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

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Abstract

We explore how the multi-dimensional aspects of 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 state of economic conditions, as well as the guidance the FOMC provides 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

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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. The Federal Open Market Committee (FOMC) first accompanied their decision with a statement in February 1994 and although statements were ad-hoc for most of the 1990s, they are now a regular and closely-monitored FOMC release. 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 central bank communication 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. 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. This allows us to focus on multi-dimensional monetary policy and we can contribute answers to two major questions in the literature. First, we use our extracted measures of communication as variables in a Factor-Augmented VAR (FAVAR) (Bernanke, Boivin, and Eliasz 2005) to examine the effect of central bank communication on macroeconomic and financial variables. Second, we examine which specific dimensions of monetary policy communication drive these effects.

To be more precise on the dimensions of monetary policy that we have in mind, consider a central bank that, on average, makes decisions that are well-described by a rule for nominal interest rates in the spirit of Taylor (1993):

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

where f is the vector of reaction coefficients, Ω_t is the vector of economic inputs to the rule and ϵ_t is the deviation from that rule at time t. Agents can use their knowledge of this rule, together with expectations of the inputs to the decision, in order to form their beliefs on future decisions and future interest rates.

When the central bank announces its decision at time t, it reveals i_t. It is the behaviour of this interest rate variable that attracts most attention in the analysis of the effects of monetary policy. We consider that the central bank can also communicate through its statement, and we consider that this communication adds two additional dimensions to monetary policy. Since we will empirically measure these two aspects that the central bank can communicate about, we will be in a unique position to study the dynamic effects of central bank communication. The two additional dimensions of monetary policy that we consider are communication about:

State of Economy: the FOMC's belief about the current and expected economic outlook Ω_t.

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

Our main finding in this paper is that, at least in the US in the last 18 years, central bank communication on future interest rates (forward guidance) seems to have been much more important than their communication of current economic conditions. However, we find that neither communication has particularly strong effects on real economic variables in our FAVAR, especially relative to the effect of the actual policy stance.

Of course, issues of central bank communication have been studied before 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.

A key motivating paper for this literature is Gürkaynak, Sack, and Swanson (2005) (GSS). They show, using an event study approach analysing 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

[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 factors in their analysis of FOMC statements from 1990 to 2004.

10-year Treasury yields. They conclude that expectations of future decisions are key and that the statements are what help to affect investor expectations.[2]

While GSS is an important paper which indicates that central bank communication reveals information to investors and thereby influences their expectations, 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 (days), 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). Given that we measure two specific aspects of the central bank communication directly, we can use these measures to assess the importance of each dimension. As such, we view our work as highly complementary to the GSS event-study methodology.

The major empirical 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 (as in 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 to examine the content of what central banks are trying to communicate to the markets and the public.

The first obvious advantage of the use of automated techniques rather than a purely narrative approach to study the statements is scalability without concerns about consistency of the application of the method. With automated methods it is then easy to extend the sample to include more recent data, 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. Of course, narrative methods might be able to pick up some of the nuance of statements

[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.

more precisely. We make use of both in this paper.

In terms of the computational approaches, we use Latent Dirichlet Allocation (LDA) and dictionary methods to extract the content of official interest rate communications (statements) by the Federal Reserve. 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 used 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; Acosta (2015) looks at how the FOMC responded to calls for greater transparency; and our own recent work examining the effect of transparency on the deliberation of the FOMC using LDA applied to FOMC transcripts (Hansen, McMahon, and Prat 2014).

Hendry and Madeley (2010) and Hendry (2012) are closely related papers focusing on Canada. The objective of both papers is to understand how central bank communication affects markets, and both use text-mining tools in this endeavour. As well as different tools from text-mining, and applying them to a different country, the main difference between our paper and these papers is that we look at a broader set of reactions, whereas these papers focus on the response of returns and volatility in interest rate markets.

The closest paper in the literature is Lucca and Trebbi (2009). They also applied computational linguistic tools to FOMC statements and measure the effects on the macroeconomy including in a VAR framework. The main contribution of our work relative to their work is that we separately look at the effect of different dimensions of monetary policy. We also apply different tools from computational linguitics (both LDA for topic modelling and dictionary methods to measure tone). Finally, as a small difference, we examine the effects in a FAVAR which allows us to look at a wide variety of macroeconomic effects, though our ordering variables is similar.

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 three dimensions empiricially. We then introduce the macroeconometric methodology (FAVAR) before exploring the results and concluding.

2 Dimension 1: Stance of current monetary policy

Before we turn to the measurement of communication, we begin by discussing the most traditional dimension of monetary policy - the stance of current policy. Most studies focus only on this single aspect of monetary policy. In the FAVAR model of Bernanke, Boivin, and Eliasz (2005), as in VAR analyses in Christiano, Eichenbaum, and Evans (1999) or Stock and Watson (2001), the effective Fed Funds rate (i_t), is included as a driving variable affecting the economy.

However, as our analysis covers 1998 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 Federal Funds Target Rate once it hits the ZLB, the estimated 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. Finally, given the FOMC made significant use of large-scale asset purchases as a part of a credit-easing policy, the concern is that using i_t as the measure of monetary stance is not at all appropriate.

The solution we adopt is to use the shadow rate data from Wu and Xia (2014).[4] Using a shadow rate term structure model, the authors derive a measure s_t to assess the current stance of monetary policy at the ZLB. This shadow rate is given by the minimum value between the effective Fed Funds Rate and the shadow rate. This means that the monetary stance is measured by the effective Fed funds rate when interest rates are above the ZLB, but can become negative at the ZLB. Figure 1 plots the measure of monetary stance (s_t) that we use.

3 Dimension 2: Views about the economy

Given the lags in the availability of economic data, and the fact that monetary policy decisions are made as forward looking decisions, the FOMC make decisions using an information set that may differ from those of the public. As such, the second dimension of monetary policy that the FOMC can provide information on is its beliefs about the state of the economy.

We derive empirical measures using a novel approach to combine "the two Ts": Topic and Tone. That is, we need to know first whether the central bank is talking about the state of the economy, Ω_t, the topic, and then we need to measure how they are talking about it (tone). In this paper, we make use of Latent Dirichlet Allocation (LDA) to

[4]There are other similar approaches to calculating a shadow rate including Bauer and Rudebusch (2013) and Krippner (2013).

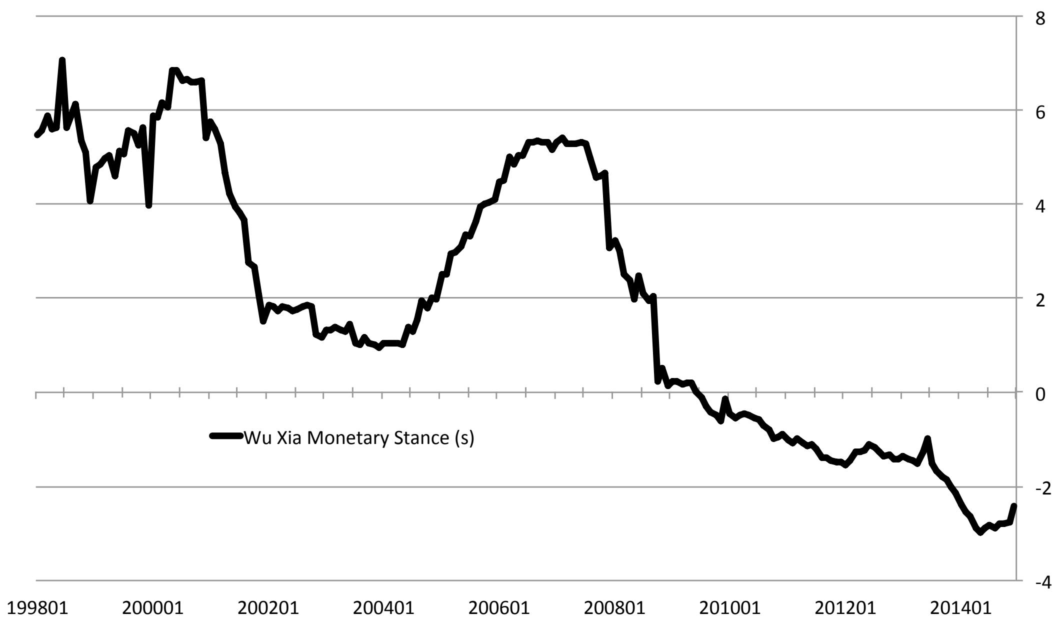


Figure 1: Federal Reserve Monetary Stance: Shadow rate (Wu and Xia 2014)

measure when they are talking about economic topic and a balance measure based on dictionary methods, or word counting, to measure tone. Our proposed way of combining these two approaches allows us 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. We now discuss in more detail our empirical strategy to measure the FOMC statements on the state of the economy.

