Shocking language: Understanding the macroeconomic effects of central bank communication[*]

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Abstract

We explore how different information released by the FOMC has effects on both market and real economic variables. Using tools from computational linguistics, we measure the information released by the FOMC on the current state of economic conditions, as well as how clearly they guide markets about future monetary policy decisions. Employing these measures within a FAVAR framework, we find that shocks to forward guidance are more important than the FOMC communication of current economic conditions in terms of their effects on market and real variables. Nonetheless, neither communication has particularly strong effects on real economic variables.

Keywords: Monetary policy, communication, Vector Autoregression

JEL Codes: E52, E58, D78

1 Introduction

It is now widely accepted that many aspects of modern monetary policy aim to manage inflation expectations (King, Lu, and Pastén 2008). This is because economic agents forward-looking decisions typically depend on expected real interest rates over reasonably long horizons (up to, and beyond, 20 years for major investment decisions). Given that the central bank controls nominal interest rates only at very short maturities, private sector economic agents must take a view on both the likely future developments in the economy, as well as the reaction of the central bank to these developments, in order to establish their expectations of longer term real interest rates.

Central bank communication has emerged as a key tool for central banks in their attempts to control inflation expectations. Blinder, Ehrmann, Fratzscher, Haan, and Jansen (2008), in their survey of the large literature that has developed examining different aspects of communication by monetary authorities, define it broadly as the information that the central bank makes available about its current and future policy objectives, the current economic outlook, and the likely path for future monetary policy decisions. An important and open area in monetary policy is how to design central banks to optimise their policy outcomes (Reis 2013), and the question of optimal communication strategy is central to this discussion.

Before we can study optimal communication by central banks, we need to understand the effects of different strategies on a variety of macroeconomic and market variables. This issue has been studied in both theoretical models (for example, the model-based evaluation of central bank communication strategies in Eusepi and Preston (2010)), and there is also an emerging empirical literature. For example, Ehrmann and Fratzscher (2007) examine the communication strategies of the ECB, Bank of England and the Federal Reserve; Ranaldo and Rossi (2010) examines the financial market effects of Swiss National Bank announcements; Hayo and Neuenkirch (2010) considers the predictability of future Fed rates using information in announcements; Berger, Ehrmann, and Fratzscher (2011) looks at the ECB and media reaction; and Hayo, Kutan, and Neuenkirch (2012) focuses on asset market reactions to Fed communications.

Gürkaynak, Sack, and Swanson (2005) (GSS) show, using an event study approach analysising movements in financial markets data around FOMC interest rate decisions, that central bank announcements move markets.[1] In fact, the statement accounts for most of the movements in 5- and 10-year Treasury yields. They conclude that expectations of future decisions are key and that the statements are what help to affect investor

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[1] Specifically, they decompose the effects of FOMC announcements on financial markets into different factors and reject that a single factor related to the policy actions sufficiently explains the movements. Instead, they identify two (but not more) factors in their analysis of FOMC statements from 1990 to 2004.

expectations.[2]

GSS is an important paper which indicates that central bank communication reveals information to investors and thereby influences their expectations. However, a downside of their methodology is that they do not measure the communication. Instead, the effects of policy, and their identified 'path factor' is revealed from the immediate response of particular asset prices. Though they find that "FOMC actions were priced into the federal funds futures market almost immediately", the detail and complexity of the FOMC statement has increased substantially since the financial crisis and especially since the deployment of unconventional monetary policy (Hernández-Murillo and Shell 2014).[3] This means that if the full understanding and reaction took longer, and the immediate response was only transitory, we might get a very misleading view of the effects of the statements from this methodology. A second downside is that we do not learn *what* information is being revealed to investors (Woodford 2012).

In this paper, we measure two specific aspects of the central bank communication directly and, using these measures, make two contributions to this literature. First, we then use standard macroeconometric tools for monetary policy analysis, augmented using the extracted measures of communication, to examine how shocks to the statement affect macroeconomic and financial variables. In particular, we use a Factor-Augmented VAR (FAVAR) as developed by Bernanke, Boivin, and Eliasz (2005). As such, the analysis allows us to examine the dynamic effects of central bank communication on these variables. We view this as complementary to the event-study methodology. Second, we can examine which aspects of the communication give rise to the changes in the macroeconomic variables.

A major challenge for the analysis of central bank communication, and one we address head on in this paper, is to convert the raw communication, which is typically words, into meaningful quantities which we can systematically analyse. Some approaches simply only focus on quantitative communication (such as released central bank forecasts), while others use counts of some pre-selected, keywords (see, for example, Rosa and Verga (2008)) to measure content. The main methodological contribution in this paper is to use computational linguistics, and particularly the combination of topic modelling and dictionary methods, in order examine the content of what central banks are trying to communicate to the markets and the public.

In particular, we use Latent Dirichlet Allocation (LDA) and a dictionary method to extract what official interest rate communications (statements) by the Federal Reserve

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[2]They write: "our results do not indicate that policy actions are secondary so much as that their influence comes earlier when investors build in expectations of those actions in response to FOMC statements (and perhaps other events, such as speeches and testimony by FOMC members)."

[3]This is measured by both the length of the statement, which increased from 50-200 words in the early 1990s, to more than 800 words in the first five meetings of Janet Yellen as Chair. This is reflected in the estimated Flesch-Kincaid Grade Level increasing from a range of 9-14 to 18-19.

and ECB are about.[4] LDA is widely used in linguistics, computer science, and other fields; the article that introduced it, Blei, Ng, and Jordan (2003), has over 10,000 citations in 10 years. While computational linguistic models are beginning to appear in the political science literature, their use is still mainly descriptive; for example, Quinn, Monroe, Colaresi, Crespin, and Radev (2010) use a topic model similar to LDA to study congressional speeches to see what congress is talking about. We believe that the approach of using computational linguistics to create measures of communication from large databases of text has broader applications beyond monetary policy analysis and can help bringing economics into the increasingly important world of "Big Data". Existing work using computational linguistics tools to analyse monetary policy data include Bailey and Schonhardt-Bailey (2008) and Schonhardt-Bailey (2013) who focus on arguments and persuasive strategies adopted by policymakers; Fligstein, Brundage, and Schultz (2014) who apply LDA to the FOMC transcripts in order to examine the concept of "sense-making" on the FOMC; and our recent work examining the effect of transparency on the deliberation of the FOMC using LDA applied to FOMC transcripts (Hansen, McMahon, and Prat 2014).

We find that, at least in the last 11 years in the US, the central bank communication on future interest rates (forward guidance) seems to have been much more important than their communication of current economic conditions. Moreover, neither communication has particularly strong effects on real economic variables in our FAVAR.

The remainder of the paper proceeds as follows. We first discuss the idea behind the effects of central bank communication and how we measure these aspects empiricially. We then introduce the macroeconometric methodology (FAVAR) before exploring the results and concluding.

2   Measurement of Communication

If, as is often the case, we consider that the central bank, on average, follows a rule for nominal interest rates, in the spirit of Taylor (1993), captured by:

$$i_t = f \times \Omega_t + \epsilon_t \tag{1}$$

where f is the vector of reaction coefficients, Ω_t is the vector of economic inputs to the rule. The central bank, when it makes a decision at time t, reveals i_t and it can also communicate through its statement. Broadly, it can communicate about:

State of Economy: the current economic outlook Ω_t.

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[4]For the ECB, we will use press conferences.

Forward Guidance / Shock: its expected deviations from this average rule (ϵ_t), or a commitment to follow some path that may deviate from the average rule.

One issue is the extent to which any forward guidance is Delphic or Odyssean as described by Campbell, Evans, Fisher, and Justiniano (2012). The distinction, related to the Greek classical stories, is whether the FOMC provides information about their view of the future ('Delphic') or whther they commit themselves to a future path of interest rates ('Odyssean'). Such a distinction, and how one interpets FOMC forward guidance, is not uncontroversial as the discussion of the Campbell, Evans, Fisher, and Justiniano (2012) paper makes clear. In this paper, we will not be able to get a distinction that is perfectly Delphic or Odyssean. Rather we shall measure the certainty in their statements about expected future path of interest rates without distinguishing between whether this is because they are committing to a particular path in the Odyssean sense, they are signalling a forecast of the future direction of changes in the economic outlook (Meyer 2012), or whether they think that other objectives, beyond their usual ones, are driving likely decisions more (Romer 2012). We shall return to this distinction below.

The novel empirical approach taken in this paper is to use techniques from computational linguistics, applied to the statements of the FOMC, to measure the extent to which the information provided is about the current outlook for the economy, and to what extent it provides a guide for the future. Of course, it is possible to think at an even greater level of disaggregation, such as trying to measure the extent to which the statement reveals new information about the labour market, or price developments, but we leave that for future research.

Specifically, we derive empirical measures "the two Ts": Topic and Tone. That is, we need to know first whether the central bank is talking about Ω_t or how the central bank expects to set rates in the future (topic), and then we need to measure how they are talking about it (tone). In this paper, we propose the use of Latent Dirichlet Allocation (LDA) to measure topic and a balance measure based on dictionary methods to measure tone. We now discuss these two empirical approaches in more detail.

2.1 Topic modelling

As mentioned in the introduction, we use Latent Dirichlet Allocation to model the topic of each paragraph of the FOMC statements. A very popular algorithm developed by Blei, Ng, and Jordan (2003) and used for information retrieval, Hansen, McMahon, and Prat (2014) provide a full description along with the statistical foundations.[5] Here, we simply outline the basic steps and intuition for the algorithm.

LDA is essentially a very fleixble clustering algorithm for words that groups words

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[5]Blei and Lafferty (2009) contains an overview of LDA and some of its extensions.

into topics on the basis of repeated co-occurrence across paragraphs. There are two inputs to the algorithm. The first input that the user must supply is a corpus of the documents of text to be analysed; in this paper the corpus is the full history of FOMC statements accompanying decisions on monetary policy where we group words at the level of an individual paragraph in a statement. However, before using the words in the LDA analysis, we first remove stop words (such as 'the', 'a' and 'and') and also stem the remaining words which reduces them to a common linguistic root ('economy' and 'economic' both become 'economi'). The second input is a number of topics that the algorithm should form; we use a 15-topic model.

The are two broadly defined outputs. The algorithm will form, in our case, 15 topics which are probability distributions over words and tell the user the words which tend to go together. The algorithm also forms document distributions which contain probabilities that capture the fraction of words policy makers devote to the different topics in their communications. For example, it might suggest that a paragraph in a statement (our level of LDA analysis) is 0.75 about topic A and 0.2 about topic B and so on.[6]

To get more precise, topic models estimate K topics each of which is a distribution $\beta_k \in \Delta^V$ over the V unique tokens (words) in the corpus vocabulary. LDA is flexible enough to allow unique tokens to belong to more than one topic. LDA will also generate a predictive distribution over topics $\widehat{\boldsymbol{\theta}}_d \in \Delta^K$ for each document, where Δ^K is the K-simplex. However, given that we estimate the topic model at the paragraph level, rather than use the predictive distribution, we prefer to work with the word to topic allocations directly (this is an intermediate step in the LDA algorithm to generate $\widehat{\boldsymbol{\theta}}_d$. In particular, let $\phi_{p,k,d} = n_{p,d}(k)/n_{p,d}$ be the fraction of paragraph p words allocated to topic k, where $n_{p,d}(k)$ is the number of paragraph p word allocated to topic k, and $n_{p,d}$ is the total number of words in the paragraph. We will define a paragraph as being about topic k when this estimated topic allocation fraction $\phi_{p,k,d}$ is greater than some critical proportion ($\alpha = 0.5$).

