Text Shocks and Monetary Surprises:
Text Analysis of FOMC Statements with Machine Learning

Amy Handlan*

October 20, 2020

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Abstract

This paper studies how information in Federal Reserve communication affects expectations and other economic variables, over and above the effects of setting the federal funds rate. To do this, I adapt neural network methods from the computer science literature to analyze the text in Federal Open Market Committee (FOMC) post-meeting statements. In particular, I examine the relationship between FOMC statements and high-frequency changes in fed funds futures (FFF) prices around the release of those statements. I find that actual FOMC statements account for four times more variation in FFF prices than only announcing changes to the target federal funds rate. More generally, the monetary policy shock literature tries to identify exogenous changes in monetary policy to study its effects on the economy. In this paper, I create a new monetary policy shock series for 2005-2014 by projecting FFF prices onto FOMC statements using the neural network. In particular, if the neural network predicts a particular FOMC statement should have a large effect on FFF prices, that statement is said to be a large policy shock. Furthermore, the text shock series is capturing the effects of forward guidance directly from variation in the wording of FOMC statements. I then estimate the effect of these "text shocks" on economic and financial variables. I show that real interest rates have a correlation with my text shocks that is two times larger than with pure FFF price changes. Using changes in FFF prices as a monetary shock, rather than my text shocks, produces responses in output and inflation that are minimal and in the wrong direction. Conversely, my text shocks series produce responses in output and inflation that are qualitatively consistent with theory. That is, a contractionary monetary shock is associated with decreases in both output and inflation.

Keywords: FOMC statements, forward guidance, machine learning, monetary policy shocks, neural network, text analysis

JEL Codes: C45, E43, E44, E52, E58, G01

*Department of Economics, University of Minnesota and Federal Reserve Bank of Minneapolis. 1925 Fourth South St., Minneapolis, MN 55455. Email: handl039@umn.edu. Website: https://sites.google.com/umn.edu/amy-handlan. The views expressed herein are those of the author and not of the Federal Reserve Bank system. I would like to express my deepest appreciation to my committee - Christopher Phelan, V.V. Chari, and Loukas Karabarbounis - for their valuable advice and support. For their helpful comments and suggestions, I also wish to thank Jacob Adenbaum, Robert Barsky, Ross Batzer, Anmol Bhandari, Jonas Fisher, Larry Jones, Ellen McGrattan, Vitoria R. de Castro, Dana Shaat, as well as seminar participants from the University of Minnesota, the Federal Reserve Bank of Chicago, and Vanderbilt University. Finally, I thank the University of Minnesota Doctoral Dissertation Fellowship and the AEA Summer Fellows Program for their financial support.

1 Introduction

The Federal Open Market Committee (FOMC), the policy-making branch of the Federal Reserve (Fed), meets 8 times a year to discuss monetary policy and set the federal funds rate (FFR). Since May 1999, the FOMC has released a statement discussing its current and future policy objectives and assessments of US economic performance. The portion of statements that discusses future policy and future economic conditions is referred to as forward guidance. The Fed claims that they release these statements to increase transparency of monetary policy actions and provide guidance to public expectations. If forward guidance impacts the real economy by changing expectations then Fed announcements can be a viable tool to influence the economy, especially in periods when other policy tools are unavailable, like the zero-lower-bound. This raises the question: how do *the words* of FOMC statements impact expectations of future monetary policy, and more specifically future federal fund rates?

This paper studies how the information in Federal Reserve communication affects expectations and other economic variables over and above the effects of setting the federal funds rate. I adapt neural network methods from the computer science literature to use FOMC post-meeting statements to predict high-frequency changes in fed funds futures (FFF) prices. Changes in these prices encompass changes in market expectations of how the FOMC will set the federal funds rate in the future. Using the neural network, FOMC statements, and internal FOMC meeting materials, I create a monetary policy shock series called "text shocks." A positive text shock means that the FOMC announcement has shifted the path of federal-funds-rate expectations up. So, a positive text shock can also be thought of as a contractionary monetary policy shock.

This series represents innovations of monetary policy and I can use the series to study monetary policy's effect on the macroeconomy. There are three key results from this series: first, the variation in FFF prices accounted for by the FOMC statement text is four times that accounted for by changes in target federal funds rate. Second, using my text shocks to represent monetary policy I show that monetary policy has a larger effect on real interest rates compared to the literature. Third, if the FOMC releases a statement that produces a positive text shock then output decreases and inflation decreases, as is consistent with monetary theory.

To predict FFF price changes from FOMC statement text, I use the state-of-the-art neural network for text analysis from Yang, Dai, Yang, Carbonell, Salakhutdinov and Le (2020). A neural network, generally speaking, is a parametric approximation of a potentially non-parametric or complex function from input to output variables (Athey and Imbens, 2019). In this paper, the neural network predicts changes in FFF prices using the joint occurrence of FOMC statement text. For quantitative analysis, words are represented as vectors so an FOMC statement is a matrix of numbers. These word-vectors, also called word embeddings in the text analysis literature, are such that the more similar words are the closer their vectors are. The real advantage of using a neural network is that because it incorporates complex features of the text, like word order and word interdependencies, for prediction tasks. Other text analysis methods that have been used in economics – such as clustering words into topics or using word counts to create sentiment indices - overlook these features (Gentzkow, Kelly and Taddy, 2019).

After fitting the parameters of the neural network to predict shifts in FFR expectations from FOMC statements, I create a new monetary policy shock series. What I call "text shocks" are created following two steps. First, I project changes in FFF prices onto the FOMC statement text with the neural network. This is to identify the changes in FFF prices that come from the announcement and not from other attitudes from trading in the futures market (Lucca and Moench, 2015; Neuhierl and Weber, 2018). At this stage, the series would represent market reactions from the FOMC statement. However, FOMC statements include information about the economy that is more precise than what markets have in addition to monetary policy actions or guidance. All of these components are influencing FFF prices. To create a series that represents new monetary policy we want the latter without the former. Other papers, such as Romer and Romer (2004), strip their shock series of the FOMC's private information using internal FOMC forecasts of macroeconomic variables. In a similar fashion, I look to the FOMC's internal meeting materials; however, I do so for the alternative versions of the post-meeting statements.

The alternative statements in the FOMC meeting materials are statements that the

FOMC could have released but did not. I use alternative statements for meetings from 2005-2014 that have been released to the public.[1] With the neural network trained on the actual FOMC statements, I predict the change in FFR expectations for all alternative statement for each FOMC meeting. These alternative statements all include the Fed's assessment of the current state of the economy, but they differ in their forward guidance action. Therefore, the average predicted expectation shift for the alternative statements represents that common element. The second step in producing my shock series is then to subtract this average from expectation changes predicted from the first step. This leaves the shock series as representing monetary policy actions and not the Fed's description of the economy. I call this the "cleaned text shock." This cleaned text shock series is the change in fed funds future prices caused by the FOMC statement text and controls for the FOMC statement including non-monetary policy information that could influence markets.

I test if the cleaned text shock series captures a sense of forward guidance by looking at the correlation between the shock and fed funds futures prices at different horizons. I find that as the future horizon increases, the correlation between the future price and the cleaned text shock increases. Also, the text shock accounts for more variation in fed funds futures prices as the futures horizon increases. Gertler and Karadi (2015) use a similar argument to explain how their shock series represents the Fed's forward guidance.

To study the transmission of monetary policy text shocks on other economic variables, I proceed in two steps. First, I regress nominal and real interest rates at one to ten year horizons on the cleaned text shock. I compare the regression for a variety of shock series: the cleaned text shock, changes in fed funds futures prices, the shock series from Nakamura and Steinsson (2018), and the shock series from Gertler and Karadi (2015). All of these shocks series have similar minimum and maximum values and are measured in basis points.

I find that all the shock series are similarly correlated with nominal interest rates. That is, a one basis point increase in any of the shocks is correlated with about a one basis point increase in nominal treasury yields. However, for real interest rates, I find the coefficients for the text shocks are about twice the size as the other shock series. So, a one

[1]The statements are found in Bluebooks from January 2005 - 2010 and the Tealbooks form June 2010 - December 2014. Materials are released on a five year lag.

basis point increase in the text shock is associated with a two to four basis point increase in treasury-inflation-protected security (TIPS) yields (real interest rates). Meanwhile, a one basis point increase in fed funds future prices, Nakamura and Steinsson (2018) shocks, or Gertler and Karadi (2015) shocks account for one to two basis point increase in TIPS yields. From this exercise, I conclude that monetary policy has a larger effect on real rates than other high-frequency-identified monetary policy shocks would indicate.

Second, I use an external instrument, vector autoregression (VAR) approach to study the relationship between monetary policy shocks and other macroeconomic variables. As in Gertler and Karadi (2015), I include industrial production, Consumer Price Index (CPI), one year treasury yield, and an excess bond premium measure in the estimation. Following Ramey (2016), I use the local projection method from Jordà (2005) to produce impulse response functions. I compare the responses of these macroeconomic variables to impulses of my text shocks with the Gertler and Karadi (2015) shock series. As in the replication of Gertler and Karadi (2015) in Ramey (2016), I find that in the local projection framework that the Gertler and Karadi (2015) shock series produce minimal responses in output, inflation, and excess bond premium variables. In fact, a contractionary Gertler and Karadi (2015) shock is associated with slight increases to inflation and output. However, an increase in the cleaned text shock series is associated with responses in output, inflation, and excess bond premium that are consistent with monetary theory. That is, when using the text shock to represent monetary policy innovations, a contractionary shock produces decreases in output and inflation but an increase in the excess bond premium. This indicates that the Fed's forward guidance through its wording of FOMC statements is a quantitatively important channel in which monetary policy impacts the economy.

The rest of the paper proceeds as follows: Section 2 discusses related literature that studies monetary policy communication. Section 3 details data sources and preparation methods. Section 4 describes the text-analysis method and results for predicting monetary surprises with FOMC statement text. Section 5 describes the creation of the new monetary policy shock series, text shocks. Next, section 6 includes comparisons of my shock series with others from the literature. And in section 7, I conclude.

2 Literature Review

This paper contributes to two strands of the monetary policy literature: the literature on identifying monetary policy shocks and the literature on text analysis of monetary policy announcements. This paper's contribution to the former is a new monetary shock series. For the later, this paper is the first to use a neural network for text analysis of central bank communication.

The literature on estimating the effects of monetary policy and information shocks is large. The subset that this paper relates to is the literature that uses high-frequency changes in asset prices, usually federal funds futures (FFF) prices, to calculate unanticipated changes in the federal funds rate and its expected path (Campbell, Evans, Fisher and Justiniano, 2012; Gertler and Karadi, 2015; Gurkaynak, Sack and Swanson, 2004; Kuttner, 2001; Nakamura and Steinsson, 2018). These papers use the change in FFF prices over a small period of time, from before to after the FOMC statement is released, as proxys for exogenous innovations or shocks to monetary policy. Unanticipated changes in the federal funds rate (FFR) set at the current meeting, measured with changes in prices for FFF contracts that expire at the end of this month, are often called monetary surprises. Changes in FFF that expire a further in the future then capture the change in market expectations of FFR to be set at future meetings. These longer horizon expectation shifts are sometimes referred to as *monetary policy news shocks, forward guidance shocks, or information shocks*. But instead of keeping track of the entire expectations path, economists either focus on the expectations for the one FOMC meeting, as in Gertler and Karadi (2015), or use the first principal component of multiple fed fund futures price changes to capture the common variation across fed fund futures contracts in a single dimension, as in Nakamura and Steinsson (2018) and Gurkaynak et al. (2004).[2] These papers find that shocks to expectations of future monetary policy action have large effects on interest rates and macroeconomic variables, including output growth, inflation, and financial risk measures (Campbell et al., 2012; Gertler and Karadi, 2015; Gurkaynak et al., 2004; Kuttner, 2001; Nakamura and Steinsson, 2018; Ramey, 2016).

[2]Principal component analysis is a method used to reduce dimensionality of data. Using the eigenvalue decomposition of a dataset's covariance matrix, data is projected to new dimensions according to its variance. The first principal component, the first coordinate in the new dimensions, captures the greatest common variance of the original variables.

My paper differs from the others in this literature in two key ways. First is that I drop the assumption that FFF price changes in the small window around the FOMC statement release are *only* influenced by the monetary policy announcement. Instead, with the neural network for text analysis, I project the change in FFR expectations onto the FOMC statement text directly to extract the portion of asset price changes caused by the text. Second, is the explicit use of the wording of FOMC statements. This is relevant for being able to study the effects of forward guidance because the variation is forward guidance policy will show up as variation in wording of the monetary announcements.

The other literature that this paper contributes to is the one that uses text analysis to study the effects of monetary policy communication. Gentzkow et al. (2019) provide a survey of text analysis of central bank communication. Generally, this field has focused on either estimating how the public and investors respond to monetary announcements or estimating the Fed's objective function. In both cases, the methods for text analysis has evolved over recent years. But my paper fits in with the former categorization. For overviews of the latter literature, please reference the following papers Cieslak and Vissing-Jorgensen (2020); Hansen, McMahon and Prat (2018); Shapiro and Wilson (2019).

FOMC announcements may have a large effect on the economy through changing the public's expectations. To better understand this expectations channel, economists are working with advanced text analysis methods to quantitatively measure the variation in wording of monetary policy announcements. For example,Hansen and McMahon (2016) produce two measures: one of expansionary-versus-contractionary sentiment and the other of uncertainty in FOMC post-meeting statements. They do this using a combination of LDA and word counts from expansionary and contractionary word lists. Based on this measure, they find that central bank communication has little impact on real economic variables.

However, more commonly, economists look at the Fed's impact on asset prices as a mechanism for monetary policy announcements to impact the reset of the economy. Cieslak and Schrimpf (2019) compare the relative effect of monetary and non-monetary news in FOMC announcements on financial risk premia. They find that both information types influence market expectations. Husted, Rogers and Sun (2017) create a monetary policy uncertainty measure by counting the uncertainty words in newspaper articles about the

Federal Reserve. They find that an increase in monetary policy uncertainty translate to higher credit spreads and lower output. Handlan (2020) uses weighted differences in words in sequential FOMC statements to show that larger changes in the wording of successive FOMC statements causes larger movements in high-frequency fed fund futures prices. Jegadeesh and Wu (2017) use a combination of LDA and sentiment-word frequencies, but to study the FOMC minutes. They find that their overall sentiment measures of the minutes are not correlated with market expectations, but they do document that market volatility decreases around the release of FOMC minutes. Indicating new information being integrated into financial markets. However, more advanced text analysis methods may be needed to find the overall effect of an announcement.