3.1 Measuring Economic Topics using LDA

LDA is a very popular algorithm developed by Blei, Ng, and Jordan (2003) and used for information retrival. Here we use it to discover the topic of each sentence of the FOMC statements. In this subsection we outline the basic steps and intuition for the algorithm. Hansen, McMahon, and Prat (2014) provide a full description along with the statistical foundations.[5]

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

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

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 sentence 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 sentence 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 sentence p words allocated to topic k, where $n_{p,d}(k)$ is the number of sentence p words allocated to topic k, and $n_{p,d}$ is the total number of words in the paragraph. We will define a sentence as being about topic k when this estimated topic allocation fraction $\phi_{p,k,d}$ is greater than some critical proportion (α).

In fact, we estimate the LDA model using a collapsed Gibbs sampling algorithm. As such, we get measures of topic allocation for every iteration of the chain. The data that we work with has been extracted from the best-performing (in an information matching sense) chain but we draw 20 samples from points in the chain that are thinned using a thinning interval of 50. We then take an average over the 20 samples.

We estimate our 15-topic LDA on the full corpus of 142 FOMC decision statements, split into sentences, up to March 2015 (although we will estimate our FAVAR on a slightly shorter sample of the data between 1998 and 2014). The LDA-estimated topics cover different aspects of the FOMC communication. We select five topics which relate to the discussion of the economic situation. The key words (tokens) in the economic topics are presented as word clouds in figure 2:[7]

Topic 2: A topic which focuses on inflation and prices.

Topic 14: Another topic concerning inflation and prices.

Topic 4: A topic covering the demand side of the economic outlook.

[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.

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

Topic 6: A topic about the labour market issues.

Topic 9: A topic covering the prospects for growth.

3.2 Measuring tone with dictionary methods

Once we identify those sentences that are about the economic situation topics, we using only these relevant sentences to create our time-series balance measure of the FOMC statement on the economic situation using dictionary methods, or more simply, word counting. 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).

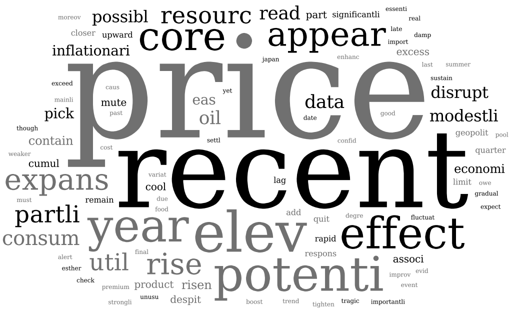
The idea is as follows. Let $\ell = (t_1, \ldots, t_N)$ be a list of unique terms and d be a document, which we can also think of as a list of (possibly non-unique) terms. We can then define $n_d(\ell)$ to be the raw count of terms in ℓ in document d, and either use this alone to index d, or else apply some normalization (like dividing by the total number of terms in d). Our approach to combining the tone and topic algorithms is to view a document as an ordered sequence of sentences $d = (\pi_{1,d}, \ldots, \pi_{\Pi_d,d})$ where Π_d is the total number of sentences in document d. We identify the sentences 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 sentences, compute the fraction of words that lies in list ℓ and normalise by the total number of words in sentences.

To measure the tone of the sentences on the economic situation, we use "directional" word lists measuring words associated with expansion and contraction as used in Apel and Blix Grimaldi (2012). For example, in table 1 we list some of the words that we associate with contraction and expansion.[8] 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 by isolating topics related to the economy, we hopefully have (at least partly) corrected for this.

Using those sentences about the economic situation, we create our time-series balance measure of the FOMC statement on the economic situation as follows:

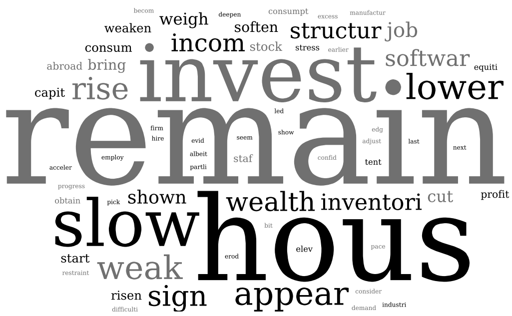
$$\text{EcSit}_t = \frac{n_{Pos,t} - n_{Neg,d}}{TotalWords_t^{EC}} \tag{2}$$

[8]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.



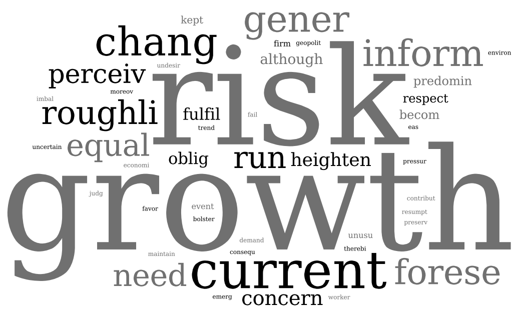
(a) Topic 2

(b) Topic 14



(c) Topic 4

(d) Topic 6



(e) Topic 9

Figure 2: Topics Covering FOMC views of the Economic Situation

Table 1: Example of Contraction and Expansion Words

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

Notes: * indicates that any word ending is acceptable.

where $n_{Pos,t}(n_{Neg,t})$ is the number of posive (negative) words in those sentences about the economy, and $TotalWords_t^{EC}$ is the total number of words about the economic situation.[9] 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 line on the economy from the January 2010 Statement:

> "Household spending is expanding at a moderate rate but remains constrained by a weak labor market, modest income growth, lower housing wealth, and tight credit."

This sentence is about topic 4 and it contains 18 words, of which one is expansionary (expanding) and three are contraction words (lower, moderate, weak). On its own, it would get a balance score of $\frac{-2}{18}$. But, in fact, we aggregate all the lines about the economy from that statement and create the balance on the aggregated text which in this case yields an overall negative balance (-0.07). We repeat this excercise is completed for every statement, conducting the analysis on statements about one of the economic topics.

Figure 3 shows the constructed index 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. This is because 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. If there was a statement but no mention of the economic situation, as occurred in the mid-1990s, the value of the index would be zero.

[9]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.

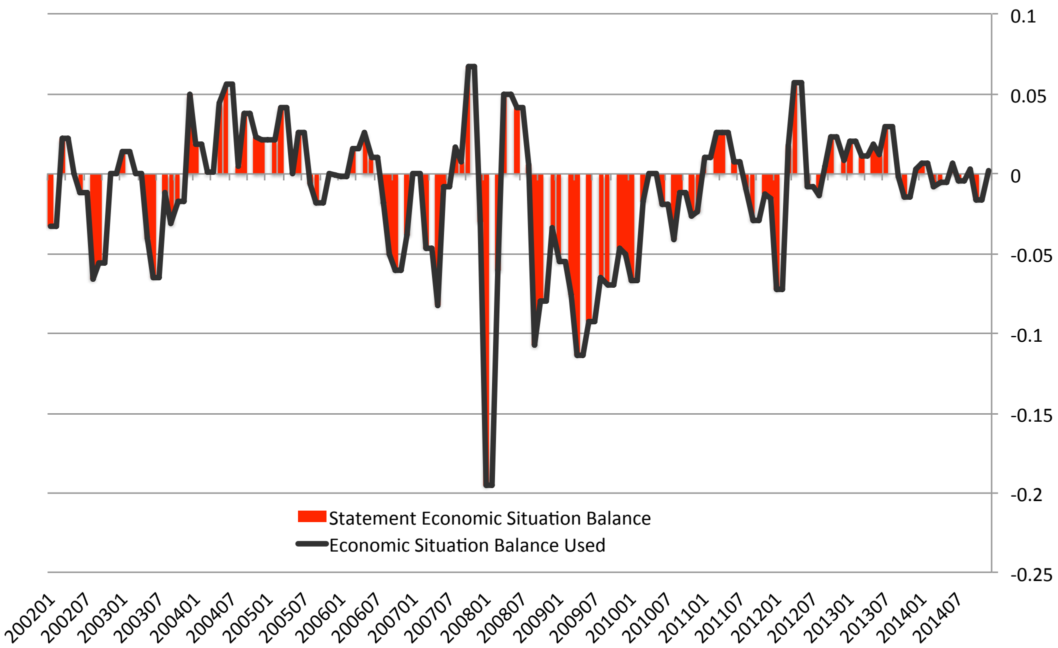


Figure 3: EcSit_t: Statement by statment and monthly index

4 Dimension 3: Forward Guidance

The basic idea of forward guidance that we wish to capture is communication after meeting t that captures the forward looking views of the committee as to how they see interest rate decisions in future meetings. 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 whether 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 Brookings meeting discussion of the Campbell, Evans, Fisher, and Justiniano (2012) paper makes clear. In this paper, we will not get a distinction that is perfectly Delphic or Odyssean. Rather we shall measure the direction of guidance, the amount of guidance given and the certainty in their statements about expected future path of interest rates. We shall not distinguish 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).