Before we turn to the results of LDA for this paper (discussed below), we take a motivating example of the power of LDA applied to monetary policy, using the FOMC transcript analysis of Hansen, McMahon, and Prat (2014). Figure 1a represents the estimated topic distribution, , most associated with economic recession as a word cloud; the larger the word in the cloud, the more often it is used by FOMC members talking about that topic. Figure 1 plots the amount of time the FOMC as a whole spends on this topic. We also plot the uncertainty index of Baker, Bloom, and Davis (2013) (BBD hereafter). The relationship between BBD-measured uncertainty and FOMC attention towards recession concerns is quite strong, with both spiking in the late 1980's and during times of war.

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[6]Once estimated at a given level of aggregation, it is possible to aggregate document distributions up using a process called querying. See Hansen, McMahon, and Prat (2014) for details.
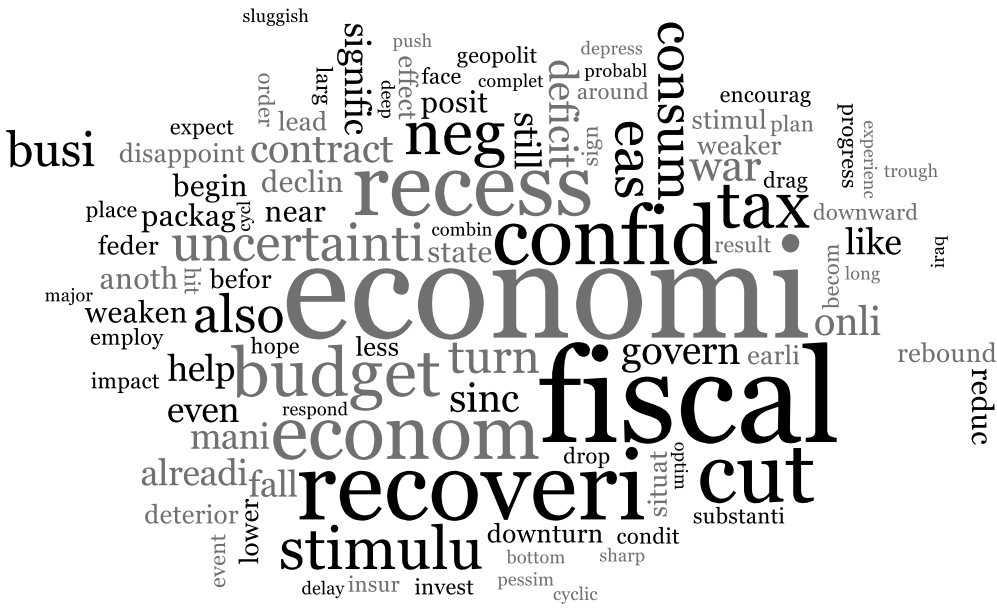
(a) Topic 45—"Recession"
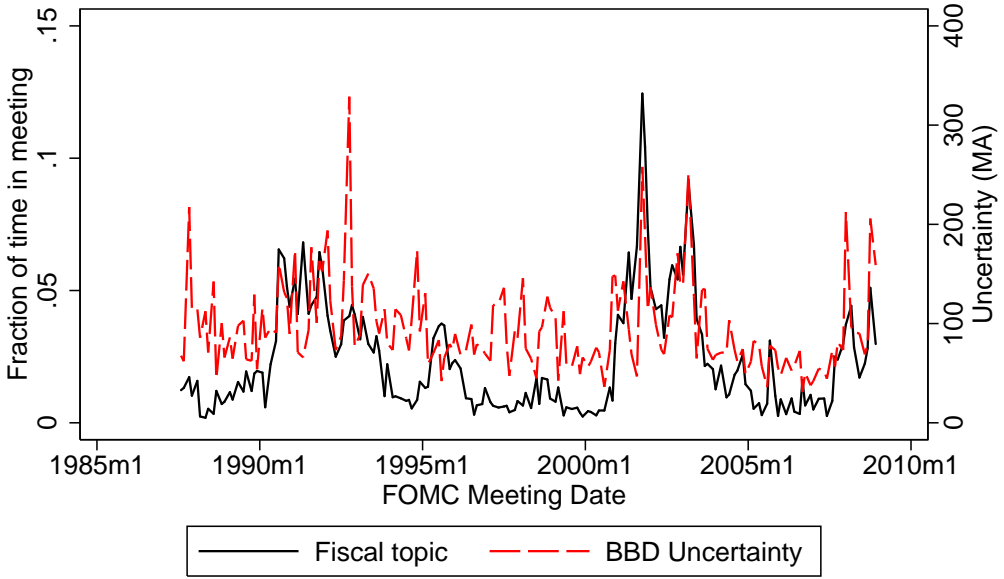
(b) BBD uncertainty and discussion of topic 45

Figure 1: BBD uncertainty measure and FOMC attention to recession issues

Contraction	Expansion
decreas*	increas*
decelerat*	accelerat*
slow*	fast*
weak*	strong*
low*	high*
loss*	gain*
contract*	expand*

Figure 2 displays the main risk and uncertainty topic. It also plots the attention it received during FOMC meetings against the BBD index. While the two series co-move, it is particularly noteworthy that the estimates suggest that in the run-up to the financial crisis in 2007 the market was not yet concerned with risk while the FOMC was increasingly discussing it.

2.2 Measuring tone with dictionary methods

Dictionary methods, or more simply word counting, work as follows. Let $\ell = (t_1, \ldots, t_N)$ be a list of unique terms and d be a document, which we can also think of as a list of (possibly non-unique) terms. We can then define $n_d(\ell)$ to be the raw count of terms in ℓ in document d, and either use this alone to index d, or else apply some normalization (like dividing by the total number of terms in d). This is a common way of measuring market sentiment in the finance literature, where word lists are chosen to reflect positive and negative tone and applied to media text or company results releases; see, for example, Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), Loughran and McDonald (2011) and Loughran and McDonald (2014).

In this paper, we will use three main word lists to form two measures of tone. The first two lists take "directional" word lists measuring words associated with expansion and contraction as used in Apel and Blix Grimaldi (2012). For example:[7] where * indicates that any word ending is acceptable. Of course, these methods work best at finer and finer levels of topic disagregation. Increasing risk is not typically a sign of economic expansion but we have ways to (at least partly) correct for this which we outline below.

Using the counts of contraction $(-)$ and expansion $(+)$ words, we can form a balance measure which is given by:

$$\text{Tone}_d = \frac{n_{+,d} - n_{-,d}}{n_d}$$

The other word list that we will use concerns measuring uncertainty or ambiguity in a document. For this we use, as a base, the 'ambiguity' word list developed by Loughran

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[7]The appendix contains the full list of words that we use in the analysis in this paper along with their frequency of occurence. This list does not include words which we looked for but which were not found in the FOMC statements.

(a) Topic 40—"Risk"

(b) BBD uncertainty and discussion of topic 40

Figure 2: BBD uncertainty measure and FOMC attention to risk

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and McDonald (2011) and augment it with some words used specifically to convey certainty or uncertainty in monetary policy. As this is measuring a single dimension of the paragraph, we use:

$$\text{Uncertainty}_d = \frac{n_{Uncertainty,d}}{n_d} \qquad (2)$$

2.3 Combining Topic and Tone

We propose a simple way of combining these two approaches that allows one to measure topic-level tone which helps to deal, somewhat, with the weakness of dictionary methods. That is, rather than just measure words associated with expansion, we can measure expansion words associated with GDP growth rather than risk premia.

To do this, we can view a document as an ordered sequence of paragraphs $d = (\pi_{1,d}, \ldots, \pi_{\Pi_d,d})$ where Π_d is the total number of paragraphs in document d. We identify the paragraphs in which topic k makes up at least α fraction of attention as measured by $\phi_{p,k,d}$ allocation variable defined earlier. Then, within this set of paragraphs, compute the fraction of words that lies in list ℓ and normalise by the total number of words in those paragraphs.

Before we turn to the actual implementation of this analysis, it is worth pausing and considering two reasons for the use of automated techniques rather than, as others have done, a purely or even partly narrative approach to score statements according to their extent of guidance. The first obvious advantage of automation is scalability without concerns about consistency of the, for example, research assistant who is scoring the statements. With automated methods it is then easy to extend the sample to include other sources of communication such as FOMC speeches, or to extend it to other central banks. The second advantage is precisely that the researcher does not have to worry that too much prior knowledge of the big announcements is allowed to determine the choices made in creating the indices. Nonetheless, given that narrative methods might be able to pick up some of the nuance of statements more precisely, we believe there is a role for both methods as complements.

2.4 Analysis of FOMC Statements

The FOMC first accompanied their decision with a statement in February 1994 although statements were ad-hoc for most of the 1990s. In total, we use 136 statements in our analysis (up to September 2014), although we estimate our 15-topic LDA on the full corpus of 142 FOMC decision statements up to March 2015.

The LDA-estimated topics cover different aspects of the FOMC communication. We

select four topics which relate to the discussion of the economic situation, and find six topics that capture the nature of the FOMC's forward guidance.

The key tokens in the economic topics are presented as word clouds in figure 3:[8]

Topic 2: A topic which focuses on the outlook for demand and consequnces for the monetary policy decision.

Topic 4: Captures statements about the supply side of the economy.

Topic 11: Similar to topic 2 but captures the language used in a different time period.

Topic 13: Captures discussion of the demand side of the economy, as well as aspects of supply.

Once we identify those paragraphs that are mostly about the economic situation (using a topic allocation of more than 50% about the four economic topics), we using only these relevant paragraphs and create our time-series balance measure of the FOMC statement on the economic situation as follows:

$$\text{EcSit}_t = \frac{n_{Pos,t} - n_{Neg,d}}{TotalWords_t^{EC}} \tag{3}$$

where $n_{Pos,t}(n_{Neg,t})$ is the number of posive (negative) words in those paragraphs about the economy, and $TotalWords_t^{EC}$ is the total number of words about the economic situation. This gives a balance measure which can be greater than zero (more words associated with expansion) or less than zero (more contraction words).

For example, consider the following paragraph on the economy from the March 2004 Statement which is mostly about topic 4:

> "The Committee continues to believe that an accommodative stance of monetary policy, coupled with robust underlying growth in productivity, is providing important ongoing support to economic activity. The evidence accumulated over the intermeeting period indicates that output is continuing to expand at a solid pace. Although job losses have slowed, new hiring has lagged. Increases in core consumer prices are muted and expected to remain low."

This paragraph contains a total of 30 words, two words related to expansion but three related to contraction (from our list). Overall the index value is $\frac{2-3}{30} = -0.033$. We repeat this excercise is completed for every paragraph about one of the economic topics.

The forward guidance topics capture both the date-based guidance of the FOMC in recent recent years, but also FOMC statements about the balance of risks as seen by the

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[8]Note that the figure plots the stemmed tokens as these are the unit of LDA analysis.

(a) Topic 2

(b) Topic 4

(c) Topic 11

(d) Topic 13

Figure 3: Topics Covering FOMC views of the Economic Situation

FOMC. Figure 4 presents the word clouds for the six identified forward guidance related topics:

Topic 0: Captures the part of statements describing the interest rate stance.