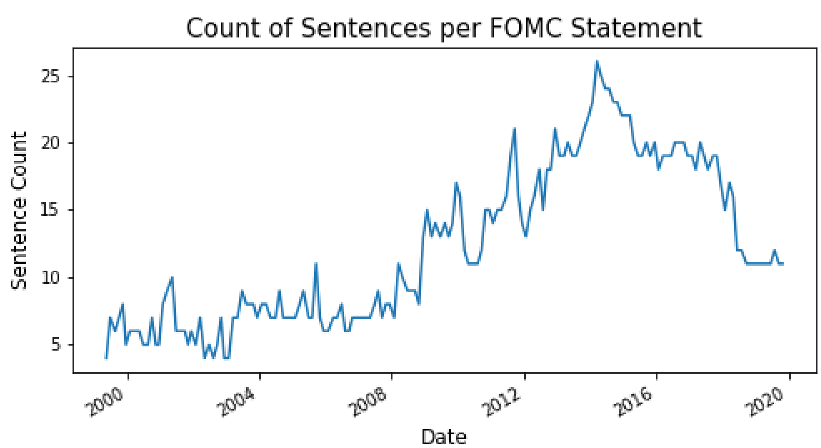
So far, papers using computational text analysis to study central bank communication only depend on occurrences of words, but do not capture word order or have a sense of context. For example, the phrases "*inflation* went up, but *employment* did not" and "*employment* went up, but *inflation* did not" would produce the same measures. Word clustering or word count methods both share this shortcoming. Methods that use neighboring words, called n-grams, would also miss information content spread out throughout a sentence. For example, a bigram looks at the frequency of sequential word pairs. For the following sentence, "economic growth slowed, but is likely to expand at a rapid pace," a bigram would count "growth slowed" but would miss that the point of the sentence is that economic growth is expected to increase.

Deep neural networks for text analysis are state-of-the-art methods in computer science and in linguistics. Neural networks are able to account for nonparametric relationships between words which gives this text analysis tool a way to approximate context. Furthermore, the way the networks interact words also pick up long-term dependencies. That means the "expand at a rapid pace" and "slowed" could both be associated with "economic growth" for prediction. Gentzkow et al. (2019) acknowledge that there is room in economics for machine learning methods of text analysis. This paper addresses this gap in the literature by applying a neural network text analysis method to study central bank communication.

3 Data

The sample period for my analysis is from May 1999 through October 2019. The FOMC post-meeting statements during this period were sourced from the Board of Governors of the Federal Reserve System website.[3] I collected the time of release from a combination of the timestamps on the statements themselves, online newspaper article timestamps that print the FOMC statements, and Federal Reserve Board announcements on times.[4] Table A1 in the appendix lists all 165 statements with their date and time of release. I drop unscheduled FOMC meetings' statements from the sample. This is because I want the change in asset prices that occurs around the statement's publication to be from the content of the statement, not a combination of the statement wording and the surprise that there was meeting.

Figure 1: Number of Sentences in FOMC Statements, 1999-2019



Note: The above counts are for FOMC statements that have already been cleaned, described in section A.3.1

These statements generally discuss the current economic environment, the new target federal funds and discount rate, and information about the FOMC's expectations for the future of the economy. Following the 2008 Financial Crisis, the statements also discussed unconventional monetary policy, such as quantitative easing programs. This added topic

[3]FOMC statements are at: https://www.federalreserve.gov/monetarypolicy/fomc.htm

[4]The following two links contain FOMC announcements related to the scheduling of post-meeting statement release times: https://www.federalreserve.gov/newsevents/pressreleases/monetary20130313a.htm, and https://www.federalreserve.gov/newsevents/pressreleases/monetary20110324a.htm

and the inability of the FOMC to use changes in rates to influence expectations increased the length of statements post-2008, as seen in Figure 1.

Alternative versions of post-meeting statements are provided to FOMC members in their pre-meeting materials. Pre-meeting materials that are sent to FOMC members before the policy meetings describe the state of the economy and recommend policy actions. These materials are bundled into books. Since 2010, that has been the Tealbook A and B. Previously there were Greenbooks and a Bluebook. These books are released to the public on a five year lag and are also available on the Board of Governors of the Federal Reserve System website. Drafts for alternative versions of FOMC post-meeting statements are clearly displayed in the Tealbook B's and in the Bluebooks from January 2005 through December 2014. Prior to 2005, wording for statement drafts is spread-out throughout the book and is not clearly labeled. Accordingly, I limit the sample to statement alternatives that are written in their own section and clearly labeled in the pre-meeting materials.

Tick-level time-of-sale data on federal fund futures at the one to six month horizons was purchased from CME Group. I have this price data for the entire sample of May 1999 through October 2019. As is common in applied monetary economics, I use FFF prices as a proxy for market expectations of how the FOMC will set federal funds rate at future meetings. This stems from how the FFF contract is priced: the contract settlement price is determined by the average effective federal funds rate over the final month of the contract. Looking at the price of a FFF contract that expires at the end of this month (FFF_t^1) before an FOMC meeting (t) would be priced[5]

$$FFF_t^1 = 100 - \left(\frac{d}{m}\, r_{t-1} + \frac{m-d}{m}\, \mathbb{E}_t[r_t] \right) \tag{1}$$

where d is the day of meeting, m is the total number of days in the month, r_{t-1} is the federal funds rate before the meeting and r_t is the federal funds rate set at the meeting. $\mathbb{E}_t[r_t]$ is the expectation of how the FOMC will set the federal funds rate at the current meeting evaluated right before the FOMC meeting - "right before" as 10 minutes before the statement is released. The FFF price 10 minutes before the FOMC statement is released then

[5] Although I use the notation FFF_t^1, the actual contract name is $FF1$. I use the triple "F" notation to clarify differences between fed funds futures (FFF) and the federal funds rate (FFR)

incorporates information in the market up to that point. Comparing this price to the FFF price 20 minutes after the FOMC statement is released ($t+\Delta$) will then be influenced by any new information contained in the monetary policy announcement.[6] The FFF price change can then be rearranged to represent the *monetary surprise*, the change in expectations of the federal funds rate for the current meeting:

$$\mathbb{E}_{t+\Delta}[r_t] - \mathbb{E}_t[r_t] = \frac{m}{m-d}\left(FFF_t^1 - FFF_{t+\Delta}^1\right) \tag{2}$$

I also consider how the current FOMC announcement influences expectations over the federal funds rate for the next meeting ($t+1$):

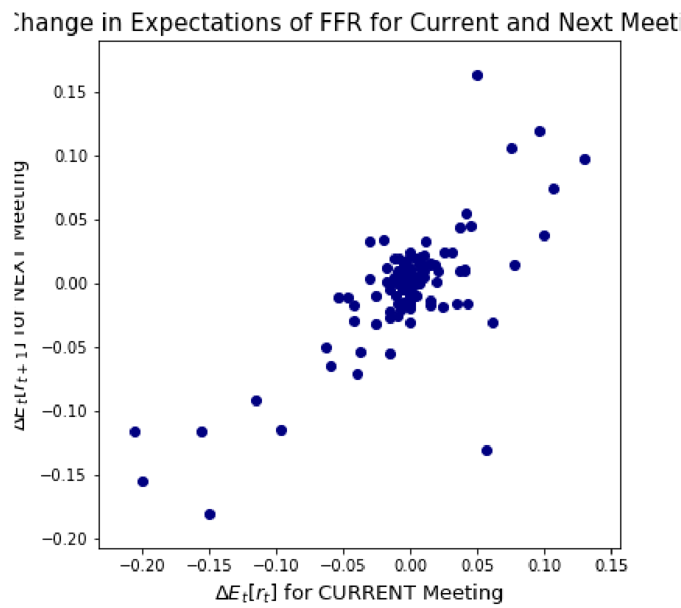
$$\mathbb{E}_{t+\Delta}[r_{t+1}] - \mathbb{E}_t[r_{t+1}] = \frac{m_2}{m_2-d_2}\left(FFF_t^n - FFF_{t+\Delta}^n - \frac{d_2}{m_2}\left(\mathbb{E}_{t+\Delta}[r_t] - \mathbb{E}_t[r_t]\right)\right) \tag{3}$$

This requires using the FFF contract that will expire in the month of the next meeting, n months from the current month. FOMC meetings are not equally spaced, so the FFF contract used to reference the next meeting month changes for each meeting. Notice that the monetary surprise influences the path of expectations. Figure 2 shows that changes in the expectations of the federal funds rate at the current meeting and for the next FOMC meeting are highly correlated.

To only focus on a single dimensional representation of expectations, I use the first principal component of these two variables as the baseline expectations representation. Following Nakamura and Steinsson (2018), I re-scale this principal component such that a one-unit increase corresponds to a 100 basis point increase in the daily change of a one year treasury yield. Translating the first principal component back to changes in federal funds rate expectations, a one unit increase in the first principal component would translate to the federal funds rate being set 168 basis points higher than expected and a 180 basis point increase in the expectations for the federal funds rate at the next FOMC meeting. For the rest of the paper, I will interchangeably refer to this measure as the change in federal funds

[6]FOMC press conferences are typically 30 minutes after the FOMC statement is released. Accordingly, looking at the FFF prices after the FOMC statement is released but before the press conference is so that the price change is picking up the effect of the statement and not the conference.

Figure 2: Change in Expectations of Current vs. Next Fed Funds Rate



Note:$\Delta E[r]$ is the first principal component of two variables: the change in expectations today of the federal funds rate at the current meeting $\Delta E_t[r_t]$ and the next meeting $\Delta E_t[r_{t+1}]$. Federal funds rate expectations are calculated from changes in fed funds futures prices.

rate expectations or the change in fed funds futures prices.

Throughout the paper I also use data on the target federal funds rate, treasury yields, industrial production, consumer price index (CPI), and excess bond premium. Daily target federal funds rate data is pulled from FRED. When the target federal funds rate is a range of values, I take the average of the of range to get a single number representation of the target federal funds rate. Monthly data on industrial production and CPI is also collected from FRED. Daily data for treasuries and Treasury Inflation Protected Securities (TIPS), representing nominal and real interest rates respectively, are from Gürkaynak, Sack and Wright (2006) and Gürkaynak, Sack and Wright (2010), receptively. Both data sets are available on the Federal Reserve Board's website.[7] I use the monthly measure for excess bond premium from Gilchrist and Zakrajsek (2012), which is also available on the Fed's website.[8]

[7]Treasuries: https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html, and TIPS: https://www.federalreserve.gov/pubs/feds/2008/200805/200805abs.html

[8]https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv

4 Text Analysis and Neural Network Background

I use an off-the-shelf neural network for text analysis from the computer science literature to approximate the mapping from FOMC statement text to changes in federal funds rate (FFR) expectations. I use the pre-trained neural network from Yang et al. (2020), called XLNet. In this section, I will give an overview of the text analysis neural network from Yang et al. (2020). I then will discuss the application of their method to FOMC statements. Finally, this section will wrap up with an evaluation of the fitted neural network's ability to predict unanticipated shifts in FFR expectations compared to using changes in the target rate to predict expectation shifts. I will also walk through examples how changes in FOMC statement wording changes the neural network predictions to shed some light the nuances the neural network picks up.

4.1 Text Analysis Neural Network (XLNet)

The neural network from Yang et al. (2020), called XLNet, is considered a state-of-the-art method for text analysis tasks like translation, question and answer, classification, and regression. In other words, their method is flexible enough to approximate mappings from text to text, text to categories, or text to continuous numbers. In this subsection of the paper I will discuss broadly the text analysis neural network. However, for more detailed information on the network structure, an overview of text analysis, and an overview of neural networks are in Appendix A.3.

As is common for computational text analysis, Yang et al. (2020) then convert words into numerical representations. They build their dictionary that maps words from their collection of documents to numbers to input into the neural network. Specifically, they break words into sub-word units to decrease the overall size of the vocabulary.[9] Each sub-word is called a token. For each token they create a 768x1 vector based on co-occurrence of sub-word units in the corpus using a clustering algorithm. In the end, similar sub-words will have similarly oriented vectors in 768-dimensional space. However, these vectors do not

[9]For example, if there is a vocabulary of "decreasing," "increasing," "inflating," "decreased," and "inflated" could be broken into the following list of subwords: "in," "de," "creas," "flat," "ing," "ed."

account for context. So, the vector for "bank" would be the same whether it was referring to a financial institution or to the side of a river. To capture context is why researchers turned to neural networks.

Yang et al. (2020) train their neural network to predict missing words from input text. The parameters in the neural network update such that the neural network is able to more accurately predict the missing word. They use a large collection of texts to train their neural network for this task. The collection of texts includes BookCorpus(11,038 books), English Wikipedia (6 mil. articles), Giga5 (9.9 mil. news articles), ClueWeb12 (733 mil. webpages), Common Crawl (1K+ TB text from webpages). The generality of this large collection helps to build a foundation in the neural network parameters that can "understand" the English language. Ultimately, the network parameters are learning relationships between words.

Yang et al. (2020) then take the network structure and trained weights as an initial starting point for a variety of other tasks that are considered benchmark exercises in the text-analysis literature. Further adjustment of parameters on these new tasks is called finetuning. Yang et al. (2020) show that by using the pre-trained weights, they were able to achieve higher accuracy on the new tasks compared to not using pre-trained weights and compared to other text analysis methods. This idea of taking parameters fitted to a large general collection of texts and then using them as initial parameters before finetuning for a new task is called transfer learning. Yang et al. (2020) and others find that transfer learning also decreases the data requirements for similar accuracy on new tasks. For example, Howard and Ruder (2018) show that training samples as small as 100 observations can be successfully used for finetuning text analysis neural networks.

4.2 Application to Monetary Policy Statements and Expectations

In this paper, I use the network structure and word representations from Yang et al. (2020). Furthermore, I use the pre-trained base XLNet parameters as initial values for my task: predicting changes in FFR expectations from FOMC statement text. I include a general overview of the training algorithm, including pre-training and fine-tuning, in section A.3.4. To prepare the text for training, I remove URLs, time of release, and voting records of FOMC members from the statements. A more detailed description of text cleaning is in section A.3.1.

I split my sample into training and testing samples. I split the data using stratified K-fold and split the data into 5 subsets. I condition the splitting the meeting observations on how the target federal funds rate changed, who the Fed Chair was, and if the date was pre- or post-2007. One of the subsets becomes the testing sample and the remaining observations are used as the training sample. As robustness checks, I rotate the subsample that is used for testing and use the dataset complement as training. This is called a "k-fold cross validation" or a "leave-one-out cross-validation (LOOCV)." The results for this version of the paper are for one such training-testing split.

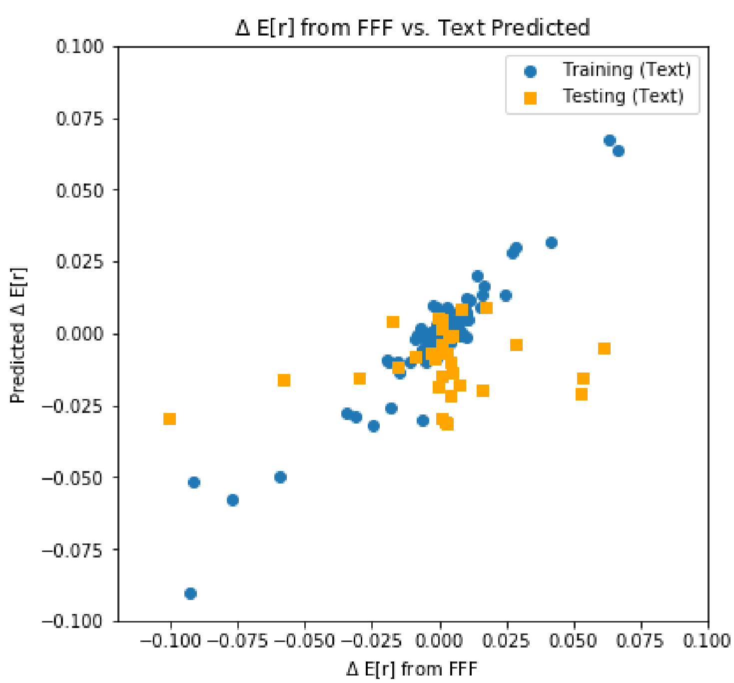
I fine-tune the pre-trained neural network from (Yang et al., 2020) to predict changes in FFF from the text of a FOMC statement. As is the standard in machine learning spheres, the metric for evaluating the performance of the trained network is based on how well it can accurately predict changes in FFF for FOMC statements that were not used to train the network parameters. In their summary of machine learning in economics, Athey and Imbens (2019) comment that evaluation of neural network models is inherently different from traditional econometric models. For the former the emphasis is on ability to predict outcome variables given input variables. Meanwhile, the latter focuses on estimating parameters that are functions of the joint distribution of data, construct confidence intervals of those estimates, and rely on theoretical foundations for efficiency of those estimators. Because I use a neural network approach, I will be using that literature's method for evaluating the results.

