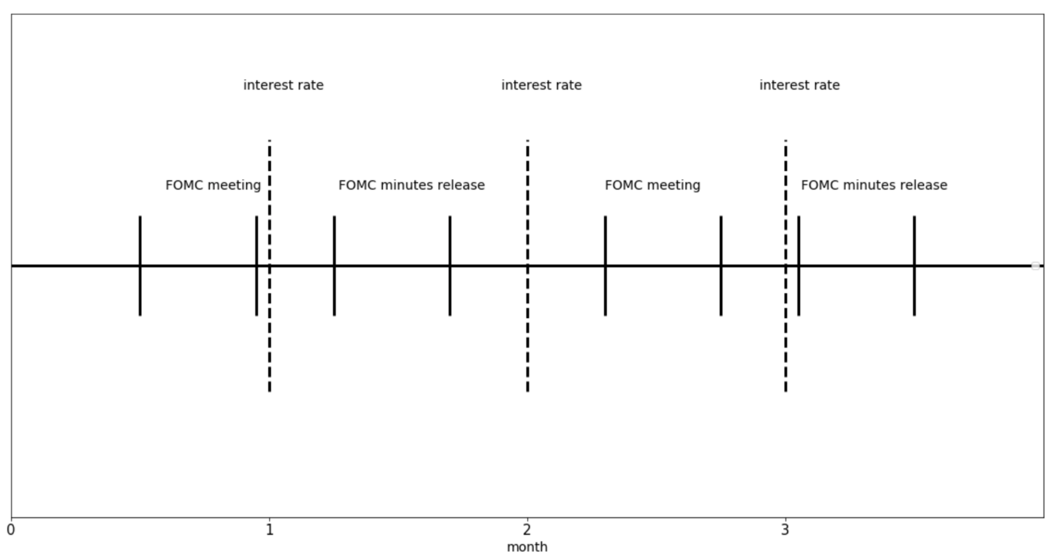


Figure 1: Timing of the events

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

Changes in the federal funds rate target themselves are immediately and clearly observable to all financial market participants within minutes of the announcement (Gurkaynak et al. (2005)), while by contrast FOMC transcripts become publicly available 5 years after the meeting. Therefore, it is impossible to react to FOMC transcripts. At the same time FOMC transcripts contain more information than FOMC minutes, which are available to the public after three weeks.

The timing of events (Figure 1) makes it possible to use each transcript at date t as a feature[2] and the effective FFR at the beginning of the next month as a target variable[3], since the interest rate at the beginning of the next month is free from the effect of the release of the minutes and there might also be enough time for market participants to digest to the policy statement. Before 1979, the FOMC did not announce its target interest rate after the meetings. In February 1994, the FOMC formally announced its policy changes for the first time.

Fitting the federal funds rate at the beginning of the next month from FOMC transcripts and interpreting residuals between the actual federal funds rate and this fit as monetary policy shocks can be approved in the framework presented by Christiano et al. (1999), who identified a monetary policy shock as the disturbance in an equation of the form (1):

$$S_t = f(\Omega_t) + \sigma_s \varepsilon_t^s \tag{1}$$

where S_t is the instrument of the monetary authority (the federal funds rate), f is a linear function that relates S_t to the information set Ω_t. The random variable, $\sigma_s \varepsilon_t^s$, is a monetary policy shock. One interpretation of f and Ω_t is that they represent the monetary authority's feedback rule and information set, respectively. One interpretation of $\sigma_s \varepsilon_t^s$ is that it reflects exogenous shocks to the preferences of the monetary authority, perhaps due to stochastic shifts in the relative weight given to unemployment and inflation. These shifts could reflect shocks to the preferences of the members of the FOMC, or to the weights by which their views are aggregated. A change in weights may reflect shifts in the political power of individual committee members or in the factions they represent Christiano et al. (1996).

[2]A feature in machine learning means a right hand side variable in a regression

[3]A target variable in machine learning means a left hand side variable in a regression

2.2 Transcript processing

I follow Acosta (2015) for the text processing strategy. First, terms from a stoplist are excluded (Appendix A presents the full list of stopwords). This list contains common words that contribute little meaning to the documents: names and surnames of participants, dates, numbers, some general expressions. The excluded words are predominantly prepositions and pronouns. Also, last names of FOMC member, months, and Federal Reserve District numbers are excluded from the text. Additionally, words must contain fewer than 15 characters. The upper limit should catch some typographical errors or errors in the processing of the original files, such as a conjoining of words – for example, federalreservesystem. But unlike Acosta (2015), I keep all verbs in all tenses (was, is, will, and so on) because they play an important role in this context (following Puri (2016)). The full stop list contains 1,959 words (Appendix A).

At the second stage, words were "stemmed" to their root. I used the Porter stemmer, which removes the most common morphological and inflexional endings from words in English[4]. Finally, the text was split into 3-gram and 4-gram; that is partitioned into tuples of 3/4 of a word each[5]. I applied an economics filter to these grams as in Shapiro & Wilson (2019), who kept only sentences that contain words from the Oxford Dictionary of Economics (Black et al. (2009)).

There are two distinct ways to represent the text: as a sparse matrix of features (where each column corresponds to a particular word and a cell is the frequency of this word in a document) or as an n-dimensional vector (which is a sequence of numbers instead of words).

The first representation is the *Bag-of-words*, which converts a word to a sparse vector. For the bag-of-word representation of features I have tokenised 3-grams/4-grams into a vector where the coefficient for each token is based on TF-IDF, which is Term Frequency - Inverse Document Frequency. Term Frequency summarises how often a given word appears within a document. Inverse Document Frequency downscales words that appear a lot across documents. TF-IDF consists of word frequency scores that try to highlight words that are more interesting

[4]For example, the terms economy, economic, economical, economically, economics, economize would all be reduced to the word econom.

[5]An example of 3-grams text representation. The sentence: the quick brown fox jumped over the lazy dog. 3-grams of the sentence: the quick brown, quick brown fox, brown fox jumped, fox jumped over, jumped over the, over the lazy, the lazy dog.

– frequent in a document but not across documents (2).

$$tf - idf(t, d, D) = tf(t, d) \times log(\frac{D}{df_t}) \tag{2}$$

where, $tf(t, d)$ is the frequency of a term within a document, D is the total number of documents, df_t is the number of documents containing t.

Bag-of-words models are surprisingly effective but loose information about word order. Splitting the transcripts to 3/4 grams helps to capture local word order but it induces data sparsity and high dimensionality.

The second representation is the *Word Embedding*, which transforms each word into an n-dimensional vector. The meaning of a word can be reflected in its embedding, a model is then able to use this information to learn the relationship between words. For the Word Embedding it is possible to use a layer of Neural Networks, or, alternatively, some pre-trained model (Word2Vec by Google, GloVe by the Stanford NLP Group, etc.).

Word2Vec is an unsupervised algorithm developed by Google that tries to learn meaningful vector representations of words from a dataset of text. It does so based on the distributional hypothesis, which states that words that appear in the same context, probably have similar meanings (Mikolov et al. (2013)). I employ the Neural Network trained on part of the Google News dataset (about 100 billion words). The model contains 300-dimensional vectors for 3 million words and phrases (*Google Archive* (2019)).

The main challenge in dealing with the data is that the dimensionally of the vocabulary (unique tuples) is much higher than the number of documents (the total number of documents is 316). Therefore, it is essential to employ some feature selection or dimensionality reduction algorithm. One way of dealing with this is to select the most important features (grams) either on the basis of some criteria (the most important features based on chi^2 are presented in Appendix B) or on the basis of the frequency (Appendix C). The second option is to reduce the dimensionality somehow while preserving all the relevant information.

To deal with the dimensionality reduction problem in a reasonable way, I filtered out grams that did not contain at least one economics-related term. The vocabulary size for 3-grams is reduced from 4,022,272 to 1,366,373 and for 4-grams is reduced from 4,672,873 to 1,670,500 unique tuples. Secondly, I used the Word2Vec embedding to find the vector meaning for each tuple by averaging the word vectors of each word within a tuple. The dimensionality of TF-IDF is $d \times n$ and the dimensionality of the word embedding is $n \times k$, where d is the number of documents, n is the vocabulary size and k is the dimensions of the vector representations of words. To reduce the dimensions of features and extract the meanings of documents, I employed (3).

$$\underset{d\times n}{TF-IDF} \times \underset{n\times k}{Embedding} = \underset{d\times k}{\mathrm{X}} \tag{3}$$

In addition to reducing the dimensionality, this representation should capture the meaning of the documents, since one of the main results of Mikolov et al. (2013) states that the word vectors can be somewhat meaningfully combined using just a simple vector addition. That is explained by the fact that semantically similar words are also close on the basis of cosine similarity from the Word2Vec vectors.

3 Results

3.1 Basic regressors with TF-IDF

I employ basic regressors for the TF-IDF representation of documents with 3-grams and 4-grams as features[6] and the effective federal funds rate as a target variable[7]. TF-IDF is an unsupervised learning algorithm that words frequencies. The most frequent features are presented in Appendix C.

The basic regressors include Linear regression, Ridge and Lasso regressions with corresponding L2 and L1 regularisations (regularisation is important since the feature space is a sparse high-dimensional matrix), K-nearest neighbours, Support Vector Regression, and Bayesian Ridge regression. The loss functions and performance of the regressors with TF-IDF features are shown in Appendix D. An ensemble combines the predictions from all regressors with equal weights. The goal of using the ensemble is to combine the predictions of several models built with a given learning algorithm to improve generalisability and robustness over a single model.

With the baseline settings for regressors and a 90:10 train-test split, the ensemble with 2,000 most frequent 2-grams, 3-grams and 4-grams features shows the minimum mean squared error (MSE) (Appendix D). Among all regressors, the KNN is the best performer with an MSE of 0.98. With a 10-fold cross validation and tuned settings for the regressors, the results are similar: the ensemble with 2,000 2-4 grams features shows the lowest MSE and the KNN is

[6] Matrix X in a regression

[7] y in a regression

the best performing regressor with an MSE of 0.98. 2-4 grams features shows the minimum MSE and the KNN is the best performing regressor with MSE 0.97.

3.2 Basic regressors using Doc2Vec and TF-IDF

Table 1 presents the loss functions of the basic regressors and their performance on the 3- and 4-grams vector representation of documents. The aim is to predict the federal funds rate at the beginning of the next month. We can see that the performance is better than when using the TF-IDF alone. The best regressors are Ridge and Bayesian Ridge with corresponding mean squared errors of 0.31 and 0.28/0.40 for 3/4 grams features. The MSE for the ensemble of all regressors is 0.44 for 3-grams and 0.45 for 4-grams, while the MSE for the ensemble without Linear Regression and SVR is 0.29 for 3-grams and 0.28 for 4-grams.

Table 1: Regressors with 1 train-test splits

Regressor	Linear	Ridge	LASSO	KNN	SVR	Bayes Ridge
Loss function	$\|\|y - X\hat{\beta}\|\|_2^2$	$\|\|y - X\hat{\beta}\|\|_2^2 + \lambda\|\|\hat{\beta}\|\|_2^2$	$\|\|y - X\hat{\beta}\|\|_2^2 + \lambda\|\|\hat{\beta}\|\|_1$	-	$\frac{1}{2}\|\|\hat{\beta}\|\|_2^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*)$	$\mathbb{E}_\beta\{MSE[\beta(\lambda)]\|\sigma^2, Y, X\} = \sigma^2\sum_{j=1}^{p}(d_{jj}^2 + \lambda)^{-1}$
MSE 3-gram	2.63	0.31	0.41	0.83	3.45	0.28
MSE 4-gram	1.43	0.31	0.48	0.51	2.13	0.40

d_{jj}^2 is a singular values decomposition of X. λ is the penalty parameter

For further analysis, I exclude the Support Vector Machine (SVR), since it has the highest MSE. The MSE between the actual federal funds rate and the mean of the ensemble predictions within 30,000 random train-test splits for the vector representation of FOMC transcripts with 4-grams is 0.55. The average mean squared error over 30,000 train test splits is 0.675 for the vector representation of FOMC transcripts with 3-grams. The average MSE with pooled predictions from these two representations is 0.60. The average predictions over 30,000 different train-test splits are presented in Figure 2. We can see here that it is more difficult to predict effective FFR from FOMC transcripts over the period of Great Inflation. In addition, there are unpredicted spikes over the period of the 1980s, 1984, 1988–1989, 1995–1996, 2001 and in the period 2002–2003.

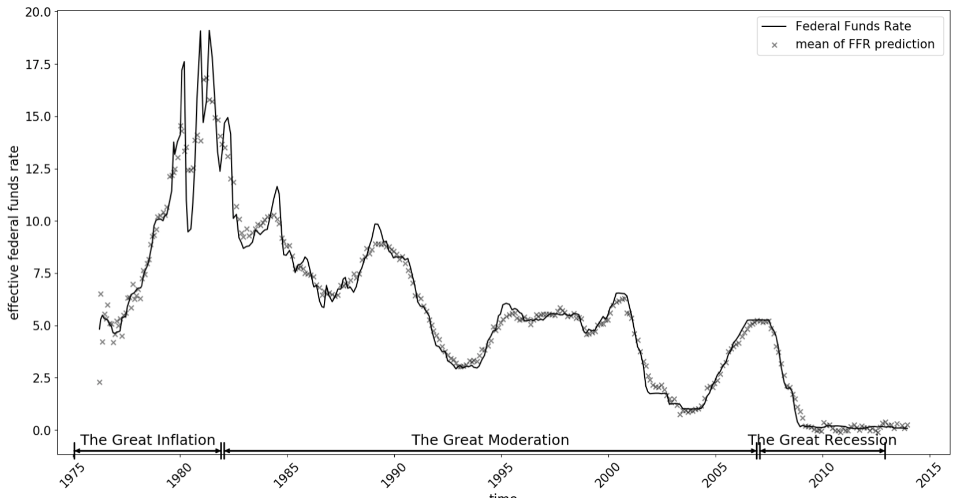


Figure 2: The effective Federal Funds Rate and the mean of ensemble predictions using vector representations of documents and 4-grams features

30,000 different train-test splits

The imprecise fit during the 1970s and at the beginning of the 1980s can be explained by the Fed's monetary policy change in that period. During the 1970s, the Fed targeted money supply and not the federal funds rate. Consumer prices rose at an increasingly rapid rate in the 1970s and early 1980s, with inflation exceeding 10 per cent per annum. The relationship between inflation, economic activity, and measures of money growth was unstable. In 1979, the Fed began targeting money supply to fight inflation. Paul Volcker raised rates and kept them there to fight inflation. As a result, the federal funds rate fluctuated a great deal between 1979 and 1982. In 1982, the Fed returned to targeting the federal funds rate. Despite the fact that the federal rate hit the zero lower bound in December 2008 and the Fed did not resume increasing rates until December 2015, the predictions for that period are quite precise.

More precise predictions after the Great Moderation might also reflect an increasing degree of FOMC transparency, as was noted by Acosta (2015), for instance. However, the fact that the mean prediction is quite precise before the 1980s might discount this caution. If transparency is gradually improving, the predictions also should become more precise with time, but the predictions for 1978–1979 are quite precise. Moreover, rapid spikes in the federal funds rate are difficult to predict from the FOMC transcripts throughout the whole period. We can note that the precision of predictions does not change with the rotation of Federal Reserve governors.

The robustness of the results is discussed in Appendix E. We can see that in the case of vector normalisations (so that each vector has unit length) the results are the same. Moreover, in the case of the repetition of 30,000 train-test splits the differences in the results are negligible.

The errors between the average prediction over 30,000 different train-test splits and the effective FFR are shown in Figure 3. Since the predictions are quite precise, the cyclical pattern of these errors is less clearly observable, but the spikes in 1989, 1995 and 2001 remain visible. During the period of Great Inflation, the mean predictions of the effective FFR from FOMC transcripts are the most inaccurate.