Topic 3: Captures the interest rate stance but also the explicit forward guidance seen most recently from the FOMC. We present an example of this kind of statement below.

Topic 6: Captures earlier forward guidance. We present an example of this kind of statement below.

Topic 8: Captures the forward guidance provided alongside some of the earlier liquidity operations.

Topic 10: Captures the earlier balance of risks discussions used as an early form of forward guidance as early as 2003 (Yellen 2013). We present an example of this kind of statement below.

Topic 14: Also captures the more recent forward guidance provided by the FOMC.

Our index of forward guidance measures the extent of certainty or definitiveness about statements regarding future interest rate moves; a less uncertain statement represents more forward guidance. To do this, we a list of "Ambiguity / Uncertainty" words and create:

$$\text{FwdGuide}_t = \frac{n_{Ambi,t}}{TotalWords_t^{FG}} \tag{4}$$

where $n_{Ambi,t}$ is the count of uncertainty words and $TotalWords_t^{FG}$ is the total number of words in the paragraphs about forward guidance after removing stop words. By construction, this measure is bounded below by zero and increases indicate less certainty in statements about future interest rates.

This forward guidance statement, which comes from January 2007, is estimated to be about topic 10 and has a $\text{FwdGuide}_t = 0.286$ owing to the inclusion of four words associated with ambiguity:

> "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."
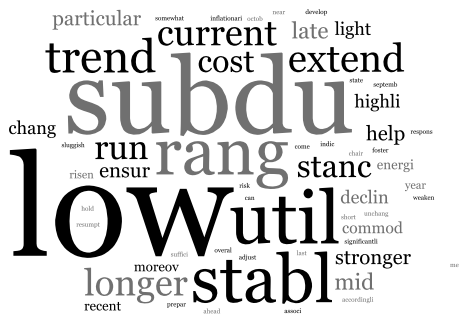
This next example of a forward guidance statement comes from December 2011. It is mostly assigned to be about topic 6 but only contains a single word from the uncertainty list and so is measured to be more certain ($\text{FwdGuide}_t = 0.0625$).
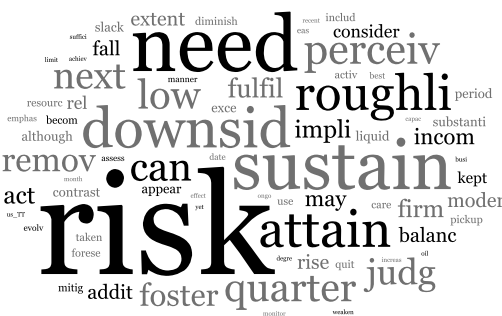
(a) Topic 0

(b) Topic 3

(c) Topic 6

(d) Topic 8

(e) Topic 10

(f) Topic 14

Figure 4: Topics Covering FOMC Forward Guidance

"The Committee also decided to keep the target range for the federal funds rate at 0 to 1/4 percent and currently *anticipates* that economic conditions–including low rates of resource utilization and a subdued outlook for inflation over the medium run–are likely to warrant exceptionally low levels for the federal funds rate at least through mid-2013."

This next paragraph, coming a year later in December 2012, is mostly about topic 3, and also contains a single uncertainty word but this is set amidst many more words so FwdGuide$_t$ falls to 0.0166:

"To support continued progress toward maximum employment and price stability, the Committee expects that a highly accommodative stance of monetary policy will remain appropriate for a considerable time after the asset purchase program ends and the economic recovery strengthens. In particular, the Committee decided to keep the target range for the federal funds rate at 0 to 1/4 percent and currently *anticipates* that this exceptionally low range for the federal funds rate will be appropriate at least as long as the unemployment rate remains above 6-1/2 percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committee's 2 percent longer-run goal, and longer-term inflation expectations continue to be well anchored. The Committee views these thresholds as consistent with its earlier date-based guidance. In determining how long to maintain a highly accommodative stance of monetary policy, the Committee will also consider other information, including additional measures of labor market conditions, indicators of inflation pressures and inflation expectations, and readings on financial developments. When the Committee decides to begin to remove policy accommodation, it will take a balanced approach consistent with its longer-run goals of maximum employment and inflation of 2 percent."

Figures 5a and 5b show the constructed indices as bars (with each bar representing an FOMC statement after a meeting). As can be seen there are breaks in the monthly time-series of these contructed indices that affect the use of the series as a monthly time-series. The first is that in some months there is no FOMC meeting and as such there is no time-series for that month. In these cases, we simply use value of the statement in the last meeting. The second is that in a few instances there was a meeting, and a statement, but no discussion of the economy and/or forward guidance in the statement. This is particularly true for forward guidance in early 2003. In such cases, we replace the time-series with a neutral value for the index and so we use the series mean. These two adjustments give rise to a continuous monthly time-series which is also plotted in 5.

Finally, using our method of identifying content related to the economic situation and content related to future interest rate actions, we count the number of meaningful words
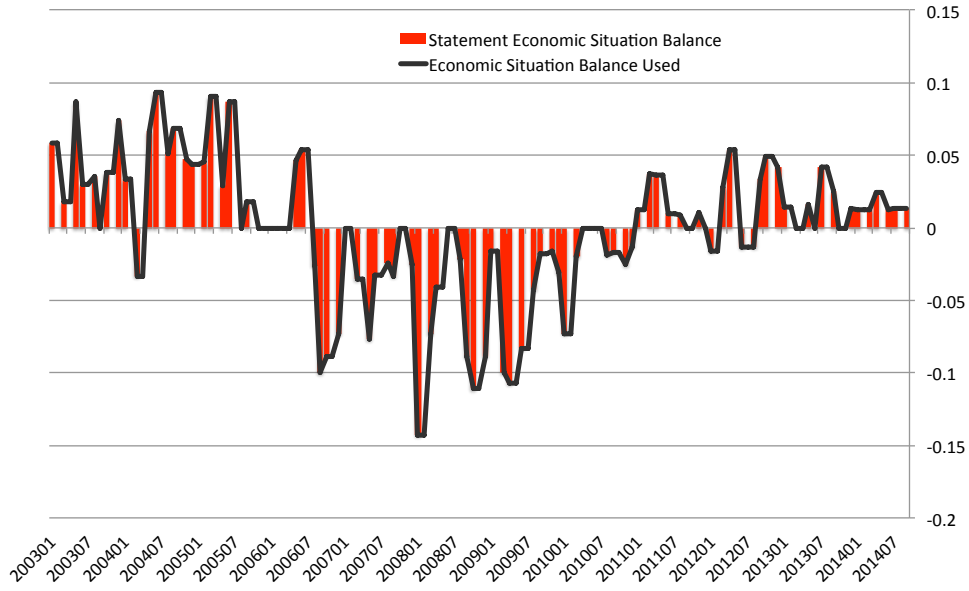
(a) EcSit$_t$: Statement by statment and monthly index
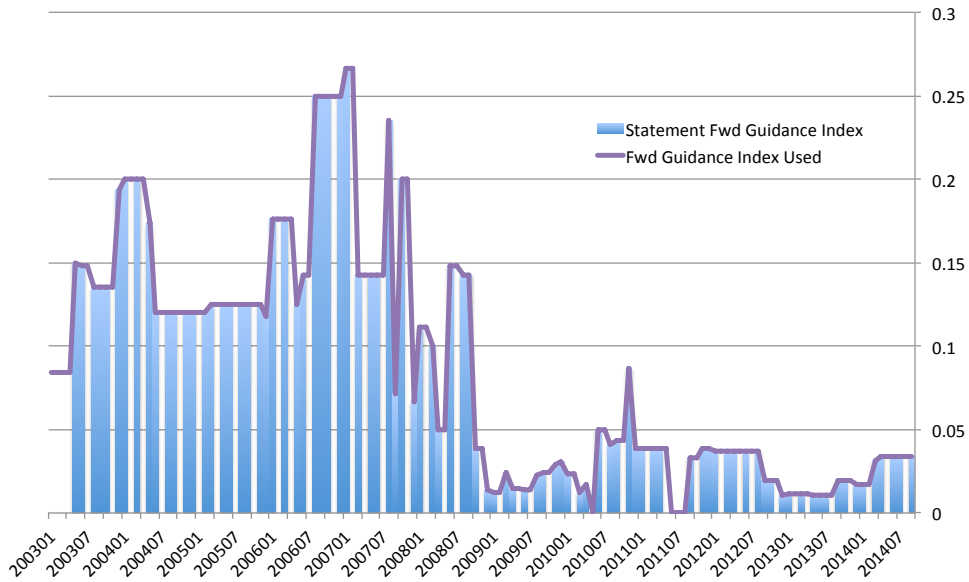
(b) FwdGuide$_t$: Statement by statment and monthly index

Figure 5: Two Indices of FOMC Statement Communication

(after stripping out the stop words) allocated to paragraphs identified as being about the economic topic (but not necessarily the specific words from economic topic), the number of words in forward guidance paragraphs and the number of other words (covering other topics) in the statements. Two things stand out. First the well-documented growing length of the FOMC statement increasing from around 100 words to over 350; including stop words, the statements have increased from around 200 words in early 2003 to over 1000 words in 2015. Second, there is a growing role for what we pick out as forward guidance.
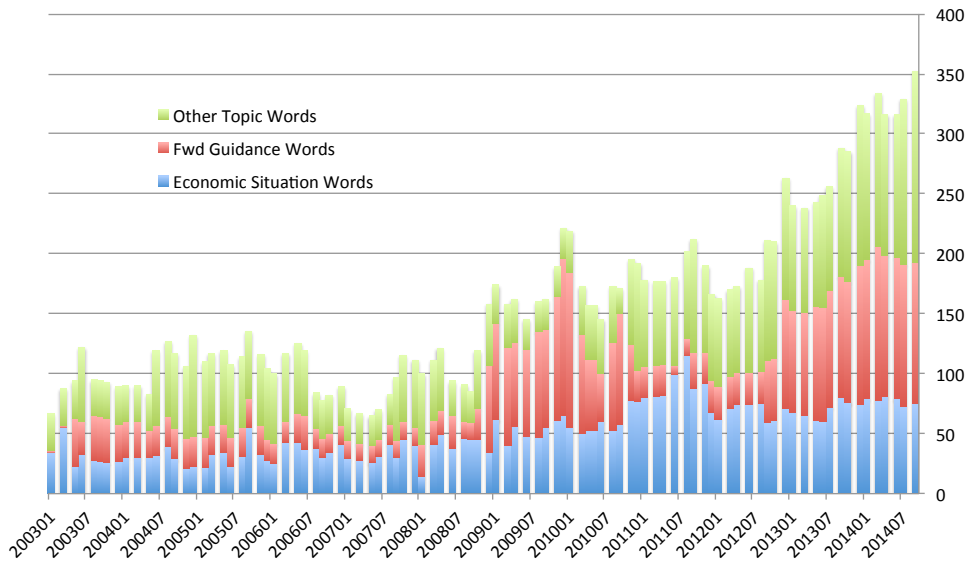

Figure 6: Numbers of words allocated to the two topics in the FOMC Statement

3   Econometric Methodology: FAVAR Analysis

In this paper we use a Factor-Augmented Vector Autoregression model (FAVAR), as developed by Bernanke, Boivin, and Eliasz (2005), in order to investigate the effects of the extra dimensions of the monetary policy announcements that we measure using the two time-series indices. The FAVAR model considers:

Driving Variables Y_t**:** M observed variables (each from $t = 0, 1, ..., T$) which are assumed to drive the economy.