Individual parameters of the neural network are not interpretable in the same way as estimators from parametric models (Athey and Imbens, 2019). Accordingly, it is not possible to interpret the effect of one word or phrase over another. The primary goal of this paper and these text-analysis methods is to first see if we can make accurate predictions by approximating complex functions. Although I will not be able to explain the causal mechanism behind the FOMC-statements-market-expectations relationship with the trained neural network, I will be able to approximate the relationship and use prediction to create quantitative measures to describe Fed communication over time.

4.3 Evaluation of Text Analysis Neural Network

Neural networks are different from traditional econometric models because their evaluation is based on their ability to predict out-of-sample data, that is, data that was not used to train the neural network weights (Athey and Imbens, 2019). To evaluate the prediction, I use the Pearson correlation between the predicted output and the actual output values for the testing data. Figure 3 graphs the actual $\Delta E[r]$ on the horizontal axis against the $\widehat{\Delta E[r]}$ predicted from FOMC statement text through the neural network. The blue circle dots are the training sample while the orange squares are the testing sample. The testing sample's prediction has a 20% correlation with actual $\Delta E[r]$ data. The training sample has a much higher prediction accuracy because the neural network weights change to match $\widehat{\Delta E[r]}$ and $\Delta E[r]$. Together, plotting the training and testing data, I there is a 72% correlation between the actual data and the neural network output. Figure A1 graphs $\widehat{\Delta E[r]}$ and $\Delta E[r]$ over time.

Figure 3: Neural Network Prediction on Training and Testing Samples



Note: The horizontal axis is the output variable and the vertical axis is the predicted value from the neural network. The scale is such that 0.025 on the horizontal axis represents a change in $\Delta E[r]$ by 2.5 basis points.

The large difference between in-sample and out-of-sample accuracy means that there is likely overfitting of the neural network because it is able to match in-sample data much better than out-of-sample data. In machine learning, there are a few tricks to minimize overfitting problems and make the neural network more generalizable to new data.

The first is by limiting the network training through the learning rate and number of training iterations. When there are too many training iterations, the researcher can see that eventually the out-of-sample prediction accuracy stops increasing and begins to decrease. This is a sign of the network weights overfitting the training data. When the learning rate is too high, this degradation of out-of-sample prediction happens more quickly, meaning over fewer training iterations. Because I am using a transfer learning approach, the parameters of the neural network start out as having a general weighting scheme for interpreting words in text. So limiting how much the parameters can update, either within each iteration or over all iterations, would help keep the weighting more generalizable. I also track the out-of-sample accuracy while training occurs and stop training of the network once out of sample prediction decreases from the previous iteration. This intuitively leads to an decrease for the in-sample prediction accuracy. The importance is to strike a balance between teaching the network about the desired mapping - from FOMC statements to changes in expectations - and training the network to the point of overfitting.

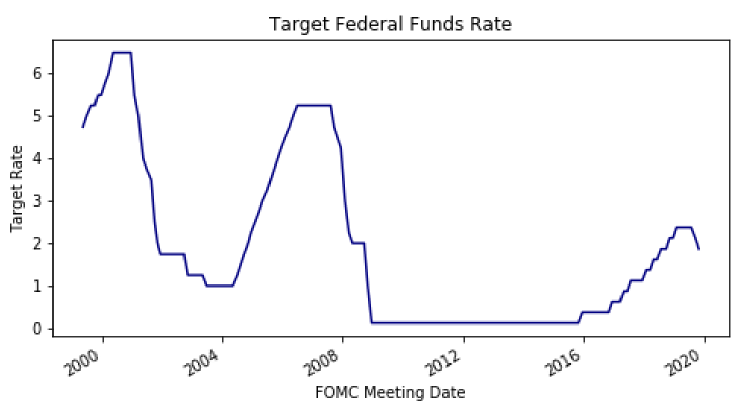
The second approach is to find more data. In terms of machine learning problems, 165 observations is incredibly small even with a transfer learning approach. However, there are only so many FOMC statements that have been made over time. One approach would be to artificially augmenting the training sample with a method called 'back-translation.' Computer scientists have shown that translating text inputs to a different language and then translating them back to the original language with a software like Google Translate can create synthetic training observations that improve network performance. The underlying assumption is that Google Translate will create small variations in word order or word choice without dramatically changing the tone or content of the text. Accordingly, the back-translated statement can be assigned the same change in expectations as the original FOMC statement it was created from. Preliminary results from this robustness check produce similar results as above and the computer science literature has shown that this method can work for small samples (Howard and Ruder, 2018). Accordingly, I proceed with the neural network trained on the 132 FOMC statements.

Therefore, I interpret these differences as representing changes in expectations that were not caused by the announcements. It is possible that this is due to the networks' poor ability to approximate the underlying mapping from FOMC statement to expectation changes. Because there is no standard theory in the computer science literature to verify the quality of a neural network other than out-of-sample prediction, I complete the following exercise to put the accuracy of the neural network in a more familiar context.

4.4 Comparison with Changes in Target Federal Funds Rate

Some in the monetary policy literature consider using the change in the target federal funds rate (FFR) as a sufficient statistic to represent monetary policy. However, following the 2008 Financial crisis when the Fed set the FFR to zero for an extended period of time highlighted that monetary policy extends beyond setting the target rate. Figure 4 shows how the target FFR has changed over the sample period.

Figure 4: Target Federal Funds Rate Over Time, 1999-2019



Note: Daily target federal funds rate data is pulled from FRED. When the target federal funds rate is a range of values, I take the average of the of range to get a single number representation of the target federal funds rate.

To give context for the impact of monetary policy announcements on expectations, I compare the predictive power of changes in the target rate on FFR expectations. That is, I regress changes in FFR expectations on the change in the target rate.

$$\Delta E_t[r] = \beta_0 + \beta_1 \Delta TargetFFR \tag{4}$$

To compare apples to apples, I estimate the Equation 4 on the same observations I used to fit the neural network parameters. The regression results in Table 1 show that a increasing the federal funds rate by 0.25, the common increment for changes in the target rate, is associated with a 0.015, about one half standard deviation, increase in first principal component measure of FFR expectations.

Table 1: Regress Federal Funds Rate Expectations on Targets (In-sample)

	$\Delta E[r]$
Δ Target FFR	0.06***
	(0.01)
Intercept	0.00
	(0.00)
N	132
R^2	0.25
Adj. R^2	0.25

Note: $\Delta E[r]$ is the first principal component of changes in expectations of federal funds rate for the current FOMC meeting and next FOMC meeting. Δ Target FFR is the change in the target federal funds rate announced at the current meeting. The sample size is 132 because the regression is estimated on the training sample. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Using this coefficient, I calculate the predicted change in expectations for observations in the testing data. I use out-of-sample prediction accuracy to compare the prediction power of the neural network with FOMC statement text versus the regression with change in the target federal funds rate. I report both the Pearson correlation between the predicted change in expectations $\widehat{\Delta E[r]}$ compared to the actual change of expectations $\Delta E[r]$ and the R^2 value in Table 2. I find that the statement text can better predict changes in expectations out-

Table 2: FOMC Statement vs. Target Rate Out-of-Sample Prediction Comparison

	FOMC Statement Text	Δ Target FFR
Correlation ($\widehat{\Delta E[r]}$,$\Delta E[r]$)	0.2	0.1
R^2	0.04	0.01
N	33	33

Note: Parameters for each prediction method are fitted to the training data. Then those parameters are used to predict changes in expectations for the testing sample (N=33).

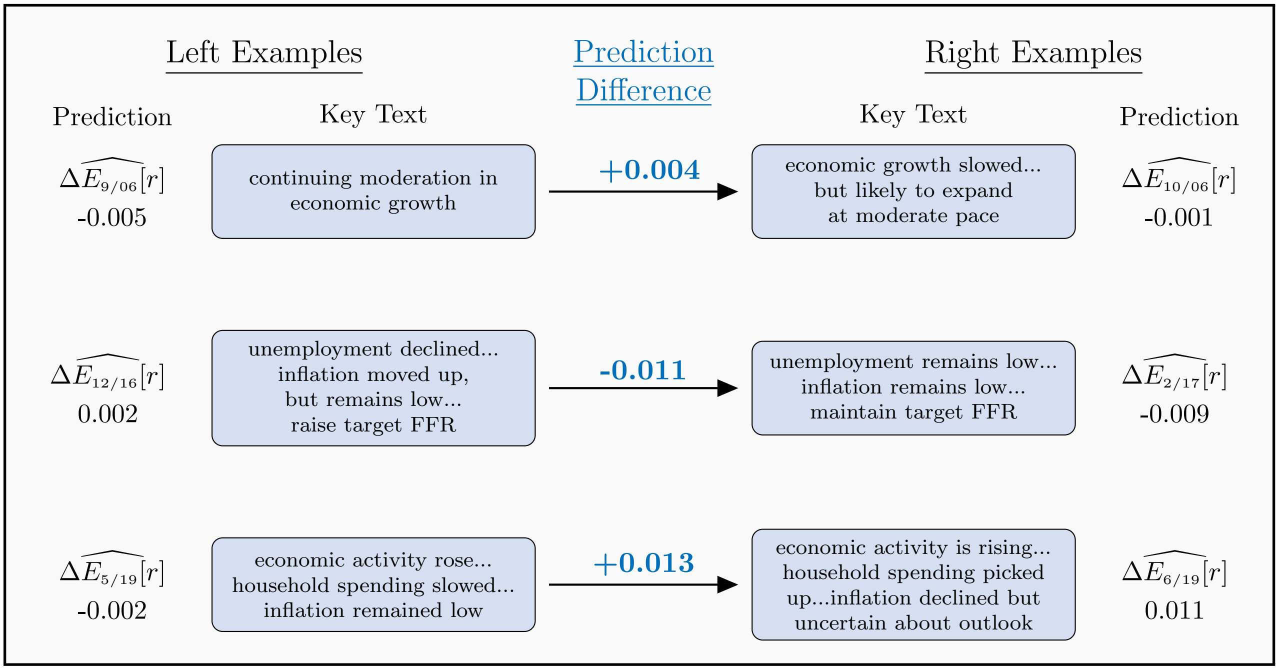
of-sample than using the target rate. When looking at correlation, the statement text is twice as accurate. When considering the R^2 measure, the statement text can explain four times the out-of-sample variation compared to predictions from changes in the target FFR. Figure A2 graphs $\widehat{\Delta E[r]}$ predicted from the target rate against $\Delta E[r]$, similar to Figure 3.

This difference is likely due to the FOMC statement contains the multiple dimensions of information. Accordingly, unexpected changes in expectations are responding to this new information and the statement text is able to capture more than just the single dimension of the federal funds rate target. Ultimately, this comparison is meant to convey, that even though the neural network is not able to strongly predict changes in expectations out of sample, it can do better than traditional measures of monetary policy changes that are publicly available when FOMC statements are released.

4.5 Different Wording Leads to Different Predictions

To shed some light on the neural network predictions, in this section I include examples of what the neural network predicts for different FOMC statements. The main exercise is to show two statements that are identical except for small differences in the text. Then to look at difference in what the neural network predicts for the statements' corresponding FFR expectation shifts. In Figure 5, there are three statement pairs for comparison. The text in

Figure 5: Neural Network Prediction for Different FOMC Statements



Note: Each row is comparing two FOMC statements that have very similar text. The differences are what is written in the blue boxes. Full statement text is in Table A2. These are example statements have few differences in wording as to be able to identify what is causing the change in neural network predictions.

the graphic highlights the text that is different between the two statements in each row.

The first row compares the September 2006 statement with the October 2006 statement. Both imply that economic growth is currently slow. Both kept the target federal funds rate unchanged. But the October 2006 statement adds that the FOMC expects the economy to expand. As a naive reader, knowing nothing else besides this difference, one would expect the Octboer 2006 statement to increase federal funds rate expectations more than the September statement because traditional monetary theory indicates that inflation follows economic growth, which would trigger contractionary policy action and the Fed would increase the FFR. Other text analysis methods, such as bigrams or trigrams which look at occurrences of neighboring two or three words, would likely identify these two statements as identical. One of the strengths of the neural network method is that it can pick up on relationships between words that are connected even if the words are not literally next to each other. This shows up as a difference in predictions of 0.004. The number is about one half of a standard deviation.

The second row compares the December 2016 and February 2017 statements. Moving from the December 2016 to February 2017 statements, the main differences are going from a notion of higher inflation to one of lower inflation. We would expect that statements that discuss low inflation and no target federal funds rate changes to have a relatively more negative change in expectations compared to a statement that raises the target rate and discusses increasing inflation. The network also picks up this difference.

The final row compares the May 2019 and June 2019 statements. This comparison shows how the FOMC's confidence in their guidance impacts the neural network prediction. Both the May 2019 and June 2019 statements talk about increases to economic growth and low inflation. However, the June 2019 statement qualifies its prediction of inflation going forward. Moving from a statement where inflation is likely to stay low to a statement where the FOMC is uncertain about the path of inflation would likely encourage market to expect possible increases in federal funds rates in the future to match the potentially rising inflation. The neural network shows this as a positive difference in switching from the May 2019 to the June 2019 statements.

5 Monetary Policy Text Shocks

Federal funds rate (FFR) expectations are often measured with fed funds futures (FFF) where the change in FFF prices represent unanticipated change in monetary policy. This comes from the the efficient market hypothesis, that says all publicly available information is incorporated into asset prices. So changes in the asset prices in a small time window represent incorporation of new information into prices. In terms of fed funds futures, whose pricing structure is based on FFR expectations, a change in prices represents unanticipated changes in FFR expectations. If the change was expected, then the futures price would not have changed.

In papers like Gertler and Karadi (2015), FFF price changes themselves are used as a proxy for structural monetary policy shocks. Timing restrictions for evaluating FFF prices mean that change in fed funds futures prices in a small window around when the FOMC announcement release are mostly caused by FOMC announcement. However, other factors

– such as market momentum or attitudes of traders – can impact asset prices even in that small window (Lucca and Moench, 2015; Neuhierl and Weber, 2018). And the researcher must separate the effect of exogenous shocks and the Fed's policy response to the state of the economy. Gertler and Karadi (2015) regress changes in fed funds futures on internal economic forecasts in the FOMC's meeting materials and use the residual from this regression as the exogenous shock. This cleaned-up shock has minimal impact on economic variables.