4.1 Manually Identifying Statements about Forward Guidance

In order to identify the relevant paragraphs in each statement, we use the narrative approach. Specifically we employ a research assistant, guided by the list in Campbell, Evans, Fisher, and Justiniano (2012), to select the statements related to discussions of future decisions. The forward guidance paragraphs capture conditional statements about the extent of monetary support going forward, the date-based guidance of the FOMC in recent recent years, and also FOMC statements about the balance of risks as seen by the FOMC.

As an example of the first kind, we capture statements such as from December 2013: "To support continued progress toward maximum employment and price stability, the Committee today reaffirmed its view 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."

For the second type, we capture statements such as that of June 2012: "To support a stronger economic recovery and to help ensure that inflation, over time, is at the rate most consistent with its dual mandate, the Committee expects to maintain a highly accommodative stance for monetary policy. In particular, the Committee decided today 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 late 2014."

For the last type, the August 1999 statement contains an example: "Today's increase in the federal funds rate, together with the policy action in June and the firming of conditions more generally in U.S. financial markets over recent months, should markedly diminish the risk of rising inflation going forward. As a consequence, the directive the Federal Open Market Committee adopted is symmetrical with regard to the outlook for policy over the near term."

In this sense we are slightly broader than the typical research design that assumes that August 2003 was the first use of forward guidance. In particular, that statement pointed out:

> "The Committee perceives that the upside and downside risks to the attainment of sustainable growth for the next few quarters are roughly equal. In contrast, the probability, though minor, of an unwelcome fall in inflation exceeds that of a rise in inflation from its already low level. The Committee judges that, on balance, the risk of inflation becoming undesirably low is likely to be the predominant concern for the foreseeable future. In these circumstances, the Committee believes that policy accommodation can be maintained for a considerable period."

4.2 Measuring Amount, Direction and Certainty of Guidance

In deciding how to measure the extent of forward guidance, one clear thing is that if there are no words about future interest rates, there is no forward guidance. The other thing that should be clear is that guidance can, as it typically is, suggest more expansionary policy or, much more rarely, likely contractionary policy.[10] Finally, there are occasions when the guidance is more clear cut, and others when the FOMC is more cautious in its guidance.

Once the forward guidance paragraphs have been identified manually, it is trivial to determine the direction of guidance. In particular, as we plot for each of the statement dates in Figure 4a, we classify a statement about more expansionary monetary policy as -1, a neutral stratement as 0 and a statement about contractionary monetary policy as $+1$.

To measure the amount of guidance given we could choose between measuring the number of words dedicated to the paragraphs about forward guidance, or we could normalise this measure relative to the whole statement (measuring the share of the statement dedicated to forward guidance. Given the trend increase in the length of statements, we choose to measure the amount of guidance using the latter share measure.[11] This is plotted in Figure 4b and shows the committee provided most quantity of guidance around 2009 and then from the middle of 2012.

Finally, in order to measure how 'certain', as opposed to cautious, the FOMC is in their statement about forward guidance, we return to using dictionary methods described above. For this we use the 'ambiguity' word list developed by Loughran and McDonald (2011) and augment it with some words used specifically to convey certainty or uncertainty in monetary policy. To measure this aspect of the paragraph, we use:

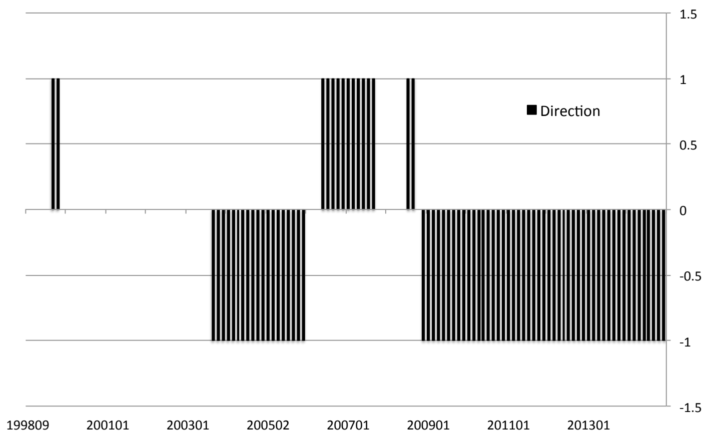
$$\text{Uncertainty}_t = \frac{n_{Uncertainty,t}}{n_t^{FG}} \tag{3}$$

where $n_{Uncertainty,t}$ is the number of uncertain words used in the paragraphs about forward guidance at time t, and n_t^{FG} is the total number of words about forward guidance at time t.[12]

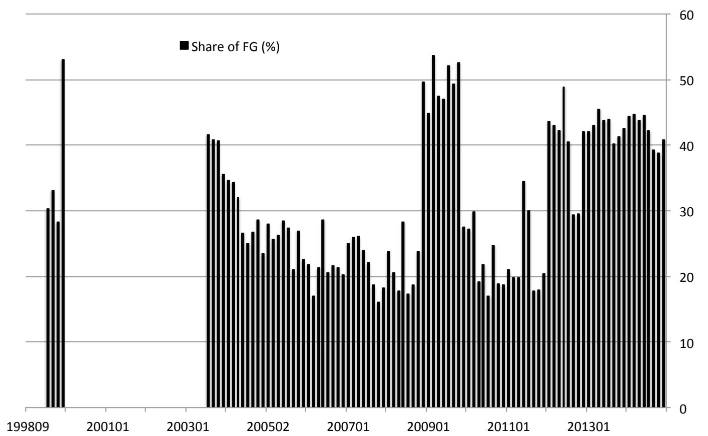
[10] The May 2006 statement is an example: "The Committee judges that some further policy firming may yet be needed to address inflation risks but emphasizes that the extent and timing of any such firming will depend importantly on the evolution of the economic outlook as implied by incoming information. In any event, the Committee will respond to changes in economic prospects as needed to support the attainment of its objectives."

[11] However, the overall indexed (once normalised) is almost identical whichever of the measures we choose. This is shown in Figure 5.

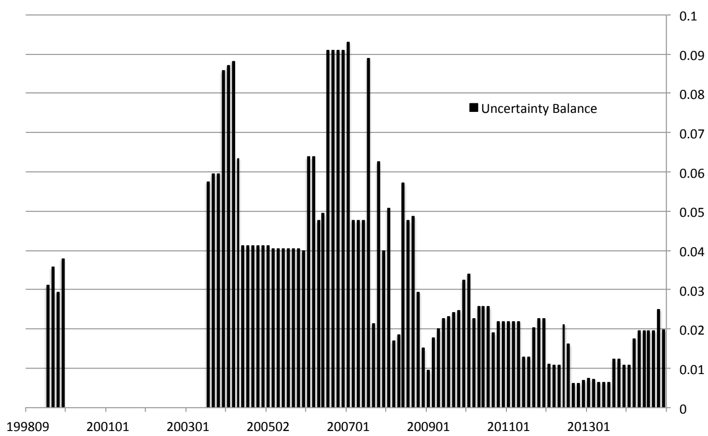
[12] As an alternative approach, we could use the certainty/uncertainty measure as a signal for the variance of future monetary policy shocks. We leave this for future research.



(a) Direction of Guidance



(b) Share of statement dedicated to Guidance



(c) Uncertainty words in Guidance Statement

Figure 4: Components of FG index

4.3 The Overall FG_t Index

Our overall index of forward guidance is then a combination of the three forward guidance measures as follows:

$$\text{FG}_t = \frac{\text{ShareFG}_t \times \text{DirectionFG}_t}{\text{Uncertainty}_t}. \tag{4}$$

We normalise this measure such the largest negative value (the instance of the largest, relatively certain, expansionary forward guidance statement) is given by -1. Figure 5 shows the constructed index both as bars (representing an FOMC statement) and as the monthly series in which we fill in the gaps according the last statement. This index picks up nicely that, since late 2008, the FOMC have used their strongest ever forward guidance suggesting expansionary monetary policy. The index actually hits its lowest point at the end of 2012 when the Fed retain the 'considerable time' phrase in their expectations about continued easing monetary policy, but they also add more discussion about the bond-buying program and the fact that interest rates will remain near zero for a considerable amount of time after the conclusion of the bond-buying programme.

