Essays on Monetary Policy

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*I would like to thank Professor Michael McMahon for his guidance and assistance in this endeavour.

Contents

This is a summary of the four chapters that comprise this D.Phil. thesis.[1] This thesis examines two major aspects of policy. The first two chapters examine monetary policy communication. The second two examine the causes and consequences of a time-varying reaction function of the central bank.

1. Central Bank Communication and Higher Moments

In this first chapter, I investigate which parts of central bank communication affect the higher moments of expectations embedded in financial market pricing.

Much of the literature on central bank communication has focused on how communication impacts the conditional expected mean of future policy. But this chapter asks how central bank communication affects the second and third moments of the financial market's perceived distribution of future policy decisions. I use high frequency changes in option-prices around Bank of England communications to show that communication affects higher moments of the distribution of expectations. I find that the relevant communication in the case of the Bank of England is primarily confined to the information contained in the Q&A and Statement, rather than the longer Inflation Report.

2. Mark My Words: The Transmission of Central Bank Communication to the General Public via the Print Media

In the second chapter, jointly with James Brookes, I ask how central banks can change their communication in order to receive greater newspaper coverage, if that is indeed an objective of theirs.

We use computational linguistics combined with an event-study methodology to measure the extent of news coverage a central bank communication receives, and the textual features

[1] Word Count: 62338

that might cause a communication to be more (or less) likely to be considered newsworthy. We consider the case of the Bank of England, and estimate the relationship between news coverage and central bank communication implied by our model. We find that the interaction between the state of the economy and the way in which the Bank of England writes its communication is important for determining news coverage. We provide concrete suggestions for ways in which central bank communication can increase its news coverage by improving readability in line with our results.

3. Uncertainty and Time-varying Monetary Policy

In the third chapter, together with Michael McMahon, I investigate the links between uncertainty and the reaction function of the Federal Reserve.

US macroeconomic evidence points to higher economic volatility being positively correlated with more aggressive monetary policy responses. This represents a challenge for "good policy" explanations of the Great Moderation which map a more aggressive monetary response to reduced volatility. While some models of monetary policy under uncertainty can match this comovement qualitatively, these models do not, on their own, account for the reaction-function changes quantitatively for reasonable changes in uncertainty. We present a number of alternative sources of uncertainty that we believe should be more prevalent in the literature on monetary policy.

4. The Element(s) of Surprise

In the final chapter, together with Michael McMahon, I analyse the implications for monetary surprises of time-varying reaction functions.

Monetary policy surprises are driven by several separate forces. We argue that many of the surprises in monetary policy instruments are driven by unexpected changes in the reaction function of policymakers. We show that these reaction function surprises are fundamentally different from monetary policy shocks in their effect on the economy, are likely endogenous to the state, and unable to removed using current orthogonalisation procedures. As a result monetary policy surprises should not be used to measure the effect of a monetary policy "shock" to the economy. We find evidence for reaction function surprises in the features of the high frequency asset price surprise data and in analysing the text of a major US economic forecaster. Further, we show that periods in which an estimated macro model suggests policymakers have switched reaction functions provide the majority of variation in monetary policy surprises.

Central Bank Communication and Higher Moments*

Tim Munday†

Abstract

How does central bank communication affect the distribution of expected policy rates? Much of the literature on central bank communication has focused on how communication impacts the conditional expected mean of future policy. This paper asks how central bank communication affects the second and third moments of the financial market's perceived distribution of future policy decisions. I use high frequency changes in option-prices around Bank of England communications to show that communication affects higher moments of the distribution of expectations. I find that the relevant communication in the case of the Bank of England is primarily confined to the information contained in the Q&A and Statement, rather than the longer Inflation Report.

*Thanks to Michael McMahon who provided excellent guidance on this project. Also thanks to John Muellbauer, Stephen Hansen, Martin Ellison, Francesco Lippi, Eric Swanson, and four anonymous reviewers who provided numerous suggestions for this paper which I am very grateful for.

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1. Introduction

Since the 1990s, central banks have increasingly used communication as a policy instrument. As central bank transparency became more popular, policy makers were encouraged to use their communication to manage the expectations of future policy decisions. This widened the scope of central bank policy to include not only the direct control of short-term interest rates, but longer dated interest rates as well, whose values are dependent on the expectations of future central bank actions.[1] Blinder et al. (2008) called the change in central bank philosophy from the pre-1990s when central banks were tight-lipped about their policies to the present day communication deluge a "revolution in thinking".

Much has been written on how managing expectations of the conditional public expectation of the future policy instrument can improve the conduct of monetary policy (Woodford 2005), provide support for an explicit inflation target (Orphanides and Williams 2004), and allow central banks to affect the economy when traditional policy is hamstrung by the effective lower bound (Del Negro, Giannoni, and Patterson 2012). Furthermore, an expansive empirical literature has revealed strong evidence that expectations of future policy rates are affected by central bank communication (Gürkaynak, Sack, and Swanson 2005; Boukus and Rosenberg 2006; Andrade and Ferroni 2021) although the channels through which this happens remain contested.

This paper focuses on how central bank communication affects higher moments of the distribution of expectations. Specifically, how does the Bank of England's communication affect the variance and skew of expectations about future policy rates? These higher moments are measured using the changes in option prices around central bank communication events. Hansen, McMahon, and M. Tong (2019) (HMT) investigate how central bank communication affects uncertainty as measured by the term premia. This paper's measurement strategy of the second moment of expectations differs from theirs in that HMT only consider uncertainty to the extent that long-run term premia reflect that uncertainty. The approach taken in this paper — using option price data rather than yield curve data — is not contaminated

[1] In the age of asset purchases, having an effect on longer maturity assets can also be implemented directly by the purchase or sale of them.

by communication regarding asset purchases or forward guidance, both of which would move long-term yields and be captured in HMT's methodology but do not speak directly to changes in the second moment of expectations.

I utilise computational linguistics tools to analyse central bank communication. More specifically, I use Latent Dirichlet Allocation (Blei, Ng, and Jordan 2003) to organise the Bank of England's communications into topics. This process transforms each publication into a distribution over topics. For example, a Q&A press conference session might be represented as being 10% about growth, 20% about uncertainty, and so on. Using these topic shares shrinks the high-dimensional text data that the Bank of England releases down to a size small enough to be analysed.

The option data used to calculate the distribution of expected interest rates is from the Bank of England (Clews, Panigirtzoglou, and Proudman 2000). I focus on the one-year-ahead distribution of expected interest rates. An event study methodology is used to identify how much the Bank of England's communication changes the option-implied distributions of expectations. This event study style approach to studying monetary policy surprises is common (Kuttner 2001; Gertler and Karadi 2015; Nakamura and Steinsson 2018). However, in this paper option-implied pdfs are used to evaluate higher moments of expectations (as opposed to interest rate futures to evaluate the first moment). I demonstrate that these surprises to higher moments are persistent over time, and corroborate their interpretation by examining media coverage in their immediate aftermath.

I use machine learning techniques to (i) test whether the topics in the text data are relevant in explaining gyrations in the variance and skew of option-implied expectations on the days on which the Bank of England makes a communication announcement, and (ii) to produce a ranking of which topics are most important in moving the higher moments in the distribution of expected interest rates. I find firm evidence that the Bank of England's communication explains movements in the second and third moments of option-implied expectations. Determining which publication is driving the communication effect is difficult given that the content of the publications is highly correlated. This caveat notwithstanding, I find evidence that the effect is driven by the Statement text in the case of the second moment, and by the press conference Q&A and the Statement in the case of the third moment. Text from the Inflation Report seems to have little to no effect. More specifically, I find that HMT's suggestion that the Inflation Report text is important for explaining movements in the second moment disappears once the dynamic effects described by Tang (2019) are accounted for. The results derived from the machine learning procedure are corroborated by a Dynamic Factor Model, and are robust to the sample period used.

The strong correlation between one day changes in option implied higher moments, and the text released by the central bank can only be claimed as causal if one believes that no omitted variable affects both the text and the daily change in financial markets. To the extent that I can, I try to purge the estimates of these omitted variables by orthogonalising with respect to previous texts and numerical information. However, while the text for the Inflation Report is pre-agreed and pre-written prior to the day of the release, and so cannot be influenced by events taking place on the day; the same cannot be said of the Q&A. A causal claim is often made in the monetary policy shock literature when using tight windows around monetary policy decisions, but this paper stops short of making that claim — particularly in the case of the Q&A text. The effect of the text on financial markets is large and significant, but one cannot rule out other interpretations without cleaner identification via a natural experiment or otherwise. Moreover, I find that the surprises in higher moments are predictable based on information available prior to the day of communication (as is often found with standard monetary policy surprises (Bauer and Swanson 2020)).

This paper builds on the literature surrounding the effect of monetary policy decisions and monetary policy communication on financial market variables. There is a long literature on identifying monetary policy "shocks" through high-frequency movements in financial variables around monetary policy events (Kuttner 2001; Gürkaynak, Sack, and Swanson 2005; Gertler and Karadi 2015). More recently, the finding that an information effect of central bank communication was confounding monetary policy shock measures (Nakamura and Steinsson 2018;

Tang 2013) has led to a number of papers isolating various components of monetary policy surprises, including communication effects. Miranda-Agrippino and Ricco (2021) project surprises on to a measure of the central bank information set to remove information effects; Cieslak and Schrimpf (2019) and Jarociński and Karadi (2020) use sign restrictions in financial markets to separate information shocks from monetary policy shocks; and Leombroni et al. (2021), Altavilla et al. (2019), and Andrade and Ferroni (2021) use the timings of central bank communication to separate the effect of communication on financial markets from monetary policy decisions. This paper, whilst related to this literature, differs in several important ways. Given the long time needed to ingest the Inflation Report (Hansen, McMahon, and M. Tong 2019), this paper uses one-day changes in financial market variables, and is not concerned with the components in the financial market surprises that it measures. I only aim to show that communication is important for explaining the changes in investors' distribution of expectations — labelling the parts of communication that have that effect as information shocks, monetary policy shocks or otherwise is left for further research. I do not comment on whether the communication effect that I document is an information effect — in the sense that the text reveals additional information about the distribution of the various states of the economy — or a monetary policy effect — in the sense that the text reveals something about the distribution of possible monetary policy actions in response to the economy. It is likely some combination of the two, and this is shown to be the case when considering the press reaction to large movements in higher moments. Until 2015, the text studied in this paper was released at a different time to the Bank of England's monetary policy decision, negating the need for any high-frequency separation of communication and decisions as in Leombroni et al. (2021). Nonetheless, including the period from 2015 onwards makes little difference to the results.

The second strand of literature that this paper is related to is one concerning textual analysis of central bank communication. This literature uses a set of common tools available in natural language processing to investigate numerous areas of monetary policy. Hansen and McMahon (2016) examine how the FOMC statements impact the US economy through a FAVAR, Hansen, McMahon, and M. Tong (2019) analyse how Bank of England inflation report topics are related to high-frequency movements in financial markets, S. Hendry and Madeley (2010) investigate the impact of Bank of Canada statements on returns and volatility, Ehrmann and Talmi (2020) suggest that Bank of Canada statements that are less similar to previous releases cause more market volatility, Born, Ehrmann, and Fratzscher (2014) examine central bank communication on financial stability and its effect on the stock market, Tang (2017) finds that communication about the labour market increases financial market sensitivity to labour market news, and Ter Ellen, Larsen, and Thorsrud (2021) construct monetary policy surprises by examining the textual content of Norges Bank communications and comparing it to news reports in the run-up to the publication. This paper uses methods common across many of these papers (LDA, penalised regression, text cleaning) to investigate a new question of monetary policy communication.

The paper is structured as follows. Section 2 outlines the financial and text data, and details the text analysis procedure. Section 3 constructs a measure of surprises to the second and third moments of expectations and shows that they are persistent and are corroborated by media reports. Section 4 uses the methodology of Hansen, McMahon, and M. Tong (2019) to demonstrate that the topics in the Bank of England's communications are important for moving the option-implied variance and skew of future expectations of monetary policy. But that the result of Hansen, McMahon, and M. Tong (2019) — that the Inflation Report drives the second moment of expectations — is not robust. Section 5 concludes.

All the data and code for replicating this paper can be found at `https://github.com/TimMunday/HigherMomentsRep`

2. Data and methodology

2.1. Data

2.1.1. Financial data

I use the option-implied short sterling risk-neutral probability density functions calculated using the methodology set out in Clews, Panigirtzoglou, and Proudman (2000) and made available by the Bank of England. Clews, Panigirtzoglou, and Proudman (2000) take end-of-day settlement prices on sterling futures options contracts, interpolate across the delta smile, and then apply the result of Breeden and Litzenberger (1978) to obtain a non-parametric estimate of the implied probability distribution of three-month Libor twelve months ahead. Figure 1 shows the first, second and third moments of the probability distributions over time. Figure 2 shows the probability density functions over the entire sample. There is a large shift in the density functions following the 2008 financial crisis making the shape of the earlier densities difficult to visualise. Figure 3 addresses this by showing the density functions pre- and post- September 2008 on separate graphs.

The data are daily and run from January 1998 to October 2018. There are some trading days for which data are not available because there was not sufficient price discovery in the market for an adequate density function to be constructed. There are three days on which communication events took place but for which adequate pdfs could not be calculated. They are: 11-02-1998, 09-08-2000 and 11-11-2009. These communication events are excluded from the analysis.

Using an option-implied probability density function (pdf) as a measure of the market's subjective pdf comes with the caveats that (i) market participants may not be risk neutral, which the estimation procedure assumes, and (ii) estimating a constant maturity pdf necessitates interpolation between the contracts currently being traded on the market. This paper is concerned with the daily *change* in the second and third moments of the probability distribution, so it is an identifying assumption of this paper that neither of the errors that these caveats imply vary on a daily basis. In other words, I assume that the market preference for risk — denoted by the “deep parameters” in the market traders’ utility functions — and the interpolation errors are approximately invariant day to day.

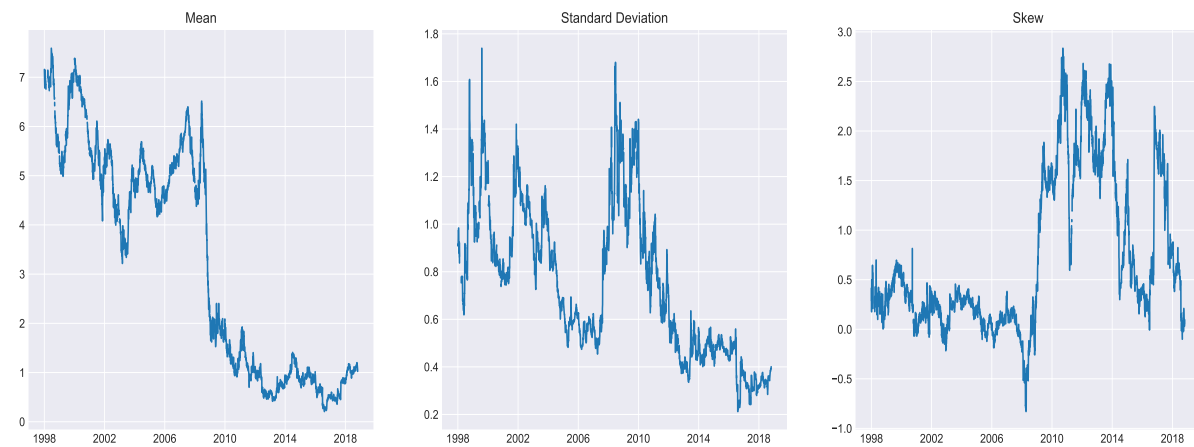

Fig. 1. Time series moments for three-month Libor implied probability distributions, twelve months ahead

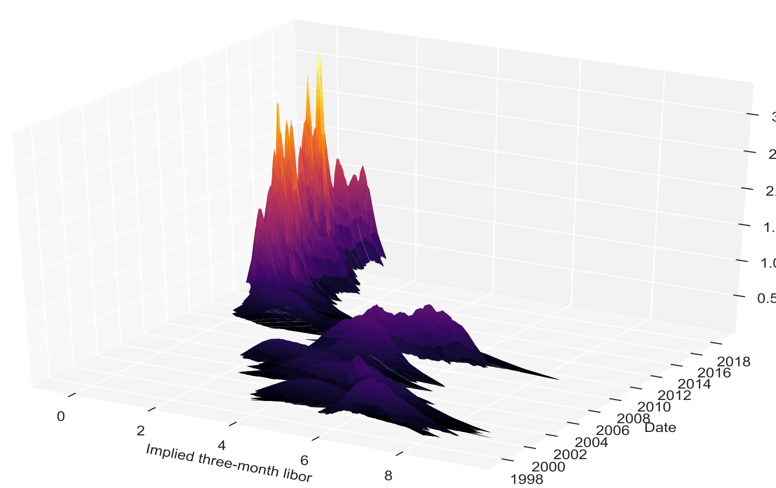

Fig. 2. Three-month Libor implied probability distributions, twelve months ahead

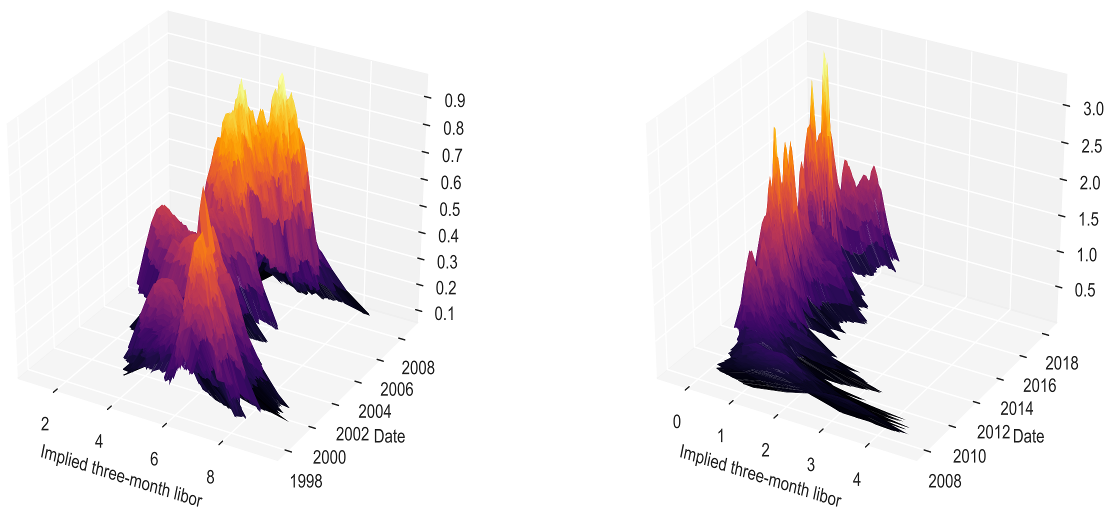

Fig. 3. Three-month Libor implied probability distributions, twelve months ahead (Jan 1998 - Sep 2008) and (Oct 2008 - Oct 2018)

2.1.2. Text data

I collect the text of three different types of communications that are released by the Bank of England: the Inflation Report, the Introductory Statement made at press conferences, and the transcripts of Q&As that follow the Introductory Statement.[2] All of these publications are released at quarterly frequency.

The Inflation Report text data run from 1998 to 2018.[3] The Introductory Statement text data run from 2001 to 2018. The Q&A data run from 2007 to 2018. The Introductory Statements and Q&As occur on the same day as the Inflation Report. From August 2015 onward, the Bank of England moved to a regime where in addition to the Inflation Report, the Introductory Statement and the Q&A, a monetary policy decision and the minutes accompanying that decision were also released on the same day. In Appendix Section 6.3, I show that the

[2] Future research could also include minutes and speeches.

[3] Data from 1998 to 2015 were kindly provided by Stephen Hansen, Michael McMahon and Matthew Tong.

findings are robust to this regime change.

In the case of the Q&A data, only responses by members of the Monetary Policy Committee are considered communication. Questions from journalists are excluded.

2.2. Topic Modelling

The total corpus of text data comprises of 22725 paragraphs of text (17815 from the Inflation Reports, 3749 from the Q&As and 1125 from the Introductory Statements). In natural language processing parlance, each block of text to be modelled is referred to as a "document". To avoid confusion I will refer to *publications* when referring to sources of communication (Inflation Reports, Q&As, Introductory Statements), and *paragraphs* instead of documents when referring to instances of text to model.

As is common with text data, high-dimensionality prohibits the use of the raw data in analysis. I use Latent Dirichlet Allocation (LDA) to project the data onto a lower-dimensional space. LDA has become a common dimensionality reduction tool in text analysis since it was popularised by Blei, Ng, and Jordan (2003). A more detailed explanation of the process can be found in Appendix Section 6.1.

The LDA process is performed on the entire corpus at the paragraph level.[4] Then, having produced the distribution of words assigned to each topic, every publication is separately queried to obtain a publication level distribution of topics.[5] This transforms each publication into a distribution over topics. For example, a Q&A press conference session might be represented as consisting of 10% topic 1, 20% topic 2, and so on. Since LDA is an unsupervised model, there is no explicit interpretation of the topics offered by the process.

Figure 4 shows the top twenty most likely words' probabilities in four topics (out of a total of 30) that the LDA procedure produces. I have provided an intuitive label for each topic. A full list of all thirty topics and their word distributions can be found in Appendix Section 6.4.

[4]With a larger sample of data, the model would be trained on a separate sub-sample to that which the researcher is interested in. Given the small sample of publications I have, this is not possible. Although future work might be able to use other central bank's text as an out-of-sample training data set.

[5]This is not the same as the average topic distribution for the paragraphs within the publication. It is as if the publication is treated as a new paragraph, and the model is asked to determine its topic distribution following training on the entire corpus.

One can see that the topics are broadly interpretable. However, despite my own judgement that the word distributions within topics are intuitive, it is not possible to more scientifically evaluate whether these groupings of words are meaningful without resorting to much more labour intensive methods, such as the experimental design of Chang et al. (2009).

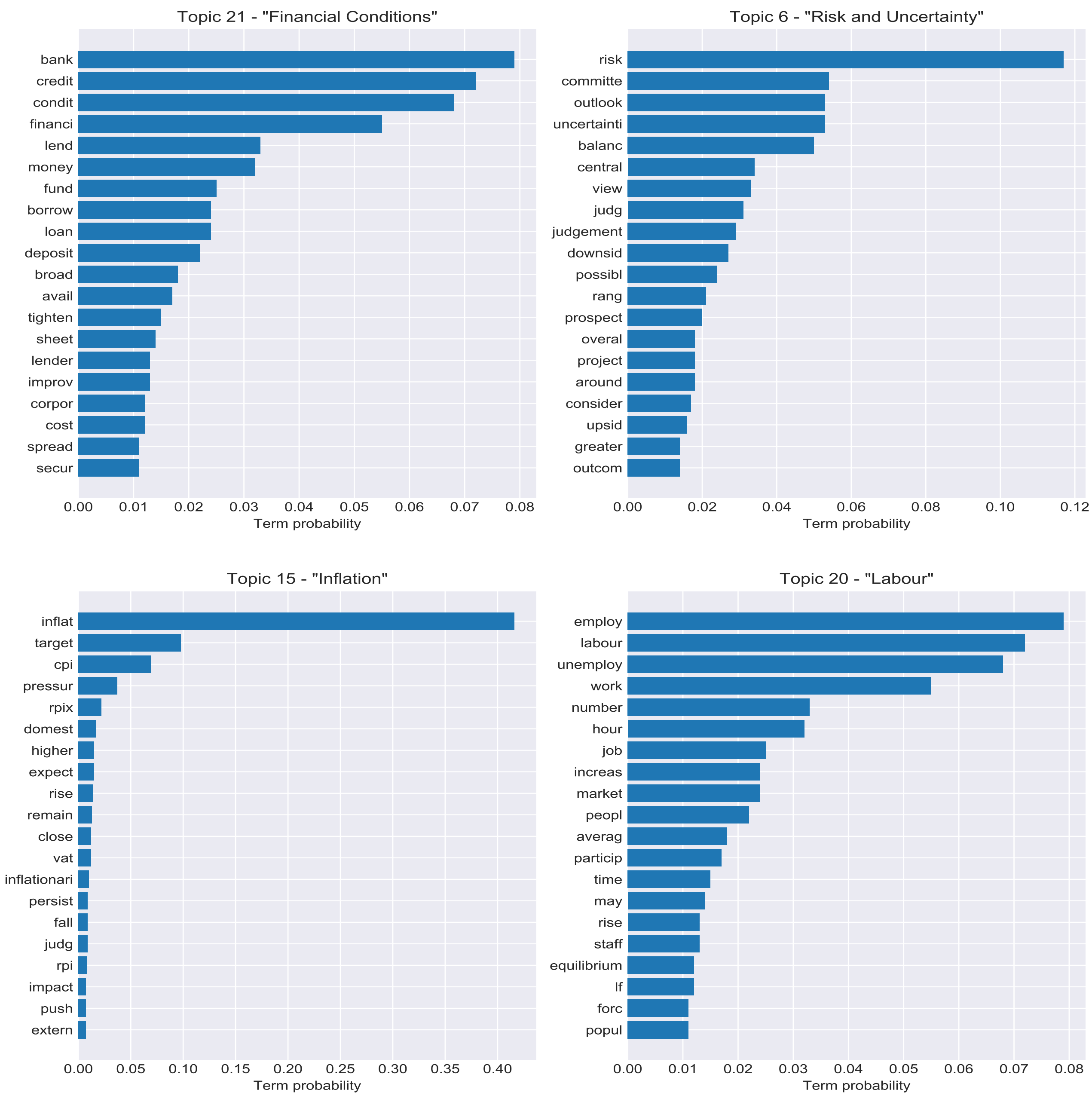

Fig. 4. Example Topics

3. Surprises to higher moments

In this section I explain the measurement of the surprises to higher moments, their persistence, and present qualitative evidence of their validity.

3.1. Construction of surprises

High frequency identification of monetary policy shocks uses the change in a financial market variable during a window around a policy announcement, and labels that as the monetary policy "surprise" (e.g. Kuttner 2001; Cochrane and Piazzesi 2002; Nakamura and Steinsson 2018; Leombroni et al. 2021; Jarociński and Karadi 2020). In the case considered by this paper, given (i) the illiquidity of option price data, and (ii) the need for longer time periods for text to be ingested by the market (Hansen, McMahon, and M. Tong 2019), a one day frequency is used.

The communication days considered by this paper are days on which both textual and numerical information is released. The Inflation Report (which occurs on the same day as the Q&A and the Statement) includes numerical forecasts from the Bank of England.

Changes in observed option-implied moments could be due to the release of the numerical information, rather than the narrative information. Indeed, there is good evidence that this numerical information can be relevant for intra-day market dynamics (Rholes and Sekhposyan 2021).

To remedy this, the numerical information is purged through OLS regressions. For each option-implied moment, an OLS regression is run with the implied moment time series as the dependent variable, and the numerical information included in the Inflation Report as the independent variables.[6] The residuals of these regression are saved and used in all further analysis.

[6] Specifically the forecasts for: CPI inflation mode 1 year ahead and its one period change, CPI inflation variance 1 year ahead and its one period change, CPI inflation skew 1 year ahead and its one period change, GDP growth mode 1 year ahead and its one period change, GDP growth variance 1 year ahead and its one period change, GDP growth skew 1 year ahead and its one period change. It could be argued that the relevant variables are the surprises relative to a market consensus for these variables. Alas the most relevant series, such as the variance of CPI inflation one year ahead, do not have reliable market consensus forecasts.

When it comes to determining whether textual information drives the movements in higher order moments in Section 4, textual features are also stripped of the effect of numerical information using the same procedure.

Figure 5 shows the construction of the surprises: the change in the higher moments of market implied expectations around a communication event, followed by stripping the effect of any numeric information from these changes as detailed previously.

This process does not change the measures we obtain significantly. The reason being that there is little variation in the numeric forecasts that are relevant for uncertainty. Indeed, since November 2011, the variance of forecasted CPI inflation 1 year ahead (the horizon that this paper examines) has taken the same value (1.80) for 26 out of 28 quarterly forecasts. For the two quarters it was not 1.80, it was 1.83.

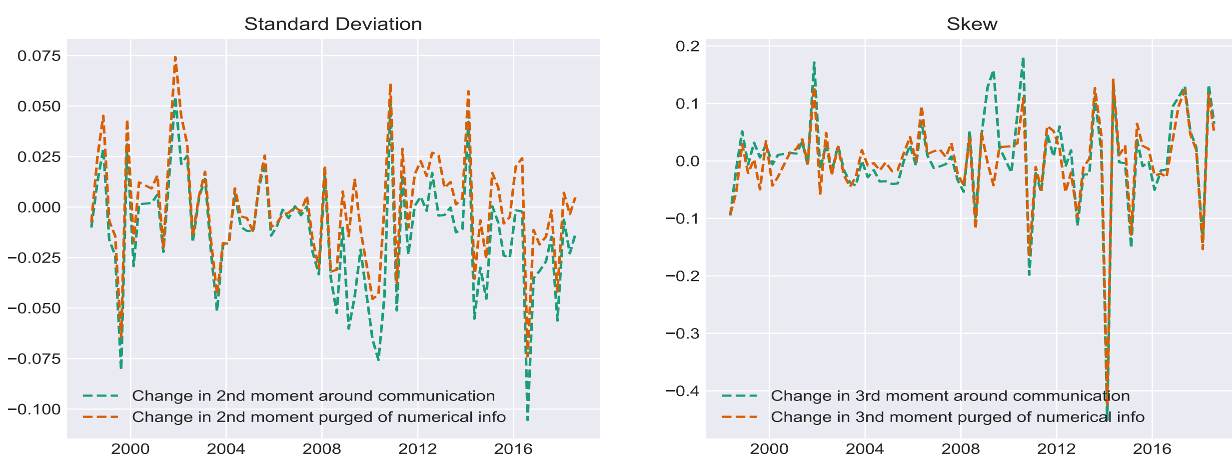

Fig. 5. Surprises to higher moments on Bank of England days

These surprises (the one day change in an option implied moment around a communication day orthogonalised with respect to the released numerical information) are the variable that this paper aims to show is influenced by textual data in Section 4.

3.2. Persistence of surprises

A concern in using financial market prices in windows around announcements and interpreting these as some form of monetary policy surprise is that the surprises themselves may not be persistent. If, following a so-called "surprise", the market reverts back to its pre-surprise level on the same or next day, then it is either the case that monetary policy surprises are small in comparison to other forces that move expected interest rates, or the identification scheme is not capturing any monetary policy surprise at all. I analyse how persistent the effect of the narrative surprises considered in this paper are by running local projections (Jordà 2005) of the form:

$$y_{t+s} = \beta_0 + \beta_1 y_{t-1} + \beta_2 z_t + v_t^s \tag{1}$$

Where y_{t+s} is a moment of the expected distribution of short rates one-year-ahead s days after an announcement made on date t, z_t is the surprise that occurred on day t — as defined either by the one day change in a higher moment, or that same one day change purged of numerical information — and v denotes an error term. I run these regressions for s from 0 to 30, to see how persistent the surprises are over the course of 30 trading days.

Equation 1 asks whether, conditional on the distribution of expectations the day before the Bank of England communicated, the surprise that occurred s days ago is still significant in determining financial market expectations today. Figure 6 shows the impulse responses of one day changes in the second and third moments. Figure 7 shows the same exercise but for when these one day changes have been purged of the effects of numerical information. Over time, as more shocks from data releases, foreign central banks and external sources move market prices, one would expect the significance of β_2 to wane. That said, it takes a considerable amount of time for the t-values related to β_2 to become non-significant. The high persistence of the surprise demonstrates how significant a driver communication is of the higher moments of market implied expectations.

Fig. 6. Equation 1 local projection impulse responses for a one-day change as the surprise

Fig. 7. Equation 1 local projection impulse responses for a one-day change purged of numerical information as the surprise

As a comparison, I perform the same local projection exercise on shocks to the first moment, derived by the orthognolisation procedure of Miranda-Agrippino (2016). Figure 8 shows that the impulse responses have (i) a similar magnitude, and (ii) a similar level of persistence.

Surprises to the first moment of market expectations of monetary policy have been extensively studied, particularly with respect to their correct identification (Kuttner (2001), Gürkaynak, Sack, and Swanson (2005), Nakamura and Steinsson (2018), to name a few). Surprises to higher moments have been long overlooked, and have similar magnitudes and persistence in financial markets.

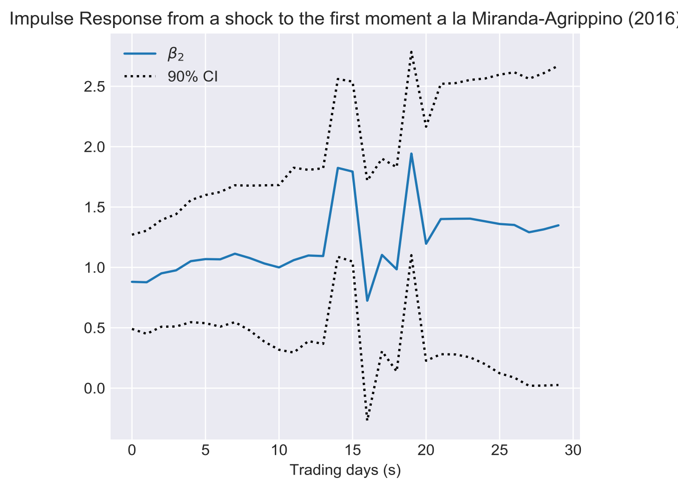

Fig. 8. Equation 1 local projection impulse responses from a shock to the first moment

Some of the empirical surprises to the second moment in Figure 5 are positive. To partially address the question of why a central bank may want to release text that led to an increase in perceived risk (outside of the explanation that they are merely communication a fact about the general macro environment becoming more risky), I take the surprises constructed by this paper to the model of Morris and Shin (2002) in Appendix Section 6.2.

3.3. Surprises or shocks

Having measured a surprise in financial markets as the unexpected change in some asset price around an event of interest, many papers in the monetary policy shock literature go on to — after stating some needed assumptions — manipulate these surprises into "shocks" (Nakamura and Steinsson 2018; Miranda-Agrippino 2016), or to use them as instruments for shocks in proxy SVARs (Gertler and Karadi 2015; Jarociński and Karadi 2020; Miranda-

Agrippino and Ricco 2021).

Ramey (2016) defines shocks as needing to "have the following characteristics: (1) they should be exogenous with respect to the other current and lagged endogenous variables in the model; (2) they should be uncorrelated with other exogenous shocks; otherwise, we cannot identify the unique causal effects of one exogenous shock relative to another; and (3) they should represent either unanticipated movements in exogenous variables or news about future movements in exogenous variables."

The surprises defined earlier do not satisfy these conditions. Importantly, in Section 6.2 I show that the one period changes in higher moments are predictable from surveys conducted prior to the monetary policy communication.

It is not uncommon for high-frequency asset price moves to be predictable and therefore not able to be classed as exogenous shocks, or indeed instruments for shocks (Bauer and Swanson 2020; Cieslak 2018; Ramey 2016).

As a result this paper cannot answer questions that pertain to the effect of uncertainty on the economy, where the source of the uncertainty is monetary policy communication.

Indeed the true "shocks" that one would want to study to answer these questions are the parts of the text that represent meaningful updates of information not known to the agent in question prior to the communication. What one observes is the effect of that information on higher moments as embedded in option prices. An attempt to measure these shocks is beyond the scope of this paper, but future work could look to using the text itself to identify shocks in addition to the financial market data, perhaps using the methodology of Nesbit (2020).

Given that this paper aims to show that communication affects higher moments, but does not attempt to separate out *why* those moments changed, it cannot answer the question of whether higher moments are changing because the text revealed information about the distribution of the state of the economy, or because the text revealed information about the distribution of possible monetary policy reactions to the state of the economy. The former of these would look similar to a the "information effect" documented in the monetary policy shock literature, the latter would look similar to a "reaction function shock" (McMahon and

Munday 2022). This is an interesting question; not least because the two shocks have different welfare implications. Nonetheless, an investigation of this is left for future research.

3.4. Case Studies

To provide a more convincing argument that the change in the residual (i.e. purged of numerical information) standard deviation or skewness around a central bank publication is a good measure of whether or not a Bank of England publication caused a change in the higher moments of expectations, I consider the interpretation of the press following a publication. Specifically, I look at the largest and smallest moves in the second and third moments, and examine the Financial Times's write up of the Bank of England communication the following day to see whether the FT analysis of the meeting can be reconciled with the market reaction.

The sample of publication dates and their associated market movements are displayed in Figure 9. The results are displayed in Table 1. The results show that — at least when market moves are large — the common interpretation of the Bank of England's communication is similar between financial journalists and market participants. This should help assuage any fears that the use of option-implied pdfs does not capture the effect of Bank of England communication adequately.

The case studies can additionally shed some light on the issue discussed briefly in the previous section of whether the text is revealing information on the economy or on the reaction function of the central bank. It seems it is probably a mixture of the two. Examining the FT excerpt from November 2010, when a large increase in the second moment occurred, one sees that there are "more risks than usual" to the Bank's forecast (information on the economy), but also that the MPC was "unusually divided" (information on the central bank reaction function).

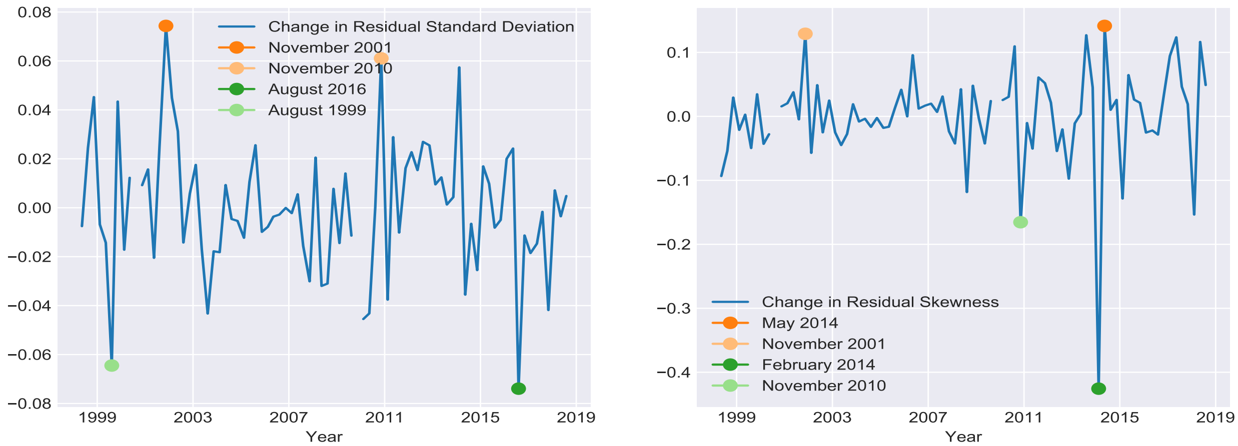

Fig. 9. Change in residual moments over time

Table 1: FT articles and interpretation of large moves in the moments of market expectations

Moment	Type	Date	FT Heading	FT article excerpt	Interpretation
Standard Deviation	Largest	November 2001	Britain set to avoid recession, says Bank	Britain has only a one in 10 chance of suffering a recession, Mervyn King...said yesterday - bringing expectations of future interest rate cuts down sharply...[the Bank] suggested for the first time in more than a year that underlying inflation was more likely to end the period above the government's 2.5 per cent target than below it - although the probabilities were finely balanced at 51 per cent to 49 per cent.	Announcement that probabilities are "finely balanced" around the outlook suggests greater uncertainty.
		November 2010	King outlines risks	The Bank noted that there were even more risks than usual to its forecast. Moreover, members of the monetary policy committee were unusually divided	Communication focused on there being a greater degree of uncertainty around the outlook causing an increase in standard deviation of expected interest rate distribution.
	Smallest	August 2016	Carney issues stark warning with package to ease Brexit downturn	The Bank of England launched its biggest stimulus package since the financial crisis yesterday...in an attempt to cushion a looming Brexit-induced downturn	The Bank finally unveils its response to Brexit, reducing uncertainty around the future policy path.
		August 1999	More gain with less pain	The Bank of England's monetary policy committee said in its latest Inflation Report that output had grown faster than it expected three months ago, with inflation more subdued.	No obvious interpretation.
Skew	Largest	May 2014	Carney damps expectations of rates rise	In the [IR]... the official text and forecasts painted a picture of robust growth, which was likely to require interest rate rises a little earlier than the monetary Policy Committee had expected in February	The IR text seems to have moved markets to believe that the time for lift-off was nearer, extending the right hand tail of the interest rate expectation distribution.
		November 2001	Britain set to avoid recession, says Bank	Britain has only a one in 10 chance of suffering a recession, Mervyn King...said yesterday - bringing expectations of future interest rate cuts down sharply	Interest rate rises now more likely given Banks positive outlook, shifting the right hand tail of the distribution outwards.
	Smallest	February 2014	BoE set to hold rates beyond election	[The Bank ditched] the previous guidance that linked interest rates to unemployment	Under the previous commitment, the distribution of future rates - truncated at the Bank's effective lower bound, which at the time was believed to be 0.5% - was highly positively skewed. But a relaxing of a commitment to raise rates in the near term as unemployment dipped below 7%, reigned the long positive tail of interest rate expectations inwards.
		November 2010	King outlines risks	although the Inflation Report offered a balanced view of the risks...investors bet that the Bank did not plan to pump new stimulus into the economy any time soon	Investor reaction was that rate rises off the lower bound were less likely, so the right hand tail of the interest rate distribution moved inwards.

4. Narrative Information

The topic modelling procedure briefly detailed in the Section 2, and more extensively documented in Appendix Section 6.1, reduced the dimensions of the text data. LDA transformed each publication (for example, the Inflation Report released on the 11th of February 1998) to a length 30 vector which describes a distribution over 30 topics. Since one might argue that it is not only the level of the topic proportions that may move expectations, I include the one-period change in topic proportions for each publication, as in Hansen, McMahon, and M. Tong (2019). More specifically: the Inflation Report text data is represented by an 83 (number of publications) by 60 (30 topics, and 30 changes in topics) matrix, the Q&A text data is represented by a 45 (number of publications) by 60 (30 topics, and 30 changes in topics) matrix, and the Introductory Statements by a 71 (number of publications) by 60 (30 topics, and 30 changes in topics) matrix.

This paper is concerned with how communication from the Bank of England affects the change in the higher moments of the option-implied density function of one-year-ahead short-term interest rates. I use an event-study framework to identify the effect of communication on the distribution of expectations. End-of-day settlement prices are used to calculate risk neutral probability distributions. I use the daily change in the second and third moments of expected interest rates on days when the Bank of England communicates with the public as a measure of how much the Bank of England has shifted the higher moments of expected interest rates. Whilst more recent literature on monetary policy shocks has used intra-day identification (Nakamura and Steinsson 2018; Jarociński and Karadi 2020), option prices are not liquid enough to do so. Moreover, there is good reason to think that documents as long as the Inflation Report may take several hours for the market to digest, too long to be captured by the shorter windows of intra-day methods.

The following section follows the methodology of HMT to show that narrative information exists in the Bank of England's communication that explains variation in the higher moments of market expectations. Whilst the methodology is the same, this section of the paper differs in four main ways. Firstly, this paper's measurement strategy of the second moment of expectations differs from HMT's in that HMT only consider uncertainty to the extent that long-run term premia reflect that uncertainty. The approach taken in this paper — using option price data rather than yield curve data — is more direct and is not contaminated by communication regarding asset purchases or forward guidance, both of which would move long-term yields and be captured in HMT's methodology but do not speak directly to changes in the second moment of expectations. Secondly, I also consider the third moment of expectations, which is important when considering expectations in an environment in which the Effective Lower Bound is occasionally binding. Thirdly, this paper considers the Inflation Report, Statement and the Q&A as potential drivers of expectations, not only the Inflation Report. Finally, this paper accounts for the dynamic effects which significantly dampen the effects found by HMT, as documented by Tang (2019).

4.1. Permutation exercise

To investigate whether or not there is any information at all in the topic proportions that is relevant in explaining the changes in the moments of expected interest rates, I follow the permutation procedure of HMT.

Because of the small number of publications, and large number of topic variables, the curse of dimensionality means that I use penalised regression techniques. I use elastic net regressions (Zou and Hastie 2005) specified with the daily change in a moment of the distribution of expected interest rates as the dependent variable, and the topic shares as the independent variables.[7] The penalty term for non-zero regression coefficients is an additive function of both the L1 and L2 norm.[8] The relative weight given to the penalty on the L1 norm versus the L2 norm (α) is set to 0.99 and the relative weight given to the entire penalty term versus the sum of squared errors (λ) is estimated using leave-one-out cross validation.[9] For each

[7]Similar results were found when using the Autometrics algorithm of Doornik (2009) which builds on the General to Specific modelling of Krolzig and D. F. Hendry (2001), instead of penalised regressions.

[8]Specifically, elastic net regressions choose a vector of coefficients β to minimise $\sum_i (y_i - x_i^T \beta)^2 + \lambda(\alpha \sum_i |\beta_i| + (1-\alpha)\sum_i \beta_i^2)$

[9]For a grid of possible values of λ, remove one observation from the data set, estimate an elastic net on the remaining data, calculate the forecast for the removed observation. Repeat this for all data points. The λ chosen is the one that minimises the mean squared forecast error.

relationship I investigate, the permutation procedure works as follows:

1. Fit an elastic net regression, which penalizes non-zero coefficients, and save the number of non-zero coefficients;
2. Randomly permute the financial market data series (the dependent variable), so that the moves in moments are not matched to the topic proportions which prevailed on that day;
3. Re-run the elastic net regression on the permuted data, saving the number of non-zero coefficients;
4. Repeat items 2. and 3. 500 times.

I compare the number of non-zero coefficients returned under the correct data (from 1.), with the distribution of non-zero coefficients returned under the randomly permuted data (from 2. and 3.). This comparison informs how important the topic proportions in explaining option-implied moments.

Firstly, the permutation procedure is applied using elastic net regressions that use all 180 topic time series (three publication types, each with sixty topic time series) as the independent variables, and, separately, the changes in the first, second, and third moments of the implied expectations distribution on the day of a Bank of England communication as the dependent variables. Figure 10 shows the results.

There is good evidence that the text is relevant for the first, second and third moments. That the text is related to movements in the first moment of expectations is perhaps not surprising. Indeed high-frequency identification around the ECB's Q&A has shown that important information for mean market expectations is released then (Leombroni et al. 2021). More interestingly, and the focus of this paper, is the evidence that the text is related to the second and third moments of expectations — and that the evidence for this link is almost as strong as it is for the first moment.

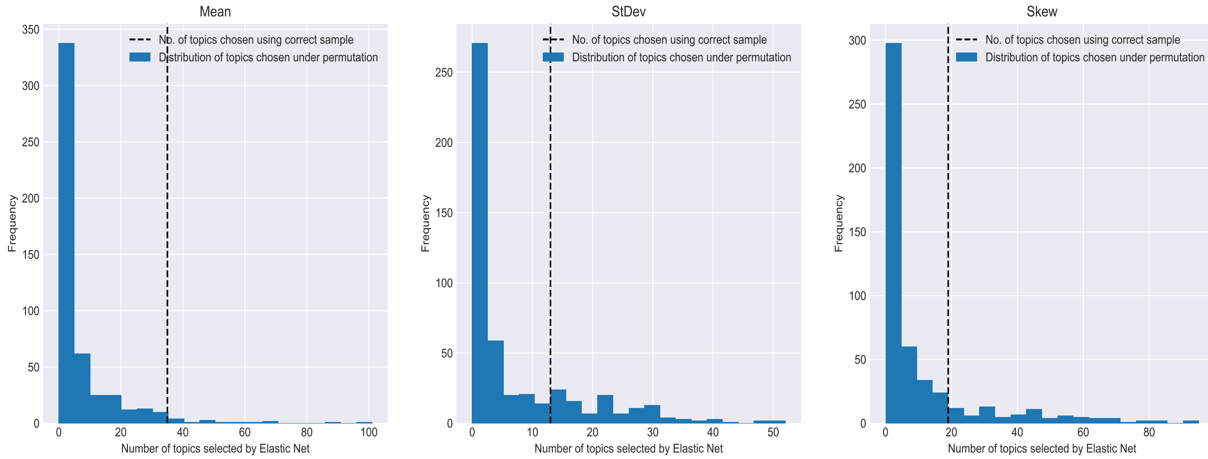

Fig. 10. Permutation test for all 180 topic time series on the first three moments

4.1.1. Investigating the Inflation Report's link to the second moment

HMT claim that the information contained in the Inflation Report is relevant for the long-term yields they study through its effect on the second moment of investors' expectations.

I investigate this claim using direct data on the second moment of expectations as calculated from option prices.

I find that, at first glance, there is evidence to support the hypothesis that the textual information in the IR is useful in explaining variation in the second moment of expectations. However, this finding is not robust. Following the findings of Tang (2019), that HMT's results are potentially sensitive to controlling for lagged topics, I control for the dynamics before engaging in the permutation exercise.

Specifically, I regress each topic on its own lags, and take the residual.[10] This residual is then used in the permutation exercise. If the causal link claimed by HMT, that the information in the IR on publication day directly effects the second moment of investors' distribution of expectations, then controlling for the information in IRs that were published in previous quarters should have no effect.

[10]Four lags are used as the data is mostly quarterly, but the result is robust to other lag specifications.

I find, in a result similar to the findings of Tang (2019), that these lags do matter. Indeed, the moderate evidence in favour of HMT's hypothesis concerning textual data in the IR vanishes once dynamics are accounted for. The evidence for this is displayed in Figure 11.

There may be other reasons that this result vanishes in the setting considered by this paper. One reason could be because the change in an option-implied moment is a far narrower measure of market impact. Much of the narrative information the Bank of England releases will affect the 10-year rate. HMT argue that uncertainty conveyed by the narrative information is the main driver of the 10-year rate, but they cannot control for narrative information concerning forward guidance or quantitative easing, both of which would impact on the 10-year rate in far more conventional ways.[11] In this paper, only narrative information that affects the moments specified by the one-year-ahead option-implied distribution is informative. Another reason for the differing results is that the type of uncertainty that manifests in one-year-ahead futures contracts — which this paper uses — may be smaller than that which operates at ten years ahead — which HMT focus on. One reason that can be ruled out is the different sample periods: this paper includes the period 2015-2018, whilst HMT's sample stops at 2015. Section 6.3 repeats the analysis for the period up to 2015 and finds similar results.