I use the FOMC statement text and the trained neural network to address these concerns when creating my new monetary policy shock measure. A projection of the change in fed funds futures prices directly onto the wording of the FOMC statement looks at the change in federal funds rate expectations (measured with fed funds futures prices) explained by the monetary policy announcement itself. This projection separates other market effects on expectations from the effect of monetary policy shocks.

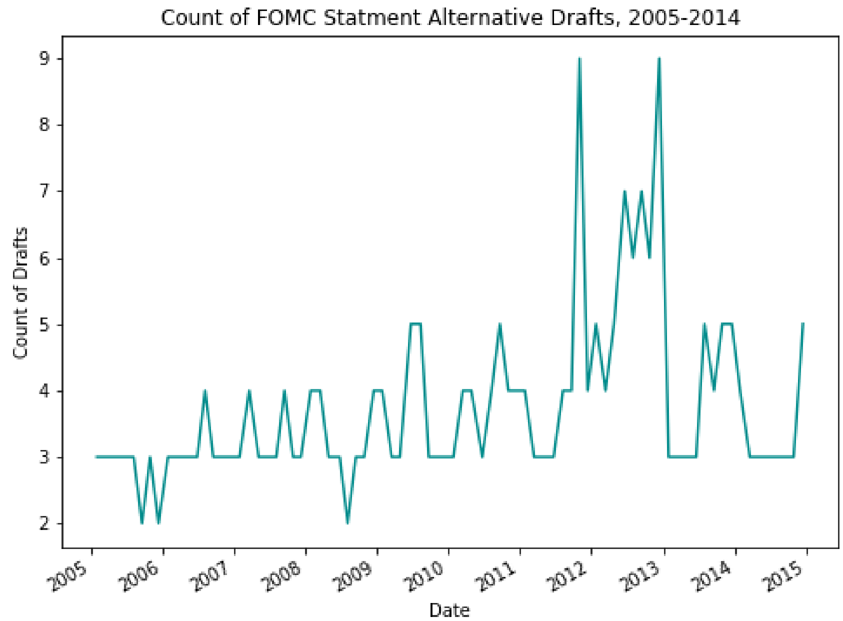
$$\textbf{Text Shock}_t = \widehat{\Delta E_t[r]}_{released} \tag{5}$$

However, this measure still has the issue that it is capturing both revelation of more precise information about the current economic situation and the monetary policy action. To have a measure of monetary policy, the former component must be separated out (Gertler and Karadi, 2015; Ramey, 2016; Romer and Romer, 2004).

To do this, I use predicted changes in FFR expectation for alternative FOMC statements to control for potential statements the FOMC could have released. Alternatively worded statements are included in the FOMC's meeting materials, called the Tealbooks and Bluebooks. These materials include information about about economy, forecasts, and policy recommendations. These books are sent to FOMC members at least one week before FOMC meeting takes place. However, the books are only released to the public on a five year lag. Figure 6 shows the number of alternative statements from 2005-2014, the period in which I have access to clearly identifiable alternative statements.

The actual statement and the alternative statements in FOMC meeting materials were all drafted with the same information. I represent the Fed's private information as the average of predicted expectation changes from alternative statements. So, the difference

Figure 6: Number of Alternative Statements by FOMC Meeting, 2005-2014



Note: section A.3.1 details collection and cleaning of alternative statements.

between the average change in expectations and the change in expectations from the actual statement that was released is the cleaned proxy for structural monetary policy shocks. This "cleaned monetary policy text shock" is the series I use in later analysis. For each FOMC meeting in this period, I calculate the monetary policy text shock according to Equation 6:

$$\textbf{Cleaned Text Shock}_t = \widehat{\mathbb{E}_t[r]}_{released} - \frac{1}{|Alts_t|} \sum_{i \in Alts_t} \widehat{\mathbb{E}_t[r]}_i \tag{6}$$

where t indexes FOMC meetings, i indexes the alternatives statements among the collection of alternatives at meeting t: $Alts_t$. The statement that was actually released is indexed as $i = I$. Therefore, $\widehat{\mathbb{E}_t[r]}_I$ represents the projection of the change in FFR expectations onto the actual FOMC statement and $\widehat{\mathbb{E}_t[r]}_i$ is the counterfactual change in FFR expectations for alternative i. I create this shock series for every meeting in January 2005 through December 2014. This date range is limited by the availability of FOMC meeting materials that contain the alternative statements.

This shock measure, ex ante, is representing forward guidance because it is calculated from variation in the wording of FOMC statements. However, I can also show that the cleaned text shock is quantitatively picking up forward guidance effects by regressing changes in FFR expectations at different horizons on the cleaned text shock. More specifically, consider different regression specifications for expectations of federal funds rate h meetings away from the current meeting t, for $h \in \{0, 1, 2, 3\}$:

$$\Delta E_t[r_{t+h}] = \beta_0^h + \beta_1^h(\text{Cleaned Text Shock}_t) \tag{7}$$

Below in Table 3, there are two patters indicating that the shock is picking up forward guidance. First, that as h increases, the coefficient β_1^h increases. The descriptive statistics indicate that $\Delta E_t[r_{t+h}]$ is of similar magnitudes for all h. Second, the R^2 is also increases as h increases across the model specifications. Conversely, the uncleaned text shock or using expectations represented by fed funds futures do not have these properties.

Table 3: Cleaned Text Shock and Forward Guidance

	$\Delta E_t[r_t]$	$\Delta E_t[r_{t+1}]$	$\Delta E_t[r_{t+2}]$	$\Delta E_t[r_{t+3}]$
Intercept	-0.01*	-0.00	-0.00	-0.01
	(0.00)	(0.00)	(0.00)	(0.01)
Cleaned Text Shock$_t$	1.88***	1.99***	2.20***	2.16***
	(0.31)	(0.33)	(0.33)	(0.38)
N	80	80	80	43
R^2	0.32	0.31	0.36	0.44
Adj. R^2	0.32	0.30	0.35	0.42

Note: $E_r[r_{t+h}]$ represents expectations at meeting t about FFR h meeting(s) away. Expectations for each horizon are calculated with fed funds future prices. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

6 Comparison with Other Monetary Shock Series

In this section, I will compare the text shock and cleaned text shock series to other monetary policy text shocks from the literature. All of the following shock series are based, at least in part, on high-frequency identification arguments.

Table 4: Monetary Policy Shock Series

Series Name	Abbreviation	Description
Cleaned Text Shocks	$\widehat{\Delta E[r]}_{clean}$	Predicted effect on expectations from FOMC statement wording stripped of Fed's private information
Text Shocks	$\widehat{\Delta E[r]}_{text}$	Prediction from FOMC statement input into the trained neural network
PC1 FFF Price Changes	$\Delta E[r]_{FFF}$	First principal component of change in fed funds futures ($\Delta E_t[r_t]$, $\Delta E_t[r_{t+1}]$)
Gertler and Karadi (2015) Shocks	GS Shock	Daily change in 1-year treasury yield instrumented with change in 3-month fed funds future (FF4)
Nakamura and Steinsson (2018) Shocks	NS Shock	First principal component of change in fed funds futures ($\Delta E_t[r_t]$, $\Delta E_t[r_{t+1}]$) and Eurodollar futures at 2,3,4 quarters

Note: Summary statistics for the monetary policy shock series are in Table A3

Table A3 includes summary statistics of each of the shock series. The main takeaway from that table is that the series' ranges are all very similar. Accordingly, differences in coefficient magnitudes in the subsequent sections is begin driven by what these shocks represent, not scaling differences.

In the following subsections, I will compare the effects of the new text shocks with other shock series from the literature. First, I will show what theses series say about monetary policy's effect on nominal and real interest rates. Then I will estimate different impulse response functions to show what these shock series reveal about monetary policy's effect on other macroeconomic variables.

6.1 Nominal and Real Interest Rates

In this section, I compare the effect of monetary shock series on nominal and real interest rates at different horizons. The daily change in Treasury yields represent the change in nominal interest rates. The daily change in TIPS yields represent the change in real interest rates. The daily change is calculated on the end-of-day yields for the day before to the day of the FOMC announcement. Table A4 and Table A5 include the summary statistics for the interest rate changes. The change in fed funds futures used to calculate the shock series occurs within a smaller, nested event window of the treasury and TIPS yield changes. This timing restriction implies the daily change in treasuries is not impacting the regressors.

The regression specification is as follows:

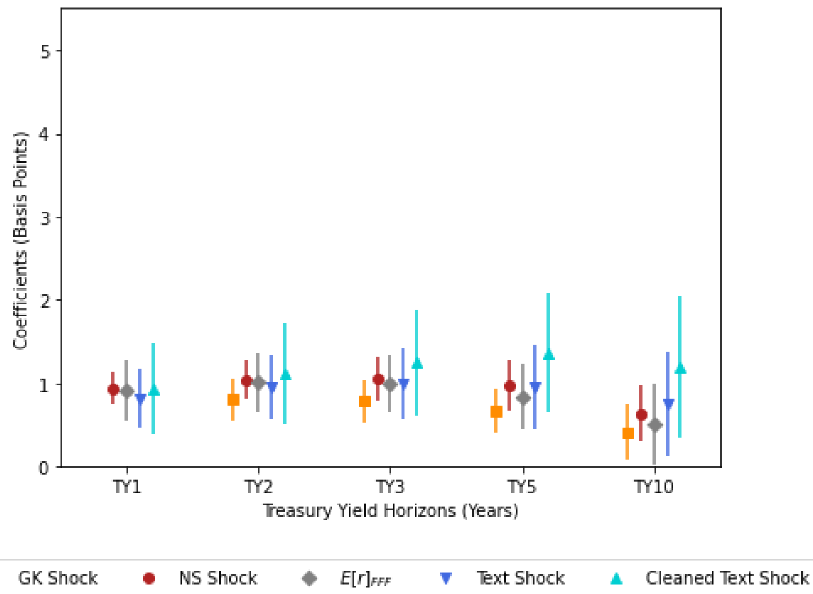
$$\Delta Yield^{\ell,i} = \beta_0^{\ell,i,k} + \beta_1^{\ell,i,k} \ (monetary\ shock)^k + \varepsilon^{\ell,i,k} \tag{8}$$

where ℓ indicates either Treasury or TIPS yields, i is the horizon of the yield, ranging from 1 year to 10 years, k indexes the shock series from Table 4. The regression results are summarized in coefficient plots for nominal interest rates in Figure 7 and of real interest rates in Figure 8. Regression results for each (ℓ, i, k) specification shown these plots are detailed in section A.1.5 and section A.1.6 for nominal and real rates, respectively.

A large cleaned text shock means that the predicted effect of the released FOMC statement is substantially different from the predicted effect of all alternative statements. The text shock and the cleaned text shock have similar effects on nominal interest rates compared to the NS Shocks and GK Shocks.

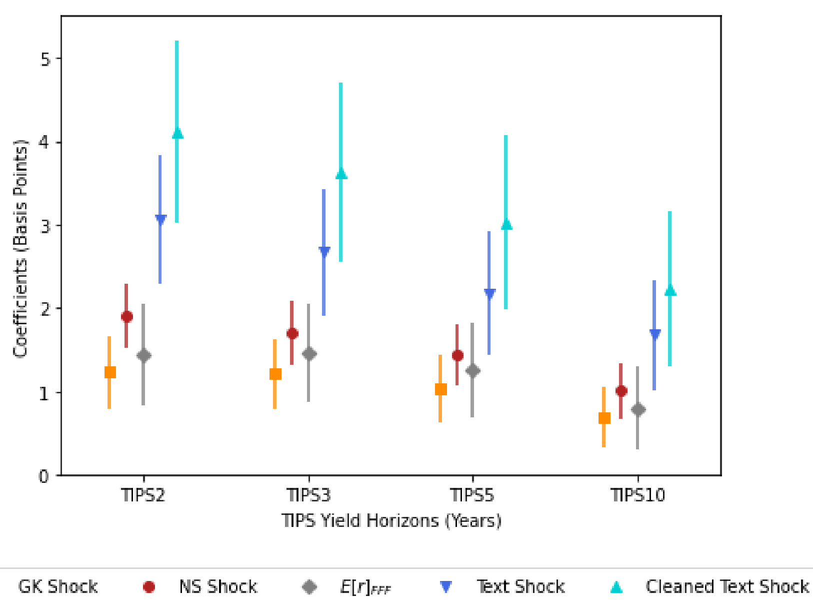
However, the text shocks have a much larger correlation with real interest rates compared to GK Shocks or NS Shocks. The coefficient is approximately double. The summary statistics show that the range of these shock series are similar, so the differences in coefficients is not driven by variability in scales across the shock series. I argue that the projection of asset prices onto the FOMC statement text is the important difference. To interpret this graph would be that the text shocks are picking up a larger effect of monetary policy on the real economy through the expectations channel compared to the literature.

Figure 7: Nominal Interest Rates and Monetary Shocks



Note: The dots represent coefficients for different OLS regressions. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. The time sample is for 2005-2014 for all regressions.

Figure 8: Real Interest Rates and Monetary Shocks



Note: The dots represent coefficients for different OLS regressions. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. The time sample is for 2005-2014 for all regressions.

6.2 VAR with External Instrument Approach

To study the transmission of monetary policy announcements to other variables in the economy I estimate a vector autoregression (VAR) with an external instrument approach. As in Gertler and Karadi (2015), I include log industrial production, log consumer price index (CPI), one-year treasury yield, and excess bond premium in the VAR. The excess bond premium is from Gilchrist and Zakrajsek (2012) and represents the risk premium from the difference between private and public bonds. Incorporating this variable in the VAR allows the monetary shock to influence economic variables through financial markets. Summary statistics for these variables are in the appendix in Table A6.

$$Y_t = [g_t, \pi_t, ty_t, ep_t] \tag{9}$$

and g_t is the natural logarithm of industrial production, π_t is the natural logarithm of the Consumer Price Index, ty_t is the the 1-year treasury yield, and ep_t is the excess bond premium from Gilchrist and Zakrajsek (2012). I index the elements of Y_t by i.

Structural monetary shocks are then represented by $\epsilon_{2,t}$, where $Y_{2,t} = ty_t$. Because this is not measurable, economists use a proxy Z_t for these shocks such that:

$$\mathbb{E}[z_t \ \epsilon_{2,t}] \neq 0 \qquad \mathbb{E}[z_t \ \epsilon_{-2,t}] = 0 \tag{10}$$

As discussed in an earlier section, I argue that the cleaned monetary policy text shocks meet this condition. Although the series $\mathbb{E}_t[r]$, the first principal component of changes in expectations of the FFR at the current and next meeting, and $\widehat{\mathbb{E}_t[r]}_{text}$, the projection of changes in FFR expectations onto the FOMC statement text, seem to violate Equation 10, I still show the impulse response functions if they were to be used as proxies for monetary policy shocks for comparison. The different shock series will be indexed by k:

$$\{\text{GK shock, FF4, FFF PC1, Text Shock, Cleaned Text Shock}\}$$

I convert shocks to a monthly frequency such that months without FOMC meetings have a monetary policy shock of zero. Table A7 includes summary statistics for the monthly shock series. In Gertler and Karadi (2015), GK shock series is converted to a monthly series by using a rolling average so that even months without FOMC meetings can have non-zero monetary shocks. I use changes in the 3 month ahead FFF (FF4) to calculate the GK shock series without the rolling aggregation.