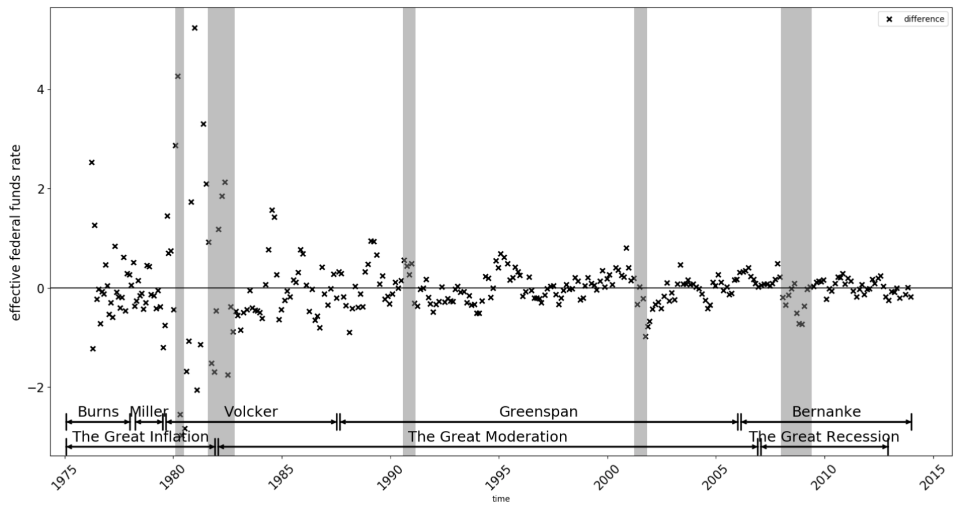


Figure 3: Extracted errors between the effective and the predicted FFR using vector representations of documents and 4-grams features

Shaded areas indicate NBER based Recession Indicators for the United States

30,000 different train-test splits

Appendix F presents different interpolation methods for mean errors over the whole sample period 1976M4:2014M1. But following Romer & Romer (2004), I used zeros for the months where a FOMC meeting was not held. I have 453 monthly observations in total. For the sake of comparison, Appendix F also shows the difference between the effective FFR and the federal funds rate target. We can see that the errors are not the same as the errors between predictions and the actual federal funds rate.

Appendix G discusses the comparison of my measure of monetary policy shocks and the measure by Romer & Romer (2004). This comparison shows that during the 1970s two measures have similar time-series patterns. During some periods my measure and that of Romer & Romer (2004) are symmetrically different (in opposite directions), as can be seen from Figure G.1 (c)

4 Applications

4.1 Romer and Romer (2004)

Romer & Romer (2004) dealt with endogenous Fed responses to macroeconomic indicators using quantitative and narrative records to infer the Federal Reserve's intentions for the federal funds rate around FOMC meetings. This series was regressed on the Federal Reserve's internal forecasts to derive a measure free of systematic responses to information about future developments. The resulting series of monetary shocks should be relatively free of both endogenous and anticipatory actions. The authors employed the new measure to analyse the output and inflation responses to monetary developments.

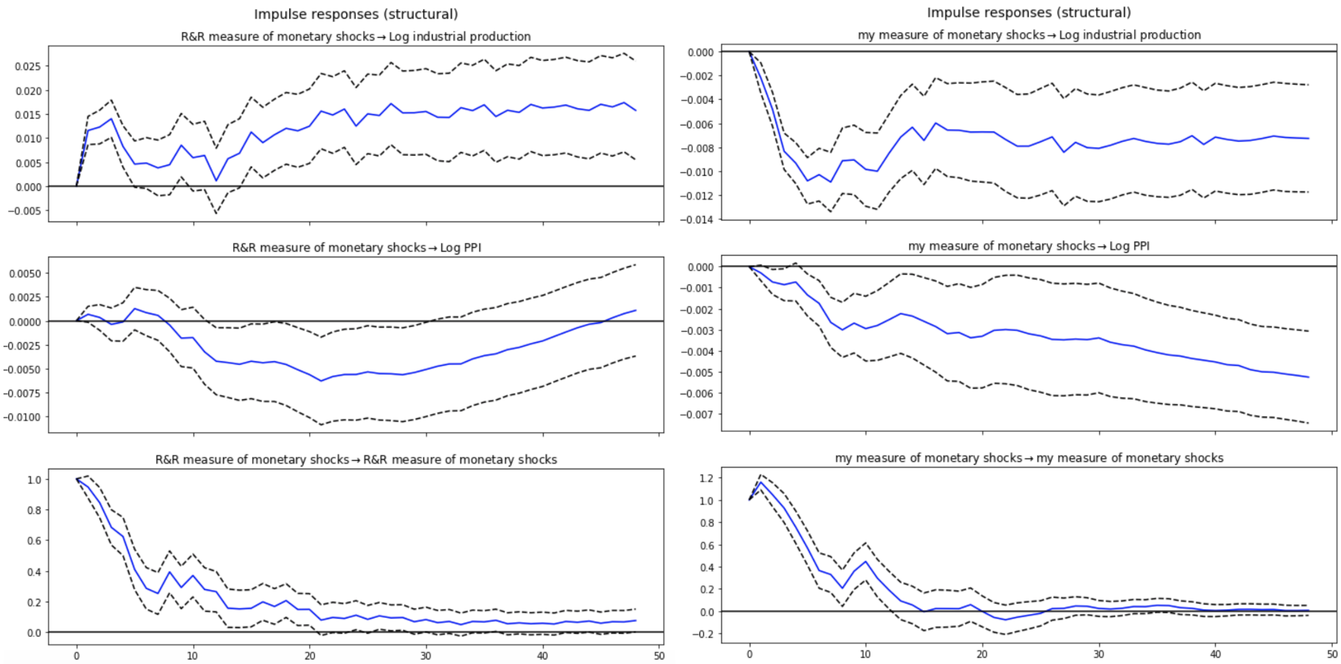
Romer & Romer (2004) used both the published summaries of FOMC discussions contained in the FOMC Record of Policy Actions and the more complete accounts contained in the FOMC Minutes and, later, the FOMC Transcripts. They also used the FOMC document Monetary Policy Alternatives, or the Bluebook, that is prepared for each FOMC meeting. Additionally, they employed a pair of internal memos from the Federal Reserve showing the expected federal funds rate.

According to the theory, in the standard three-variable Structural Vector Autoregression (SVAR) with economic activity, inflation and monetary policy instrument impulse responses to a monetary policy shock should appear as follow: in response to a contractionary monetary policy shock real activity measures should decline and prices should eventually go down (Bernanke et al. (2005), Romer & Romer (2004)). Appendix H shows the replication of Romer & Romer (2004) with their data within a three-variable SVAR (the log industrial production, the log producer price index, and a Romer & Romer (2004) measure of monetary policy shocks) with 36 lags. Since their series start from January 1969 and mine start from April 1976, I truncate Romer & Romer (2004) data so that it starts from April 1976. Additionally, I employ 12 lags instead of 36: first, with the truncation the study period became shorter; second, Romer & Romer (2004) used Christiano et al. (1996) VAR settings implemented with a one-year lag and substituted with a 3 year lag since the one-year lag assumption is very strong and highly questionable; third, my results are robust to changing the lag length to 36 months (Figure I.1).

The results with the Romer & Romer (2004) measure (Figure 4 (a)) show that an impulse response function of industrial production to a contractionary monetary policy shock is not robust to the truncation of their sample: economic activity expands in response to the contractionary monetary policy shock and does not decrease after 4 months (as in Appendix H). Industrial production increases during the first, second and third months after the shock, and subsequently starts to decrease untill the tenth month after the shock, but then starts to increase again. Within this identification scheme, we can see that the contractionary monetary policy shock somehow boosts economic activity, while according to the theory the response should be the opposite. The response of inflation shows the sign of the "price puzzle": inflation increases right after the shock (in the second month) and starts to decrease in the tenth month after the contractionary monetary policy shock with a peak decrease at the twenty-first month after the shock, after which it starts to increase again. Romer & Romer (2004) admitted uncertainty concerning the lag in the impact of policy on prices: in some specifications, the price level begins falling within six months after the policy shock, while in others it is unchanged for as much as 22 months.

The responses in terms of economic activity and inflation to my measure of monetary policy shocks (Figure 4 (b)) show more consistent results which are in line with macroeconomic theory: after a contractionary monetary policy shock both economic activity and inflation decline. Industrial production starts to decline one month after the shock attaining a minimum in the seventh month, and starting to recover slowly thirteen months after the shock. Inflation starts to decline one month after the contractionary shock and this process gradually continues during the whole 4-year period.

It is also worth pointing out that the magnitude of impulse responses in inflation and economic activity to Romer & Romer (2004) and my measures of monetary policy shocks are quite similar, which might also approve the appropriateness of my measure of monetary policy shocks.



(a) Identification with Romer and Romer measure

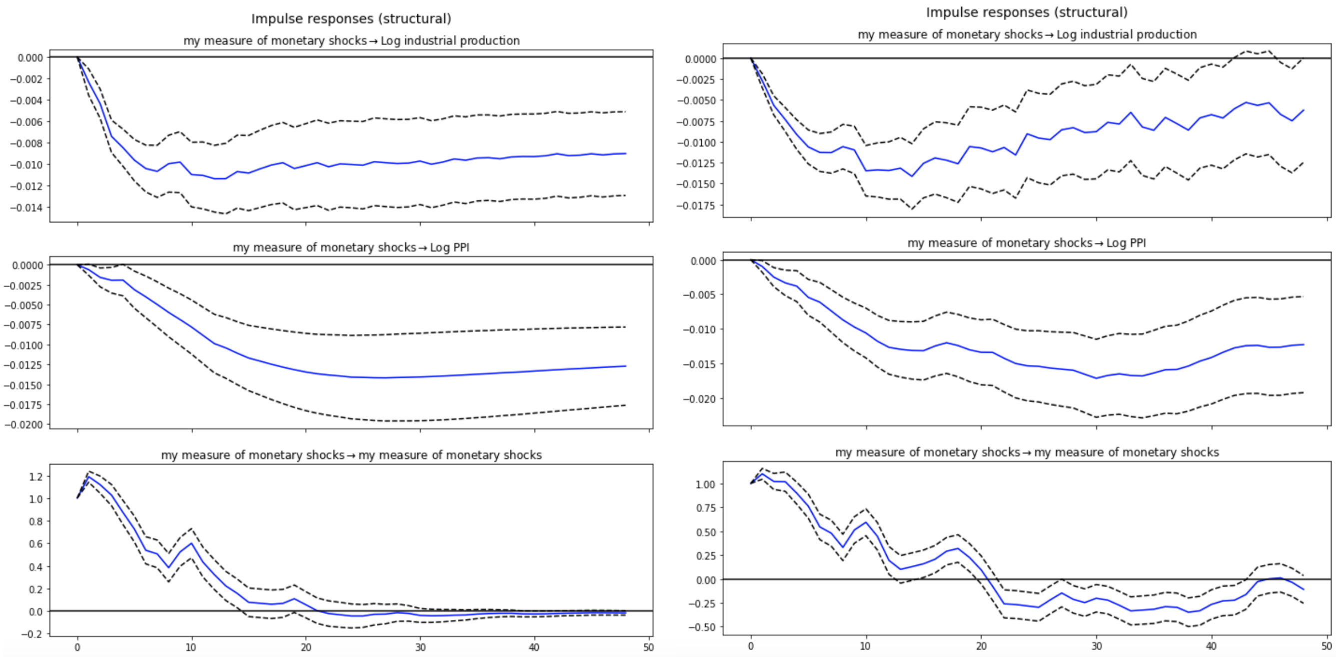
(b) Identification with my measure

Figure 4: Contractionary monetary policy shock using Romer & Romer (2004) and my measure, SVAR(12) (1976–1996)

dashed line - one standard deviation confidence intervals

My identification is fully robust to the lag length change (Figure I.1): the shapes of the impulse response functions for economic activity and inflation are very similar to the shapes in Figure 4.

Lastly, I exploit all the data available for the three variable SVAR, 1976:M4–2014:M1. I use not-seasonally adjusted industrial production and producer price indices from *Fred: Economic Data* (2019). The results are shown in Figure 10. Here we can see that the shape of the impulse responses with my measure of monetary policy shocks is fully robust to changing the length of the series. With the 12-month lag, inflation falls in the first month after the shock, and continues to fall gradually throughout the 4-year period. The decline in industrial production starts right after the shock, peaking the peak in the twelfth month. While in the SVAR(36), the peak of the fall in industrial production is during the fourteenth month, after which it starts to recover. Inflation falls immediately one month after the contractionary shock and this fall is quite persistent during the whole study period.

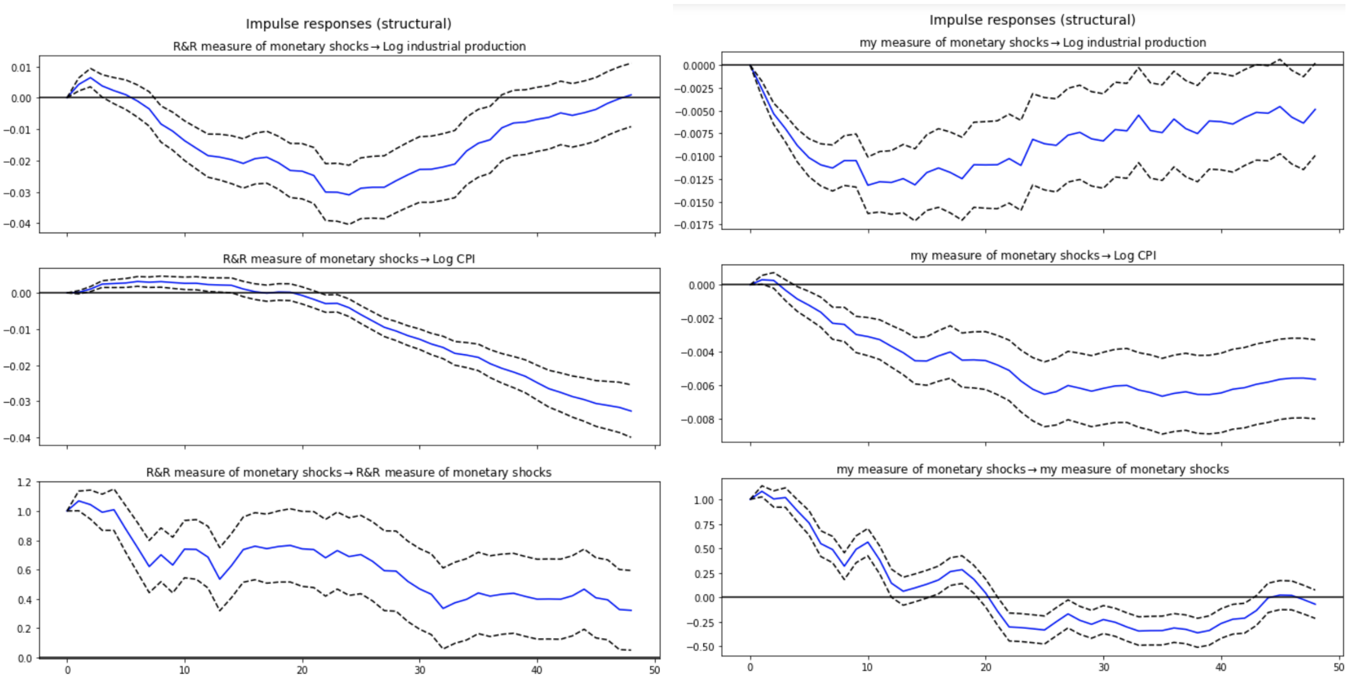


(a) Identification with my measure SVAR(12) (b) Identification with my measure SVAR(36)

Figure 5: Contractionary monetary policy shock using my measure, SVAR(12) and SVAR(36) (1976–2014)

dashed line - one standard deviation confidence intervals

As an additional robustness check, I use the log of the consumer price index instead of the log of the producer price index in SVAR. Figure 6 shows the results, where the left panel uses Romer & Romer (2004) measure of exogenous shocks and the right panel uses my measure. According to the results, there is a visible price puzzle from the third month to the 12th month after the contractionary monetary policy shock in the SVAR(36) using Romer & Romer (2004) measure (Figure 6 (a)). In the SVAR(36) using my measure (Figure 6 (b)), the price puzzle is visible only for the first month and has a smaller magnitude compared to Figure 6 (a). The prices eventually go down in the second month after the shock. While the price response is puzzling in these identification schemes, my measure of the exogenous federal fund rate change is still more consistent with the theory and has a much smaller and shorter price puzzle than the identification using the Romer & Romer (2004) measure.