[11] The authors suggest that asset purchases and forward guidance are not driving the 10-year rate because the effect is driven by the economic conditions section of the Inflation Report. But this section can still indirectly inform whether or not asset purchases or forward guidance will be used by the Bank of England as policy responses to current economic conditions.

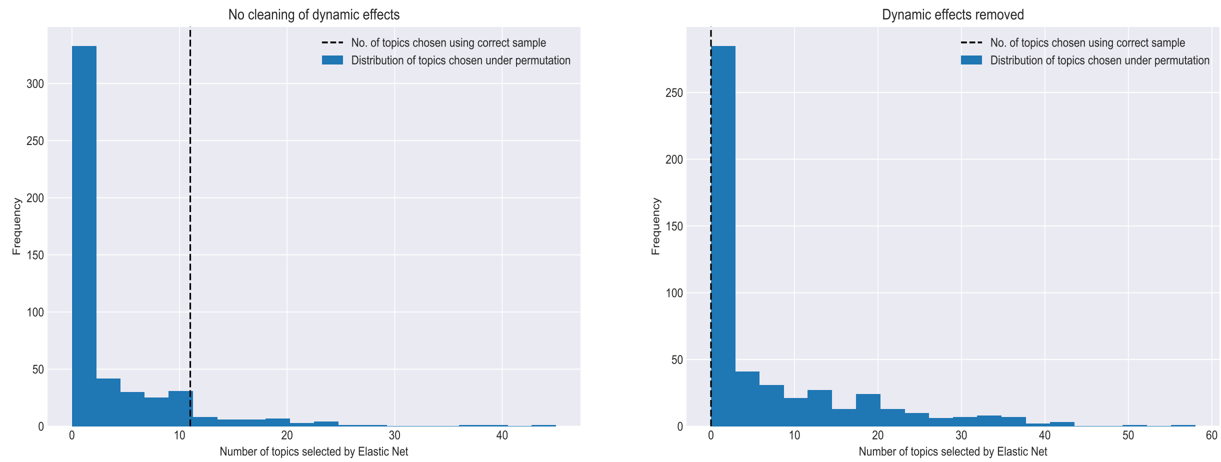

Fig. 11. Permutation test for Standard Deviation using uncleaned vs. cleaned data

In the following analyses, all topics have been stripped of any dynamic effects.

4.1.2. Standard Deviation

Given that there is evidence that narrative information affects the second moment of expectations of future interest rates, I investigate which publications are driving this effect. To do this, I test the topic proportions for each publication separately using the permutation test. The reason for treating the publications separately is due to the timing of the communications. The journalists who ask the questions during the Q&A have read the Inflation Report and heard the Introductory Statement before the Q&A starts. As a result, the questions that they ask are based on the information in the Inflation Report and Introductory Statement. Testing all the topic proportions together could result in topics from the Inflation Report being selected by the elastic net regression because they affect the topics that arise in the Q&A. Testing the publications separately allows the exercise to determine whether there is any information in the Q&A at all. However, this comes with the caveat that one cannot determine whether the Q&A matters on its own, or if it only matters because it serves to clarify points from the Inflation Report and the Introductory Statement.

Figure 12 shows the results of the permutation procedure where the elastic net regression is specified with the change in the second moment of the option-implied pdf as the dependent variable, and, separately, the 60 topic time series for each publication type as the independent variables.

The second moment is influenced almost entirely by the Statement. There is little evidence that either the Inflation Reports, or the Q&As have any effect at all on the second moment. This is in contrast to HMT's view that the narrative information in the Inflation Report informs uncertainty. HMT do not investigate the importance of either the Q & A or the Statement in their analysis.

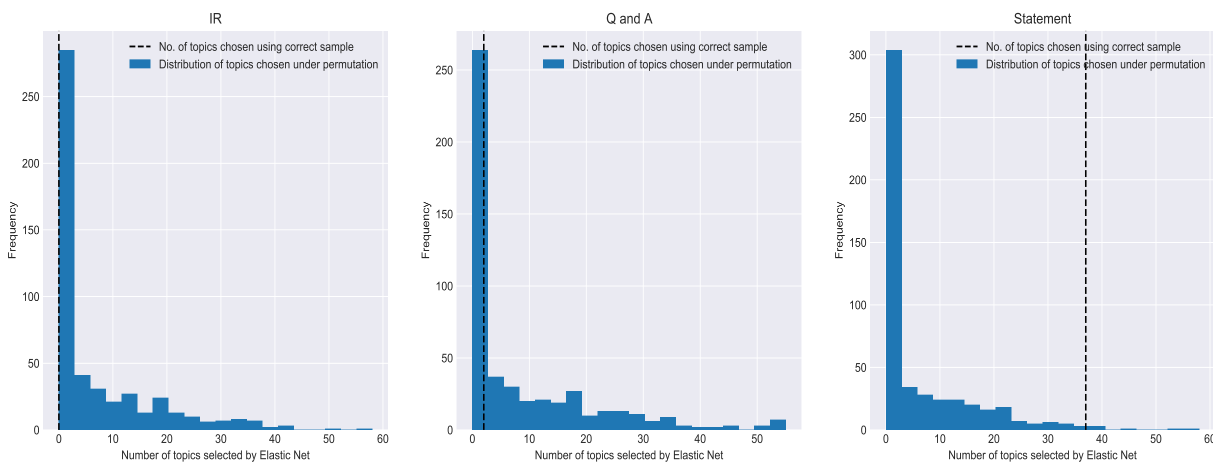

Fig. 12. Permutation test for Standard Deviation

4.1.3. Skew

I repeat the exercise for the third moment. Figure 13 shows the results of the permutation procedure where the elastic net regression is specified with the change in the third moment of the option-implied pdf as the dependent variable, and, separately, the 60 topic time series for each publication type as the independent variables.

The third moment is mostly influenced by the topic allocations present in the Statement and the Q & A. There is some evidence that the Inflation Report text influences the third moment.

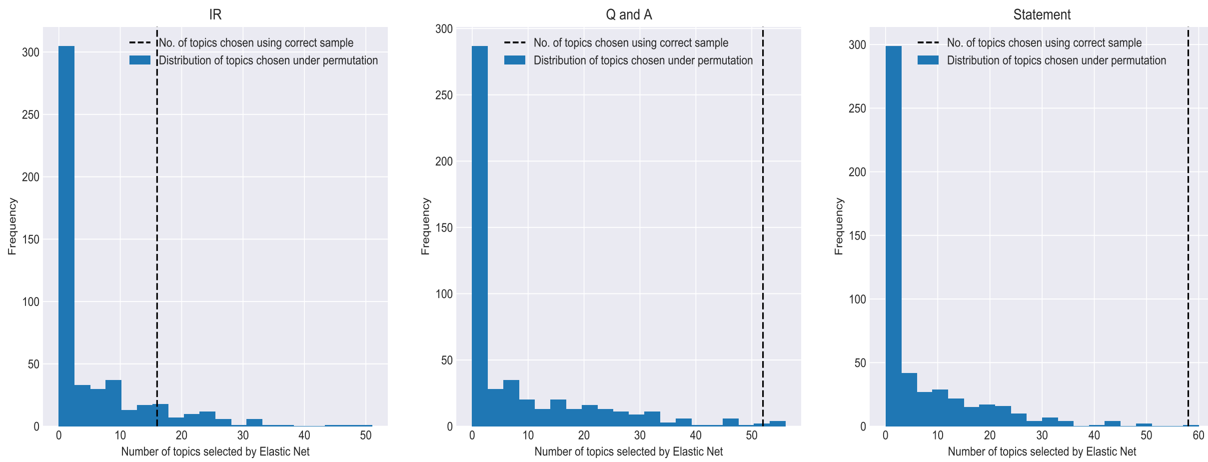

Fig. 13. Permutation test for Skew

4.1.4. Interpretation

These results suggest that the inclusion of the text from the Statement and the Q&A is important when performing analysis of central bank text. To focus on the Inflation Report is to miss the most informative publications for influencing higher order moments of expectations.

Whilst the above results do provide strong evidence that there is information in the Statement and the Q&A for explaining changes in higher order moments, that does not constitute a formal causal relationship.

Any causal interpretation relies on the text being unrelated to excluded factors that could influence the one-day changes in option implied moments. To the extent that I can, I have tried to purge the estimates of these omitted variables by orthogonalising with respect to previous texts and numerical information. Moreover, the text for the Inflation Report is pre-agreed and pre-written prior to the day of the release, and so cannot be influenced by events taking place on the day; although the same cannot be said of the Q&A. Furthermore, whilst decisions on interest rates are clearly correlated with the released text and the first moment of interest rates, it's not clear that they would inform the higher moments (and indeed decisions only coincide with our text in the latter part of the sample, which our results are robust to excluding see Appendix Section 6.3).

Nevertheless, the exercise above does not warrant causal interpretation. Text is rarely exogenous, and the above effects are not cleanly identified by natural experiment or otherwise.

4.2. Bootstrap exercise

Above, the permutation exercise revealed that the narrative information released by the Bank of England is informative for the second and third moments of one-year-ahead expectations of short-term interest rates. With respect to the second moment, only the Statement seems to be important. With respect to the third moment, both the the Q&A topic proportions and the Statement topics were informative. In both cases, there was no little or no evidence that the Inflation Report topic proportions had an effect.

However, the permutation exercise did not provide any information on how important each topic was relative to other topics. t-values are not possible to calculate when estimating penalised regressions without additional debiasing procedures (Chernozhukov et al. 2018). Furthermore, taking the variables with non-zero coefficients from the elastic net and then entering them into an OLS regression to calculate standard errors runs into the post-selection inference problem (Berk et al. 2013).

A bootstrap procedure, detailed in Tibshirani, Wainwright, and Hastie (2015), and used by HMT is adopted. 500 new samples are generated by drawing (with replacement) from the original data. For each new sample, a new elastic net regression is estimated, and the topic series with non-zero coefficients are recorded. The percentage of samples in which a given topic series is returned with a non-zero coefficient by the bootstrap exercise is used as a measure of how important that variable is in explaining the moves in market-implied moments.

4.2.1. Standard Deviation

In the case of the second moment, the permutation exercise indicated that the only topics that mattered were those derived from the Statement. Therefore, in the case in which the dependent variable is the change in the second moment, the bootstrap procedure is only applied to the relationship between the topic series of the Statement and the second moment.

Table 2 shows, for the top 15 most selected topics, the percentage of times a topic was selected in the bootstrap procedure, and the coefficient of that topic in the true-sample elastic net regression. If the topic was returned with a zero coefficient by the true-sample elastic net regression, NaN is displayed in the coefficient column.

It may be the case that one can always provide intuitive reasons why some topics are often selected or have a particular sign on their coefficient from the elastic net regressions, regardless of whether these intuitions are correct. Indeed, the mappings between the information released by the central bank, the signals that creates, and the ultimate market outcomes are highly complex and multidimensional, making intuitive explanations difficult. This caveat notwithstanding, many of the results in Table 2 are interpretable. I will examine one that stands out.

The most important topics for explaining movements in the second moment are Topic 4 and Topic 3. These topics could be characterised as "semantic uncertainty". They include words such as "may", "discuss", "think", "question", which reflect to what extent the Bank is couching its announcements with caveats and uncertainty. They are estimated to have positive signs, because as the Bank of England sounds more uncertain, investors also become more uncertain.

The intuitive nature of the most important topics, whilst not conclusive, is prima facie evidence that our methodology is is not merely picking up noise.

Table 2: Elastic net results for Statement text on the change in Standard Deviation

	Bootstrap %	Stems	Coefficient
Topic 4	0.98	think. can. look. will. know. thing. last. question. actual	156.19
Topic 3	0.974	may. section. reflect. factor. recent. weak. discuss. box. part	183.08
Topic 20	0.958	employ. labour. unemploy. work. number. hour. job. increas. market	173.45
Δ **Topic 16**	0.944	product. suppli. capac. demand. margin. spare. economi. crisi. slack	141.78
Δ **Topic 14**	0.94	hous. market. increas. activ. price. rise. mortgag. indic. recent	-122.67
Δ **Topic 23**	0.928	fall. reflect. chart. declin. fallen. past. part. larg. recent	129.68
Δ **Topic 29**	0.922	year. averag. around. past. next. expect. tabl. month. littl	-121.97
Δ **Topic 28**	0.922	sterl. uk. trade. export. import. net. exchang. depreci. good	145.84
Δ **Topic 25**	0.914	polici. monetari. committe. mpc. meet. bank. decis. maintain. set	104.00
Δ **Topic 26**	0.904	sector. survey. servic. output. suggest. manufactur. indic. privat. evid	-94.34
Topic 14	0.9	hous. market. increas. activ. price. rise. mortgag. indic. recent	-87.39
Topic 13	0.9	growth. continu. remain. demand. recoveri. domest. support. pace. grow	129.51
Topic 27	0.898	month. year. chart. rose. fell. annual. earlier. previou. compar	123.30
Topic 16	0.852	product. suppli. capac. demand. margin. spare. economi. crisi. slack	-78.73
Δ **Topic 22**	0.842	rate. interest. market. impli. offici. path. rise. expect. futur	81.70

4.2.2. Skew

In the case of the third moment, the permutation exercise indicated that topic series from both the Q&A and the Statement were important. Therefore, in the case in which the dependent variable is the change in the third moment, the bootstrap procedure is applied first to the relationship between the topic series of the Q & A and the third moment (Table 3), and then to the relationship between the topic series of the Statement and the third moment (Table 4).

Table 3: Elastic net results for Q&A text on the change in Skew

	Bootstrap %	Stems	Coefficient
Topic 4	0.948	think. can. look. will. know. thing. last. question. actual	-266.12
Δ Topic 9	0.934	will. time. adjust. come. much. might. need. economi. given	-499.01
Δ Topic 21	0.9	bank. credit. condit. financi. lend. money. fund. borrow. loan	387.89
Δ Topic 1	0.886	asset. bank. purchas. market. bond. yield. equiti. corpor. billion	-184.14
Δ Topic 14	0.86	hous. market. increas. activ. price. rise. mortgag. indic. recent	362.55
Topic 26	0.856	sector. survey. servic. output. suggest. manufactur. indic. privat. evid	108.68
Topic 12	0.856	effect. impact. govern. lower. fiscal. reduct. increas. reduc. public	111.47
Δ Topic 2	0.848	price. oil. import. energi. rise. good. increas. commod. higher	-113.41
Topic 19	0.846	growth. wage. cost. earn. pay. labour. pressur. higher. rise	116.44
Topic 15	0.846	inflat. target. cpi. pressur. rpix. domest. higher. expect. rise	352.23
Δ Topic 28	0.844	sterl. uk. trade. export. import. net. exchang. depreci. good	-148.00
Topic 27	0.838	month. year. chart. rose. fell. annual. earlier. previou. compar	-170.79
Topic 24	0.83	measur. estim. data. revis. use. account. differ. base. inform	291.54
Topic 29	0.826	year. averag. around. past. next. expect. tabl. month. littl	-58.51
Δ Topic 15	0.824	inflat. target. cpi. pressur. rpix. domest. higher. expect. rise	121.73

Table 4: Elastic net results for Statement text on the change in Skew

	Bootstrap %	Stems	Coefficient
Δ Topic 27	0.936	month. year. chart. rose. fell. annual. earlier. previou. compar	226.44
Topic 2	0.908	price. oil. import. energi. rise. good. increas. commod. higher	-179.08
Topic 4	0.892	think. can. look. will. know. thing. last. question. actual	-233.57
Δ Topic 16	0.862	product. suppli. capac. demand. margin. spare. economi. crisi. slack	-649.20
Δ Topic 20	0.836	employ. labour. unemploy. work. number. hour. job. increas. market	176.28
Topic 15	0.832	inflat. target. cpi. pressur. rpix. domest. higher. expect. rise	-400.53
Δ Topic 21	0.824	bank. credit. condit. financi. lend. money. fund. borrow. loan	368.64
Δ Topic 13	0.82	growth. continu. remain. demand. recoveri. domest. support. pace. grow	572.22
Topic 23	0.806	fall. reflect. chart. declin. fallen. past. part. larg. recent	1.27
Topic 25	0.77	polici. monetari. committe. mpc. meet. bank. decis. maintain. set	715.18
Δ Topic 2	0.77	price. oil. import. energi. rise. good. increas. commod. higher	-65.92
Δ Topic 8	0.762	report. point. august. februari. novemb. around. time. percentag. lower	189.26
Δ Topic 4	0.76	think. can. look. will. know. thing. last. question. actual	197.13
Topic 22	0.754	rate. interest. market. impli. offici. path. rise. expect. futur	-301.60
Δ Topic 3	0.746	may. section. reflect. factor. recent. weak. discuss. box. part	-92.66

Examining Tables 3 and 4, it is again possible to construct some intuitive stories around some of the results presented, assuaging fears that the Elastic Net process is producing nonsensical results.

The simplest stories are those than revolve around the effective lower bound (ELB). Figure 1 shows that there was little movement in the third moment of the option-implied pdfs until the 2008 financial crisis. This is because the Bank of England lowered rates to the ELB, truncating the distribution of future rates, and creating a strong positive skew. Any communication about when rates might rise off the ELB therefore influences the skew of the distribution.

The change in Topic 9, which might be labelled the "forward guidance" topic is one of the most important topics from the Q&A in explaining movements in the third moment. This could be because as the Bank speaks more about lift-off from ELB, the skew of the expected distribution of rates is affected. One might ascribe a similar story to Topic 22.

There is also good reason that Topic 20, the "labour market" topic is deemed important by the bootstrapping exercise. When guiding the market as to when the Bank of England was going to raise rates from the ELB, the Bank said that they would not raise rates until unemployment fell below %7.[12]

4.3. Dynamic Factor Model Analysis

Another way to deal with the high dimensionality of the regression problem is via a factor analysis. This method comes with the added benefit that one can explicitly model the dynamics of the textual factors. This addresses Tang (2019)'s finding that the topics of Bank of England inflation reports are predictable based on their past values, and means that the first stage stripping out of dynamic effects used for the Elastic Net procedure is not needed. It is not a surprise *per se* that central bank text is correlated over time as the themes central banks discuss are slow moving – but Tang (2019) finds that the R^2 of regressions relating text to changes in yields in HMT are reduced when past information is removed. This is not a feature of the data one would expect if past information had already been incorporated by the market. By explicitly modelling these dynamics, I can assuage fears that the effects found in the previous analysis are not coming from an external, slower moving, source than the text released on the day that I measure the change in market beliefs.

The dynamic factor model serves as a cross check to the results presented in the permutation exercise that: (i) the IR has little or no effect on higher moments, (ii) the second moment is primarily affected by the text of the Statement, and (iii) the third moment is affected by the text of the Statement and the Q&A.

Dynamic factor models have a long history in macroeconomic analysis, and have been used consistently to answer economic questions hamstrung by high dimensionality, and have more recently been used extensively in the nowcasting literature (Geweke 1977; Forni et al. 2000; Stock and Watson 2002a; Stock and Watson 2002b; Giannone, Reichlin, and Small 2008; Doz, Giannone, and Reichlin 2011). A review of some of the literature can be found in Stock and

[12]The Introductory Statement of the August 2013 Press Conference states that "the MPC intends not to raise Bank Rate above its current level of 0.5% at least until the Labour Force Survey headline measure of unemployment has fallen to a threshold of 7%".

Watson (2016).

The dynamic factor model that I will use, where the factors follow an AR(1) process, can be written:

$$y_{it} = \lambda_{01} + \lambda_i f_t + \epsilon_{it} \tag{2}$$

$$f_t = \alpha f_{t-1} + v_t \tag{3}$$

$$\epsilon_t \sim i.i.d.\mathcal{N}(0, \Sigma) \tag{4}$$

$$v_t \sim i.i.d.\mathcal{N}(0, \Phi) \tag{5}$$

I assume that Φ is diagonal, i.e. I impose cross sectional orthogonality, but allow for heteroskedasticity. f_t is a vector of five factors, which each develop according to an AR(1) process. The observable series, y_{it}, are the topic series and the financial market identified changes in higher moments.

The model is estimated via maxmimum likelihood using the methodology of Doz, Giannone, and Reichlin (2011), Bańbura, Giannone, and Reichlin (2011) and Bańbura and Modugno (2014). This methodology uses the EM algorithm to fit parameters and so is suited to our case with a large number of parameters to estimate.[13]

The variance-covariance matrix is estimated using quasi-maximum likelihood that is valid in the presence of misspecification. Intermediate steps within the calculation use the observed information matrix estimator of Harvey (1989).

This paper is interested in whether the factors — which capture the features of the textual data whilst reducing the dimensionality — are statistically significant in explaining the identified one day changes in higher moments from financial markets. Put more simply, we are concerned with the estimated $\hat{\lambda}_i$ vector for the equation where the change in higher moments is the dependent variable.

The estimated $\hat{\lambda}_i$ coefficients are reported in Table 5 for eight different model specifications.

[13]Of course, Bayesian estimation of dynamic factor models is possible as well and is often used, for example in Lopes and West (2004) and Jarociński and Lenza (2015).

The eight specifications come from estimating models separately for each of the three types of text, and jointly, for two different moments.

Table 5 tells a similar story to the Elastic Net exercise. Only one factor from the Inflation Report data is significant in explaining changes in the second moment. Zero factors from the Q&A are significant, and three factors from the Statement are significant. No factors from the Inflation Report data are significant in explaining changes in the third moment. Both the Q&A and Statement provide factors that are statistically significant for explaining movements in the third moment.

Table 5: Estimates of coefficients from a Dynamic Factor Model

	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	$\hat{\lambda}_5$
IR - var	0.049	-0.126	-0.034	0.00	-0.098**
	(0.222)	(-0.458)	(-0.324)	(0.00)	(-2.168)
Q & A - var	-0.023	-0.1	-0.009	-0.041	-0.014
	(-0.215)	(-0.76)	(-0.166)	(-0.104)	(-0.024)
Statement - var	-0.101***	-0.046**	-0.063**	-0.014	-0.023
	(-6.234)	(-2.073)	(-2.135)	(-0.677)	(-1.074)
Entire text - var	-0.074**	-0.018	-0.039***	-0.013	0.004
	(-1.964)	(-0.696)	(-2.941)	(-0.224)	(0.051)
IR - skew	-0.078	-0.129	0.001	-0.034	0.151
	(-0.783)	(-0.55)	(0.006)	(-0.425)	(0.469)
Q & A - skew	-0.015	0.1	0.01	0.06***	0.029
	(-0.085)	(0.726)	(0.056)	(2.965)	(0.058)
Statement - skew	0.082***	0.066***	-0.003	0.006	0.033*
	(4.315)	(5.036)	(-0.194)	(0.566)	(1.887)
Entire text - skew	-0.044***	-0.007	0.017	-0.063	-0.084
	(-14.867)	(-0.057)	(0.112)	(-0.935)	(-1.204)

t values in parentheses. ***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.1

5. Conclusion

Typically analysis of central bank communication focuses on influencing the first moment of expectations. Using option-price measures of the second and third moment of one-year-ahead expectations of short rates this paper suggests that communication is a major factor in determining higher moments of expectations.

Furthermore, I show that, in the case of the Bank of England, it is the Statement and the Q&A that are primarily driving the higher moments of investors' expectations, in contrast to the previous literature.

Whilst research into central bank communication using natural language processing tools is still in its early stages, the results presented in this paper show clear evidence that a significant amount of central bank communication is related to higher moments of expectations. Analysis of communication that does not consider this is missing an important aspect of central bank policy.

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6. Appendix

6.1. LDA

Latent Dirichlet Allocation (LDA), popularised by Blei, Ng, and Jordan (2003), is a probabilistic topic model used to reduce the dimensionality of text data.

In the economics literature it has been used on central bank text to examine transparency (Hansen, McMahon, and Prat 2017), on newspaper text for forecasting purposes (Larsen and Thorsrud 2019), and on economic journal text to examine whether economic research leads or lags developments in the economy (Lüdering and Winker 2016). Other projection methods used in the economics literature include counting instances of words contained in a pre-specified dictionary (Baker, Bloom, and Davis 2016), using single value decomposition on the document-term matrix in a process called Latent Semantic Analysis (S. Hendry and Madeley 2010), or reducing dimensionality by modelling the conditional probability of words given the surrounding words — often called "word-embeddings" (Soto 2021).

Before modelling, I pre-process the text data. This involves (i) removing words that are only one character long, (ii) removing common words (e.g. "it", "the") known as stopwords, and (iii) stemming the words using the Porter Stemmer. This last step reduces each word to its linguistic root. For example, both *recovery* and *recoveries* are reduced to *recoveri*. After pre-processing, the text data comprises of 1057406 stems, 5961 of which are unique.

The total corpus modeled is comprised of P paragraphs, which themselves are made up of a dictionary of V unique words. Each paragraph p is a collection of words $(w_{p,1}, ..., w_{p,N_p})$ where the order of the words is not considered (this is referred to as a bag-of-words model). There are K topics, each of which has a probability vector over the V terms $\beta_k \in \Delta^{V-1}$. Each paragraph has probability vector over the K topics $\theta_p \in \Delta^{K-1}$.

LDA assumes a specific mechanism through which each paragraph is created:

- For each topic $(k = 1, 2...K)$, independently draw a distribution over words (β_k) from a Dirichlet(η) distribution
- For each paragraph $(p = 1, 2...P)$, independently draw a distribution over topics (θ_p)

from a Dirichlet(α) distribution

- Then for each word in a given paragraph ($w_{n,p}$):
  - Randomly draw a topic ($z_{n,p}$) from the topic distribution assigned to that paragraph (θ_p)
  - Randomly draw a word from that topic's distribution of words ($\beta_{z_{n,p}}$)

The generative process described above defines a joint probability distribution over the observed data w and the latent variables θ, β, z. The joint distribution is

$$P(\beta, \theta, z, w) = \Big(\prod_p \prod_n P(w_{p,n}|z_{p,n}, \beta)\Big)\Big(\prod_p \prod_n P(z_{p,n}|\theta_p)\Big)\Big(\prod_p (P(\theta_p|\alpha)\Big)\Big(\prod_k P(\beta_k|\eta)\Big) \tag{6}$$

The inference problem is to compute the posterior distributions of words for each topic (β_k for all k), and the topic distribution for every paragraph (θ_p for all p), given the words I observe w, the number of topics K, and the hyperparameters on the Dirichlet priors α and η. This posterior distribution is

$$P(\beta, \theta, z|w) = \frac{P(\beta, \theta, z, w)}{P(w)} \tag{7}$$

The numerator of this fraction is the joint distribution defined above. This is simple to evaluate computationally given the values of the latent variables. The denominator is the probability of producing the set of words w under any topic model. Whilst in theory one could calculate this by summing the joint distributions over all possible configurations of the LDA topic structure, computationally this is infeasible (Blei 2012).

The researcher must then approximate the denominator. This paper uses a Gibbs Sampling algorithm from Griffiths and Steyvers (2004). The algorithm works by creating a Markov Chain, whose limiting distribution is equal to the distribution the researcher wants to approximate. Then, one can draw samples from the sequence of random variables produced by the Markov Chain in order to approximate the limiting distribution.

The procedure, explained in both Griffiths and Steyvers (2004) and Hansen, McMahon, and Prat (2017), first integrates out the θ and β terms, leaving only the topic allocations z in the sampling stage. The conditional distribution of the topic assignment of the nth word in paragraph p $z_{p,n}$ given the topics assigned to the other words $z^{-(p,n)}$ and the observed words w is

$$P(z_{p,n} = k | z^{-(p,n)}, w) \propto \frac{m_{k,w_{p,n}}^{-(p,n)} + \eta}{\sum_v m_{k,v}^{-(p,n)} + \eta V} (n_{p,k}^{-(p,n)} + \alpha) \tag{8}$$

Where $m_{k,v}^{-(p,n)}$ is the number of times word v is assigned to topic k excluding the word the algorithm is currently considering $w_{p,n}$, and $n_{p,k}^{-(p,n)}$ is the number of words in paragraph p assigned to topic k excluding the word the algorithm is currently considering.

This conditional distribution can be used as the sampling equation with which to approximate the full joint distribution. More specifically, the sampling procedure allocates some initial random assignment of words to topics, then uses the sampling distribution to produce the conditional distribution. Using the conditional distribution a new topic is drawn for the word $w_{p,n}$, the conditional distribution is updated, and the algorithm moves onto the next word. This process runs through every word in the document, and is repeated a large number of times. In the case of this paper, I discard the first 50 iterations, only sample every 50 iterations thereafter, and take 100 samples in total, of which the last 20 are kept. In total that makes 5050 iterations.

After a given iteration the predicted distributions β and θ are given by

$$\hat{\beta}_{k,v} = \frac{m_{k,v} + \eta}{\sum_v m_{k,v} + V\eta} \tag{9}$$

$$\hat{\theta}_{p,k} = \frac{n_{p,k} + \alpha}{\sum_k n_{p,k} + K\alpha} \tag{10}$$

Following Griffiths and Steyvers (2004) α is set to $\frac{50}{K}$, η to $\frac{200}{V}$ and K to 30. The number of topics K chosen by the researcher is an important input to the LDA process. Chang et al. (2009) show that as K increases, likelihood (model fit) improves, but the interpretability of the topics declines. K equal to 30 is chosen because it both provides a small enough topic space with which to analyse the data and produces intuitive topic word groupings. Nevertheless it is somewhat an arbitrary choice, and an area in which more research would be valuable.

6.2. *Application to Morris and Shin (2002)*

Section 4 demonstrated that the textual information released by the Bank of England is strongly related to investors' uncertainty regarding the economy. When considering the cases in which uncertainty rises after a Bank communication it is not possible, using the results presented, to say whether the Bank of England is merely communicating that the economy has become more uncertain, thus increasing uncertainty about future interest rates, or whether the Bank itself has communicated that it will be more erratic in the future.

Prima facie, it is not clear that a central bank would ever want to increase uncertainty regarding their future decisions. There are well documented costs to uncertainty, both theoretical (Bloom 2009) and empirical (Fernández-Villaverde et al. 2011; Baker, Bloom, and Davis 2016), and so it might seem likely to be optimal from a welfare standpoint if the central bank decreases uncertainty about its future decisions. Indeed, lower uncertainty is argued to be one of the main benefits of central bank transparency (Geraats 2002).

When looking for a framework to help explain why uncertainty may increase as a result of central bank communication, the obvious candidate is Morris and Shin (2002).

In a seminal paper, Morris and Shin (2002) show that precise communication is not always welfare-improving. Indeed, they show that in some cases, the central bank prefers to release less precise information to the public. The following section uses the surprises from option implied moments and additional data from surveys to provide evidence to support Morris and Shin's model.

The key part of the model is that central bank communication increases the accuracy of individual agents' assessments of the true state of the economy, but it will decrease the weight put on the agents' private information, thereby biasing the *average* assessment away from the true state. A sketch of their model, where possible using their notation, is presented below.

The economy is made up of a continuum of agents of measure 1. Each agent makes a choice, a_i. Agents have two objectives: (i) to make their choice of a_i close to the true, unknown, state of the economy θ, and (ii) to make their choice of a_i close to the other agents' choices.

An agent's payoff is given by:

$$u_i = -(1-r)(a_i-\theta)^2 - r\left(\int_0^1 (a_j-a_i)^2 dj - \int_0^1\int_0^1 (a_k-a_j)^2 dk dj\right) \tag{11}$$

Where r is the extent of strategic complementarities in actions and a_j is the action of another agent.

Agents do not know θ, and observe both a public and a private signal regarding its value. The public, y, and private, x_i, signals are both formed as linear combinations of the true state θ and a noise term which is normally distributed with zero mean.

$$\begin{aligned} y &= \theta + \eta \\ x_i &= \theta + \epsilon_i \\ \eta &\sim N(0, \sigma_\eta^2) \\ \epsilon_i &\sim N(0, \sigma_\epsilon^2) \end{aligned} \tag{12}$$

Taking the first order condition, agent i's optimal action given their information set I_i is a function of their own expectation of the state and the average action of the other players.

$$a_i(I_i) = (1-r)E_i(\theta) + rE_i(\bar{a}) \tag{13}$$

Morris and Shin show that there is a unique equilibrium in which agents' actions are a linear function of their two signals:

$$a_i(I_i) = \frac{\alpha y + \beta(1-r)x_i}{\alpha + \beta(1-r)} \tag{14}$$

Where α and β are the inverse of the noise variances, σ_η^2 and σ_ϵ^2 respectively.

Morris and Shin then ask what the impact on expected welfare is of α and β. Welfare

(W) is defined as the average of individual utilities, scaled by $\frac{1}{(1-r)}$.

$$
\begin{aligned}
W &= E\Big(-\int_0^1 (a_i-\theta)^2 di\Big) \\
&= -\frac{\alpha+\beta(1-r)^2}{(\alpha+\beta(1-r))^2}
\end{aligned}
\tag{15}
$$

Morris and Shin describe two results. First, (described in Morris and Shin (2002)) that social welfare is strictly locally decreasing in α, the precision of the central bank's signal, if and only if

$$\alpha < \beta(1-r)(2r-1) \tag{16}$$

And second, (described in Morris, Shin, and H. Tong (2006)) that if the central bank must choose between releasing a signal, and not releasing one at all (equivalent to choosing $\alpha = 0$), then it is welfare maximising to not release the signal if and only if

$$\alpha < \beta(2r-1) \tag{17}$$

Of course, one could write down other models in which it is optimal to increase uncertainty. Possibly the Central Bank is worried about its reputation, and so prefers to be ambiguous in order to avoid a cost of reneging on its published plans. All the same, this paper takes the Morris and Shin model seriously, and aims to shed light on it.

Morris and Shin's insight is that in both of the cases described by equations 16 and 17, under certain parameters welfare is *increased* if the central bank is *more* ambiguous, i.e. welfare is decreasing in transparency.

Clearly, since $r < 1$, equation (7) is harder to satisfy than equation (8). And indeed the criticism of Svensson (2006) is that the parameters needed for equation 16 to hold are unlikely to arise.[14]

Nonetheless, equations (7) and (8) reveal that if information is not welfare-improving, it is when α is low relative to β. In other words, if σ_η is high relative to σ_ϵ, then the central bank

[14] He noted two necessary conditions that follow if the inequality in equation 16 holds: $r \in (0.5, 1)$, and $\frac{\sigma_\epsilon^2}{\sigma_\eta^2} \leqslant \frac{1}{8}$, which he argues are unlikely to be fulfilled.

(since the central bank is assumed to want to maximise the Social Welfare Function) is more likely to exhibit communication that increases uncertainty, either by being more ambiguous at the margin or by not releasing information at all.

One caveat to this, is that in Morris and Shin (2002), any signal from the Central Bank leads to a decrease in the posterior cross section variance of a_i. The cross sectional variance can be written:

$$Var(a_i) = \left(\frac{\beta(1-r)}{\alpha + \beta(1-r)} \right)^2 \frac{1}{\beta} \tag{18}$$

Clearly, if $\alpha > 0$, i.e. a signal is released by the Central Bank, then cross sectional variance falls.

The evidence presented in this paper shows that the variance of beliefs often increases following a signal. This can be rationalised by realising that the Morris and Shin world is a one-shot game word, in which there are no prior beliefs about α. If, instead, agents had a common prior α_0, then the released α, if lower than the prior, will lead to increased dispersion.[15]

The above discussion of the model leads to a simple and testable prediction: that the Bank of England is more likely to choose to produce communication that leads to an increase in market uncertainty (because it is welfare-improving to do so) if σ_ϵ is low, i.e. if private sector beliefs are clustered.

Using the surprises constructed before as a measure of how ambiguous the Bank of England chooses to be, and the variance or range of the one-year-ahead expectations of interest rates from the Reuters survey of economists as a proxy for σ_ϵ^2, the hypothesis can be taken to the data.[16]

[15]This would not require agents to update fully to the new value of α of course, any convex combination of α_0 and α will cause an increase in dispersion if $\alpha < \alpha_0$.

[16]The Reuters survey is a survey of professional economists: primarily economist at financial institutions. Each economist provides their forecasts of the Bank of England Bank Rate (the primary short term interest rate instrument) at various horizons. The survey was previously conducted at a quarterly frequency, but is monthly in the latter part of the sample. The survey covers a large number of forecasters. In the survey for forecasting Q4 2019 Bank Rate, there were 93 potential respondents, of whom 28 did not submit forecasts in Q4 2018 as a one-year ahead forecast.

Figure 14 shows the mean one-year-ahead forecast for Bank Rate given by the Reuters survey, and the variance of responses around that mean.

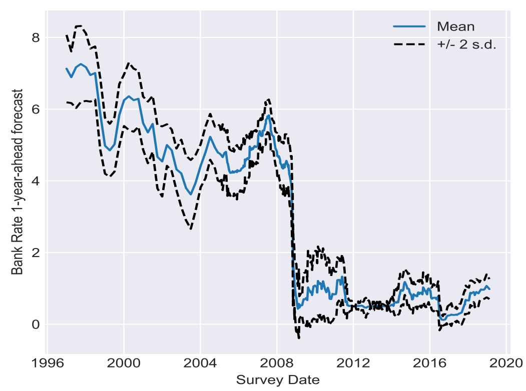


Fig. 14.

A simple OLS regression of the following form should, if the inequalities in Equations 16 & 17 hold or come close to holding, show a negative coefficient on the variance of private expectations.

$$s_t = \gamma_0 + \gamma_1 \hat{\sigma}^2_{\epsilon,t-1} + u_t \tag{19}$$

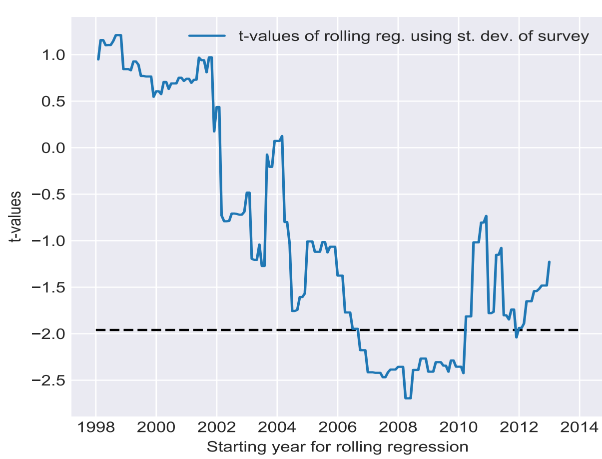
Where s_t is the communication surprise as defined previously, and $\hat{\sigma}^2_{\epsilon,t-1}$ is a proxy for the variance of private sector beliefs from the Reuters survey.

Across the whole sample there is no evidence of any relationship (Table 6, regressions (i) and (ii)). This is in line with Svensson's argument that the Morris and Shin inequalities are unlikely to hold. Nevertheless, there is evidence that the negative relationship predicted by the Morris and Shin inequalities holds during the Great Recession and its aftermath (Table 6, regressions (iii) and (iv)). It is easier to see this relationship in a rolling regression. Figure 15 shows that the negative relationship is strongest in 6-year regressions that start in 2008 (i.e. in the period 2008-2014).

Table 6: Regression results

	Dependent variable: s_t (narrative surprise)			
	(i)	(ii)	(iii)	(iv)
Constant	✓	✓	✓	✓
$\hat{\sigma}^2_{\epsilon,t-1}$ (Survey standard deviation)	-0.007		-0.08**	
	(-0.29)		(-2.35)	
$\hat{\sigma}^2_{\epsilon,t-1}$ (Survey range)		-0.0008		-0.02*
		(-0.13)		(-1.80)
Sample period	1998-2019	1998-2019	2008-2014	2008-2014

t-values in parentheses. ***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.1



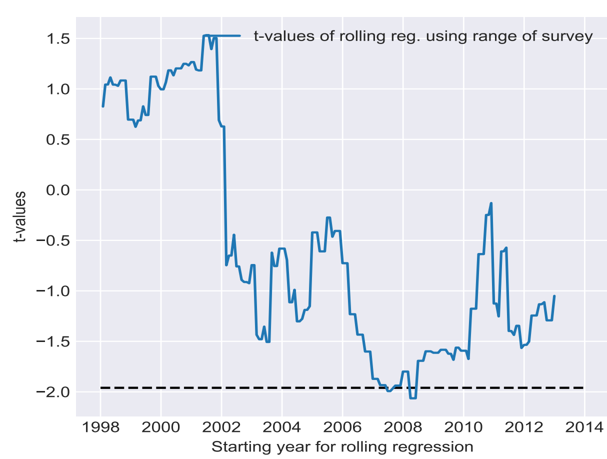


Fig. 15. Six year rolling regression t-values of Equation 19

The conditions needed for more ambiguous communication to be welfare improving occur over this period because the value of $\frac{\beta}{\alpha}$ is very large.

Figure 16 shows the inverse variance and range of the one-year-ahead forecasts for Bank rate from the Reuters survey.[17] Estimates of β are much higher in the 2011-2015 period, because the variance of the expectations around future interest rates (as a result of a low variance about future states of the economy) collapsed.

The relevant question to ask is if the ratio between β and α rose enough to cause equations 16 and 17 to hold, or become close to holding, during this period. There is strong evidence that β rose considerably, but it is not possible to independently show that α did not rise commensurately over the same period. Nonetheless, the large increase in the estimates of β do dampen the criticism of Svensson (2006), that it would be unlikely for β to be over eight times larger than α. In some data points β is infinite, as the private sector beliefs formed around a single point (for the purposes of Figure 16 these points have been replaced by the next highest value). Thus if α is defined at all, then both equations 16 and 17 will hold.

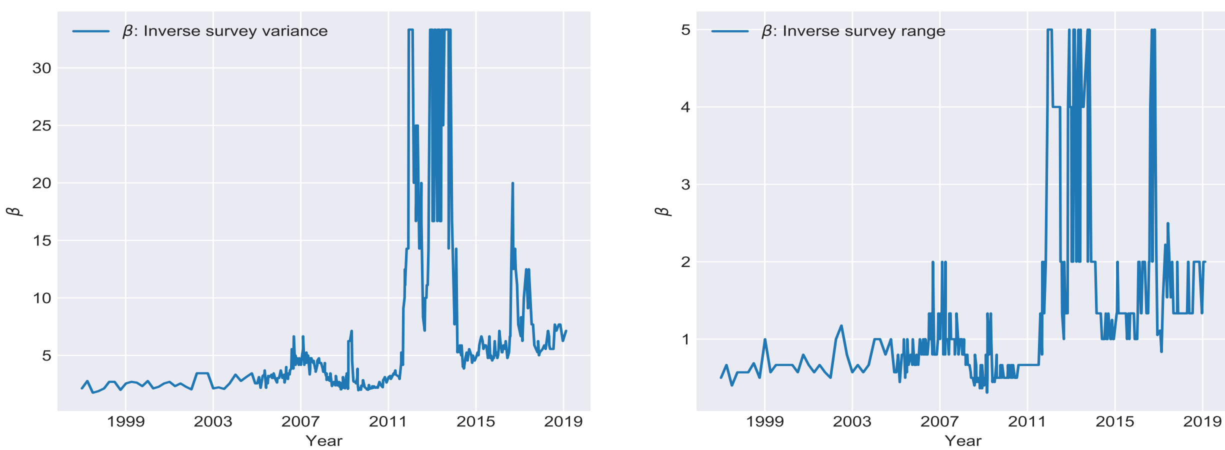


Fig. 16. Estimates of β from the Reuters survey of economists

Thus, this paper provides direct evidence to support Morris and Shin (2002). The period 2008-2014, which was characterised by historically low rates and clustered expectations of future rates, led to led to conditions such that it was possible for the Morris and Shin inequalities to hold (Figure 15). Moreover, the evidence suggests that the Morris and Shin inequalities

[17] Occasions where the variance or range was zero have been replaced by the lowest non-zero variance or range to avoid undefined values of β

came closer to holding because of a sharp rise in β, or in other words a collapse in the variation of private sector expectations (Figure 16). As a result, precise information may have become welfare decreasing, leading the Bank of England to at times produce communication that was more likely to increase uncertainty.

6.3. *Robustness to 'Super Thursday'*

From August 2015 onward the Bank of England began making a policy announcement and releasing the associated minutes to that decision on the same day as the Inflation Report.

The sample used in this paper runs from 1998 to 2018. A potential flaw in the results presented in Section 4 is that the "communication" effect picked up is driven by the post 2015 regime. The policy announcement reveals information about the central bank's reaction function. For example, a particularly surprising policy change may inform market traders of the central bank's erratic nature, and lead them to increase the variance of their expected future policy distributions.

To investigate this, I run the tests from Section 4 on just the pre August 2015 sample. The results from the pre 2015 sample broadly corroborate the full sample results in Section 4. Figure 17 shows that the only form of communication that matters for the second moment is the Statement in the pre-2015 period. Figure 18 shows strong evidence that the topic proportions in the Q&A influence the third moment, and little evidence for an effect from the Inflation Report. One result that does seem to be sensitive to the pre 2015 period sample is the effect of the Statement on the third moment. Over the entire sample the Statement had a strong effect on the third moment - this seems to disappear once the post Augsut 2015 sample is excluded.