In the text I compare the impulse responses to FF4 and the cleaned text shock. The impulse response graphs for the GK shock, the first principal component of expectations calculated from FFF, and the uncleaned text shock are in the appendix.[10] As a robustness check, I intend to interpolate shocks for months without FOMC meetings, as a monthly rolling average in Gertler and Karadi (2015) or quarterly sum as in Nakamura and Steinsson (2018). This will be added later.

I use the local projection method from Jordà (2005) to graph impulse response functions for the different shock series and for the components of Y_t. I follow the Ramey (2016). Therefore, I run a separate regression for each shock, indexed by k, and component of Y, indexed by i, and h indexes the number of months in the future, such that:

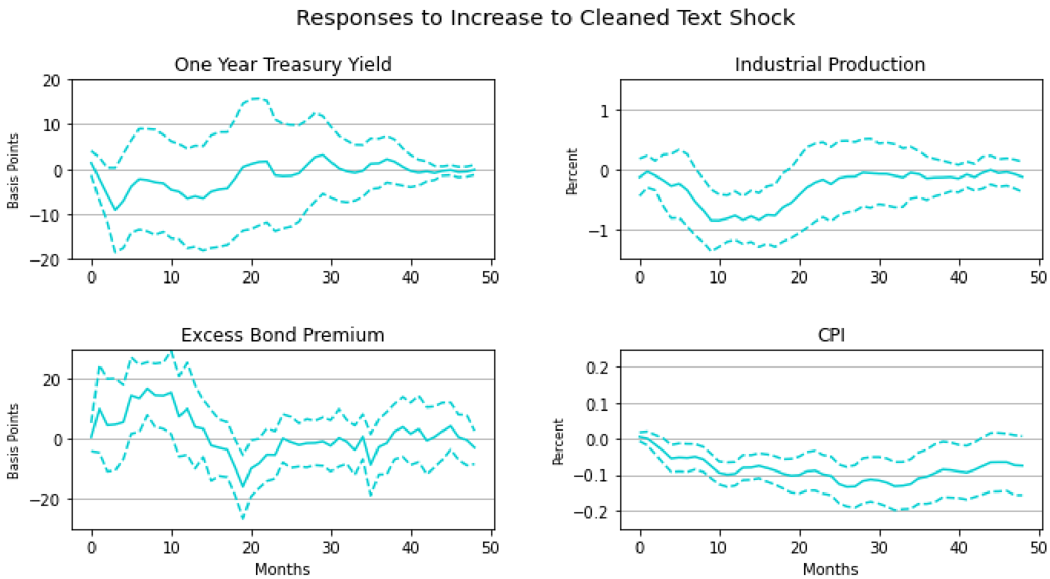
$$Y_{i,t+h} = \theta_{i,k,h} Shock_{k,t} + controls + \eta_{i,k,h} \tag{11}$$

Standard errors are calculated Newey and West (1987) to account for serial correlation of the error terms.

The impulse response functions are responses of macroeconomic variables to a 100 basis point increase to the monetary policy shock. For all the shock series, this represents a contractionary shock. For the Gertler and Karadi (2015) shock this means FF4 price decreases by 100 bp, so expectations increase by 100 bp. For the text shock, a 100 bp increase represents an 100 bp increase in FFR expectations caused by FOMC announcement, after controlling for the private information of the Fed.

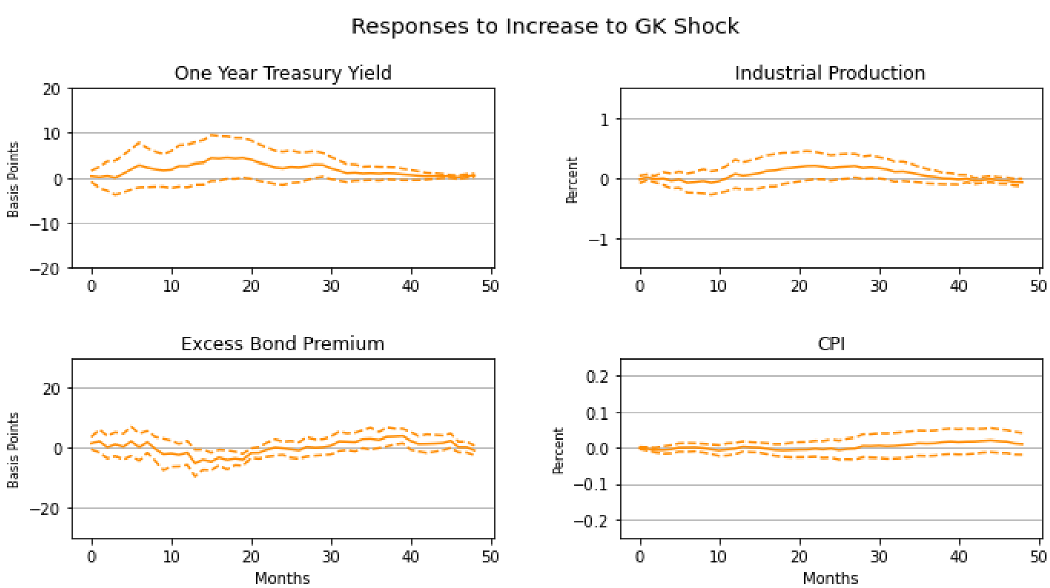
[10] Figure A7, Figure A6, and Figure A5, respectively

Figure 9: Impulse Responses to Cleaned Text Shock



Note: Impulse responses are calculated using the local projection method from Jordà (2005). Confidence bands are at the 90% level. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. The above are responses to a 100 basis point increase in the shock series (not pictured).

Figure 10: Impulse Responses to GK Shock (Non-Aggregated, FF4)



Note: Impulse responses are calculated using the local projection method from Jordà (2005). Confidence bands are at the 90% level. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. The above are responses to a 100 basis point increase in the shock series (not pictured).

Figure 9 shows that macroeconomic variable responses are much larger for impulses to the cleaned text shock compared to the GK shocks in Figure 10. In particular, a 100 basis point increase to the cleaned text shock is associated with a one percent decrease in output, a .1 percent decrease in inflation, and almost a 20 percent increase in the excess bond premium after about 10 months. These responses are qualitatively consistent with monetary theory that indicates a contractionary shock should decrease output and inflation.

Figure 10 shows similar results as in Ramey (2016). In particular an increase to the GK shock actually produces small increases in output and inflation and a decrease in the excess bond premium.

One panel in Figure 9 that does not seem to fit is the response of the one year treasury yield to a contractionary text shock. This poor fit is expected considering the correlation between the cleaned text shock and changes in the one year treasury yield has large standard errors and is not statistically different from zero at higher confidence levels.

Overall, these figures show that the cleaned text shock series is representing information different from other shock series in the literature and produces impulse responses that are consistent with the literature.

7 Conclusion

This paper uses a state-of-the-art text analysis neural network to map FOMC statement text to federal funds rate expectations. Using the trained neural network and alternative versions of statements from FOMC meeting materials, I produce a new monetary policy shock series - which I call "cleaned text shocks." An FOMC statement is said to be a large policy shock the neural network predicts it to have a large affect on fed funds futures prices that are above and beyond the average predicted effects of alternative wordings of the statements. In other words, if this shocks series picks up the forward guidance effect of FOMC statements through their word choice.

This paper then compares and contrasts the cleaned text shock series to other monetary policy shock series identified with high-frequency fed funds futures price changes. In terms of summary statistics, the cleaned text shocks are similar to other series. Furthermore, they are similarly correlated with nominal interest rates.

However, I find that the coefficients relating the cleaned text shocks and real interest rates are twice the size of coefficients for other shock series from the literature. This means that shock measures that only use asset price changes are missing information about the effect of monetary policy on the real economy. Differences continue into the VAR estimation. Responses of output, inflation, nominal interest rates, and the excess bond premium to impulses in Gertler and Karadi (2015) shocks with the cleaned text shocks are dramatically different. As Ramey (2016), using the local projection method to graph impulse responses show the responses of macroeconomic variables are generally not statistically different from zero. Also, qualitatively, they respond in directions that counter the conventional monetary policy theory. However, in response to an increase in the cleaned text shock, macroeconomic variables change as the theory would predict. That is, a contractionary monetary (text) shock produces lower output, lower inflation, and increases to the excess bond premium. Ultimately, this paper shows that monetary policy does influence the economy. Furthermore, it that the Fed affects the economy with its influence over market expectations of future monetary policy and that forward guidance matters.

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A.1 Table Appendix

A.1.1 FOMC Announcement Times

Table A1: FOMC Statement Release and Press Conference Times, 1999-2019

Statement Date	Statement Time	Press Conference
05/18/1999	02:15 PM	
06/30/1999	02:15 PM	
08/24/1999	02:15 PM	
10/05/1999	02:15 PM	
11/16/1999	02:15 PM	
12/21/1999	02:15 PM	
02/02/2000	02:15 PM	
03/21/2000	02:15 PM	
05/16/2000	02:15 PM	
06/28/2000	02:15 PM	
08/22/2000	02:15 PM	
10/03/2000	02:15 PM	
11/15/2000	02:15 PM	
12/19/2000	02:15 PM	
01/31/2001	02:15 PM	
03/20/2001	02:15 PM	
05/15/2001	02:15 PM	
06/27/2001	02:15 PM	
08/21/2001	02:15 PM	
10/02/2001	02:15 PM	
11/06/2001	02:15 PM	
12/11/2001	02:15 PM	
01/30/2002	02:15 PM	
03/19/2002	02:15 PM	
05/07/2002	02:15 PM	
06/26/2002	02:15 PM	
08/13/2002	02:15 PM	
09/24/2002	02:15 PM	
11/06/2002	02:15 PM	
12/10/2002	02:15 PM	
01/29/2003	02:15 PM	
03/18/2003	02:15 PM	
05/06/2003	02:15 PM	
06/25/2003	02:15 PM	
08/12/2003	02:15 PM	
09/16/2003	02:15 PM	
10/28/2003	02:15 PM	
12/09/2003	02:15 PM	
01/28/2004	02:15 PM	
03/16/2004	02:15 PM	
05/04/2004	02:15 PM	
06/30/2004	02:15 PM	
08/10/2004	02:15 PM	
09/21/2004	02:15 PM	

Statement Date	Statement Time	Press Conference
11/10/2004	02:15 PM	
12/14/2004	02:15 PM	
02/02/2005	02:15 PM	
03/22/2005	02:15 PM	
05/03/2005	02:15 PM	
06/30/2005	02:15 PM	
08/09/2005	02:15 PM	
09/20/2005	02:15 PM	
11/01/2005	02:15 PM	
12/13/2005	02:15 PM	
01/31/2006	02:15 PM	
03/28/2006	02:15 PM	
05/10/2006	02:15 PM	
06/29/2006	02:15 PM	
08/08/2006	02:15 PM	
09/20/2006	02:15 PM	
10/25/2006	02:15 PM	
12/12/2006	02:15 PM	
01/31/2007	02:15 PM	
03/21/2007	02:15 PM	
05/09/2007	02:15 PM	
06/28/2007	02:15 PM	
08/07/2007	02:15 PM	
09/18/2007	02:15 PM	
10/31/2007	02:15 PM	
12/11/2007	02:15 PM	
01/30/2008	02:15 PM	
03/18/2008	02:15 PM	
04/30/2008	02:15 PM	
06/25/2008	02:15 PM	
08/05/2008	02:15 PM	
09/16/2008	02:15 PM	
10/29/2008	02:15 PM	
12/16/2008	02:15 PM	
01/28/2009	02:15 PM	
03/18/2009	02:15 PM	
04/29/2009	02:15 PM	
06/24/2009	02:15 PM	
08/12/2009	02:15 PM	
09/23/2009	02:15 PM	
11/04/2009	02:15 PM	
12/16/2009	02:15 PM	
01/27/2010	02:15 PM	
03/16/2010	02:15 PM	
04/28/2010	02:15 PM	
06/23/2010	02:15 PM	
08/10/2010	02:15 PM	

Statement Date	Statement Time	Press Conference
09/21/2010	02:15 PM	
11/03/2010	02:15 PM	
12/14/2010	02:15 PM	
01/26/2011	02:15 PM	
03/15/2011	02:15 PM	
04/27/2011	12:30 PM	02:15 PM
06/22/2011	12:30 PM	02:15 PM
08/09/2011	02:15 PM	
09/21/2011	02:15 PM	
11/02/2011	12:30 PM	02:15 PM
12/13/2011	02:15 PM	
01/25/2012	12:30 PM	02:15 PM
03/13/2012	02:15 PM	
04/25/2012	12:30 PM	02:15 PM
06/20/2012	12:30 PM	02:15 PM
08/01/2012	02:15 PM	
09/13/2012	12:30 PM	02:15 PM
10/24/2012	02:15 PM	
12/12/2012	12:30 PM	02:15 PM
01/30/2013	02:15 PM	
03/20/2013	02:00 PM	02:30 PM
05/01/2013	02:00 PM	
06/19/2013	02:00 PM	02:30 PM
07/31/2013	02:00 PM	
09/18/2013	02:00 PM	02:30 PM
10/30/2013	02:00 PM	
12/18/2013	02:00 PM	02:30 PM
01/29/2014	02:00 PM	
03/19/2014	02:00 PM	02:30 PM
04/30/2014	02:00 PM	
06/18/2014	02:00 PM	02:30 PM
07/30/2014	02:00 PM	
09/17/2014	02:00 PM	02:30 PM
10/29/2014	02:00 PM	
12/17/2014	02:00 PM	02:30 PM
01/28/2015	02:00 PM	
03/18/2015	02:00 PM	02:30 PM
04/29/2015	02:00 PM	
06/17/2015	02:00 PM	02:30 PM
07/29/2015	02:00 PM	
09/17/2015	02:00 PM	02:30 PM
10/28/2015	02:00 PM	
12/16/2015	02:00 PM	02:30 PM
01/27/2016	02:00 PM	
03/16/2016	02:00 PM	02:30 PM
04/27/2016	02:00 PM	
06/15/2016	02:00 PM	02:30 PM
07/27/2016	02:00 PM	
09/21/2016	02:00 PM	02:30 PM
11/02/2016	02:00 PM	
12/14/2016	02:00 PM	02:30 PM
02/01/2017	02:00 PM	
03/15/2017	02:00 PM	02:30 PM
05/03/2017	02:00 PM	
06/14/2017	02:00 PM	02:30 PM
07/26/2017	02:00 PM	
09/20/2017	02:00 PM	02:30 PM
11/01/2017	02:00 PM	
12/13/2017	02:00 PM	02:30 PM
01/31/2018	02:00 PM	
03/21/2018	02:00 PM	02:30 PM
05/02/2018	02:00 PM	
06/13/2018	02:00 PM	02:30 PM
08/01/2018	02:00 PM	
09/26/2018	02:00 PM	02:30 PM
11/08/2018	02:00 PM	
12/19/2018	02:00 PM	02:30 PM
01/30/2019	02:00 PM	
03/20/2019	02:00 PM	02:30 PM
05/01/2019	02:00 PM	
06/19/2019	02:00 PM	02:30 PM
07/31/2019	02:00 PM	
09/18/2019	02:00 PM	02:30 PM
10/30/2019	02:00 PM	