Unobserved factors F_t**:** K factors which capture the evolution of unobserved state variables which drive the economy.

Observed economic time series X_t**:** N time-series which we are interested in understanding the evolution of in reaction to shocks.

The structure of the relationships between these variables is given by:

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\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \tag{5}
$$

where

$$
X_t = \Lambda^F F_t + \Lambda^Y Y_t + e_t \tag{6}
$$

where equation (6) is called the 'observation equation' and it tells us that F_t and Y_t are the driving forces of the observed economic time series, and equation (5) is called the 'transition equation'. [9] This framework would be a standard VAR if we omit F_t and instead include important time-series in Y_t. However, if we have omitted important information then our VAR estimates are biased and can lead to very misleading results. The classic price puzzle is an example of this. The FAVAR approach allows us to include (and look at the reaction of) a large number of variables without running into the curse of dimensionality.

In the original baseline FAVAR model of Bernanke, Boivin, and Eliasz (2005), only the Fed Funds Target rate is included as a driving variable affecting the economy ($Y_t = [i_t]$). Moreover, there is a single factor ($K = 1$).[10] Instead, in this paper we include either three or four dimensions of the monetary policy news in the Y_t vector. In the more parsimonious policy model, we use four factors ($K = 4$) and use three measures of monetary stance:

$$
Y_t = \begin{bmatrix} \text{EcSit}_t \\ \text{i}_t \\ \text{FwdGuide}_t \end{bmatrix}. \tag{7}
$$

However, as the analysis covers 2003 to 2014, this period is significantly affected by the zero lower bound (ZLB) on nominal interest rates. This is problematic because economic conditions may be pretty poor, but since the FOMC cannot change the FFR once it hits the ZLB, the estimated FFR reaction to economic conditions would be less than is otherwise the case. Moreover, there is a period around September 2008 during which the FFR was cut very aggressively as a result of the failure of Lehman Brothers and the ensuing financial markets disruption, but a relatively large recession followed nonetheless.

This gives rise to two main concerns. First, whether the estimated traditional monetary policy shocks would be well identified using 7. Second, given the FOMC made significant use of large-scale asset purchases around the time that they also provided

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[9]Here it is written as order 1 (1 lag) but any order p version can be written as a VAR(1) using the 'companion form'.

[10]One issue with the standard FAVAR approach is that it is not possible to impose that some factors can react to the policy shocks because the factors have no labels. Belviso and Milani (2006) estimate a 'structural FAVAR ' in which they actually identify specific titles for the factors.

clearer forward guidance, the concern is that the more parsimonious system picks up the effects of QE policy rather than forward guidance. We therefore also estimate:

$$Y_t^{\mathrm{QE}} = \begin{bmatrix} \mathrm{EcSit}_t \\ \mathrm{i}_t \\ \mathrm{QE}_t \\ \mathrm{FwdGuide}_t \end{bmatrix}. \tag{8}$$

where QE_t is proxied by the change in U.S. Treasury Securities Securities Held Outright by the Federal Reserve. Using this extended set of policy variables, we include three factors ($K = 3$).

3.1 Steps in the estimation of the FAVAR model

We estimate the FAVAR defined by equations (5) and (6) using the two-step approach that uses principle components to estimate the factors:

1. estimate the factors using principal components - $\hat{F}_t$.

2. estimate the VAR in $\hat{F}_t$ and Y_t.

As there are identification assumptions made in both steps, we shall now be more precise on these two steps. As our approach follows closely the approach of Bernanke, Boivin, and Eliasz (2005), readers familiar with FAVAR analysis can skip to section 3.2 which outlines the identification approach specific to this paper.

3.1.1 Step 1: Estimation of $\hat{F}_t$

We extract the first $K + M$ (number of factors plus number of Y_t variables) principal components of X_t which is called $\hat{C}(F_t, Y_t)$. These are linear combinations of F_t and Y_t.

We are interested in identifying the structural shocks to all (or at least a subset) of the Y_t variables but we cannot identify the shocks if the estimated factors include the effects of Y_t. Essentially, the problem is that the approach to estimating the principal components does not account for the fact that Y_t is observed. Therefore we need to purge the $\hat{C}(F_t, Y_t)$ of the effects of the Y_t variables that we are interested in shocking.

We follow the identification approach of Bernanke, Boivin, and Eliasz (2005) that has also been used many by others since:

Identification Assumption 1 *A subset of X_t do not react contemporaneously to shocks to Y_t; we call these 'slow-moving variables'. We can therefore use the principal components across these variables to identify the $\hat{F}_t$ to use in the FAVAR.*

Precisely, we:

1. estimate the principal components in the slow-moving X_t variables and call these $\hat{C}^*(F_t)$; under the identification assumption 1 these principal components do not contain reaction to Y_t.

2. regress

$$\hat{C}(F_t, Y_t) = \beta_c \hat{C}^*(F_t) + \beta_y Y_t + \eta_t \tag{9}$$

3. Define:

$$\hat{F}_t = \hat{C}(F_t, Y_t) - \beta_y Y_t \tag{10}$$

3.1.2   Step 2: Estimation of a VAR in $\hat{F}_t$ and Y_t

We then estimate a standard VAR using Bayesian estimation. Define:

$$Z_t = \begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} \tag{11}$$

Then (5) becomes our reduced form (estimated) model:

$$Z_t = A Z_{t-1} + v_t \tag{12}$$

with v_t the reduced-form residuals satisfying $\mathbb{E}[v_t v_t'] = \Omega$. This estimation gives us $\hat{A}$ and $\hat{\Omega}$.

If we consider that there is a true structural model of the economy in which:

$$H Z_t = B Z_{t-1} + u_t \tag{13}$$

where u_t are the structural shocks we are interested in and the structural variance-covariance matrix is given by $\mathbb{E}[u_t u_t'] = D$.

We can map the reduced form estimates to the strutural model using:

$$Z_t = H^{-1} B Z_{t-1} + H^{-1} u_t \tag{14}$$

and noting that $\hat{A} = H^{-1}B$, $\hat{v} = H^{-1}u_t$ and, the key for identification as it is the only equation linking observables and structural coefficients, $\hat{\Omega} = \mathbb{E}\left[H^{-1}u_t u_t' H^{-1'}\right] = H^{-1}DH^{-1'}$. To map the estimated variance-covariance matrix of residuals to H^{-1} we need restrictions on the coefficients in D and H^{-1}; $\hat{\Omega}$ only provides $\frac{N^2+N}{2}$ unique values (since symmetric).

Identification Assumption 2 *Through restrictions on the coefficients of structural variance-*

covariance matrix $(D = I_N)$, as well as assuming that H^{-1} is lower triangular (Choleski indentification), we can identify the H^{-1} matrix from the $\hat{\Omega}$ estimates.

The first part of identification assumption 2, assuming the structural shocks are independent from one another and also normalisation of the variance of the structural shocks to 1, provides all but $\frac{N^2-N}{2}$ restrictions on H^{-1}. Assuming that H^{-1} is lower triangular, then we get $\frac{N^2-N}{2}$ zero restrictions. This Choleski identification amounts to ordering restrictions: a lower triangular H^{-1} says that the reduced form residual for the first ordered variable depends only on its own structural shock, the second variable depends on its own shock and the shock to the first variable, and so on for each variable.

3.2 Using the framework to measure the impact of statements

We estimate our FAVAR using monthly data. The sample period used is January 2003 to September 2014. We start in 2003 in order to concentrate on a period in which the FOMC was making statements after all their meetings and this is a period during which the FOMC was more likely to both describe the economic situation as well give some guidance on the expected future path of interest rates. We end in September 2014 due to availability of NAPM survey data in the Federal Reserve FRED database. This means that the total time series dimension, after losing some observations to the stationarity correction, is 141 monthly observations.

In this paper, as described in equation (7) above, we include our three policy variables in Y_t of our FAVAR. The Choleski ordering identification means that Federal Funds Rate decisions at time t depend on lagged values of all the endogenous variables, as well as shocks to the economic factors and the FOMC view of the economic situation as measured by our balance index. Shocks to forward guidance are, by identification assumption 2, assumed not to affect the current interest rate decision.

We include four factors estimated using principle components on the X_t time-series data. Our X_t matrix of time-series variables contains 78 variables. Appendix A presents the list of time-series data used, the sources as well as how we transform the data. As required by identification 1, we need to define which variables react contemporaneously with policy changes and which are 'slow-moving'. The appendix provides the full list, but broadly we consider markets data to be fast-moving and most macro variables to be slow-moving.

We estimate the FAVAR using Gibbs Sampling with 10,000 draws sampled after a burn-in of 3,000 draws. The confidence bands provided with estimates are derived using the estimated distribution of 10,000 draws. In the baseline analysis, we use 7 lags though we have also used 4 lags and 13 lags.

4 Results

First we examine the effect of shocks to the FOMC's monetary policy. Unlike traditional monetary policy shocks papers, our interest in this paper is more on the statement effects. We therefore focus on the shocks to the description of the current economic situation, and the shock to degree of uncertainty about interest rates going forward. The main analysis is based on the larger system including QE ((8)) though we also present some of the results based on (7). After the impulse response analysis, we examine the contribution of these shocks to the variance of US macroeconomic data.

4.1 The effect of a change in Forward Guidance: impulse response analysis

We first look at the response of a change to the forward guidance element of the FOMC statement FwdGuide_t. The shock, shown in 7, involves an increase in uncertainty about the future decisions on interest rates; a positive shock is, in our interpretation, less forward guidance.
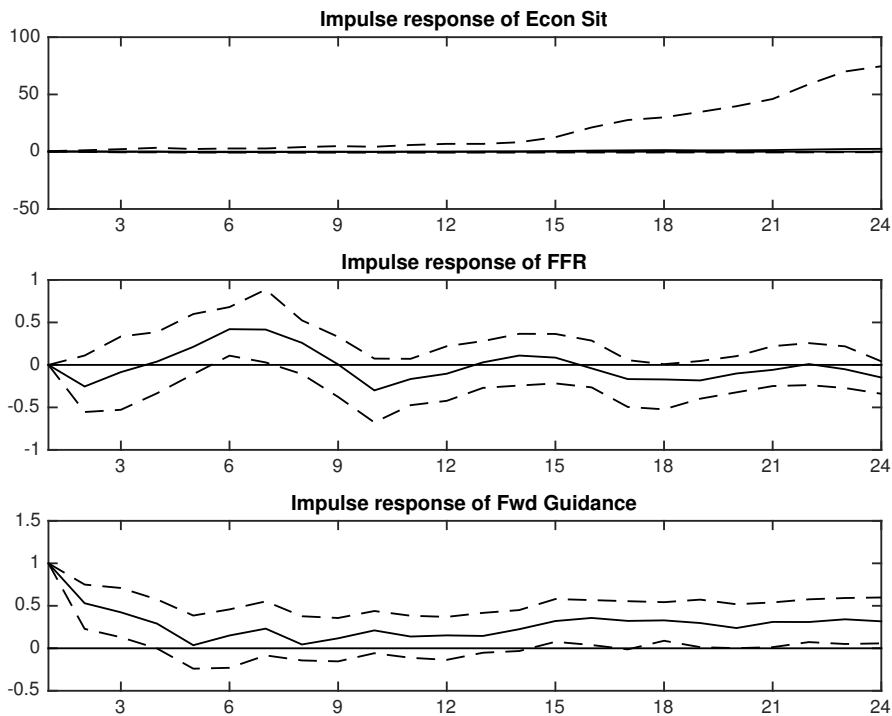