(a) Identification with Romer & Romer (2004) measure

(b) Identification with my measure

Figure 6: Contractionary monetary policy shock using CPI instead of PPI, SVAR(36)

dashed line - one standard deviation confidence intervals

It should be noted that the difference in magnitudes might be due to different subsamples: Romer & Romer (2004) timespan is 1969–1996 and my timespan is 1976–2014. Christiano et al. (1999) noticed two possibilities for the difference in impulse responses in different subsamples: (1) the difference in impulse responses might reflect a change in the size of the typical monetary policy shock; (2) the other possibility is that it reflects a change in the dynamic response to a shock of a given magnitude. But the qualitative inference about the effects of a monetary shock is robust across subsamples.

Appendix J presents additional robustness checks: a contractionary monetary policy shock with the Consumer Price Index and 12 month lag. Here we can see that results are robust to different treatments of the time-series. Additionally, Figure J.1 shows SVAR(12) results with different order, where my measure of monetary shocks is ordered first. This is a more natural way to apply timing restrictions if one believes that the shock is exogenous. Here we can see that in this identification scheme the effect of an identified monetary policy shock is still contractionary.

Since my measure of monetary policy shocks should be exogenous with respect to the Federal reserve reaction function, it is reasonable to check the importance of Cholesky identifying assumptions. Recursive ordering as an identification strategy is widely criticised because of timing assumptions: one can claim that inflation and economic activity respond in the same period to a monetary policy shock. If one has an available shock series there is no need for additional identifying assumptions; it is possible to evaluate impulse response functions (IRFs) to the shock directly following the framework for calculating responses via local projections (Jordà (2005)). Ramey (2016) and Ramey & Zubairy (2018) used local projections with an exogenous shock identified outside SVAR to calculate IRFs without any timing restrictions as follows (4):

$$y_{t+h} = \alpha^h + \beta_h shock_t + \phi x_{t-l} + u^h_{t+h} \tag{4}$$

, where α^h denotes the regression constant, x_t is a vector of control variables, and $shock_t$ is the identified shock variable. The coefficient β_h corresponds to the response of y at time $t+h$ to the shock variable (shock) at time t. The impulse responses are the sequence of all estimated β_h.

All regressions include two lags of the shock (to mop up any serial correlation), the log industrial production, and the log CPI[8]. But there are no other contemporaneous variables except for the *shock* in the equations. Therefore, there are no timing restrictions in this identification. Figure 7[9] shows the results of the proposed identification with the Federal Fund rate as a policy instrument (part (a)) and my measure of monetary policy shocks (part (b)).

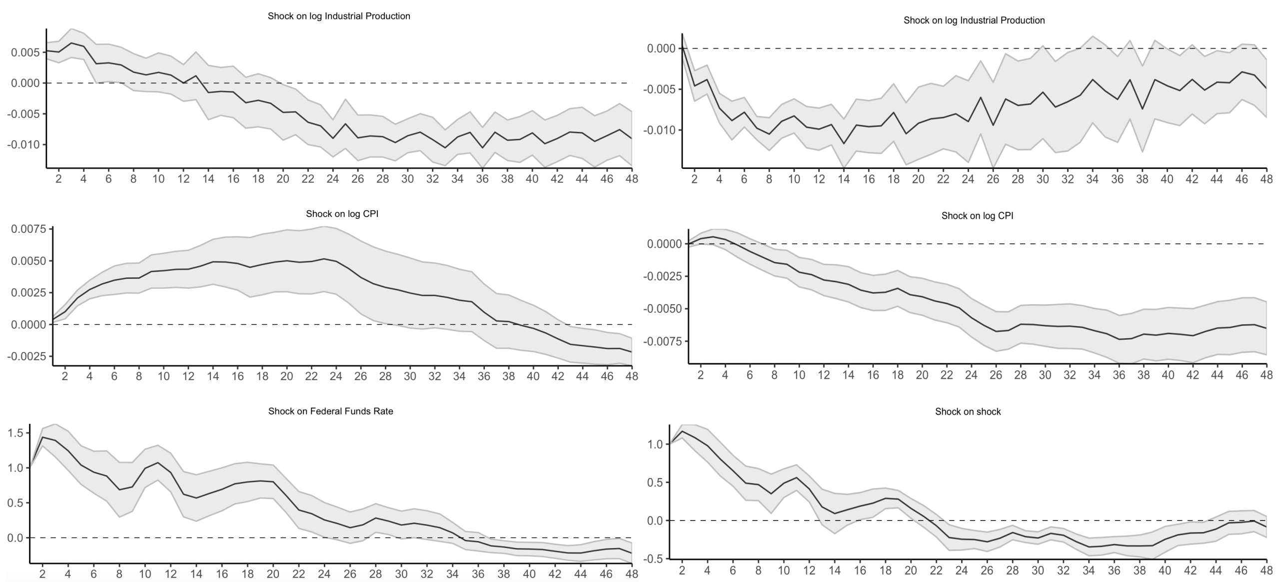
Part (a) shows the results while employing the federal funds rate as a shock variable without any timing restrictions. Here we can see the identified shock is not a contractionary monetary policy shock: industrial production and inflation both increase on impact. The expansionary effect lasts for eight months for industrial production, and twenty eight months for inflation. This identification shows the importance of timing restrictions for the correct identification of the effect of a contractionary monetary policy shock when using the federal funds rate as a policy instrument.

From part (b) we can see that the identified shock using my measure is a contractionary monetary policy shock even without recursive timing restriction. That is contrary to the results with Romer & Romer (2004) measure. Ramey (2016) conducted the same exercise for Romer & Romer (2004) measure and found that short-run timing restrictions do matter in

[8]The point estimates are similar if more lags are included

[9]I am grateful to Adämmer (forthcoming) for an excellent R package for calculating IRFs via local projections (Jordà (2005))

their case: industrial production rises and the unemployment rate falls for the first several months, and the points estimates are statistically different from zero; moreover, there is a pronounced price puzzle for the first two years, and most of those estimates are statistically different from zero. One possible explanation for these puzzles is a failure of the Greenbook forecasts to capture all of the information the Federal Reserve uses. Ramey (2016) states that the most obvious explanation for these results is that the FOMC responds to more information than even the Greenbook forecast, and making the Romer & Romer (2004) shock orthogonal to current output and prices (i.e. the recursiveness assumption) helps cleanse the shock of these extra influences.



(a) Identification with the Federal funds rate

(b) Identification with my measure

Figure 7: Contractionary monetary policy shock via local projections, 2 lags
shaded area - one standard deviation confidence intervals based on Newey & West (1987) standard errors

4.2 Gertler and Karadi (2015)

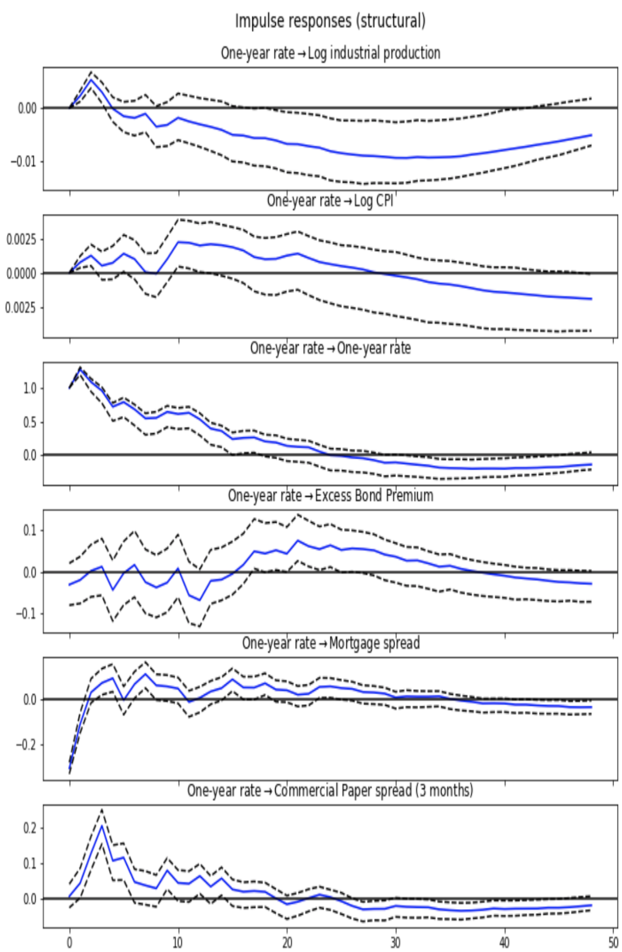
To evaluate the nature of monetary policy transmission, Gertler & Karadi (2015) analysed the joint response of a variety of economic and financial variables to exogenous monetary policy surprises. The authors use unexpected changes in the federal funds rate and Eurodollar futures on FOMC dates to measure policy surprises. Their hybrid approach employs high-frequency identification measures of policy surprises as external instruments in a set of VARs to identify the effects of monetary shocks. The authors employed this approach in order to deal with the simultaneity problem: within a single period, policy shifts not only influence financial variables, they may be responding to them as well; even if the central bank is not directly responding to the financial indicators, it may be responding to underlying correlated variables left out of the VAR. The VARs that Gertler & Karadi (2015) consider include output, inflation and a variety of interest rates.

The replication of the four-variable VAR of Gertler & Karadi (2015) with the one-year government bond rate as a policy indicator is shown in Appendix K. A contractionary monetary policy shock leads to a decline in the excess bond premium on impact, which is counterintuitive. The VAR includes two economic variables, log industrial production and the log consumer price index, the one-year government bond rate (the policy indicator), and a credit spread, specifically the Gilchrist & Zakrajšek (2012) excess bond premium.

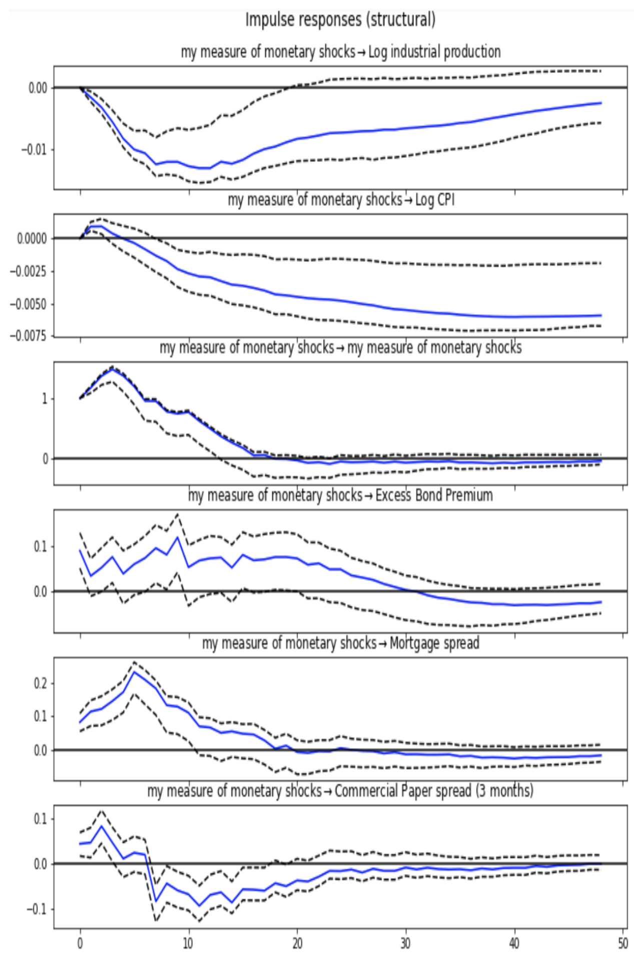
Since my measure of monetary policy shocks should be free from the policy responses to any anticipation and financial variables, it is possible to use my measure in the settings of Gertler & Karadi (2015) and compare the results. The studied time span is 1979:M7–2012:M6. Figure 8 presents the results of the VAR with a short-run timing restriction (Cholesky identification) with Gertler & Karadi (2015) the one-year government bond rate (Figure 8 (a)) and my measure of monetary policy shocks (Figure 8 (b)).

From Figure 8 (a) it can be that the response of the excess bond premium on impact is not statistically significant, but the response of the mortgage spread is negative and statistically significant on impact, which is counterintuitive and shows that the one-year government bond rate might reflect anticipation effects and responses to financial indicators.

Figure 8 (b) shows responses to a monetary policy shock identified using my measure. Here we can see that impulse responses from financial variables are completely in line with the results of Gertler & Karadi (2015) with external instruments: excess bond premium, mortgage spread and commercial paper spread all increase in response to a contractionary monetary policy shock. The effect on the excess bond premium and the mortgage spread is persistent for about ten subsequent months. The effect of a contractionary monetary policy shock on the commercial paper spread is subsequently positive and persistent for about five months. The sign and persistence of the effect are in line with the results of Gertler & Karadi (2015) setting with external instruments. This result might also confirm that my measure of monetary policy shocks is free from anticipation and responses of the monetary authority to financial variables.