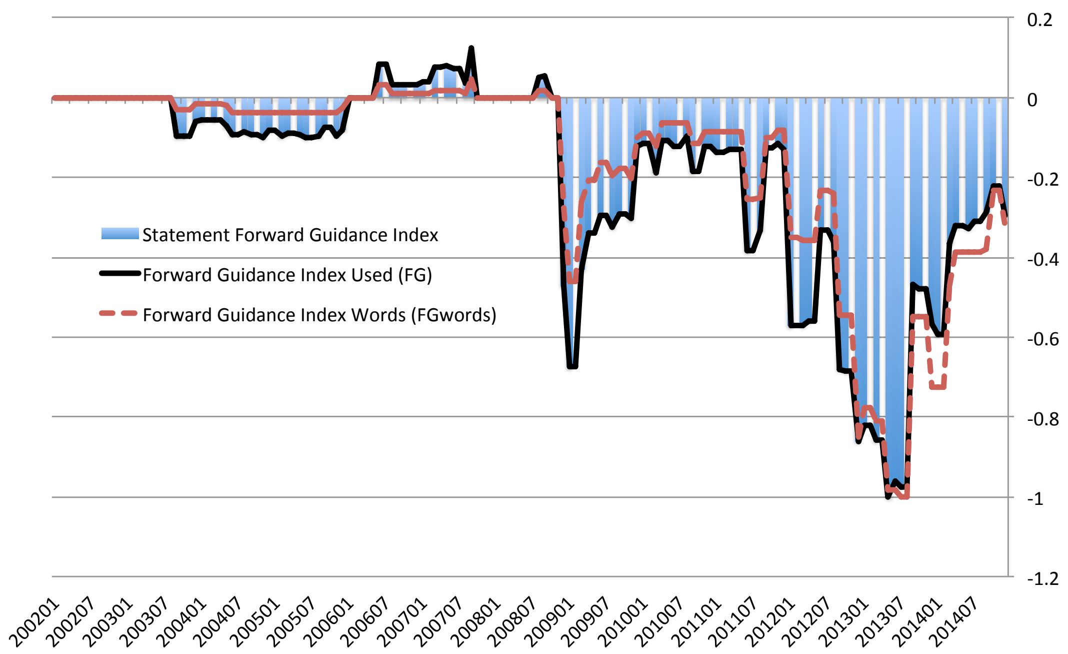


Figure 5: FG_t: Statement by statment and monthly index

5 Econometric Methodology: FAVAR Analysis

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:

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

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'. [13] 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 ($K = 1$).[14]

We have three dimensions of the monetary policy announcements - the description of the economic situation ($EcSit_t$), the current stance (s_t) and the forward guidance (FG_t). We will estimate our multi-dimensional monetary policy FAVAR using four factors

[13] 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'.

[14] 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.

($K = 4$) and the three measures included in the Y_t vector:

$$Y_t = \begin{bmatrix} \text{EcSit}_t \\ \text{s}_t \\ \text{FG}_t \end{bmatrix}. \tag{7}$$

5.1 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 5.2 which outlines the identification approach specific to this paper.

5.1.1 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

$$\hat{C}(F_t, Y_t) = \beta_c \hat{C}^*(F_t) + \beta_y Y_t + \eta_t \tag{8}$$

3. Define:

$$\hat{F}_t = \hat{C}(F_t, Y_t) - \beta_y Y_t \tag{9}$$

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

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

$$Z_t = \begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} \tag{10}$$

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

$$Z_t = AZ_{t-1} + v_t \tag{11}$$

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

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

$$HZ_t = BZ_{t-1} + u_t \tag{12}$$

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

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

$$Z_t = H^{-1}BZ_{t-1} + H^{-1}u_t \tag{13}$$

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, $\hat{\Omega} = \mathbb{E}\Big[H^{-1}u_t u_t{}' H^{-1'}\Big] = H^{-1}DH^{-1'}$. 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.

5.2 Using the framework to measure the impact of statements

We estimate our FAVAR using monthly data. The sample period used is January 1998 to December 2014. We start in 1998 in order to concentrate on a period in which the FOMC was making statements after all their meetings. This is also the start of the 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 December 2014. This means that the total time series dimension is 204 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 76 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 20,000 draws sampled after a burn-in of 10,000 draws and then we thin the 20,000 draws down to 400 draws by keeping only every 50th sample along the chain. The confidence bands provided with estimates are derived using the estimated distribution of 4000 draws. In the analysis, we use 7 lags.

6 Results

First we examine the effect of shocks to the FOMC's monetary stance using analysis of impulse response functions (IRF). Unlike traditional monetary policy shocks papers, we then shift our attention to the statement effects in terms of forward guidance (FG_t) and shocks to the assessment of the economic situation ($EcSit_t$). After the impulse response analysis, we examine the contribution of these shocks to the variance of US macroeconomic data. The results presented here are for the FAVAR estimated with 7 lags (monthly data) and with three factors included, using the sample from January 1998 to December 2014. The results are similar if we use two or four factors, and also if we use 4 lags or 13 lags.

6.1 The effect of a change in FOMC monetary stance

We here examine the effects of traditional monetary policy shocks, namely those arising from shocks to the Federal Funds Rate (FFR) and, at the ZLB, asset purchase shocks. Figures 6 to 9 present the impulse responses to such a shock. Although this is the standard type of monetary policy shock, it is worth noting that our inclusion of two additional policy variables may capture some of the effects that would typically be part of the monetary policy shock. For example, if on a given date the Fed has a more positive view of the economy than the (lagged) data suggests, this might be typically captured as a deviation from the normal monetary policy rule (a monetary shock) whereas in our framework this is captured by the EcSit_t index.

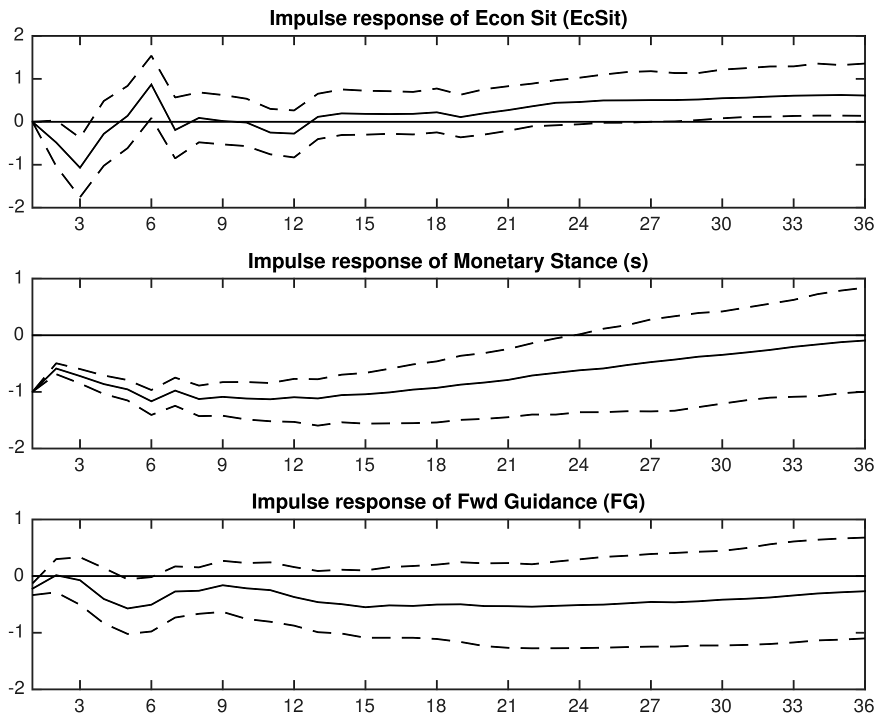


Figure 6: IRF Response to Monetary Stance (s_t) shock: Policy Variable Reaction

Figure 6 presents the shock that we analyse. Perhaps due to the period that we estimate (1998-2014), the shock is quite persistent. This is partly as a result of being directly persistent, but also because expansionary policy is found to typically lead to expansionary forward guidance which itself pushes down on the monetary stance.