Figure 7: IRF Response to FwdGuide_t shock: Policy Variable Reaction

The shock has the desired effect on market rates as shown in figure 7. As might be expeected given the typical deployment of forward guidance at a time when short-term rates are historically low, there is little near-term effect on shorter maturity bonds. However, less certainty about future rates tends to increase longer maturity bonds significantly. It

also plays a role in driving corporate bond yields including in the near term. This result is consistently found across different specifications; figures 9 and 10 present the equivalent figures for the more parsimonious model with both 3 and 4 factors estimated.
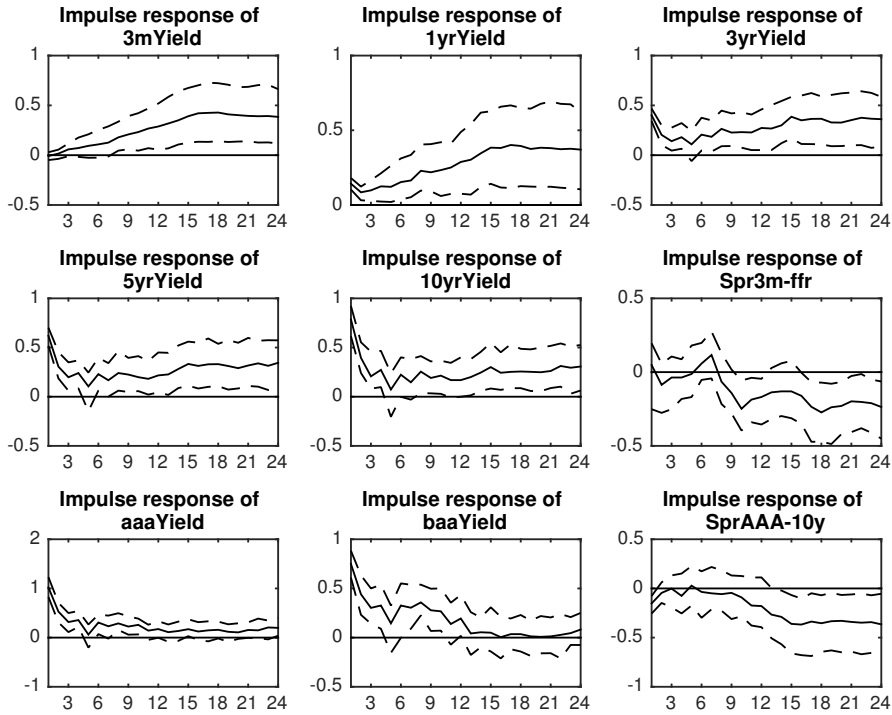

Figure 8: IRF Response to FwdGuide$_t$ shock: Yields Reaction

These results seem longer lived than the findings of Wright (2012). He uses a daily VAR and identifies monetary policy shocks under QE using heteroskedasticity (particularly that monetary policy shocks are relatively more volatile around U.S. monetary policy announcements.) He finds that expansionary monetary policy shocks boost asset prices but that the effects are not long-lived. A main difference is that we have tried to isolate the effects of specific aspects of communication.

The shocks to forward guidance also affect market variables in the expected way. For example, equity is estimated to respond positively to more certainty about future behaviour. The impulse responses of a selection of markets variables is presented in 11.

However, the effects on real variables are much less clear cut and much noisier (figure 12). Though imprecisely estimated, more certain forward guidance would reduce unemployment somewhat and, with a delay of a year, tend to increase orders and activity reflected in the manufacturing and non-manufacturing NAPM surveys.
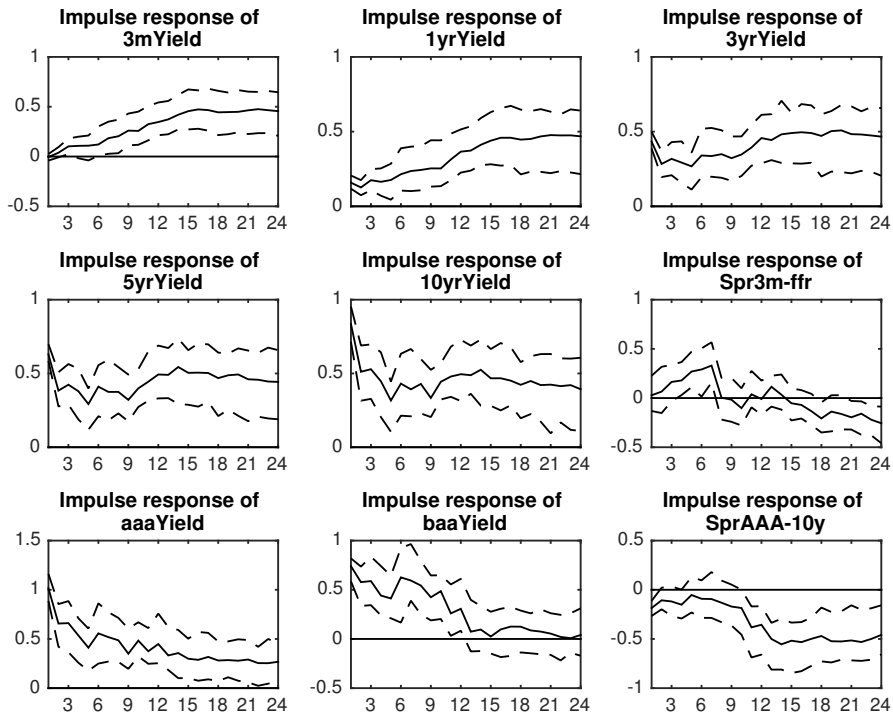
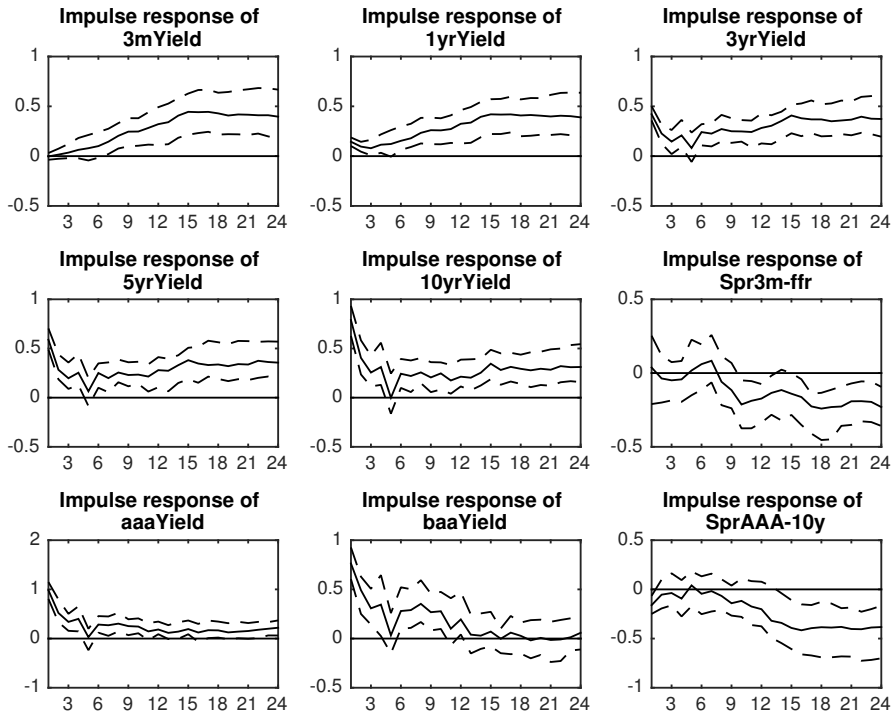**Figure 9:** IRF Response to FwdGuide$_t$ shock: Yields Reaction in model (7) with 3 factors

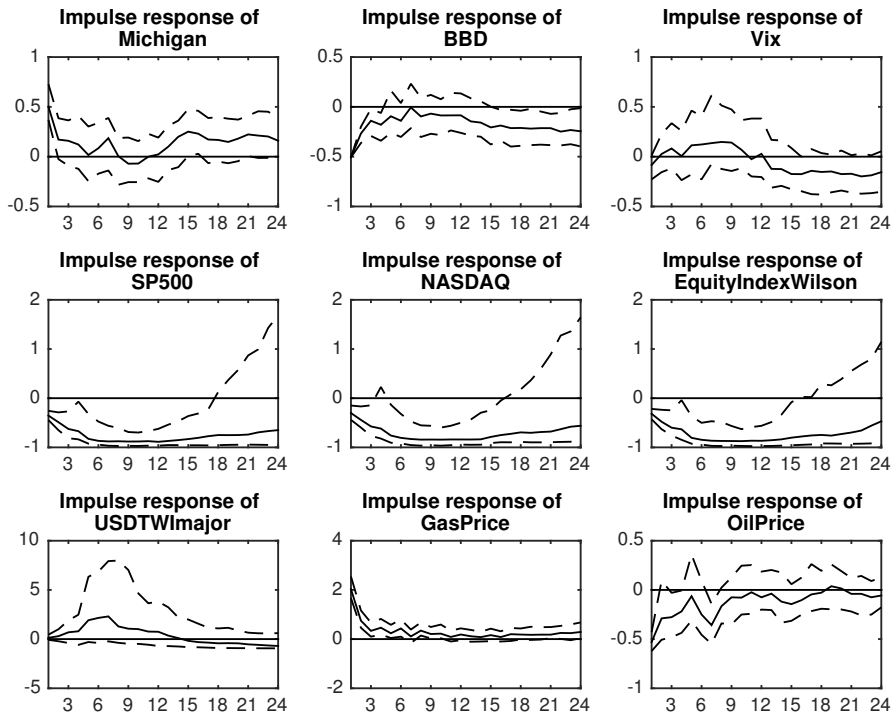**Figure 10:** IRF Response to FwdGuide$_t$ shock: Yields Reaction in model (7) with 3 factors

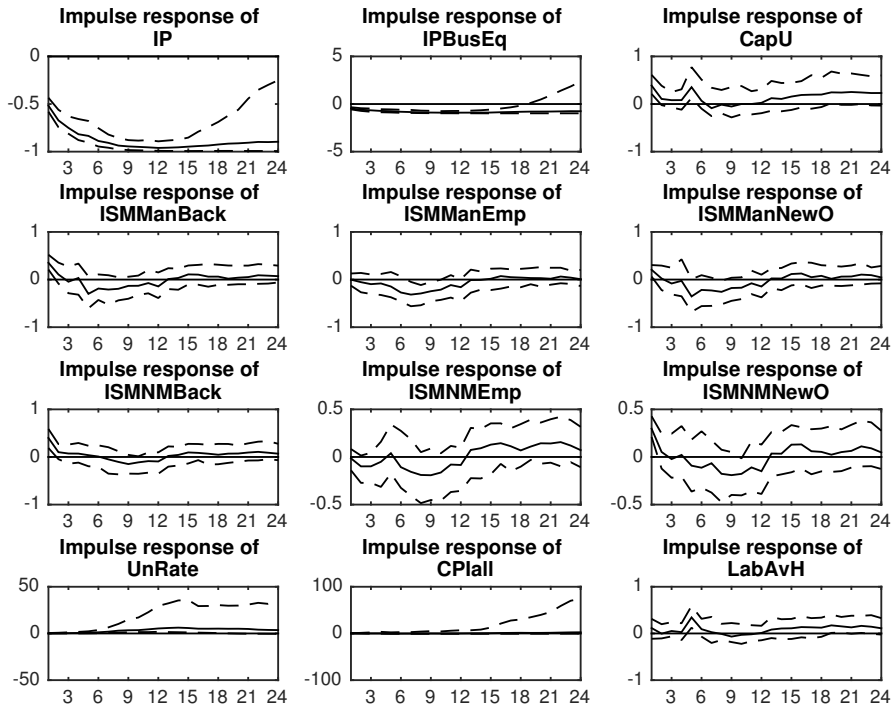**Figure 11:** IRF Response to FwdGuide$_t$ shock: Markets Reaction