(a) Gertler & Karadi (2015) data



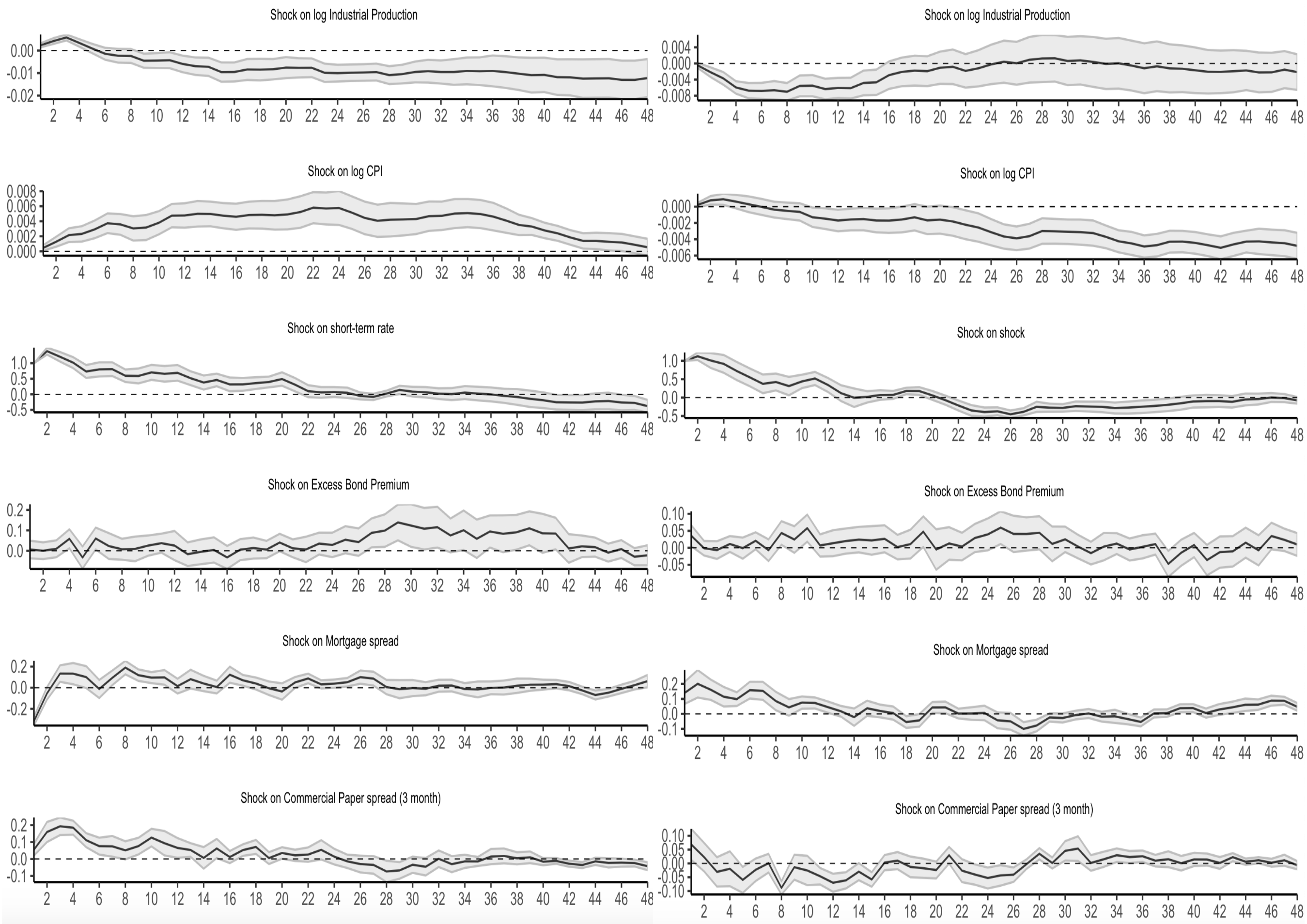
(b) Identification with my measure of monetary shocks

Figure 8: Monetary Shock with Corporate and Mortgage Premia, SVAR(12) (1979–2012)

Monte Carlo standard errors, dashed line - 68% confidence bands

Additionally, it is possible to relax the Cholesky identification scheme for the monetary policy transmission mechanism and calculate IRFs via local projections without any timing restrictions, as in (4). The control variables are two lags of the shock itself, industrial production, the CPI, the Gilchrist & Zakrajšek (2012) excess bond premium spread, mortgage spread, and the commercial paper spread. I do not include the current values of the control variables except for the shock variable, so I am not imposing the recursiveness assumption.

Part (a) of Figure 9 shows IRFs with a short-term rate as a *shock* variable, while part (b) presents IRFs with my measure of monetary policy shocks as a *shock* variable in (4).



(a) Identification with the short-term rate (b) Identification with my measure

Figure 9: Contractionary monetary policy shock with Corporate and Mortgage Premia via local projections, 2 lags

shaded area - one standard deviation confidence intervals based on Newey & West (1987) standard errors

It can be seen from the IRFs that in the case of using a short-term rate as a *shock* variable in local projection identification without any timing identifying restrictions, a unit shock does not have a contractionary effect on the economy: real economic activity and inflation both increase. Moreover, excess bond premium and mortgage spread both decrease on impact, which is counterintuitive in the case of a contractionary monetary policy shock.

Part (b) of Figure 9 shows IRFs via local projections with my shock variable. One can see that real economic activity decreases two months after a contractionary monetary policy shock, while inflation declines in about the tenth month after the shock. Impulse responses from excess bond premium, mortgage spread and commercial paper spread are completely in line with the results of Gertler & Karadi (2015).

4.3 Tests for omitted fundamentals

Since I used the data only from the FOMC transcripts in constructing my series, the question arises whether it reflects exogenous monetary policy changes. Table 2 presents the regression results on whether my series are correlated with any of the time-series measures, which might be important for the Fed in their monetary policy changes. Independent variables were differenced to ensure stationarity. It can be seen from the results that the US/UK exchange rate with a 2-month lag is correlated with my measure with an interpolation at 5% significance level, but none of the series is correlated at the 1% level of significance. It is well-known that an exchange rate might be in the monetary policy feedback rule (as was pointed out by Christiano et al. (1999) among others). But neither monetary base, nor S&P500 with lags is correlated with my measure. Although errors which were not interpolated are not correlated with any of the independent variables. So these measures might be considered exogenous.

Table 2: Exogeneity test

	Dependent variable:			
	interpolated errors	errors [10]	interpolated errors 2 [11]	errors 2
	(1)	(2)	(3)	(4)
S&P500 lag -1	0.0001 (0.001)	0.00000 (0.001)	0.0002 (0.001)	0.00000 (0.001)
S&P500 lag -2	0.001 (0.001)	0.0003 (0.001)	0.001 (0.001)	0.0003 (0.001)
Monetary base lag -1	−0.00000 (0.00000)	−0.00000 (0.00000)	−0.00000 (0.00000)	−0.00000 (0.00000)
Monetary base lag -2	−0.00000 (0.00000)	−0.00000 (0.00000)	−0.00000 (0.00000)	−0.00000 (0.00000)
PPI lag -1	0.014 (0.026)	0.011 (0.024)	0.015 (0.027)	0.011 (0.024)
PPI lag -2	0.044 (0.028)	0.033 (0.025)	0.044 (0.028)	0.033 (0.025)
Exchange rate US/UK lag -1	−1.321 (0.824)	−0.494 (0.748)	−1.329 (0.833)	−0.494 (0.748)
Exchange rate US/UK lag -2	1.613** (0.818)	0.645 (0.742)	1.646** (0.827)	0.645 (0.742)
Exchange rate US/Canada lag -1	1.365 (2.096)	1.111 (1.902)	1.253 (2.119)	1.111 (1.902)
Exchange rate US/Canada lag -2	−1.277 (2.092)	−1.087 (1.898)	−1.166 (2.114)	−1.087 (1.898)
Constant	−0.598 (0.476)	−0.291 (0.432)	−0.635 (0.481)	−0.291 (0.432)
Observations	454	454	454	454
R^2	0.032	0.014	0.033	0.014
Adjusted R^2	0.010	-0.009	0.012	-0.009

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3 shows the regression results with Romer & Romer (2004) variables, which the authors used to purify their measure of monetary shocks.

Table 3: Exogeneity test with Romer & Romer (2004) data

	Dependent variable:	
	Errors	Errors 2
	(1)	(2)
Intended funds rate before the meeting(level)	0.144*** (0.031)	0.149*** (0.031)
Forecast of the percentage change in the GDP/GNP deflator for the previous quarter	0.001 (0.031)	−0.001 (0.031)
Forecast of the percentage change in the GDP/GNP deflator for the current quarter	0.079 (0.056)	0.081 (0.056)
Forecast of the percentage change in the GDP/GNP deflator one quarter ahead	0.083 (0.095)	0.082 (0.096)
Forecast of the percentage change in the GDP/GNP deflator two quarters ahead	−0.085 (0.106)	−0.081 (0.108)
The innovation in the forecast for the percentage change in the GDP/GNP deflator for the previous quarter	0.103 (0.072)	0.110 (0.073)
The innovation in the forecast for the percentage change in the GDP/GNP deflator for the current quarter	−0.080 (0.079)	−0.078 (0.079)
The innovation in the forecast for the percentage change in the GDP/GNP deflator one quarter ahead	−0.108 (0.133)	−0.111 (0.134)
The innovation in the forecast for the percentage change in the GDP/GNP deflator two quarters ahead	−0.246 (0.155)	−0.241 (0.157)
Forecast of the percentage change in real GDP/GNP for the previous quarter	0.005 (0.072)	0.012 (0.073)
Forecast of the percentage change in real GDP/GNP for the current quarter	0.016 (0.082)	0.006 (0.083)
Forecast of the percentage change in real GDP/GNP one quarter ahead	−0.059 (0.121)	−0.057 (0.123)
Forecast of the percentage change in real GDP/GNP two quarters ahead	−0.051 (0.137)	−0.050 (0.138)
The innovation in the forecast for the percentage change in GDP/GNP for the previous quarter	−0.053 (0.112)	−0.061 (0.113)
The innovation in the forecast for the percentage change in GDP/GNP for the current quarter	−0.124 (0.131)	−0.129 (0.132)
The innovation in the forecast for the percentage change in GDP/GNP one quarter ahead	0.402* (0.208)	0.415* (0.211)
The innovation in the forecast for the percentage change in GDP/GNP two quarters ahead	−0.425* (0.247)	−0.431* (0.250)
Forecast for the unemployment rate for the current quarter	−0.178*** (0.062)	−0.186*** (0.062)
Constant	0.304 (0.407)	0.325 (0.412)
Observations	181	181
R^2	0.319	0.320
Adjusted R^2	0.243	0.245
Note:		*p<0.1; **p<0.05; ***p<0.01

It can be seen here that both levels of the intended funds rate before the meeting and the Greenbook forecast for the unemployment rate for the current quarter are correlated using my measure. If the correlation with the intended funds rate before the meeting does not contradict the plausibility of my measure, the correlation with the unemployment forecast should be considered with care. Figure J.1 present a further investigation of the series. The correlation might be explained by the high variation of both series at the beginning of the

[10] errors are my measure of monetary policy shocks

[11] errors 2 are from the predictions with unit length vectors

1980s. But since researchers agree that during that period monetary policy shocks were more volatile (Christiano et al. (1999)) and the Structural VAR includes industrial production, which should capture the real economic activity, the correlations might still preserve the exogeneity of the identified structural shock from the SVAR.

Table 4 shows the further investigation between the Greenbook forecast of unemployment and my measure of policy shocks. As can be seen, for the whole time span 1976–2014 the coefficient of the unemployment forecast is insignificant.

Table 4: My measure of monetary policy and Greenbook unemployment forecast

	Dependent variable:
	My measure of monetary shocks
Unemployment forecast for the current quarter	−0.041 (0.027)
Constant	0.275 (0.179)
Observations	316
R^2	0.008
Adjusted R^2	0.004
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 10 shows the comparison of structural shocks from the SVAR(36) using my measures and those of Romer & Romer (2004). Here we can see that at the beginning of the 1980s both structural shocks are more volatile than at the end of the studied period. Clarida et al. (1998) noted that from the late 1960s through the early 1980s, the US economy experienced high and volatile inflation along with several severe recessions. Since the early 1980s, inflation has remained steadily low, while output growth has been relatively stable. Christiano et al. (1999) pointed out that at the same time, there is strong evidence that the variance of the policy shocks changed over time. Their interpretation is that the early 1980s was a period in which policy shocks were very large, but that the shocks were of comparable magnitude and substantially smaller size throughout the rest of the post-war period. Moreover, we can see that the identified structural shocks are more distinct from the mid-1980s.

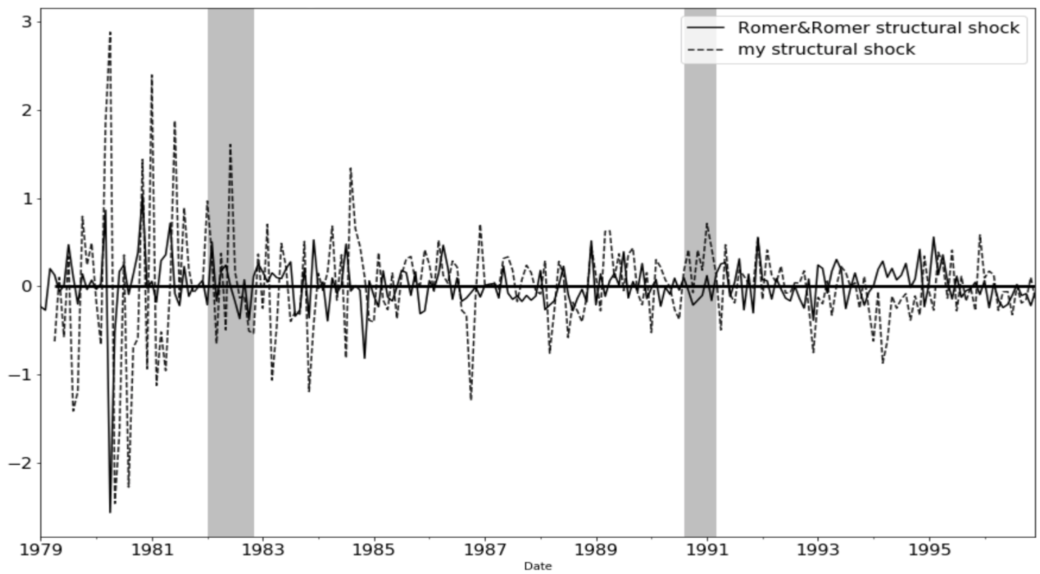


Figure 10: Structural shocks from SVAR(36) (1979–1996)

Shaded areas indicate NBER based Recession Indicators for the United States

Figure 11 shows the identified monetary policy shocks from the SVAR(36) using my measure of monetary policy shocks for the whole studied period. The identified shocks look similar to the monetary policy shocks identified in previous studies (see Christiano et al. (1999) for a complete discussion). It can be seen here that the structural monetary shocks become less volatile from the beginning of the 1990s compared to the 1970s and 1980s. Clarida et al. (1998) demonstrated that there is a significant difference in the way monetary policy was conducted pre and post October 1979. During the Volker-Greenspan era, the Federal Reserve adopted a proactive stance towards controlling inflation: it systematically raised real as well as nominal short-term interest rates in response to higher expected inflation. Within the Volker-Greenspan regime, the Federal Reserve adjusted interest rates sufficiently to stabilise any changes in expected inflation.

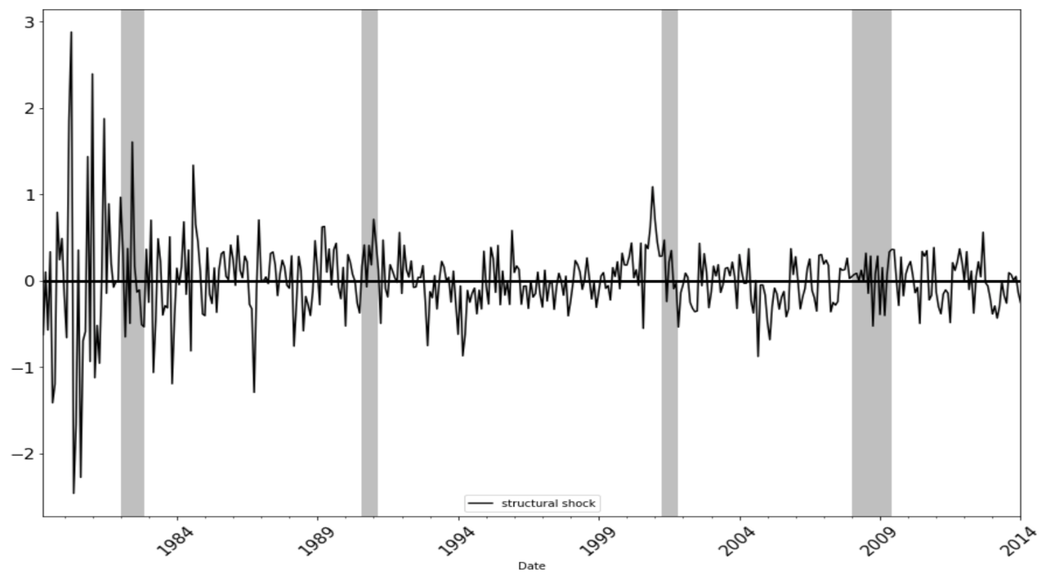


Figure 11: Structural shocks from SVAR(36) (1979–2014)

Shaded areas indicate NBER based Recession Indicators for the United States

The dynamics of the monetary policy shocks is in line with the findings of Ramey (2016), who stated that because monetary policy has been conducted so well in the last several decades, true monetary policy shocks are rare.