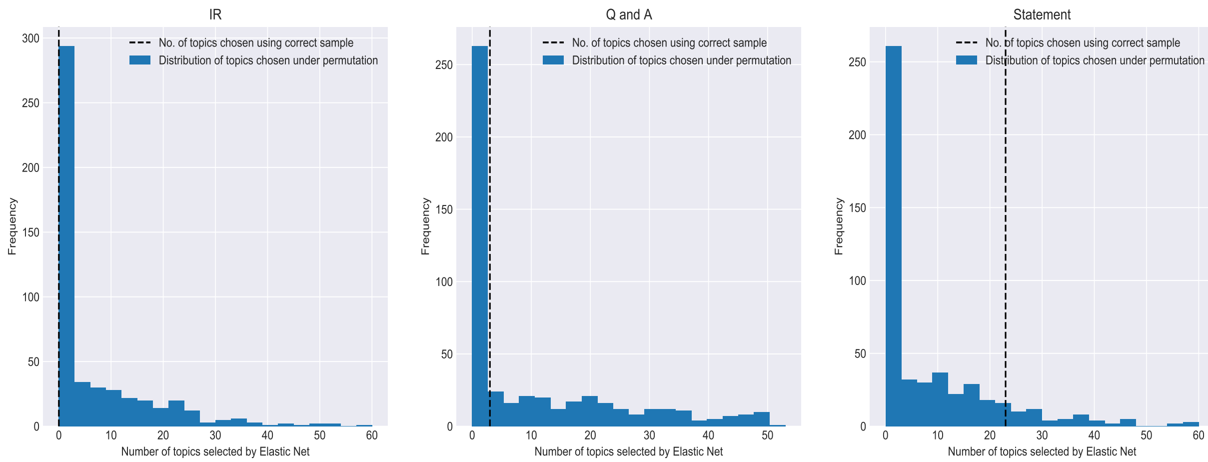


Fig. 17. Pre August 2015: Standard Deviation Elastic Net permutation test

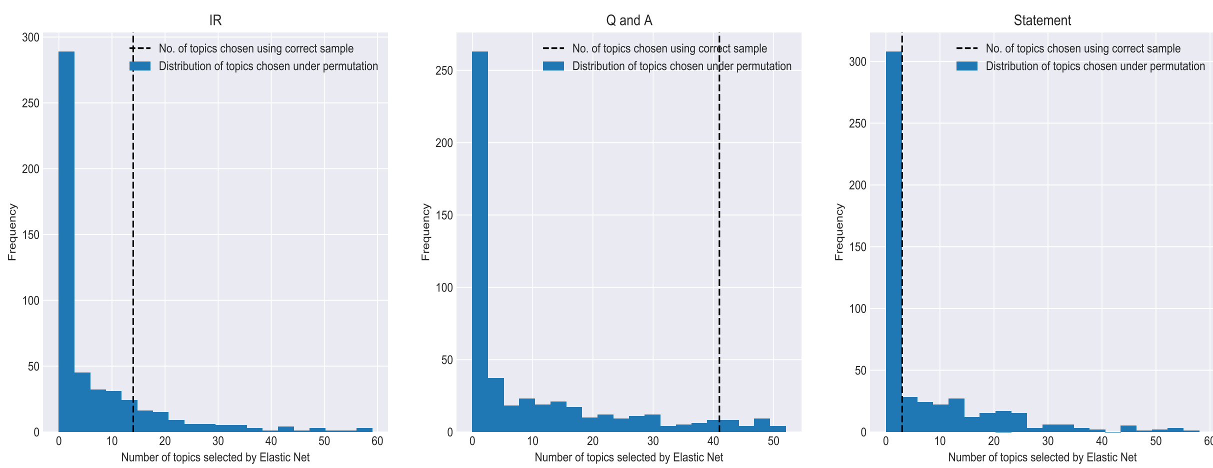


Fig. 18. Pre August 2015: Skew Elastic Net permutation test

	Topic 0		Topic 1		Topic 2		Topic 3		Topic 4		Topic 5		Topic 6	
1	household	0.132	asset	0.08	price	0.35	may	0.093	think	0.061	term	0.2	risk	0.117
2	spend	0.103	bank	0.077	oil	0.058	section	0.081	can	0.029	expect	0.179	committe	0.054
3	incom	0.079	purchas	0.055	import	0.044	reflect	0.068	look	0.024	near	0.065	outlook	0.053
4	consumpt	0.069	market	0.046	energi	0.041	factor	0.057	will	0.021	remain	0.057	uncertainti	0.053
5	consum	0.063	bond	0.033	rise	0.033	recent	0.053	know	0.02	medium	0.046	balanc	0.05
6	real	0.062	yield	0.027	good	0.029	weak	0.04	thing	0.02	short	0.036	central	0.034
7	save	0.033	equiti	0.027	increas	0.026	discuss	0.04	last	0.018	outlook	0.029	view	0.033
8	increas	0.025	corpor	0.027	commod	0.025	box	0.035	question	0.017	littl	0.029	judg	0.031
9	debt	0.021	billion	0.024	higher	0.025	part	0.031	actual	0.015	consist	0.029	judgement	0.029
10	futur	0.02	financ	0.021	cost	0.023	past	0.03	happen	0.014	continu	0.024	downsid	0.027
11	confid	0.018	financi	0.019	food	0.019	page	0.03	quit	0.013	longer	0.024	possibl	0.024
12	sale	0.017	stock	0.016	futur	0.017	temporari	0.018	cours	0.012	level	0.019	rang	0.021
13	wealth	0.017	debt	0.016	retail	0.017	associ	0.016	mean	0.011	measur	0.018	prospect	0.02
14	may	0.016	investor	0.014	ga	0.017	underli	0.016	peopl	0.011	although	0.018	overal	0.018
15	retail	0.015	increas	0.014	pass	0.015	explain	0.016	reason	0.011	broadli	0.012	project	0.018
16	ratio	0.014	govern	0.014	non	0.012	addit	0.012	tri	0.01	indic	0.012	around	0.018
17	current	0.012	issuanc	0.014	input	0.011	develop	0.011	big	0.01	rise	0.012	consider	0.017
18	financi	0.01	spread	0.013	servic	0.01	persist	0.011	differ	0.01	run	0.012	upsid	0.016
19	expenditur	0.009	reserv	0.013	produc	0.009	relat	0.01	want	0.009	ahead	0.011	greater	0.014
20	level	0.009	gilt	0.013	contribut	0.008	boost	0.01	clear	0.008	close	0.011	outcom	0.014

Table 7: Topics 0 - 6: Stems and probabilities

	Topic 7		Topic 8		Topic 9		Topic 10		Topic 11		Topic 12		Topic 13	
1	growth	0.335	report	0.145	will	0.133	invest	0.134	chang	0.097	effect	0.065	growth	0.104
2	gdp	0.092	point	0.106	time	0.051	busi	0.084	will	0.063	impact	0.038	continu	0.09
3	quarter	0.091	august	0.066	adjust	0.046	compani	0.074	affect	0.056	govern	0.037	remain	0.083
4	slow	0.056	februari	0.063	come	0.033	capit	0.056	can	0.037	lower	0.032	demand	0.064
5	output	0.044	novemb	0.062	much	0.031	may	0.054	depend	0.034	fiscal	0.032	recoveri	0.056
6	weaker	0.032	around	0.05	might	0.028	demand	0.034	impact	0.033	reduct	0.027	domest	0.033
7	stronger	0.026	time	0.048	need	0.026	level	0.031	extent	0.032	increas	0.026	support	0.028
8	trend	0.02	percentag	0.045	economi	0.019	stock	0.027	rel	0.032	reduc	0.026	pace	0.026
9	slowdown	0.02	lower	0.043	given	0.019	profit	0.025	influenc	0.025	public	0.026	grow	0.023
10	quarterli	0.016	higher	0.035	mean	0.018	increas	0.021	tend	0.023	year	0.025	weak	0.021
11	somewhat	0.013	start	0.032	period	0.017	rel	0.021	develop	0.022	plan	0.022	pick	0.02
12	strong	0.013	averag	0.029	difficult	0.015	reduc	0.02	factor	0.022	overal	0.02	eas	0.019
13	grew	0.012	slightli	0.018	case	0.015	firm	0.02	exampl	0.021	offset	0.019	gradual	0.019
14	slightli	0.012	may	0.017	occur	0.014	uncertainti	0.017	movement	0.02	cut	0.017	strong	0.018
15	activ	0.011	day	0.017	face	0.013	rais	0.013	effect	0.019	budget	0.016	subdu	0.018
16	estim	0.011	level	0.014	possibl	0.012	improv	0.012	therefor	0.013	tax	0.015	modest	0.016
17	half	0.01	littl	0.014	process	0.012	inventori	0.012	determin	0.013	announc	0.015	although	0.016
18	tabl	0.009	chart	0.013	far	0.011	low	0.008	gener	0.012	nomin	0.015	recov	0.014
19	pick	0.009	run	0.011	place	0.011	exampl	0.008	directli	0.01	result	0.014	strengthen	0.013
20	third	0.009	index	0.01	reason	0.011	aggreg	0.007	sensit	0.01	higher	0.013	robust	0.013

Table 8: Topics 7 - 13: Stems and probabilities

	Topic 14		Topic 15		Topic 16		Topic 17		Topic 18		Topic 19		Topic 20	
1	hous	0.095	inflat	0.416	product	0.094	economi	0.072	project	0.158	growth	0.106	employ	0.079
2	market	0.067	target	0.098	suppli	0.079	euro	0.056	forecast	0.115	wage	0.091	labour	0.072
3	increas	0.047	cpi	0.069	capac	0.068	unit	0.055	period	0.076	cost	0.084	unemploy	0.068
4	activ	0.036	pressur	0.037	demand	0.052	area	0.05	mpc	0.061	earn	0.052	work	0.055
5	price	0.033	rpix	0.022	margin	0.036	world	0.045	central	0.061	pay	0.051	number	0.033
6	rise	0.033	domest	0.017	spare	0.033	global	0.042	chart	0.046	labour	0.042	hour	0.032
7	mortgag	0.031	higher	0.015	economi	0.033	countri	0.032	assum	0.04	pressur	0.038	job	0.025
8	indic	0.025	expect	0.015	crisi	0.03	state	0.029	assumpt	0.035	higher	0.028	increas	0.024
9	recent	0.024	rise	0.014	slack	0.03	activ	0.028	path	0.025	rise	0.021	market	0.024
10	may	0.023	remain	0.013	potenti	0.029	prospect	0.028	condit	0.019	product	0.021	peopl	0.022
11	equiti	0.021	close	0.012	compani	0.026	uk	0.027	horizon	0.018	increas	0.017	averag	0.018
12	level	0.019	vat	0.012	degre	0.024	kingdom	0.024	show	0.016	real	0.016	particip	0.017
13	low	0.015	inflationari	0.01	level	0.023	market	0.019	end	0.016	unit	0.016	time	0.015
14	valu	0.015	persist	0.009	output	0.023	econom	0.017	outturn	0.016	settlement	0.015	may	0.014
15	properti	0.015	fall	0.009	pressur	0.021	emerg	0.017	profil	0.015	recent	0.014	rise	0.013
16	although	0.015	judg	0.009	within	0.021	develop	0.015	shown	0.014	pick	0.011	staff	0.013
17	number	0.012	rpi	0.008	pre	0.02	financi	0.013	throughout	0.013	nomin	0.011	equilibrium	0.012
18	risen	0.012	impact	0.007	recess	0.02	major	0.013	probabl	0.013	may	0.01	lf	0.012
19	associ	0.011	push	0.007	weak	0.015	concern	0.013	impli	0.012	subdu	0.01	forc	0.011
20	suggest	0.011	extern	0.007	extent	0.012	outlook	0.012	base	0.011	contribut	0.01	popul	0.011

Table 9: Topics 14 - 20: Stems and probabilities

	Topic 21		Topic 22		Topic 23		Topic 24		Topic 25		Topic 26		Topic 27	
1	bank	0.099	rate	0.424	fall	0.135	measur	0.073	polici	0.093	sector	0.124	month	0.097
2	credit	0.078	interest	0.113	reflect	0.097	estim	0.07	monetari	0.056	survey	0.112	year	0.073
3	condit	0.052	market	0.074	chart	0.094	data	0.065	committe	0.056	servic	0.065	chart	0.051
4	financi	0.046	impli	0.03	declin	0.059	revis	0.056	mpc	0.053	output	0.063	rose	0.05
5	lend	0.04	offici	0.029	fallen	0.054	use	0.034	meet	0.039	suggest	0.058	fell	0.049
6	money	0.038	path	0.026	past	0.039	account	0.029	bank	0.031	manufactur	0.041	annual	0.041
7	fund	0.033	rise	0.02	part	0.037	differ	0.024	decis	0.026	indic	0.032	earlier	0.029
8	borrow	0.03	expect	0.019	larg	0.031	base	0.024	maintain	0.023	privat	0.031	previou	0.023
9	loan	0.021	futur	0.014	recent	0.029	inform	0.021	set	0.022	evid	0.024	compar	0.023
10	deposit	0.02	forward	0.012	sharpli	0.023	weight	0.018	econom	0.017	agent	0.021	septemb	0.019
11	broad	0.02	basi	0.011	lower	0.022	suggest	0.016	provid	0.016	report	0.019	june	0.019
12	avail	0.017	bank	0.011	sharp	0.02	indic	0.016	vote	0.016	busi	0.018	sharpli	0.018
13	tighten	0.015	curv	0.01	rel	0.019	current	0.015	member	0.014	region	0.017	januari	0.018
14	sheet	0.012	low	0.009	much	0.018	compon	0.014	stimulu	0.014	industri	0.015	decemb	0.016
15	lender	0.012	chart	0.009	follow	0.017	chang	0.014	appropri	0.014	construct	0.013	volatil	0.015
16	improv	0.012	unchang	0.008	share	0.015	provid	0.013	note	0.012	consist	0.013	last	0.015
17	corpor	0.011	lower	0.008	risen	0.014	nation	0.012	economi	0.011	recent	0.012	march	0.015
18	cost	0.01	move	0.008	mid	0.014	publish	0.011	stabil	0.011	accord	0.011	index	0.014
19	spread	0.01	particip	0.008	despit	0.013	gdp	0.01	rate	0.01	balanc	0.011	octob	0.014
20	secur	0.01	follow	0.008	earli	0.013	previous	0.009	immedi	0.01	data	0.011	level	0.014

Table 10: Topics 21 - 27: Stems and probabilities

	Topic 28		Topic 29	
1	sterl	0.092	year	0.225
2	uk	0.083	averag	0.089
3	trade	0.073	around	0.078
4	export	0.07	past	0.054
5	import	0.069	next	0.048
6	net	0.049	expect	0.048
7	exchang	0.044	tabl	0.04
8	depreci	0.031	month	0.039
9	good	0.024	littl	0.039
10	appreci	0.021	broadli	0.039
11	account	0.019	ago	0.026
12	domest	0.018	remain	0.025
13	deficit	0.017	slightli	0.024
14	demand	0.017	half	0.015
15	kingdom	0.017	recent	0.014
16	world	0.016	extern	0.012
17	current	0.016	close	0.011
18	eri	0.014	flat	0.011
19	contribut	0.014	respond	0.011
20	effect	0.013	ahead	0.011

Table 11: Topics 28 - 29: Stems and probabilities

Mark My Words: The Transmission of Central Bank Communication to the General Public via the Print Media*

Tim Munday[†], James Brookes[‡]

Abstract

We ask how central banks can change their communication in order to receive greater newspaper coverage. We write down a model of news production and consumption in which news generation is endogenous because the central bank must draft its communication in such a way that newspapers choose to report it, whilst still retaining the message the central bank wishes to convey to the public. We use our model to show that standard econometric techniques that correlate central bank text with measures of news coverage in order to determine what causes central bank communication to be reported on will likely prove to be biased. We use computational linguistics combined with an event-study methodology to measure the extent of news coverage a central bank communication receives, and the textual features that might cause a communication to be more (or less) likely to be considered newsworthy. We consider the case of the Bank of England, and estimate the relationship between news coverage and central bank communication implied by our model. We find that the interaction between the state of the economy and the way in which the Bank of England writes its communication is important for determining news coverage. We provide concrete suggestions for ways in which central bank communication can increase its news coverage by improving readability in line with our results.

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1. Introduction

Central Bank communication to the general public is important. The control of household and firm expectations, particularly when operating monetary policy at or close to the effective lower bound, can in theory be a powerful tool for modern central bankers. In addition, central banks also have a democratic obligation to speak to the general public (Binder 2017a). Central bank power, legitimacy, and in many cases independence, are granted by the public under the tacit agreement that the central bank remains accountable. As a result, communication to the public has been part of a growing body of research since Blinder, Ehrmann, Fratzscher, De Haan, and Jansen (2008) and Blinder (2009).

The provision of information to households and firms can have real effects on the economy. Randomised Controlled Trials (RCTs), where a treatment group is given information about an economic variable (typically inflation), show significant effects in the survey respondents' expectations and subsequent actions in households (Coibion, Georgarakos, Gorodnichenko, and Van Rooij 2019; Kryvtsov and Petersen 2021) and firms (Coibion, Gorodnichenko, and Kumar 2018; Coibion, Gorodnichenko, and Ropele 2020).

However notwithstanding the RCT evidence that communication can have substantial effects on the economy as a policy tool, direct communication from central banks to the public has had an "abysmal track record" of influencing expectations (Coibion, Gorodnichenko, Kumar, and Pedemonte 2020) despite central banks' best efforts. Consumers and firms (i) know little about the central bank and their objectives (Van der Cruijsen, Jansen, De Haan, et al. 2015; Haldane and McMahon 2018), (ii) pay scant attention to inflation dynamics in low-inflation environments (Candia, Coibion, and Gorodnichenko 2020; Cavallo, Cruces, and Perez-Truglia 2017), (iii) don't react to monetary policy announcements (D'Acunto, Hoang, and Weber 2020), and (iv) rarely if ever read monetary policy reports or other forms of direct communication (Kumar, Afrouzi, Coibion, and Gorodnichenko 2015).

Nonetheless, survey evidence (Haldane and McMahon 2018; Bholat, Broughton, Ter Meer, and Walczak 2019), and theoretical analysis (Haldane, Macaulay, and McMahon 2020) has suggested that altering aspects of communication can overcome some of these problems of communication to the general public.

Given the lack of *direct* engagement with central bank communication, reaching the public via the print media has become a route of interest for central banks looking to communicate. There is evidence that the media's interpretation of central bank communication can move financial markets (Hayo and Neuenkirch 2012; Hendry 2012), and that professional forecasters predominantly rely on media reports to process central bank news (Hayo and Neuenkirch 2015). Turning to communication with the general public, Blinder and Krueger (2004) find that TV and newspapers are the two top sources for economic information for the general public, and Larsen, Thorsrud, and Zhulanova (2021) provide evidence that news topics are good predictors of households inflation expectations. But the survey evidence is somewhat mixed as to how effective central bank communication is at altering consumer beliefs when filtered through the news media (Coibion, Gorodnichenko, and Weber 2019; Lamla and Vinogradov 2019). The policy question is then how to draft communication such that it receives the news coverage the central bank desires, whilst retaining the important messages that we know from RCTs can have large effects on agents, and therefore the real economy.

We taken as given the desire to communicate to the public, given the large potential affects it can have on the real economy (as evidenced by RCTs). Further, we are not concerned with *what* central banks communicate. The messages that central banks want to convey are those that help them achieve their mandates, whether that is messaging regarding the future path of interest rates, or their reaction functions, or warnings against cryptocurrency. We are concerned with *how* to frame these messages such that they reach their intended audience.

To that end, the question that this paper endeavours to answer is how to construct communication that receives media coverage. This problem is not trivial since the media is not a straight-forward conduit for central bank communication. Newspapers can write on many topics, and will optimally choose to produce news that ensures their readers' attention. As a result, the problem of the central bank is to draft its communication in such a way that newspapers choose to report it, whilst still retaining the key messages it wishes to convey to the public.

The large potential real economy effects of communication to the public combined with democratic obligations have meant that most central banks expend considerable effort talking to the public. That said, much central bank communication is not meant for the public and is directed at other actors, often the financial markets. This paper focuses solely on communication to the public, given its relatively small importance in academic literature compared to communication to financial markets (Blinder, Ehrmann, Fratzscher, De Haan, and Jansen 2008).

We are the first paper to develop a model in which the central bank, the newspapers and the agents in the economy produce and consume news (respectively). Our model does not presume that text generation by the central bank is exogenous. The optimising behaviour of the media in our model, and the central bank's response to that, means that central bank communication production is endogenous. Central banks must write "newsworthy" communication if it is to be reported on in the press. The central bank is forward looking and anticipates the effect on the news cycle of its communication. In this sense, we draw on the work of Gentzkow and Shapiro (2010), who find that the demand of consumers drives media slant. In our model the state of the economy also affects consumers preferences for news. The model is sequential and is solved under perfect and complete information.

The model serves to illustrate that estimating the relationship between central bank communications and their coverage in newspapers is a high-dimensional inference problem, compounded by highly complicated relationships between variables. We show that most econometric techniques that correlate news coverage of central bank communications with features of said communications will produce biased results because they do not account for the optimising behaviour of both the central bank and the print media in the news production and consumption process.

The relationship between the news coverage a central bank receives, and the features of their communication is a difficult object to estimate for three reasons. First, we are dealing with text (both news and communication) which is high dimensional. We will use a neural network approach to deal with this. Second, we have a high dimensional relationship between news coverage and the features of the speech to estimate. There are many features of communication that could be related to news coverage. We will use techniques from the double machine learning literature to deal with this. Finally, and arguably most importantly, central bank communication is endogenous, as is the news. Both are influenced by external events. To deal with this we will create a new way of performing event studies where textual data is present.

Before we can estimate any relationships between communication and the news coverage it receives, we need to measure the variables in our model. We measure: the proportion of a newspaper article that is paraphrased or strongly influenced by central bank text, and a vector of textual features of central bank communication.

We measure the first of these using a novel event-study methodology. More specifically, we take every newspaper article in two approximately one and half day windows around 1211 Bank of England communication events that contain the words ‘Bank of England’. We then calculate the weighted change in the document-term matrices of the news between the two windows where the weights are related to how similar the newspaper articles are to the Bank of England’s own communication. This provides us with a measure of how much the news flow has changed as a result of a central bank communication. To calculate this weighted similarity measure, we use a combination of word2vec (Mikolov, Sutskever, Chen, Corrado, and Dean 2013) — an embedding based approach based on a shallow neural network — and soft cosine similarity (Sidorov, Gelbukh, Gómez-Adorno, and Pinto 2014).

We measure the vector of textual features of central bank communication that could potentially alter its news coverage using an annotation pipeline rooted in computational linguistics. Our vector of features has three main components: topics, linguistic processing features, and news-values features. Topics are measured using a dictionary method derived from the tags given by Guardian journalists to articles in the business section of their newspaper. Linguistic processing features and news-values features are measured using a large range of different annotation methods, primarily based on computational linguistic toolkits. In total, we create 351 measures, drawing on literature from journalism studies, psycholinguistics, computational linguistics, and economics, to determine what makes events receive news coverage. We go far beyond any other study on central bank communication, or indeed on news coverage of any publicly released communications, in our thoroughness for measuring textual features.

The model solution implies an extremely high number of features to estimate parameters for — 4695 in total. Indeed this high dimensionality problem is common to many textual analyses. To deal with the dimensionality issue and (approximately) retain the unbiased estimates that traditional econometric estimation methods have, we use the desparsified LASSO (Van de Geer, Bühlmann, Ritov, and Dezeure 2014; Adamek, Smeekes, and Wilms 2020).

We find that the *interactions* between the state of the economy and all three categories of textual feature (content, linguistic processing, and news-values) are important for explaining the pass through of central bank communication to the mainstream media. We find that the state of the economy on its own has no significant impact on the news coverage of central bank communication.

Furthermore, we find that it is the variance of economic variables that, when interacted with textual features of central bank communication, influences the news coverage of central bank communication.

On the textual side, after performing feature selection on our 351 possible drivers of newsworthiness, we find five main categories of features are significant in explaining the news coverage that central bank communication receives, and derive five policy implications from them. These are that the central bank, if it is designing communication that it wants to reach the general public, should:

1. Keep things simple. Our results show that one should avoid introducing embedded clauses and separable particle verb structures.
2. Be personal. Use *we/us/you* to engage the reader.
3. Keep related ideas together. Long dependence arcs reduce the likelihood of newspaper coverage.
4. Summarise the message in the first sentence of the document.
5. Use facts and figures.

Each of these recommendations is produced by accurately measuring the relevant features of the Bank of England communications and their media coverage. We believe that applying the above suggestions to central bank communication will improve news coverage and ultimately help central banks reach a wider audience. We are the first — to our knowledge — to provide such specific data-driven recommendations. Moreover, we can rule out many other well-used traditional measures of readability (e.g. Flesch-Kincaid scores) as irrelevant for news coverage (see also Munday and Brookes in preparation).

That it is style — in other words how you write — that matters for whether your communication generates news coverage is interesting because it is somewhat of a free lunch for central banks. They can keep the content of their communication the same, and by altering the manner in which its delivered, they can affect the real economy.

These style recommendations may seem obvious. However, our procedure is one of feature selection, and all the included features are typically "obvious" for good writing. Therefore, some of the more interesting results are the features we find *do not* matter for news coverage. These include the vast majority of topics discussed by the Bank of England. This is surprising. One would imagine that topics about unemployment and inflation may receive greater news coverage than ones regarding precious metal prices, but that does not seem to be the case. Further, simple measures like the Flesch-Kincaid score, or sentence length, are also not significant in our analysis. Clearly one always wishes to "write simply", but we can be quite specific about what that means with our results.

Our paper predominantly builds on two different literatures. The first examines the role of central bank communication using text analysis. Much of this literature centers around how central bank communication, appropriately measured via various natural language processing techniques, affects financial market variables and the real economy. S. Hansen and McMahon (2016) examine how the FOMC statements impact the US economy through a FAVAR. S. Hansen, McMahon, and Tong (2019) analyse how Bank of England inflation report topics are related to high-frequency movements in financial markets. Hendry and Madeley (2010) investigate the impact of Bank of Canada statements on returns and volatility. Ehrmann and Talmi (2020) suggest that Bank of Canada statements that are less similar to previous releases cause more market volatility. And Born, Ehrmann, and Fratzscher (2014) examine central bank communication on financial stability and its effect on the stock market. A smaller literature examines central bank communication in the media. For example, Hendry (2012) and Hayo and Neuenkirch (2012) supplement the text of the Bank of Canada with subsequent market news reports to determine which basic features of both pieces of text move financial markets.

Other papers examine the role of the media in transmitting central bank communication rather than purely financial market implications, but generally stay within the bounds of whether or not the central bank is perceived positively or negatively in the media. Berger, Ehrmann, and Fratzscher (2011) use a manually labelled dataset from ECB staff of how favourably the media report ECB monetary policy decisions, and find that decisions that have large informational content and those that have been preceded by large numbers of statements gain the most favourable coverage.[1] Lamla and Sturm (2013) perform a similar analysis (using a dataset labelled manually by a private company) to investigate how expectations of future monetary policy decisions portrayed in the media are affected by interest rate decisions. Rybinski (2019) uses dictionary methods to generalise these manual approaches and apply a similar analysis to the case of the Polish central bank. Binder (2017b) is an exception to the focus on favourability and uses a manually coded dataset from PEW to determine whether communication events influence the prominence of the Federal Reserve (and its chair) in the news. Our paper goes much further than the current literature, explicitly modelling the news coverage process, creating a far richer measure of news coverage of a communication using an embedding based approach, and finally forming over 4000 features (351 textual and 11 economic and various polynomials and interactions between them) which could potentially cause a communication to be newsworthy and examining which features are important.[2] This allows us to understand which features of central bank communication can be manipulated in order to increase news coverage in far greater detail than any other study whilst explicitly controlling for the state of the economy.

The second strand of literature analyses features that may influence news coverage of an event. Galtung and Ruge (1965)'s seminal paper examining news articles on crises in four Norwegian newspapers spawned a subfield of journalism studies aimed at developing taxonomies of so-called "news values" (e.g. Bednarek and Caple 2017; Harcup and O'Neill 2017). Piotrkowicz (2017) computationally operationalises 6 aspects of news-value to

[1] Applied to the case of South Africa in Reid, Du Plessis, et al. (2011)

[2] An interesting, although largely unrelated paper to ours, that uses news text around monetary policy meetings is Ter Ellen, Larsen, and Thorsrud (2021), in which the authors compare the restricted document term matrix, projected down using SVD, between Norges Bank communications and the preceding articles, and use this as a measure of narrative monetary policy shocks.

predict readership engagement with news headlines taken from The Guardian and New York Times. Building on this literature, inspired in particular by Piotrkowicz (2017)'s study, we develop annotation schemes for 9 dimensions of news-values.

Intimately interwoven with the inherent news-value of an event is the extent to which the text describing it can be successfully comprehended by the reader. Comprehensibility has recently been of interest to scholars in a wide range of economics sub-fields. For instance, Guay, Samuels, and D. Taylor (2016) analyse the obfuscating effects of financial statement complexity; Amadxarif, Brookes, Garbarino, Patel, and Walczak (2019) analyse the linguistic complexity of prudential regulation; Fullwood (2016) compares the readability of central bank communications with other genres of text. However, in general, researchers analysing economic texts for their readability have far too often used vastly simplified models of language comprehension. For example, it has been assumed that classical readability metrics—comprising minimal features such as word length and sentence length—can adequately model text complexity. But research in the cognitive psychology of language has demonstrated that language processing is far more complex and cannot be captured by such metrics (see, for instance, the contributions in Rueschemeyer and Gaskell 2018). At the same time, research in computational linguistics has developed superior tools and techniques by which we might computationally model language comprehension (e.g., Gonzalez-Garduno and Søgaard 2017; Howcroft and Demberg 2017). Building on this recent research in computational readability and drawing on research into the cognitive psychology of language, we design a suite of novel linguistic features across three core levels of linguistic comprehension — word access, sentence parsing, and discourse integration — to better capture the reading experience.

Our paper makes three main contributions to the literature: (i) it is the first to structurally model central bank communication to the public via the print media, (ii) it develops a comprehensive feature set of potential newsworthy features that go well beyond simple approaches used before (e.g. Flesch-Kincaid scores, Haldane and McMahon (2018)), and (iii) we perform inference by estimating our model equations using an event study approach and machine learning techniques that allow us to make policy recommendations that are free from the omitted variable bias of other, more rudimentary, studies, for how central banks should alter their communication in order to reach a greater share of the population.

The paper is structured as follows. Section 2 outlines the model framework. Section 3 discusses the data sources. Section 4 details the computational linguistic approaches we use to measure the degree of news coverage a central bank communication receives. Section 5 details the features of central bank communication that may influence its newsworthiness, and how we measure them. Section 6 contains the estimation procedure used to create our estimates for what influences newsworthiness, and discusses the results and their policy implications. Section 7 concludes. There is a large technical appendix that mainly deals with the motivation behind the textual features we measure, and their calculation.

2. Framework

The framework presented in this section is a simple model of news production and consumption in a three agent world under perfect and complete information. The model contains three agents: the central bank, a representative newspaper, and a continuum of consumers.

Our model serves to illustrate that if one wants to estimate which textual features of the central bank's communication cause increased newspaper reporting: (i) any reasonable way of measuring the textual features of the news text and the central bank text quickly leads to high a dimensionality issue in which the number of parameters to estimate exceeds the sample size, and (ii) the optimal nature of central bank communication production, where the central bank must manipulate its communication to be “newsworthy” in order to receive news coverage, whilst still retaining the message it wants to transmit to the public, causes the content produced by the central bank to be a function of the desired news characteristics of consumers, the central bank's own objectives regarding communication to the public, and the state of the economy.

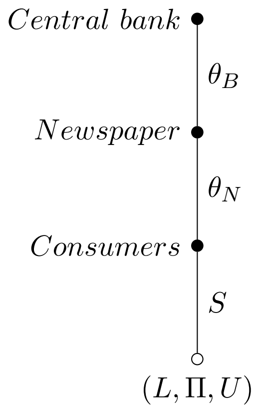
These two points are a result of the endogenous nature of central bank text production. The first leads us to use shrinkage methods to perform feature selection. The second means that when we do feature selection we will create omitted variable bias unless we explicitly account for the relationship between features. Indeed most methods for determining why certain central bank communications receive news coverage that rely on simple correlations between news coverage and text without explicitly modelling the high-dimensional relationships implicit in the text will return biased results. Consequently, we estimate the relationship given by our model equation using the de-sparsified LASSO (Van de Geer, Bühlmann, Ritov, and Dezeure 2014). See Section 6 for the estimation procedure.

This paper explicitly recognises that central bank communication is endogenous and designed to reach consumers. Thus, central banks must balance their desired message — which, for example, may be a complicated and heavily caveated one — with the desires of consumers for simpler messages.

Our model is parsimonious, and aims to accurately capture the salient features of central bank text production and consumption. It is not a model of information being released by a central bank, after which agents engage in updating their beliefs in order to fulfil some objective (Morris and Shin 2002). Rather it takes the literature on news consumption as its starting point (Gentzkow and Shapiro 2010), and then builds the role of the central bank and the newspaper to come to a fully-fledged model.

News is produced and consumed within the same period. There are three stages in the model. First, the central bank publishes content with characteristics described by vector θ_B. The representative newspaper produces news with characteristics θ_N comprised of a combination of central bank content and other news. Finally, share S of consumers decide to buy the newspaper if buying it would give them positive utility. All agents are rational and there is perfect and complete information. Since all information sets are singletons, we solve for a sequentially rational nash equilibrium in pure strategies using backward induction.

Fig. 1. Structure



2.1. Consumers

The consumer side of the model is influenced by Gentzkow and Shapiro (2010). Every day, a continuum of consumers choose whether or not to read the news. Gentzkow and Shapiro are concerned with one possible characteristic of the news: political slant. We want to study multiple characteristics of the news, so we extend their utility function such that θ is a vector of characteristics. A consumer, indexed c, has utility function:

$$U_c = \bar{u}_c - \gamma(\theta_N - \theta^*)^T W(\theta_N - \theta^*) + \epsilon_c \tag{1}$$

Where $\bar{u}_c$ represents some autonomous shift in the taste for news, θ_N is a measure of characteristics of the news, θ^* is a measure of the desired characteristics of the news (common to all consumers), W is a diagonal weight matrix (common to all consumers), and ϵ_c is an idiosyncratic taste shock.

Furthermore, we conjecture that consumers' desired characteristics of the news, θ^*, are dependent on the state of the economy, which we denote by vector z. Thus we can write $\theta^* = \theta^*(z)$. For ease of notation we will mainly use the simpler notation of θ^*, but it is worth remembering that these desired characteristics are not completely exogenous or time-invariant.

Household c consumes the news on a given day if $U_c \geq 0$. We assume, as in Gentzkow and Shapiro (2010), that ϵ_c is distributed i.i.d. uniform across households on an interval that includes the maximum and minimum values of $-\gamma(\theta_N - \theta^*)W(\theta_N - \theta^*)^T + \epsilon$. As a result, we can write the share of households consuming the news, S, as:

$$S = \delta - \gamma(\theta_N - \theta^*)^T W(\theta_N - \theta^*) + \epsilon \tag{2}$$

Where δ is a constant, and γ has been rescaled after having been integrated over ϵ_c.

2.2. Newspapers

We consider a representative newspaper that is a profit maximiser. Furthermore, since we are only considering news related to monetary policy, we can think of the newspaper's problem as more accurately being the journalist's problem.

The journalist tasked with economic reporting has one choice variable: k. k represents the fraction of an article that directly paraphrases the central bank. The journalist faces a trade-off. Writing news that satisfies consumer desires will sell more papers, but requires effort. Paraphrasing the central bank may not align with consumer desires, but is costless.

An article produced by the newspaper is constructed as follows. Proportion k of the article is paraphrased central bank communication, and has characteristics equal to that of the central bank's communication (θ_B). Proportion $1 - k$ of the article is created by the newspaper. Since the newspaper is profit maximising, proportion $1 - k$ of the article will be exactly aligned with consumer desires (θ^*). [3]

The characteristics of the news content produced by the newspaper, θ_N, can be written:

$$\theta_N = k\theta_B + (1-k)\theta^* \tag{3}$$

The newspaper maximises profit, which can be written as:

$$\Pi = \lambda S - C(1-k) \tag{4}$$

Where C is a cost function which we assume to be quadratic: $C(1-k) \equiv \alpha(1-k)^2$. Subbing in for S from the consumer demand equation gives:

$$\Pi = \lambda(\sigma - \gamma(k\theta_B + (1-k)\theta^* - \theta^*)^T W(k\theta_B + (1-k)\theta^* - \theta^*) + \epsilon) - \alpha(1-k)^2 \tag{5}$$

Newspapers optimally choose k. Taking the first order condition with respect to k gives:

$$\frac{\partial \Pi}{\partial k} = -2\lambda\gamma k(\theta_B - \theta^*)^T W(\theta_B - \theta^*) + 2\alpha(1-k) = 0 \tag{6}$$

Rearranging for k gives a key model equation:

$$k = \alpha\left(\alpha + \lambda\gamma(\theta_B - \theta^*)^T W(\theta_B - \theta^*)\right)^{-1} \tag{7}$$

This equation states that the proportion of newspaper text directly paraphrasing the central bank communications, k, is high when the central bank releases text with characteristics (θ_B) that are close to consumer desires (θ^*).[4]

[3] Note we don't allow the characteristics to offset.The newspaper cannot set the characteristics of the article in the part which they create as to cancel out the paraphrased part, and arrive at a news article that has characteristics exactly in line with consumer desires. One could argue that this rules out "schizophrenic" articles that are one half central bank communication and one half football scores (for example).

[4] In a larger model with heterogenous groups of consumers, the central bank would also need to balance appealing to its own target demographic, *and* the newspapers' target demographic.

2.3. Central bank

To incorporate that the central bank's production of content is not exogenous and may take into account consumer preferences, we model the central bank's problem as follows.

The central bank has some over-arching set of objectives that relate to monetary policy communication to the public. First amongst these objectives is the anchoring of inflation expectations at target. Other objectives may include civic engagement or influencing household and firm expectations of variables other than inflation.

Let's suppose that the central bank has a (weighted) quadratic loss function, L, over the deviations from this small vector of objectives, y, from their target values $\bar{y}$:

$$L = (y - \bar{y})^T H(y - \bar{y}) \tag{8}$$

Where H is a positive definite diagonal weight matrix.

The central bank's only instrument to achieve these particular objectives (it still retains its usual monetary policy tools to achieve other objectives) is the characteristics of the text it produces, θ_B. The objectives, y, are a function of the news the consumer receives, θ_N.

The central bank takes the gradient vector of its loss function with respect to its instrument.

$$\nabla L(\theta_B) = 2(y(\theta_N) - \bar{y})^T H J_{\theta_B}(y) = 0 \tag{9}$$

Where $J_{\theta_B}(y)$ denotes the Jacobian matrix of y with respect to θ_B.

There are possibly many solutions to this set of equations. Our aim is only to convince the reader that the solution is that the central bank sets θ_B as a function of its objectives, the state of the economy (including the central bank's more traditional policy tools), and consumer desired characteristics.

If one assumes that the central bank can achieve the global minimum of its loss function, i.e. it sets $y(\theta_N) = \bar{y}$ through its manipulation of its instrument θ_B, then the global minimum solution is detailed as follows. Other solutions that satisfy the first order conditions, but are not global minima are detailed in Appendix Section 8.1.

Assuming that the function which maps the news consumers receive to the central bank's objectives is invertible we can write:

$$\begin{aligned} y(\theta_N) - \bar{y} &= 0 \\ \theta_N &= y^{-1}(\bar{y}) \end{aligned} \tag{10}$$

For ease of notation, we denote $y^{-1}(\bar{y})$ as θ_B^*, to represent the central bank's desired characteristics for the elements of θ_N. So rewriting the above equation and then combining with Equations 3 and 7 gives:

$$\begin{aligned} \theta_N - \theta_B^* &= 0 \\ &= k\theta_B + (1-k)\theta^* - \theta_B^* \\ &= \alpha\theta_B + \lambda\gamma(\theta_B - \theta^*)^T W(\theta_B - \theta^*)\theta^* - \theta_B^* \end{aligned} \tag{11}$$

This is a quadratic equation in the vector θ_B. If it has a solution, the solution(s) for a given element, j, of θ_B are:

$$\theta_{B,j}^{opt} = \theta_j^* + \frac{(\theta_{B,j}^* - \theta_j^*)\left(\alpha + 2\lambda\gamma w_j(\theta_{B,j}^* - \theta_j^*)^2 \pm \sqrt{\alpha^2 - 4\lambda\gamma(\alpha + \lambda\gamma w_j(\theta_{B,j}^* - \theta_j^*)^2)\sum_{i\neq j}(\theta_{B,i}^* - \theta_i^*)^2}\right)}{2\gamma\lambda\sum_i(\theta_{B,i}^* - \theta_i^*)^2} \tag{12}$$

This is a non-linear equation in which θ_B, the vector of textual features describing the central bank's communication, is a function of consumers' desired characteristics, θ^* and the central bank's desired characteristics, θ_B^*.[5]

Intuitively, the optimal choice of characteristic j by the central bank, $\theta_{B,j}^{opt}$, is a weighted average between the central bank's own desired characteristic $\theta_{B,j}^*$ and the consumer's desired characteristic θ_j^*. The central bank must balance communicating exactly what it desires, and communicating in a way that will reach consumers. This is the fundamental trade-off of our model.

[5] Clearly if Equation 12 holds $\forall j$, then $\theta_N = \theta_B^*$, and so the solutions are global minima of the loss function because they set $L = 0$. As a result, there is no need to check the second order condition, the only condition that must be met is that the solutions exist. i.e. that:

$$\alpha^2 - 4\lambda\gamma(\alpha - \lambda\gamma w_j(\theta_{B,j}^* - \theta_j^*)^2)\sum_{i\neq j}(\theta_{B,i}^* - \theta_i^*)^2 > 0 \quad \forall j \tag{13}$$

Intuitively, this restriction can be understood as not allowing the preferences of the central bank, θ_B^* to stray too far from the preferences of the consumer, θ^*. Since we posit that both are driven by the state of the economy, z, this does not seem too far fetched.

For notation, we rewrite the solution in Equation 12, or indeed the approximate solution if there is no exact one:

$$\theta_{B,j}^{opt} = \theta_{B,j}\left(\theta^*, \theta_B^*\right) \tag{14}$$

We can rewrite Equation 7 as:

$$k = \alpha\left(\alpha + \lambda\gamma\left(\theta_B\left(\theta^*, \theta_B^*\right) - \theta^*\right)^T W\left(\theta_B\left(\theta^*, \theta_B^*\right) - \theta^*\right)\right)^{-1} \tag{15}$$

Note that θ_B is observed by us, the researchers, but preferences θ^* and θ_B^* are not.

2.4. Desired Characteristics

The key model equation is Equation 15. We can rearrange this into an equation which can be estimated:

$$\begin{aligned} k &= \frac{\alpha}{\alpha + \lambda\gamma\sum_i w_i\left(\theta_{B,i}\left(\theta^*(z), \theta_B^*(z)\right) - \theta_i^*(z)\right)^2} \\ \frac{1-k}{k}\frac{\alpha}{\lambda\gamma} &= \sum_i w_i\left(\theta_{B,i}\left(\theta^*(z), \theta_B^*(z)\right) - \theta_i^*(z)\right)^2 \end{aligned} \tag{16}$$

Where z is a vector of economic variables that affect the desired characteristics for economic news.

This is an equation which is linear in the w_i's: the diagonal elements of W. We assume that consumer desired characteristics θ^* for a given feature i, have the following relationship:

$$\theta_{i,t}^* = \bar{\theta}_i^* + \pi_i^T z_t \tag{17}$$

Where π_i is a $(M \times 1)$ coefficient vector which maps the state of the economy z to the desire for feature i.

A simple rational inattention model in which the consumer demand for news is isomorphic to their 'attention', would suggest the consumer desires in our model should vary linearly with the inverse prior variance of the variable in question (Sims 2003).

The elements of z used in estimation are specified in Section 3 and include both the level and variance of many characteristics of the economy.

Now our equation becomes:

$$\begin{aligned}
\frac{1-k}{k}\frac{\alpha}{\lambda\gamma} &= \sum_i w_i \left(\theta_{B,i} - \bar{\theta}_i^* - \pi_i^T z\right)^2 \\
&= \sum_i w_i \left(\theta_{B,i}^2 + (\bar{\theta}_i^*)^2 + (\pi_i^T z)^2 - 2\theta_{B,i}\bar{\theta}_i^* - 2\theta_{B,i}(\pi_i^T z) + 2\bar{\theta}_i^*(\pi_i^T z)\right)
\end{aligned} \tag{18}$$

In terms of observables, this is:

$$\frac{1-k}{k} = \beta_0 + \beta_1^T(\theta_B^T\theta_B) + \beta_2^T\theta_B + \beta_3^T(z \otimes \theta_B) + \beta_4^T z + \beta_5^T(z \otimes z) \tag{19}$$

Where we have defined:

$$\begin{aligned}
\beta_0 &= \frac{\alpha}{\lambda\gamma}\sum_i w_i(\theta_i^*)^2 \\
\beta_1 &= \frac{\alpha}{\lambda\gamma}[w_0, w_1, ..., w_N] \\
\beta_2 &= -2\frac{\alpha}{\lambda\gamma}[w_0\bar{\theta}_0^*, w_1\bar{\theta}_1^*, ..., w_N\bar{\theta}_N^*] \\
\beta_3 &= -2\frac{\alpha}{\lambda\gamma}[w_0\pi_0^T, w_1\pi_1^T, ..., w_N\pi_N^T] \\
\beta_4 &= 2\frac{\alpha}{\lambda\gamma}[w_0\bar{\theta}_0^*\pi_0, w_1\bar{\theta}_1^*\pi_1, ..., w_N\bar{\theta}_N^*\pi_N] \\
\beta_5 &= \frac{\alpha}{\lambda\gamma}[w_0(\pi_0 \otimes \pi_0), w_1(\pi_1 \otimes \pi_1), ..., w_N(\pi_N \otimes \pi_N)]
\end{aligned} \tag{20}$$

Adding in time subscripts gives the equation we wish to estimate:

$$\frac{1-k_t}{k_t} = \beta_0 + \beta_1^T(\theta_{B,t}^T\theta_{B,t}) + \beta_2^T\theta_{B,t} + \beta_3^T(z_t \otimes \theta_{B,t}) + \beta_4^T z_t + \beta_5^T(z_t \otimes z_t) \tag{21}$$

This equation relates the observable features of the text the central bank produces (θ_B) and the state of the economy (z), to the degree of reporting that central bank communication receives (k).

The inclusion of Kronecker products in Equation 21 causes the dimensionality to become unmanageable for standard econometrics once we start to include the full set of features that comprise θ_B and controls that comprise z: point (i) made at the beginning of this section. Point (ii), that the textual features of the central bank's communication are themselves functions of the state of the economy, can be deduced from Equation 12.

Both of these points have been ignored by the nascent empirical literature in this area, where the use of a model to motivate relationships between communication and other variables of interest is rare.

This model posited that the central bank was forward looking and thus its communication is a function of (i) consumer desired characteristics for news, (ii) the state of the economy via the central bank's own objectives, and (iii) the state of the economy via its impact on consumer demand for news.[6] The model results in Equation 21; an equation, linear in parameters, that links news coverage, textual features and the state of the economy.

What if news production has no demand side? Our model incorporates the demands of consumers for news as an important part of the central bank's (and the newspaper's) problem in determining the production of news. As a result of this, the central bank's communication is a combination of what the central bank wants to publish (θ_B^*) and what consumers want to read (θ^*). If consumers always bought the newspaper regardless of its content, then W becomes a matrix of zeros, k is always 1, the journalist does no work (she simply copies the central bank's communications into the newspaper), and the central bank can print its exact desired message (θ_B^*) knowing that it will reach all consumers verbatim. Patently, this is not how central bank communication works. Central banks have large public communication departments, research how to increase the penetration of their communication to the public through altering its form (Haldane and McMahon 2018), and think deeply about how to balance their desired communication with its palatability to a general readers.

Now we use the result of the framework just outlined, that news coverage of central bank communication (k) is a function of the communication itself (θ_B) and the state of the economy (z) through an equation such as Equation 21, to answer the question as to *which* features of communication or the economy matter for news coverage

The data and the techniques applied to that data to create the variables needed are detailed in Sections 3 and 4 and 5. The methodology used to estimate the β coefficients of Equation 21 is detailed in Section 6.

[6]From our own discussions with the Bank of England's communication department, this model accurately captures the trade-offs they face when drafting communication.

3. Data

3.1. Bank of England communications data

We study the communication of the Bank of England. The Bank of England communications data comes from a number of sources. Text data on the Introductory Statements and Inflation Reports are from S. Hansen, McMahon, and Tong (2019), the Q and A text data and Inflation Reports past 2015 are from Munday (2022), and the speech and minutes data were scraped from PDFs provided by the Bank of England. We do not include articles directly written by the Bank of England in newspapers as Op-Eds, or interviews given to newspapers that are published (essentially) verbatim. We are concerned with communication that the Bank itself publishes that may be targeted at the general public (at least in part).

The length of the series and number of communication instances are described in Table 1.

Table 1: Bank of England Communication Data

	Inflation Report	Q and A	Introductory Statement	Minutes	Speeches
First Observation	1998-02-11	2007-05-16	2001-02-14	1997-07-16	1997-06-12
Last Observation	2018-08-02	2018-08-02	2018-08-02	2019-05-02	2019-05-30
No. of observations	83	45	71	253	654
Total No. of words	1,682,165	311,511	29,301	1,475,554	2,386,576
No. of unique words	10,835	7,369	3,780	9,743	30,650

The intra-day timing of Bank of England communications varies over the sample. Figure 2 plots the intra-day publication times of Bank of England communications in our sample against the dates they were published. All timing data are from Bloomberg. We do not use intra-day timing data for speeches, namely because the time at which a speech is scheduled is often (i) inaccurate to when the speech was actually given, and (ii) not the same as when the speech text was released to a wider audience.

Both Table 1 and Figure 2 show how a large share of the communications corpus is comprised of the speeches and minutes. The other salient feature of Figure 2 is the move to “Super Thursday” in August 2015. This represents a stark break in Bank of England publication practices. Prior to August 2015, the Inflation Report, Q and A, Introductory Statement and Minutes did not coincide with the interest rate decision. From mid-2015 onwards, every interest rate decision is accompanied by publication of the Minutes, and every other interest rate decision is accompanied by the publication of both the Minutes and the Inflation report, with the Introductory Statement and Q and A following shortly afterwards.

Fig. 2. Timing of Bank of England communications

We analyse the Speeches, Minutes, Introductory Statements and Q and A's as separate communication events. For the Inflation Report, we analyse each section of the Inflation Report separately. We do this because (i) it reduces the length of the text of each chunk of communication text to a similar size, (ii) it allows us to determine which, if any, sections of the Inflation Report are influencing the news, (iii) the sections of the Inflation Report are labelled by content, and have changed over time (as explained below), and analysing them individually accounts for these changes.

Table 2: Inflation Report Section Key

Section code	Feb 1998- Aug 2002	Nov 2002- Aug 2005	Nov 2005 - May 2015	Aug 2015 - Aug 2018
0	Overview	Overview	Overview	
1	Money and asset prices	Money and asset prices	Money and asset prices	
2	Demand and output	Demand	Demand	Demand and output
3	The labour market	Output and supply	Output and supply	Supply and the labour market
4	Costs and prices	Costs and prices	Costs and prices	Costs and prices
5	Mon. pol. since the prev. report	Mon. pol. since the prev. report		
6	Prospects for inflation	Prospects for inflation	Prospects for inflation	Prospects for inflation
7				Global economic and fin. developments
8				Monetary policy summary

Table 2 shows how the sections of the Inflation Report have evolved over time. In some cases, when the content is similar between sections despite the name of the section changing, we treat them as identical sections for our analysis (e.g. Demand vs Demand and Output). When the content is considerably different, we analyse a new section as a separate type of communication (e.g. Overview vs Monetary Policy Summary).

3.2. Newspaper data

The newspaper data are provided by Dow Jones on a Bank of England license. The data cover five major British daily newspapers: The Daily Mail, The Daily Mirror, The Guardian, The Sun, and The Times.[7] [8] [9] Collectively these papers have a monthly physical circulation of 3,420,888, and account for 42% of the total circulation of the top

[7]These data do not include the sister Sunday papers

[8]The dataset does not include papers that are aimed at a predominantly financial audience, such as City AM or the Financial Times. These papers have lower circulation, and do not transmit news to the general public in the way that we are concerned with studying here.

[9]There is a question of whether the newspaper data is relevant at all if journalists at the papers in our sample are simply copying from newswire services. Firstly we don't think this is true since many of the newspapers in our sample regularly send reporters to question the Bank of England governor at the press conferences. But more importantly, the central bank — at least in our formulation of the problem — cares about the end product that reaches the general public. Controlling what is put out on newswires is an intermediate step that the central bank may also want to optimise, but it is not what the public reads.

16 non-Sunday papers recognised by the Audit Bureau of Circulations and reported on by the Press Gazette.[10]. However, physical circulation does not account for (i) reaching consumers via online platforms, (ii) the proportion of the physical printed copies that are actually bought and read. Table 3 shows estimates by PAMCo of the total reach of the newspapers in our dataset. Combined, the newspapers in our sample have an estimated total monthly reach of 115,000,000 people (which is greater than the UK population since many consumers are reached by multiple newspapers in a month), which is 47% of the estimated total monthly reach of all UK non-Sunday non-regional newspapers covered by PAMCo. [11]

Table 3: Circulation of British Newspapers within our dataset

	Monthly Estimated Audience (000s)				
	Total	Phone	Tablet	Desktop	Print
The Daily Mail	24,775	17,026	2,415	4,123	6,398
The Daily Mirror	27,045	21,948	2,798	2,662	3,142
The Guardian	23,810	17,525	2,703	6,377	2,755
The Sun	32,438	25,399	3,276	3,413	7,135
The Times	7,629	3,793	709	1,102	3,285

Source: PAMCo 3 2019: Jul '18 – Jun '19 (June '19 Comscore data).

3.3. Economic data

We include a broad range of economic variables to try and capture any economic state variables that affect preferences for economic news. The unemployment rate, industrial production growth, the 10 year government bond rate and the CPI inflation rate are included to control for variables that may influence consumer demand for economic news. The 1-year OIS rate and its daily change are included to control for news that is written

[10]Data from ABC. Accessed on 11/11/2019 https://www.pressgazette.co.uk/national-newspaper-abcs-guardian-sees-smallest-circulation-decline-for-july-2019/

[11]The data is constructed by combining a face-to-face survey of 35,000 adults aged 15 and above, direct measures of online audiences from comScore, and adjusting for duplicate readers who consume the news through both physical and digital mediums via a digital panel.

in reaction to market movements.[12]

In addition we include the inverse variance (calculated over the previous year) of all of these variables, to control for preferences for news that take the forms predicted by the rational inattention literature (Sims 2003).