Figure 12: IRF Response to FwdGuide$_t$ shock: Real Variables Reaction

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4.2 The effect of a change in Economic Situation Balance: impulse response analysis

We now turn to examine the effects of a shock to $EcSit_t$. A positive shock is equivalent to the FOMC statement talking more about economic expansion in their post-meeting statement. Figure 13 presents the shock, and the response of the other policy variables, while figures 15 to 16 present the response of the other variables we have analysed before.
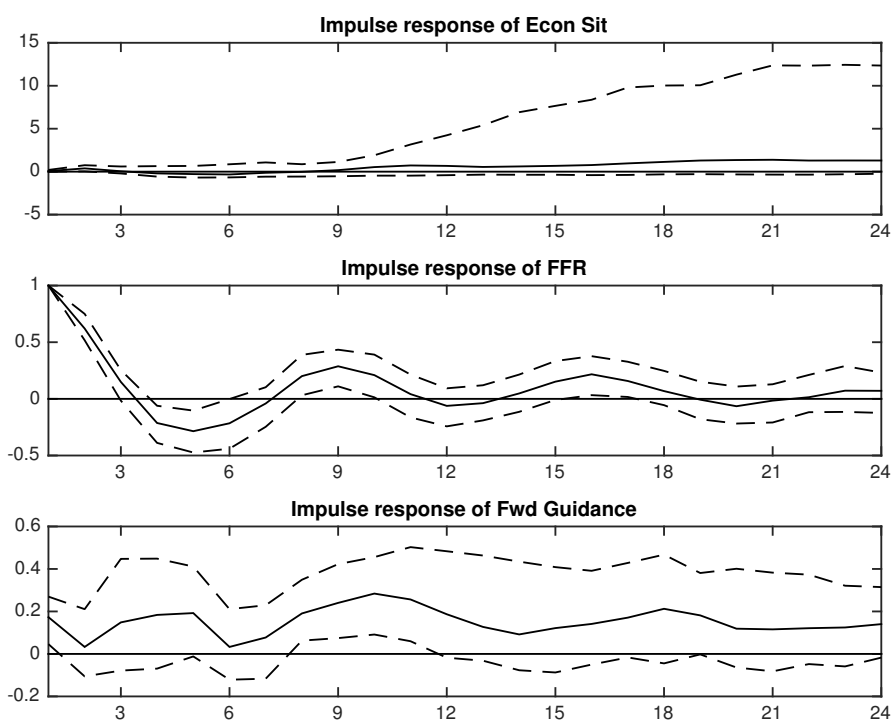

Figure 13: IRF Response to $EcSit_t$ shock: Policy Variable Reaction

There is almost no significant reaction of yields (figure 14), markets variables (15) nor real variables. This is despite being ordered first of the monetary policy variables. It seems that the FOMC shocks that reveal the current economic situation do not affect the variables in the way that FOMC guidance about their future policy. Perhaps this is because the markets react more to other, more quantitative, information released by the FOMC or that they update their views of the economy in a similar way to the FOMC in response to economic releases.

4.3 Analysis of the Forecast Error Variance Decomposition

To further explore the role that each dimension of FOMC policy and communication plays, we can turn to the analysis of Forecast Error Variance Decompositions (FEVD) from the FAVAR system. This is, like the impulse response functions, derived from the structural VMA representation. Specfically, it looks at the variance in the h period
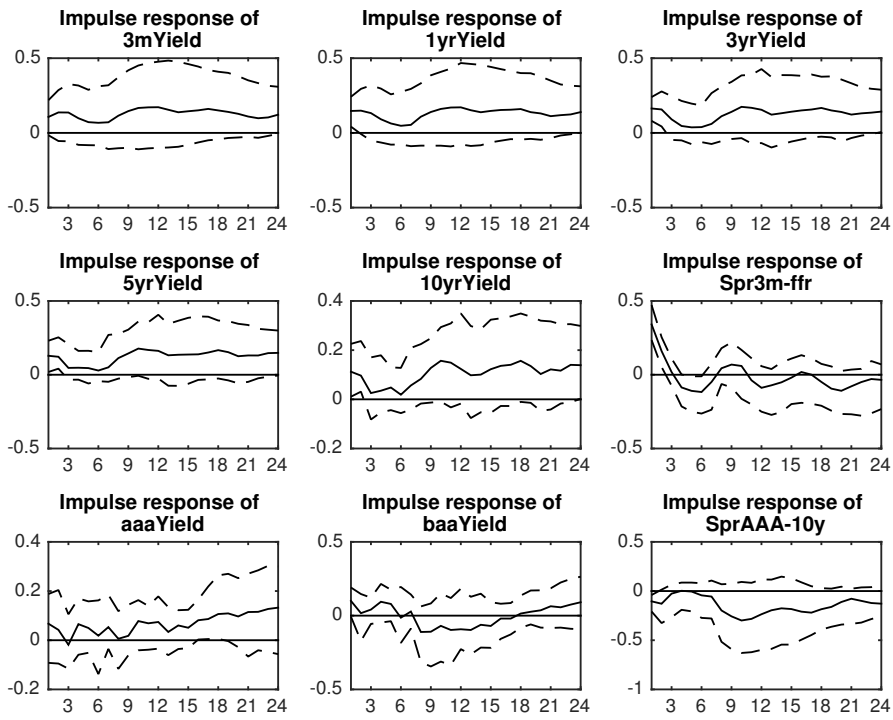
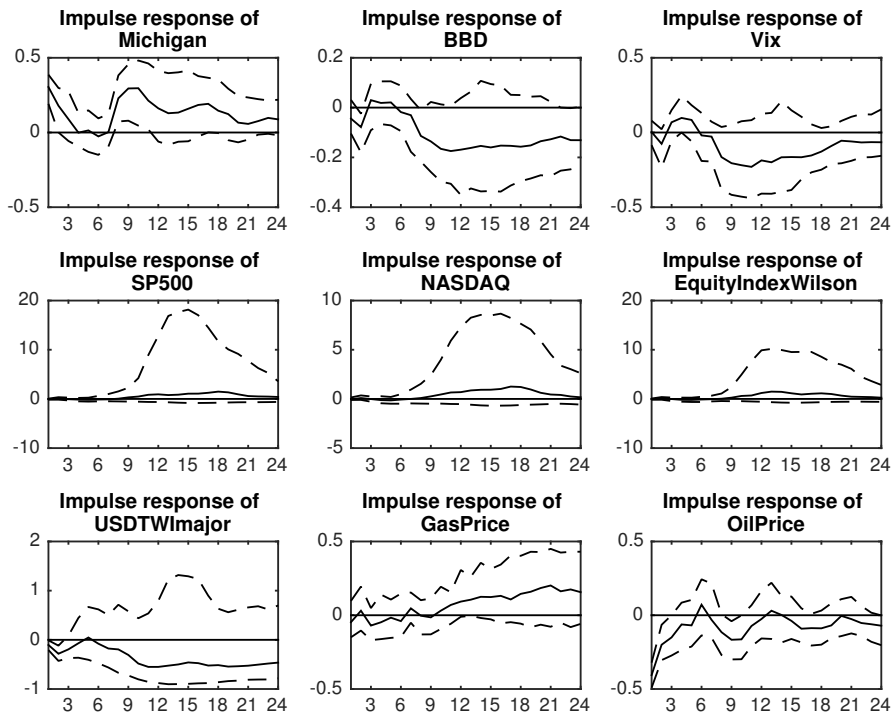**Figure 14:** IRF Response to EcSit$_t$ shock: Yields Reaction

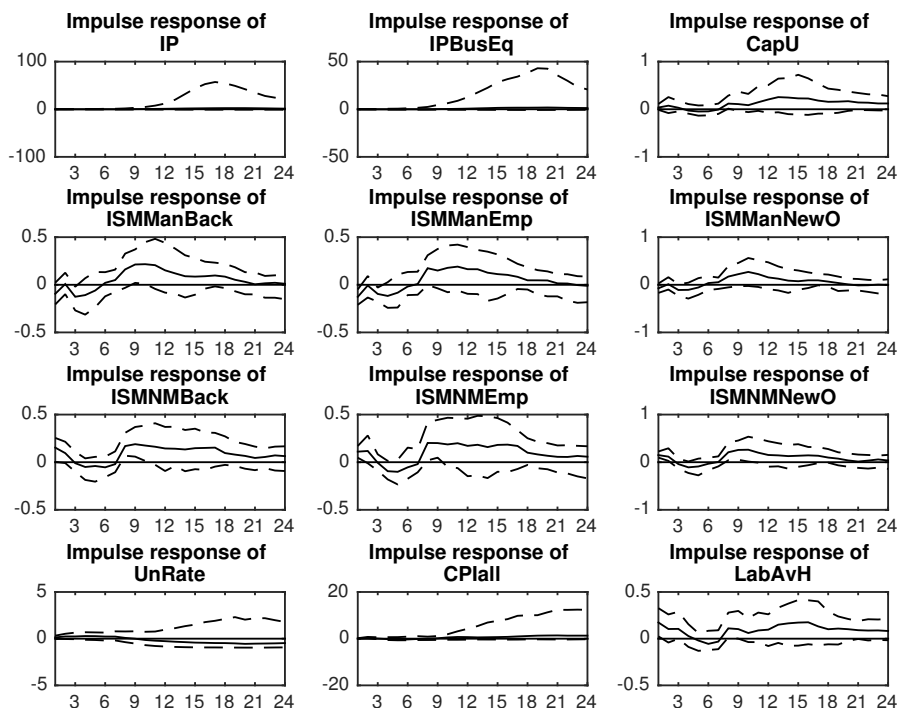**Figure 15:** IRF Response to EcSit$_t$ shock: Markets Reaction

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Figure 16: IRF Response to EcSit$_t$ shock: Real Variables Reaction

ahead forecast error that can be attributed to each shock. Hence, we can use the FEVD to quantify how important different shocks are for each variable at different horizons.

Figure 17 shows the FEVD explained by monetary shocks for a selection of rates (17a), market variables (17b) and real variables (17c). These are shown for 1 month, 6 month, 12 month and 60 month forecast horizons. The results reinforce the earlier IRF results. Shocks to FwdGuide$_t$ seem to explain the movement of yields data, especially at longer maturities, but they explain only a small portion of the shocks to market data and real variables. In all cases, the shocks to EcSit$_t$ explain a smaller amount of the variability in the variables.