Table 5 shows the results for the omitted fundamentals test for structural monetary policy shocks from the SVAR(36). Independent variables were differenced to ensure a stationarity. Here we can see that none of the variables is statistically significant.

As an additional robustness check, I employed a LASSO with 130 monthly macroeconomic variables, which include the main macroeconomic indicators from the McCracken & Ng (2015) database. All variables were transformed to a stationary form and lagged for one month. Additionally, all variables were standardised for the LASSO. Table J.1 presents the results, which indicate that none of macroeconomic indicators is important for the identified structural monetary policy shocks from the SVAR(36), and all the coefficients are zero.

Table 5: Exogeneity test for structural monetary policy shocks from SVAR(36)

	Dependent variable:		
	Interpolated monetary shocks	Monetary shocks	Monetary shocks cumulated
	(1)	(2)	(3)
S&P500 lag -1	−0.0005 (0.0005)	−0.0004 (0.001)	−0.001 (0.001)
S&P500 lag -2	0.0002 (0.001)	−0.001 (0.001)	−0.001 (0.001)
Monetary base lag -1	−0.000 (0.00000)	−0.00000 (0.00000)	−0.00000 (0.00000)
Monetary base lag -2	−0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
PPI lag -1	−0.003 (0.014)	0.002 (0.018)	0.004 (0.018)
PPI lag -2	−0.003 (0.015)	−0.004 (0.019)	−0.001 (0.019)
Exchange rate US/UK lag -1	0.253 (0.479)	0.511 (0.594)	0.423 (0.597)
Exchange rate US/UK lag -2	−0.274 (0.475)	−0.561 (0.589)	−0.516 (0.592)
Exchange rate US/Canada lag -1	−0.292 (1.201)	0.364 (1.490)	0.613 (1.497)
Exchange rate US/Canada lag -2	0.349 (1.201)	−0.374 (1.490)	−0.619 (1.497)
Constant	−0.033 (0.274)	0.107 (0.340)	0.172 (0.342)
Observations	418	418	418
R^2	0.006	0.007	0.009
Adjusted R^2	-0.019	-0.018	-0.015

Note: *p<0.1; **p<0.05; ***p<0.01

5 Conclusions

Identifying the effect of an unanticipated monetary policy shock is one of the major challenges in empirical macroeconomics since the federal funds rate changes might exhibit endogeneity (the Fed's response to macroeconomic changes) and anticipation (the Fed's response to the expected macroeconomic conditions).

To determine the effect of an exogenous monetary policy shock on economic activity and inflation, this paper employs a new method of defining the exogenous federal funds rate changes with the help of machine learning and a Neural Network. My approach defines unexpected interest rate changes as those which cannot be predicted from the Federal Market Committee Meetings. Since the transcripts become publicly available after a lag of 5 years, the release of this information could not have any impact on the federal funds rate changes directly. Additionally, my approach is fully automated and does not depend on personal judgments or perceptions.

The movements in output and inflation in response to my new measure of monetary shocks are fully in line with macroeconomic theory: output and inflation both decline in response to a contractionary monetary policy shock. The findings are robust to the truncation of the series and different lag lengths.

Additionally, it has been shown that my measure of monetary policy shocks can be used to study the monetary policy transmission mechanism: it has been shown that a contractionary monetary policy shock leads to an increase in excess bond premium, mortgage spread and commercial paper spread. This result also confirms that my measure of monetary policy shocks is free from anticipation and endogenous responses of the monetary authority to financial variables.

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Appendix A. Stop words

Table A.1: Stop words

a	about	above	across	after	afterwards
again	against	agree with president	alan	alans	all
all else ing equal	almost	alone	along	already	also
alternate	although	altig	altmann	alvarez	always
am	am going to	am not sure	among	amongst	amoungst
amount	an	and	and don t	and dont know	and dont think
and going to	and it s	and may be	and others have	and seems to	and so forth
and that s	and there are	and there is	and think is	and this is	and want to
and would be	angell	anne	another	any	any questions or comments
anyhow	anyone	anything	anyway	anywhere	appear to be
appear to have	appears to be	appended to this transcript	april	are appended to this	are likely to
are not going	are tal about	are there any	are trying to	around	as
as far as	as has been	as long as	as numr people have	as opposed to	as others have said
as shown bottom left	as shown middle left	as shown top left	as shown top panel	as st can judge	as to how
as to what	as to whether	ashton	at	at same time	at this point
august	axilrod	back	bailey	balbach	balles
baughman	baxter	be	be able to	be consistent with	be happy to
be willing to	beattie	became	because	beck	become
becomes	becoming	beebe	been	been able to	before
beforehand	behind	being	below	ben	bernanke
bernard	beside	besides	beth	between	beyond
bies	bill	black	blanchard	blinder	bloom
boehne	both	bottom	boykin	brandt	brayton
broaddus	broida	broidas	browne	bullard	burns
but	by	call	can be seen	chairman	charles
christine	christopher	clouse	co	coldwell	come back to
committee	con	connors	continues to be	corrigan	could
couldnt	coyne	cross	cry	cumming	danforth
daniel	danker	david	davig	davis	de
deborah	december	dennis	describe	detail	do
do is to	do not know	do not think	do want to	does seem to	doesnt seem to
doing	don t have	don t it s	don t know	don t know how	don t know if
don t know what	don t that s	don t think	don t want	dont feel stgly about	dont have any
dont have to	dont know how	dont know if	dont know what	dont know whether	dont think have
dont think is	dont think would	dont want to	down	driscoll	dudley
due	duke	during	dynan	each	eastburn
eg	eichard	eight	eighth	eisenbeis	eisenmenger
either	eleven	eleventh	elizabeth	else	elsewhere
empty	engen	english	enough	eric	esther
etc	ettin	evan	evans	even	ever
every	everyone	everything	everywhere	except	executive
farar	faust	february	federal open market	federal open market committee	feldman
ferguson	few	fifteen	fifth	fifty	fill
find	fire	first	fisher	five	for
ford	former	formerly	forrestal	forty	found
four	fourth	fousek	fox	friedman	frierson
from	from time to time	front	fuhrer	full	further
gardner	garrett	geithner	gentlemen	george	get
gillum	give	glenn	go	go back to	going to
going to do	going to get	going to go	going to take	goodfriend	governor
gramley	gramleys	gramlich	green	greenspan	guffey
gust	guynn	hakkio	happy to answer any	has been some	has not been
has to be	has to do with	have en able to	have en tal about	have talked about	have to

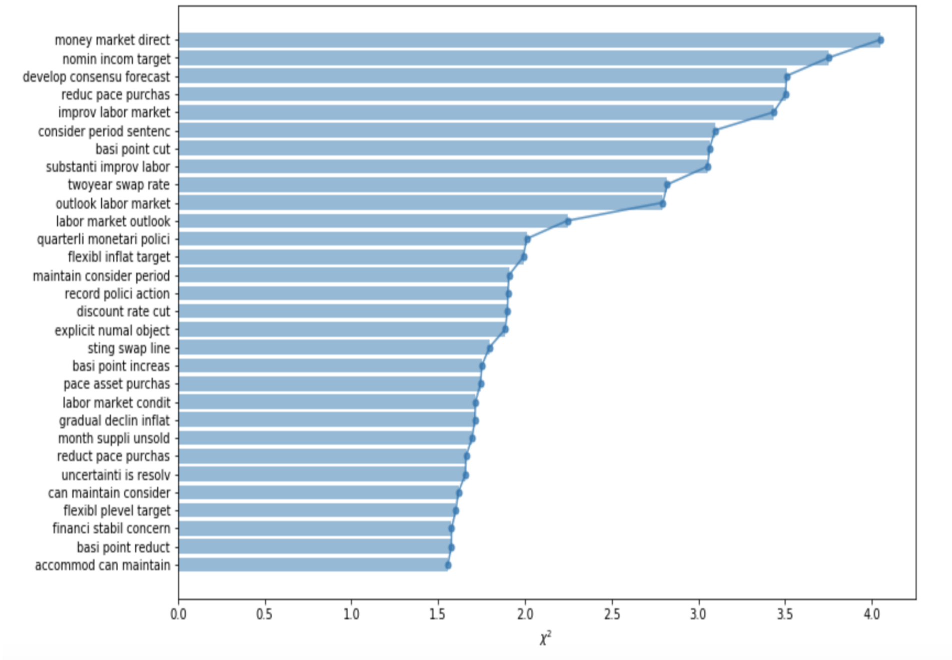
Table A.2: Stop words

have to be	have to do	have to take	having	he	hed
hehere	heis	hel	hell	heller	hence
hendricks	henry	her	here	hereafter	hereby
herein	hereupon	hers	herself	hes	hetzel
hilton	him	himself	his	hoeing	hoenig
holland	hollands	holmes	hooker	horn	hoskins
how	howard	however	hows	hundred	hunter
i	id	ie	if	if not would somebody	if there are no
if there is	if want to	if were to	ill	im	in
in my view	inc	indeed	interest	into	is expected to
is important to	is not going	is there any	is there is	is very similar to	it
it s hard to	it s important to	it s not	it s not clear	it seems to	it would be
its	itself	ive	jackson	james	janet
january	jeff	jeffrey	jennifer	jeremy	jerome
john	johnson	jon	jonathan	jordan	joyce
judson	july	june	just want to	just wanted to	kalchbrenner
kamin	karen	keehn	keep	keir	keleher
kelley	keran	kichline	kimbrel	king	know
know how to	known	kocherlakota	koenig	kohn	krane
krieger	kroszner	kusko	lacker	lang	last
latter	latterly	laubach	laware	leahy	least
lebow	less	let	lets	levin	liang
like	likely to	lilly	linda	lindsey	lockhart
logan	loretta	lorie	ltd	luecke	lunch
m not sure	made	madigan	mannion	many	march
mark	martin	materials used by are	matthew	mattingly	may
may be some	may want to	mayo	mcandrews	mcdonough	mcintosh
mcnees	mcteer	me	meanwhile	meek	meeting
melzer	memorandum	merrill	messrs	mester	meulendyke
meyer	michael	michelle	might	might want to	mill
miller	mine	minehan	mishkin	more	moreover
morris	morton	moskow	mosser	most	mostly
move	mr	mrs	ms	much	mullineaux
mullins	must	my	my own view is	my sense is	my view is
myself	name	namely	narayana	need to be	need to do
neither	nellie	nelson	never	nevertheless	next
next year or two	nine	ninth	no	nobody	none
noone	not quite sure what	not want to	not would somebody to	nothing	november
nowhere	oconnell	october	of	off	often
oliner	olson	oltman	on	once	one
one way or another	only	onto	or	or something that	other
others	otherwise	ought	our	ours	ourselves
out	out to be	over	own	paragraph	pardee
parry	part	partee	parthemos	patrikis	pence
per	perelmuter	perhaps	petersen	phillips	pianalto
please	plosser	poole	potter	powell	prell
president agree with recommendation	president president yes	president yes president	promisel	put	question is whether
rasche	raskin	rather	re	re going to	reeve
reifschneider	reinhart	reserve bank new york	rice	right thing to do	rimbrel
rivlin	robert	roberts	robertson	rolnick	ron
roos	rose	rosenblum	rosengren	rosine	roush
rudd	rudebusch	ruth	same	sandra	santomero
sarah	say	scheld	schultz	scott	second

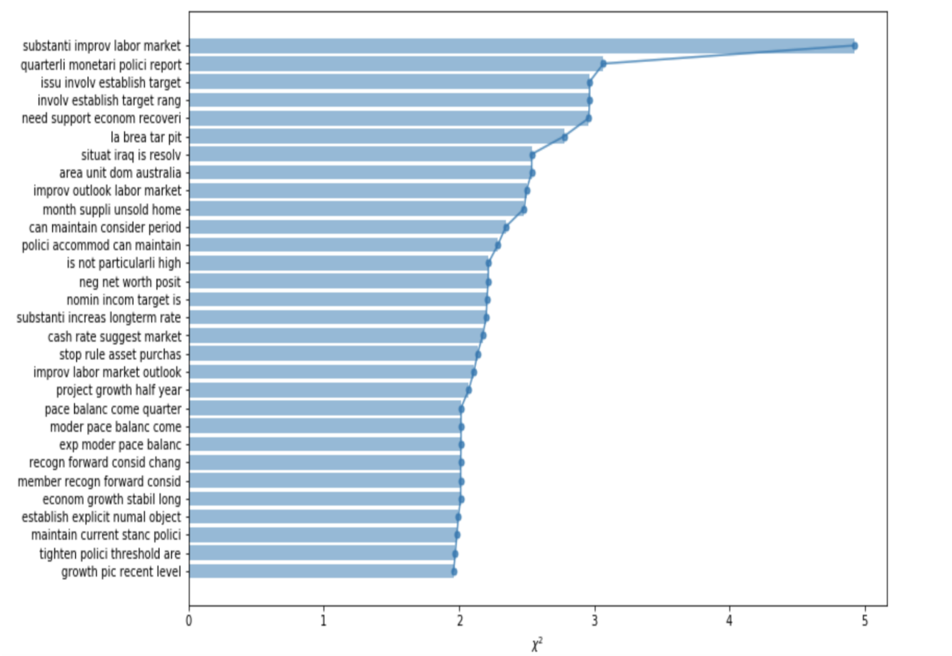
Table A.3: Stop words

second second without objection	secretary	secretarys note this statement	see	seem	seem to be
seem to have	seemed	seemed to be	seeming	seems	seems to be
seems to have	seems to to	seger	sellon	september	serious
session	seventh	several	shanks	shant	she
shed	sheets	shell	shes	should	show
shown bottom left panel	shown middle right panel	sichel	side	siegman	simon
simpson	since	sincere	six	sixth	sixty
skidmore	slifman	smith	sniderman	snidermans	so
so moved without objection	so there is	solomon	some	somehow	someone
something	sometime	sometimes	somewhere	sooner rather than later	ssteve
stacey	stein	stephen	stern	sternlight	steve
steven	steves	still	stockton	struckmeyer	such
sullivan	syron	system	t want to	table	take
tarullo	teeters	ten	tenth	tevlin	than
thank	that	that s what	thats	the	the bottom line is
the first is	the materials used by	the question is how	their	theirs	them
themselves	then	thence	there	there could be	there has en no
there has en some	there have been	there is	there may be	there might be	thereafter
thereby	therefore	therein	theres	thereupon	these
they	theyd	theyll	theyre	theyve	thick
thin	think	think going to	think is important	think is very	think it s
think should be	think that s	think would have	third	this	this is time to
this is very	thomas	those	though	three	through
throughout	thru	thus	timlen	to	to add to
to and to	to be	to be able	to be careful	to be consistent	to be some
to be sure	to begin to	to come up with	to deal with	to do and	to do is
to do so	to do this	to give us	to go to	to go up	to have
to have been	to have to	to keep mind	to take into account	to talk about	to this transcript appendix
to to be	to try to	to want to	to what extent	together	tom
too	top	toward	towards	tracy	troy
true	truman	trying to do	trying to figure out	tschinkel	twelfth
twelve	twenty	two	un	under	until
up	upon	us	us to be	used by are appended	very
very difficult to	very hard to	via	vice	vicechairman	volcker
walich	waller	wallich	wallichs	want to be	want to do
want to get	want to go	want to make	warsh	wascher	way to go
we	we re	we re going	we re not	we re tal about	we ve seen
weber	wed	weide	well	were	weve
what	what has been	what has en happening	what is going in	what think is	what to do
what we re	what we re doing	what will happen	whatever	whats	when
whence	whenever	whens	where	whereafter	whereas
whereby	wherein	wheres	whereupon	wherever	whether
whether or not	which	which think is	while	whitesell	whither
who	whoever	whole	whom	whos	whose
why	whys	wilcox	will have to	willes	william
williams	wilson	winn	with	with respect to	within
without	would	would agree with	would be	would be to	would be useful
would be very	would have been	would have to	would prefer to	would seem to	would somebody to move
would want to	wouldnt want to	year or so	yellen	yes	yes president president
yes president yes	yet	you	youd	youll	your
youre	yours	yourself	yourselves	youve	zickler

