ONLINE APPENDIX

Text Shocks and Monetary Surprises:

Text Analysis of FOMC Statements with Machine Learning

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A Data and Methods

A.1 Fed Funds Futures Prices

Looking at the price of a FFF contract that expires at the end of this month (FFF^1_t) before an FOMC meeting (t) would be priced[1]

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

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 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.[2] 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:

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

I also consider how the current FOMC announcement influences expectations

[1] Although I use the notation FFF^1_t, 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).

[2] 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.

over the federal funds rate for the next meeting $(t+1)$:

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

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.

A.2 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 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, Kelly and Taddy (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

[“apple”,“banana”,“dog”,“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.4 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 A1: Neural Network Example as Figure

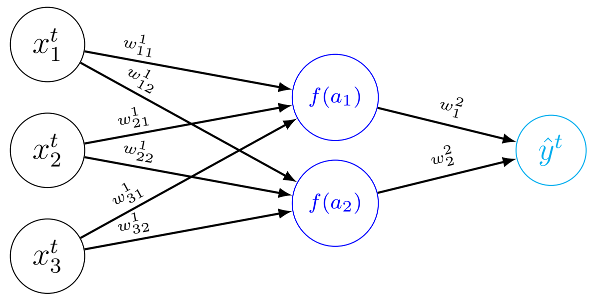

Figure A2: Neural Network Example as Matrices

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

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

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 A1 and Figure A2 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.5 XLNet Overview

As is common for computational text analysis, Yang, Dai, Yang, Carbonell, Salakhutdinov and Le (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.[3] 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 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

[3]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."

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.

B Table Appendix

B.1 Example Statements

Table B1: 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... 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 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.... 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

B.2 Nominal Interest Rates and Shock Series

Table B2: 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 B3: 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 B4: 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 B5: 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 B6: 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.

B.3 Real Interest Rates and Shock Series

Table B7: 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 B8: 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 B9: 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 B10: 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 B11: 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.