5   Conclusion

In this paper we empirically explore the channels through which central bank communication has effects as established by previous authors. Moreover, we have tried to ascertain whether the effects of FOMC communication on markets is persistent and whether there are effects on real variables. Using tools from computational linguistics, we have measured two important characteristics of FOMC statements and found that, at least in the last 11 years in the US, the central bank communication on future interest rates seem to have been much more important than their communication of current economic conditions. Nonetheless, neither communication has particularly strong effects on real economic variables in our FAVAR.
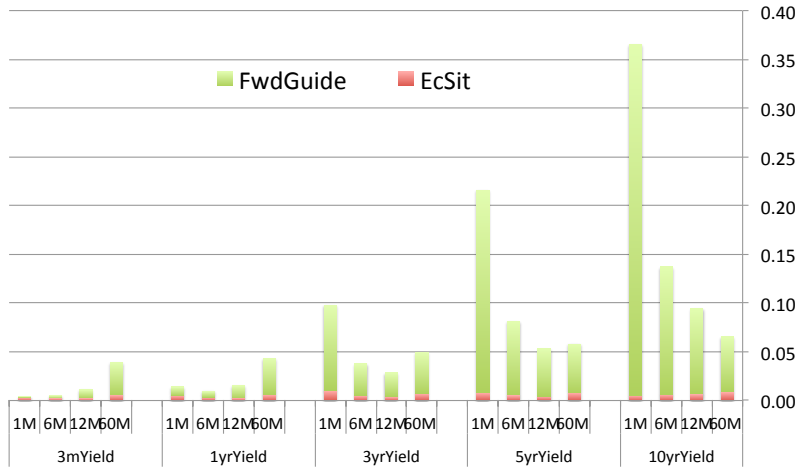
(a) Yields
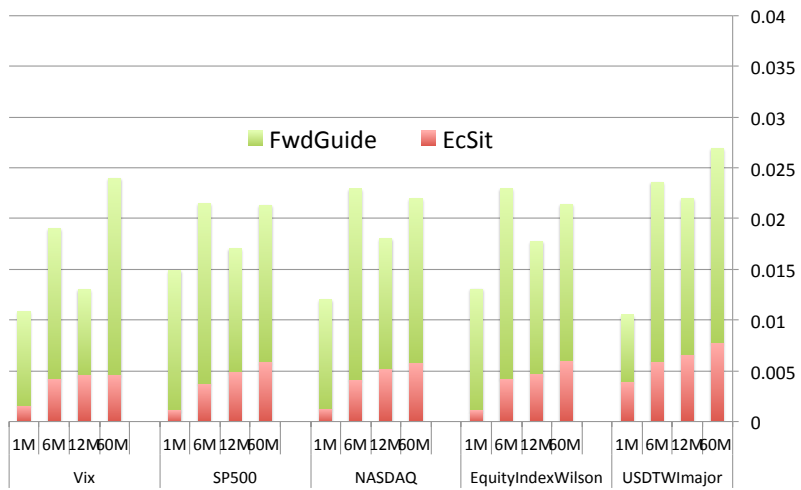
(b) Market Variables
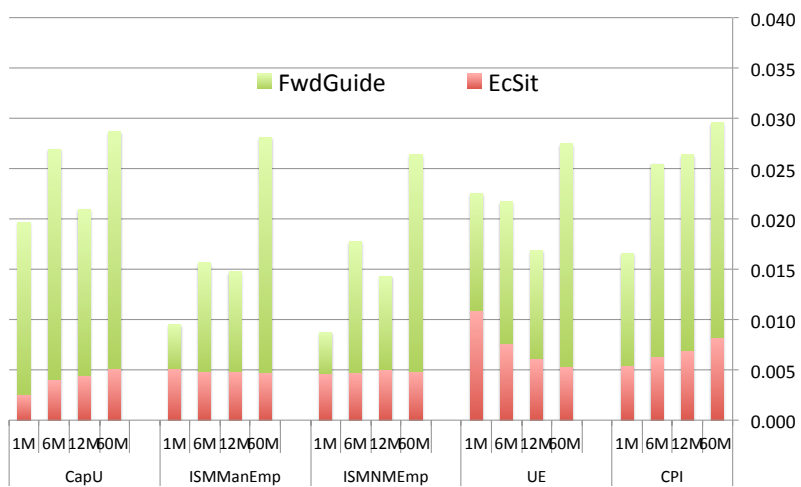
(c) Real Variables

Figure 17: Forecast Error Variance Decomposition Analysis

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A number of extensions of this paper are warranted in future work. The first is to extend the analysis to other forms of FOMC communication; perhaps speeches and other communications such as the FOMC meeting minutes might contain information that investors learn from and that affects economic outcomes. Second, it would useful to see if there is a time-varying role of the effects of central bank communication. In particular, the effects of central bank communication may change when interest rates hit the zero lower bound. Finally, it would be useful to extent the analysis to other countries and thereby see if communication plays a similar role. We leave these for future work.

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A   US Macroeconomic Data Used in X_t^{US}

Short title	FRED code	Transform code	Slow-move code	Long Description
BBD	USEPUINDXM	4	0	Economic Policy Uncertainty Index for United States
RealHP	ShillerHP	5	1	Case-Shiller Real House Price index
SoldHouses	HSN1F	5	1	New One Family Houses Sold: United States
NomHP	MSPNHSUS	5	1	Median Sales Price for New Houses Sold in the United States
IP	INDPRO	5	1	Industrial Production Index
IP-BusEq	IPBUSEQ	5	1	Industrial Production: Business Equipment
IP-DurC	IPDCONGD	5	1	Industrial Production: Durable Consumer Goods
IP-DurMat	IPDMAT	5	1	Industrial Production: Durable Materials
IP-DurMotor	IPG3361S	5	1	Industrial Production: Durable Goods: Motor vehicle
IP-Man	IPMAN	5	1	Industrial Production: Manufacturing (NAICS)
IP-Mat	IPMAT	5	1	Industrial Production: Materials
IP-NdurCons	IPNCONGD	5	1	Industrial Production: Nondurable Consumer Goods
CapUMan	MCUMFN	5	1	Capacity Utilization: Manufacturing (NAICS)
CapU	TCU	5	1	Capacity Utilization: Total Industry
CapU-ManDur	CAPUTLGMFDS	5	1	Capacity Utilization: Durable manufacturing
M1	M1SL	5	1	M1 Money Stock
M2	M2SL	5	1	M2 Money Stock
MB	AMBSL	5	1	St. Louis Adjusted Monetary Base
ExcReserves	EXCSRESNS	5	0	Excess Reserves of Depository Institutions
OilPrice	MCOILWTICO	5	0	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma
GasPrice	MHHNGSP	5	0	Henry Hub Natural Gas Spot Price
ISM-ManBack	NAPMBI	1	1	ISM Manufacturing: Backlog of Orders Index
ISM-ManEmp	NAPMEI	1	1	ISM Manufacturing: Employment Index
ISM-ManNewO	NAPMNOI	1	1	ISM Manufacturing: New Orders Index
ISM-ManProd	NAPMPI	1	1	ISM Manufacturing: Production Index
ISM-ManPrice	NAPMPRI	1	1	ISM Manufacturing: Prices Index
ISM-NMActivity	NMFBAI	1	1	ISM Non-manufacturing: Business Activity Index
ISM-NMBack	NMFBI	1	1	ISM Non-manufacturing: Backlog of Orders Index
ISM-NMEmp	NMFEI	1	1	ISM Non-manufacturing: Employment Index
ISM-NMNewO	NMFNOI	1	1	ISM Non-manufacturing: New Orders Index
ISM-NMPrice	NMFPI	1	1	ISM Non-manufacturing: Prices Index
Lab-EmpTot	PAYEMS	5	1	All Employees: Total nonfarm

Lab-AvEarn	AHETPI	5	1	Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private
Lab-EmpCons	USCONS	5	1	All Employees: Construction
Lab-EmpGoods	USGOOD	5	1	All Employees: Goods-Producing Industries
Lab-EmpSer	SRVPRD	5	1	All Employees: Service-Providing Industries
Lab-AvH	CEU0500000007	5	1	Average Weekly Hours of Production and Nonsupervisory Employees: Total Private
Unemployment rate	UnRate	4	1	Unemployment Rate
P-CED	PCEPI	5	1	Personal Consumption Expenditures: Chain-type Price Index
PPI-all	PPIACO	5	1	Producer Price Index for All Commodities
PPI-Cons	PPIFCG	5	1	Producer Price Index by Commodity for Finished Consumer Goods
PPI-Finished	PPIFGS	5	1	Producer Price Index by Commodity for Finished Goods
PPI-FinishLessEnergy	PPILFE	5	1	Producer Price Index by Commodity for Finished Goods Less Food & Energy
CPI-apparel	CPIAPPSL	5	1	Consumer Price Index for All Urban Consumers: Apparel
CPI-all	CPIAUCSL	5	1	Consumer Price Index for All Urban Consumers: All Items
CPI-Medical	CPIMEDSL	5	1	Consumer Price Index for All Urban Consumers: Medical Care
CPI-trans	CPITRNSL	5	1	Consumer Price Index for All Urban Consumers: Transportation
USD-Bra	TWEXOMTH	5	0	Trade Weighted U.S. Dollar Index: Other Important Trading Partners
USD-Can	EXCAUS	5	0	Canada - U.S. Foreign Exchange Rate
USD-China	EXCHUS	5	0	China - U.S. Foreign Exchange Rate
USD-Jap	EXJPUS	5	0	Japan - U.S. Foreign Exchange Rate
USD-Mex	EXMXUS	5	0	Mexico - U.S. Foreign Exchange Rate
USD-Swiss	EXSZUS	5	0	Switzerland - U.S. Foreign Exchange Rate
USD-UK	EXUSUK	5	0	U.S. - U.K. Foreign Exchange Rate
USD-TWI	TWEXBMTH	5	0	Trade Weighted U.S. Dollar Index: Broad
USD-TWImajor	TWEXMMTH	5	0	Trade Weighted U.S. Dollar Index: Major Currencies
RPDIpc	A229RX0	5	1	Real Disposable Personal Income: Per capita
RPDI	W875RX1	5	1	Real personal income excluding current transfer receipts
TotalLoans	TOTALSL	5	1	Total Consumer Credit Owned and Securitized, Outstanding
Michigam	UMCSENT	1	1	University of Michigan: Consumer Sentiment
SP500	ShillerSandP	5	0	S&P500 Equity Index
SP500-PE	ShillerPE	4	0	S&P500 PE ratio
NASDAQ	NASDAQCOM	5	0	NASDAQ Composite Index
EquityIndex-Wilson	WILL5000INDFC	5	0	Wilshire 5000 Total Market Full Cap Index
Vix	VIXCLS	4	0	CBOE Volatility Index: VIX
1yrYield	GS1	1	0	1-Year Treasury Constant Maturity Rate
10yrYield	GS10	1	0	10-Year Treasury Constant Maturity Rate
3yrYield	GS3	1	0	3-Year Treasury Constant Maturity Rate
3mYield	GS3M	1	0	3-Month Treasury Constant Maturity Rate

5yrYield	GS5	1	0	5-Year Treasury Constant Maturity Rate
aaaYield	AAA	1	0	Moody's Seasoned Aaa Corporate Bond Yield
SprAAA-10y	AAA10YM	1	0	Moody's Seasoned Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity
baaYield	BAA	1	0	Moody's Seasoned Baa Corporate Bond Yield
SprBAA-10y	BAA10YM	1	0	Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity
Spr10y-2y	T10Y2YM	1	0	10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity
Spr10y-3m	T10Y3MM	1	0	10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity
Spr10y-ffr	T10YFFM	1	0	10-Year Treasury Constant Maturity Minus Federal Funds Rate
Spr3m-ffr	TB3SMFFM	1	0	3-Month Treasury Bill Minus Federal Funds Rate

B   The effect of a change in Fed Funds Rate: impulse response analysis

We here examine the effects of traditional monetary policy shocks, namely those arising from shocks to the Federal Funds Rate (FFR). Figures B.1 to B.4 present the impulse responses to such a shock.