The result is that market yields in a number of fixed income markets are pushed down persistently and across the yield curve (Figure 7). 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 such that the yield curve twists down. Corporate yields also fall.

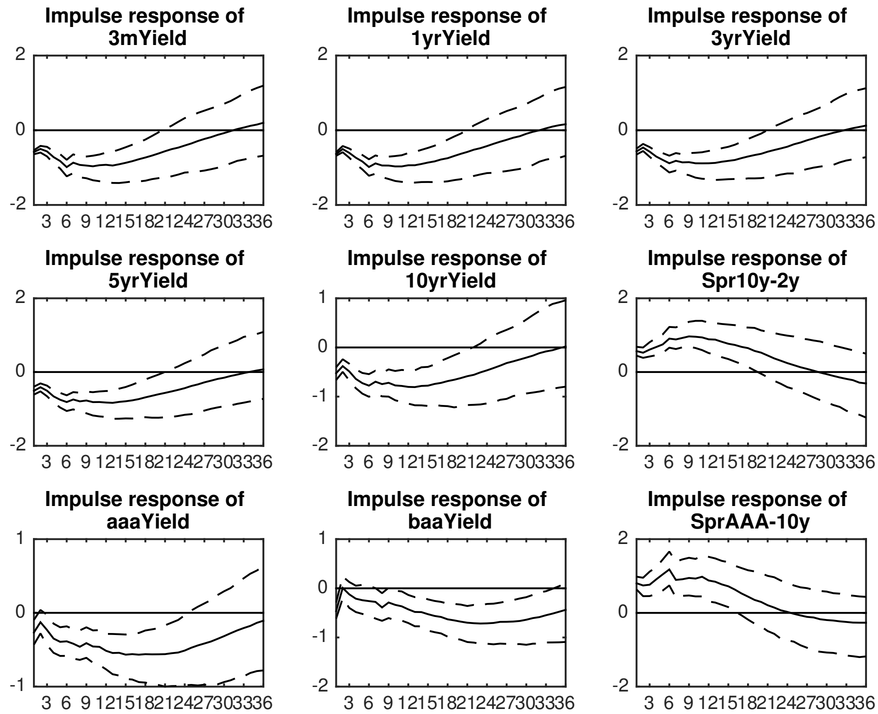


Figure 7: IRF Response to a Monetary Stance (s_t) shock: Yields Reaction

The reaction of many of the market variables is imprecisely estimated (figure 8). A decrease in the monetary stance tends, with a lag, to increase confidence, and reduce measures of uncertainty and volatility. It also pushes up on equity prices but this effect is very imprecisely estimated.

The effect on real variables is also somewhat imprecisely estimated. Figure 9 shows the responses. Nonetheless, the effect of a monetary easing is to lower unemployment and prices (e.g. CPI) and to push up on measures of economic activity. These effects tend to take around 18 months to take effect.

6.2 The effect of a change in Forward Guidance

We next look at the response of a change to the forward guidance element of the FOMC statement FG_t. The shock, shown in 10, involves the FOMC communicating an expansionary stance about the future decisions on interest rates; a negative shock is, in our interpretation, more forward guidance.

The shock has the desired effect on market rates as shown in figure 10. 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, more expansionary forward guidance about future rates tends to decrease longer maturity bonds significantly. It also plays a role in driving corporate bond yields including in the near term after the statement.

These results seem longer lived than the findings of Wright (2012). He uses a daily