Data for all these variables except the 1 year OIS rate is taken from FRED. The 1 year OIS rate is taken from Bloomberg. The 1 year OIS rate only starts in the year 2000. So whilst the training of the word vectors can take place on the Bank's corpus extending back to 1997, the analysis performed on news coverage in Section 6 is based on the 2000-2018 period.

[12]Appendix Section 8.5 shows regressions that suggest that news coverage is related to high frequency financial market variables, and so they are variables one would want to control for.

4. Measurement of media coverage

We want to estimate Equation 21. In this section we discuss the construction of k, a variable which measures news coverage of a central bank communication. This involves a novel event-study methodology that leverages natural language processing tools. In Section 5 we discuss how we measure the features of the text contained in θ_B.

4.1. Event study methodology

In our framework, k is the proportion of the news that is directly paraphrasing Bank of England communication. We could proxy this by manually coding a dummy variable as to whether a given central bank communication received news coverage. However, on the scale we wish to perform analysis, this is not possible. We have over 1000 communication events, and every newspaper article of five British newspapers (online and print) since 1997. To determine whether a given Inflation Report received news coverage, let alone whether or not it was the Inflation Report as opposed to the subsequent Q & A, would be very labour intensive. Thus we seek an automated approach. Not only does this save time, it allows us a more precise measurement of k, and permits our methodology to be easily applied to other research questions.

Using Natural Language Processing, we could measure k using the similarity between the news that reports on the Bank of England's communication, and said communication. However, this approach has two problems. Firstly, any external ongoing economic events that both newspapers and the Bank of England comment on will be picked up as newspapers reporting Bank of England content. Secondly, central bank communication that is written in a more journalistic style will again be picked up as newspapers reporting Bank of England content.

To remove these confounding factors, we calculate a measure of the communication *surprise* imparted by the Bank of England for each communication event, and use this as a proxy for k. In practice, this is the *change* in similarity between (i) the news the day before and the central bank communication, and (ii) the news the day after and the central bank communication. This event study approach is our identification strategy. By capturing changes in newsflow that only relate to central bank communication we will be able to perform inference.

A simple made-up example follows to illustrate this point.

Suppose, for the sake of this example, that the Chinese economy suddenly slows down. The Bank of England communicates its concern to wage and price setters (i.e. the public). It releases a statement to relay its message. Its statement reads "The MPC is concerned about the Chinese economy'". It releases this statement on day t at 12 noon exactly. An article was published the day before (day $t-1$) stating that "The Chinese economy is slowing considerably and the UK could be impacted". Furthermore, an identical article was published the day afterwards (day $t+1$) along with two additional articles that reported on the Bank's communication. See Figure 3.

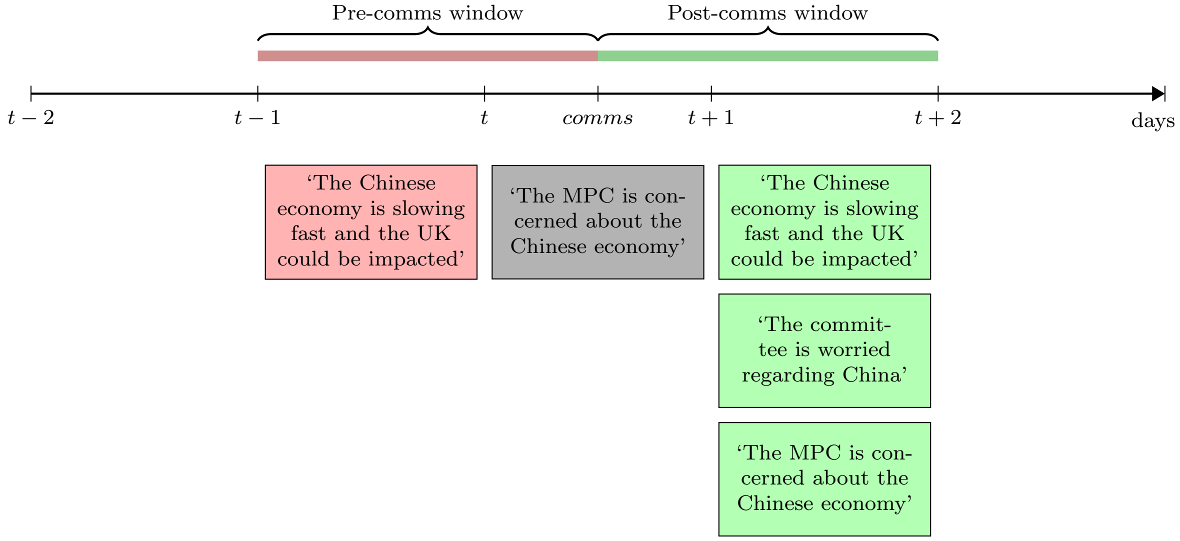
One way to measure k would be to calculate the similarity (defined more precisely in the following subsection) between the communication and the post-communication articles. However, a method that did not account for the articles prior to the Bank's communication would be likely to count the article on the day afterwards as being influenced by the Bank's communication since they both contain the words "Chinese economy".

To guard against this we take the *change* between (i) the average similarity of articles in the post-communication window and the communication, and (ii) the average similarity of articles in the pre-communication window and the communication.

Denoting $\tilde{k}$ as our empirical measure of k we can write:

$$\tilde{k} = sim(news_{t+1}, publication) - sim(news_{t-1}, publication) \tag{22}$$

Fig. 3. Timeline of example communications event



4.2. Defining similarity

It is fair to say that much of the press coverage following Central Bank communication is an interpretation of the Bank's words. To try and capture to what extent the *message* of the central bank transmits into the news media we use a technique from Natural Language Processing, called word embeddings (Mikolov, Chen, Corrado, and Dean 2013) combined with soft-cosine similarity (Sidorov, Gelbukh, Gómez-Adorno, and Pinto 2014) to measure the similarity between central bank communication and news articles.[13]

It is worth noting that this measure combines two separate sources of vectors. Word embeddings are word-specific vectors, in our case of length 100, which are the result of a supervised machine learning algorithm. Term-frequency vectors are document-specific vectors which map words from a dictionary to their frequency in a document.

Following Mikolov, Chen, Corrado, and Dean (2013) and Mikolov, Sutskever, Chen, Corrado, and Dean (2013), word embeddings have become a popular way of representing individual words as vectors, whilst retaining desirable features of the words. Famously, word embeddings retain the semantic relationships between words, insofar as — if trained on the appropriate corpus — the vector for *King* minus the vector for *Man* plus the vector for *Woman* yields a vector similar to that of *Queen*.

[13]Doc2vec, the analagous form of word2vec for document embeddings is another possible way to get at a measure of similarity that we want, but we have reason to doubt its accuracy on a corpus as small as our own.

In our case we use the word2vec Continuous Bag of Words implementation. This implementation takes a word within a sentence as the variable that a shallow neural network is asked to predict. We then provide the words surrounding the word in question (the "context") to the neural network, and ask it to predict the missing word. We train on the entire corpus of Bank communications and news articles.

We use a total window size of 10 — so any word within five words either side of the word we want to predict is included as an input. The neural network then "learns" to predict words based on their context. Or, it maximises the probability of the correct word, given the context. The word embeddings we extract are the weights the network eventually uses to perform its predictive task. A more detailed explanation is found in Appendix Section 8.2.

We pre-process our data in this case by by removing words less than two letters, removing punctuation, removing all stopwords (words like *and* and *the*, that for this particular purpose add more noise than signal to the data), and converting all uppercase letters to lowercase.

Once each word in the dictionary has been assigned a word2vec vector, we move on to calculating the soft-cosine similarity between two documents.

Cosine similarity is the use of the cosine of an angle between two vectors as a measure of how similar the vectors are. In our case the vectors in question are unigram term frequency vectors. If one was to use pure cosine similarity on these vectors, only words that co-occur in both texts (i.e. the news article and the Bank of England communication) would translate into a higher cosine similarity. Soft cosine similarity, a measure that has been show to outperform many methods in text-similarity competitions (Charlet and Damnati 2017), uses the embeddings derived from the word2vec procedure to weight the cosine similarity measure.

It is instructive to consider an example.[14] Suppose that we want to compare the similarity of the Bank of England's two word communication 'strong growth', with the news article published the following day of 'high growth'. Since there are only three words in the dictionary — {*strong, growth, high*} — we can visualise the term frequency

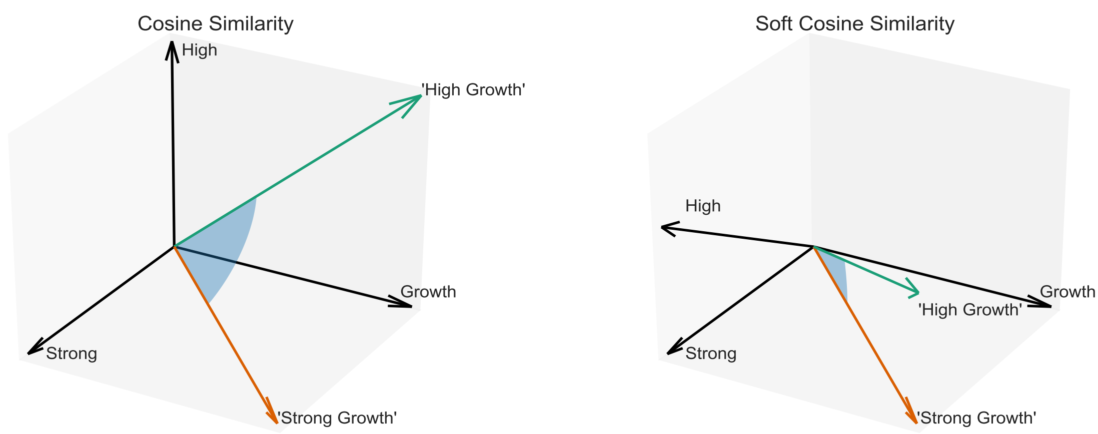
[14]The idea for this example comes from the python package gensim's documentation. See https://github.com/RaRe-Technologies/gensim/blob/develop/docs/notebooks/soft_cosine_tutorial.ipynb

vectors on a 3d chart (Figure 4). Calculating the cosine similarity between the term frequency vectors (1, 1, 0) and (0, 1, 1) is simple and yields a similarity of $\frac{1}{2}$. However this calculation ignores the fact that *high* and *strong* are used as synonyms in this case. Indeed, the vector-space representations of *high* and *strong* are orthogonal to one another.

Soft cosine similarity uses the cosine similarity between the word embedding vectors (the set of word specific vectors) to weight the cosine similarity calculation between the term frequency vectors (the set of document vectors).

This is illustrated in Figure 4. The word embeddings for *high* and *strong* have high cosine similarity, so the term-frequency representations of these words cease to be orthogonal. Calculating the cosine similarity on the non-orthogonal vectors yields the soft-cosine similarity, which is higher (i.e. the angle between the vectors is smaller) than without the word-embedding weights.

Fig. 4. Cosine similarity versus soft-cosine similarity



Mathematically, soft cosine similarity adds an extra weighting term to the cosine similarity formula.

$$CosineSim(a, b) = \frac{\sum_{i=1}^{N} a_i b_i}{\sqrt{\sum_{i=1}^{N} a_i^2}\sqrt{\sum_{i=1}^{N} b_i^2}} \tag{23}$$

$$SoftCosineSim(a,b) = \frac{\sum\sum_{i,j}^{N} s_{i,j} a_i b_j}{\sqrt{\sum\sum_{i,j}^{N} s_{i,j} a_i a_j}\sqrt{\sum\sum_{i,j}^{N} s_{i,j} b_i b_j}} \tag{24}$$

Where $s_{i,j}$ is the similarity between word i and word j as measured by the *cosine* similarity of their word2vec vector representations.

Having calculated the soft-cosine similarity for all articles with respect to the Bank's communication, we can take the change in the average between the windows as our measure of k.

4.3. Implementation

We take all the relevant news articles that are published in a window before a Bank communication event, and all the relevant news articles that occur in a window afterwards. For our analysis, relevant is defined as containing the words "Bank of England". We treat articles from our set of newspapers identically.

When performing the analysis on our dataset the event windows vary slightly based on the form of communication. For Inflation Reports, Introductory Statements, and Minutes, we take our pre-announcement window as any articles published before the time of publication on the same day or the day before, and our post-announcement window as any articles published after publication on the day of the announcement or on the day afterwards. For the Q and A, we take the same approach to the pre-announcement window, but allow a gap of 2 hours before the post-announcement window begins to allow the Q and A to have finished before we collect the news articles. For speeches, we do not use the time at which the speech was delivered or published to the public, so our windows exclude any articles published on the same day, and only cover articles published on the day before or after the speech took place.

Our measure has two important features. Firstly, it is a measure of how much the content of the news has changed as a result of an official communication event. Indeed, if the news content is the same in both windows, the measure will return a value of 0. Secondly, it is adjusted for how much of the change in news content can be ascribed to the Bank's communication. The largest readings will take place when the news in the pre-announcement window is unrelated to the Bank's communication - i.e. it was not trailed in the press beforehand, or indeed forecasted by press articles leading up to the communication event - and when the news in the post-announcement window is closely related to the Bank's own message.

One caveat to our approach is that similarity does not capture the accuracy of reporting of central bank communication — indeed it is possible to write news of central bank communication that is subtly inaccurate, yet very similar textually to the original communication.[15]

Returning to the original example, the same diagram with the similarity measures now imposed can be seen in Figure 5 and the results of the similarity measure calculations are displayed in Table 4.

Table 4 shows that the post-communication article which is an exact copy of the pre-communication article has an identical similarity score. When we take the difference in some moment between the two distributions of pre and post articles (in our case, the mean), we control for the confounding effect of news stories that were already in the press before the Bank of England made a communication.

Furthermore, Figure 5 highlights the fact that post-communication article number two, whilst having a meaning that is very similar to the Bank's communication, would score zero on a cosine similarity measure (as there are no identical common words that aren't stopwords), but recieves a positive soft-cosine similarity score because it uses synonyms.

Our measure, as explained above, uses a similarity matrix between words to help weight similarity queries between documents. In the example, one of the synonyms used in post-communication article number 2 is *worried* in place of *concerned* which the Bank of England communication uses. The word2vec model tells us that the similarity ($s_{i,j}$) between these two words is 0.85. As a result, when computing the soft-cosine similarity between post-communication document 2 and the Bank's communication, the words *worried* and *concerned* do not return a contribution of zero to the similarity score, as would be the case with normal cosine similarity.

We can see in Figure 5 that the measure gives post-communication article number 2

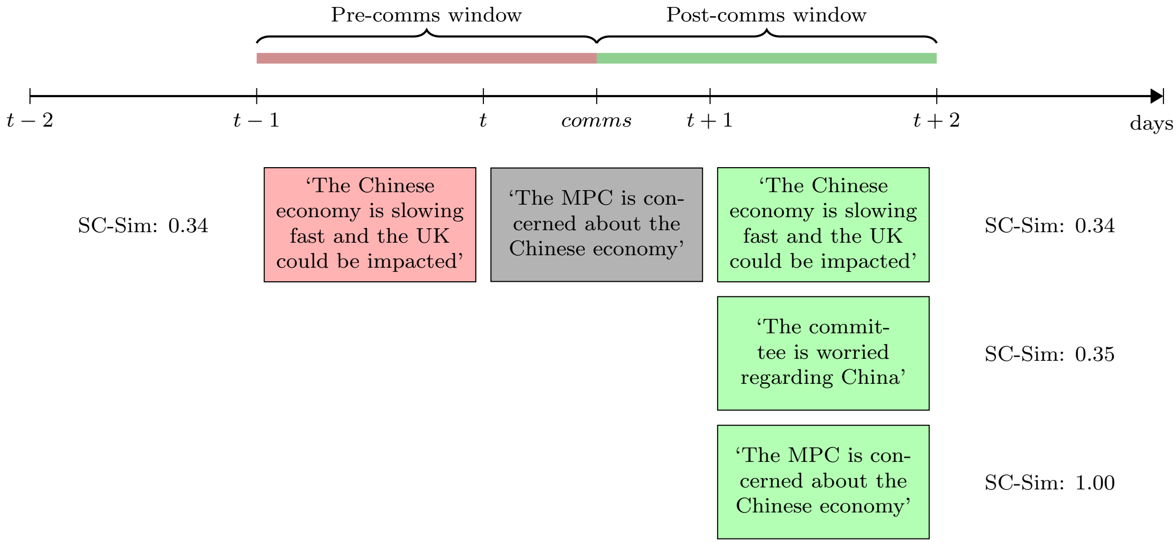
[15] This is not the only caveat, although it is probably the main one. Our measure does also not capture where the article was presented in the newspaper (i.e. was it on the front page) as our data does not include the relevant information. We also don't determine the tone of the coverage from our measure.

a score of 0.35, higher than post-communication article 1. Finally we take the difference in the average scores between the two windows to arrive at our measure. Our example receives a k of 0.22. This is a relatively high score, which should be expected: there was little trailing of the Bank's message in the press, and one article reported what the Bank said verbatim.

We perform this exercise for all of the Bank of England's communications. Figure 6 shows the time series of our measures of k.[16]

In Appendix Section 8.3, we show that, as would be expected, the kernel density estimates for the soft cosine similarity scores of articles in the pre-communication window are shifted substantially closer to zero versus those in the post-communication window.

Fig. 5. Timeline of example communications event

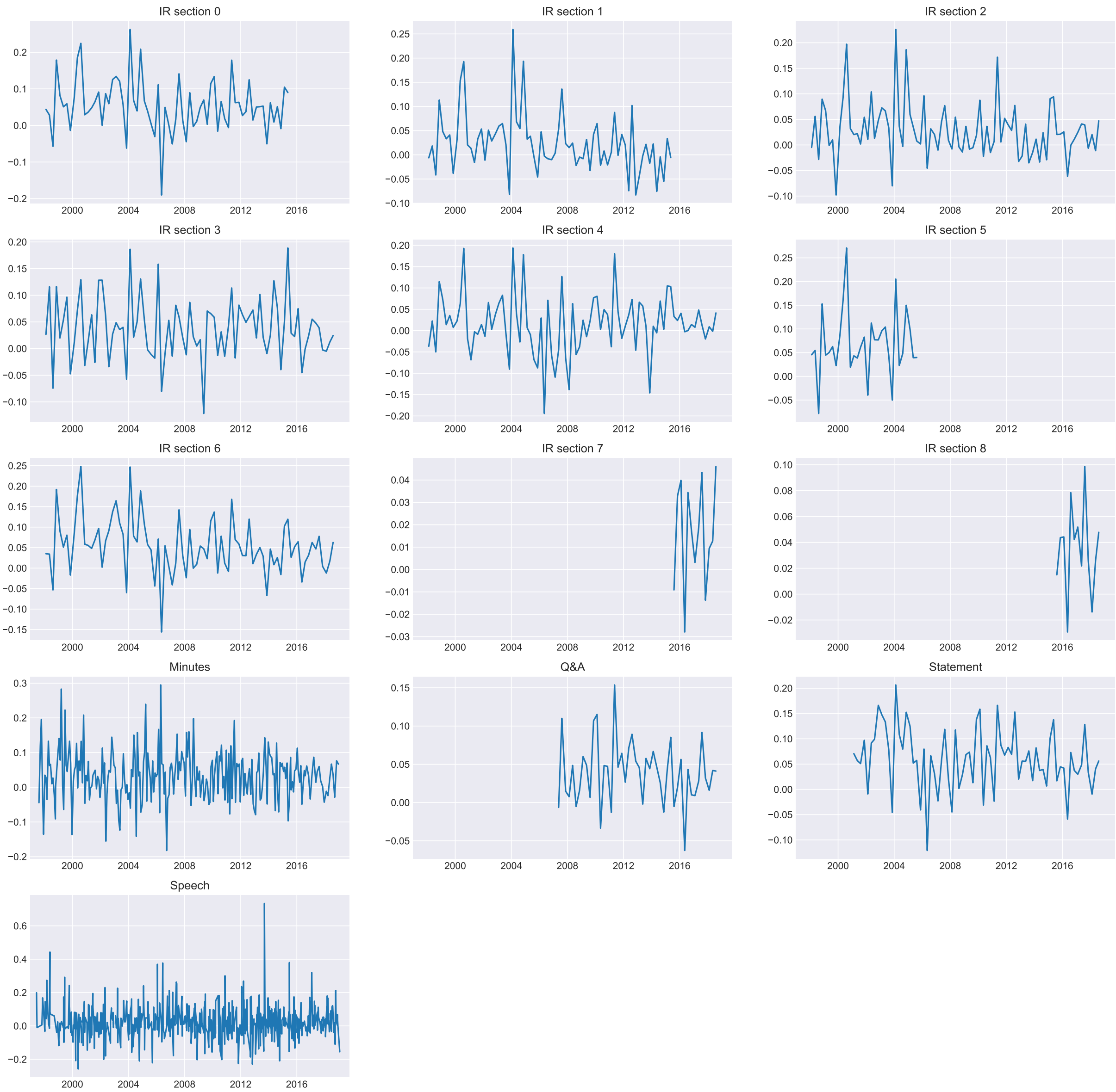


[16] Although most values of k are greater than zero, negative values do occur. These occur when the news before a communication is similar to the communication, and the news afterwards is different. In essence this means that the Bank had little impact on the news flow, and perhaps the content was already known to consumers owing to previous newspaper coverage. In our estimation procedure, negative values of k do not have a different economic interpretation to values of k that are close to zero, since the scale of k does not matter. Ultimately we will transform k to a mean zero, standard deviation 1 variable anyway.

Table 4: Calculating the measures of an example communications event

	Pre-communication		Post-communication		Difference in averages
	Per-article	Average	Per-article	Average	
Measure	0.34	0.34	0.34	0.56	0.22
			0.35		
			1		

Fig. 6. Estimates of k for all Bank of England communications



5. Measurement of text features

What factors might influence whether an event is picked up in the news? In this section, we briefly discuss the set of characteristics of central bank text, θ_B, that we surmise may be associated with our outcome variable k, the proportion of newspaper text that paraphrases Bank of England communication events.[17]

In total we measure 351 different variables that make up the vector θ_B. The explanation of these variables is the only issue dealt with in this section. For a much more detailed account of the motivation behind including each of these measures, and the specific manner in which we calculate them, the reader is directed to an extensive discussion in Appendix Section 8.4.

First we include dummy variables for all the different types of communication we study: 9 sections of the Inflation Report, the minutes, the Q & A, and speeches. We also include a dummy variable as to whether there was a monetary policy decision made on the same day as the communication.

To motivate our textual feature sets, we draw on scholarly investigations into the cognitive psychology of language processing and crucially news values and news discourse (e.g. Galtung and Ruge (1965), Bednarek and Caple (2017), and Harcup and O'Neill (2017)).

For some central bank communication to be picked up by the media, we assume that it has to be of topical interest (TOPIC), quickly and efficiently processed (LINGUISTIC PROCESSING), and contain certain characteristics that journalists and newspaper editors value (NEWS VALUES). Thus, we decompose θ_B into these three components, the last two with three and nine sub-components respectively:[18]

1. TOPIC: θ_B^{TP}
2. LINGUISTIC PROCESSING: θ_B^{LP}

[17] To be clear, we don't have data on whether or not the Bank of England provided background talks with journalists for speeches — which would clearly be useful to control for. For the Q & A, IR, Minutes and Statement, for most of the sample journalists have been allowed early access to the text to encourage news coverage.

[18] In addition, journalism scholars suggest that news media pick-up is also influenced by other factors, such as other stories competing for space, reporter availability, proximity of the communication event to a given deadline, etc. Bednarek and Caple (2017) term these NEWS SELECTION FACTORS. For us, these are features that are excluded by design or are unmeasurable, and as such are caught up in the error term ϵ, or are else captured by our controls.

(a) lexical access
(b) syntactic processing
(c) discourse processing

3. NEWS VALUES: θ_B^{NV}
   (a) size
   (b) impact
   (c) sentiment
   (d) personalization
   (e) proximity
   (f) facticity
   (g) uncertainty
   (h) prominence
   (i) novelty

Below we enumerate and briefly discuss these features.

5.1. Topic

We wish to measure the extent to which Bank communication touches on topics that consumers want to read about — i.e. that are contained in their preference vector θ^*. We measure 49 different topics using simple dictionary methods. To find these topics, we first obtain Guardian articles containing the word *economy* since January 1st 2000 until the present day, a total of 13203 articles. We then store the tags that these articles are assigned. Tags are attached manually by Guardian journalists. There are over 50,000 distinct tags across the Guardian's text corpus.

We remove tags that have been used less than 100 times. We then use a k-means clustering algorithm to group the tags into distinct groups based on the vectors given by a word2vec algorithm trained on the corpus. The optimal number of clusters, 49, is determined by the silhouette score across a grid search. These 49 clusters form the topics of content that we wish to measure.

Once the tags are clustered, we take the centroids of the clusters, and take the ten words — excluding numbers and words that are clearly typos[19] — that are closest to the centroid from our word embeddings. These ten words form a dictionary for each topic that is used to measure the extent to which that topic is discussed by the Bank of England. More specifically, our measure for each topic is the total sum of the occurrences of the words in the topic dictionary for a given communication, divided by the length of the communication.

For a discussion of why alternative topic measures are not used, we refer the interested reader to Appendix Section 8.4.

5.2. Linguistic Processing

Our linguistic processing features relate to three main goals in interpreting an incoming (written) linguistic signal that will influence whether a central bank communication is picked up by the media. One can think of our linguistic processing features as capturing how easy it is to read a given central bank communication.[20]

- We (i.e, language users) have to identify that a string of text is a potential word, and if so, access information about it from our mental lexicon—for instance, its meaning(s), part-of-speech, phonological make-up, etc. We also need to resolve ambiguities around meaning. The point at which we have successfully accessed a word and correct information about it is called *lexical access.*
- Next, we need to fit each word together to arrive at a representation of the meaning of the sentence. This is *syntactic processing.*
- Finally, we need to integrate the sentence just processed into the prior discourse (and potentially world knowledge). This is called *discourse processing.*

5.2.1. Lexical access

To capture lexical access — one dimension of "readability" that will influence whether the media reports a central bank communication — we measure for the Bank of England's

[19] The reason for this being that typos and numbers are likely to have vectors associated with them that are close to the random vector assigned at the beginning of the word2vec training. The fact that they are close to our centroids is just random chance.

[20] Note that we have obviously simplified things here. For instance, we completely ignore individual differences that may bear on an individual's ability to comprehend a text. For a full and complete treatment, we direct the interested reader to the very accessible introductory text of Warren (2013).

communications: the mean frequency of words in the document (as computed on an auxiliary word-frequency dataset), the number of contexts in which an individual has experience of the words (using survey evidence), the age of acquisition of the words, the percentage of people who say they know the words used (word prevalence), how close a word is to a previous occurrence in the text (repetition priming), how likely a word is given its context (expectancy, operationalised by a word vector engine), the word status (whether content or function, operationalised by a PoS tagger), the grammatical categories of the words (again operationalised by PoS tagging), the length of the words (including not only the number of characters, but the number of individual sound units, syllables, and morphemes), the concreteness of words (whether the referent of a word can be perceived by the senses), the emotionality of words, the number of different meanings of words (lexical ambiguity), and the number of word neighbours (both phonological and orthographic). As throughout this section, a detailed explanation of the motivation for using these measures, and the specific mechanisms for calculating them can be found in Appendix Section 8.4.

5.2.2. Syntactic Processing

We detail next features that are intended to capture the processing costs associated with the comprehension of syntax (sentence structure) and its interface with meaning (semantics).

Drawing on and adapting Bornkessel-Schlesewsky and Schlesewsky (2009, p. 90)'s list of requirements of a syntactic processor, we aim to featurise five aspects of sentence parsing:

1. formal structure building;
2. grammatical dependency relation linking;
3. working memory and storage limitations;
4. expectation;
5. ambiguity processing and conflict resolution.

In more detail, to capture the syntactic processing cost of central bank communication, we measure: the mean sentence rate for various syntactic constituent structures that may influence readability (based on a constituency parse), the mean sentence rate of syntactic dependency relations, the proportion of sentences in a document for which the sentence's root is instantiated by a verb, variables that capture the extent of "working memory" needed by the reader to process the sentence (including dependency arc lengths, number of negatives, offset distances, number of leaves per sentence constituency parse, number of non-binary branching constants, number of non-terminal nodes in the parsed tree of a sentence, the tree height, and many more), how surprising the sentence is (calculated using the Shannon information content of the sentence's best constituency parse), syntactic production similarities and part of speech type-token ratios, structural ambiguity of the sentences, and the proportion of explicit variants of several common grammatical structures (*not* versus *-nt*, for example).

5.2.3. Discourse Processing

Having accessed words and parsed the incoming linguistic input text into its constituent parts, the language comprehender next needs to construct a mental representation of the text. Below we featurise four main aspects of discourse processing:

- identifying the topic of the discourse;
- constructing propositions and representations for new discourse entities;
- determining how each sentence is connected to other sentences;
- and identifying referents for linguistic expressions.

The variables we calculate to measure the ease of discourse processing of central bank communication are: the extent to which the first sentence summarises the whole document (calculated via the similarity between the word embedding vectors of the first sentence to the rest of the text), the number of propositions and representations (including the number of noun phrases, the number of entities, and the number of adverbials about the discourse itself, and many more), temporal cohesion measures (whether the document's tense composition coheres across sentences), lexico-semantic cohesion measures (the extent to which there is lexical and semantic overlap between sentences), referential cohesion measures (the extent to which the same discourse referent maintains the same grammatical relation across sentences), discourse relation measures (whether various categories of inter-sentential discourse connection are overtly signalled, e.g. *similarly, however, in addition,* *next*), and metrics relating to coreference resolution (how easy it is for readers to relate pronouns like 'it' to noun phrases that they refer to).

5.3. News-values

We now move outline our third main dimension of textual features—NEWS-VALUES—namely, there are certain characteristics of any published news article that have made it 'newsworthy', i.e. "worthy of being published as news" (Caple 2018). We have drawn on academic journalism research since the 1960s, from Galtung and Ruge (1965) through Bednarek and Caple (2017), to identify 9 news values each measured in several ways: SIZE (measured by comparative or superlative modifiers, intensifiers, and other indicators), IMPACT (similar to size, and measured using synonyms of the word 'impact', the number of resultative conjunctions, result-state predicates and perfect aspect verb constructions), SENTIMENT (measured using dictionary methods), PERSONALISATION (measured by the number of named entities, personal pronouns, animate subjects, and many more), PROXIMITY (measures that try to capture the geographical and cultural proximity to the reader), FACTICITY (measured by the number of entities recognised in the text as likely belonging to factual statements), UNCERTAINTY (measured using dictionary methods), PROMINENCE (measured by the number of references to the Bank of England governor), and NOVELTY (including a measure of the textual dissimilarity between the communication and all the other documents published by the Bank of England in the last thirty days).

Altogether, θ_B comprises of a total of 351 features that we chose to measure based on an extensive review of the literature.

In this way our approach differs from other studies of central bank text that primarily use NLP to reduce dimensionality (S. Hansen, McMahon, and Tong 2019; Larsen, Thorsrud, and Zhulanova 2021; Munday 2022). We measure *specific* features of said communication in order to investigate their relationship to an outcome variable (in our case reporting in the media).

6. Estimation

We have discussed how the variables contained in the model are measured. We now want to estimate the equation given by the structural model (Equation 21) to determine which features of central bank communication and which features of the state of the economy are associated with increased news coverage.

6.1. Method

Our framework, detailed in Section 2, delivered a model equation: Equation 21. Appending an approximation error to this equation gives:

$$\frac{1-k_t}{k_t} = \beta_0 + \beta_1^T(\theta_{B,t}^T\theta_{B,t}) + \beta_2^T\theta_{B,t} + \beta_3^T(z_t \otimes \theta_{B,t}) + \beta_4^T z_t + \beta_5^T(z_t \otimes z_t) + \epsilon_t \qquad (25)$$

Equation 25 suffers from a dimensionality problem. The Kronecker product terms cause the number of coefficients we want to estimate to be substantially larger than the number of observations. For example, if one wanted to measure only 100 features of the text and 10 features of the economy, that would result in 1310 composite features in total (excluding the intercept), close to the total number of observations.

If the goal was to *predict* $\frac{1-k}{k}$ then we could apply an approximately sparse regression model (e.g. a LASSO model à la Robert Tibshirani (1996)) that implemented a regularisation approach to shrink the dimension to an appropriate size.

Our goal, however, is perform causal inference on the parameters. And methods that perform well at prediction often achieve that predictive ability at the cost of biased or non-consistent coefficient estimates (Leeb and Pötscher 2008a; Leeb and Pötscher 2008b). If one tried, for example, to select a subset of variables that were important from Equation 25 using a LASSO model, and then do inference by performing OLS on the selected variables, then substantial omitted variable bias would be likely to occur. For example, suppose a member of θ and a member of z are highly correlated with each other. From the perspective of prediction, including both is inefficient, and so one variable will likely be dropped in the process of regularisation — suppose for argument's sake it is the member of z. But now we have excluded a variable that is highly correlated with a variable of interest, the member of θ, leading to significant omitted variable bias.

This problem is not just a possibility in our case. The solution to the central bank's problem, Equation 12, suggests that the correlation between the controls (z) and the variables of interest (θ) is likely to be strong. Dropping variables that are not predictive of $\frac{1-k}{k}$ in order to overcome the dimensionality issue will prevent us from performing inference.

We turn to the de-sparsified LASSO of Van de Geer, Bühlmann, Ritov, and Dezeure (2014) to perform estimation. The de-sparsified LASSO (sometimes called the de-biased LASSO) is a semi-parametric method which allows the researcher to perform inference on a subset of parameters in a high-dimensional model. We follow the treatment of Adamek, Smeekes, and Wilms (2020) who establish the uniform asymptotic normality of the de-sparsified LASSO in the time series case allowing for heteroskedastic and serially correlated errors.

The de-sparisifed LASSO is a shrinkage method. Shrinkage methods apply structure to the parameter vector that the researcher wants to perform inference on in order to circumvent the problem of high-dimensionality. In our case we apply an assumption of weak sparsity to the parameter vector $[\beta_1, \beta_2, \beta_3, \beta_4, \beta_5]$: within the true structural parameter vector, there are only a few entries that are not exactly or close to zero.

The de-sparsified LASSO applies shrinkage to the parameter vector, thus performing variable selection. However, this variable selection results in the exact post-selection inference issue outlined before (Leeb and Pötscher 2008a). To correct for this the de-sparsified LASSO uses node-wise regressions (regressions of each variable on the right hand side on all other regressors) to de-bias the estimates of the parameter vector.[21]

The de-sparsified LASSO of Van de Geer, Bühlmann, Ritov, and Dezeure (2014) provides estimates of the parameter vector in the form:

[21] Alternative methods for performing valid inference in high-dimensional settings include those that use selective inference — i.e. performing inference conditional on a model selected via shrinkage (Tian and J. Taylor 2017; J. Taylor and Robert Tibshirani 2018; Fithian, Sun, and J. Taylor 2014; Ryan Tibshirani, Rinaldo, Robert Tibshirani, Wasserman, et al. 2018) typically under the assumption of IID data; and orthogonalizing the parameter of interest to the estimation of the other parameters using double selection (sometimes called double machine learning) (Belloni, Chernozhukov, and C. Hansen 2014; Chernozhukov, Chetverikov, et al. 2018), a method that has been extended to various time series cases in Chernozhukov, Härdle, Huang, and Wang (2019), Hecq, Margaritella, and Smeekes (2019), and Babii, Ghysels, and Striaukas (2020).

$$\hat{b} = \hat{\beta} + \frac{\hat{\Theta} X^T (y - X\hat{\beta})}{T}$$

Where $\hat{\beta}$ is the biased parameter vector from a typical LASSO regression of y on X, $\hat{b}$ are the "corrected" estimates of the parameter vector, T is the sample length, and $\hat{\Theta}$ is a matrix constructed from the set of node-wise regressions.

More specifically, the LASSO estimates from the nodewise regressions yield the parameters:

$$\hat{\gamma}_j := argmin\left(\frac{||x_j - X_{-j}\gamma_j||_2^2}{T} + 2\lambda_j ||\gamma_j||_1\right) \tag{26}$$

where X_{-j} is X with x_j removed.

We can also extract the estimated loss from the loss functions of the nodewise regressions:

$$\hat{\tau}_j^2 := \frac{1}{T}||x_j - X_{-j}\hat{\gamma}_j||_2^2 + 2\lambda_j ||\hat{\gamma}_j||_1 \tag{27}$$

Defining $\hat{\Gamma}$ as the stacked matrix of the parameter vectors $\hat{\gamma}$ with ones along the diagonal, and $\hat{\Upsilon}^{-2} := diag(\frac{1}{\hat{\tau}_1^2}, ..., \frac{1}{\hat{\tau}_N^2})$ then we can write that $\hat{\Theta} := \hat{\Upsilon}^{-2}\hat{\Gamma}$.

Adamek, Smeekes, and Wilms (2020) show that under the assumption of weak sparsity of the parameter vector, and other general conditions that the desparsified LASSO is asymptotically normal, including where inference is performed on weakly dependent data and where the "errors may exhibit serial dependence, heteroskedasticity and fat tails". This allows us to perform valid inference on the estimated parameter vector in the case this paper describes.

Furthermore, one should note that our identification scheme is based on (i) the event study methodology outlined in Section 4 removing confounding factors from influencing out dependent variable, and (ii) a selection on observables approach through controlling for the state of the economy and a large number of textual features. Unfortunately, as often in macroeconomics, there is no natural experiment for us to exploit.

In total we estimate all 4695 parameters of Equation 25 using 1211 instances of Bank of England communication and their corresponding news coverage.

6.2. Results

Before we perform inference on elements of the parameter vector $[\beta_1, \beta_2, \beta_3, \beta_4, \beta_5]$, we ask a broader question. Is the information in the right hand side variables of Equation 21 significant in explaining the variance in the left hand side variable? Or in other words, is there information in textual features and the state of the economy that explains the extent to which central bank communication is reported on in the news?

In a non-high-dimensional setting the answer could be found by performing an F-test on the entire set of regressors. Unfortunately, owing to the number of regressors in our model, this is not possible. We follow the approach in Bühlmann (2013) and Van de Geer, Bühlmann, Ritov, and Dezeure (2014) in which a test statistic regarding the significance of a group of variables can be constructed using the maximum individual test statistic of the group when performing inference via the de-sparsified LASSO.[22] The p-values for these tests are displayed in Table 5.

Firstly, we find that textual features matter. The p-value for whether θ_B and $\theta_B^T\theta_B$ matter, i.e. whether one can set $\beta_1 = \beta_2 = 0$ to zero, is zero to three decimal places. Secondly, we find that the *interaction* between the state of the economy and textual features is also important: the p-value that $\beta_3 = 0$ is also zero to three decimal places. We find that the state of the economy on its own is not significant in explaining news coverage. The p-value for whether $\beta_4 = \beta_5 = 0$ is not below a critical value of 0.01, so we cannot reject this null hypothesis. Finally, overall, the regressors in Equation 21 explain a significant proportion of the variance in the dependent variable (see the final row of Table 5) — with the most useful variables for explaining news coverage either textual features or their interactions with the economy.

[22] Specifically, as in (Van de Geer, Bühlmann, Ritov, and Dezeure 2014), for any fixed group G, conditionally on the features X, the asymptotic distribution of

$$\max_{j \in G} n|\hat{b_j}|^2/\sigma_\epsilon^2 \hat{\Omega_{j,j}}$$

, where $\hat{b}$ are the desparsified coefficient estimates, σ^2 is a consistent estimate for the error variance, and $\hat{\Omega} = \hat{\Theta}\hat{\Sigma}\hat{\Theta}^T$, under the null hypothesis that $\beta_j = 0 \quad \forall j \in G$ is asymptotically equal to the maximum of dependent $\chi^2(1)$ variables whose distribution can be simulated.

Table 5: Significance of groups of variables

H0	No. of coefficients	p-value
$\beta_1 = \beta_2 = \vec{0}$	752	0.000
$\beta_3 = \vec{0}$	3861	0.000
$\beta_4 = \beta_5 = \vec{0}$	132	0.301
$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \vec{0}$	4695	0.000

Turning to inference on individual parameters we can ask the question: which variables are significant in explaining news coverage? Inference on individual parameters raises another issue related to the high-dimensionality of our equation — namely that of multiple comparisons. When testing 4695 coefficients for significance, as we are in our case, a regression that comprised purely white noise variables as both dependent and independent variables would result in approximately 5% of coefficients returning as "significant" under a critical p-value of 0.05. To adjust for this, we use the Benjamini-Hochberg adjustment (Benjamini and Hochberg 1995) to control the False Discovery Rate (the expected proportion of false discoveries amongst the rejected hypotheses). Table 6 shows the coefficients that are significant at the 5% global False Discovery Rate. One can see that the corrected p-values decline by around two orders of magnitude compared to the unadjusted p-values, once we correct for the multiple comparisons problem.

Table 6: Significant Coefficients

Definition	$\hat{\beta}$	Class	p-value	Corrected p-value
Topic 40 ('Bonds') × IP growth inv. var	-162.62	Topics	1.67e-07	7.10e-05
proportion VB × IP growth inv. var	283.10	Lexical processing	1.58e-07	7.10e-05
proportion WP × IP growth inv. var	219.75	Lexical processing	1.35e-07	7.10e-05
proportion TO × infl inv. var	207.70	Lexical processing	1.81e-07	7.10e-05
mean number of content words in doc × IP growth inv. var	153.21	Lexical processing	2.29e-04	4.14e-02
proportion PRP × IP growth inv. var	-142.50	Lexical processing	2.80e-04	4.69e-02
proportion particle (universal) × IP growth inv. var	-160.40	Lexical processing	4.48e-05	1.24e-02
proportion PRP × unemp rate	-172.61	Lexical processing	2.26e-04	4.14e-02
mean contextual expectancy for word × IP growth inv. var	-184.13	Lexical processing	1.70e-04	3.46e-02
proportion particle (universal) × infl inv. var	-186.44	Lexical processing	1.15e-06	4.15e-04
proportion RP × infl inv. var	-187.84	Lexical processing	6.07e-05	1.58e-02
proportion PRP squared	-207.55	Lexical processing	1.23e-04	2.75e-02
proportion PRP × IP growth inv. var	-253.89	Lexical processing	1.77e-07	7.10e-05
proportion RP × IP growth inv. var	-285.00	Lexical processing	8.12e-10	7.62e-07
degree to which the first sentence is a 'headline' squared	-89.32	Discourse Processing	1.43e-05	4.46e-03
mean number of full auxiliaries per sentence × infl inv. var	300.74	Syntax Processing	1.73e-12	2.02e-09
mean dependency arc lengths per sentence × IP growth inv. var	230.11	Syntax Processing	6.81e-06	2.28e-03
prt rate per sentence × IP growth inv. var	188.53	Syntax Processing	8.94e-05	2.10e-02
prt rate per sentence × infl inv. var	180.94	Syntax Processing	2.53e-04	4.40e-02
prt rate per sentence squared	132.73	Syntax Processing	1.99e-04	3.90e-02
number CONJP squared	-106.12	Syntax Processing	6.67e-05	1.65e-02
number SQ × infl inv. var	-214.36	Syntax Processing	1.23e-07	7.10e-05
proportion resultative conjucts × infl inv. var	142.84	News-values	1.35e-04	2.87e-02
proportion MONEY × infl	-244.92	News-values	3.75e-08	2.94e-05
proportion MONEY squared	-261.06	News-values	3.61e-17	8.48e-14
proportion MONEY × IP growth inv. var	-297.52	News-values	3.78e-21	1.78e-17
proportion governor × infl inv. var	-340.46	News-values	7.56e-14	1.18e-10
Q & A Dummy × infl inv. var	157.17	Other	2.93e-05	8.60e-03

Before we analyse the significant coefficients in Table 6 it is worth briefly discussing what is *not* significant. The dummy variable that denoted that a monetary policy decision took place on the same day as a communication was insignificant. This is corroborated by the fact that the state of the economy z and its Kronecker product $z \otimes z$ are both jointly not significant, as shown in Table 5, and have no single variable that is significant at the 5% level in Table 6. This not only suggests that slow moving variables that capture the state of the economy (GDP, the unemployment rate, CPI Inflation) do not — on their own

— influence news coverage of the Bank of England's communication, but that changes in monetary policy stance captured by the one-day difference in the 1-year OIS rate also do not influence news coverage of the Bank's communication.

There is one main broad conclusion one can draw from the significant coefficients in Table 6. The interaction between textual features and the state of the economy is important. Of the 28 significant coefficients, all but five are interaction terms. How you write your communication matters — but how much it matters is state-dependent to a large degree. More surprisingly, the state-dependence of the impact of textual features on news coverage largely owes to the inverse variance of state variables. Of the 23 significant coefficients that are interaction terms between textual features and state variables, 21 include the inverse variance of a state variable. What does this tell us? That it is the second moment of the economy that matters for determining news coverage. Uncertainty of has had a lot of attention in relation to the macroeconomic cycle (S. Baker, Bloom, and Davis (2016) and Christiano, Motto, and Rostagno (2014) to name only two). We find that it is also important for the news cycle. For example, information from the Q and A gets more news coverage when the inverse variance of CPI inflation is low. Or in other words, the Q and A is more likely to be reported on when the variance of inflation is high, and potential comments on its direction and central bank reactions to it are at their most newsworthy.

We now turn to a discussion of the significant coefficients for the textual variables in Table 6. Before we do so, we make a number of preliminary comments. First, as noted, the important textual features are interactions with features relating to the state of the economy. In what follows, we concentrate exclusively on the textual part of the interaction, but the reader should always bear in mind that the effect is conditional on the state of the economy.

Finally, we constructed our model with $\frac{1-k}{k}$ as the response. Thus, a *negative* sign on a coefficient indicates that for an increase in the variable of interest, news coverage *increases*. On the other hand, a *positive* sign on the coefficient indicates that for an increase in the variable of interest, news coverage *decreases*. This transformation also changes the interpretation of the coefficients. A coefficient of, for example, 90 means that a one standard deviation increase in the feature of interest increases $\frac{1-k}{k}$ by 90, all else equal. But that increase in 90 is a decrease in k from, for example, 0.1 to 0.01.

Topic Conditional on the state of the economy, text that discusses the bond market receives more news coverage in the popular press. This can be seen by a negative coefficient of -162 in line 1 of Table 6. There are potentially many reasons for this, foremost amongst them the prominence of QE and forward guidance as important new tools in the period studied, that would have received lots of news coverage for their effects on bond yields. Interestingly, the effect of discussing other topics is statistically insignificant, including inflation and the labour market. This may be due to the (relative) stability of these markets in the face of economic crises when compared to earlier periods in economic history. Or it could be that enough noise has been introduced to our estimation procedure as to attenuate some of our estimated coefficients towards zero.

Clearly, at an extreme, the content of the Bank of England's communication must matter. If the Bank of England released a publication that said that short term interest rates would rise next year to 50%, then this would receive news coverage. Our point is that within our sample and at the margin, the topics that the Bank publishes on do not seem to have much effect on the likelihood of news reporting. As an example, an Inflation Report that had slightly more content on the labour market than usual does not, at least on our results, change the journalist's decision of how closely to paraphrase that report in the next day's newspaper. The way in which that document is written, however, does alter that decision.

Linguistic Processing Our linguistic processing features concern lexical processing, sentence processing, and discourse processing.

Lexical Processing The significant coefficients relating to lexical processing features are contained in lines 2-14 in Table 6. Working from the top of Table 6 we find that increased textual amounts of base forms of verbs (denoted VB), infinitival-*to* (denoted TO), *wh*-personal-pronouns (denoted WP), and content words result in less text being picked up by the press (conditional on the state of the economy). On the other hand, increased amounts of personal pronouns (denoted PRP), adverbs (denoted RP), particles, and greater word contextual expectancy result in more text being picked up by the press (conditional on the state of the economy).

Some of these effects can be explained by reference to processing complexity, that is, keeping things simple so that the consumer can easily understand the message. For instance, base forms of verbs together with *to*-infinitives introduce non-finite embedded clauses and *wh*-personal-pronouns introduce relative clauses, which are another type of embedded clause. Embedded clauses often involve higher processing costs than simpler structures (see e.g. Bornkessel-Schlesewsky and Schlesewsky 2009, particularly Chapter 10). Studies of readability that use simpler measures such as Flesch-Kincaid scores will partly capture this feature. But sentence length only correlates with the use of embedded clauses. Our results suggest that it is the structure itself that lends publications to be more (or less) newsworthy.

Prima facie, it is somewhat curious as to why a larger relative frequency of content words in a document results in a text getting less news coverage, given that content words are by definition more informative than function words. Content words, such as adjectives, adverbs, nouns and verbs, one would expect to be correlated with greater news coverage that function words, such as pronouns, adpositions (e.g. to, with) and numerals. There are two possible reasons for this. First, that content words are generally less frequent and thus harder to process than function words, and it may be that this feature is masking the more basic effect of word frequency. Or second, that function words really do make for more newsworthy content - particularly, we believe, through the use of numerals (a result that is corroborated in the News-values section of coefficients), or through personal pronouns (a result that repeatedly occurs and is discussed below). Given the strength of evidence that personal pronouns are important for news coverage, we are inclined to argue that the content words ratio is partially picking up the effect of these pronouns.

Moving down Table 6, we see many negative coefficients involving personal pronouns (denoted PRP). We interpret these negative coefficients to relate to the *personalisation* of the text. This, we believe, has two main effects. First, it engenders a more colloquial, involved style designed to engage the audience in the narrative and attract a wider lay readership (Biber 2003; Biber and Gray 2012). The extensive use of personal pronouns, such as *we, us, you*, results in a more "chatty" style of prose, which lends itself to reporting in the popular press. Secondly, personal pronouns denote personal views of Monetary

Policy Committee members. Whilst speaking as an institution ("the Bank of England thinks X or Y") may be of use to present messages with one voice, making those messages personal results in greater news coverage ("We think X", "I think Y").