Appendix B. The most important features based on chi^2



(a) Most important 3-gram features



(b) Most important 4-gram features

Figure B.1: Most important features based on chi^2 for the Federal Funds Rate

Appendix C. The most frequent features

Table C.1: Most frequent features

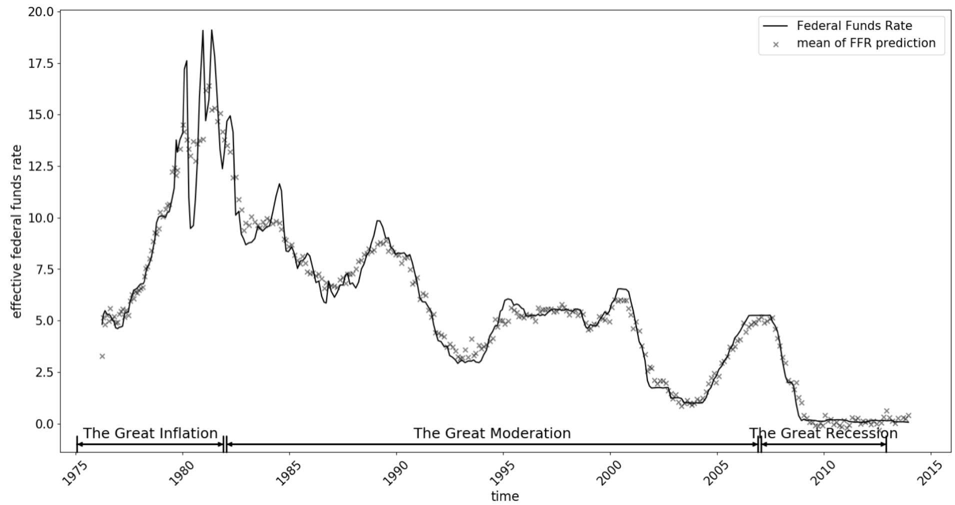
3-grams	4-grams	2-4 grams
'annual rate percent'	'basi point basi point'	'are not'
'asset purchas program'	'commerci real estat market'	'balanc sheet'
'busi fix invest'	'domest open market oper'	'basi point'
'commerci real estat'	'fed fund rate is'	'central bank'
'current account deficit'	'feder fund rate averag'	'core inflat'
'fed fund rate'	'feder fund rate is'	'econom growth'
'feder fund rate'	'feder fund rate percent'	'economi is'
'foreign central bank'	'feder fund rate rang'	'exchang rate'
'foreign exchang market'	'feder fund rate target'	'fed fund''
'fund rate is'	'foreign exchang valu dollar'	'fed fund rate'
'fund rate percent'	'fund rate averag percent'	'feder fund'
'fund rate rang'	'fund rate basi point'	'feder fund rate'
'fund rate target'	'futur seek condit reserv'	'feder reserv'
'improv labor market'	'immedi futur seek condit'	'financi market'
'labor forc particip'	'increas feder fund rate'	'forecast is'
'labor market are'	'labor forc particip rate'	'fund rate'
'labor market condit'	'labor market are tight'	'growth is'
'middl left panel'	'labor market remain tight'	'growth rate'
'monetari polici is'	'lesser reserv restraint accept'	'half year'
'money market direct'	'level feder fund rate'	'have had'
'money market fund'	'money market mutual fund'	'have not'
'open market oper'	'path feder fund rate'	'inflat expect'
'percent annual rate'	'percent annual rate quarter'	'inflat is'
'percent fund rate'	'percent feder fund rate'	'inflat rate'
'rate basi point'	'rang feder fund rate'	'inter period'
'real estat market'	'real feder fund rate'	'is not'
'real fund rate'	'seek condit reserv market'	'is percent'
'tight labor market'	'stabil sustain econom growth'	'labor market'
'unemploy rate is'	'target feder fund rate'	'market are'
'unit labor cost'	'will now continu present'	'market is'

Appendix D. Performance of Basic Regressors

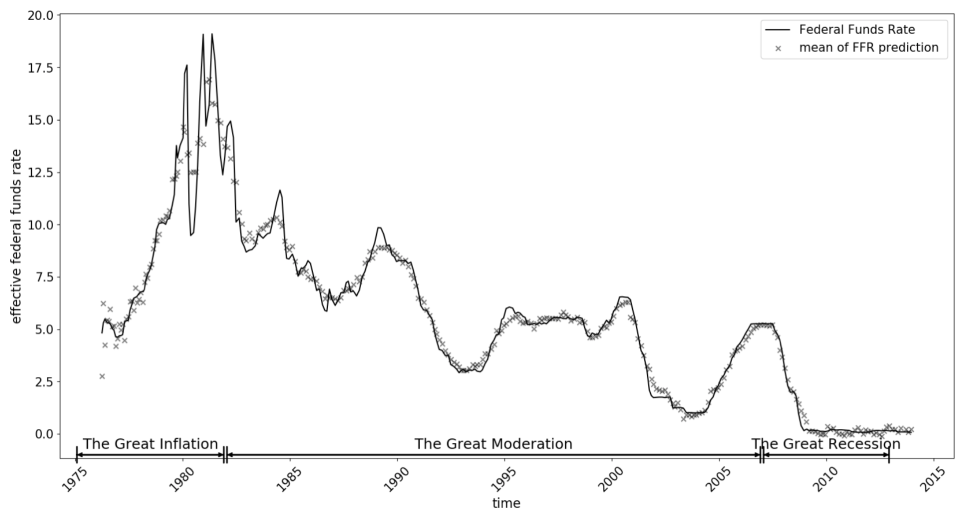
Table D.1: MSE of basic regressors with TF-IDF

Loss function	OLS $\lvert\lvert y-X\hat{\beta}\rvert\rvert_2^2$	Ridge $\lvert\lvert y-X\hat{\beta}\rvert\rvert_2^2+\lambda\lvert\lvert\hat{\beta}\rvert\rvert_2^2$	LASSO $\lvert\lvert y-X\hat{\beta}\rvert\rvert_2^2+\lambda\lvert\lvert\hat{\beta}\rvert\rvert_1$	KNN -	SVR $\frac{1}{2}\lvert\lvert\hat{\beta}\rvert\rvert_2^2+C\sum_{i=1}^N(\xi_i+\xi_i^*)$	Bayesian Ridge $\mathbb{E}_\beta\{MSE[\beta(\lambda)]\lvert\sigma^2,Y,X\}=\sigma^2\sum_{j=1}^p(d_{jj}^2+\lambda)^{-1}$	Ensemble
MSE measure with baseline settings							
top $tf-idf$ 100 features 3-grams	4.15	3.20	6.62	2.47	13.18	3.11	3.74
top $tf-idf$ 100 features 4-grams	2.32e+25	5.01	9.97	5.05	13.37	4.96	6.43e+23
top $tf-idf$ 1000 features 2-grams	2.14	1.68	7.70	1.82	14.35	1.63	2.72
top $tf-idf$ 1000 features 3-grams	2.06	1.66	10.56	1.45	14.43	2.06	3.06
top $tf-idf$ 1000 features 4-grams	3.86	2.76	14.40	3.48	14.47	3.28	4.30
top $tf-idf$ 2000 features 3-grams	1.97	1.70	11.92	1.74	14.50	1.98	3.45
top $tf-idf$ 2000 features 4-grams	1.95	2.04	14.40	2.09	14.52	1.95	3.36
top $tf-idf$ 1000 features 2-4 grams	1.92	1.65	7.80	1.42	14.36	1.55	2.67
top $tf-idf$ 2000 features 2-4 grams	1.54	1.67	8.6	0.98	14.46	1.55	2.62
top $tf-idf$ 3000 features 2-4 grams	1.51	1.80	9.06	1.39	14.49	1.54	2.87
top $tf-idf$ 1000 from NN features 2-4 grams	1.27	1.29	1.57	1.59	1.30	1.28	1.31
top $tf-idf$ 2000 from NN features 2-4 grams	1.46	1.28	1.58	1.46	1.34	1.37	1.36
top $tf-idf$ 3000 from NN features 2-4 grams	1.62	1.77	1.79	1.71	1.60	1.71	1.67
MSE measure with tuned settings							
top $tf-idf$ 100 features 3-grams	4.15	3.05	3.30	2.42	3.67	3.11	2.89
top $tf-idf$ 100 features 4-grams	2.32e+25	4.90	5.17	5.05	4.81	4.96	6.43e+23
top $tf-idf$ 1000 features 2-grams	2.14	1.57	1.79	1.82	2.00	1.62	1.43
top $tf-idf$ 1000 features 3-grams	2.06	1.72	1.66	1.45	1.97	1.91	1.47
top $tf-idf$ 1000 features 4-grams	3.86	2.76	4.41	2.97	2.38	3.28	2.73
top $tf-idf$ 2000 features 3-grams	1.97	1.98	1.86	1.74	1.98	1.98	1.65
top $tf-idf$ 2000 features 4-grams	1.95	1.89	3.25	2.21	1.94	1.93	1.71
top $tf-idf$ 1000 features 2-4 grams	1.92	1.51	1.85	1.43	1.92	1.54	1.37
top $tf-idf$ 2000 features 2-4 grams	1.54	1.43	2.30	0.98	1.80	1.51	1.32
top $tf-idf$ 3000 features 2-4 grams	1.51	1.53	2.45	1.39	1.74	1.54	1.45
top $tf-idf$ 1000 from NN features 2-4 grams	1.54	1.43	2.30	0.97	1.80	1.51	1.30
top $tf-idf$ 2000 from NN features 2-4 grams	1.54	1.46	2.30	0.97	1.80	1.51	1.34
top $tf-idf$ 3000 from NN features 2-4 grams	1.53	1.46	2.30	0.97	1.80	1.51	1.71

Appendix E. Robustness of results

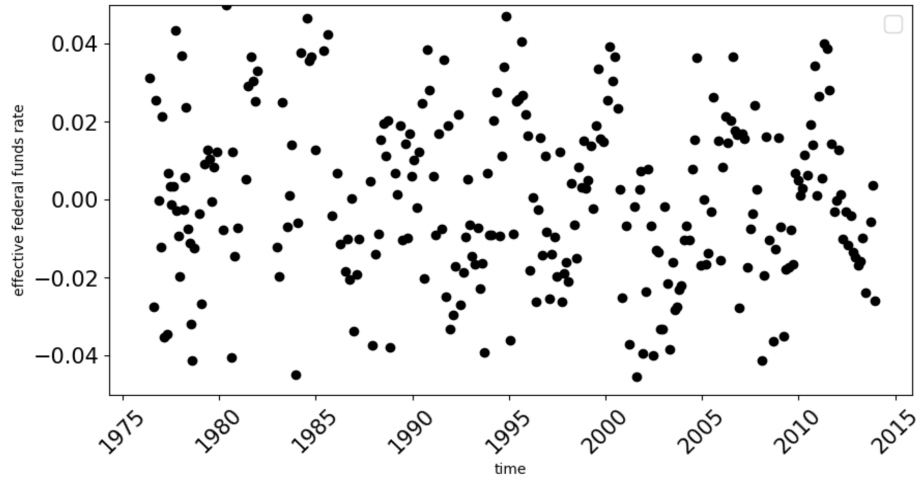


(a) Errors between the effective FFR and the predicted one from normalised vector representations of documents (3-grams, MSE is 0.66)

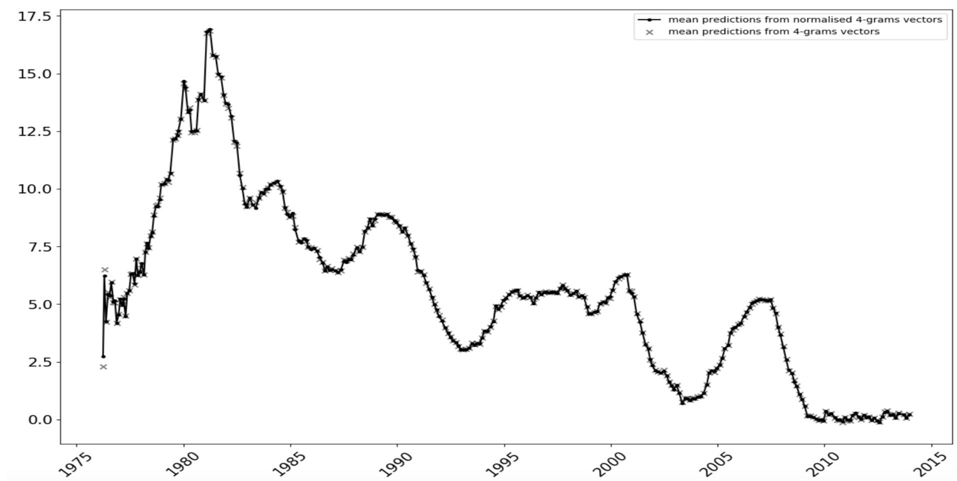


(b) Errors between the effective FFR and the predicted one with normalised vector representations of documents (4-grams, MSE is 0.54)

Figure E.1: Robustness of result



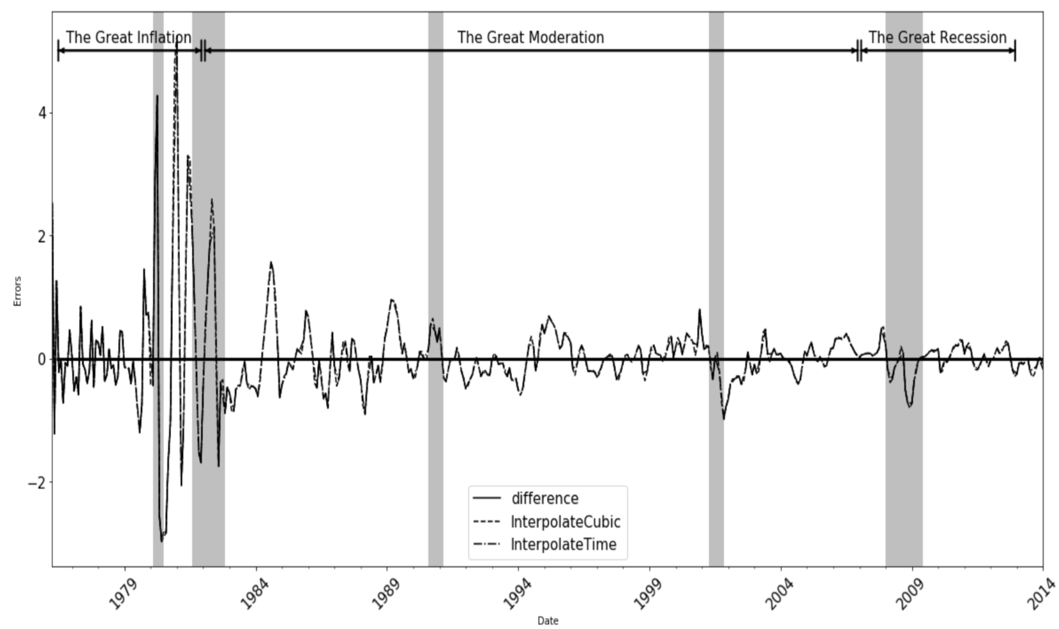
(a) Difference between predictions from 4 grams and normalised 4 gram features