Dates are sourced from the "FOMC Calendar" and "Transcripts and other historical materials" pages on the Federal Reserve Board Website: https://www.federalreserve.gov/monetarypolicy.htm. Times of meetings and press conferences are based on scheduled releases detailed in announcements https://www.federalreserve.gov/newsevents/pressreleases/monetary20130313a.htm and https://www.federalreserve.gov/newsevents/pressreleases/monetary20110324a.htm

A.1.2 Example Statements

Table A2: Examples of Prediction from FOMC Statements

Text	ΔFFR	$\Delta E[r]$	$\widehat{\Delta E[r]}$
September 2006: The Federal Open Market Committee decided today to keep its target for the federal funds rate at 5-1/4 percent. **The moderation in economic growth appears to be continuing, partly reflecting a cooling of the housing market.** Readings on core inflation have been elevated, and the high levels of resource utilization and of the prices of energy and other commodities have the potential to sustain inflation pressures. However, inflation pressures seem likely to moderate over time, reflecting reduced impetus from energy prices, contained inflation expectations, and the cumulative effects of monetary policy actions and other factors restraining aggregate demand. Nonetheless, the Committee judges that some inflation risks remain. The extent and timing of any additional firming that may be needed to address these risks will depend on the evolution of the outlook for both inflation and economic growth, as implied by incoming information.	0	-0.003	-0.005
October 2006: The Federal Open Market Committee decided today to keep its target for the federal funds rate at 5-1/4 percent. **Economic growth has slowed over the course of the year, partly reflecting a cooling of the housing market. Going forward, the economy seems likely to expand at a moderate pace.** Readings on core inflation have been elevated, and the high level of resource utilization has the potential to sustain inflation pressures. However, inflation pressures seem likely to moderate over time, reflecting reduced impetus from energy prices, contained inflation expectations, and the cumulative effects of monetary policy actions and other factors restraining aggregate demand. Nonetheless, the Committee judges that some inflation risks remain. The extent and timing of any additional firming that may be needed to address these risks will depend on the evolution of the outlook for both inflation and economic growth, as implied by incoming information.	0	0.001	-0.001

Text	ΔFFR	$\Delta E[r]$	$\widehat{\Delta E[r]}$
December 2016: Information received since the Federal Open Market Committee met in November indicates that the labor market has continued to strengthen and that economic activity has been expanding at a moderate pace since mid-year. Job gains have been solid in recent months and the unemployment rate has declined. Household spending has been rising moderately but business fixed investment has remained soft. Inflation has increased since earlier this year but is still below the Committee's 2 percent longer-run objective, partly reflecting earlier declines in energy prices and in prices of non-energy imports. Market-based measures of inflation compensation have moved up considerably but still are low; most survey-based measures of longer-term inflation expectations are little changed, on balance, in recent months. Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. The Committee expects that, with gradual adjustments in the stance of monetary policy, economic activity will expand at a moderate pace and labor market conditions will strengthen somewhat further. Inflation is expected to rise to 2 percent over the medium term as the transitory effects of past declines in energy and import prices dissipate and the labor market strengthens further. Near-term risks to the economic outlook appear roughly balanced. The Committee continues to closely monitor inflation indicators and global economic and financial developments. In view of realized and expected labor market conditions and inflation, the Committee decided to raise the target range for the federal funds rate to 1/2 to 3/4 percent. The stance of monetary policy remains accommodative, thereby supporting some further strengthening in labor market conditions and a return to 2 percent inflation. In determining the timing and size of future adjustments to the target range for the federal funds rate, the Committee will assess realized and expected economic conditions relative to its objectives of maximum employment and 2 percent inflation. This assessment will take into account a wide range of information, including measures of labor market conditions, indicators of inflation pressures and inflation expectations, and readings on financial and international developments. In light of the current shortfall of inflation from 2 percent, the Committee will carefully monitor actual and expected progress toward its inflation goal. The Committee expects that economic conditions will evolve in a manner that will warrant only gradual increases in the federal funds rate; the federal funds rate is likely to remain, for some time, below levels that are expected to prevail in the longer run. However, the actual path of the federal funds rate will depend on the economic outlook as informed by incoming data. The Committee is maintaining its existing policy of reinvesting principal payments from its holdings of agency debt and agency mortgage-backed securities in agency mortgage-backed securities and of rolling over maturing Treasury securities at auction, and it anticipates doing so until normalization of the level of the federal funds rate is well under way. This policy, by keeping the Committee's holdings of longer-term securities at sizable levels, should help maintain accommodative financial conditions.	0.25	0.0014	0.0015

Text	ΔFFR	$\Delta E[r]$	$\widehat{\Delta E[r]}$
February 2017: Information received since the Federal Open Market Committee met in December indicates that the labor market has continued to strengthen and that economic activity has continued to expand at a moderate pace. Job gains remained solid and the unemployment rate stayed near its recent low. Household spending has continued to rise moderately while business fixed investment has remained soft. Measures of consumer and business sentiment have improved of late. Inflation increased in recent quarters but is still below the Committee's 2 percent longer-run objective. Market-based measures of inflation compensation remain low; most survey-based measures of longer-term inflation expectations are little changed, on balance. Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. The Committee expects that, with gradual adjustments in the stance of monetary policy, economic activity will expand at a moderate pace, labor market conditions will strengthen somewhat further, and inflation will rise to 2 percent over the medium term. Near-term risks to the economic outlook appear roughly balanced. The Committee continues to closely monitor inflation indicators and global economic and financial developments. In view of realized and expected labor market conditions and inflation, the Committee decided to maintain the target range for the federal funds rate at 1/2 to 3/4 percent. The stance of monetary policy remains accommodative, thereby supporting some further strengthening in labor market conditions and a return to 2 percent inflation. In determining the timing and size of future adjustments to the target range for the federal funds rate, the Committee will assess realized and expected economic conditions relative to its objectives of maximum employment and 2 percent inflation. This assessment will take into account a wide range of information, including measures of labor market conditions, indicators of inflation pressures and inflation expectations, and readings on financial and international developments. In light of the current shortfall of inflation from 2 percent, the Committee will carefully monitor actual and expected progress toward its inflation goal. The Committee expects that economic conditions will evolve in a manner that will warrant only gradual increases in the federal funds rate; the federal funds rate is likely to remain, for some time, below levels that are expected to prevail in the longer run. However, the actual path of the federal funds rate will depend on the economic outlook as informed by incoming data. The Committee is maintaining its existing policy of reinvesting principal payments from its holdings of agency debt and agency mortgage-backed securities in agency mortgage-backed securities and of rolling over maturing Treasury securities at auction, and it anticipates doing so until normalization of the level of the federal funds rate is well under way. This policy, by keeping the Committee's holdings of longer-term securities at sizable levels, should help maintain accommodative financial conditions.	0	-0.004	-0.009

Text	ΔFFR	$\Delta E[r]$	$\widehat{\Delta E[r]}$
May 2019: Information received since the Federal Open Market Committee met in March indicates that the labor market remains strong and that economic activity rose at a solid rate. Job gains have been solid, on average, in recent months, and the unemployment rate has remained low. Growth of household spending and business fixed investment slowed in the first quarter. On a 12-month basis, overall inflation and inflation for items other than food and energy have declined and are running below 2 percent. On balance, market-based measures of inflation compensation have remained low in recent months, and survey-based measures of longer-term inflation expectations are little changed. Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. In support of these goals, the Committee decided to maintain the target range for the federal funds rate at 2-1/4 to 2-1/2 percent. The Committee continues to view sustained expansion of economic activity, strong labor market conditions, and inflation near the Committee's symmetric 2 percent objective as the most likely outcomes. In light of global economic and financial developments and muted inflation pressures, the Committee will be patient as it determines what future adjustments to the target range for the federal funds rate may be appropriate to support these outcomes. In determining the timing and size of future adjustments to the target range for the federal funds rate, the Committee will assess realized and expected economic conditions relative to its maximum employment objective and its symmetric 2 percent inflation objective. This assessment will take into account a wide range of information, including measures of labor market conditions, indicators of inflation pressures and inflation expectations, and readings on financial and international developments.	0	-0.009	-0.002
June 2019: Information received since the Federal Open Market Committee met in May indicates that the labor market remains strong and that economic activity is rising at a moderate rate. Job gains have been solid, on average, in recent months, and the unemployment rate has remained low. Although growth of household spending appears to have picked up from earlier in the year, indicators of business fixed investment have been soft. On a 12-month basis, overall inflation and inflation for items other than food and energy are running below 2 percent. Market-based measures of inflation compensation have declined; survey-based measures of longer-term inflation expectations are little changed. Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. In support of these goals, the Committee decided to maintain the target range for the federal funds rate at 2-1/4 to 2-1/2 percent. The Committee continues to view sustained expansion of economic activity, strong labor market conditions, and inflation near the Committee's symmetric 2 percent objective as the most likely outcomes, but uncertainties about this outlook have increased. In light of these uncertainties and muted inflation pressures, the Committee will closely monitor the implications of incoming information for the economic outlook and will act as appropriate to sustain the expansion, with a strong labor market and inflation near its symmetric 2 percent objective. In determining the timing and size of future adjustments to the target range for the federal funds rate, the Committee will assess realized and expected economic conditions relative to its maximum employment objective and its symmetric 2 percent inflation objective. This assessment will take into account a wide range of information, including measures of labor market conditions, indicators of inflation pressures and inflation expectations, and readings on financial and international developments.	0	0.0112	0.0113

A.1.3 Summary Statistics

Table A3: Statistics of Monetary Shocks, FOMC Meetings from 2005-2014

	PC1 FFF Prices	Text Shock	Cleaned Text Shock	NS Shock	GK Shock: FF4	GK shock: TY1(FF4)
count	80	80	80	74	80	80
mean	-0.0000	-0.0027	0.0011	0.0039	-0.0018	-0.0042
std	0.0215	0.0158	0.0113	0.0321	0.0395	0.0294
min	-0.1009	-0.0900	-0.0685	-0.1452	-0.19	-0.1441
25%	-0.0012	-0.0058	-0.0029	-0.0034	-0.005	-0.0066
50%	0.0013	-0.0007	0.0022	0.0076	0	-0.0029
75%	0.0027	0.0031	0.0060	0.0186	0.0063	0.0017
max	0.0631	0.0675	0.0406	0.0679	0.115	0.0825

Note: "NS shock" is from Nakamura and Steinsson (2018) and is the first principal component of fed funds futures and Eurodollar futures. "PC1 FFF Prices" is the first principal component of fed funds futures prices representing target fed funds rate expectations at the current and next FOMC meetings. This is the NS shock without Eurodollar futures. "GK Shock: FF4" is the change in the 3 month ahead fed funds future price (FF4)."GK shock: TY1(FF4)" is the daily change in the 1 year treasury yield instrumented with the FF4. Work in the text is for the latter version of the GK shock.

Table A4: Statistics of Nominal Interest Rate Changes, FOMC Meetings, 2005-2014

	$\Delta\ TY_1$	$\Delta\ TY_2$	$\Delta\ TY_3$	$\Delta\ TY_5$	$\Delta\ TY_{10}$
count	80	80	80	80	80
mean	-0.0009	0.0018	0.0025	0.0012	0.0004
std	0.0544	0.0661	0.0772	0.0918	0.0923
min	-0.2045	-0.2641	-0.3477	-0.4708	-0.5189
25%	-0.0198	-0.027	-0.0314	-0.0385	-0.0356
50%	0.0019	-0.0008	0.0009	0.008	0.0135
75%	0.0189	0.0322	0.0469	0.0444	0.0569
max	0.2023	0.2296	0.2263	0.1844	0.2019

Note: The above represent the daily change in the h-year treasury yields (ΔTY_h). The yield change is evaluated from end-of-day before FOMC announcement day to the end of the day of the FOMC announcement. Data is from Gürkaynak et al. (2006).

Table A5: Statistics of Real Interest Rate Changes, FOMC Meetings, 2005-2014

	$\Delta\ TIPS_2$	$\Delta\ TIPS_3$	$\Delta\ TIPS_5$	$\Delta\ TIPS_{10}$
count	80	80	80	80
mean	-0.0072	-0.0081	-0.0074	-0.0047
std	0.1183	0.1141	0.1094	0.0963
min	-0.5215	-0.5499	-0.5818	-0.5705
25%	-0.0467	-0.0476	-0.0509	-0.0353
50%	-0.0024	0.0032	0.009	0.0072
75%	0.0484	0.0522	0.0451	0.0463
max	0.3637	0.2998	0.2187	0.1569

Note: The above represent the daily change in the h-year TIPS yields ($\Delta TIPS_h$). The yield change is evaluated from end-of-day before FOMC announcement day to the end of the day of the FOMC announcement. Data is from Gürkaynak et al. (2010).

Table A6: Statistics for VAR variables, Monthly for 2005-2014

	log IP	log CPI	EBP	TY_1
count	120	120	120	120
mean	4.60	5.39	0.04	1.64
std	0.05	0.05	0.85	1.88
min	4.47	5.29	-0.92	0.09
25%	4.57	5.35	-0.40	0.20
50%	4.61	5.40	-0.22	0.42
75%	4.63	5.44	-0.01	3.41
max	4.67	5.48	3.47	5.20

Note: All logs are natural logarithms. Industrial production (IP) and Consumer Price Index (CPI) are sourced from FRED. The Excess Bond Premium (EBP) is from Gilchrist and Zakrajsek (2012). The 1 year Treasury Yield (TY_1) is from Gürkaynak et al. (2006).

Table A7: Statistics for Monetary Shocks, Monthly 2005-2014

	Text Shock	Cleaned Text Shock	PC1 FFF	GK Shock: FF4	GK Shock: FF4 rolling average
count	120	120	120	120	90
mean	-0.0018	0.0007	-0.0000	-0.0012	-0.005371
std	0.0129	0.0092	0.0175	0.0322	0.032843
min	-0.09	-0.0685	-0.1009	-0.1900	-0.206291
25%	-0.0016	-0.0014	0	0	-0.0048
50%	0	0	0	0	0
75%	0.0008	0.0036	0.0013	0	0.0037
max	0.0675	0.0406	0.0631	0.1150	0.0561

Note: For all but the last column, the shocks are zero for any month that does *not* have an FOMC meeting. "GK Shock: FF4 rolling average" is aggregated as a rolling average over the past month to create the monthly series. For this latter column, it means that months without FOMC meetings will have non-zero shock values.