Particles (words like "not", but also the addition of "'s" to denote possession) are also related to greater news coverage. Particles often encode information more economically than other types of phrase (Hinrichs and Szmrecsanyi 2007). They are an important dimension of simplistic writing — a feature that leads them to encourage publications to make it into the newspapers.

The final category of lexical processing features that appears in Table 6 is contextual expectancy. This is measured using `spacy`'s word vector engine to return the similarity score between a target word in a sentence, and the prior context. Contextual expectancy matters because during reading, the reader is predicting the upcoming word (Schuberth and Eimas 1977; Kutas and Hillyard 1984). In other words, upcoming words are already being accessed from the mental lexicon ahead of their being read. When a word is read that is not expected, we have to retrieve that unexpected word, causing a processing difficulty. Publications that are written in a way such that the reader is primed for the upcoming words receive more news coverage.

Discourse Processing The LASSO model selects only one variable from the set of discourse processing features, namely a text's headlining score. This feature indicates the degree to which the first sentence in a text summarises (i.e. serves as a headline for) the main content, and was operationalised using the word embedding similarity between the first sentence and the rest of the text (see the Appendix for more details). The sign on the coefficient for this feature indicates that documents in which the first sentence more successfully summarises the main content are result in more news coverage.

Why should this feature matter? It has been consistently shown that individuals process passages better when they are given context, whether that is a picture, a title, or a summary first sentence introducing the topic, before reading the passage (Dooling and Lachman 1971; Bransford and Johnson 1972; Cirilo and Foss 1980; Haberlandt, Berian, and Sandson 1980; Kieras 1980). Note in addition that this feature is relevant regardless of the state of the economy.

Syntax Processing Continuing to move down Table 6, we find that — conditional on the state of the economy — the use of fully realised auxiliaries, constructions involving long dependency arcs, and particle-verb constructions (denoted prt in Table 6) result in decreased news pick-up for texts. On the other hand, the use of conjunction phrases and main clause interrogatives result increased news pick-up.

Full auxiliaries (e.g. *will, is, have*) have informationally more compact contracted variants (-*'ll*, -*'s*. -*'ve*) (Krug 1994). In addition, contracted variants occur relatively more frequently in speech and interactive writing styles (Biber 1988), putatively making the text seem less formal and more accessible. Both seem plausible reasons behind the correlation between auxiliaries in Bank of England text and subsequent news coverage.

The same explanation may also explain the dispreference in news reportage for Bank publications including lots of particle-verbs, which are textually less economical than single-word verbs. Particle verb structures, which involve a lexical verb and a prepositional or adverbial particle (for instance *pick... up, slow ... down*), are typically separated: the verb has to maintained in working memory until it can be integrated with the particle. Too many of such long-distance separations in a given sentence will induce increased processing costs.

We surmise that the coefficient on the dependency arc length variable reflects the choice of newspaper editors to avoid copying complex language. Dependency arcs map the relationships between words that readers must manage whilst reading a sentence. A considerable body of research has investigated the role of *working memory* and *storage limitations* in sentence processing (Gibson 1998; Gibson 2000). When reading a sentence, we process each word incrementally over time, integrating each word one by one into the structure being built. As the sentence unfolds, it is necessary to retrieve information that has gone before and link current information with it. This burdens the sentence processor, because linguistic material has to be held in memory until it can be fully integrated.

We take as an example two sentences from Jaeger and Tily (2011). The first sentence (5-a) is relatively easy to process, while (5-b) for most readers is almost impossible (although it does actually make perfect sense).

(1) a. This is the malt that was eaten by the rat that was killed by the cat.

b. This is the malt that the rat that the cat killed ate.

The reason (5-a) is easier to process than (5-b) is because in the former the dependency relations between the individuals words are fairly *local*. In (5-b), by contrast, both *that* and *the rat* have to be stored in working memory until the verb *ate* is encountered (they are the object and subject of *ate*, respectively). These *long-distance* or *non-adjacent* dependencies overtax memory resources and result in processing difficulty.

News-values Finally, we see that several features pertaining to a story's news-values are relevant. Specifically, increases in the relative frequency of mentions of money or the governor in the text result in greater news reportage. One reason for this is that news editors and journalists prize a story's FACTICITY, the extent to which it includes facts and figures, and a story's PROMINENCE, the extent to which it includes references to prominent individuals.

The references to the governor could also denote that a opinions expounded in a speech or publication hold more sway with reference to future monetary policy decisions, and so are more likely to be reported on. One can also see the similarities with the earlier finding that personal pronouns affect news coverage favourably — making opinions on the economy personal is important if the aim is to reach the public via the print media.

We summarise the above findings into five concrete proposals for improving the likelihood of central bank communication being reported on in the news, and therefore reaching its intended audience. If a central bank is drafting communication that it wants to reach the general public, it should:

1. Keep things simple. Our results show that one should avoid introducing embedded clauses and separable particle verb structures, as they can increase complexity.

   But this is not any form of simplicity. All readers know simple and easy to read writing when they see it. Defining it is much more difficult. Often researchers have to use proxies such as sentence length or word length to capture readability. We can be more specific and identify which features of text improve readability, to the extent that these features then lead to greater news coverage. These features are all discussed above, but include: reducing embedded clauses, making use of particles, writing words that will not surprise your reader or seem out of place and not using full auxiliaries but using contractions instead.

2. Be personal. Use *we/us/you* to engage the reader, as such words personalise the text.

   Not only does this engender a more colloquial style, it also helps denote personal views which are likely to be more newsworthy than "Bankwide" views.

3. Write in short sentences.

   Short sentences have always been an aim for those wanting to write simply. Our results show that it is not sentence length *per se* that matters. Indeed, sentence length returned an insignificant coefficient in our analysis. What matters is the dependency arcs that the reader must navigate to understand a sentence. Writing in short sentences is an easy way to reduce dependency arcs.

4. Summarise the message in the first sentence of the document, to signpost what is to come.

5. Use facts and figures and make the story prominent by referring to influential Bank staff.

Many, or indeed perhaps all, of these are often included in style guides or writing guides. Our recommendations differ in their specificity. We do not find any effect of word length on whether a publication gets news coverage. We do not find that writing intensifiers (e.g. extremely, maximally) or superlative modifiers (e.g. worst, best) makes news coverage more likely. In fact we find that the vast majority of textual features have no effect at all on newsworthiness. Our results help turn vague statements about how to write into specific recommendations that can be easily implemented by the author.

Central banks should be aware that the effectiveness of these measures is dependent on the state of the economy. We found that altering the style of text often had differing effects on news coverage depending on the volatility of the economy. Nonetheless, we believe that applying the above suggestions to central bank communication will improve news coverage and ultimately help central banks reach a wider audience.

7. Conclusion

The importance of communication to the public given the large effects such communications can have (as evidenced in RCTs) is clear. What is less clear is how to reach the public as a central bank. A primary method is through the print media. But for central banks opting for this route, they face a problem: how to write communication that is deemed "newsworthy", such that it is reported on, whilst simultaneously retaining any important messages. To try and shed light on this issue, we wrote a model of news production and consumption. This model showed that correlating textual features of communication with a measure of news coverage would, unless we were careful, likely result in biased estimates. We measured the variables in our model using an event study approach to deal with endogeneity, and a series of computational linguistic techniques, including a comprehensive set of features that could matter for whether a communication is reported on. We estimated our model using machine learning techniques, and found that it's not only *what* you say that matters, but also *how* you say it. Interestingly, we found that the drafting of the publication mattered much more (within sample) than the content, suggesting that central banks can improve news coverage without compromising their intended messages.

Given the large number of different textual features we measure, and the manner in which we do feature selection, we were able to move beyond broad notions of "good" or "simple" writing that one might suppose would engender more news commentary, and give specific suggestions for writing style. That said, whilst we find that typical measures of readability fall short, it is an open question how well these measures proxy for our more sophisticated calculations. In any case, our recommendations can be much more precise about the structure of the writing (e.g. dependency arcs), whilst simple measures of readability (e.g. sentence length) don't tell the writer the exact mechanism they need to target to improve their text.

Our findings come with, of course, a number of caveats. Clearly our results rely on an in-sample estimation that does not fully explore the space of writing styles or topics. There are no Bank of England publications on many topics, and so we cannot say whether or not talking to that topic would be newsworthy. Furthermore, our measure of news coverage, whilst sophisticated, clearly misses many aspects that are important to central banks. Foremost amongst these is accuracy, which is only partly captured by our similarity scores.

It is worth noting that our methodology is completely general to any institution, not just central banks. Measuring the extent of news coverage and then using the high-dimensional techniques outlined to perform simultaneous feature selection and inference can easily be applied to examine which textual features engender news coverage for public institutions, figures, and private firms.

Often communication to the public is not the stated aim of a communication from a central bank. Central banks engage with many different actors in the economy, the public being only one of these. But communicating to the public is an important policy instrument, and our paper has concrete policy suggestions for how central banks should mould their communication if they want it be newsworthy and reach the wider populous.

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8. Appendix

8.1. Alternative solutions to the central bank's problem

The central bank's problem was to satisfy its first order condition:

$$\nabla L(\theta_B) = 2(y(\theta_N) - \bar{y})^T H J_{\theta_B}(y) = \vec{0} \tag{28}$$

In the main text, we assumed that the central bank found a global minimum, and set $y = \bar{y}$ through manipulating θ_B.

If we index the vector of objectives and the diagonal elements of H by i and the vector of textual features by j, then a solution to the above first order condition requires that:

$$\sum_i (y_i - \bar{y_i}) h_i \frac{\partial y_i}{\partial \theta_{B,j}} = 0 \quad \forall j \tag{29}$$

Since we have not specified a function that maps θ_B to y the partial derivative is left unevaluated. As a result, there may be many other solutions other than the global minimum assumed in the main text or, indeed, none at all.

If the length of y is greater than one, then there are potentially many solutions to the first order condition. If y is scalar, then we either have $y = \bar{y}$ — which is the global minimum solution dealt with in the main text — or $\frac{\partial y}{\partial \theta_{B,j}} = 0 \quad \forall j$. In fact the latter of these conditions leads to a set of linear solutions detailed below. Nonetheless, the possibility of non-linear solutions (or indeed a combination of linear and non-linear solutions) motivates our flexible approach in Section 6.

The central bank's first order conditions under the assumption of a scalar y can be written:

$$\frac{\partial y}{\partial \theta_{B,j}} = 0 \quad \forall j \tag{30}$$

Using the chain rule gives:

$$\nabla y(\theta_N) \frac{\partial \theta_N}{\partial \theta_{B,j}} = 0 \quad \forall j \tag{31}$$

Where $\nabla y(\theta_N)$ denotes the gradient vector of y with respect to θ_N.

We know the partial derivative of θ_N with respect to θ_B; subbing this in gives a system of equations of the form:

$$\nabla_y(\theta_N)\left(\mathbf{1}_j - (\theta_B - \theta^*)\left(\frac{k}{\alpha}2\gamma\lambda w_j(\theta_{B,j} - \theta_j^*)\right)\right) = 0 \quad \forall j \tag{32}$$

Where $\mathbf{1}_j$ denotes a vector of zeros except for element j which is one.

This system of equations can be manipulated such that any element j can be represented in terms of another element i:

$$\theta_{B,j} = \theta_j^* + \frac{w_i}{w_j}(\theta_{B,i} - \theta_i^*)\left(\frac{\frac{\partial y}{\partial \theta_{N,j}}}{\frac{\partial y}{\partial \theta_{N,i}}}\right) \tag{33}$$

Subbing this in gives

$$\left(\frac{\partial y}{\partial \theta_{N,j}}\right)^2 = 2\frac{k}{\alpha}\lambda\gamma w_j(\theta_{B,j} - \theta_j^*)^2\left(\left(\frac{\partial y}{\partial \theta_{N,j}}\right)^2 + \sum_{i\neq j}\left(\frac{\partial y}{\partial \theta_{N,i}}\right)^2\frac{w_i}{w_j}\right) \tag{34}$$

Subbing in for k gives

$$\left(\frac{\partial y}{\partial \theta_{N,j}}\right)^2 = \frac{2\lambda\gamma w_j(\theta_{B,j} - \theta_j^*)^2\left(\left(\frac{\partial y}{\partial \theta_{N,j}}\right)^2 + \sum_{i\neq j}\left(\frac{\partial y}{\partial \theta_{N,i}}\right)^2\frac{w_i}{w_j}\right)}{\alpha + \lambda\gamma\left(w_j(\theta_{B_j} - \theta_j^*)^2 + \sum_{i\neq j} w_j\left(\frac{w_i(\theta_{B,j}-\theta_j^*)\frac{\partial y}{\partial \theta_{N,j}}}{w_j\frac{\partial y}{\partial \theta_{N,i}}}\right)^2\right)} \tag{35}$$

Rearranging gives the linear solutions:

$$\theta_{B,j} = \theta_j^* + \frac{\alpha\left(\frac{\partial y}{\partial \theta_{N,j}}\right)^2}{2\lambda\gamma w_j\left(\left(\frac{\partial y}{\partial \theta_{N,j}}\right)^2 + \sum_{i\neq j}\left(\frac{\partial y}{\partial \theta_{N,i}}\right)^2\frac{w_i}{w_j}\right) - \left(\left(\frac{\partial y}{\partial \theta_{N,j}}\right)^2\left(\lambda\gamma w_j + \lambda\gamma\sum_{i\neq j} w_j\left(\frac{w_i(\theta_{B,j}-\theta_j^*)\frac{\partial y}{\partial \theta_{N,j}}}{w_j\frac{\partial y}{\partial \theta_{N,i}}}\right)^2\right)\right)} \tag{36}$$

So there is a set of linear solutions that do not achieve the global minimum.

8.2. *Word2Vec*

Word2Vec (Mikolov, Sutskever, Chen, Corrado, and Dean 2013; Mikolov, Chen, Corrado, and Dean 2013) is a popular method for transforming words into vectors using their context within a corpus.

Word2Vec uses a shallow (two layer) neural network to produce the vectors. There are two implementation methodologies: Continuous Bag of Words (CBOW) or Skip-Gram. CBOW asks a neural network to predict a target word, given the context of the word (i.e. the words found in a small window around the target word). Skip-gram does the opposite, it asks a neural network to predict the context, given a target word. We use the CBOW implementation.

After training the network, the weights corresponding to the hidden layer are extracted and used as the vector representations for the dictionary of words found within the corpus. These weights are denoted W in the explanation below.

8.2.1. *Architecture*

The entire corpus has V unique words. For each word in the corpus, we take the context words — words within a window of length C from the target word — and use them to target the word in question. For example, in the sentence "the cat sat on the mat", if we were targeting "sat" and the (symmetric) window length, C, was 4, then we would try to predict "sat" based on the inputs "the", "cat", "on", "the".

For each word w_i, denote x_{w_i} as the unique one-hot encoded length V vector for that word. Upon being inputted to the network, each contextual word input vector, x_{w_i}, is multiplied by a V by N weight matrix (W), where N is the number of nodes in the hidden layer. This is the weight matrix we will eventually extract and call our "word embeddings". The mean weighted vector of the C input vectors is then fed to the hidden layer of neurons. Mathematically, the input to the hidden layer is:

$$h = \frac{1}{C} W^T (x_1 + x_2 + ... + x_C) \tag{37}$$

The hidden layer is fully connected and has a linear activation function. It passes the weighted sum of its inputs to the subsequent N by V weight matrix, W'. The subsequent weighted output is a V length vector, that we denote U:

$$U = hW' \tag{38}$$

Finally, we use softmax to the posterior distribution of words, conditional on their context:

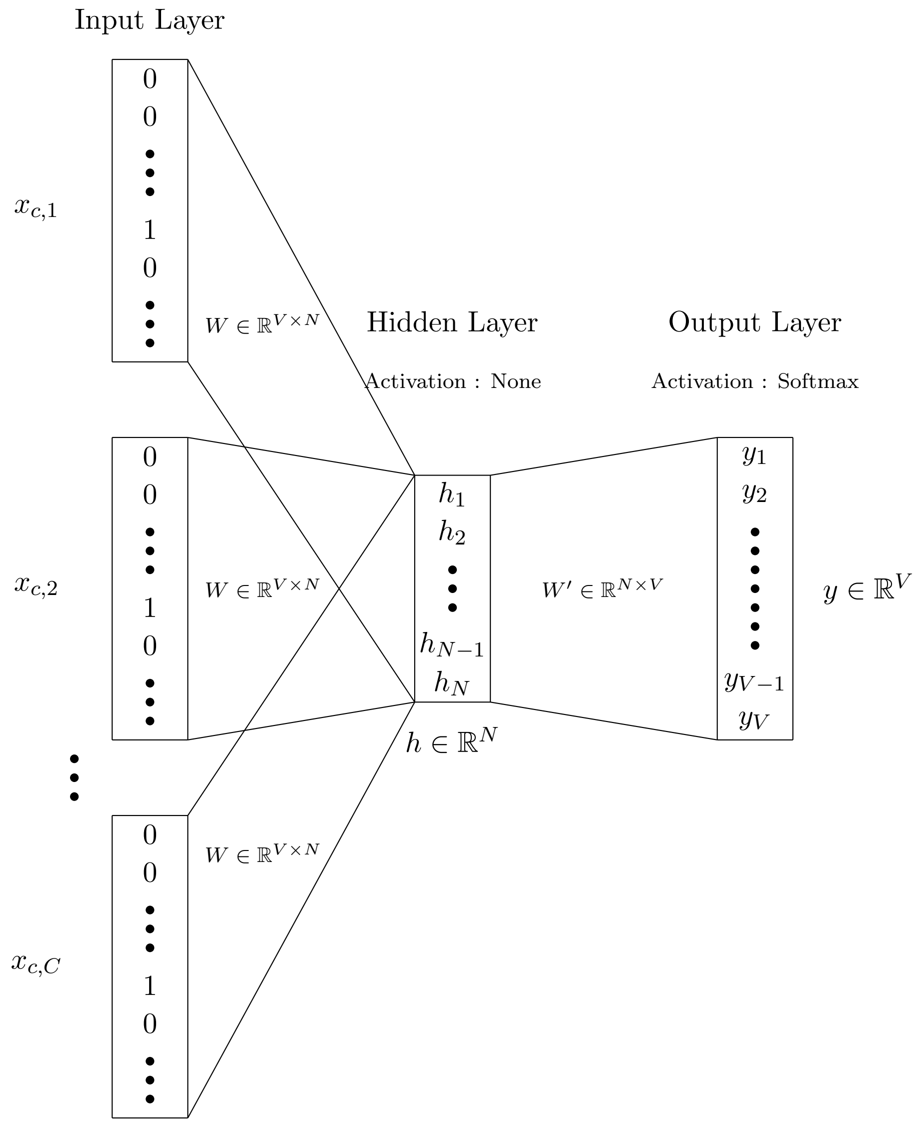
$$p(w_j|w_{c,1}, ..., w_{c,C}) = \frac{exp(u_j)}{\sum_{i=1}^{V} exp(u_i)} = y_j \tag{39}$$

Where u_j is the jth element of the vector U. Denoting the posterior distribution vector across the vocabulary y, we can then compare the prediction of the network, y, with the true result: a one-hot encoded vector of the target word of length V.

The problem is then one of supervised learning. We train the network to minimise the error between the posterior distribution y and the true result.

A sketch of the network architecture is shown below:

Fig. 7. Word2Vec neural network architecture



8.2.2. Training

The objective is to maximise the conditional posterior probability of observing the true target word, given the context words. We can write the loss function as:

$$
\begin{aligned}
L &= -log(y_j) \\
&= -u_j + log \sum_{i=1}^{V} exp(u_i)
\end{aligned}
\tag{40}
$$

Both weight matrices, W and W', are updated during training. Updating is done via a form of gradient descent called backpropagation. For each training example (a word, in a sentence, in a document), one can calculate the error of the neural network, and use that to update the weight matrices. Denote the row of W that refers to word w_i as $v_{w_i}^T$ and the equivalent row of W' as $v_{w_i}'^T$. The updating procedures for each matrix are as follows for a given training instance. For a full derivation of these see Rong (2014).

$$
\begin{aligned}
v_{w_{c,k}} - \frac{1}{C} \cdot \eta \cdot \frac{\partial L}{\partial h_i} \rightarrow v_{w_{c,k}} \quad for\, k = 1, 2, ..., C \\
v_{w_j}' - \eta \cdot e_j \cdot h \rightarrow v_{w_j}' \quad for\, j = 1, 2, ..., V
\end{aligned}
\tag{41}
$$

Where e_j is the prediction error of the output layer (i.e. $y_j - t_j$ where t_j is a one-hot encoded vector of the target word), and η is the learning rate.

Unfortunately, training the network using the exact process described by the above equations is computationally infeasible. For each training instance, to update v' one has to iterate over every word in the vocabulary of size V and calculate the prediction errors.

We use negative sampling to optimize the computation of training the network. Instead of iterating over every word in V, we only update based on the true output word, and G instances of 0's in the one-hot encoded vector t_j. The noise distribution for this sampling process is as in Mikolov, Sutskever, Chen, Corrado, and Dean (2013): a uniform distribution raised to the power of 0.75. As a result, the training objective is also modified to that of Mikolov, Sutskever, Chen, Corrado, and Dean (2013):

$$
L = -log\left(\sigma(v_{w_j}'^T h)\right) - \sum_{w_i \in S_{neg}} log\left(\sigma(-v_{w_i}'^T h)\right) \tag{42}
$$

Where σ denotes the sigmoid function, and S_{neg} denotes the negative subsample. Consequently, the updating equation for v' becomes:

$$
v_{w_j}' - \eta \left(\sigma(v_{w_j}'^T h) - t_j\right) h \rightarrow v_{w_j}' \quad for\, w_j \in S \tag{43}
$$

Where S denotes the full subsample, i.e. the negative subsample and the true target word.

8.2.3. Parameterisation

We set the context window, C to 10, i.e. 5 words either side of the target word. The hidden layer size N is set to 100. The number of negative samples to draw G is set to 5. The initial learning parameter, η is set to 0.025. We train over 20 epochs.

8.2.4. Performance relative to pre-trained vectors

We train our word vectors on the entire Bank of England communication corpus as detailed in Table 1. One can, of course, use pre-trained word vectors from larger corpora and use these instead. For example one can use the Word2Vec vectors trained on about 100 billion words from Google News (Mikolov, Sutskever, Chen, Corrado, and Dean 2013; Mikolov, Chen, Corrado, and Dean 2013), or the GloVe vectors trained on Wikipedia (6 Billion tokens) or Twitter (2 Billion tweets, 27 Billion tokens) (Pennington, Socher, and Manning 2014). The advantage of using these pre-trained vectors is that they cover a much wider scope of vocabulary, having been trained on a larger corpus. The disadvantage is that they do not capture domain specific knowledge that one gets if one trains on the Bank of England corpus. Table 7 shows the most similar words to the word 'economy' according to the pre-trained vectors just mentioned, and according to our own vectors. Since 'economy' is not too specific, all the models seem to output sensible similar words. Table 8 shows the most similar words to the word 'cpi'. The pre-trained models, having not seen the word 'cpi' in the context it is used by the Bank of England have a hard time producing similar words. Our model, on the other hand, performs much better, outputting words such as 'rpi' and 'inflation'. Since our strategy to measure news coverage of Bank of England communication is based on the similarity of word vectors between the Bank's communication and the news, the performance of our internally trained word vectors in capturing domain specific knowledge illustrates the benefit of training the vectors ourselves rather than relying on pre-trained models.

Table 7: Most similar words to the word 'economy' across models

GloVe Wikipedia	GloVe Twitter	Word2Vec Google News	This paper
economic	economic	economic	economies
growth	growth	econ_omy	economic
recession	government	economies	recovery
economies	recession	theeconomy	growth
recovery	markets	ecomony	demand
downturn	debt	recession	eurozone

Table 8: Most similar words to the word 'cpi' across models

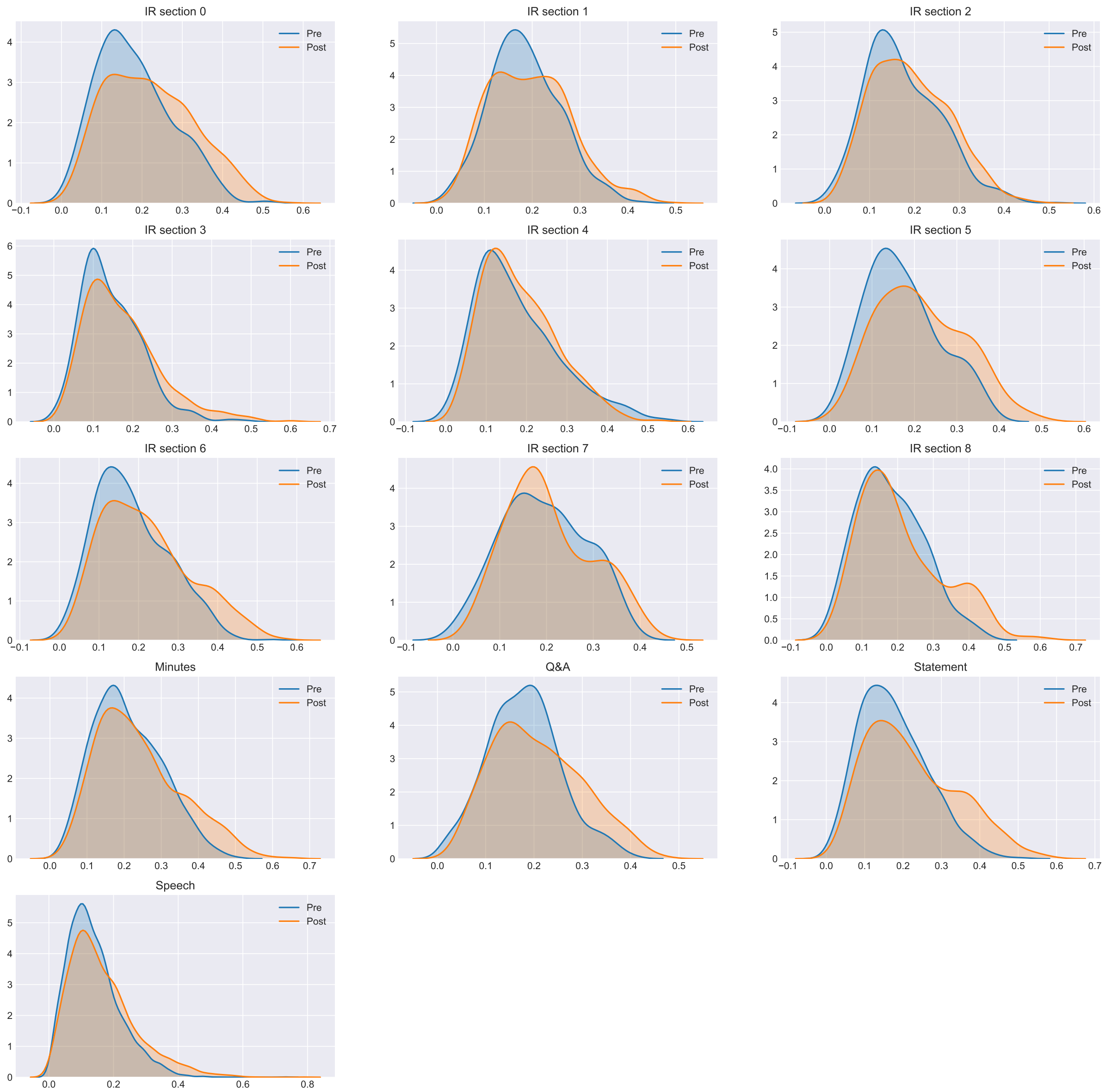
GloVe Wikipedia	GloVe Twitter	Word2Vec Google News	This paper
ppi	cpmi	==_null	rpix
0.1	europeia	1pp	rpi
gdp	stf	infla	hicp
inflation	petrobras	cmp	rpiy
0.2	redução	MBytes	headline
0.3	cachoeira	idx	inflation

8.3. Visualisation

8.3.1. Visualising k

Firstly, we plot the kernel densities of the similarity of all articles in the post-communication window and in the pre-communication window for the measure defined previously (Figure 8). The distributions are skewed positive in the post-communication window compared to the pre-communication window. This is a useful sanity check. Articles that occur after the communication are more likely to either quote or be semantically similar to the Bank of England communication compared to articles published before the communication. This suggests that (i) articles in the press often draw on Bank communication for their content, and (ii) Bank communication is not simply reacting to the news cycle.

Fig. 8. Semantic similarity measure Kernel Densities in pre and post windows



8.3.2. Visualising topics

Figures 9, 10, 11 show the content elements of θ_B for the minutes. Each chart shows the number of instances of a word in a given topic dictionary divided by the length of the minutes, for all minutes since 1998.

Some topics are extremely rarely commented on in the minutes: Topic 17 — which is concerned with the FTSE100 — and Topic 26 — which is concerned with international economic organisations — are basically never mentioned. Other topics show distinct low frequency movements over time: Topic 34 — which is concerned with fiscal austerity — spikes under the period of fiscal tightening following the 2010 election. Other topics exhibit little trend over time, but significant meeting to meeting variation: Topic 14 — which is concerned with the economy — is one such topic.

Fig. 9. Content measures for Topics 0 to 17 in the minutes

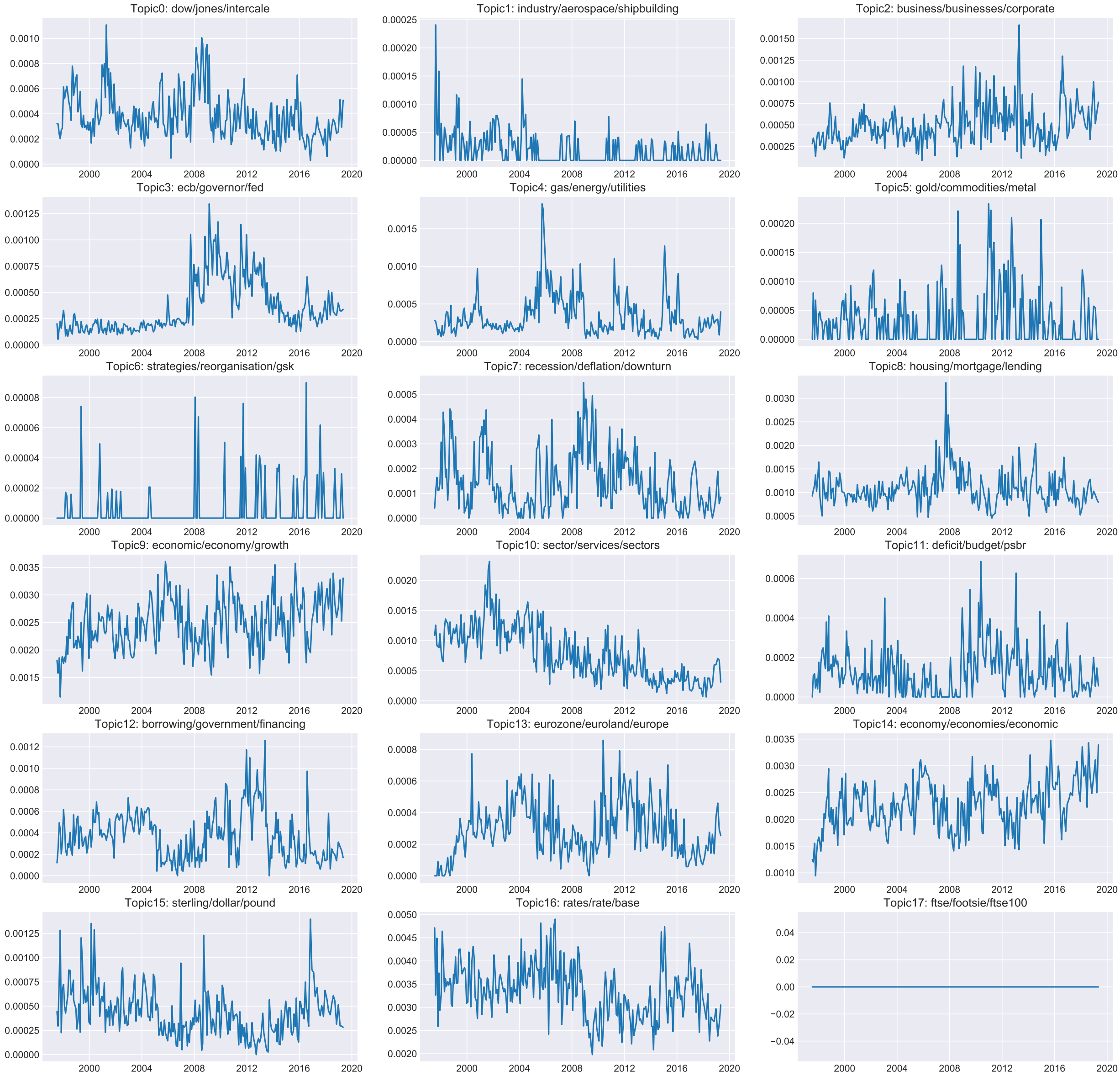


Fig. 10. Content measures for Topics 18 to 35 in the minutes

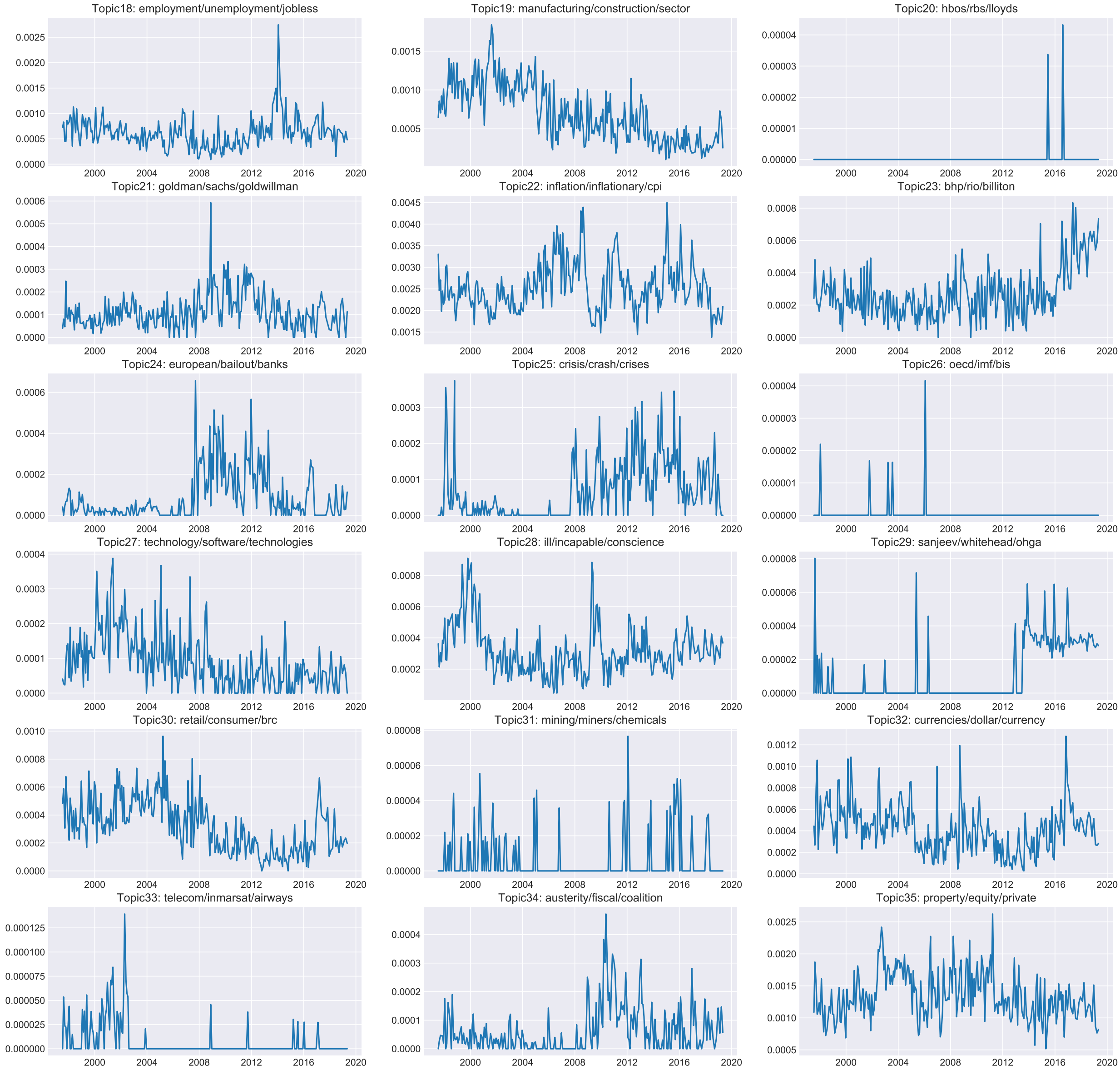
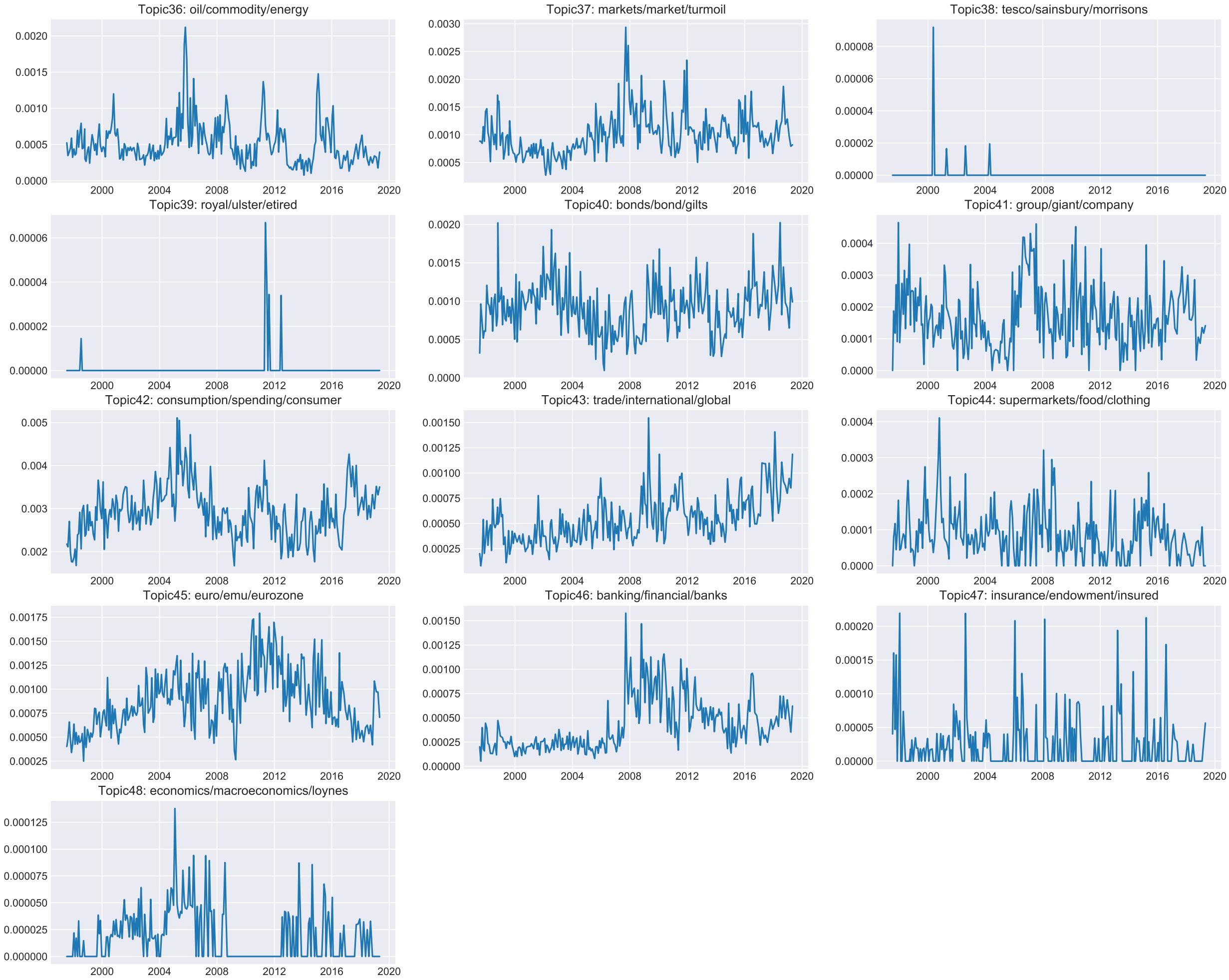


Fig. 11. Content measures for Topics 36 to 48 in the minutes



8.4. Measurement of text features

This section presents in far greater detail the motivation behind including all 351 of our textual features based on an extensive review of the literature. Furthermore, it contains the specific definitions of the measures we calculate and the programs used to implement the measurements. To signpost what follows, this appendix section has the following structure:

1. Topic
2. Linguistic Processing
   (a) Lexical Access and Processing
   (b) Syntactic Processing
   (c) Discourse Processing
3. News-Values
   (a) Size
   (b) Impact
   (c) Sentiment
   (d) Personalization
   (e) Proximity
   (f) Facticity
   (g) Uncertainty
   (h) Prominence
   (i) Novelty

8.4.1. Topic

We wish to measure the extent to which Bank communication touches on topics that consumers want to read about — i.e. that are contained in their preference vector θ^*. We measure 49 different topics using simple dictionary methods. To find these topics, we first obtain Guardian articles containing the word 'economy' since January 1st 2000 until the present day, a total of 13203 articles. We then store the tags that these articles are assigned. Tags are attached manually by Guardian journalists. There are over 50,000 distinct tags across the Guardian's text corpus.

Tags have two 'levels', an upper and a lower level. The upper level represents a broader category than the lower level. For example, a 2014 article titled "Recycling, saving energy, reducing waste: how is it going for you?" is tagged on the upper level as 'environment' and on the lower level has three tags of: 'recycling', 'plasticbags', and 'energyefficiency'. For our purposes we only consider tags with the upper level tag of 'business' which encompasses all economics reporting from the Guardian. This is in total 886 tags.

We split the string of the lower level tag into the most likely set of words using a probabilistic model based on Zipf's law.[23] In the above example 'energyefficiency' gets split into 'energy' and 'efficiency'.

Then, we use the word-embeddings trained on the entire news and Bank communication corpus that we constructed during our measurement of k to assign each lower level tag an average word embedding (obviously if the lower level tag is just one word, then the average word embedding is just the embedding of that word). The tag 'energyefficiency' will be assigned a word embedding of length 100 that is the average of the embeddings for 'energy' and 'efficiency'.

We remove tags that have been used less than 100 times. We then use a K-means clustering algorithm to group the tags into distinct groups. The optimal number of clusters, 49, is determined by the silhouette score across a grid search. These 49 clusters form the topics of content that we wish to measure.

Once the tags are clustered, we take the centroids of the clusters, and take the ten words — excluding numbers and words that are clearly typos[24] — that are closest to the centroid from our word embeddings. These ten words form a dictionary for each topic that is used to measure the extent to which that topic is discussed by the Bank of England. More specifically, our measure for each topic is the total sum of the occurences of the words in the topic dictionary for a given communication, divided by the length of the communication.

Dictionary methods — counting certain words relating to a topic of interest — are a very common and simple method for measuring content. They have been applied most

[23]See Python package `wordninja` for more details: `https://github.com/keredson/wordninja`.

[24]The reason for this being that typos and numbers are likely to have vectors associated with them that are close to the random vector assigned at the beginning of the word2vec training. The fact that they are close to our centroids is just random chance.

notably to measurement of uncertainty in text (S. Baker, Bloom, and Davis (2016), Manela and Moreira (2017), Soto (2019)).

We could have opted for an unsupervised approach to content modelling, such as Latent Dirichlet Allocation (Blei, Ng, and Jordan 2003). This would have involved estimating a generative model of text production on some external corpus (e.g. the Guardian articles), and then querying the Bank of England communications to determine each communication's distribution over the estimated topics. However, for our purposes there are a number of issues with this approach. Since words are not unique to topics, it is difficult to justify ex-post labelling of topics as being related to certain content features. This is particularly the case if the random seed used in LDA changes — potentially altering the topics. Using word embeddings escapes this problem because each of our topics is simply a cluster around a *specific* word embedding, and so the closest word to that embedding can be said to be the label of the topic. Indeed, in cases in which LDA has been used, the authors applying the method generally shy away from ex-post labelling which we explicitly want to do here (S. Hansen, McMahon, and Tong (2019), Munday (2022)), and use LDA as a dimensionality reduction tool only.

The list of words for each topic, and the tags associated with them are detailed in Appendix Section 8.6. It's worth noting that some of the topics look to be simply noise (topics 0 and 29), and we would expect these topics to return insignificant results when regressed against k. Some of the topics are clearly topics that consumers are interested in, but the Bank is unlikely to comment on (e.g. Topic 38, which is to do with retail supermarkets), but this is by design. We want to include topics that consumers care about but that the Bank may regard as unimportant — how to trade off talking about topics close to consumers interests versus those close to the Bank's is the exact problem we outlined mathematically in Section 2.

8.4.2. Linguistic processing

Lexical Access and Processing

We begin our discussion of language processing with lexical access and processing features, which deal with dimensions relating to:

- an individual's exposure to a particular word (in general, exposure to a word increases its activation, and thus ease of processing);
- formal linguistic properties of the word;
- semantic features of the word;
- and neighbourhood effects.

Usage Rates and Exposure

Frequency One of the earliest and most robust findings in psycholinguistics that has been replicated across experimental paradigms is that frequency of usage plays a central role in accessing words from the mental lexicon (Howes and Solomon 1951; Forster and Chambers 1973; Whaley 1978). In language comprehension and production, high-frequency words are accessed more rapidly and more accurately than low-frequency words. In particular, the effect is not binary, i.e. only between low versus high frequency words, but persists throughout the frequency range (Embick, Hackl, Schaeffer, Kelepir, and Marantz 2001).

To operationalize this feature, we drew on frequency information from the SUBTLEX-UK database of Van Heuven, Mandera, Keuleers, and Brysbaert (2014). This database contains frequency information for over $160,000$ word types from subtitles of BBC programs. Frequencies derived from this recent database have been shown to better predict individuals' word processing performance than those derived from other databases. (It is worth noting in passing that a well-used traditional metric of readability—the Dale–Chall measure (Dale and Chall 1948)—is based on extremely old data and deficient notions of word frequency.)

We extracted word tokens and word lemmas from each document using the `spacy` package for Python (Honnibal, Montani, Van Landeghem, and Boyd 2020). For each word token within each document, we then measured its type frequency and lemma frequency in SUBTLEX-UK.[25] This results in two vectors of length n_d, where n_d is the number of words in document d: a type frequency vector $type_d$ and lemma frequency vector $lemma_d$. To provide summary measures for each document, we computed the mean from each of

[25] Type frequency is the frequency of a word form in the text, such as *banks* or *strengthening*. Lemma frequency is the frequency of a word's dictionary entry form, such as *bank* or *strengthen*.

these vectors to yield two frequency attributes per document.

Contextual Diversity A relatively recent finding in psycholinguistic research is the importance of a word's CONTEXTUAL DIVERSITY—the number of contexts in which an individual has experience of a word (Adelman, Brown, and Quesada 2006; Plummer, Perea, and Rayner 2014). In the presence of contextual diversity, the above-mentioned strong effect of usage frequency in isolation seems to be somewhat attenuated.

To build this feature, we took type-based contextual diversity scores from the subtitle corpus of Van Heuven, Mandera, Keuleers, and Brysbaert (2014).[26] Following the above procedure, we built one contextual diversity feature (mean contextual diversity).

Age of Acquisition Words acquired early in life are processed faster than words acquired later, even when other variables are controlled for (see Johnston and Barry 2006 for an overview).

We obtained type-based age-of-acquisition information from the dataset of Kuperman, Stadthagen-Gonzalez, and Brysbaert (2012), and again derived one summary feature based on the mean.

Prevalence Brysbaert, Mandera, McCormick, and Keuleers (2019) find that *word prevalence*, "the percentage of people who indicate they know the word", explains an additional 3.6% of variance in word-processing studies.

We operationalize the feature of prevalence using the dataset of Brysbaert, Mandera, McCormick, and Keuleers (2019), which along with overall prevalence scores also contains scores split by respondent's gender (male or female). As sociological information may be important in explaining word access across individuals, we include this information to derive 4 prevalence features: (1) overall prevalence scores, (2) prevalence scores for females, (3) prevalence scores for males, and (4) the difference of the last two mentioned scores. Again, these features are computed first at the word token level, and then summarized at the document level by taking the mean.

[26] Lemma-based contextual diversity is not available.

Repetition Priming Recent prior exposure to a word facilitates its re-access (D. Scarborough, Cortese, and H. Scarborough 1977). This is called REPETITION PRIMING. The prior mention of the token of interest is termed the *prime* and the token of interest is termed the *target*. For instance, consider the following extract:

(2) ... and [inflation$_{PRIME}$] will stay above our target. But if we set interest rates too high or raise them too rapidly then the economy will be too weak, and [inflation$_{TARGET}$] will fall below our target.

In example (2), the second occurrence of *inflation* is the target, and we say that it is "primed" by the first occurrence of *inflation*, which is the prime. This makes the second occurrence of *inflation* more available, and eases its processing.

We use three programs. Our first program checks whether a word occurs in the prior context and fires a boolean.

Second, given that memory decays with distance and can thus impact on word retrieval, we used a second program that first checks whether a word occurs in the prior context; if it does, we take the reciprocal of the distance (in tokens) between the prime and the target; if it does not occur, we give it a score of zero. For example, in (2), the target has an offset index of 28 and its nearest prime has an offset index of 1, for a score of $1/(28-1) = 0.\overline{037}$.