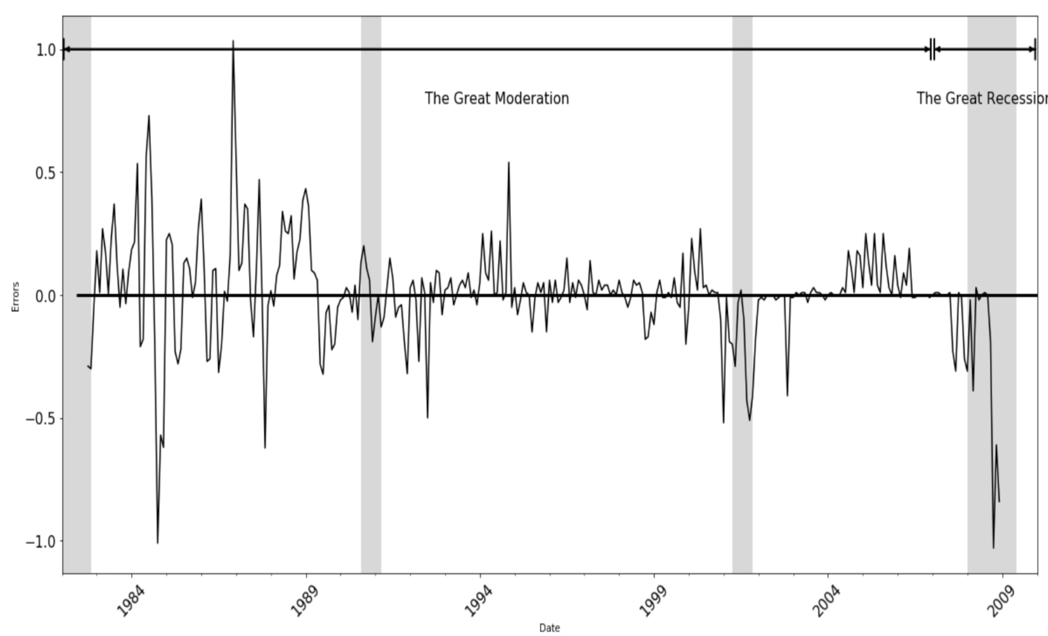
(b) Mean predictions for 4 grams features and normalised 4 grams features

Figure E.2: Robustness of result

Appendix F. Interpolation of errors



(a) Errors



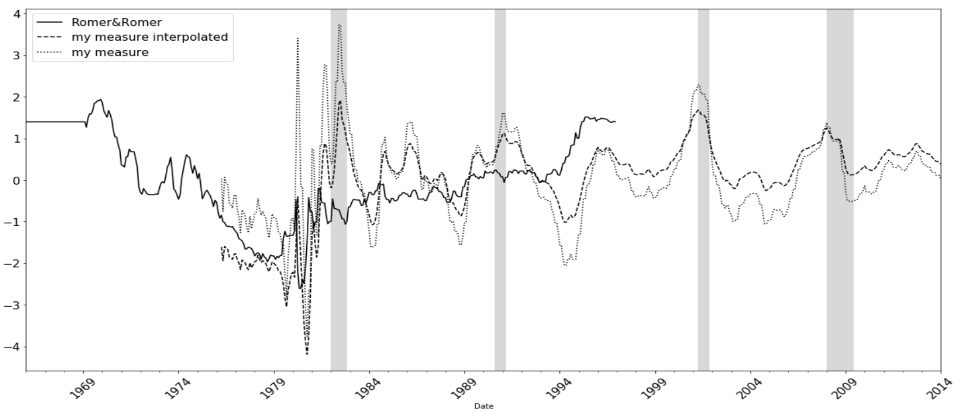
(b) Difference between effective FFR and Federal Funds target rate

Figure F.1: Interpolation of errors

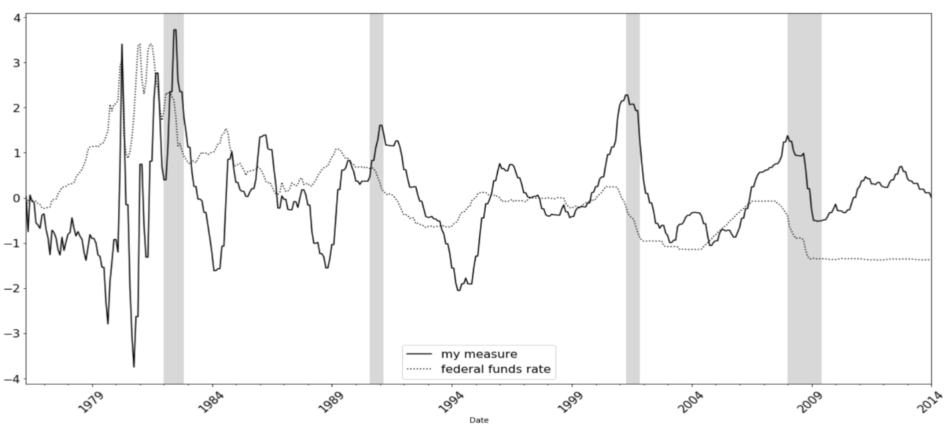
Shaded areas indicate NBER based Recession Indicators for the United States

30,000 different train-test splits

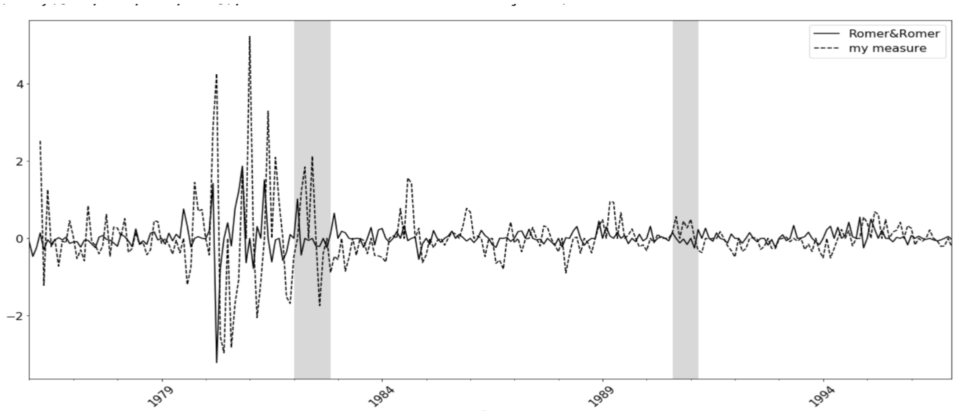
Appendix G. Comparison of measures



(a) My and Romer&Romer measures



(b) My measure and the federal funds rate



(c) My and Romer&Romer measures, non-cumulative

Figure G.1: Comparison of measures

Appendix H. Replication of Romer & Romer (2004)

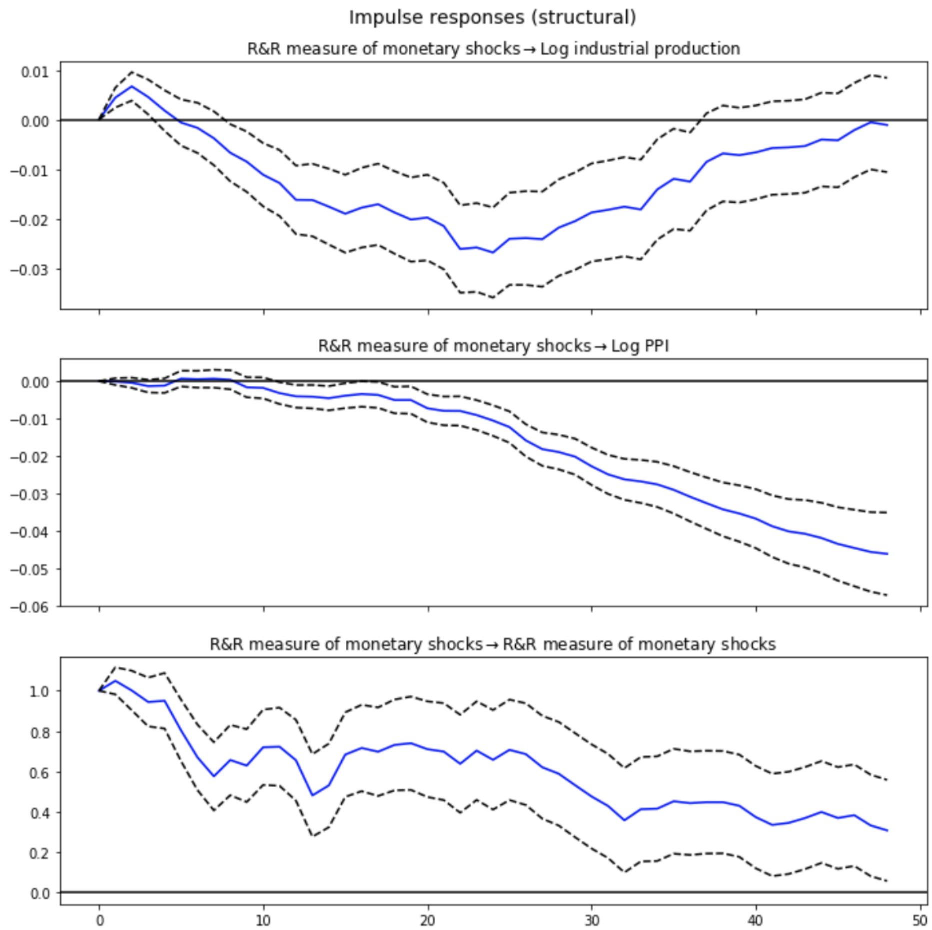
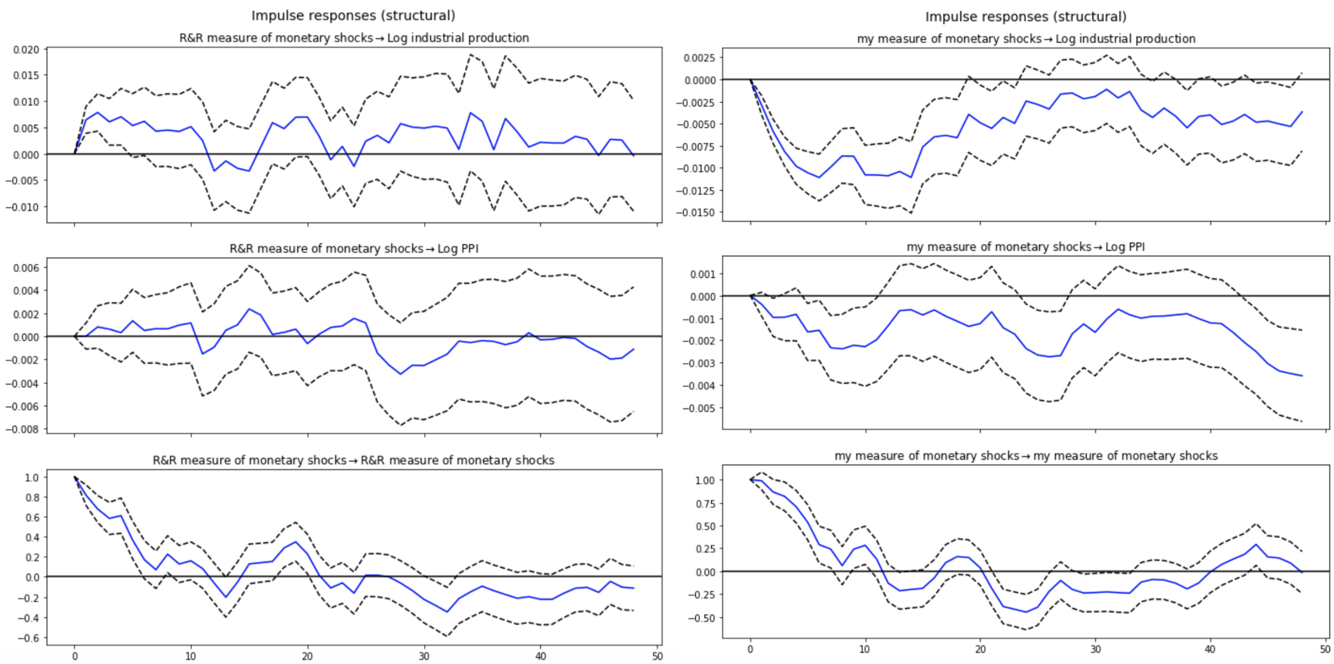


Figure H.1: Contractionary monetary policy shock by Romer & Romer (2004) SVAR(36) (1966–1996)

dashed line - one standard deviation confidence intervals

Appendix I. Replication of Romer & Romer (2004) with truncated period and my results



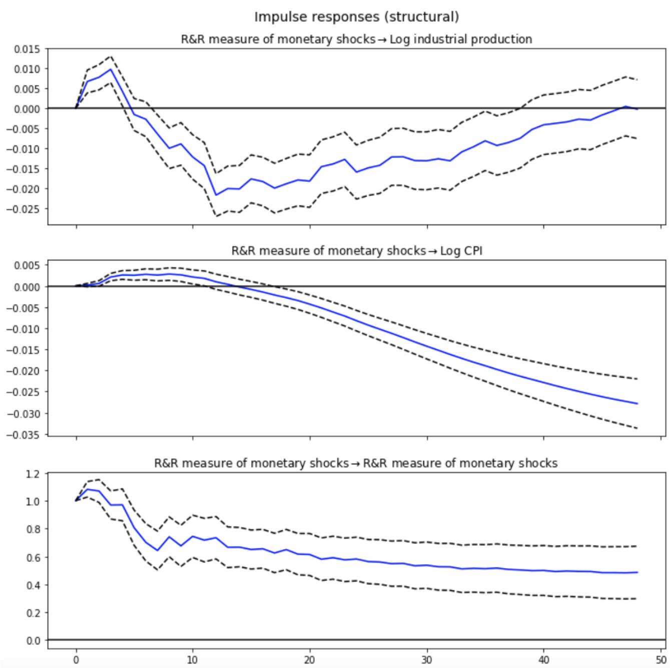
(a) Identification with Romer and Romer measure

(b) Identification with my measure

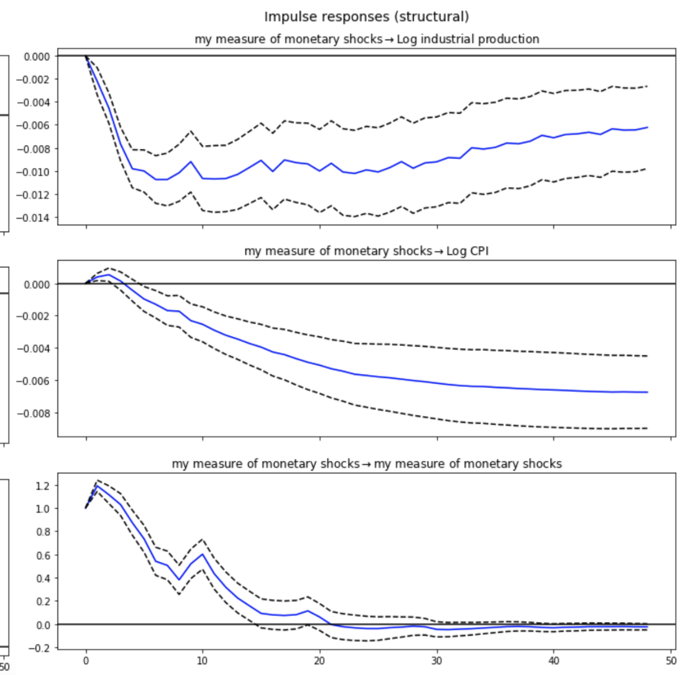
Figure I.1: Contractionary monetary policy shock using Romer & Romer (2004) and my measure, SVAR(36) (1976–1996)

dashed line - one standard deviation confidence intervals

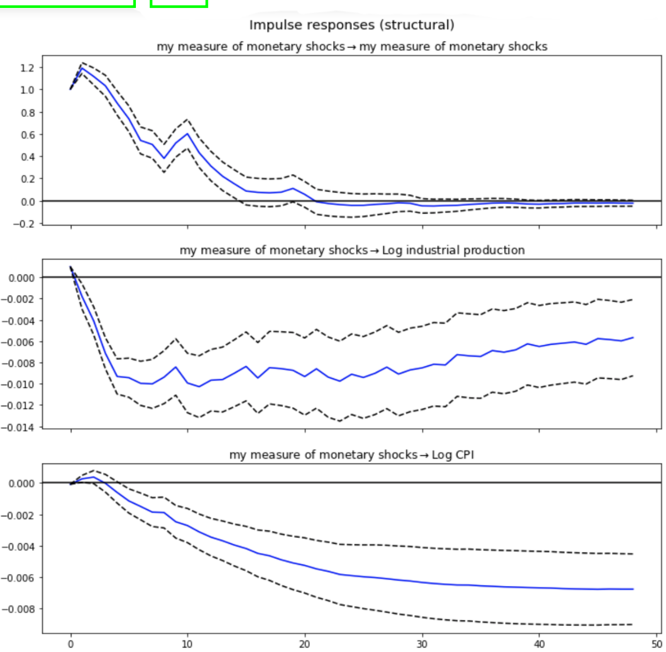
Appendix J. Additional SVAR results



(a) Identification with Romer & Romer (2004) measure



(b) Identification with my measure



(c) Identification with my measure, shock ordered first

Figure J.1: Contractionary monetary policy shock using CPI instead of PPI, SVAR(12)

dashed line - one standard deviation confidence intervals

Appendix K. Replication of Gertler & Karadi (2015)