A.1.4 Forward Guidance Regressions for Other Shock Series

Table A8: First Principal Component of FFF and Expectations Over Different Horizons

	$\Delta E_t[r_t]$	$\Delta E_t[r_{t+1}]$	$\Delta E_t[r_{t+2}]$	$\Delta E_t[r_{t+3}]$
Intercept	-0.00**	-0.00*	-0.00	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta E[r]_{FFF}$	1.80***	1.68***	1.54***	1.76***
	(0.05)	(0.05)	(0.09)	(0.12)
N	165	165	163	82
R^2	0.89	0.86	0.65	0.71
Adj. R^2	0.89	0.86	0.65	0.71

Note: $E_r[r_{t+h}]$ represents expectations at meeting t about FFR h meeting(s) away. Expectations for each horizon are calculated with fed funds future prices. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Table A9: Uncleaned Text Shock and Expectations Over Different Horizons

	$\Delta E_t[r_t]$	$\Delta E_t[r_{t+1}]$	$\Delta E_t[r_{t+2}]$	$\Delta E_t[r_{t+3}]$
Intercept	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
$\widehat{\Delta E[r]}_{text}$	1.71***	1.57***	1.56***	1.71***
	(0.14)	(0.14)	(0.15)	(0.22)
N	165	165	163	82
R^2	0.47	0.44	0.39	0.42
Adj. R^2	0.47	0.44	0.38	0.41

Note: $E_r[r_{t+h}]$ represents expectations at meeting t about FFR h meeting(s) away. Expectations for each horizon are calculated with fed funds future prices. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

A.1.5 Nominal Interest Rates and Shock Series

Table A10: Cleaned Text Shock and Nominal Interest Rates

	$\Delta\ TY_1$	$\Delta\ TY_2$	$\Delta\ TY_3$	$\Delta\ TY_5$	$\Delta\ TY_{10}$
Intercept	-0.00	0.00	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Cleaned Text Shock	0.94*	1.12*	1.25**	1.37*	1.20
	(0.55)	(0.61)	(0.64)	(0.72)	(0.85)
N	80	80	80	80	80
R^2	0.04	0.04	0.03	0.03	0.02
Adj. R^2	0.03	0.02	0.02	0.02	0.01

Note: $\Delta\ TY_h$ represents daily change in h-year treasury yield from before to after FOMC announcement. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Table A11: Text Shock and Nominal Interest Rates

	$\Delta\ TY_1$	$\Delta\ TY_2$	$\Delta\ TY_3$	$\Delta\ TY_5$	$\Delta\ TY_{10}$
Intercept	0.00	0.00	0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Text Shock	0.82**	0.96**	1.00**	0.96*	0.76
	(0.35)	(0.39)	(0.42)	(0.51)	(0.63)
N	80	80	80	80	80
R^2	0.06	0.05	0.04	0.03	0.02
Adj. R^2	0.04	0.04	0.03	0.01	0.00

Note: $\Delta\ TY_h$ represents daily change in h-year treasury yield from before to after FOMC announcement. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Table A12: First Principal Component of FFF and Nominal Interest Rates

	$\Delta\ TY_1$	$\Delta\ TY_2$	$\Delta\ TY_3$	$\Delta\ TY_5$	$\Delta\ TY_{10}$
Intercept	-0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
PC1 FFF	0.91**	1.01***	1.00***	0.84**	0.51
	(0.36)	(0.35)	(0.35)	(0.39)	(0.48)
N	80	80	80	80	80
R^2	0.13	0.11	0.08	0.04	0.01
Adj. R^2	0.12	0.10	0.07	0.03	0.00

Note: $\Delta\ TY_h$ represents daily change in h-year treasury yield from before to after FOMC announcement. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Table A13: Nakamura and Steinsson (2018) Shock and Nominal Interest Rates

	$\Delta\ TY_1$	$\Delta\ TY_2$	$\Delta\ TY_3$	$\Delta\ TY_5$	$\Delta\ TY_{10}$
Intercept	-0.01	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
NS Shocks	0.94***	1.04***	1.06***	0.98***	0.64*
	(0.19)	(0.23)	(0.26)	(0.30)	(0.33)
N	74	74	74	74	74
R^2	0.29	0.24	0.19	0.11	0.05
Adj. R^2	0.28	0.23	0.18	0.10	0.03

Note: $\Delta\ TY_h$ represents daily change in h-year treasury yield from before to after FOMC announcement. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Table A14: Gertler and Karadi (2015) Shock and Nominal Interest Rates

	$\Delta\ TY_1$	$\Delta\ TY_2$	$\Delta\ TY_3$	$\Delta\ TY_5$	$\Delta\ TY_{10}$
Intercept	-	0.01	0.01	0.00	0.00
	-	(0.01)	(0.01)	(0.01)	(0.01)
GK shock	-	0.81***	0.79***	0.67**	0.42
	-	(0.25)	(0.25)	(0.27)	(0.34)
N	-	80	80	80	80
R^2	-	0.13	0.09	0.05	0.02
Adj. R^2	-	0.12	0.08	0.03	0.01

Note: $\Delta\ TY_h$ represents daily change in h-year treasury yield from before to after FOMC announcement. GK Shock is the 1 year treasury yield instrumented with the high-frequency change in 3-month-ahead fed fund future price. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

A.1.6 Real Interest Rates and Shock Series

Table A15: Cleaned Text Shock and Real Interest Rates

	$\Delta\ TIPS_2$	$\Delta\ TIPS_3$	$\Delta\ TIPS_5$	$\Delta\ TIPS_{10}$
Intercept	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Cleaned Text Shock	4.11***	3.62***	3.03***	2.24***
	(1.26)	(1.10)	(0.88)	(0.67)
N	80	80	80	80
R^2	0.15	0.13	0.10	0.07
Adj.R^2	0.14	0.12	0.09	0.06

Note: $\Delta\ TIPS_h$ represents daily change in h-year TIPS yield from before to after FOMC announcement. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Table A16: Text Shock and Real Interest Rates

	$\Delta\ TIPS_2$	$\Delta\ TIPS_3$	$\Delta\ TIPS_5$	$\Delta\ TIPS_{10}$
Intercept	0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Text Shock	3.06***	2.67***	2.18***	1.68***
	(0.85)	(0.77)	(0.65)	(0.47)
N	80	80	80	80
R^2	0.17	0.14	0.10	0.08
Adj.R^2	0.16	0.13	0.09	0.06

Note: $\Delta\ TIPS_h$ represents daily change in h-year TIPS yield from before to after FOMC announcement. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Table A17: First Principal Component of FFF and Real Interest Rates

	$\Delta\ TIPS_2$	$\Delta\ TIPS_3$	$\Delta\ TIPS_5$	$\Delta\ TIPS_{10}$
Intercept	-0.01	-0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
PC1 FFF	1.44**	1.46**	1.26**	0.80
	(0.68)	(0.62)	(0.55)	(0.49)
N	80	80	80	80
R^2	0.07	0.08	0.06	0.03
Adj.R^2	0.06	0.06	0.05	0.02

Note: $\Delta\ TIPS_h$ represents daily change in h-year TIPS yield from before to after FOMC announcement. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

Table A18: Nakamura and Steinsson (2018) Shock and Real Interest Rates

	$\Delta\ TIPS_2$	$\Delta\ TIPS_3$	$\Delta\ TIPS_5$	$\Delta\ TIPS_{10}$
Intercept	-0.02	-0.02	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
NS Shocks	1.91***	1.71***	1.44***	1.01***
	(0.56)	(0.49)	(0.42)	(0.35)
N	74	74	74	74
R^2	0.26	0.22	0.17	0.11
Adj.R^2	0.25	0.21	0.16	0.10

Note: $\Delta\ TIPS_h$ represents daily change in h-year TIPS yield from before to after FOMC announcement. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

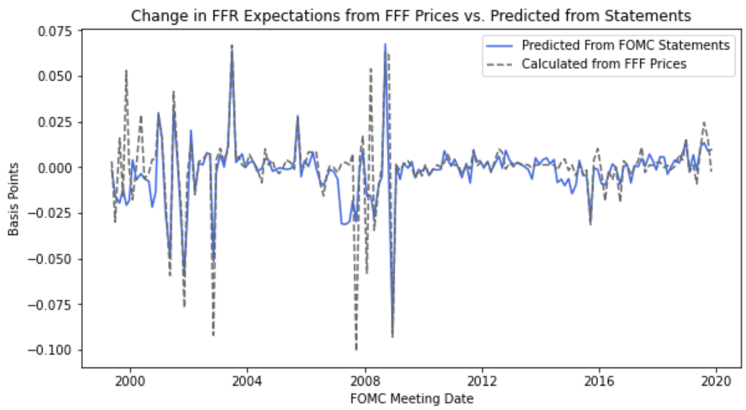
Table A19: Gertler and Karadi (2015) Shock and Real Interest Rates

	$\Delta\, TIPS_2$	$\Delta\, TIPS_3$	$\Delta\, TIPS_5$	$\Delta\, TIPS_{10}$
Intercept	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
GKshock	1.23**	1.21***	1.04***	0.69*
	(0.49)	(0.45)	(0.40)	(0.36)
N	80	80	80	80
R^2	0.09	0.10	0.08	0.04
Adj.R^2	0.08	0.09	0.07	0.03

Note: $\Delta\, TIPS_h$ represents daily change in h-year TIPS yield from before to after FOMC announcement. GK Shock is the 1 year treasury yield instrumented with the high-frequency change in 3-month-ahead fed fund future price. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. * is significance at the 10% level, ** is significance at the 5% level, and *** is significance at the 1% level.

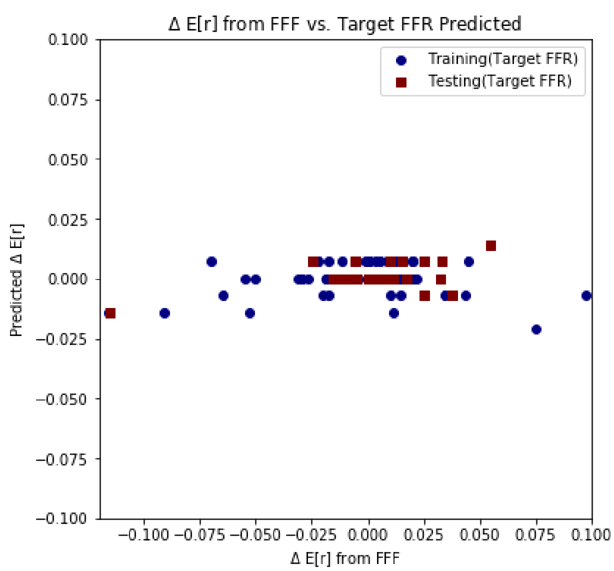
A.2 Graph Appendix

Figure A1: Compare $\Delta E[r]$ and Text-Predicted $\widehat{\Delta E[r]}$ Over Time



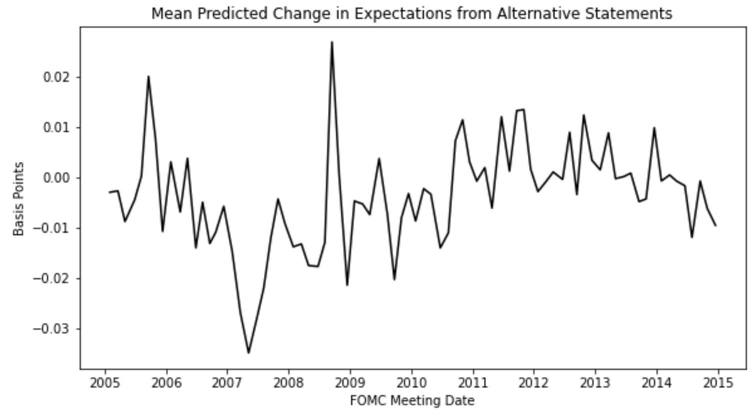
Note: $\Delta E[r]$ is the first principal component of two variables: changes in expectations of the federal funds rate for the current meeting and the next meeting. These expectations are calculated from changes in fed funds future prices from 10 minutes before to 20 minutes after the FOMC announcement is released. $\widehat{\Delta E[r]}$ is prediction of the previous variable from the FOMC statement text and the neural network.

Figure A2: Compare $\Delta E[r]$ and Target-FFR-Predicted $\widehat{\Delta E[r]}$



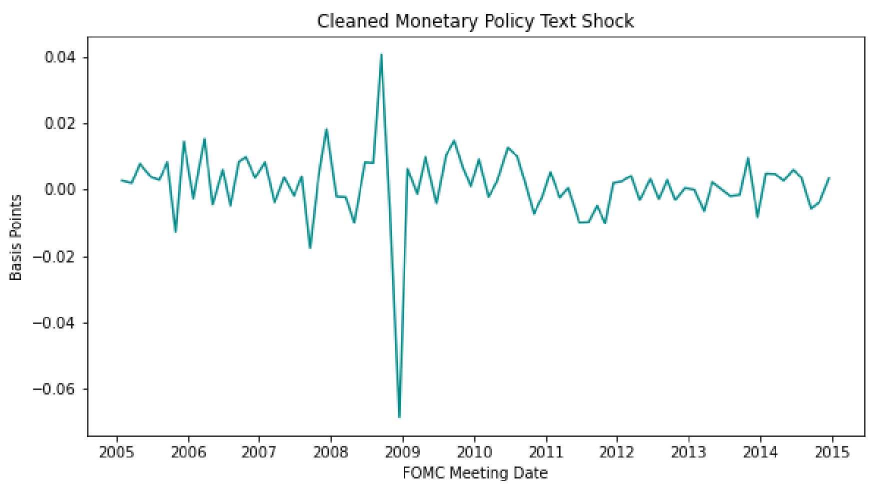
Note: $\Delta E[r]$ is the first principal component of two variables: changes in expectations of the federal funds rate for the current meeting and the next meeting. These expectations are calculated from changes in fed funds future prices from 10 minutes before to 20 minutes after the FOMC announcement is released. $\widehat{\Delta E[r]}$ is prediction of the previous variable from changes in the target federal funds rate at the current meeting.

Figure A3: Mean Predicted $\Delta E[r]$ for Alternative FOMC Statements



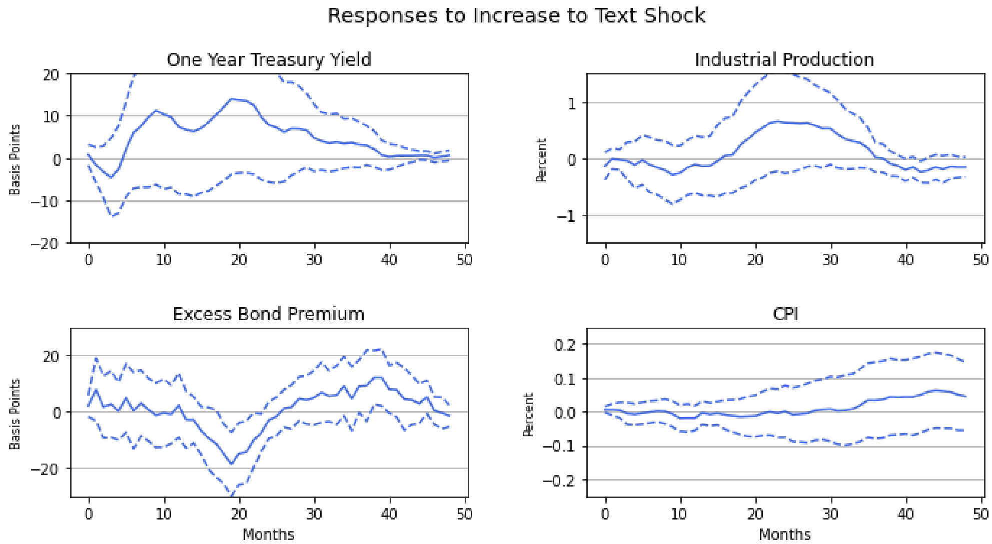
Note: Alternative versions of FOMC statements are included in the Bluebooks and Tealbooks (FOMC meeting materials). I feed each alternative into the trained neural network to get a predicted change in FFR expectations. This graph is then the average of predictions from every alternative for each FOMC meeting from 2005-2014.