Third, given that human memory may decay logarithmically rather than linearly (see Singh, Tiganj, and Howard 2018), we also took the natural log of the sum of the second measure and unit constant. In the above example, we have $\log_e\{1 + 1/(28-1)\} \approx 0.036$.

We measured the above three variables at the word-type and word-token level, to derive six features summarized by the document means.

Expectancy in the Sentential or Discourse Context Lexical access is also facilitated (pre-empted) by the sentential context (e.g., Schuberth and Eimas 1977; Kutas and Hillyard 1984).[27] This suggests that during comprehension language users are predicting the upcoming context. In other words, upcoming words are already being accessed from the mental lexicon ahead of their being read. When a word is read that is not expected,

[27]For instance, using an electrophysiological paradigm, Federmeier and Kutas 1999 showed that words that are unexpected within the sentence or discourse context induce larger N400 amplitudes than words that fit the context perfectly (N400 is a negative-going potential peaking around 400 ms after the onset of a stimulus).

we have to retrieve that unexpected word from the mental lexicon, and this causes a processing difficulty. For example, in the sentence below, taken from Federmeier and Kutas (1999), the word *roses* fits the context perfectly. Words such as *tulips*, even though it is from the same semantic field of FLOWERS, are unexpected in the context and cause a processing delay.

(3) The gardener really impressed his wife on Valentine's Day. To surprise her, he had secretly grown some {roses, tulips}.

We operationalized this feature by using `spacy`'s word vector engine to return the similarity score between a target word (e.g. *roses*) and the prior context (e.g. *...his wife on Valentine's day...*) Thus, according to our measure, for the example above, *roses* receives a fit with the context of 0.38, while *tulips* has a lower score of 0.22. We have our one summary feature for this dimension of lexical access (document mean).

Formal Word Properties

Word Status Psycholinguists have also found some evidence for the differential processing of CONTENT words (words with rich semantic content) versus FUNCTION words (words with grammatical functions and minimal semantic content) (Pulvermüller 1999). For instance, Pulvermüller, Lutzenberger, and Birbaumer (1995) showed that the processing of function words is localized in the left-hemisphere of the brain, whereas content words are processed bilaterally.

We first used `spacy`'s part-of-speech (PoS) tagger to perform annotation. Then, for each relevant token (i.e. excluding symbols, punctuation, and whitespace), we fired a binary variable for whether the token was a content word (i.e. adjective, adverb, interjection, noun, proper noun, verb) or a function word (i.e. adposition, auxiliary, coordinating conjunction, determiner, numeral, particle, pronoun, subordinating conjunction). Then, to derive a single measure for at the document level, we took the ratio of the number of content words to the number of content words and function words combined—namely:

$$ContentWordRatio = \frac{Count(content)}{Count(content) + Count(function)}.$$

Grammatical Category Relatedly, specific parts-of-speech may be processed differently (West and Stanovich 1986).

Using information from `spacy`'s PoS tagger, we extracted the relative frequency for each broad part of speech in the document (as listed in Table 9; Nivre et al. 2016). To provide more nuanced information, we also extracted relative frequencies for fine-grained PoS tags (Penn Treebank: Marcus, Santorini, and Marcinkiewicz 1993).

We derived 14 broad PoS features and 33 fine-grained PoS features. (Recall that these are proportions, so we simply have a single measure for each PoS-type.) The following two tables detail the PoS tags that we consider. (Note that these tables were originally drawn from `https://spacy.io/api/annotation#pos-tagging`, which no longer exists).

Table 9: Broad Part-of-Speech tagset with description and examples

Part-of-Speech Tag	Description	Examples
ADJ	adjective	big, old, green, incomprehensible, first
ADP	adposition	in, to, during
ADV	adverb	very, tomorrow, down, where, there
AUX	auxiliary	is, has (done), will (do), should (do)
CCONJ	coordinating conjunction	and, or, but
DET	determiner	a, an, the
NOUN	noun	girl, cat, tree, air, beauty
NUM	numeral	1, 2017, one, seventy-seven, IV, MMXIV
PART	particle	's, not,
PRON	pronoun	I, you, he, she, myself, themselves, somebody
PROPN	proper noun	Mary, John, London, NATO, HBO
PUNCT	punctuation	., (,), ?
SCONJ	subordinating conjunction	if, while, that
SYM	symbol	\$, %, §, ©, +, -, ×, ÷, =, :)
VERB	verb	run, runs, running, eat, ate, eating

Table 10: Narrow Part-of-Speech tagset with description and examples

Part-of-Speech Tag	Description
CC	conjunction, coordinating
CD	cardinal number
DT	determiner
EX	existential there
IN	conjunction, subordinating or preposition
JJ	adjective
JJR	adjective, comparative
JJS	adjective, superlative
MD	verb, modal auxiliary
NN	noun, singular or mass
NNP	noun, proper singular
NNPS	noun, proper plural
NNS	noun, plural
PDT	predeterminer
POS	possessive ending
PRP	pronoun, personal
PRP$	pronoun, possessive
RB	adverb
RBR	adverb, comparative
RBS	adverb, superlative
RP	adverb, particle
TO	infinitival “to”
UH	interjection
VB	verb, base form
VBD	verb, past tense
VBG	verb, gerund or present participle
VBN	verb, past participle
VBP	verb, non-3rd person singular present
VBZ	verb, 3rd person singular present
WDT	wh-determiner
WP	wh-pronoun, personal
WP$	wh-pronoun, possessive
WRB	wh-adverb

Word Length Effects Word length (or 'bulk') is another pervasive factor in word recognition performance, with the simplest measures (e.g. number of characters) already incorporated in earlier computational measures of text complexity.

We used four different dimensions of word length: (1) number of characters, (2) number of phonemes (that is, the number of units of sound), (3) number of syllables, and (4) number of morphemes (e.g. *organiz-ation-s* has three morphemes, *walk-ed* has two). With one summary measure for each dimension based on the document mean, we derived four features of word bulk.

Semantics

Concreteness Concreteness refers to the extent to which the concept of a given lexical item can be perceived by one of the five senses or not. Thus, *money* is concrete, and *inflation* is not.[28]

We used concreteness ratings from the experimental study of Brysbaert, Warriner, and Kuperman (2014), in which almost $40,000$ word lemmas were rated 1 (abstract) through 5 (concrete) across over 4,000 participants, to derive one concreteness feature based on the document mean.

Emotionality Another dimension of semantics that has recently come to the fore is effect of word emotionality in word processing.[29] Words with emotional feature specifications are typically processed faster than those which are more neutral (Scott, O'Donnell, and Sereno (2012)).

We drew on the database of Warriner, Kuperman, and Brysbaert (2013) to develop a total of 3 features of emotional *valence* (word pleasantness), emotional *arousal* (the intensity of emotion provoked by the word), and emotional *dominance* (degree of control).

Lexical Ambiguity When we read a word such as *bank* we gain access to its multiple meanings, e.g. the word *bank*'s meaning as financial institution and its meaning as a place

[28]According to one theory, words denoting concrete concepts activate both a language (verbal) system and an imagistic (nonverbal) system whereas words denoting abstract concepts activate only the language system. This 'dual-coding' (activity in two interconnected systems) affords processing advantages to concrete words (Paivio 2013).

[29]Emotionality has drawn attention in monetary economics too, for instance Tuckett (2011).

alongside a river. Even in contexts in which the other meaning is complete nonsense, we still access and consider as a potential candidate the other meaning (Swinney 1979). This choice of meanings causes a processing disruption, though we are seldom aware of it. This is called *lexical ambiguity*.

We measured the degree of lexical ambiguity in a document in two ways. First, we extracted the number of meanings for each word in the document using WordNet (Miller 1995). Second, we measured the semantic diversity of a word—that is, the degree to which the contexts in which a given word occurs are similar in meaning overall (Hoffman, Ralph, and Rogers 2013). For each measure, we computed our usual mean vector.

Neighborhood Effects

Orthographic Neighborhood A target word a has an orthographic neighbor b if one can create b from a by changing a single letter in one of the word's positions (Coltheart 1987). Thus, some orthographic neighbors of the word *bank* are *balk*, *bane*, *lank*. The size of a word's neighborhood affects its access: the larger the neighborhood of a word, the faster its access (Andrews 1989).

We collected orthographic neighborhood statistics for each word in a given document from the dataset of Balota et al. (2007), and from these derived the mean vector.

Phonological Neighborhood Relatedly, a word's phonological neighborhood size refers to the number of words that can be formed from the original word by a single phoneme substitution, addition or deletion. For example, *sort* has *thought* (substitution), *sorts* (addition), and *ought* (deletion) as phonological neighbors. Mulatti, Reynolds, and Besner (2006) demonstrate that phonological neighborhood size is a stronger predictor of lexical access than orthographic neighborhood size in contexts in which words are read aloud.

As for orthographic neighborhood, we used the dataset of Balota et al. (2007) to derive our mean summary variable for this feature.

Syntactic Processing

We detail next features that are intended to capture the processing costs associated with the comprehension of syntax (sentence structure) and its interface with meaning (semantics).

Drawing on and adapting Bornkessel-Schlesewsky and Schlesewsky (2009, p. 90)'s list of requirements of an individual's syntactic processor, we aim to featurize five aspects of sentence parsing:

1. formal structure building;
2. grammatical dependency relation linking;
3. working memory and storage limitations;
4. expectation;
5. ambiguity processing and conflict resolution.

Syntactic Structure Building

Constituency Types As soon as we encounter textual material, we need to impose structure upon it and build out the individual words into larger constituent units. This forms the basis for subsequent interpretation. We call this *constituency parsing.*

Using the `spacy` add-on component `benepar` (Kitaev, Cao, and Klein 2019; Kitaev and Klein 2018), we parsed each sentence in each document into its constituents. An example of a sentence's constituent parse can be seen in Figure 12.

Table 11: Constituency parse labels

Label	Description	Label	Description
S	main clause declarative	NX	head of noun phrase in complex NPs
SBAR	subordinate clause	PP	prepositional phrase
SBARQ	direct question	PRN	parenthetical
SINV	inverted declarative	PRT	particle
SQ	inverted yes/no question	QP	quantifier phrase
ADJP	adjective phrase	RRC	reduced relative clause
ADVP	adverbial phrase	UCP	unlike coordinated phrase
CONJP	conjunction phrase	VP	verb phrase
FRAG	fragment	WHADJP	*wh*-adjectival phrase
LST	list marker	WHADVP	*wh*-adverbial phrase
NAC	not a constituent	WHNP	*wh*-noun phrase
NP	noun phrase	WHPP	*wh*-adjectival phrase

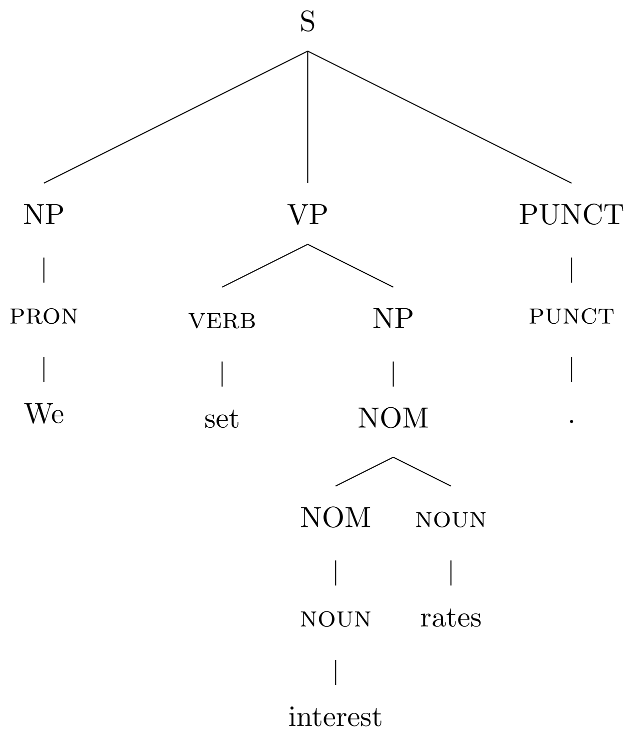


Fig. 12. Syntactic constituency parse for an example sentence: “We set interest rates.”

For each syntactic constituent type, listed in Table 11, we calculated its mean sentence rate per document.

Dependency Relation Linking

Dependency Types In order to construct a semantic interpretation of the sentence, as we build constituency structure, we need to link each syntactic constituent with a grammatical role. For example, consider again the following simple sentence:

(4) We set interest rates.

Upon identifying the noun phrase constituent *We.* we need to realise that it is the grammatical subject of the sentence; when we encounter the verb *set* we need to realise that it is the verbal root of the sentence, upon which *We* depends; when we encounter the noun phrase *interest rates*, we determine that it is the grammatical object, dependent upon *set.* We thus map the constituency built in (e.g.) Figure 12 onto a grammatical dependency parse, which links each word to its relational parent. The dependency parse equivalent of Figure 12 is given in Figure (4).

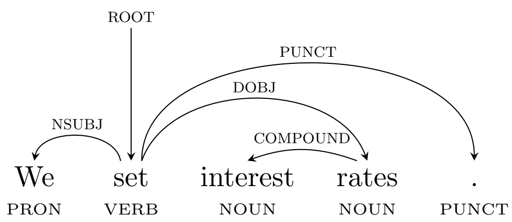


Fig. 13. Syntactic dependency parse for an example sentence *We set interest rates.* The arcs above the text denote the grammatical relations. We also show part-of-speech information below the text. This shows that *We* is involved in a nominal subject relation with respect to the root *set*, and *interest rates* is involved in a direct object relation with respect to the root. It can be seen that the root *set* is associated with 3 dependencies in this graph.

We used `spacy` to build dependency parses for each sentence within each document. Then, for each of the 48 syntactic dependency types, listed in Table 12, we calculated its mean per sentence rate.

Table 12: Dependency parse labels

Label	Description	Label	Description	Label	Description
acl	adjectival clause	csubj	clausal subject	nummod	numeric modifier
acomp	adjectival complement	csubjpass	clausal subject (passive)	oprd	object predicate
advcl	adverbial clause modifier	dative	dative	obj	object
advmod	adverbial modifier	dep	unclassified dependent	obl	oblique nominal
agent	agent	det	determiner	parataxis	parataxis
amod	adjectival modifier	dobj	direct object	pcomp	complement of preposition
appos	appositional modifier	expl	expletive	pobj	object of preposition
attr	attribute	intj	interjection	poss	possession modifier
aux	auxiliary	mark	marker	preconj	pre-correlative conjunction
auxpass	auxiliary (passive)	meta	meta modifier	prep	prepositional modifier
case	case marking	neg	negation modifier	prt	particle
cc	coordinating conjunction	nn	noun compound modifier	punct	punctuation
ccomp	clausal complement	nounmod	modifier of nominal	quantmod	modifier of quantifier
compound	compound	npmod	noun phrase as adverbial modifier	relcl	relative clause modifier
conj	conjunct	nsubj	nominal subject	root	root
cop	copula	nsubjpass	nominal subject (passive)	xcomp	open clausal complement

Root Type Some root types are more "canonical" than others; for instance, a verbal root might be considered more basic than a nominal root. Following related work in computational readability (e.g. Brunato, De Mattei, Dell'Orletta, Iavarone, and Venturi 2018), we computed the proportion of sentences within a document for which the sentence's root had a verbal instantiation.

Working Memory and Storage Limitations A considerable body of research has investigated the role of *working memory* and *storage limitations* in sentence processing (Gibson 1998; Gibson 2000). When reading a sentence, we process each word incrementally over time, integrating each word one by one into the structure being built. As the sentence unfolds, it is necessary to retrieve information that has gone before and link current information with it. This burdens the sentence processor, because linguistic material has to be held in memory until it can be fully integrated.

We take as an example two sentences from Jaeger and Tily (2011). The first sentence (5-a) is relatively easy to process, while (5-b) for most readers is almost impossible (although it does actually make perfect sense).

(5) a. This is the malt that was eaten by the rat that was killed by the cat.
    b. This is the malt that the rat that the cat killed ate.

The reason (5-a) is easier to process than (5-b) is because in the former the dependency relations between the individuals words are fairly *local.* In (5-b), by contrast, both *that* and *the rat* have to be stored in working memory until the verb *ate* is encountered (they are the object and subject of *ate*, respectively). These *long-distance* or *non-adjacent* dependencies overtax memory resources and result in processing difficulty.

We operationalize various features that can be assumed to relate to storage and integration costs. Specifically, we featurized the following.

- dependency arc lengths
  - mean dependency arc length per sentence
  - the mean maximum dependency arc length per sentence
- number of dependencies
  - mean number of dependencies per sentence
  - mean number of dependencies per root
  - mean number of dependencies per subject
- dependency location
  - mean number of left-edge dependencies per root
  - mean number of left-edge dependencies per subject
  - mean number of right-edge dependencies per root
  - mean number of right-edge dependencies per subject
  - ratio of left-edge and right-edge dependencies per root
  - ratio of left-edge and right-edge dependencies per subject
- offset distances
  - offset distance of subject
  - offset distance of root
- mean number of leaves (terminal nodes, i.e. words) per sentence
- mean number of non-binary branching constituents
- mean number of non-terminal nodes
- mean parse tree height
- mean number of words per syntactic phrase

- ratio between the length of the first syntactic phrase (usually the subject noun phrase) and the second syntactic phrase (usually the verb phrase)

Structural Expectation and Priming

Structural Expectation Other researchers in the psychology of language have focused on processing difficulty/ease as associated with the likelihood of syntactic structures in the discourse (Demberg and Keller 2008; Levy 2008). In general, structures that are more frequently encountered in a language user's experience are preferred over those that are less frequent.

We operationalized this feature by extracting the mean sentence surprisal score for each document. Specifically, this is defined as the Shannon information content of the sentence's best constituency parse, i.e. $Surprisal(parse_1) = IC(parse_1) = \log_2 P(\frac{1}{parse_1})$.

Structural Priming We have already discussed lexical priming, whereby a word is more easily accessed if it has been used already in the discourse. Psychologists of language have researched similar effects on the syntax plane. Specifically, syntactic structures that have previously been used in the discourse are easier to build than those which are encountered for the first time.[30]

We featurized this aspect of sentence process in various ways:

- dependency type type-token ratio ($2-6$ grams)
- part-of-speech type-token ratio ($2-6$ grams)
- syntactic production similarity

Structural Ambiguity Processing and Conflict Resolution

Sentence Ambiguity Score Like lexical ambiguities, structural ambiguities permeate natural language. A robust finding in the experimental literature is that such structural ambiguities result in processing difficulty and delay (for an overview see e.g.

[30]See e.g. Pinker (2014): "A bare syntactic tree, minus the words at the tips of its branches, lingers in memory for a few seconds after the words are gone, and during that time it is available as a template for the reader to use in parsing the next phrase. If the new phrase has the same structure as the preceding one, its words can be slotted into the waiting tree, and the reader will absorb it effortlessly."

Van Gompel and Pickering 2007). A famous example of *local syntactic ambiguity* is given in (6)

(6) The horse raced past the barn fell.

As we process the above sentence incrementally, we encounter the word *raced* and analyse it as the main verb of the sentence. But when we reach *fell*, we realize we've made a mistake because there's no place in the structure to attach it. Subsequently, we have to reanalyse the sentence with *raced* as a participle introducing a reduced relative clause (i.e. *(that was) raced...*) and *fell* as the main verb. This kind reanalysis causes a processing slow-down. It is called a local ambiguity because the ambiguity is resolved locally within the sentence being processed.

Other sentences exhibit *global syntactic ambiguity*, such as that in (7).

(7) The girl saw the boy with the binoculars.

The attachment of the prepositional phrase *with the binoculars* is ambiguous: it can modify the seeing event or the noun phrase *the boy.* This is a global ambiguity because the ambiguity still has to be resolved at the end of the sentence. Again, such ambiguities complicate the parsing process.

Given the importance of structural ambiguity processing in the psychological literature, we decided to construct a feature operationalizing it. Specifically, for each sentence in each document, we used a K-best parser to extract parsing surprisal scores for the two best parses. We then took the ratio of the surprisal scores, and averaged at the document level.

Explicit Structure Marking The grammar of English has available a suite of alternate ways of saying the same thing. Oftentimes, one variant is more explicit in some way than another. For instance, grammatical negation can be variably realised, where *not* is the explicit variant and *-n't* is the contracted (i.e., less explicit) variant. We can optionally omit clausal indicators; for instance in (8) the complementizer[31] *that* is omitted, with $\varnothing$ indicating its omission.

[31] This is the fancy technical term for a subordinating conjunction that introduces a complement clause. See e.g. `https://en.wikipedia.org/wiki/Complementizer`. For instance, in *The MPC judges [that the economy is stable].*, the clause *that the economy is stable* is the complement of the verb *judges* and it is introduced by the complementizer *that.*

(8) The Committee judges ∅ an increase in Bank Rate of 0.25 percentage points is warranted at this meeting.

In addition, in certain types of noun phrase, the determiner *the* is variably realized or omitted.

There is some evidence that explicit alternants can support comprehension, as their presence can reduce ambiguity and help build the correct syntactic parse (Race and MacDonald 2003; Warren 2013; Pinker 2014).

We built features for a variety of fairly frequent syntactic constructions in which one alternant can be considered more explicit than another:

- grammatical negation: *not* vs. *-n't*
- complementizer omission: *that* vs. ∅
- relative pronoun omission: *who/which* vs. ∅
- dative realization: (e.g.) *gave a boost to the economy* vs. *gave the economy a boost*
- infinitival-*to* omission: (e.g.) *help the economy to recover* vs. *help the economy recover*
- comparative choice: (e.g.) vs. *the economy is more healthy* vs. *the economy is healthier*
- *the*-omission: *the* vs. ∅
- auxiliary contraction: (e.g.) *have* vs. *'ve*
- genitive realization: (e.g) *the economy of the UK* vs. *the UK's economy* vs. *the UK economy.*
- punctuation optionally separating an adverbial clause from its parent clause

For each of these constructions, we computed the proportion of explicit realization. For instance, for *the*-realization, we simply computed the number of times a noun phrase began with *the* in a given document divided by the total number of noun phrases in a given document. If the construction happened not to occur in a given document, we include boolean features flagging this.

Discourse Processing

Having accessed words and parsed the incoming linguistic input text into its constituent parts, the language comprehender next needs to construct a mental representation of the text. Below we featurize four main aspects of discourse processing:

- identifying the topic of the discourse;
- constructing propositions and representations for new discourse entities;
- determining how each sentence is connected to other sentences;
- and identifying referents for linguistic expressions.

Topic Identification In order to be able to start building a mental representation of the text, the reader has to quickly identify what it is about. A series of experiments have shown that when the context is given – e.g. a picture, a title, a summary first sentence – readers are better able to recall the contents of the text (Bransford and Johnson 1972). We conjectured, therefore, that if the first sentence in the text effectively summarises the main content, the text will be more readily understood and recalled. We operationalized this aspect of discourse processing by using a word2vec algorithm in which we assessed the textual similarity of words in first sentence to the rest of the text. The more similar the first sentence is to the rest of the text, the more effective a summary it can be considered to be of the text as a whole.

Constructing Propositions and Representations for New Discourse Entities In constructing a mental representation of the text, comprehenders need to be able to extract relevant PROPOSITIONS from the incoming signal of the surface syntax and fix ENTITIES into memory. Propositions are the "smallest units of meaning that can be assigned a truth value", abstracted from their linguistic realization (Traxler 2011). We define entities loosely as people, places, time, things, concepts, etc., which are arguments in propositions. Consider the short discourse in (9) and one possible propositional model of it in (10):[32]

(9) DISCOURSE: "Global activity has strengthened over the last few recent months. It is likely to continue."

(10) REPRESENTATION:

[32]For much more sophisticated models that better capture the semantics of discourse, see e.g. Asher and Lascarides (2003).

```
DISCOURSE[
        RELATION1{   class = additive{
                     realization : pronominal},
                                                   PROP1(   predicate = strengthen{
                                                            tense : present,
                                                            aspect : perfect
                                                            },
                                                            theme = global-activity{
                                                            status : new,
                                                            grammatical-role : subject},
                                                            path = over-the-last-few-months{
                                                            status : new,
                                                            grammatical-role : adjunct
                                                            }
                                                   ),
                                                   PROP2(   predicate = continue{
                                                            tense : present,
                                                            modality : {
                                                            likelihood : likely
                                                            }
                                                            },
                                                            theme = It{
                                                            status : given,
                                                            grammatical-role : subject,
                                                            coreferent : global-economy-strengthening
                                                            }
                                                   )
        }
]
```

In (9)–(10), we have a discourse of two propositions (here, they correspond to sentences, but need not always) that are linked together via a pronominal anaphor, and we will use this example to illustrate our measures.

Research has shown that reading time and recall typically depends on the number of propositions that make up the text (Ratcliff and McKoon 1978).

Entities come in two flavours. They are either GIVEN, in which case a comprehender merely has to reactivate an existing mental representation, or NEW in which case the comprehender has to build an entirely new mental representation. There are substantial computational costs associated with constructing mental representations for new discourse referents (Haviland and H. Clark 1974; Gibson 1998).

We designed a suite of features intended to capture aspects of proposition construction and discourse entity representation:

- number of words – 15 in the example;
- number of sentences – 2 in the example;
- number of noun phrases – 3 in the example;
- number of named entities – our NER tagger identifies *the last few months* as a DATE entity, for a total of 1 named entity in the example;
- number of named entities normalized by the number of noun phrases – 1/3;
- number of named entities normalized by the number of tokens 1/15;
- number of named entities normalized by the number of sentences 1/2;
- proportion of noun phrases that are GIVEN – in the example, the pronoun *It* is given information, relating back to the prior clause, for a proportion of 1/3;
- proportion of noun phrases that are indefinite – the first noun phrase *Global economy* is indefinite, the second noun phrase (*over the last few months* and the pronominal noun phrase *It* are definite, and so the proportion is 1/3;
- number of adverbials about the discourse itself ('as stated above', etc) – there are zero meta-discourse adverbials in this example.

Coherence A text is coherent if the propositions that are extracted from the text can be easily connected in some way. In a classic experiment, Thorndyke (1977) demonstrated that participants who were shown a jumbled-up narrative recalled fewer ideas about the text than participants who were shown the same text in a coherent order. We operationalized features relating to i) temporal cohesion, ii) lexico-semantic cohesion, iii) referential cohesion, and iv) discourse relations.

- TEMPORAL COHESION
  - proportion of present→present tense sequences
  - proportion of present→past tense sequences
  - proportion of past→past tense sequences
  - proportion of past→ present tense sequences

- temporal homogeneity of the document
- temporal sequence homogeneity of the document

- LEXICO-SEMANTIC COHESION
  - proportion of noun phrases with a lexical chain
  - mean lexical chain span
  - mean lexical chain length
  - proportion of lexical chains spanning over half the document
  - proportion of sentences with at least one overlapping lemma
  - mean number of overlapping word per sentence
  - mean similarity between each successive pair of sentences
  - difference in mean similarity between each successive pairs versus shuffled pairs of sentences
- REFERENTIAL COHESION
  - entity graph coherence score (unweighted)
  - entity graph coherence score (weighted by number of entities)
  - entity graph coherence score (weighted by distance between mentions)
  - proportion subject → subject sequence
  - proportion subject→ object sequence
  - proportion subject→other sequence
  - proportion subject→none sequence
  - proportion object→subject sequence
  - proportion object→object sequence
  - proportion object→other sequence
  - proportion object→none sequence
  - proportion other→subject sequence
  - proportion other→object sequence
  - proportion other→other sequence
  - proportion other→none sequence
  - proportion none→subject sequence
  - proportion none→object sequence

- proportion none→other sequence
- proportion none→none sequence

- DISCOURSE RELATIONS
  - comparison connective rate per sentence
  - contingency connective rate per sentence
  - expansion connective rate per sentence
  - temporal connective rate per sentence
  - mean number of connectives per sentences

Coreference Resolution Texts are full of linguistic expressions that refer to the same entity, which we call COREFERENTS. For example, consider the short excerpt of text below in (11).

(11) [The MPC] is [committed to clear, transparent communication]. [The Monetary Policy Report] is a key part of [that]. [It] allows [the group] to share [its] thinking and explain the reasons for [its] decisions.

To introduce more terminology, *The Monetary Policy Report* in the second sentence is termed an ANTECEDENT and the *it*, which refers back to it, is called an ANAPHOR. (Here the anaphor is realized as a pronoun, but it need not be) When a reader encounters a pronominal anaphor like *it* or a noun phrase anaphor *the group*, they need to be able to rapidly identify the correct antecedent. If they match an anaphor to the wrong antecedent, discourse processing breaks down and the text becomes incoherent. The process by which readers do this is variously called COREFERENCE RESOLUTION, ANTECEDENT SEARCH, or ANAPHOR RESOLUTION.

Psycholinguists have studied how language comprehenders resolve anaphors, focusing on the factors that facilitate or hinder the process. In particular, there is an effect of distance, with longer distances between antecedent and anaphor causing processing disruption (O'Brien, Raney, Albrecht, and Rayner 1997).[33]

[33] A greater number of competing possibilities for the antecedent results in the ambiguity. In English, but especially morphologically rich languages, language users make use of grammatical information encoded on the anaphor, such as gender and number (Arnold, Eisenband, Brown-Schmidt, and Trueswell 2000). We prefer to match anaphors with antecedents that are in the same grammatical position (Grober, Beardsley, and Caramazza 1978). And we prefer to match anaphors with antecedents that are highly salient or

We utilized `neuralcoref` (K. Clark and Manning 2016), a state-of-the-art coreference resolution module for `spacy`, and engineered the following features intended to capture aspects of coreference processing:

- ANAPHOR AMBIGUITY
  - number of coreferences per coreference chain
  - mean likelihood of the coreference
  - mean coreference ambiguity score
- DISTANCE
  - mean distance (in words) between each coreferenced entity
- OTHER/GENERAL
  - number of coreference chains in the document

8.4.3. News-values

We now move on from the processing of linguistic units to motivate our third main dimension of features—NEWS-VALUES—namely, there are certain characteristics of any story that gets published as a news article 'newsworthy', i.e. "worthy of being published as news" (Caple 2018). We have drawn on academic journalism research since the 1960s, from Galtung and Ruge (1965) through Bednarek and Caple (2017), to identify 9 relevant news values: (1) SIZE, (2) IMPACT, (3) SENTIMENT, (4) PERSONALIZATION, (5) PROXIMITY, (6) FACTICITY, (7) UNCERTAINTY, (8) PROMINENCE, and (9) NOVELTY. In the following we discuss the specific granular features that make up these 10 news values.

<u>Size</u>

For events to get picked up, they need to be sizeable—that is, they need to be "of a scale large enough to warrant attention" (Montgomery 2007, p. 6). Event size (or scale) can be linguistically encoded in a number of ways, which we draw upon to derive feature sets for this dimension of news values.

foregrounded in the discourse (Almor and Eimas 2008).

- We took the document relative frequencies of **comparative or superlative modifiers** (e.g. *worse/worst, better/best, easier/easiest*). Thus is easily operationalized by checking if a word's fine-grained part-of-speech tag $PoS(w)$ is in the set of comparative or superlative tags, i.e. $PoS(w) \in \{JJR, JJS, RBR, RBS\}$ as defined in Table 10.
- We took the document relative frequencies of **numerals** (and other number terms), which was operationalized by checking if a word's high-level part-of-speech was a numeral, i.e. $PoS(w) == NUM$.
- Similarly, we took the document relative frequencies of **symbols** (e.g. %, £, $, etc.), which was operationalized by checking if a word's high-level part-of-speech was a symbol, i.e. $PoS(w) == SYM$.
- We used regular expressions on the raw text to count the relative occurrence of **intensifiers**—i.e., terms such as *extremely, exceedingly, in all respects, maximally, profoundly*. For this, we drew on Piotrkowicz (2017)'s list of such terms.
- We used regular expressions to count the relative occurrence of **quantifiers** (and other size terms)—e.g., terms such as *plethora, numerous, abundance, myriad, substantial*. Quantifier terms were taken to be those lemmas in the QUANTITY, QUANTIFIED_MASS, SIZE frames in FrameNet (C. Baker, Fillmore, and Lowe 1998).
- We computed the relative frequency of **predicates of scalar position**—e.g. *appreciate, diminish, double, dwindle, escalate, expand, fall, gain, grow,* etc. These terms were taken to be those lemmas in cause_change_of_position_on_a_scale, change_position_on_a_scale, cause_expansion, expansion, cause_proliferation_in_number and proliferating_in_number frames in FrameNet (C. Baker, Fillmore, and Lowe 1998) and those in lemmas in CALIBRATABLE_COS-45.6 verb class in VerbNet (Schuler 2005).

Impact

Similar to size is the IMPACT of an event. For an item to be newsworthy, it has to be of "considerable significance for large numbers of people" (Golding and Elliott 1979, p. 117).

For this dimension, we looked at five features.

- The relative occurrence of synonyms of ***impact*** and ***significance***.
- The relative occurrence of **resultative conjunctions**, i.e. those conjunctions that explicitly index a result discourse relation (e.g. *with the result that, so that, consequently*, etc.). We took such terms from the grammars of Quirk (1985) and Huddleston and Pullum (2002).
- The relative occurrence of **result-state predicates**. These are predicates that have a result state encoded in their lexical semantics—e.g. *die, build*.
- We also examined **potentially result-state predicates**. These are predicates that do not inherently encode a result state component, but can do in combination with other linguistic material, e.g. *run*, as in *run the economy*, is inherently an activity predicate, but can have a result state e.g. *run the economy <u>dry</u>*.
- We include the proportion of **perfect aspect verb constructions** (*has/had/having* —) as these denote past events with present consequences.

<u>Sentiment</u>

A wealth of research on news discourse has shown that SENTIMENT (viz. positivity, negativity, conflict) is a critical factor in news selection (e.g. Johnson-Cartee 2004; Harcup and O'Neill 2017; Bednarek and Caple 2017). We evaluated 6 linguistic markers of event sentiment.

- The relative occurrence of **positive** labelled words in Loughran and McDonald (2015)'s dictionary of financial sentiment terms.
- The relative occurrence of **negative** labelled words in Loughran and McDonald (2015)'s dictionary.
- In addition to the above, we measured **overall subjectivity**—i.e., the relative occurrence of both negative-labelled words and positive-labelled words in Loughran and McDonald (2015)'s dictionary, and **overall sentiment**, i.e. $(Count(positive) - Count(negative))/n$.

- We supplemented traditional features drawn from sentiment lexicons, with two features relating to conflict and contrast(ing views). Specifically, we computed the relative frequency of **contrastive predicates**, i.e. predicates that require two (and potentially in-conflict) agents, e.g. *collide, dissent, disagree, fight, negotiate*, etc. These predicates were taken to be verbs from those verb classes in VerbNet that take agent and co-agent arguments.
- The second new feature is the relative occurrence **adversative conjunctions**—i.e., terms that explicitly indicate a discourse contrast, e.g. *but, however, on the other hand*. We took such terms from the grammars of Quirk (1985) and Huddleston and Pullum (2002).

Personalization

As Johnson-Cartee (2004) puts it, "people identify with other people, and they are more able to understand and remember stories that are concretized by such examples than those that are not." We derived the following features to operationalize this dimension.

- We used named entity recognition (NER) models to identify the relative frequency of entities tagged as **PERSON**.
- We used a dictionary approach to compute the relative frequency of **personal pronouns that linguistically encode an animate entity**—e.g., *he, him, she, her*, etc.
- Another important aspect of personalization is the degree to which speakers (writers) and interlocuters (audience) are involved in the overall narrative. Accordingly, we computed the relative frequency of **local (speaker/addressee) personal pronouns**: *I, me, my, mine, you, your, yours*, etc.
- Using information from VerbNet, we computed the relative frequency of predicates that require an **animate agentive subject**, e.g. *[Mark Carney] increased interest rates.*
- Also using information from VerbNet, we computed the relative frequency of predi-

cates that require an **animate experiencer subject or object**, e.g. *[Mark Carney] feels that the economy is recovering*, *The downturn has frightened [people] into drawing out their deposits.*.

- Again, using information from VerbNet, we computed the number and proportion of predicates that require an **animate patient subject or object**, e.g. *[Many people] have died*, *The coronavirus crisis has killed [many people] directly or indirectly.*
- The relative frequency of the words ***people*** and ***person***.

Proximity

Consumers typically prefer news relating to events that have happened closer to them in some sense—usually taken to be geographically or culturally (e.g. Galtung and Ruge 1965). We operationalized this dimension of news-value as follows.

- First, to measure **geographic proximity** we took the relative occurrence of terms such as *UK, English, Scottish, British,* etc., in the document.
- Second, we chose to operationalize **cultural proximity** by measuring how close the text is to British English (versus, say, American English). For each word in the text, we measured its relative frequency in two corpora—a British English corpus and an American English corpus. We then used the log-likelihood ratio of the word, i.e. $\log(P(w_{BrE})/P(w_{AmE}))$ as a cultural proximity score for that word. We then took the mean over the document to produce an overall cultural proximity score for the document. Higher values indicate closer cultural proximity of the text to British English.

Facticity

The famous ex-BBC reporter Martin Bell (Bell 1991) remarks that the newsworthiness of a story partly depends on "the degree to which a story contains the kinds of facts and figures on which hard news thrives: locations, names, sums of money, numbers of all kinds." To measure this news value, we measured the proportion of each **entity type** in Table 13. (Note that we exclude PERSON here, because this is treated under PERSONALIZATION.)

Table 13: Named Entity Types

Tag	Description
NORP	Nationalities or religious or political groups.
FAC	Buildings, airports, highways, bridges, etc.
ORG	Companies, agencies, institutions, etc.
GPE	Countries, cities, states.
LOC	Non-GPE locations, mountain ranges, bodies of water.
PRODUCT	Objects, vehicles, foods, etc. (Not services.)
EVENT	Named hurricanes, battles, wars, sports events, etc.
WORK_OF_ART	Titles of books, songs, etc.
LAW	Named documents made into laws.
LANGUAGE	Any named language.
DATE	Absolute or relative dates or periods.
TIME	Times smaller than a day.
PERCENT	Percentage, including "%".
MONEY	Monetary values, including unit.
QUANTITY	Measurements, as of weight or distance.
ORDINAL	"first", "second", etc.
CARDINAL	Numerals that do not fall under another type.

Uncertainty

There is a preference for events that are certain and unambiguous. For instance, in their seminal article, Galtung and Ruge (1965, p. 66) note that "an event with a clear interpretation, free from ambiguities in its meaning, is preferred to the highly ambiguous event from which many and inconsistent implications can and will be made". We operationalized this news value by annotating for two features.

- We measured the proportion of words in a document that are in Loughran and McDonald (2015)'s **uncertainty lexicon**.
- We measured the proportion of words that are **modal verbs** in the document (e.g. *may, might,*, etc.).

Prominence

Events that involve prominent individuals and organizations are ripe for reportage. For example, Golding and Elliott (1979, p. 122) remark that "big names are better news than nobodies, major personalities of more interest than ordinary folk". Although there might be more sophisticated ways to measure this news value,[34] we chose to operationalize it by counting the **number of references to BoE governors** (normalized for document length).

Novelty

News *needs* to be novel in order to become picked up. For example, Van Dijk (1988) observes, '[t]he requirement that news should in principle be about new events is fundamental.' We chose to operationalize novelty in two ways.

- First, we computed the relative frequency of clauses introduced by existential-*there* (such clauses typically introduce new discourse entities onto the scene).
- Second, we evaluated the textual (dis)similarity between the target document and all other documents published in the prior 30 days before the target document's publication.

[34]For instance, we refer the interested reader to the features discussed in Piotrkowicz (2017).

8.4.4. Summary

Altogether, θ_B is comprised of a total of 351 features that we chose to measure based on an extensive review of the literature.

8.5. *Monetary policy surprises as a control*

One issue is whether to include a measure of monetary policy surprise as a control in the vector z.

Monetary policy surprises, as measured by the change in financial market prices around a monetary policy event, are often used in identification methods for calculating monetary policy shocks (Kuttner (2001), Cochrane and Piazzesi (2002), Gürkaynak, Sack, and Swanson (2005),Gertler and Karadi (2015), Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021), Jarociński and Karadi (2020)).

In the monetary policy events studied in this paper, only after August 2015 were some communication events by the Bank of England also accompanied by monetary policy decisions. The previous literature on monetary policy shocks has been primarily focused on measuring the surprises that occur around the decisions, with the notable exception of S. Hansen, McMahon, and Tong (2019).

Nonetheless, the question still arises: when financial markets move in response to central bank actions (be they releasing text or otherwise), is the impact on the news flow larger if the financial market move is larger? And - consequently - is a measure of the financial market surprise a relevant variable to include in z?

Table 14 shows the coefficients from simple linear regressions of the measures of the impulse to the news flow (k) for each section of text released against the absolute daily change in the one year OIS rate.

Normally, monetary policy 'surprises' are measured using changes in short term interest rates around a monetary policy decision. In our case, the vast majority of events in which communication is imparted do not occur on the same day as monetary policy decisions — and so short term rates, such as the overnight index swap rate — are unlikely to show any change. A longer term rate that includes investor expectations of future Bank of England decisions (Lloyd 2020), such as the one year rate, is more fitting for our study.

There are several positive and significant coefficients, primarily for sections of the Inflation Report. This is in line with previous research (S. Hansen, McMahon, and Tong (2019), and Munday (2022)), that suggests that the Inflation Report conveys important information to financial markets regarding uncertainty.

That said, the evidence presented in Tables 14 is only suggestive. It is not possible to determine the direction of causality from these regressions. Only that a greater impulse to the news flow is associated with larger concurrent moves in financial markets. This could be because if the Bank of England releases information that radically alters the outlook of future interest rate changes, this is likely to be picked up by the press, and will also move financial markets.

Nonetheless, the regressions provide *a priori* evidence that the change in the swap rate is a relevant control variable.

That said, once we add in our textual features and other control variables, the daily change in the swap rate is not significant at the 5% level in our main analysis (Table 6). This suggests that in the naive regressions in Table 14 the change in the OIS rate is proxying for other variables, such as the textual features of the Bank's communication.

Table 14: Coefficients from linear regressions of k on the change in the 1-year OIS

	k												
	IR sec. 0	IR sec. 1	IR sec. 2	IR sec. 3	IR sec. 4	IR sec. 5	IR sec. 6	IR sec. 7	IR sec. 8	Minutes	Q&A	Statement	Speech
1998-2018	6.70	10.58**	5.82*	6.44*	-0.79	1.65	8.82**	23.61	34.79	-0.96	7.99	6.14	0.36
	(0.19)	(0.01)	(0.10)	(0.10)	(0.87)	(0.78)	(0.04)	(0.17)	(0.17)	(0.62)	(0.19)	(0.14)	(0.82)
1998-2015			5.01	5.63	-0.86		8.00*			-1.43	6.43	4.67	
			(0.20)	(0.19)	(0.88)		(0.10)			(0.49)	(0.34)	(0.30)	

p-values to two decimal places in parentheses

8.6. Content measuring tables

The following tables show the dictionaries for the Topics detailed in Section 5. The first ten words in each column are the words used to create the dictionary. The words in the second part of each column are the tags from the guardian that gave us the centroids of each topic.

Topic0	Topic1	Topic2	Topic3	Topic4
dow	industry	business	ecb	gas
jones	aerospace	businesses	governor	energy
intercale	shipbuilding	corporate	fed	utilities
dickins	volkswagen	enterprise	carney	electricity
nikkei	automotive	sme	mpc	utility
vinnie	steel	enterprises	policymakers	suppliers
dicky	tata	industry	boe	coal
burrill	engineering	innovative	bank	oil
corning	industries	firms	england	installers
bootmaker	bmw	organisational	trichet	petrol
dowjones	theairlineindustry	business	bankofenglandgovernor	energy-industry
	automotive-industry	sustainable-business	european-central-bank	oilandgascompanies
	britishairways	small-business	quantitative-easing	utilities
	pharmaceuticals-industry	corporate-governance	mark-carney	gas
	musicindustry	ethicalbusiness	federal-reserve	
	steel-industry	social-enterprise	monetary-policy-committee	
	tata	avivabusiness	mervyn-king	
			andy-haldane	

Topic5	Topic6	Topic7	Topic8	Topic9
gold	strategies	recession	housing	economic
commodities	reorganisation	deflation	mortgage	economy
metal	gsk	downturn	lending	growth
copper	efficiencies	depression	mortgages	recovery
bullion	licensing	stagnation	remortgaging	macroeconomic
nickel	structures	slump	affordability	upswing
metals	ccps	stagflation	property	eurozone
titanium	logistics	deflationary	lenders	economies
zinc	infrastructure	slowdown	loans	expansion
mineral	systems	contraction	market	demand
commodities	executive-pay-bonuses	recession	housingmarket	economicgrowth
randgoldresources	taxavoidance	globalrecession	mortgage-lending-figures	useconomicgrowth
gold	job-losses	deflation		economic-recovery
vedantaresources	travelleisure			
	davos			
	investing			
	office-for-budget-responsibility			
	entrepreneurs			
	rating-agencies			
	mergers-and-acquisitions			

Topic10	Topic11	Topic12	Topic13	Topic14	Topic15	Topic16
sector	deficit	borrowing	eurozone	economy	sterling	rates
services	budget	government	euroland	economies	dollar	rate
sectors	psbr	financing	europe	economic	pound	base
industries	surplus	lending	euro	eurozone	greenback	inflation
sector's	deficits	funding	bloc	global	yen	svrs
subsectors	surpluses	debt	greece	euroland	sterling's	trichet's
areas	fiscal	servicing	continent	recovery	currencies	yields
service	shortfall	borrowing—	italy	china	sterlings	borrowing
corporations	obr	borrowings	periphery	world	yuan	messel
intermediation	headroom	government's	germany	growth	rouble	costs
services-sector	budget-deficit	government-borrowing	eurozone	useconomy	sterling	interest-rates
				global-economy	dollar	interest-rates-us
				australia-economy		
				chinese-economy		
				the-gig-economy		
				worldbank		

Topic17	Topic18	Topic19	Topic20
ftse	employment	manufacturing	hbos
footsie	unemployment	construction	rbs
ftse100	jobless	sector	lloyds
techmark	inactivity	sectors	barclays
index—averaged	joblessness	industries	regulators
shotton	productivity	cips	britannia
nasdaq	vacancies	presumptions	tsb
fste	participation	pmi	subsidiary
miners	workforce	competition	bailed
dax	migration	industrial	fsa
ftse	unemployment-and-employment-statistics	financial-sector	royalbankofscotlandgroup
	usemployment	manufacturing-sector	lloyds-banking-group
	uk-unemployment-and-employment-statistics	construction	regulators
	us-unemployment-and-employment-statistics	manufacturingdata	hsbcholdings
			northern-rock
			financial-services-authority-fsa
			hbos
			armholdings

Topic21	Topic22	Topic23	Topic24	Topic25	Topic26	Topic27
goldman	inflation	bhp	european	crisis	oecd	technology
sachs	inflationary	rio	bailout	crash	imf	software
goldwillman	cpi	billiton	banks	crises	bis	technologies
eshan	unemployment	tinto	bail	crunch	niesr	tech
ubs	prices	xstrata	greece	meltdown	thinktank	ict
goldmans	2pc	miner	ireland	turmoil	cooperation	biotechnology
prefessor	deflation	kazakhmys	counterparties	strains	imf's	telecoms
sach's	persistently	lonmin	cyprus	contagion	studies	technological
nomura	rates	10bhp	eurozone	distress	obr	equipment
morgan	wages	vale	rescue	defaults	lagarde	fintech
goldmansachs	inflation	rio-tinto	europeanbanks	debt-crisis	imf	technology
		bhpbilliton	ireland-bailout	financial-crisis	oecd	
				credit-crunch	institute-for-fiscal-studies	
				subprimecrisis		

Topic28	Topic29	Topic30	Topic31	Topic32	Topic33	Topic34
ill	sanjeev	retail	mining	currencies	telecom	austerity
incapable	whitehead	consumer	miners	dollar	inmarsat	fiscal
conscience	ohga	brc	chemicals	currency	airways	coalition
poison	westec	bumpf	exploration	renminbi	telecoms	budgetary
hindsight	arne	intermediate	mineral	greenback	vita	socialist
conformists	ibstock	grocery	pharmaceutical	sterling	energis	populist
gloomily	easyjet	brc's	wolseley	yen	biotech	coalition's
blimpish	jenning	retailers'	antofagasta	yuan	freeserve	protectionism
idiotic	todd	retailing	platinum	pound	vivendi	budgetõs
careless	pirie	disapponting	alcoa	franc	aerospace	poverty
fresnillo	barclay	retail	mining	currencies	telecoms	austerity
	anglo-american					
	marksspencer					
	ben-bernanke					
	antofagasta					
	kazakhmys					
	lehmanbrothers					
	janet-yellen					
	astrazeneca					
	johnlewis					

Topic35	Topic36	Topic37	Topic38	Topic39	Topic40
property	oil	markets	tesco	royal	bonds
equity	commodity	market	sainsbury	ulster	bond
private	energy	turmoil	morrisons	etired	gilts
rental	crude	rout	safeway	curated	assets
residential	gasoline	crisis	asda	lesney	gilt
cre	petrol	worldscope	waitrose	southerly	ious
estate	import	stockmarkets	somerfield	dutch	treasuries
corporate	wheat	contagion	debenhams	yoko	tranches
rented	copper	stockmarket	grocer	rosyth	iou
landlord	commodities	nervousness	kingfisher	shell	bunds
realestate	oil	stock-markets	tesco	royaldutchshell	bonds
privateequity		marketturmoil	j-sainsbury	royal-mail	
			morrisons		

Topic41	Topic42	Topic43	Topic44	Topic45	Topic46	Topic47	Topic48
group	consumption	trade	supermarkets	euro	banking	insurance	economics
giant	spending	international	food	emu	financial	endowment	macroeconomics
company	consumer	global	clothing	eurozone	banks	insured	loynes
division	household	exporting	supermarket	erm	ambrosianos	insurers	economist
firm	demand	bilateral	meat	currency	regulatory	assurance	economics’
conglomerate	expenditure	globally	furniture	euroland	microprudential	families’	lbs
subsidiary	growth	external	grocery	ttwa	ccps	debtline	stansfield
specialist	consumers	wto	clothes	shaded	bankers	pension	tombs
operator	concertina	china	footwear	bloc	supervise	flowergram	bowmark
groups	activity	internationa	petrol	single	reformed	grid	disadvantageously
vodafonegroup	consumerspending	internationaltrade	fooddrinks	euro	banking	insurance	economics
btgroup			supermarkets	emu	banking-reform		
co-operative-group							

Uncertainty and Time-varying Monetary Policy*

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Abstract

US macroeconomic evidence points to higher economic volatility being positively correlated with more aggressive monetary policy responses. This represents a challenge for "good policy" explanations of the Great Moderation which map a more aggressive monetary response to reduced volatility. While some models of monetary policy under uncertainty can match this comovement qualitatively, these models do not, on their own, account for the reaction-function changes quantitatively for reasonable changes in uncertainty. We present a number of alternative sources of uncertainty that we believe should be more prevalent in the literature on monetary policy.