Although the standard type of monetary policy shock, it is worth noting that, given the inclusion of our additional two policy variables, we should be able to capture some of the effects that would typically be part of the monetary policy shock. For example, if the Fed has a slightly more positive view of the economy than the data would normally suggest, this might be typically captured as a deviation from the normal monetary policy rule whereas in our framework this is hopefully captured by the EcSit_t index.
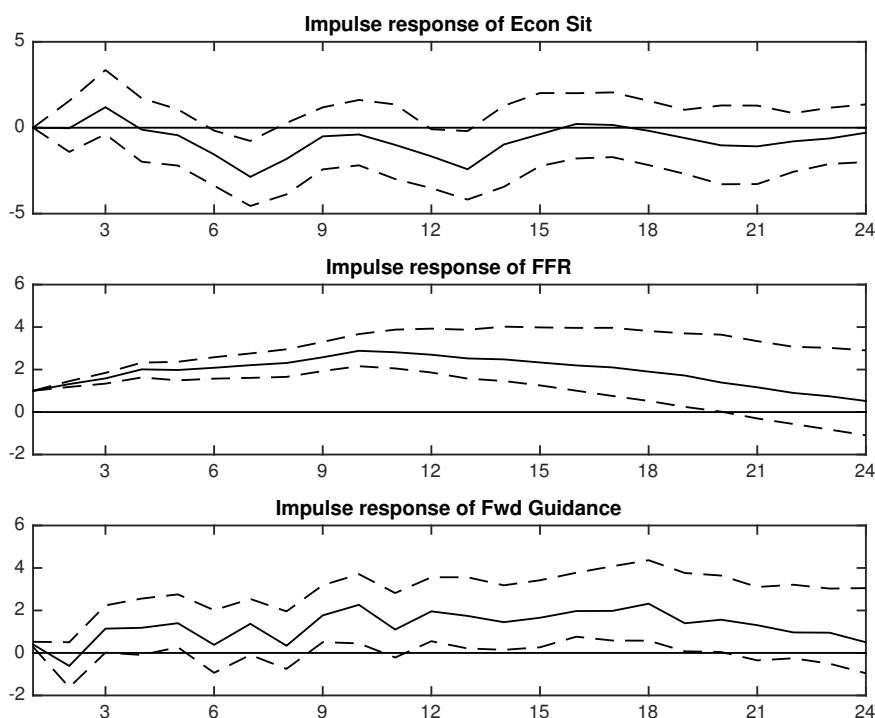

Figure B.1: IRF Response to Federal Funds Rate shock: Policy Variable Reaction

Figure B.1 presents the shock that we analyse. It represents a 100bps shock to the Federal Funds Rate.

Figure B.2 shows that the effect of this shock on market rates is to raise rates across the yield curve. The effect is greatest at the shorter end of the yield curve and if anything corporate yields fall. This likely reflects the effect of the crisis when, especially, BAA yields spiked in spite of the aggressive cuts in the FFR.

The reaction of many of the market variables is imprecisely estimated (figure B.3). The effect of the crisis also likely explains the estimated reaction of the confidence, BBD and Vix measures. An increase in the FFR is estimated to increase confidence, and reduce measures of uncertainty and volatility likely reflecting the effect of aggressive cuts as the crisis unfolded.

The effect on real variables is also somewhat imprecisely estimated and, in the case of some variables, unintuitive. Figure B.4 shows the responses. Similar responses result when we consider the model excluding the QE variable.

Table A.2: Word lists and frequency across FOMC statements in sample

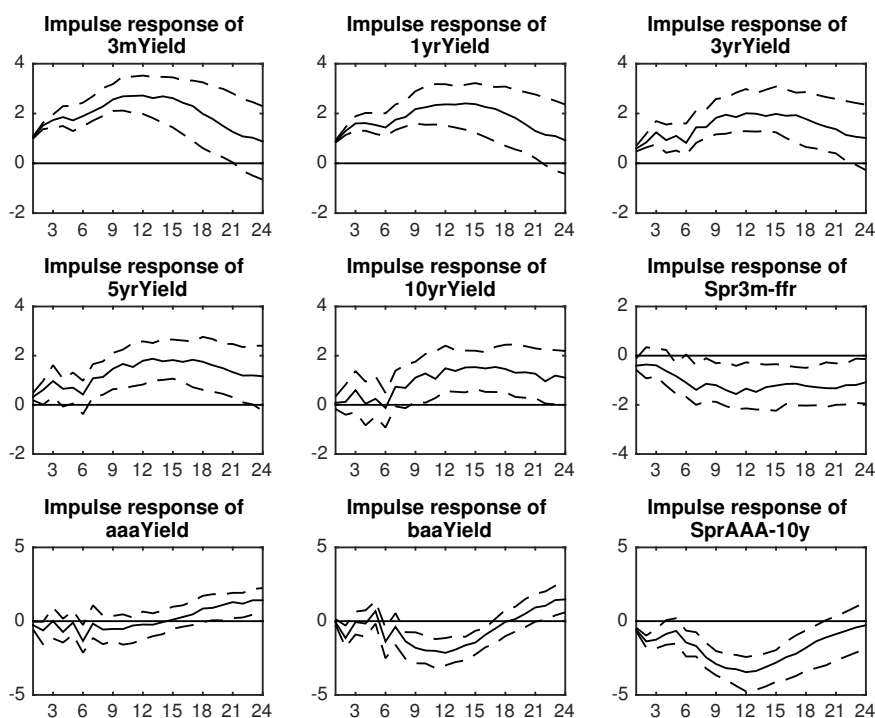| Expansion words		Contraction words		Ambiguity Words in Sample	
Stemmed Token	Frequency	Stemmed Token	Frequency	Stemmed Token	Frequency
improv	55	moder	82	condit	91
foster	52	slow	35	anticip	71
increas	42	low	33	believ	20
expand	38	weak	27	risk	14
rise	27	subdu	20	may	14
higher	14	lower	20	appear	11
risen	10	fall	13	conting	9
gain	9	slower	5	suggest	9
strong	5	weaker	3	seem	7
acceler	1	decreas	3	somewhat	4
faster	1	weaken	2	uncertainti	4
strength	1	contract	2	uncertain	3
		soften	2	possibl	2
		deceler	1	destabil	2
		cool	1	volatil	1
				tent	1
				unusu	1
				might	1
				alter	1

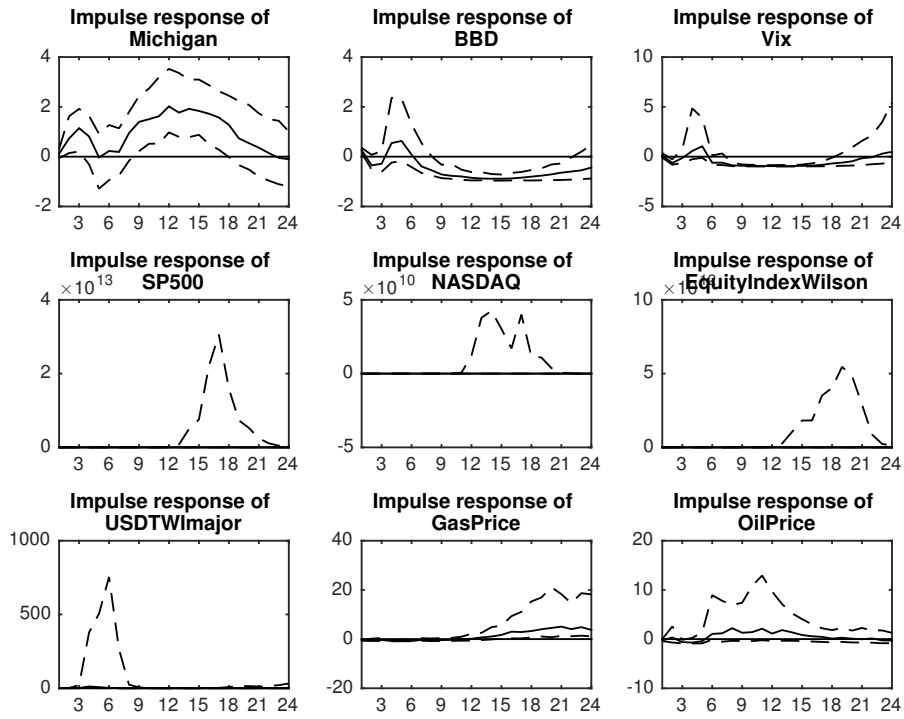**Figure B.2:** IRF Response to Federal Funds Rate shock: Yields Reaction

Figure B.3: IRF Response to Federal Funds Rate shock: Markets Reaction
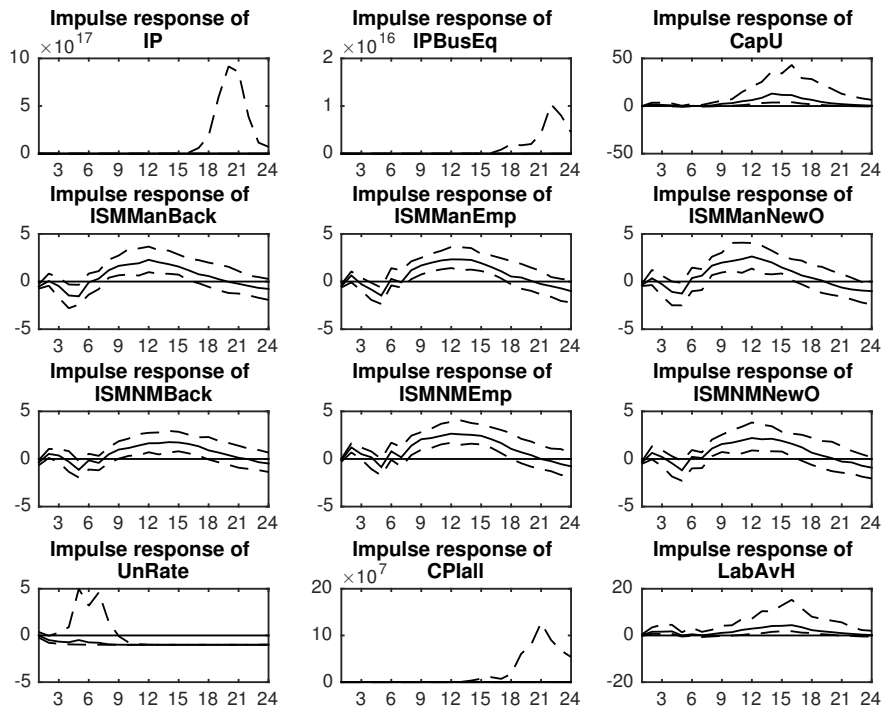

Figure B.4: IRF Response to Federal Funds Rate shock: Real Variables Reaction

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