Figure A4: Cleaned Text Shock Over Time



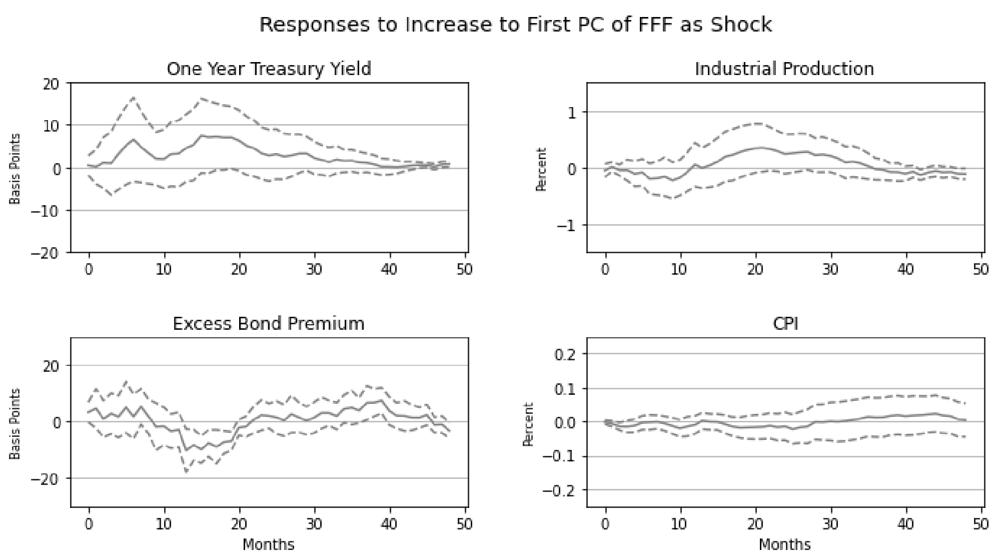
Note: This shows the cleaned text shock series from 2005-2014. This is calucated in two steps, first: the first principal component of changes in expectations of the federal funds rate for the current meeting and the next meeting are predicted by the FOMC statement text with the neural network. Second, for each meeting I subtract out the average of predicted changes in FFR expectations from every alternative statement. This produces a shock series that focuses on changes in fed fund futures predicted from the FOMC statement wording and it controls for the FOMC's private information.

Figure A5: Impulse Responses to Text Shock, $\widehat{\Delta E[r]}_{Text}$



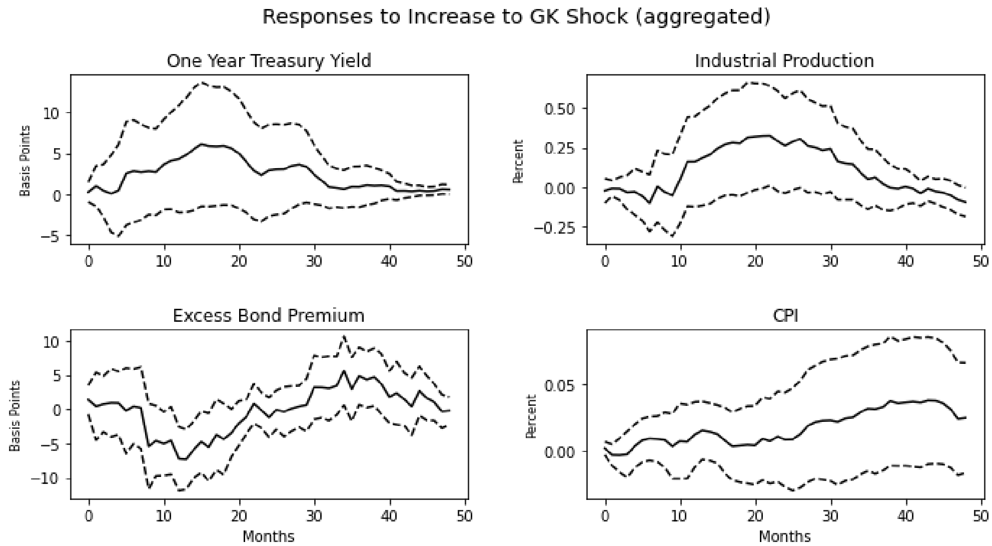
Note: Impulse responses are calculated using the local projection method from Jordà (2005). Confidence bands are at the 90% level. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. The above are responses to a 100 basis point increase in the shock series (not pictured).

Figure A6: Impulse Responses to First Principal Component of FFF, $\Delta E[r]_{FFF}$



Note: Impulse responses are calculated using the local projection method from Jordà (2005). Confidence bands are at the 90% level. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. The above are responses to a 100 basis point increase in the shock series (not pictured).

Figure A7: Impulse Responses to GK Shock (Rolling Mean)



Note: Impulse responses are calculated using the local projection method from Jordà (2005). Confidence bands are at the 90% level. Standard errors are Newey and West (1987) standard errors that correct for heteroskedasticity and autocorrelation. The above are responses to a 100 basis point increase in the shock series (not pictured). Here the vertical scales are more zoomed in to show they look like Ramey (2016). Note that using the rolling mean aggregated shocks do not significantly alter the response graphs.

A.3 Text Analysis and Neural Networks

A.3.1 Text Cleaning Method

After scraping FOMC statements from the Federal Reserve Board's website, the text needed to be "cleaned" before text-analysis could begin. First, I removed the statement release time and any website links that were included in the statement. Then I remove the list of FOMC members who vote in favor of or against the policy action. Similarly, I remove the list of regional Federal Reserve Banks for whom the funding requests were approved. Finally, I also changed any special characters so that they were all readable by the code. For instance, certain FOMC statements includes m-dashes of different lengths that could not be encoded into UTF-8 format. I had to check each special character to ensure that the statement words and punctuation were correctly saved and loadable into python.

To collect alternative FOMC statements from the FOMC meeting materials, I copied them by hand. The FOMC meeting materials, the Tealbooks and Bluebooks, are all in pdf format and difficult to automatically web-scrape. Alternative statements were written as changes from the wording of the statement released after the previous FOMC meeting. This means there are strikethroughs of text in the previous meeting's statement that are not to be included in this alternative's wording. Furthermore, new text is written in a red font and sometimes placed in parentheses. Handling all the special cases made it necessary to manually document the alternative statements.

I categorized each alternate phrasing was made into a new statement. When there were sets of alternate phrasing, I paired the first option of all the sets as one statement and then the second option for all the sets would be another statement. I did not do all the permutations for swapping in suggestions of text because this would sometimes be for swapping one word and did not seem necessary for my measures. This is a new collection of FOMC texts. Please email me if you would like access to the cleaned alternative FOMC statements.

A.3.2 Numerical Representations of Words

Representation of words for quantitative analysis has evolved substantially over recent years. Originally text analysis was always performed by researchers in what is known as a "narrative approach." This means that researchers and their assistants would read through text and create indices based on their judgments of the text. Such indices could be 'sentiment measures' – how optimistic/pessimistic is this document? - or representations of the content – like an intended federal funds rate from Romer and Romer (2004). Using narrative methods rely heavily on the researchers' subjective readings and are extremely time intensive. For scalability and replicability, text analysis methods have progressed to rely on quantitative representations of text and using computers to identify patterns in text. In the rest of the section I will cover a brief overview of computer science's representation of words as numbers. For a more detailed overview, please refer to Gentzkow et al. (2019).

A common first pass for word representations includes either using a unique number or making a dummy variable for each word in the collection of text to be analyzed. For the former, this means that words would range from 0 to some number V that represents the total number of words in the collection of documents. That is, V represents the number of words in the vocabulary. Now each document can be represented as a sequence of numbers.

If the researcher has a list of words that are indicative of a sentiment – that is, a list of optimistic/pessimistic/uncertainty words – then the count of how often words from the sentiment-list occur in the document is a representation of sentiment-intensity. This currently is one of the most common approaches to text analysis in economics (Gentzkow et al., 2019). The method for making sentiment-word lists varies from the researcher writing down words to using external identification of sentiment-word lists (Gentzkow et al., 2019;

Hassan, Hollander, van Lent and Tahoun, 2019). Hassan et al. (2019) identifies bigrams that occur in political textbook and not in an accounting textbook as a way to identify "political" words. Hansen and McMahon (2016) use a clustering algorithm to group words into topic lists. Ultimately, these lists are useful for categorical labels of words.

However for more continuous labels of words or to create a word-space that incorporates relationships between words' meanings, computer scientists looked at vector representations. Initially, each word is represented as a vector that is 1 by the size of the collection's vocabulary. For example, consider a vocabulary

$$[\text{“apple”}, \text{“banana”}, \text{“dog”}, \text{“cat”}]$$

Then “dog” could be represented as:

$$[0\ 0\ 1\ 0]$$

This can make the word-space very large and uninformative about words' meaning or relations to other words.

Assume that the meaning of words can be broken down into M dimensions, where $M < V$, and words that occur in the same documents have similar meanings. Then assign a vector with random numbers to each word in the vocabulary. Then update the values of the vectors based on which words occur together. The result of training is that words that discuss similar topics will have vectors positioned more closely in the M dimensional space. For example,

These methods have made progress for understanding targeted aspects of text analysis and are the foundation for where text analysis research is today. They cover how words are represented quantitatively. Currently, the frontier of text analysis uses word embeddings and neural networks. Neural networks can approximate non-parametric functions over complex domains. Accordingly, they are used for mapping words from text to some classification our output.

A.3.3 Introduction to Neural Networks

This section covers an introductory example to explain how neural networks are constructed, trained, and evaluated. Athey and Imbens (2019) have a more in depth discussion on the comparisons between neural networks and traditional econometric approaches. Namely, neural networks lack theoretical backing that econometric methods rely on. The way neural networks are evaluated is on their ability to predict data that was not used to fit parameters. The parameters of neural networks are not unique or identified, so there are many specific weights that can be approximating the same mapping from inputs to outputs.

Consider a dataset that has 4 continuous variables - $x_1,\ x_2,\ x_3,\ y$ - and N observations. The researcher wants to predict y from x1,x2, and x3. First split the data so that 80% can be used to train the neural network parameters and 20% of the data can be used to evaluate the neural networks generalizability as an approximation of the mapping from $x_1,\ x_2,\ x_3,$ to y.

Figure A8: Neural Network Example as Figure

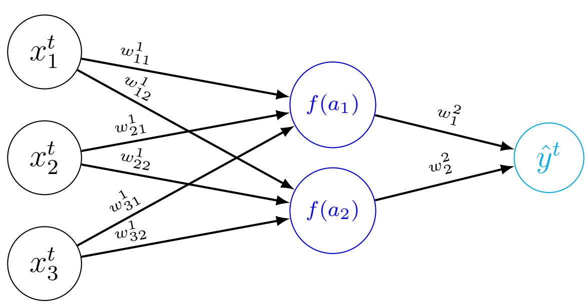


Figure A9: Neural Network Example as Matrices

$$\begin{bmatrix} x_1^t & x_2^t & x_3^t \end{bmatrix} \begin{bmatrix} w_{11}^1 & w_{12}^1 \\ w_{21}^1 & w_{22}^1 \\ w_{31}^1 & w_{32}^1 \end{bmatrix} = \begin{bmatrix} a_1^t & a_2^t \end{bmatrix}$$

$$\begin{bmatrix} f(a_1^t) & f(a_2^t) \end{bmatrix} \begin{bmatrix} w_1^2 \\ w_2^2 \end{bmatrix} = \hat{y}^t$$

The neural network maps inputs to outputs one observation at a time using a mix of non-linear transformations of linear combinations of the inputs. In this example, there are two linear combination stages and one nonlinear transformation. The researcher chooses the number of combinations and transformations in the neural network after training networks of different sizes and choosing what is best able to predict out-of-sample data.

Figure A8 and Figure A9 are the graphical representation and the matrix representation of the neural network, respectively. There are two linear combinations of x_1, x_2, x_3, they are called a_1 and a_2. The weights for these combinations can be initially random or chosen by the researcher, but they we will change as a part of training the network. Then a_1 and a_2 are transformed by function f. f would normally be some non-linear function, like a sigmoid or hyperbolic tangent function, to capture non-linearities in the relationship between inputs and outputs. If the f function were linear, then the neural network is equivalent to a linear regression.

Finally, the transformed linear combinations are themselves combined to create a predicted value $\hat{y}$. The prediction error for the current set of weights is the average of prediction errors for each observation. The functional form of the f and the fixed neural network structure (the number of linear combinations) allows the derivative of the prediction error with respect to each network parameter weight to be calculated in closed form. The way weights are updated is with an optimizer algorithm, like gradient descent. This process of updating is repeated many times so that the neural network is better able to predict the output from inputs.

Computer scientists use different approaches to handle overfitting of the neural network. Neural networks, with enough parameters and enough training iterations, can perfectly match training inputs to outputs. Capping the adjustment of network weights can change for each iteration also prevents weights from jumping wildly to perfectly predict a single observation. Keeping this rate small means that only persistent errors across observations are used to shift parameter values. Limiting the number of training iterations and the amount parameters can update are two ways computer scientists deal with overfitting. During the training process, the ability of the network to predict in sample improves. If there is a true mapping from inputs to outputs the out-of-sample prediction also will improve initially. However, as the neural network starts overfitting the training data, the out-of-sample prediction decreases. Accordingly, once the researcher sees out-of-sample prediction decrease, then they can manually stop the training. As Athey and Imbens (2019) discuss, the concern for overfitting is one reason neural networks are evaluated on their ability to predict out-of-sample data, that is, data that was not used for training.

A.3.4 Overview of Training Algorithm

1. Fix the collection of text (call this "corpus 1")
2. Prepare the text to be an numerical input to the neural network
   (a) Break words into sub-word units (called tokens)
   (b) Create 768x1 vector for each token based on co-occurrence of sub-word units in the corpus (a clustering algorithm to train the vector values so that similar words have similarly oriented vectors in 768-dimensional space)
   (c) Add special tokens to indicate ends of sentence and an observation level identifier
   (d) Add padding to make all text inputs the same length (256 for now, robustness with 512 and 900 later)
3. Train the neural network for task 1 on corpus 1
   (a) Fix the network structure and the hyperparameters (ie learning rate)
   (b) Update parameters in the network to increase prediction accuracy for training data (predicting missing words from text inputs)
   (c) Stop updating parameters
   (d) Evaluate neural network: prediction accuracy on data not used for training (testing data)
   (e) Go back to initial step and restructure neural network if needed
4. Fine-tune neural network for task 2 on corpus 2
   (a) Add additional layer to network to handle new task
   (b) Update parameters to increase prediction accuracy for new training data
   (c) Stop updating
   (d) Evaluate neural network: prediction accuracy on data not used for training (testing data)