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1. Introduction

The Great Moderation, the period of lower economic volatility identified from around the mid 1980s in the US, followed the successful disinflationary push by Paul Volcker's Federal Reserve. Among other explanations, a debate emerged about the role played by monetary policy. This debate was framed as one between "good luck", a phrase that ascribed the moderation in US economic volatility to lower variances of shocks hitting the economy, and "good policy", a phrase that ascribed the same low volatility environment to the effect of a more reactive Federal Reserve, giving the economic data only the impression of lower shock volatility. This debate has significance beyond academic self-indulgence. If the stability was simply down to good luck, then perhaps we might not be lucky going forward. If monetary policy played a central role, then hopefully we can keep chronic higher volatility largely at bay.

One challenge for the good-policy hypothesis is that following an initial increase in monetary aggression (under Volcker), there has been a decline in aggression that has coincided with the decline in volatility since the mid-1980s (under Greenspan). If it is more aggressive policy that generates lower volatility, why did the subsequent reduction in aggression not lead to growing volatility?

In this paper, we aim to shed light on the linkages *between* the two forces in the Great Moderation debate: heteroskedasticity (good luck) and changes in monetary reaction functions (good policy). We try to link these shifts together to understand the extent to which the positive comovement between aggression and volatility over the last 35 years should make us more pessimistic about the role of monetary policy in delivering economic stability.[1]

Our focus is on the link between volatility and monetary policy through policymakers' uncertainty. Policymakers argue that they face huge uncertainty that is fundamental to their policy choices (Greenspan 2004) and uncertainty might naturally follow from a more volatile economic environment. An important implication of our analysis is, therefore, to shed light on

[1] Though the financial crisis clearly marked an increase in economic volatility compared to the Great Moderation, the increase (measured by the standard deviation of real GDP growth) was smaller than similar episodes in the past and never reached the level of the 1970s.

what sources of uncertainty might matter for policy. On one hand, there is uncertainty about almost everything. But, which of these uncertainties impact their policy choices? Cieslak, S. Hansen, McMahon, and Xiao (2022) explore this issue using FOMC transcripts. We use estimated changes in reaction functions evaluated through structural models to shed light on the important sources of uncertainty.

One potential explanation is that the monetary reaction function endogenously reacts to volatility. Although the standard approach in DSGE models is to consider fixed-coefficient, time-invariant policy rules, Carney (2017) provides a discussion of why time-varying reaction functions are natural phenomenon of monetary policy in practice. For instance, he pointed out that as central banks learn about the structure of the economy over time, or as persistence of shocks varies, policymakers adjust their reaction to economic data.[2]

Most standard monetary DSGE models do not link volatility and monetary policy responses because they are certainty equivalent – this means that changes in, e.g., the volatilty of the exogenous shocks does not affect optimal policy response. Nonetheless, there are existing models of optimal monetary policy that incorporate various sources of uncertainty. Different versions of these models have different predictions, but even where the models can generate the correct comovement in volatility and monetary aggression, we will show that these traditional channels "fail" to match the data quantitatively.

Instead, we present a number of alternative uncertainty channels that are more consistent with the evidence. These include a Fed that becomes more confident in their modelling, an economy that becomes easier to assess with confidence, and a Fed that had established a credible reputation for inflation fighting and, as inflation expectations are well-anchored, does not need to be as aggressive.

A key takeaway is that there are many sources of variation that likely give rise to time-variation in the reaction function. Taking such time-variation seriously is important for the

[2] In Full-Information Rational Expectations (FIRE) models, there is full understanding by all agents about structure of the economy and endogenous variables such as output and inflation represent sufficient statistics for the shocks hitting the economy and the optimal forecast. Byrne, Goodhead, McMahon, and Parle (2022) and McMahon and Munday (2022) show that in a world where there is uncertainty in the mapping from current, observed data to the underlying shocks and the state of the economy, monetary reaction functions need to be more complex. In such situations, time-variation in the coefficients of a monetary reaction function is natural.

empirical analysis of many questions in monetary economics.

In Section 2, we start by exploring the empirical evidence on the link between volatility in the economy and the monetary authorities' reaction function. The large literature on the Great Moderation tends to focus on the period from the mid-1980s to the 2008 Global Financial Crisis (GFC). As we set out below, a part of this literature shows that both the variance of shocks hitting the economy *and* the coefficients of the reaction function changed over this period, with the changes occurring at the same time suggesting a potential link between them.

We also estimate a time-varying VAR with stochastic volatility as in Primiceri (2005). In this reduced form version of the economy, we find that the variance of inflation and the aggressiveness of the Federal Reserve are positively correlated over the sample (1950-2019). We then estimate a Markov-Switching DSGE model in which the parameters of the reaction function and the variances of shocks are allowed to vary across regimes. This again shows that the variance of shocks and reaction functions have substantially altered in the past fifty years. Furthermore, these changes are highly correlated. Periods of high volatility shocks seem to be associated with more aggressive reaction functions on the part of the Federal Reserve.

While this evidence suggests a link between monetary policy and volatility, it actually represents somewhat of a challenge to the "good policy" narrative. The typical narrative on the causal link between the Great Moderation and lower economic volatility is that it was a more aggressive Fed policy that led to the greater economic stability. If the period since the mid-1980s has typically been a less aggressive Fed policy, then why has volatility not risen.

In Section 3, we consider models of parameter uncertainty. Brainard (1967)'s is a specific analysis of parameter uncertainty. But, when modelled in this way, greater uncertainty leads to less aggression – the so-called Brainard conservatism. When the uncertainty concerns other parameters, the impact on the coefficients of the reaction function is reversed (Söderström 2002).[3] Though it is possible to match the positive co-movement of uncertainty and aggression *qualitatively*, it does not seem to be a reasonable *quantitative* match.

[3] Cieslak, S. Hansen, McMahon, and Xiao (2022) present a general framework that makes clear when different types of uncertainty will matter and, if it matters, whether it will make the policymaker more or less aggressive.

In Section 4, we turn to the framework of a robust control policymaker. Such a framework does not generally have the ambiguous impact of uncertainty on aggression. The positive comovement of uncertainty and aggression is a standard result. We illustrate this in a model of robust control policymaker in an environment with stochastic volatility. Our model aims to illustrate that greater volatility in the economy can *cause* a central bank to become more aggressive, rather than just be associated with it in the data.

Despite our model matching the signs in the data (higher shock variances leading to more aggressive reaction functions), we are again unable to reproduce the magnitudes of reaction function changes with our model. We push our policymaker to the limit of their fear regarding volatility shocks, and yet the changes in shock variances needed to alter the reaction function as much as the data suggests are too large to be plausible.

As a result, we conclude that the standard models uncertainty faced by central bankers cannot reconcile the data, or indeed the literature, on the simultaneous changes in shock variances and reaction functions. In Section 5, we consider alternative sources of uncertainty and how they might affect monetary policy. Regardless of the specific source, our analysis does reveal that sizeable shifts in optimal policy coefficients follow from shifts in the structural parameters of the model. The implications of these for empirical monetary economics are highlighted in the conclusion.

2. Empirical monetary policy reaction and economic volatility

In this section we first explore the existing literature that (i) tries to establish the cause of the declining volatility in the US economy from the mid-1980s, and (ii) the part of this literature that links the decline of volatility to the behaviour of monetary policy. We then estimate a time-varying VAR with stochastic volatility as in Primiceri (2005). This shows that the variance of inflation and the aggressiveness of the Federal Reserve are positively correlated over the sample (1950-2019). We argue that this represents a puzzle for the "good policy" narrative.

2.1. Existing literature on causes of the Great Moderation

A large literature identified the decline in economic volatility in the US in the period up to the GFC in 2008-2009; for instance, see McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Stock and Watson (2002).[4] One explanation, known as the "good luck" hypothesis, argues that reduced economic volatility was due simply to the absence of large shocks; for example, Stock and Watson (2002) tend to favour the "good luck" hypothesis attributing 70%-80% of the volatility decline to good luck. This is a somewhat pessimistic explanation because it means that future stability is far from guaranteed as we might, exogenously, return to being unlucky again.

Alternative explanations are more optimistic. Some put the improvements down to improved business practices by firms, especially regarding inventory management (see McConnell and Perez-Quiros (2000) and Kahn, McConnell, and Perez-Quiros (2002)).

The other explanation focuses on better policy by the Federal Reserve. This "good policy" explanation relies on a change in behaviour of monetary policy around the early to mid-1980s. This timing fits with the efforts by Volcker to disinflate the US economy. In a seminal paper, Clarida, Gali, and Gertler (2000) estimated monetary policy reaction functions for the US

[4] And another literature found similar declines in other advanced economies.

before and after Paul Volcker's appointment as the Federal Reserve Chair.[5] Their estimated reaction functions suggested a Federal Reserve that was much more sensitive to expected inflation in the post-Volcker era. This was interpreted as evidence of an important role for policy in the Great Moderation.

Consistent with this, many other papers also favour some form of the "good policy" explanation. Conrad and Eife (2012) find that the observed changes in inflation persistence can be explained empirically by estimating a time varying Taylor rule for the US. Bianchi (2013) estimates a Markov-Switching DSGE model that permits two regimes in which volatility and reaction function coefficients can differ, and finds that the variation in reaction function coefficients is necessary to explain macroeconomic dynamics in the US. Fernandez-Villaverde and Rubio-Ramirez (2008) find that the parameters governing monetary policy exhibit substantial drift in an estimated New Keynesian model.[6] Other papers contributing to this large strand of literature include Lubik and Schorfheide (2004) who estimate a New Keynesian model that permits indeterminacy, finding that only monetary policy post-Volcker is estimated as consistent with a determinant equilibrium, and Boivin (2006) who uses real-time data to estimate forward looking Taylor rules showing the Fed's response to inflation was weak in the 1970s but strengthened over the 1980s.

On the other side of the debate, the "good luck" camp countered that the Great Moderation exhibited a lower variance of shocks, which resulted in more gradual policy, and to estimate Taylor rules without accounting for this heteroskedasticity would lead the researcher to incorrectly conclude that the reaction function had changed. Most notably this point of view was espoused in Sims and Zha (2006), in which the authors fit a series of reduced form models to US data and find that the best fit allows time variation in the variance of disturbances only. Fernandez-Villaverde, Guerrón-Quintana, and Rubio-Ramirez (2010) find that in

[5] While there is a large academic literature on monetary policy rules, it is widely understood that policymakers do not follow algebraic policy rules. But the advantages of monetary policy commitment has meant that monetary policy frameworks and institutions have been designed so that they included rule-like features. And these features seem to be prominent enough to ensure that expectations are sufficiently well anchored whilst still incorporating the flexibility to deal with shocks as they become evidence (being revealed only slowly due to, for example, lags in data availability). As a result, both the theoretical and empirical literature on monetary reaction functions typically imposes fixed-coefficient functions.

[6] Although they leave the joint problem of estimating a drifting reaction function and heteroskedastic shocks to later work (Fernandez-Villaverde, Guerrón-Quintana, and Rubio-Ramirez 2010).

a large scale non-linear DSGE model, whilst both shock variances and reaction function coefficients vary substantially over time, the great moderation primarily owes to reduced volatility of external shocks. Other work providing evidence for this result includes Cogley and Sargent (2005) and Primiceri (2005) who both estimate VARs with drifting coefficients and stochastic volatility, and find large changes in the variance of innovations (being much larger in the late 1970s than at other times), with Primiceri (2005)'s conclusions being more confident about the fact that "the role played by exogenous non-policy shocks seems more important than interest rate policy in explaining the high inflation and unemployment episodes in recent U.S. economic history."

Of course some papers favour a combination of the two arguments. For example, Davig and Doh (2014) estimate a Markov-Switching New Keynesian model in which both policy rule coefficients and shock volatilities are permitted to vary. They find that empirically there is evidence for both changing simultaneously between the Volcker and post-Volcker periods, with the addition of the persistence of inflation also changing concurrently.

Taken together, there is substantial evidence to suggest that the economy became smoother, though the role of monetary policy in this remains the subject of debate. The literature that argues for the good policy explanation focuses on (i) findings that both structural parameters governing the variance of shocks declined and the coefficients of the reaction function have varied over time, (ii) that these changes seem to occur at the same time, and (iii) that the Fed Reserve's increased aggression to anchor inflation expectations coincides with the decline in economic volatility.

2.2. Time-Varying-Parameter, Stochastic-Volatility VAR

To illustrate this mutual change in the volatility and policy reaction, we estimate a time-varying VAR with stochastic volatility as in Primiceri (2005). In this reduced form version of the economy, we find that the variance of inflation and the aggressiveness of the Federal Reserve are positively correlated over the sample (1950-2019). While this suggests a link between monetary policy and the lower volatility, it actually represents somewhat of a challenge to the “good policy” narrative. The typical narrative on the causal link between the Great Moderation and lower economic volatility is that it was a more aggressive Fed policy that led to the greater economic stability. If the period since the mid-1980s has typically been a less aggressive Fed policy, then why has volatility not risen.

Our Bayesian time-varying parameter VAR with stochastic volatility allows both the coefficients of the VAR equations and the variance-covariance matrix of the innovations to vary over time. We estimate a three-variable VAR of order 2 including: CPI inflation, the unemployment rate, and the monetary policy stance as measured by the Treasury Bill interest rate.

Our estimation follows Primiceri (2005) and the updated estimation methodology set out in Del Negro and Primiceri (2015). We employ their identifying assumption: that monetary policy affects inflation and employment with at least a one quarter lag. We order the VAR in the standard way, with inflation first, unemployment second, and the monetary policy stance last. The ordering between inflation and unemployment is not an identification assumption, rather a normalization.

Our approach differs from these papers in two ways. First, we use a longer time series; 1953 to 2019 compared with 1953 - 2001.[7] Second, we specify wider priors on the variance of the time varying coefficients of the VAR. Or, in other words, we impose far less smoothing of the VAR coefficients compared to Primiceri (2005).[8] All other parameters are identical to Primiceri (2005).

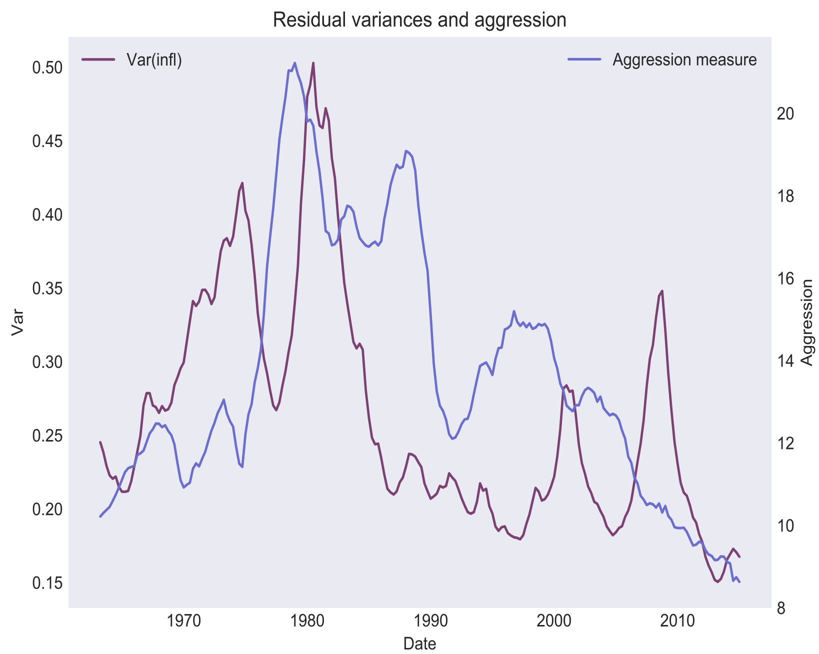
Figure 1 shows the estimated time series of the variance of shocks to inflation and the cumulative 20 quarter response in the interest rate to a one percentage point shock to inflation, labelled as the “aggression measure”.[9] Whilst clearly other factors are influencing the response of monetary policy to inflation, the broad macro trend between the two variables is consistent with higher variances of shocks coinciding with more aggressive reaction functions.

[7] The first ten years of the sample are used to initialise the priors.

[8] Specifically, we set, k_B, the parameter that premultiplies the calculated OLS estimated variance-covariance matrix for the coefficient matrix to 40, rather than 4.

[9] Note that we use the shock unit as a percentage point, since the variance of the shocks is changing over time, plotting the effect of a one standard deviation shock is not consistent across time.

Fig. 1. TVP-SV-VAR results



Figures 2 shows the estimated (modal) impulse responses to the interest rate from a one percentage point innovation to inflation over the estimation period. It shows the IRFs from just three dates, 1963 (pre-Volcker, and the first year we estimate), 1983 (Volcker) and 2003 (post-Volcker). The charts demonstrate that, viewed through the lens of our time varying parameter stochastic volatility VAR, the interest rate was most aggressive in its response to inflation during the Volcker period. Furthermore, the deviations in the impulse responses show that the change in reaction function was material, with the peak reaction of the interest rate to a 1 pp. inflation shock being nearly twice as large in 1983 compared with 1963.

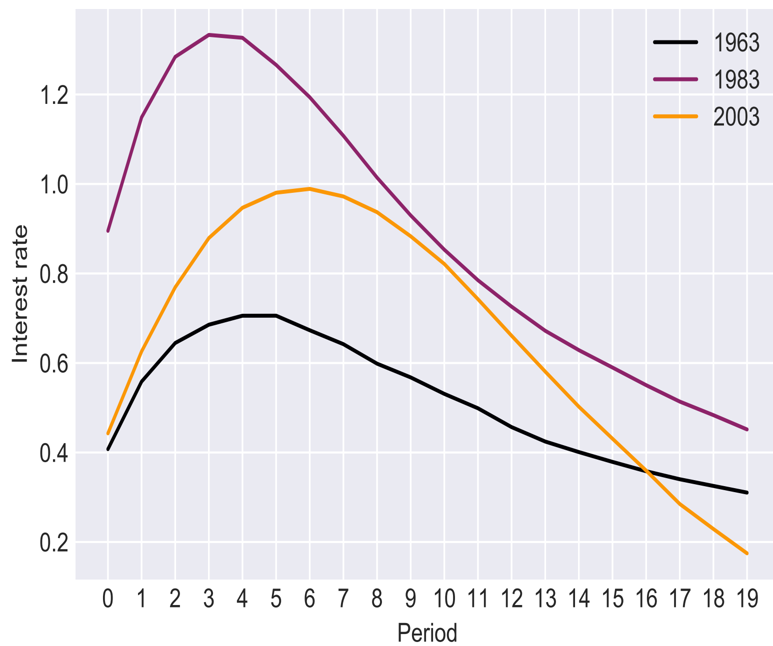


Fig. 2. Select impulse responses of a 1pp shock to inflation on the interest rate

For completeness, we show all estimated impulse response functions in Appendix Section 7.1.

2.3. Markov switching model

One caveat to this reduced-form evidence comes from Benati and Surico (2009). They argue that VARs cannot always accurately capture changes in monetary policy regimes, and can indeed interpret them as changes in the variance of shocks — the exact issue we are trying to investigate. To address this concern, we take structural approach and estimate a Markov-switching, three-equation New Keynesian DSGE model. This estimated model differs from the reduced-form, TVP VAR in that is structural, forward looking and features an equilibrium solution which helps to address these concerns. We, nonetheless, find similar correlations between shock variances and aggressiveness.

A second advantage of including an additional model to show that the data point to a positive comovement between shock variances and reaction function aggressiveness is that the model we present is identical, within regime, in its structure to the robust control model we will introduce in Section 4. The difference is that we will let the data decide the reaction function of the Federal Reserve in this section, and perform an optimal policy exercise in Section 4.

We estimate a small Markov-switching New Keynesian model in the vein of Svensson and Williams (2005) with two regimes. In each regime, we allow the variance of shocks and the coefficients governing the reaction function to change.[10] Superscript j is used to denote a parameter that is allowed to vary across regimes during the estimation procedure.

The model is a simple three equation New Keynesian model:

$$\pi_t = kx_t + \beta E(\pi_{t+1}) + u_t \tag{1}$$

$$x_t = E(x_{t+1}) - \frac{1}{\sigma}(i_t - E(\pi_{t+1}) + \bar{r}) + c_e^j e_t \tag{2}$$

$$i_t = \phi_\pi^j \pi_t + \phi_x^j x_t + \phi_{x,1}^j x_{t-1} + \phi_{i,1}^j i_{t-1} + \phi_{i,1}^j i_{t-2} + v_t \tag{3}$$

$$u_t = \rho_u u_{t-1} + c_u^j \epsilon_t^u \tag{4}$$

$$e_t = \rho_e e_{t-1} + c_e^j \epsilon_t^e \tag{5}$$

$$v_t = \rho_v v_{t-1} + c_v^j \epsilon_t^v \tag{6}$$

where u_t, e_t and ϵ are AR(1) processes with Gaussian mean-zero innovations denoted by ϵ and persistence parameters denoted by ρ.

The Taylor rule we estimate relates the central bank's policy instrument, i_t, to five variables: output and inflation in the current period, output in the previous period, and the interest rate in the previous two periods. These variables are included because if the central

[10] Fernandez-Villaverde, Guerrón-Quintana, and Rubio-Ramirez (2010) non-linearly estimate a medium-scale DSGE model with parameter drifting. They find the reaction function of the Fed post Volcker was less aggressive and the economy experienced lower shock variances, in line with the reduced form evidence presented above. Our estimation differs in its treatment of changing parameters from Fernandez-Villaverde, Guerrón-Quintana, and Rubio-Ramirez (2010) in that it is discrete: jumps between regimes happen suddenly, whilst Fernandez-Villaverde, Guerrón-Quintana, and Rubio-Ramirez (2010) have parameters that are constrained to drift slowly over time. Indeed one could see our small New Keynesian model with two regimes as an approximation of Fernandez-Villaverde, Guerrón-Quintana, and Rubio-Ramirez (2010)'s medium scale New Keynesian drifting model. Nonetheless, we reach similar conclusions regarding the timing of when policy became more aggressive and when the volatility of shocks changed.

bank acts under commitment with a quadratic loss function over volatility in inflation, output and the interest rate, the optimal policy is a linear combination of these variables (Giannoni and Woodford 2003). Furthermore, Equation (3) here is the same as Equation (16) in Section 4 under expected utility.

Much of the literature on Markov-switching DSGE models has focused on estimating models and then evaluating their fit to determine which parameters could plausibly have changed over the period in question. Typically, as we do, the reaction function of the policymaker is directly estimated (as in Clarida, Gali, and Gertler (2000)) rather than derived optimally in a time varying setting. That said, there is a strand of literature on optimal policy in regime-switching environments (Blake and Zampolli 2011; Maih 2015; Svensson and Williams 2005; Svensson and Williams 2007; Svensson and Williams 2008; Bianchi 2013), but this is typically optimal policy that occurs *in spite* of the changes in shock variances, and driven by the changes in other structural parameters. While optimal policies are functions of the structural parameters of the model, given the linear nature of the models (or their approximations), Gaussian distributions of shocks and quadratic central bank loss functions — certainty equivalence applies, and the optimal policy does not vary depending on the shock variances (Svensson and Woodford 2003).

We calibrate the some of the main structural parameters of the New Keynesian model to typical parameters. We do not aim to perfectly fit the data here, rather to try and uncover to what extent the data show changes in reaction function parameters and/or shock volatilities — and their orders of magnitude. Therefore, we keep those parameters not related to shock volatilities or the reaction function fixed across regimes.[11]

[11] For papers that allow all parameters to vary over both regimes see Svensson and Williams (2005), Svensson and Williams (2007), Svensson and Williams (2008), and Blake and Zampolli (2011). In the appendix, we allow the persistence of inflation to be time varying in order to show it is not just changes in persistence that are econometrically pushed the changes through the reaction function and volatilities.

Table 1: Calibrated parameters

Parameter	Value
β	0.99
κ	0.4
σ	2
$\bar{r}$	0
$\rho_e,\ \rho_v,\ \rho_u$	0.7

The rest of the parameters, including the transition probabilities between regimes, $p_{1,2}$ and $p_{2,1}$ are estimated using Bayesian methods. We estimate this model using quarterly data from 1960 to 2019 on inflation, output growth and the effective federal funds rate. The estimation procedure follows the perturbation methodology of Maih (2015). The specific priors given to these parameters are set out in the table below.

Table 2: Priors

Parameter	Distribution	%90 bands
c_u^1	Weibull	0.0005, 1.0
c_u^2	Weibull	0.0005, 1.0
c_e^1	Weibull	0.0005, 1.0
c_e^2	Weibull	0.0005, 1.0
c_v^1	Weibull	0.0005, 1.0
c_v^2	Weibull	0.0005, 1.0
$p_{1,2}$	Beta	0.05, 0.15
$p_{2,1}$	Beta	0.05, 0.15
ϕ_π^1	Gamma	0.5, 1.5
ϕ_π^2	Gamma	1.5, 3.0
ϕ_x^1	Gamma	0.05, 3.0
ϕ_x^2	Gamma	0.05, 3.0
$\phi_{x,1}^1$	Normal	-0.5, 0.5
$\phi_{x,1}^2$	Normal	-0.5, 0.5
$\phi_{i,1}^1$	Normal	-0.5, 0.5
$\phi_{i,1}^2$	Normal	-0.5, 0.5
$\phi_{i,2}^1$	Normal	-0.5, 0.5
$\phi_{i,2}^2$	Normal	-0.5, 0.5

Table 8 shows the estimated posterior modes of the switching parameters in each regime and their standard deviations. The point made by Fernandez-Villaverde, Guerrón-Quintana, and Rubio-Ramirez (2010) in their medium scale model with drifting parameters is also apparent in our small model with switching parameters: regimes with higher shock variances seem to coincide with more aggressive policy rules.

Table 3: Estimated Markov Switching parameters

Parameter	Regime 1: Posterior mode	Regime 2: Posterior mode
ϕ_{π}^{j}	0.64	2.52
	(0.10)	(0.35)
ϕ_{x}^{j}	0.30	1.42
	(0.06)	(0.26)
$\phi_{x,1}^{j}$	-0.05	0.03
	(0.06)	(0.20)
$\phi_{i,1}^{j}$	1.76	0.49
	(0.07)	(0.12)
$\phi_{i,2}^{j}$	-0.90	0.03
	(0.07)	(0.12)
c_{u}^{j}	0.003	0.004
	(0.0002)	(0.0004)
c_{e}^{j}	0.009	0.019
	(0.0006)	(0.002)
c_{ϵ}^{j}	0.004	0.02
	(0.0004)	(0.002)

All the variances are larger in regime 2 (and substantially so). The reaction function coefficients relating to inflation and output rise from 0.6 to 2.5 and 0.3 to 1.4 respectively. The coefficients relating to lagged output and lagged interest rates rise as well, apart from the one period lagged interest rate which falls.

The estimated changes in the reaction function are large. The smallest change in a ϕ parameter is 0.07 ($\phi_{x,1}$), and the largest is 1.9 (ϕ_{π}). Any attempt to marry the shifts in reaction function parameters to optimal reflections of volatility changes between periods must be able to match these magnitudes of the changes in reaction function coefficients. This is reinforced by considering the impulse response functions of the interest rate to an innovation to the Phillips curve. Figure 3 shows the response in both regime 1 (low volatility) and regime 2 (high volatility) to a 1 pp. innovation to the Phillips curve. One an see that the reaction of interest rates is much sharper in regime 2. This is in line with the reduced form evidence from the VAR discussed previously.

Table 4: Estimated transition probabilities

Parameter	Posterior mode
$p_{1,2}$	0.04
	(0.01)
$p_{2,1}$	0.11
	(0.03)

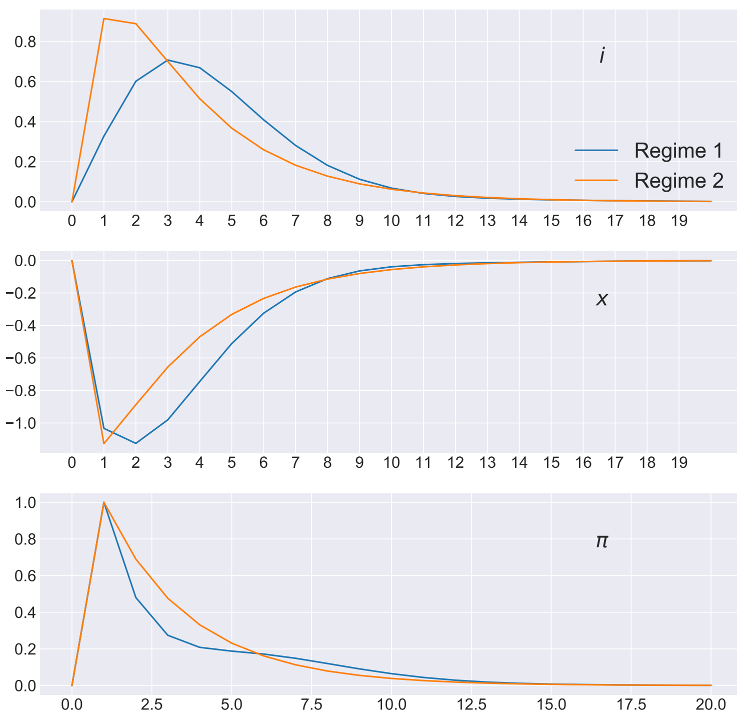


Fig. 3. Impulse responses of a 1pp shock to the Phillips Curve across regimes

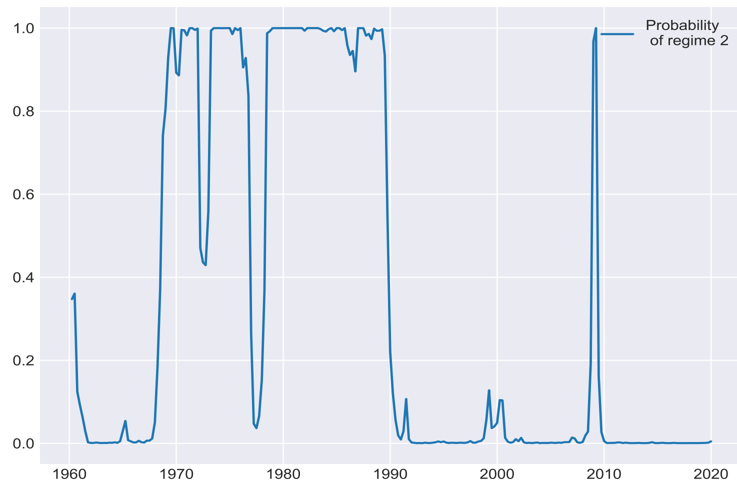


Fig. 4. Probability of regime 2

Finally, Figure 4 shows the estimated probability of being in regime two. Our simple model suggests that the Greenspan era onwards (1987-) was characterised by regime one: low shock variances and low aggression. Furthermore, the Greenspan Fed was so muted in its reaction to the state of the economy, that our estimation groups it in the same regime as that of the effective lower bound on interest rates, which broadly lasted from the end of 2009 to the end of 2015.[12]

2.4. An apparent monetary puzzle

Both the reduced-form and the structural evidence presented in this section suggests that higher variances go hand in hand with more aggressiveness on the part of the Federal Reserve. For those that wish to argue that it was Federal Reserve aggression that kept volatility at bay, this apparent puzzle seems to undermine the argument. That is, why did the initial increase in aggression cause volatility to decline, but the subsequent decline in aggression shown in Figure 1, ultimately not lead to persistent increases in volatility?

[12]Of course we could leave out this period, or try to use some sort of shadow rate. But we are interested in the reaction function of the Fed with regard to short term rates, and the reaction function that prevailed over the era of the ELB was undoubtedly a soft one (by design).

To assess whether this evidence undermines the case for monetary policy playing a causal role in the Great Moderation, we examine two environments in which uncertainty is linked to the the optimal reaction of monetary policy. The idea is that, in an environment of lower economic volatility, monetary policy endogenously becomes less aggressive. If this is the case, then the lower volatility may have caused the lower aggression after Volcker.

Of course, this explanation does not, necessarily, rescue the good policy case. The link from volatility to monetary aggression doesn't have to only operate after the 1980's as volatility fell. In fact, it is a potential alternative explanation for the increase in aggression when Volcker was appointed — higher volatility elicited a stronger Fed response. In such a case, it could be that the good luck story remains the best explanation for the Great Moderation period with the monetary policy response simply being an endogenous reaction to the bad luck, high-volatility 1970s.

3. Parameter uncertainty: Overcoming Brainard conservatism

In order to explore whether the declining volatility of the economy, whatever its initial cause, might credibly lead directly to less aggressive monetary policy, we now explore theoretical links between economic uncertainty and optimal monetary responses. As already mentioned, many models in macroeconomics have the property of certainty equivalence. Notwithstanding this, the study of the effects of uncertainty about the parameters of the economy on optimal monetary policy has a long history.

In this literature, there are many approaches that point to uncertainty causing the coefficients of the reaction function of the central bank to change to change optimally. Brainard (1967), famously, suggests uncertainty should result in greater conservatism. Specifically, when the policymaker is uncertain about the impact of their policy on outcome variables, the coefficients of the classic Taylor-rule type reaction function should attenuate when uncertainty regarding the sensitivity of inflation to the interest rate is higher. The empirical results, however, impose an important constraint - higher (lower) volatility should be related to higher (lower) aggression. Brainard-style uncertainty about the impact of the policy instrument, while no doubt prevalent among policymakers, does not seem to relate to the uncertainty that changed either *before* or *over* the Great Moderation. Cieslak, S. Hansen, McMahon, and Xiao (2022) show some general conditions for uncertainty to affect an expected loss minimising policymaker's decision. For uncertainty to be positively correlated with aggressiveness, or an anti-conservatism result, policy activism has to be associated with higher volatility. This finding helps to rule out the standard form of Brainard uncertainty but it does open the door to Brainard-style parameter uncertainty about other non-instrument parameters which lead to anti-conservatism.

For instance, Söderström (2002) shows that uncertainty about the persistence of inflation should have this effect. This suggests that growing certainty about the dynamics of inflation after the mid-1980s would be associated with reduced aggressiveness of monetary policy. Lansing (2009) shows that inflation in the US became less volatile which might make it more predictable and its dynamics less uncertain. In terms of persistence measured by autocorrelation in 20-year rolling windows, inflation is initially more persistent (driven by the 1970s and early 1980s) and then persistence falls just before the financial crisis.

While this is true qualitatively, the quantitative significance is less obvious. Consider a baseline calibration of the model in Söderström (2002) such that the reaction function coefficient on inflation (ϕ_π) and output (ϕ_y) are 1.28 and 0.94 respectively. In this baseline calibration, there is uncertainty about the key parameters including the inflation persistence term. If we then reduce the uncertainty around the inflation persistence parameter to 20% of its mid-1980s level, the coefficient on inflation declines but not at two decimal places; ϕ_π falls from 1.278 to 1.276. The decline in ϕ_y is similarly small. This despite the large decline in uncertainty.

And if uncertainty about other parameters also declined, these would work in the opposite direction. If uncertainty about all parameters reduced to 20% of its higher level, ϕ_π and ϕ_y increase overall to 1.287 and 0.954 respectively.

Moreover, if the persistence coefficient also changes, optimal policy responses change. If inflation persistence, measured by the AR(1) coefficient on lagged inflation in the Philips' Curve, increased from 0.6 in the baseline to 0.7, ϕ_π increases to 1.4 (from 1.28) despite the reduced uncertainty. Lower persistence, 0.5, augments the lower volatility and ϕ_π declines to 1.18. However, the finding of markedly lower persistence is difficult to justify empirically. In the Appendix, we present results of estimating the Markov-switching model as in Section 2.3 but allowing the persistence of inflation shocks to also change. There is a small decline in persistence (from 0.68 to 0.63), but not enough to solely generate the magnitude of reaction function changes we found in Section 2. Nonetheless, were this hypothesis to be true, it suggests that it is not the uncertainty that generates the lower aggressiveness but rather the changed structure of the entire economy.

4. Robust control and stochastic volatility

A second potential modelling framework for thinking about the effects of uncertainty on monetary policy response is robust control theory in which the central bank fears that the model they are using to make decisions is misspecified. The primary reference for robust control in applied macroeconomics is L. P. Hansen and Sargent (2008). Giordani and Söderlind (2004) show that uncertainty will typically result in aggression. This has the advantage of matching the direction of the co-movement over the Great Moderation period. Another advantage of robust control is that it allows us to be more general in how uncertainty is applied to the economy — although in practice the way in which it manifests itself through changes in the central bank reaction function will be very specific.

One theoretical contribution of this paper is that we consider the case of a central bank which acts under a robust control framework in an economy with time-varying volatility. In this world a central bank *optimally* changes the coefficients of its reaction function as volatility shocks hit the economy. This allows us to explore how a policymaker optimally alters their reaction function in response to volatility shocks.[13]

We follow the technical solution methodology of Bidder and Smith (2012) who consider an non-linear asset pricing model with robust control and stochastic volatility.

In our model, the central bank's concern over misspecification interacts with stochastic volatility. If the economy is more "noisy", the policymaker finds it more difficult to ascertain the true model of the economy. In general, and in our model, robust control prescribes more aggressive reaction functions than those that are optimal under an expected utility maximiser central bank (Giannoni 2002; Giordani and Söderlind 2004). In the case we consider, this aggressiveness is amplified (dampened) by increases (decreases) in the volatility of the economy.

We keep our model simple and abstract from extensions to robust control modelling in macroeconomics including filtering of hidden state variables (Ellison and Sargent 2012), and

[13] Although the standard robust control framework can be used to examine the effect of higher or lower volatility, the advantage of our environment is that the policymaker knows that shocks to volatility can occur, and can then worry about misspecification of the stochastic volatility model too.

using sampling to characterise the worst-case distribution (Bidder and Smith 2012; Bidder and Smith 2018). The benchmark model of the central bank is a simple two equation New Keynesian model, with stochastic volatility:

$$\pi_t = kx_t + \beta E(\pi_{t+1}) + u_t \tag{7}$$

$$x_t = E(x_{t+1}) - \frac{1}{\sigma}(i_t - E(\pi_{t+1}) + \bar{r}) + e_t \tag{8}$$

$$u_t = \rho_u u_{t-1} + exp(vol_t^u)\epsilon_t^u \tag{9}$$

$$e_t = \rho_e e_{t-1} + exp(vol_t^e)\epsilon_t^e \tag{10}$$

$$vol_t^u = \rho_{vol} vol_{t-1}^u + v_t^u \tag{11}$$

$$vol_t^e = \rho_{vol} vol_{t-1}^e + v_t^e \tag{12}$$

where ϵ and v are Gaussian mean-zero random variables.

The central bank views Equations 7-12 as the 'benchmark' model, but is concerned that this model is misspecified. The central bank expresses doubts about the model by considering alternative distributions, that are distorted distributions of the one implied by the benchmark. The 'worst-case' distribution encapsulates her concerns, and the policymaker makes policy *as if* the worst case were true.

We use multiplier preferences (L. P. Hansen and Sargent 2001; Strzalecki 2011) to represent a preference for robustness.[14] The multiplier preference formulation gives rise to a useful intuitive explanation of the procedure for determining optimal policy. Imagine that there are two agents in the central bank's optimisation procedure: an evil agent, and the central bank. These agents play a zero sum game. The evil agent is given some 'budget' to twist the distribution implied by the model in order to minimise the central banker's objective function. The central banker chooses her reaction function to maximise its objective function.

[14]Note that our model is not in the linear-quadratic framework that permits the use of Ricatti equations to find solutions. The stochastic volatility adds a non-linearity to our model, which is then easiest solved by forming a Bellman Equation.

In general the optimisation problem is of the form:

$$\max_{u_t} \min_{m_{t+1}} \sum_{t=0}^{\infty} E\left(\beta^t M_t \left(h(x_t, u_t) + \beta\theta E\left(m_{t+1} log m_{t+1} | I_t\right)\right) | I_0\right) \tag{13}$$

Where x_t is a vector of states, u_t a vector of controls, $h()$ is the central bank's per-period payoff function. m_t is the likelihood ratio between the distorted and undistorted distributions, and $m_t log m_t$ is the conditional relative entropy. m_t provides a sequence of martingale increments that define the martingale $M_t = M_0 \Pi_{j=1}^{t} m_j$ and twist the measure in the model towards alternative ('worst-case') measures. θ controls the preference for robustness, and is inversely related to the minimising agent's budget. To solve the optimisation, we invoke a series of results in L. P. Hansen and Sargent (2008), and used in Bidder and Smith (2012). Specifically, we rewrite this as a recursive problem, solve the inner problem of the minimising agent, and sub the solution back in so that we arrive at the following (more familiar) expression for the central bank's value function:

$$V(x_t) = \max_{u_t} h(u_t, x_t) - \beta\theta log E\left(exp\left(-\frac{V_{t+1}}{\theta}\right) | x_t\right) \tag{14}$$

This is the standard Epstein-Zin Bellman Equation. Mapping this onto the New Keynesian model from before gives:

$$V_t = -\frac{\pi_t^2}{2} - \frac{\lambda_x x_t^2}{2} - \frac{\lambda_i (i_t - i^*)^2}{2} - \beta\theta log E\left(exp\left(-\frac{V_{t+1}}{\theta}\right)\right) \tag{15}$$

The central bank is assumed to have a quadratic loss function over volatility in inflation, output and the interest rate, with the weights on these represented by λ coefficients. Note that the concern for deviations in i allows the IS curve to bind and gives us a closed form reaction function. This is only included for pedagogical simplicity. The closed form reaction function will have coefficients that include terms related to shock volatility. As with many other parts of the model, this form of loss function can be relaxed or complicated without changing the qualitative conclusions.

The central bank takes first order conditions with respect to Equations 7-12 and rearranges to find the optimal reaction function:

$$
\begin{aligned}
i_t = & \frac{k}{\sigma\lambda_i}\pi_t + \frac{\lambda_x}{\sigma\lambda_i}x_t - \frac{k\lambda_x}{\sigma\lambda_i R_t}x_{t-1} + \left(1 + \frac{1}{\beta R_{t-1}R_t} - \frac{\sigma+\beta\sigma+k}{\beta\sigma R_t}\right) i^* \\
& + \frac{\sigma+\beta\sigma+k}{\beta\sigma R_t} i_{t-1} - \frac{1}{\beta R_{t-1}R_t} i_{t-2}
\end{aligned} \tag{16}
$$

Where R_t is defined as:

$$
R_t = \frac{exp\left(\frac{-V_t}{\theta}\right)}{E_{t-1}\left(exp\left(\frac{-V_t}{\theta}\right)\right)} \tag{17}
$$

Note that under expected utility, $\theta \to \infty$ so, $R_t = 1\ \forall t$, and the above function collapses to the one of Giannoni and Woodford (2003).

Importantly, one can see that the parameters in the reaction function that pre-multiply the state variables are now time-varying, owing to the R_t terms.[15] These terms will react to the stochastic volatility as it changes in the economy, resulting in a time-varying reaction function of the central bank.

It is worth saying here what we mean by time varying. 'Time varying' is in reference to a linear approximation. This has typically been the meaning of time varying in the empirical literature discussed in Section 2, where Taylor rules were thought to be time varying if the coefficients in a linear approximation exhibited substantial enough variation over the time period studied. Clearly, the reaction function specified in Equation 16 does not have time varying coefficients if one specifies all non-linear variables correctly, and leaves only the fixed parameters as coefficients. The difference between a correctly specified non-linear reaction function and a time-varying approximate linear one is non existent. The reader can either think of the reaction functions we discuss here as being time varying based on stochastic volatility, or non-linear with respect to volatility, the ultimate interpretation is the same.

Equations 7 - 12, and 14 - 16 define an equilibrium in our model. We obtain an approximation to the value function (Caldara, Fernandez-Villaverde, Rubio-Ramirez, and Yao 2012),

[15] The parameters on π and x in the current period are unchanged, echoing the result of (Leitemo and Soderstrom 2008), that robust control doesn't affect the optimal current period trade off between inflation and output.

and solve using perturbation methods at fourth order. Our calibrated parameters are shown in the table below.

Table 5: Calibrated parameters

Parameter	Value
β	0.99
κ	0.4
σ	2
ρ_r , ρ_π	0.7
ρ_{vol}	0.9
λ_x	0.5
λ_i	0.2
i^* , $\bar{r}$	0
θ	4

The parameter that governs the extent of the policymaker's fear over model misspecification is θ. Often this is calibrated with reference to error detection probabilities (Anderson, L. P. Hansen, and Sargent 2003). In our case, with altering volatility in the economy, the typical error detection calibration exercise would result in a time-varying θ. We view θ as a deep parameter that is a fixed preference for robustness, and as such calibrate it at 4. This is just before the 'breakdown point' of the model. We discuss the reason for this particular calibration in the subsequent subsections.

4.1. Illustrating the effect of a desire for robustness

Our model comes with the common result that robust control central bankers are more aggressive than their expected utility maximising counterparts (who act under certainty equivalence). This is because a desire for robustness pushes the central bank to consider the worst case parameter configuration of the model in a neighbourhood around the baseline model. How far away that parameter configuration is depends on the volatility of shocks and the policymaker's fear of misspecification.

As is well known, in the New Keynesian model the most painful configuration of the world is one in which supply shocks are prominent, persistent, difficult to counteract and therefore cause large dislocations in output and inflation. Demand shocks are subject to the divine coincidence and so are not heavily featured in the worst case distributions that the policymaker considers. As a result, the policymaker is more aggressive when responding to shocks as they (wrongly) perceive the shocks to be from a less favourable environment than the one in which they actually inhabit.

To illustrate the effect of the robust control environment, we compare a standard Expected Utility (EU) policymaker and a robust control policymaker who makes policy as outlined above (RC). In Figures 5 and 6, we consider three scenarios: (i) an EU policymaker facing a demand shock to the IS curve, ϵ_t, (ii) an EU policymaker facing a demand shock to the IS curve, ϵ_t, combined with a simultaneous volatility shock to the supply curve, v_t^u, and (iii) a RC policymaker facing the demand shock, ϵ_t, as in (i). The focus on the effect of a demand shock, rather than supply shocks, is because this is the standard shock to which the monetary response is relatively straightforward and well understood within the New Keynesian model framework. Focusing the volatility shocks on the supply side of the economy also stacks the deck in favour of the robust control policymaker having a large response.[16]

The shocks, each one standard deviation, are shown in Figure 5. The top panel shows all three scenarios face equivalent demand shocks. The bottom panel shows that in only one configuration is there a shock to the volatility of Phillips curve disturbances. It is worth stressing that the IS shock and PC volatility shock do not interact. The shock to the volatility of supply shocks has no direct effect on the economy, since all supply shocks are set to zero for this exercise.

The effect of the demand shocks in these three scenarios are shown in Figure 6 which plots the reactions of the endogenous variables to these shocks. They highlight two points:

[16]We consider the effect of stochastic volatility shocks on the RC policymaker below.

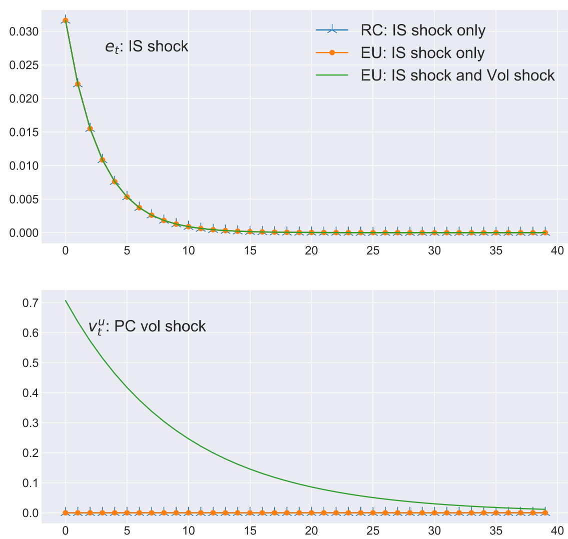


Fig. 5. Shocks to IS curve and PC curve volatility

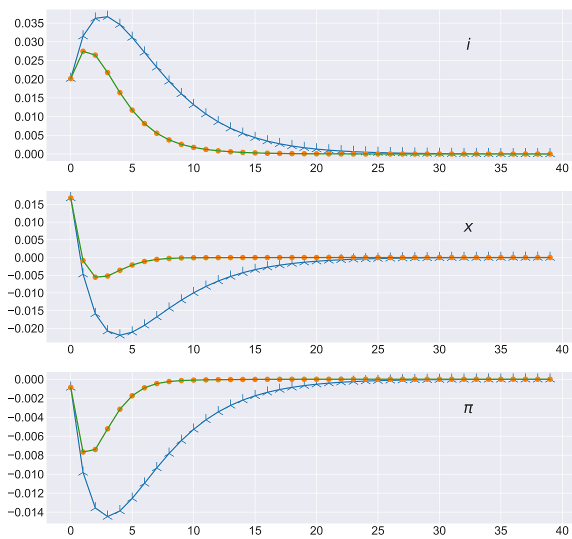


Fig. 6. Reactions of endogenous variables

1. There is no effect of stochastic volatility on the EU policymaker. Since the EU central banker acts under certainty equivalence, the imposition of a volatility shock has no effect on any of the endogenous variables. The reaction from the EU central bank to the IS shock is equivalent with or without the PC curve volatility increase, and thus the changes in inflation and output are also equivalent.
2. The RC policymaker reacts more aggressively to the same demand shocks. The robust control central bank acts as though the shock will cause greater volatility in inflation and output, and that their instrument is weak in counteracting the shock. As a result they are more aggressive in their reaction, increasing interest rates more than the EU policymaker, and causing output to significantly overshoot the target.