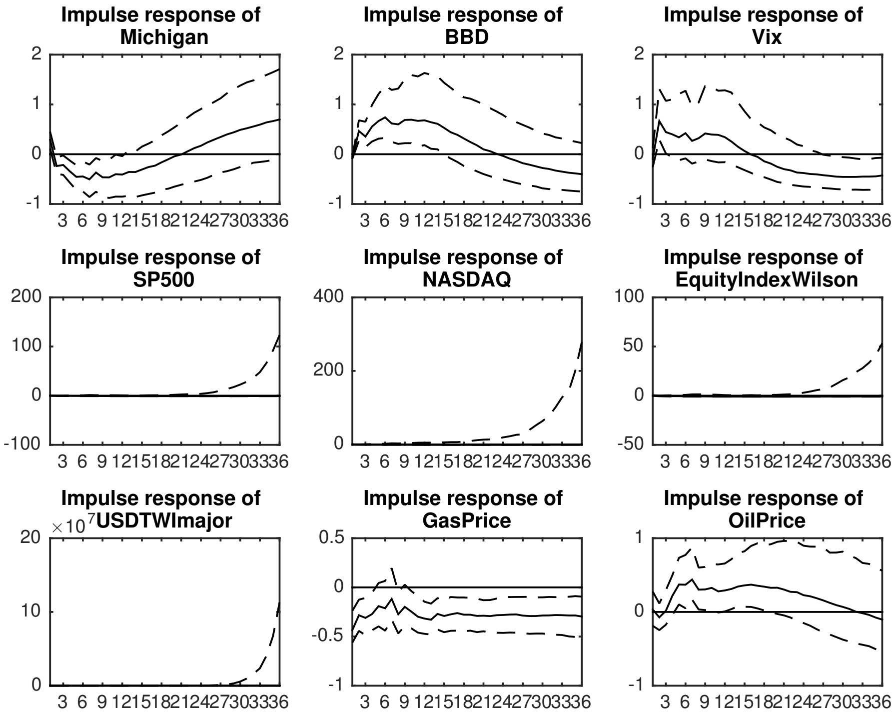


Figure 8: IRF Response to Monetary Stance (s_t) shock: Markets Reaction

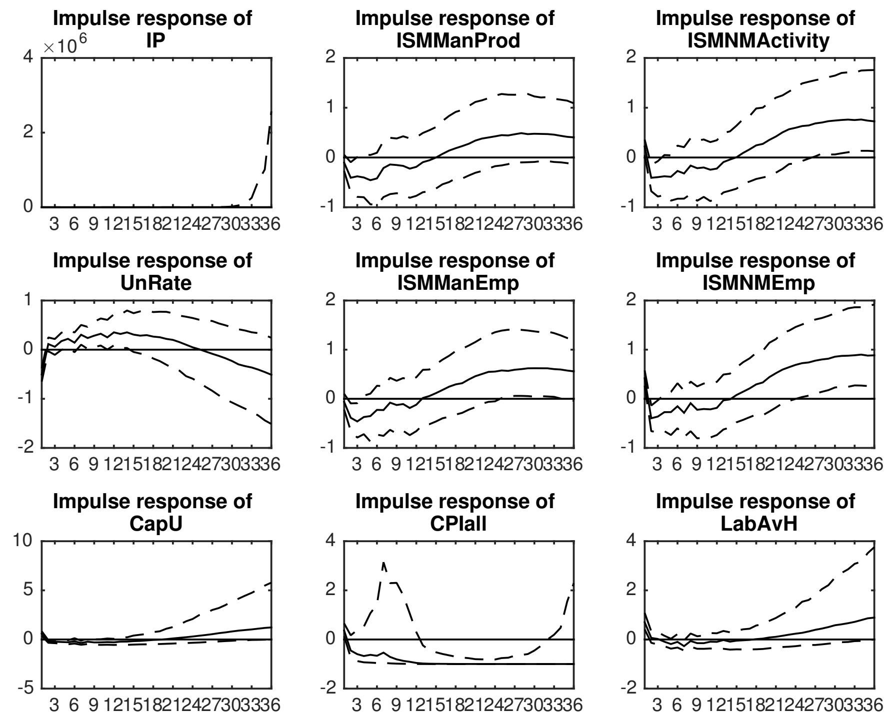


Figure 9: IRF Response to Monetary Stance (s_t) shock: Real Variables Reaction

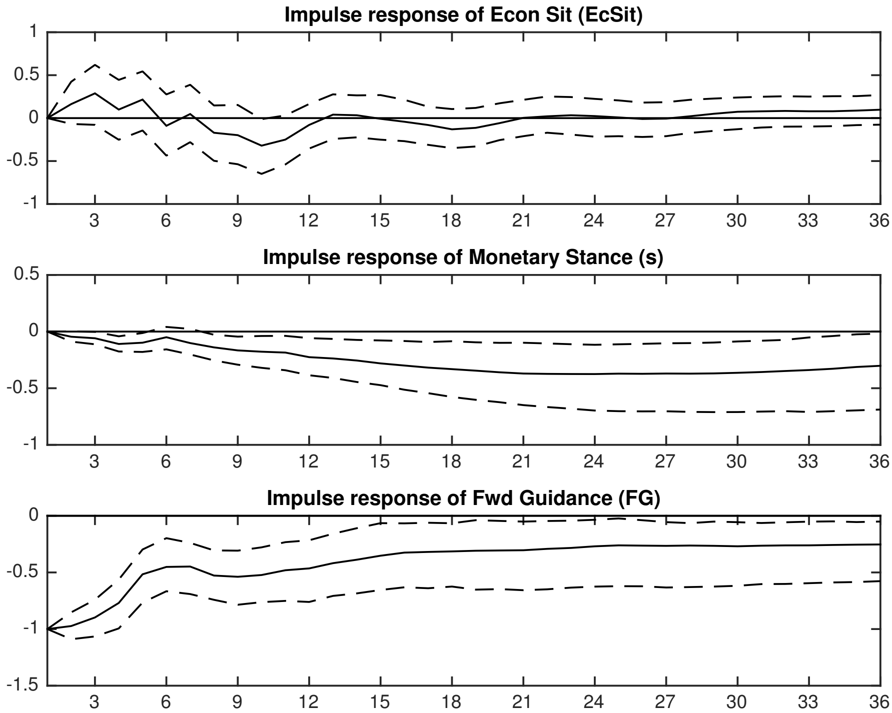


Figure 10: IRF Response to FG_t shock: Policy Variable Reaction

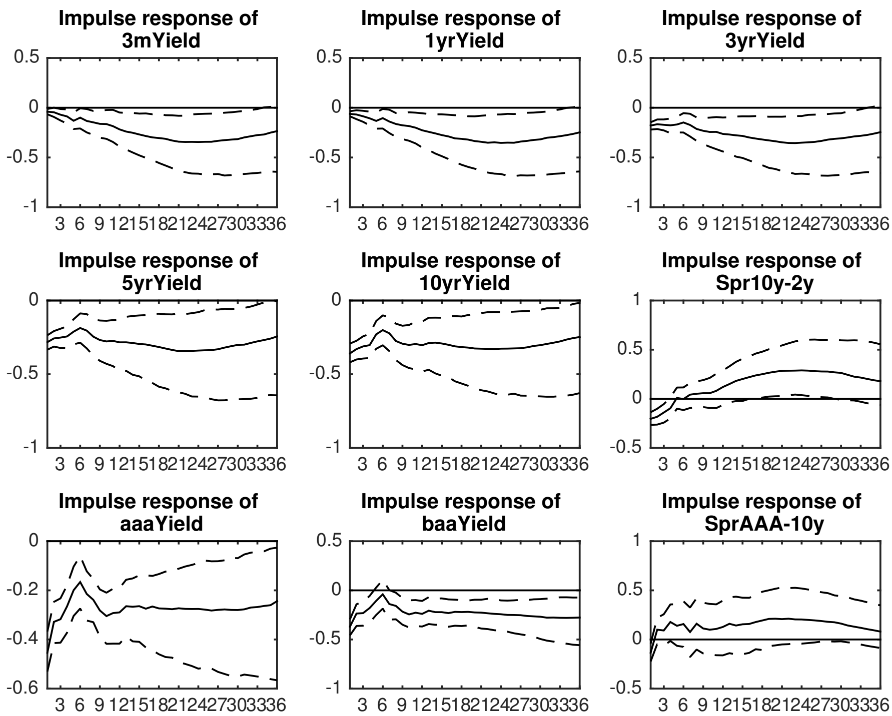


Figure 11: IRF Response to FG_t shock: Yields Reaction

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. The impulse responses of a selection of markets variables is presented in 12. For example, equity is estimated to respond positively to more certainty about future monetary expansion (though imprecisely estimated). The dollar tends to depreciate with the news.

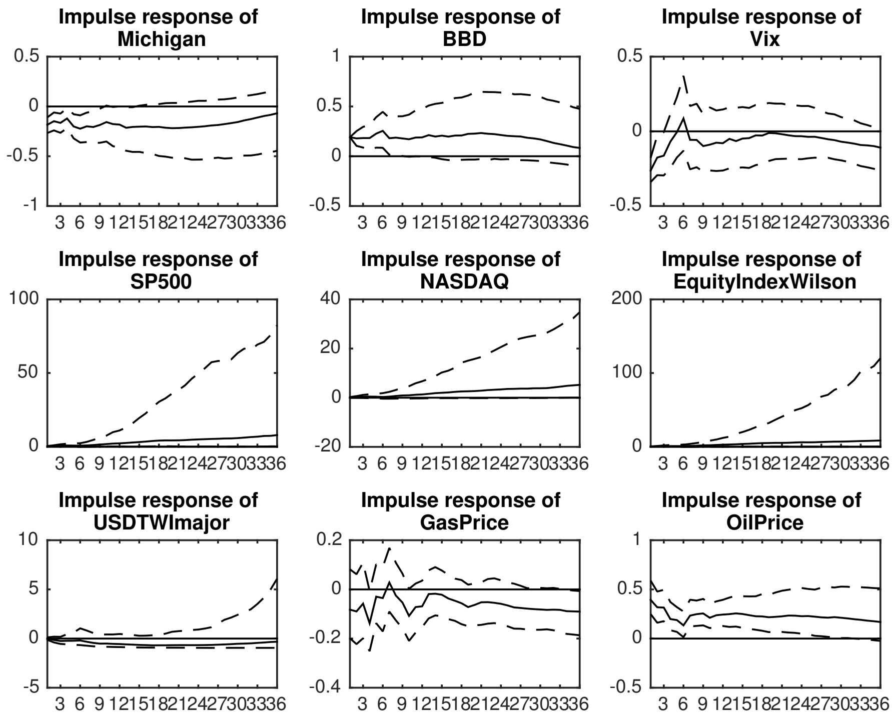


Figure 12: IRF Response to FG_t shock: Markets Reaction

However, the effects on real variables are much less clear cut and much noisier (figure 13). More expansionary forward guidance would, with a lag, start to push activity and labour market variables in the expected (or hoped) direction. But the evidence of a clear effect on real activity is difficult to gauge.

6.3 The effect of a change in Economic Situation Balance

For our final analysis of impulse responses, we turn to the effects of a shock to $EcSit_t$. A negative shock is equivalent to the FOMC statement talking more about economic contraction in their post-meeting statement. Figure 14 presents the shock, and the response of the other policy variables, while figures 16 to 17 present the response of the other variables we have analysed before.