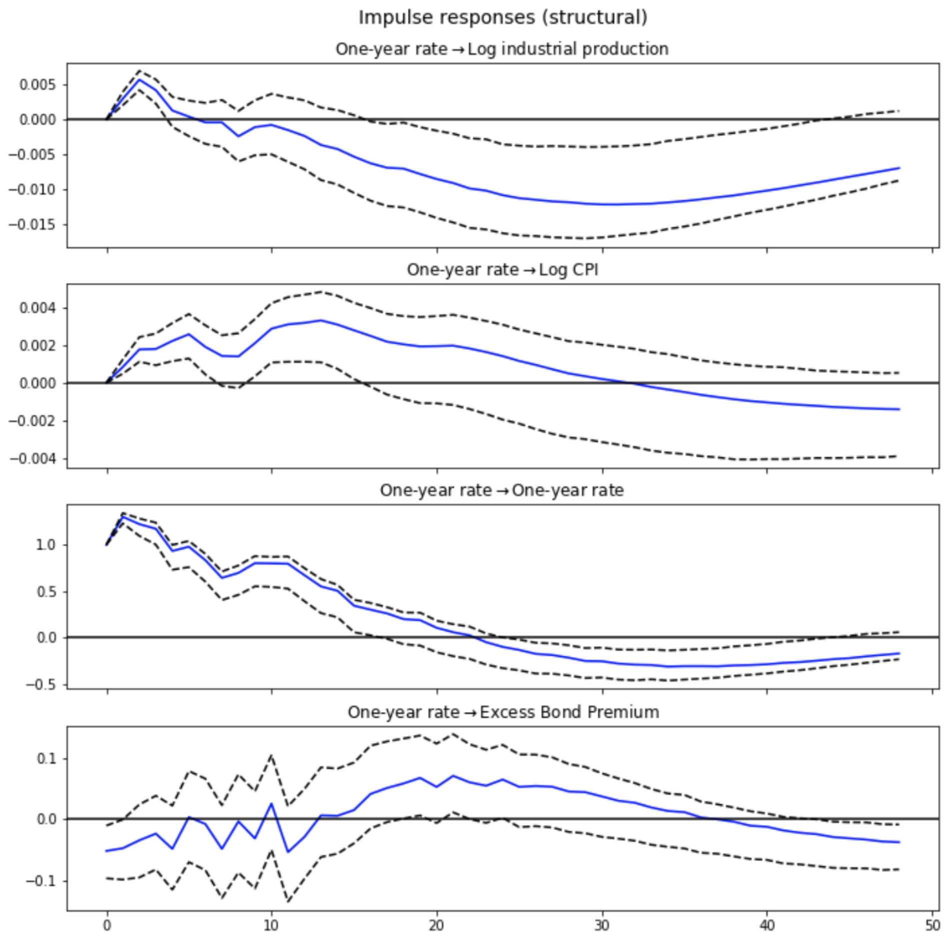
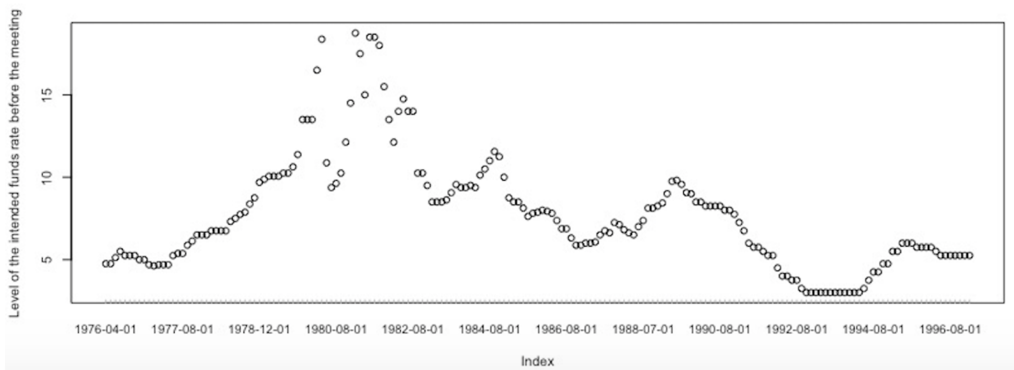


Figure K.1: Contractionary monetary policy shock by Gertler & Karadi (2015) SVAR(12) (1979:M7–2012:M6)

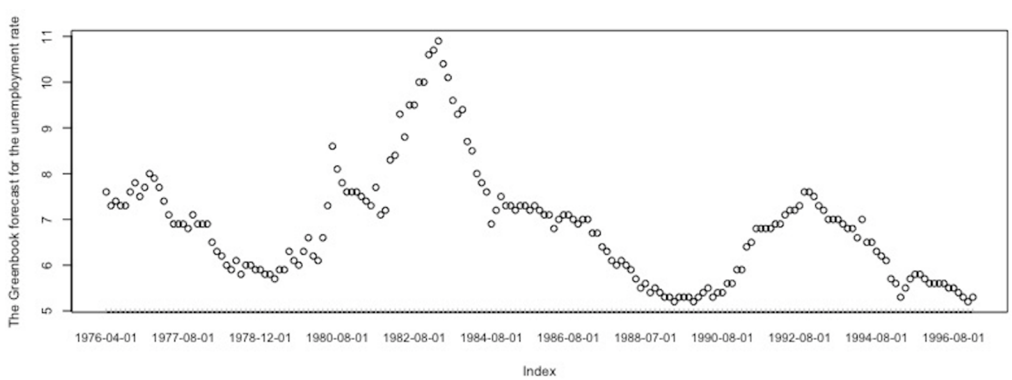
Monte Carlo standard errors, dashed line - one standard deviation confidence intervals

Appendix L. Tests for omitted fundamentals

(a) Errors from the predictions



(b) intended Federal Funds Target



(c) Greenbook unemployment forecast for current quarter

Figure L.1: Errors from the predictions and correlated time-series

Table L.1: LASSO results with FRED-MD database (lag -1) [12]

	Structural shock with Doc2Vec trained on Google News	Structural shock with Doc2Vec trained on Business News
RPI	-0.0	-0.0
W875RX1	0.0	-0.0
DPCERA3M086SBEA	-0.0	-0.0
CMRMTSPLx	-0.0	-0.0
RETAILx	-0.0	-0.0
INDPRO	0.0	0.0
IPFPNSS	0.0	-0.0
IPFINAL	0.0	-0.0
IPCONGD	0.0	0.0
IPDCONGD	0.0	-0.0
IPNCONGD	0.0	0.0
IPBUSEQ	0.0	-0.0
IPMAT	0.0	0.0
IPDMAT	0.0	0.0
IPNMAT	-0.0	0.0
IPMANSICS	0.0	-0.0
IPB51222S	0.0	0.0
IPFUELS	0.0	-0.0
CUMFNS	0.0	-0.0
HWI	0.0	-0.0
HWIURATIO	0.0	0.0
CLF16OV	0.0	-0.0
CE16OV	0.0	0.0
UNRATE	-0.0	-0.0
UEMPMEAN	-0.0	-0.0
UEMPLT5	-0.0	-0.0
UEMP5TO14	0.0	-0.0
UEMP15OV	-0.0	-0.0
UEMP15T26	-0.0	-0.0
UEMP27OV	-0.0	-0.0
CLAIMSx	-0.0	-0.0
PAYEMS	-0.0	-0.0
USGOOD	0.0	-0.0
CES1021000001	-0.0	-0.0
USCONS	-0.0	-0.0
MANEMP	0.0	0.0
DMANEMP	0.0	0.0
NDMANEMP	-0.0	-0.0
SRVPRD	-0.0	-0.0
USTPU	0.0	0.0
USWTRADE	0.0	-0.0
USTRADE	0.0	0.0
USFIRE	-0.0	-0.0
USGOVT	-0.0	-0.0
CES0600000007	0.0	0.0
AWOTMAN	0.0	0.0
AWHMAN	0.0	-0.0
HOUST	-0.0	-0.0
HOUSTNE	-0.0	-0.0
HOUSTMW	-0.0	-0.0
HOUSTS	-0.0	-0.0
HOUSTW	-0.0	-0.0
PERMIT	-0.0	-0.0
PERMITNE	0.0	-0.0
PERMITMW	-0.0	-0.0
PERMITS	-0.0	-0.0
PERMITW	-0.0	-0.0
AMDMNOx	-0.0	0.0
ANDENOx	-0.0	-0.0
AMDMUOx	-0.0	0.0
BUSINVx	-0.0	0.0
ISRATIOx	0.0	0.0
M1SL	-0.0	-0.0
M2SL	-0.0	-0.0

[12] The description of variables is presented in *FRED-MD Updated Appendix* (2019)

Table L.2: LASSO results with FRED-MD database (lag -1)

	Structural shock with Doc2Vec trained on Google News	Structural shock with Doc2Vec trained on Business News
M2REAL	-0.0	-0.0
AMBSL	0.0	-0.0
TOTRESNS	-0.0	-0.0
NONBORRES	-0.0	0.0
BUSLOANS	0.0	0.0
REALLN	0.0	-0.0
NONREVSL	-0.0	-0.0
CONSPI	0.0	-0.0
S&P 500	-0.0	-0.0
S&P: indust	0.0	-0.0
S&P div yield	-0.0	0.0
S&P PE ratio	0.0	-0.0
FEDFUNDS	0.0	0.0
CP3Mx	0.0	0.0
TB3MS	0.0	0.0
TB6MS	0.0	0.0
GS1	0.0	0.0
GS5	0.0	0.0
GS10	0.0	0.0
AAA	0.0	0.0
BAA	0.0	0.0
COMPAPFFx	0.0	0.0
TB3SMFFM	0.0	-0.0
TB6SMFFM	-0.0	-0.0
T1YFFM	0.0	-0.0
T5YFFM	-0.0	-0.0
T10YFFM	-0.0	-0.0
AAAFFM	-0.0	-0.0
BAAFFM	-0.0	-0.0
TWEXMMTH	0.0	0.0
EXSZUSx	0.0	0.0
EXJPUSx	-0.0	0.0
EXUSUKx	-0.0	-0.0
EXCAUSx	0.0	0.0
WPSFD49207	-0.0	-0.0
WPSFD49502	-0.0	-0.0
WPSID61	-0.0	-0.0
WPSID62	0.0	0.0
OILPRICEx	0.0	0.0
PPICMM	-0.0	-0.0
CPIAUCSL	0.0	0.0
CPIAPPSL	0.0	0.0
CPITRNSL	0.0	0.0
CPIMEDSL	0.0	-0.0
CUSR0000SAC	0.0	0.0
CUSR0000SAD	0.0	0.0
CUSR0000SAS	0.0	0.0
CPIULFSL	0.0	0.0
CUSR0000SA0L2	0.0	0.0
CUSR0000SA0L5	0.0	0.0
PCEPI	0.0	0.0
DDURRG3M086SBEA	0.0	-0.0
DNDGRG3M086SBEA	0.0	0.0
DSERRG3M086SBEA	0.0	-0.0
CES0600000008	0.0	0.0
CES2000000008	0.0	0.0
CES3000000008	0.0	0.0
UMCSENTx	-0.0	-0.0
MZMSL	-0.0	-0.0
DTCOLNVHFNM	0.0	0.0
DTCTHFNM	-0.0	0.0
INVEST	0.0	-0.0
VXOCLSx	0.0	0.0

Rahapoliitika šokkide tuvastamine USA Föderaalreservi eestikeelsete ärakirjade põhjal

Mitteennustatud rahapoliitika šokkide tuvastamine on k̈s põhilisemaid väljakutseid empiirilises makroökonoomikas kuna keskpanga - käsolevas artiklis USA Föderaalreservi - intressimäärade muutused on ühelt poolt endogeensed ehk sisetekkelised - Föderaalreserv reageerib enda intressimäära muutes arengutele makromajanduses (nt inflatsioonile või kogutoodangu lõhele) - ja teiselt poolt ootustele tulevikus kehtivate makromajanduslike tingimuste suhtes.

Käesolevas artiklis pakun ma välja uue lähenemise eksogeensete rahapoliitika šokkide tuvastamiseks, mis ei nõua eeldusi aluseks oleva makromajanduse struktuuri kohta ega ka rahapoliitiliste tegevuste vaatlemist. Minu lähenemise sisuks on USA Föderaalreservi intressimäära (federal funds rate) ootamatute muutuste otsene hindamine selliste nihetena, mida pole võimalik ennustada Föderaalreservi Avaturu Komitee (Federal Open Market Committee, edaspidi ka FOMC) otsustest. Sellel eesmärgil kasutan ma närvivõrkude Word2Vec lähenemist ja põhiliste masinõppe regressioonilähenemiste ansamblit ennustamaks efektiivset Föderaalreservi intressimäära (federal funds rate) FOMC arutelude tekstidest, tegemata seejuures mingeid eeldusi agridade struktuuri suhtes. Föderaalreservi intressimäära prognoosimise vigu koosolekule järgneva kuu alguses tõlgendatakse siinkohal uue rahapoliitika šokki mõõdikuna.

Uurides tuletatud rahapoliitika šokkide aegrea omadusi, ilmnes, et muutused kogutoodangus ja inflatsioonis vastusena muutustele minu poolt tuletatud uuele rahapoliitika šokki näitajale on täielikult kooskõlas makroökonoomika teooriaga: nii kogutoodang kui inflatsioon langevad vastusena rahapakkumise kokkutõmbumise šokile. Sellised tulemused on stabiilsed ka uurimistöös kasutatud aegridade lühendamise ja erinevate viitaegade kasutamise suhtes.

Käsolevas artiklis tuletatud rahapoliitika šoki näitajat saab kasutada näiteks rahapoliitika ülekandumise mehhanismide uurimiseks - nii on näidatud, et raha hulka vähendav šokk tõstab võlakirjade ülemäärast preemiat ning kinnisvaralaenude ja kommertsväärtpaberite hinnavahet. See tulemus on kooskõlas sellega, et minu rahapoliitika šoki näitaja on vaba rahapoliitika teostaja (keskpanga) reageerimisest finantsnäitajate praegustele ja tulevikuväärtustele.