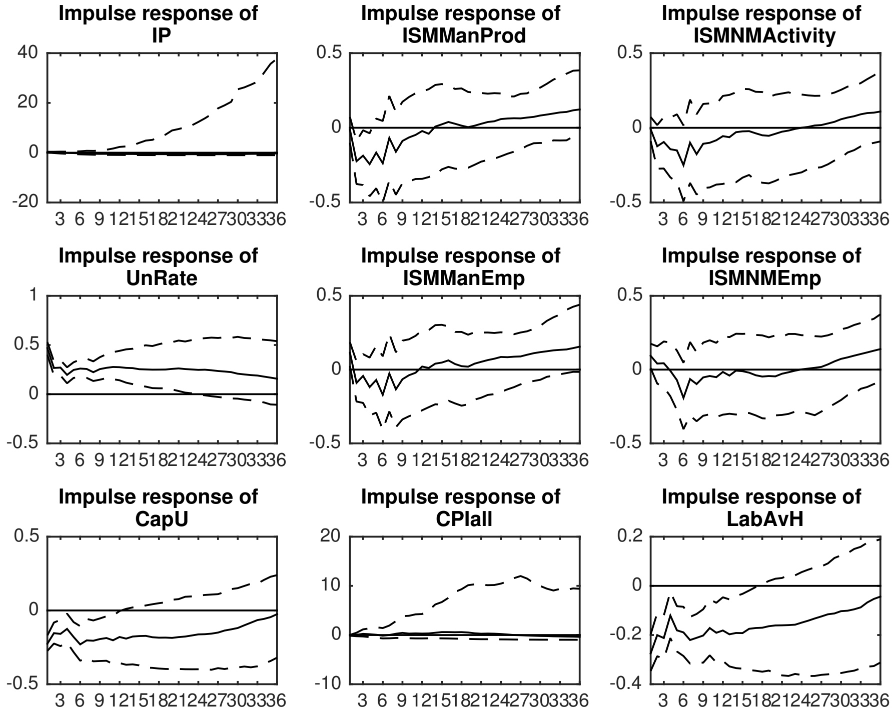


Figure 13: IRF Response to FG_t shock: Real Variables Reaction

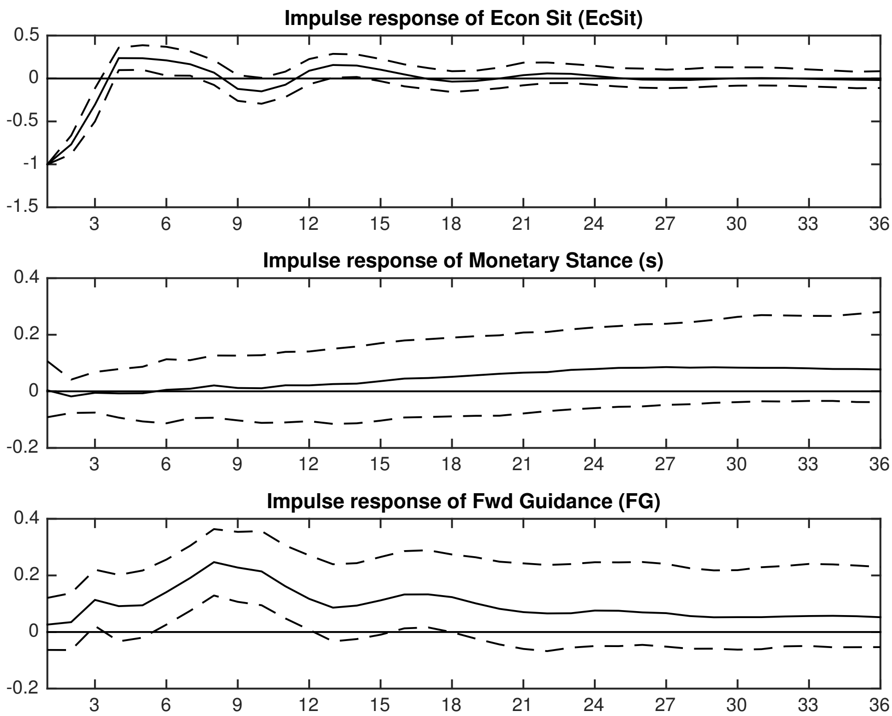


Figure 14: IRF Response to EcSit_t shock: Policy Variable Reaction

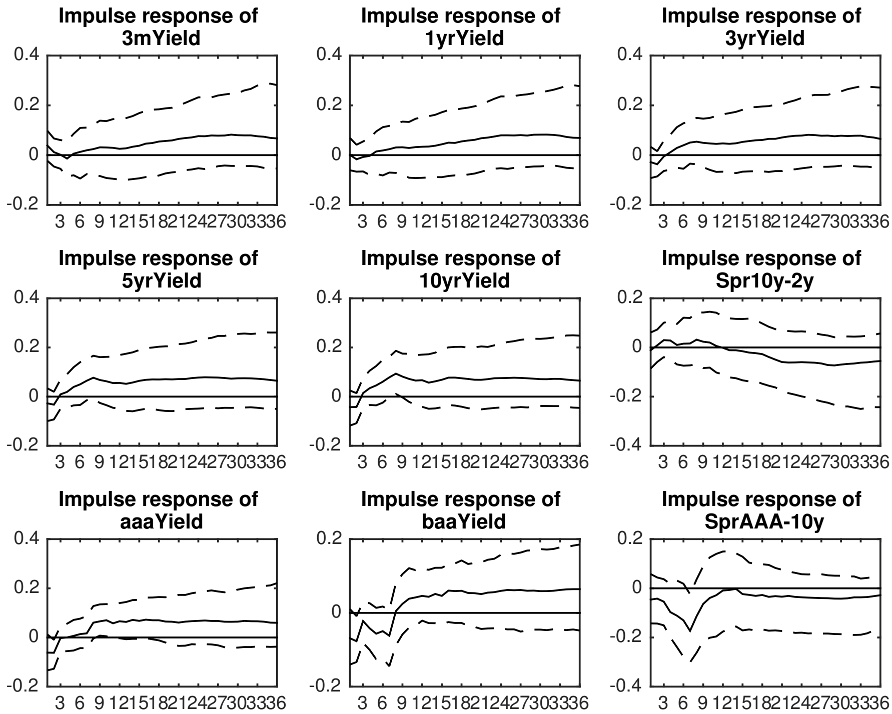


Figure 15: IRF Response to EcSit$_t$ shock: Yields Reaction

There is almost no significant reaction of yields (figure 15), markets variables (16) nor real variables.Some of the impulse responses seem to be intuitive, such as corporate bond yields falling, while others seem unintuitive, such as purchasing managers' survey responses indicating more activity about 6 months after the statement. 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 such that there is little news in the FOMC view about the economy, but only news in how the FOMC intends to react to it (captured more by FG_t).

6.4 Analysis of the Forecast Error Variance Decomposition

In order to understand how important each of these dimensions of monetary policy and communication is, we 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. Specficially, it looks at the variance in the h period 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 18 shows the FEVD explained by monetary shocks for a selection of rates (18a

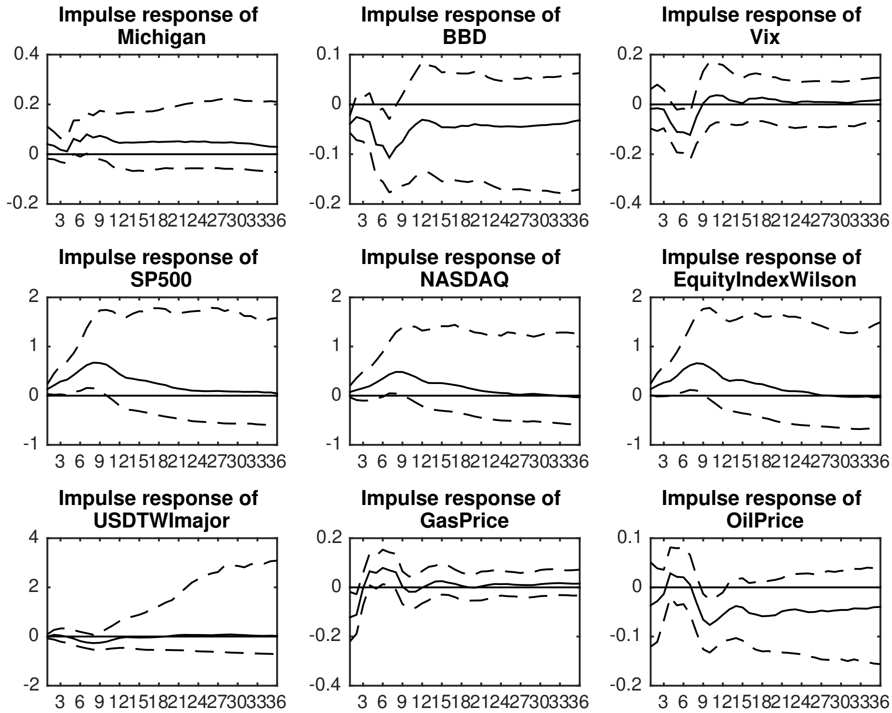


Figure 16: IRF Response to EcSit_t shock: Markets Reaction

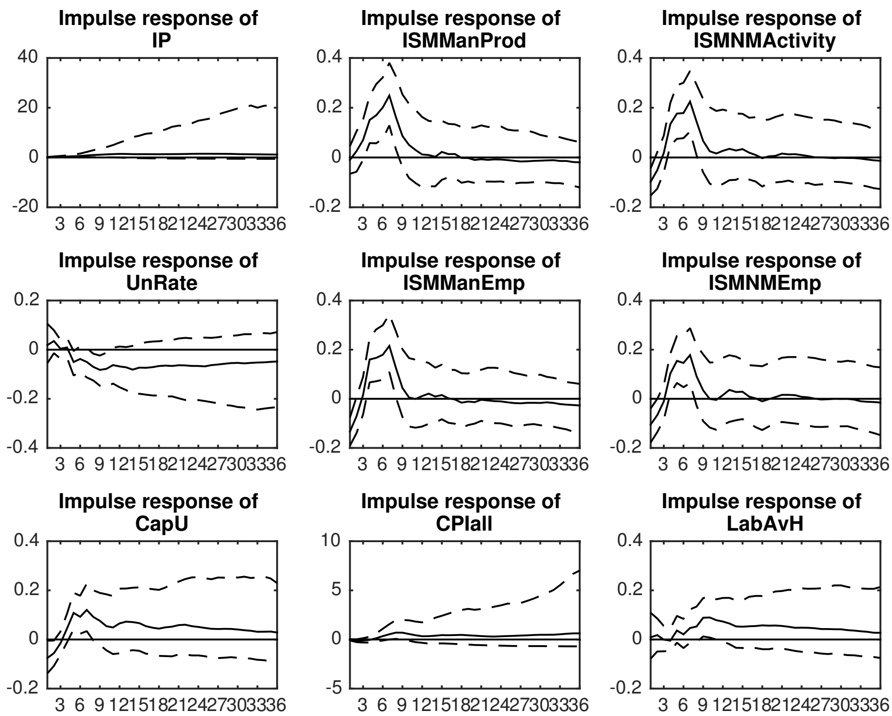
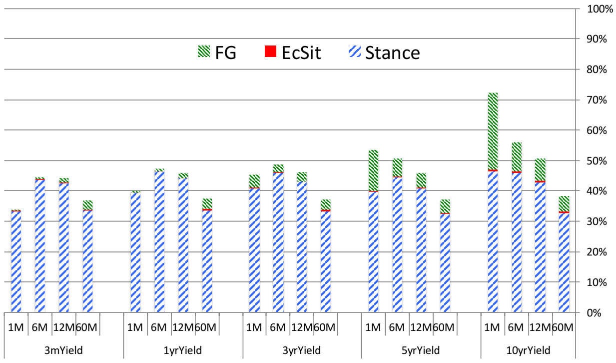
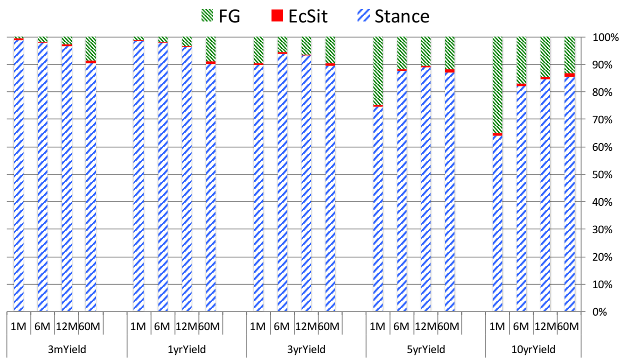


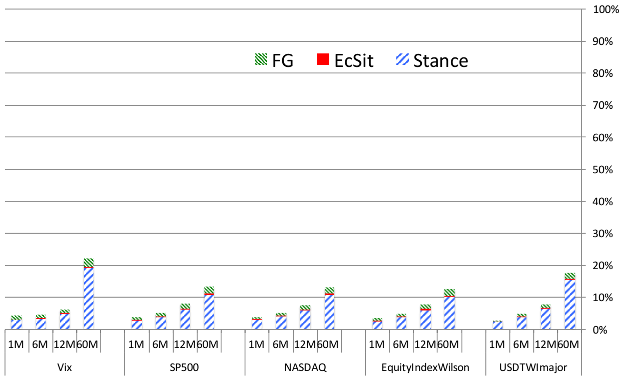
Figure 17: IRF Response to EcSit_t shock: Real Variables Reaction



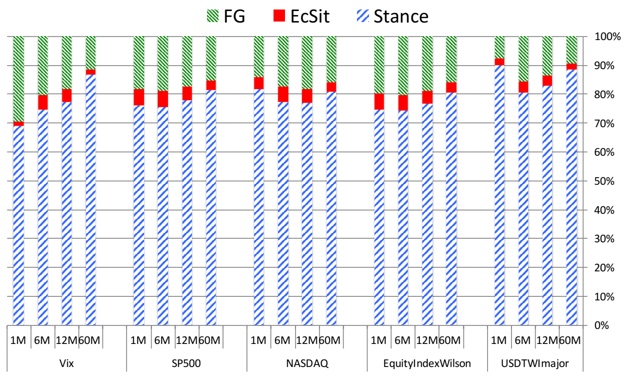
(a) FEVD: Yields



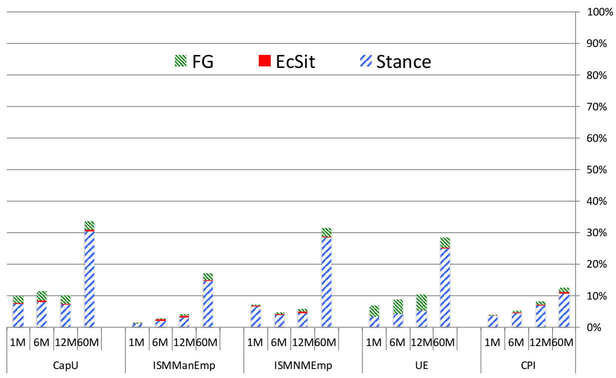
(b) Relative contribution: Yields



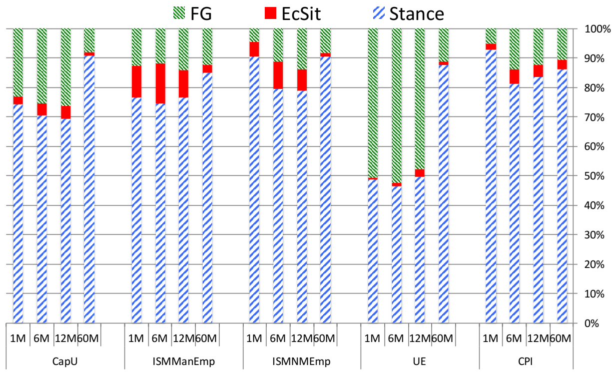
(c) FEVD: Market Variables



(d) Relative contribution: Market Variables



(e) FEVD: Real Variables



(f) Relative contribution: Real Variables

Figure 18: Forecast Error Variance Decomposition Analysis

Notes: The column on the left shows the FEVD for each of the three monetary dimensions. The column on the right simply shows the relative contribution of a given monetary dimension to the overall variance explained by the three dimensions of monetary policy together.

and 18b), market variables (18c and 18d) and real variables (18e and 18f). These are shown for one month (1M), six months (6M), one year (12M) and five year (60M) forecast horizons. The rows show, respectively, the response of yields and spreads, other financial market variables, and the response of a selection of real variables. The first column shows the contribtion of each dimension of monetary policy as a share of the total forecast error variance while the second column focuses only on the relative contribution of each of the dimensions of FOMC decisions and communication to the total contribution from monetary sources.

The contribution of all dimensions of monetary policy to the forecast error variance of the selected variables ranges between around 65% for 10 year yields at the one month horizon, to below 5% for some of the real economic variables at the one month horizon. As might be expected, as we move to longer forecast horizons, the role of the monetary dimensions tends to grow for real variables (up to around 30% for some variables) while the role in explaining yields tends to decline. Of course, at longer horizons it is other shocks (not studied here) which explain the variance of most variables. This is in line with previous VAR and FAVAR studies such as Bernanke, Boivin, and Eliasz (2005).

In terms of the relative importance of the three dimensions that we study, the most important dimension of monetary policy remains the current monetary stance accounting for at least 50% of the total monetary contribution, and typcially 60-70%. In terms of the novel dimensions studied in this paper, the results reinforce the earlier IRF results. Namely, shocks to FG_t seem to explain the movement of yields data, especially at longer maturities and at shorter forecast horizons, 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.

7 Conclusion

In this paper we empirically explore the channels through which central bank communication has effects. 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 18 years in the US, the central bank guidance on future interest rates seems to have been more important than their communication of economic conditions. Nonetheless, neither communication has particularly strong effects on real economic variables in our FAVAR.

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. Third, it could be that there are interactions between monetary stance and communication. Perhaps the stance is only found to have a strong role because of the communication that has gone with it. Finally, it would be useful to extend the analysis to other countries and thereby see if communication plays a similar role. For example, there is a longer history of forward guidance in Sweden which would be useful to analyse. 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
CapU	TCU	5	1	Capacity Utilization: Total Industry
CapUMan	MCUMFN	5	1	Capacity Utilization: Manufacturing (NAICS)
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-ManProd	NAPMPI	1	1	ISM Manufacturing: Production Index
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-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-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-all	CPIAUCSL	5	1	Consumer Price Index for All Urban Consumers: All Items
CPI-apparel	CPIAPPSL	5	1	Consumer Price Index for All Urban Consumers: Apparel
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-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

baaYield	BAA	1	0	Moody's Seasoned Baa Corporate Bond Yield
SprAAA-10y	AAA10YM	1	0	Moody's Seasoned Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity
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

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