4.2. The small effect of stochastic volatility

The novel difference in our model, relative to other optimal policy exercises, is our addition of stochastic volatility to a robust control set-up. While robust control breaks the (modified) certainty equivalence result, our model allows for policymakers who are aware of the fact that uncertainty might change. This means that the level of stochastic volatility becomes important for the central bank, who reacts by altering the coefficients of their optimal reaction function.

This novelty reveals three important points: (i) changes in the reaction function coefficients (that in our model happen as a result of stochastic volatility shocks) alter the reaction of the economy to other, orthogonal, shocks; (ii) changing coefficients in the reaction function affect the economy multiplicatively (the coefficients are multiplied by states of the economy), and as a result their effects are state-dependent, and (iii) that greater volatility in the economy can *cause* a central bank to become more aggressive, rather than just be associated with it in the data. However, whilst these points are qualitatively true, as with the parameter uncertainty effects, we find very small quantitative changes in reaction function as a result of volatility shocks.

Figures 7 and 8 show the effect of a stochastic volatility shock on the impulse responses to a 1 s.d. IS curve shock for an RC policymaker. This is the same exercise as for the EU policymaker in Figure 5; there is the response to the demand shock on its own and when accompanied by a simultaneous PC curve volatility shock. While the coefficients of the reaction function change in the presence of higher volatility, there is little difference to the naked eye in the response of the interest rate in Figure 8.

The effects really only become large enough to be noticeable at extreme shock levels. Figures 9 and 10 repeat the exercise but for a 5-s.d. shock to the IS curve *and* a 5-s.d. shock to PC curve volatility. In these charts, the distance between the yellow and blue lines denoting the different responses of the interest rate is visible. At these extreme values, the coefficient change has distinguishable effects, but it is still relatively small.

This point is also evident if we examine how the coefficients of the reaction function change in response to the shocks. This is a direct test of the effect as this is the source of the differential response of the endogenous variables emerge. As discussed earlier, the channel of volatility on optimal monetary policy comes through the R term in Equation 16. Only the coefficients relating to output in the previous period, the natural rate of interest (which is

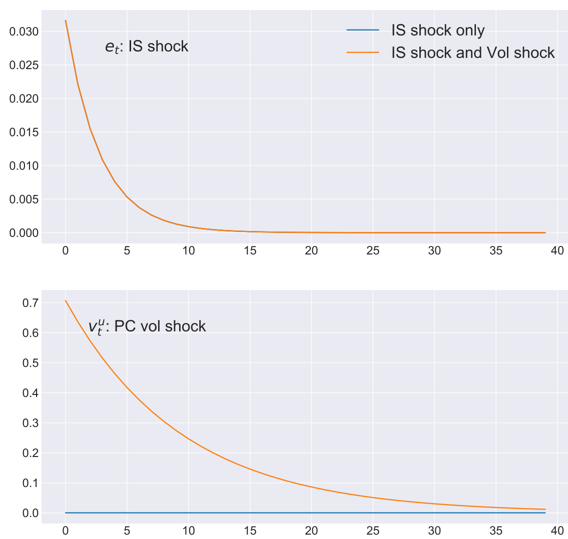


Fig. 7. Shocks to IS curve & PC curve volatility (1 s.d.)

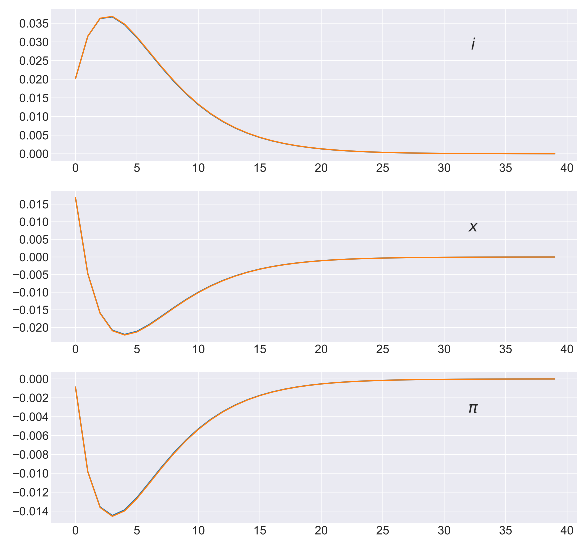


Fig. 8. Reactions of endogenous variables (1 s.d.)

not affected by the shock), the interest rate in the previous period and the interest rate two periods ago are affected by the volatility increase under robust control.

Figure 11 shows the responses of these coefficients in the case of a 1 s.d. to both the IS curve shock, and in the case of both the IS curve and PC curve volatility shock. These are the coefficient changes that underpinned the impulse responses in Figure 8. Clearly it is the affect of the volatility shock which causes the central bank to alter its reaction function. But the magnitude is so small as to not have a noticeable effect on the dynamics of the economy. This is particularly clear when we consider the magnitude of estimated changes in reaction function coefficients we found in Section 2. The optimal policy exercise here produces changes that are an order of magnitude too small.

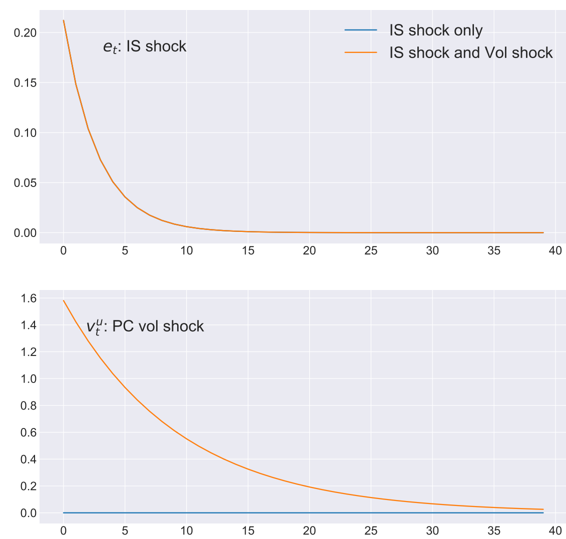


Fig. 9. Shocks to IS curve & PC curve volatility (5 s.d.)

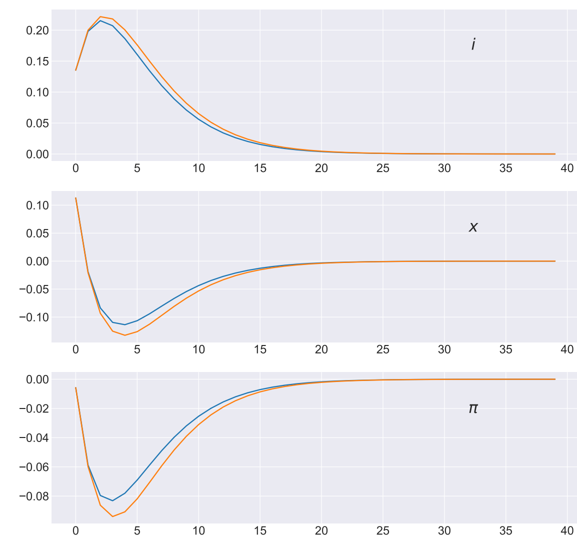


Fig. 10. Reactions of endogenous variables (5 s.d.)

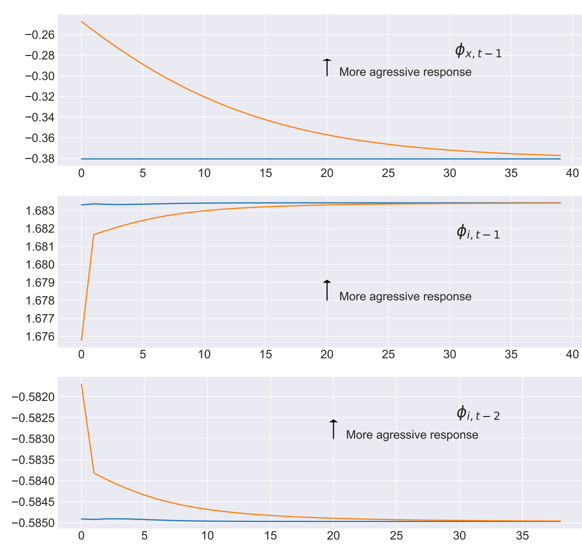


Fig. 11. Coefficient reactions

This result comes despite us stacking the deck in favour of the biggest possible effect in terms of calibrating the θ parameter. We have calibrated θ to be just before the "breakdown point" (L. P. Hansen and Sargent 2008). The breakdown point is the point at which the set of models which the minimizing agent is so large that they can choose a model that sets the minimizing function to minus infinity. At the breakdown point, solving the model is no longer possible. Just before the breakdown point is where the central bank is most sensitive to its worst case scenario worries, and therefore most affected by the volatility shocks we impose.

That is to say, we have calibrated the above exercise to feature the most extreme combination of shock variances and fear of misspecification. Even with these two extreme assumptions, the change in the reaction function in response to a 1-s.d. rise in volatility is small. Only with shocks as large as 5 s.d. are there any material effects. And even then, the changes are not large enough to match the data.

This extreme assumption not only applies to the size of the volatility shock, but also the shock to the IS curve. In our model, our coefficient innovations are multiplicative, rather than additive, in that they interact with the endogenous variables in the reaction function. As a result, the effect of coefficient innovations are state-dependent. This means that we not only need a large volatility shock to change the reaction function coefficients, but also a large IS shock to move us far enough away from steady state for the multiplicative effect of the shock to be material.

4.3. The even smaller effect of supply shocks

So far we have considered the most favourable combination of shocks to generate a large reaction function coefficient change for the robust control central banker: a volatility shock to the Phillips curve, combined with an IS curve shock. Why is this the most favourable? Because the policymaker acts as if the worst case model is true in an area around the true model. A model in which supply shocks are prevalent, large and difficult to offset is the model for which the central bank makes policy for. Increasing the volatility of the Phillips curve expands the set of models the central bank considers, thus pushing that "worst case" model further away from the truth. Below we consider the opposite case to that which we have considered so far: a volatility shock to the IS curve, and a shock to the Phillips curve.

We retain the assumption that the fear of misspecification is at the breaking point. Figures 12 and 13 show the effect of a 5 s.d. shock to the volatility of the IS curve, and a 5 s.d. shock to the PC curve. These extreme assumptions bought us a small, but at least noticeable difference in endogenous variables, when we considered shocking the volatility of the Phillips curve. In the case of shocking the volatility of the IS curve, there is no material effect at all. Figures 12 and 13 are even more striking when one considers that it is IS shocks that are depicted with such stark differences in interest rate reactions in Section 2.

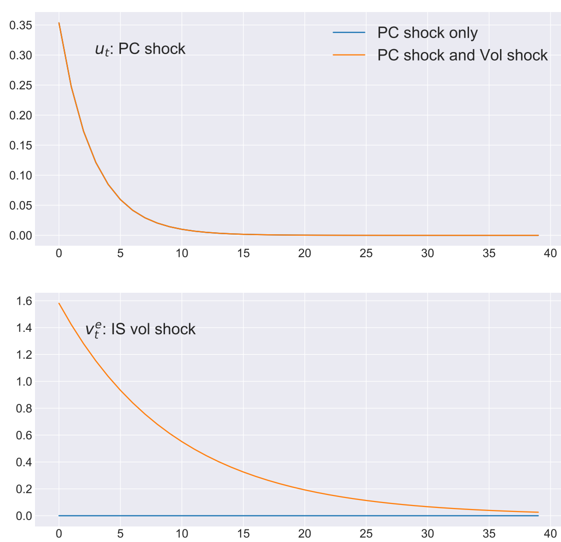


Fig. 12. Shocks to PC curve & IS curve volatility (5 s.d.)

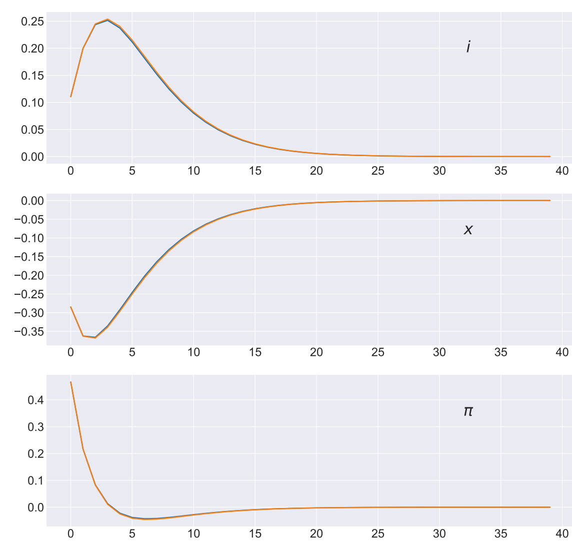


Fig. 13. Reactions of endogenous variables (5 s.d.)

4.4. Robustness

We are confident that our results are robust and are not a feature of the specific benchmark model outlined above. We have performed the same exercise on the 3-Equation backward looking model of Ball (1999) to verify the results are similar in that environment. We have also checked the role of the solution method – we have confirmed the results hold under global methods using policy function iteration (albeit on a smaller grid than we would like owing to computational constraints).

5. Economic uncertainty and monetary regimes

Policymakers argue that they face huge uncertainty that is fundamental to their policy choices (Greenspan 2004). Given this, a role for uncertainty in the policy response seems natural. However, we have shown that models using the standard environments in the literature that link uncertainty and optimal monetary policy do not yield convincing results. The standard parameter uncertainty environment typically pushes the comovement in the opposite direction to the empirical finding. And even the very general uncertainty in the robust control model, can only match qualitatively, but not quantitatively, the changing reaction of monetary policy before and after the Great Moderation. This is the main contribution of this paper – to highlight that our existing models of monetary policy under uncertainty struggle to generate meaningful reaction function variation in response to reasonable changes in economic volatility.

An important implication of our analysis is to shed light on what sources of uncertainty might matter for policy. In this section we discuss a number of other sources of uncertainty and how they might manifest themselves in the optimal response of monetary policy.

5.1. Time-varying aversion to misspecification

The previous section made clear that any attempt to estimate a robust control model with stochastic volatility — computational limitations of doing so aside — will not be able to accurately match the changes in the Federal Reserve's reaction function by having a robust control policymaker optimally respond to volatility shocks. However, the above exercises highlighted one way to generate larger shifts in the coefficients of the reaction function: time-varying aversion to misspecification.

The gap between the coefficients of the expected-utility policymaker and the robust-control policymakers is large. The difference between these optimal coefficients is down to the θ parameter. θ is inversely related to the budget for distortion (so higher values mean more trust in the baseline model). In the limit, the specification errors become increasingly constrained and the robust decision problem converges to the non-robust decision problem. In the Robust

Control framework, reducing θ is equivalent to increasing the variances of the shocks in terms of how the policymaker optimally reacts.[17]

Therefore, if our aim is to simply match the time-variation in the Fed's reaction function, this could driven by a time-varying desire for robustness. That is, there could be a feedback from monetary policy to volatility and back to monetary policy. As the economy becomes more stable, and as forecast errors decline in the late 80s and through the 90s, the policymaker becomes more sanguine about misspecification (θ increases). In such a scenario, the reaction function would become more EU-like. That is, stochastic volatility *could* drive a less aggressive Fed reaction function.

5.2. Conjunctural Uncertainty

The largest changes in the reaction function coefficients in Section 3 came when there were there were structural changes such as a decline in the persistence of inflation. Could it simply be that the perceived structure of the economy is the main driver of the reaction function?

Orphanides (2001) and Byrne, Goodhead, McMahon, and Parle (2022) emphasise policy uncertainty about the conjunctural assessment in real time. This is not the type of uncertainty that much of the literature has focused on, and is not the type of uncertainty that is typically modelled. However, Section 3 highlighted that the reaction function changes are large for changes in structural parameters.

This type of uncertainty may occur because the economy is constantly changing but the changes are not easily detected in real time (or even immediately afterward). We know that if the parameters of the economy change, or those perceived by the policymaker change, the endogenous effect on optimal policy can be substantial. Policymakers in reality, unlike their

[17] Anderson, L. P. Hansen, and Sargent (2003) introduce the idea of a detection-error probability (DEP) as a tool for calibrating θ. DEP is the probability an econometrician, who observes the data generated by the true model, would incorrectly infer which of the approximating equilibrium or the worst-case equilibrium had generated the data. Low θ (high budget for evil agent and so large distortion of the worst case model compared with the baseline model) means lower DEP – big distortions are more easily detected. A lower DEP means a more extreme degree of robustness - the econometrician can more easily tell between the models.

In general, as the variance of shocks increases, the DEP falls. The econometrician is less likely to make a detection error because the robust model gets further from the baseline and so with enough data you can tell them apart. Lower θ means this the decline is greater. The decline in DEP with volatility is also greater when the model has more persistence in the true model.

full-information, rational expectation (FIRE) model counterparts, face huge informational challenges. They do not know with certainty the dynamics of the economy and are almost certainly learning from the data.

Moreover, policymakers are likely rationally inattentive as in Bernstein and Kamdar (2022). This means that even when faced with large reams of data to analyse, their cognitive processing limits mean that they have to make choices about what to focus on. In such a scenario, the process of learning the current state becomes more difficult than the FIRE assessment of conditions.

Indeed in Svensson and Williams (2007) and Svensson and Williams (2008) the authors consider a world in which the economy is constantly switching regimes, and these regimes are unobserved by the policymaker. They find that an optimal bayesian policymaker can exhibit large shifts in their reaction function as data appears that confirm (or refute) their belief regarding which regime the economy is currently in. These changes are constantly taking place, as (i) the policymaker is continually learning from the data each period, and (ii) the economy has a probability of switching to a new regime in each period.

Of course, the structure of the economy may not actually be changing. Cho and Kasa (2017) point out that a policymaker who worries about potentially time-varying parameters, and bases actions on forecasts that incorporate this worry, can generate feedback such that despite constant deep parameters, the data generating process behaves as if the parameters are time-varying. For our argument, it is enough that policymakers perceive changing coefficients. Under this form of expectational feedback, the reduced volatility may be caused by lower parameter volatility which means the policymakers (and all decision makers) worry less about time-variation. As a result their forecast models put less weight on the possibility of time-varying parameters, and so they generate less feedback via their own policy decisions, thereby making the system more stable.

5.3. *Constrained discretion: Credibility earning and credibility burning*

A more-specific version of the conjuntural uncertainty argument just presented relates to the importance of central bank credibility and expectation management. King, Lu, and Pastén (2008) emphasise the importance of expectation management in the control of inflation; this is also a central message from New Keynesian monetary models as in Galí (2015).

But in FIRE models, in which all agents have full information of the structure of the economy, and where the central bank commits to a specific reaction function, credibility is easily established through a sufficiently aggressive fixed monetary reaction function. In practice, credibility is a much more fluid concept that policymakers must build up ("earn"), but can also use ("burn"). This conception of central bank credibility has generally been ignored in the theoretical literature on monetary policy.[18]

Given that policy operates with long and variable lags and, hence, must be forward-looking, a fundamental uncertainty is knowing which mode the central bank needs to be in. In this case, the main conjunctural assessment is how well anchored inflation expectations are. At moments when the costs of doing so are low, it makes sense to talk tough on inflation to reaffirm the central bank's commitment to being tough on inflation. Such open mouth operations can afford greater flexibility to be soft on inflation when the benefits of being soft are greatest such as in a recession.

One particular version of the credibility narrative relates to the inflation scares idea as put forward by Goodfriend (1993). He has highlighted that if inflation expectations become deanchored, and markets question the Fed's credibility in achieving price stability, inflation increases and the dynamics of inflation become more persistent. In such a circumstance, or even in advance of it, the Fed would have to shift into a different mode of countering the "inflation scare". Cieslak, S. Hansen, McMahon, and Xiao (2022), using analysis of the FOMC transcripts, show that, consistent with this idea, policymakers worry about inflation increasing even when other objective measures of inflation uncertainty are low.

[18] Debortoli, Maih, and Nunes (2014), and their related papers, are an exception in that they solve for optimal monetary policy under imperfect commitment. They show that imperfect commitment matters for optimal interest rate policy.

Our estimated changes in reaction functions point in the same direction – there is an important role for the monetary authority to switch between an inflation-fighting mode and an economy-supporting mode. Figure 4, showing the probability of being in the low shock variances and low aggression regime was high under Alan Greenspan (1987-2003). This is consistent with the establishment of credibility then buying the Fed space to be less aggressive in its anti-inflation stance and, despite this stance, inflation not accelerating away.[19]

Bianchi and Melosi (2018) explicitly consider the idea of constrained discretion in monetary policy. The central bank is able to deviate from active inflation stabilisation temporarily but at the cost of deanchoring inflation expectations. Given that agents are learning slowing about the approach being taken, longer deviations are more likely to lead to a deanchoring. In such a case, an inflation scare might precipitate a longer period of aggressive monetary response. If the Great Moderation was associated with greater credibility, the FOMC would have less fighting of inflation to do and so monetary policy would not need to be as aggressive.

This credibility approach explains the comovement puzzle as follows: the initially aggressive response from Volcker, once he was successful at establishing the Fed's inflation-fighting credibility and anchoring inflation expectations at lower levels, will be optimally followed by a decline in how aggressive monetary policy is. The Great Moderation, as an environment of anchored inflation expectations, afforded the central bank more scope to support the economy without the need to remain as aggressive toward small variations in inflation. Of course, they had to remain vigilant to the risk that inflation expectations deanchor. This is what constrained discretion involves and, at its heart, this explanation is about good policy.

[19]For instance, Angeletos and Lian (2021) and Moberly (2022), among others, revisit the issue of monetary determinacy and how adherence to the Taylor principle is regime dependent.

6. Conclusion

While a previous literature argued that the renewed aggressiveness of Fed monetary policy contributed causally to the reduced volatility of the economy, such an explanation does not easily account for the strong positive correlation between periods of high variance and periods of aggressive policymakers in the data since the mid-1980s.

We have explored the causal link between these phenomena through the lens of different models that consider monetary policy as potentially reacting to uncertainty induced by higher volatility. Neither parameter uncertainty models, nor models of a policymaker with a desire for robustness, even in an environment featuring stochastic volatility, can replicate the magnitude of the changes in estimated reaction functions we found in the data. As a result, and the main finding of the paper, is that these models do not seem to be good representations of the uncertainties that drive policy variation (even if policymakers are, clearly, uncertain about many aspects of the economy.)

On one hand, the weakness of the link from uncertainty to the optimal response of monetary policy is helpful for those that wish to argue that it was Federal Reserve aggression that kept volatility at bay. It is still possible that the initial increase in aggression after the appointment of Paul Volcker could have caused volatility to decline. But the question remains as to why the Fed became less aggressive over time since the mid-1980s. On the other hand, the question remains as to what may have caused the reduced aggression.

We have presented several alternative explanations on the important sources of uncertainty. Understanding what type of uncertainty matters is an important step to thinking about the issue of how to effectively communicate uncertainty. This is an important topic, though one we leave for future work.

Regardless of which uncertainty drives it, an important implication of our analysis is that time-variation in the reaction function is likely important. While the academic literature shows the benefits of rules and commitment, uncertainty is one reason why the academic recommendation to set monetary policy by rule is rejected in practice as discuss in Federal Reserve Board of Governors (2018). This has important implications for empirical monetary economics.

Changes in the reaction function coefficients are important because they alter the reaction of the economy to other shocks and they affect the economy multiplicatively (the coefficients are multiplied by states of the economy). As a result their effects are state-dependent. This means that, in the analysis of the effects of monetary policy, we need to be especially careful to consider what exogenous variation we use econometrically. McMahon and Munday (2022) discuss the fact that ignoring time-variation in the reaction function is extremely problematic for the use of and interpretation of analyses using market surprises to uncover the monetary transmission mechanism.

Returning to the question of what this analysis means for the future, this paper is, unfortunately, timely. Many central banks are facing significant above-target inflation for the first time in 30 years. Many central banks have been accused of miscalculating the state of the economy and the shocks that have hit it. There remains, of course, uncertainty about the correct course of action, but the balance of opinion among policymakers suggests tightening, perhaps aggressively, is the necessary course of action. Policymakers appear to be shifting very quickly into a more-hawkish, anti-inflation mode.

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7. Appendix

7.1. TVP-VAR impulse responses

Here we show the complete set of impulse responses from the time-varying parameter VAR. Figure 14 shows them in 2D, color coded for the date which they refer to. Figure 15 shows this same data, but in three dimensions, with the date added as a third axes rather than as a color.

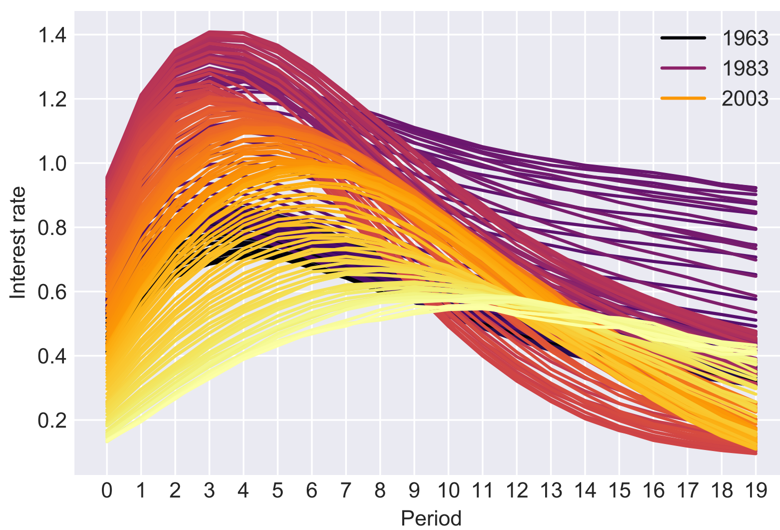

Fig. 14. All impulse responses of a 1pp shock to inflation on the interest rate

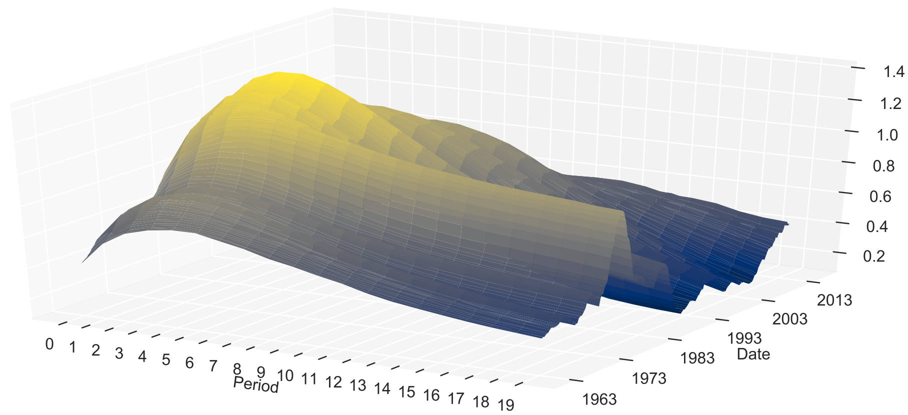

Fig. 15. All impulse responses of a 1pp shock to inflation on the interest rate

7.2. MS-DSGE with variable inflation shock persistence

Table 6: Calibrated parameters

Parameter	Value
β	0.99
κ	0.4
σ	2
$\bar{r}$	0
ρ_e, ρ_v	0.7

Table 7: Priors

Parameter	Distribution	%90 bands
c_u^1	Weibull	0.0005, 1.0
c_u^2	Weibull	0.0005, 1.0
c_e^1	Weibull	0.0005, 1.0
c_e^2	Weibull	0.0005, 1.0
c_v^1	Weibull	0.0005, 1.0
c_v^2	Weibull	0.0005, 1.0
$p_{1,2}$	Beta	0.05, 0.15
$p_{2,1}$	Beta	0.05, 0.15
ϕ_π^1	Gamma	0.5, 1.5
ϕ_π^2	Gamma	1.5, 3.0
ϕ_x^1	Gamma	0.05, 3.0
ϕ_x^2	Gamma	0.05, 3.0
$\phi_{x,1}^1$	Normal	-0.5, 0.5
$\phi_{x,1}^2$	Normal	-0.5, 0.5
$\phi_{i,1}^1$	Normal	-0.5, 0.5
$\phi_{i,1}^2$	Normal	-0.5, 0.5
$\phi_{i,2}^1$	Normal	-0.5, 0.5
$\phi_{i,2}^2$	Normal	-0.5, 0.5
ρ_u^1	Gamma	0.6, 0.8
ρ_u^2	Gamma	0.6, 0.8

Table 8: Estimated Markov Switching parameters

Parameter	Regime 1: Posterior mode	Regime 2: Posterior mode
ϕ_{π}^{j}	0.69	2.50
	(0.10)	(0.20)
ϕ_{x}^{j}	0.32	1.41
	(0.06)	(0.19)
$\phi_{x,1}^{j}$	-0.11	0.03
	(0.06)	(0.17)
$\phi_{i,1}^{j}$	1.93	0.47
	(0.04)	(0.11)
$\phi_{i,2}^{j}$	-1.06	0.04
	(0.04)	(0.10)
c_{u}^{j}	0.003	0.004
	(0.0003)	(0.0004)
c_{e}^{j}	0.009	0.02
	(0.0004)	(0.002)
c_{ϵ}^{j}	0.004	0.0239
	(0.0004)	(0.001)
ρ_{u}^{j}	0.63	0.68
	(0.04)	(0.05)

Table 9: Estimated transition probabilities

Parameter	Posterior mode
$p_{1,2}$	0.04
	(0.009)
$p_{2,1}$	0.12
	(0.03)

The Element(s) of Surprise

Michael McMahon* & Tim Munday†

Monetary policy surprises are driven by several separate forces. We argue that many of the surprises in monetary policy instruments are driven by unexpected changes in the reaction function of policymakers. We show that these reaction function surprises are fundamentally different from monetary policy shocks in their effect on the economy, are likely endogenous to the state, and unable to be removed using current orthogonalisation procedures. As a result monetary policy surprises should not be used to measure the effect of a monetary policy "shock" to the economy. We find evidence for reaction function surprises in the features of the high frequency asset price surprise data and in analysing the text of a major US economic forecaster. Further, we show that periods in which an estimated macro model suggests policymakers have switched reaction functions provide the majority of variation in monetary policy surprises.

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1. Introduction

> Some academic research on policy rules contends that tying monetary policy to a simple and unvarying policy rule can simplify the central bank's communications with the public and make monetary policy predictable and relatively easy to understand...
> The conclusions of this academic research depend on a number of assumptions that are unlikely to hold in the real world. ... in the real world, the structure of the economy changes over time, and those changes are not apparent immediately.
>
> ---
>
> Challenges Associated with Using Rules to Make Monetary Policy, Federal Reserve Board

Policymakers do not mechanically follow algebraic policy rules. This does not mean that policy is completely discretionary. Policy responses typically incorporate rule-like features which are desirable while also ensuring that policy can incorporate flexibility to deal with, for example, lags in data availability, as well being able to apply judgements in the assessment of the information that is available. The fact that policy *could not* strictly follow algebraic policy rules was stressed in Taylor (1993).[1]

In this paper, we take this argument to the monetary policy surprise literature. We show that if a substantial element of a monetary policy surprise is reaction function variation, then not accounting for such changes in the reaction function can lead researchers to misinterpret this variation as a monetary policy shock. This mistake is not innocuous in terms of its economic or econometric implications.

The use of algebraic reaction functions is a convenient way to model monetary policy. Typically, we imagine a central bank making decisions about the short term interest rate i_t as a result of some transformation $g(x_t; \phi)$, parameterised by ϕ, of a high-dimensional vector of variables that describe various aspects of the economy, x_t. Monetary policy shocks have

[1] The opening line of his conclusion reads: "This paper has endeavored to study the role of policy rules in a world where simple, algebraic formulations of such rules cannot and should not be mechanically followed by policymakers."

traditionally been denoted by appending an error term, ϵ_t to this equation:

$$i_t = g\left(x_t; \phi\right) + \epsilon_t \tag{1}$$

In a model, x_t contains endogenous variables to which the central bank responds. This ensures that policy varies systematically with the state of the economy. To understand the effect of monetary policy in the model, we can examine the dynamics after an exogenous shock to the interest rate from ϵ_t. This *theoretical* construction of shocks is designed such that if one traces a shock, ϵ_t, through a model, one can see the effect of an exogenous change in the interest rate on endogenous variables of interest.

However, the theoretical (and pedagogical) desire for shocks has also influenced the *empirical* monetary policy literature. To measure the effects of monetary policy, it is vital to avoid endogeneity bias; looking at the unconditional movements of the economy and the interest rate, you might naively conclude that lower interest rates are associated with weakening of the economy. But this would reflect the endogenous reaction of policy. Therefore, various approaches have been undertaken to purge interest rate movements of their endogenous variation. This includes approaches in VARs (Sims 1992), narrative methods (C. Romer and D. Romer 2004), high frequency financial market surprises (Gertler and Karadi 2015), and others. In essence, empiricists have gone looking for ways to either measure monetary policy shocks directly, or find instruments for them.

Much of the recent empirical literature has taken surprises (the unexpected component of policy decisions) and used these as a path to shocks (ϵ). Surprises can contain many elements, one of which are shocks. But the use of them can lead the researcher astray if we do not consider the other elements. This was made apparent by Nakamura and Steinsson (2018)'s view that an important element of surprises was an information effect (an unexpected change in x in the terms of Equation 1). We continue this argument and posit that unexpected changes in the coefficients of the reaction function are driving a substantial amount of variation in monetary policy surprises.

One reason that we believe this to be true is that policymakers do not view themselves as following fixed reaction functions. And these central bankers do not think of themselves as having an ϵ_t in their process for setting interest rates; such shocks are a convenient, purely academic construct. To policymakers, and macroeconomists at central banks, all policy decisions are endogenous reactions to the economy.[2]

If policymakers optimally change how they react to the state of the economy as the economy evolves, and they introduce no randomness into their decision, then the actual reaction function will be given by:

$$i_t = f\left(x_t; \psi_t\right) \tag{2}$$

Where the previously fixed coefficients of the function (ϕ) have been replaced by time varying counterparts (ψ_t). How can we reconcile this formulation with the empirical approaches taken? Mathematically, there is an equivalence mapping between $g\left(x_t; \phi\right) + \epsilon_t$ and $f\left(x_t; \psi_t\right)$. If the coefficients of the mapping can time vary, it is always possible to allow the ψ_t coefficients to change such that they absorb all the deviation of the policy from some fixed-coefficient reaction function.

Such an equivalence mapping may not be innocuous. Firstly, to the extent that the reaction function affects the economy as it does within a model, changes in the reaction function coefficients are important in that they change the entire dynamic system of the economy. Misinterpreting a change in the reaction function of the central bank as a monetary policy shock misses that, unlike a monetary policy shock, a change in the reaction function completely alters the impact of other shocks on the economy. Specifically, the solution of the model is a function of the reaction function coefficients, which have now altered. Therefore, the empirical impulse response estimated on these reaction function surprises will include the effect that the changing reaction function has on the other shocks that are currently passing through the economy.

A second, and perhaps less obvious, reason why changes in reaction functions cannot be relabelled as monetary policy shocks is that changes in the reaction function of the central

[2] If shocks do occur it is likely only due to the spurious rounding errors of monetary policy decisions that are taken typically in increments of 25bps for interest rates, and large round numbers of asset purchases, when the true state of the economy demands a non-round amount of monetary policy.

bank have a state-dependent impact on the economy. A monetary policy shock as it is usually modelled, an additive innovation to a model equation, has an effect always and everywhere no matter the state of the economy. And — if the model is linear — this effect on the economy is the same regardless of the state. The same cannot be said for reaction function changes, which have no effect at the steady state of the economy, and large effects when the economy is far away from steady state.

These two issues arise even if the changes in reaction function are themselves exogenous. In this case, monetary policy surprises (as measured by high frequency changes in asset prices) will contain both reaction function shocks and monetary policy shocks (if they exist). Impulse responses derived from these surprises will trace out the effect of a mixture of both shocks. That is not a problem *per se* but the impulses responses will answer a different question to which the econometrician is usually asking. They will not show the answer to "what is the effect of a one-off exogenous 25bp increase in the interest rate in a given period", rather they will show "what is the average effect of a one-off 25bp increase in the interest rate either due to an exogenous shock, or due to the central bank becoming more aggressive with respect to an unspecified state variable, the weights of which depend on the relative prominence of these two forces in the data." Furthermore, the impulse responses for each of these two driving forces can be substantially different, particularly empirically, so confusing them may not be an innocuous mistake.

Finally, and more importantly, even if these two issues did not arise, empirically we believe using monetary policy surprises would still be problematic. The monetary policy surprise term will not be exogenous in circumstances where the reason for deviating from the average reaction function behaviour is itself an endogenous reaction to the state of the economy. We make this case using the interpretations of a macroeconomic forecasting team, the stylised facts of empirical monetary surprises, and an estimated macro model. In this case, measured monetary policy surprises will be endogenous, owing to the inclusion of endogenous reaction function variation, and therefore not capturing exogenous policy variation. We will also argue that this endogenous variation is extremely hard to purge using current methods. As a result they cannot be used to instrument for monetary policy shocks, as is common in the literature.

Of course, monetary policy surprises still remain a useful tool for understanding the information that moves financial markets. Decomposition of the surprises into constituent drivers as in Gürkaynak, Sack, and Swanson (2004) or Swanson (2021) still contain valuable information for scholars.

In Section 2 we motivate our approach for reaction function variation as a driving force behind monetary policy surprises. We first distinguish between shocks and surprises, and then set out a framework which makes clear that, ex ante, shocks are no less likely to cause surprises than information effects or reaction function surprises. We then set out why we think that reaction function surprises have characteristics that make them different to existing confounders to surprise measures.

In Section 3 we examine a novel dataset of reports of a major Federal Reserve forecasting team from a bulge bracket bank. We find no evidence that their ex-post (subjective) interpretations of their own forecast mistakes relate to "shocks" (in the academic sense), or information effects (Nakamura and Steinsson 2018). Indeed, their explanations seem to be based on some form of unexpected reaction function variation. Reaction function surprises are, according to those who study the FOMC for living, the predominant drivers of monetary policy surprises. Further, many of their explanations for why the reaction function changed unexpectedly are endogenous to the state of the economy.

In Section 4 we examine the empirical features of monetary policy surprises and assess whether these are consistent with reaction function changes. Not only do these features not fit the full information rational expectation framework that permits the use of surprises as shocks, but they fit the explanation of reaction function variation being an important element in creating surprises. Furthermore, we show that attempts to clean monetary policy surprises from information effects will not remove reaction function surprises — and, to the extent that these reaction function changes are endogenous — this invalidates the use of monetary policy surprises in the construction of shocks.

In Section 5 we estimate a Markov-switching DSGE model in which the reaction function of the Federal Reserve is permitted to switch across regimes. We show that, empirically, the regime switches happen concurrently with when the largest financial market high frequency monetary policy surprises occur. Even though the former is estimated on quarterly macro data, and the latter based on 30 minute moves in asset prices. This leads us to believe that reaction function surprises are a plausible candidate for some monetary surprises, and cannot be disregarded.

We then show that these reaction function changes are optimal. One can find structural parameters that vary simultaneously with the reaction function empirically. When these changing parameters are combined with an optimal policy set up, they deliver time varying reaction functions.

Finally, we show that the empirical impulse response functions calculated in periods in which we estimate that reaction function variation is driving monetary policy surprises are starkly different from the responses calculated using data from other periods — thus demonstrating the pitfalls of ignoring reaction function shocks.

In summary, reaction function variation is empirically well supported in the macro data. Surprises in reaction functions are common explanations of market participants. And, reaction function surprises fit the stylized facts of high frequency monetary policy surprises that have been documented elsewhere in the literature. Furthermore, the unwillingness of the literature to consider them so far has meant that monetary policy surprises are often used as instruments for shocks. However, if, as in this paper, reaction function surprises are an important element of monetary policy surprises and are themselves endogenous to the economy, monetary policy surprises are also endogenous and cannot be used in shock construction.

2. What are monetary policy surprises?

The empirical monetary economics literature uses monetary policy surprises to inform shocks. These surprises are typically measured as the change in asset prices in small windows around monetary policy announcements. They are then used as instruments for shocks, or — under certain theoretical assumptions — as direct measures of shocks themselves.

In this section we outline a framework for measuring monetary policy surprises. It shows that reaction function changes are, at least potentially, an important driver of surprises. This has implications for whether such asset price surprises can be construed as shocks, or fit the criteria to be used as instruments.

2.1. Shocks vs. Surprises

Monetary policy surprises are relatively easy to define: they are the part of a monetary policy decision that is unexpected to a given agent or group of agents. Often they are measured using asset prices (Kuttner 2001; Gertler and Karadi 2015; Jarociński and Karadi 2020; Miranda-Agrippino and Ricco 2021), so the surprise is to the marginal market participant. But they could, for example, be the surprise to a journalist (Ter Ellen, Larsen, and Thorsrud 2021; Acosta 2022) or forecasting team (see Section 3).[3]

Shocks are a much more difficult concept to pin down. Previously we wrote that shocks were essentially the empirical counterparts to the theoretical constructs macroeconomists use to trace out features of their models. Ramey (2016) outlines three key characteristics for shocks:

1. exogeneity with respect to the other current and lagged endogenous variables;
2. uncorrelatedness with other exogenous shocks so that we can identify unique causal effects of the exogenous shock;
3. they should be unanticipated movements in exogenous variables or news about future movements in exogenous variables.

[3]There are many papers using market surprises, too many to cite here, but they include Campbell et al. (2012), Krishnamurthy and Vissing-Jorgensen (2012), Inoue and Rossi (2018), Cieslak and Schrimpf (2019), and Bundick and Smith (2020).

She also adds a fourth condition which is that “they should be economically meaningful”.

Clearly, according to these definitions, surprises and shocks are different concepts. Monetary policy surprises do not fulfill any of Ramey’s conditions. Surprises to exogenous variables only fulfill condition (3) of Ramey’s list. And even that they may fulfill only partially, since the surprise is always measured based on the information set of a given group of agents. Different groups will receive different surprises, whilst the monetary policy shock is delivered to the macroeconomy as a whole.

It is, therefore, quite possible to have a shock that is not at all captured by a surprise. This is particularly the case because surprises are typically measured over monetary policy announcements (or announcements and speeches in the case of Bauer and Swanson (2022)). Imagine a scenario in which a new Fed Chair is announced who is known to have said that they will hike rates every meeting for the next ten years (let’s assume the committee vote with them for this example). This is a monetary policy shock and fits all conditions of Ramey’s list, but there will be no monetary policy surprises for the next ten years of meetings. C. Romer and D. Romer (2004) is a study that explicitly searches for shocks in a narrative analysis of FOMC meetings, and disregards the issue of whether or not these shocks are subsequently surprising. More recent attempts at this include Aruoba and Drechsel (2022) who use machine learning on FOMC text to calculate the predicted endogenous response to the states, and denote any action that differs from that as a “shock”.

Similarly, surprises do not have to contain shocks. Monetary policy surprises can occur due to the economy being stronger than the market agents expected leading to an unexpected increase in the interest rate (Nakamura and Steinsson 2018). But these “information effects” are not shocks since they are (by definition) endogenous to the state of the economy.

Because surprises and shocks do not overlap completely, it has become commonplace to use surprises as instruments (Gertler and Karadi 2015). The logic behind this is that the researcher may miss some shocks, but will hopefully capture enough exogenous variation in the interest rate to rid any analysis of endogeneity bias.

But we argue that surprises may still fail in this role as instruments. We believe this for two reasons. Surprises are not exogenous to macroeconomic variables. This has been well documented (as in, for example Miranda-Agrippino and Ricco (2021)). But the typical response has been to run a linear regression of surprises on some macroeconomic variables, and label the residual as the "true" surprise. However, we will make the case that many of this endogenous variation owes to reaction function surprises. And that these reaction function surprises are difficult to orthogonalise away. Secondly, monetary policy surprises contain a mixture of different shocks. In particular they will contain reaction function shocks (the shock counterpart to a reaction function surprise). As a result using them as instruments for shocks violates characteristics (1) and (2).

2.2. Elements of surprises: a framework

Let us define the surprise in short term interest rates, Δ_t, as the difference between the realised interest rate and the market's expected interest rate:

$$\Delta_t = i_t - \mathbb{E}_{M,t-1}\left(i_t\right) \tag{3}$$

Let us also suppose the policymaker makes decisions on the instrument i_t by inputting a vector of states x_t into function f with parameters ψ_t, and then adding some exogenous monetary policy "shock" ϵ_t. This gives:

$$\Delta_t = f\left(x_t;\psi_t\right) - \mathbb{E}_{M,t-1}\left(f\left(x_t;\psi_t\right) + \epsilon_t\right) + \epsilon_t \tag{4}$$

Note that we do not preclude the market from forming expectations about the shock, ϵ_t, if they so wish.

To simplify things, let us assume that f is approximately linear, so that $f(x_t;\psi_t) \approx \psi_t x_t$ where ψ_t is a row vector of coefficients. Furthermore, we rewrite the expectations of the market of any variable z as equal to the true value of z plus some forecast error: $\mathbb{E}_{M,t-1}\left(z_t\right) = z_t + e_t^z$. Finally, allow the possibility that ψ_t and x_t are determined jointly, and as such the covariance between them cannot be ignored.[4] Indeed, we explicitly want to allow ψ_t to be a function of the endogenous variables in the economy, an idea which we will extend in Section 5.

For now, let us assume ψ_t is time varying without specifying why. We will revisit this below, where we make the case for the variation to likely be endogenous. Under these assumptions we can decompose the observed market surprises as follows:

$$
\begin{aligned}
\Delta_t &\approx \psi_t x_t - \mathbb{E}_{M,t-1}\left(\psi_t x_t\right) + \epsilon_t - \mathbb{E}_{M,t-1}\left(\epsilon_t\right) \\
&= \psi_t x_t - \left(\psi_t + e_t^{\psi}\right)^T \left(x_t + e_t^x\right) + \epsilon_t - \mathbb{E}_{M,t-1}\left(\epsilon_t\right) + Cov(\psi_t, x_t) \\
&= \underbrace{e_t^{\psi} x_t}_{\substack{\text{reaction function}\\ \text{surprise}}} + \underbrace{\psi_t e_t^x}_{\text{information surprise}} + \underbrace{e_t^{\psi} e_t^x}_{\text{combination surprise}} + \underbrace{e^{\epsilon_t}}_{\substack{\text{monetary policy}\\ \text{shock surprise}}} + \underbrace{Cov(\psi_t, x_t)}_{\textit{covariance}}
\end{aligned}
\tag{5}
$$

Market surprises, under this very general framework, comprise of five elements: the addition of four separate surprises and a covariance term. The reaction function surprise is the result of the market misperceiving the reaction function of the central bank. The information surprise (or "information effect", Nakamura and Steinsson (2018)) is due to the market misperceiving the state of the economy. The combination surprise is the interaction between these two effects. Finally the monetary policy shock surprise is the part of the monetary policy shock that the market is surprised by. Under certain assumptions, for example that the market makes no attempt to forecast the "shock", then the monetary policy shock surprise is just the original monetary policy shock (ϵ_t).[5]

Equation (5) shows that monetary policy surprises are, *ex-ante*, as likely to be caused by reaction function surprises as information surprises or monetary policy shocks. Of course, if any of these policy updates are signalled in advance of the decision and press release, they would be built in to the market expectations and not contribute to the surprise around the announcement.

[4] If we tighten this assumption it just removes the covariance between ψ_t and x_t.

[5] Note this is different from saying the shock is unforecastable. The market may still forecast that there will be an exogenous movement in interest rates. It may not be rational to do so, but we are being as general as possible in this framework.

Earlier papers, if they have considered these other sources of surprises, have often assumed that market forecasts are made under full information rational expectations settings, and so the first three surprises (and covariance term) in Equation (5) are non-existent or white noise. Those that have not relied on these strong assumptions, for example Miranda-Agrippino and Ricco (2021), assume a fixed reaction function, and so can (under their assumptions) clean the surprises of the information effects leaving just the monetary policy shocks and some noise. Even those that do consider a varying reaction function (Bauer and Swanson 2020; Bauer and Swanson 2022) argue that regressing the monetary policy surprises on several state variables and then using the residual is enough to create a series that is deemed exogenous (a point on which we disagree, which we discuss further in the subsequent sections). As a result, previous studies have often used some form of monetary policy surprises as a measure for shocks directly, or as instruments for them.

One study that allows for variation over time in the effect of surprises, and the state of the economy, is Lewis (2019). By doing so, he then finds a substantial role for what we would call reaction function surprises, writing that "few monetary policy announcements sparked significant shocks, but those that did can be characterized as the introduction of new policies or the unexpected extension of existing policies." However, the author goes on to then assume that these shocks are exogenous when thinking about their macroeconomic effects. In this paper we argue that these "introduction of new policies" are likely reaction function surprises that are an endogenous reaction to the economy.

2.3. What are reaction function surprises?

Reaction function surprises are unexpected changes in the mapping from the state of the economy to the central bank's interest rate. For example, if the Fed raises rates because they are placing an unexpectedly (with respect to the market's prediction) large weight on the latest retail sales data, that would be classed as a reaction function surprise in our framework. A reaction function *shock*, such as caused the sudden appointment of a new Fed Chair following an unexpected death of a previous one, is a change in the reaction function that satisfies

Ramey (2016)'s criteria.

Previously, we introduced a function $f()$ that maps some observables to the policy instrument. We now follow in the spirit of Byrne, Goodhead, McMahon, and Parle (2022) and decompose $f()$ into two functions:

$$
\begin{aligned}
i_t &= f\left(x_t; \psi_t\right) + \epsilon_t && (6)\\
&= \gamma\left(\delta\left(x_t; \beta_t\right); \theta_t\right) + \epsilon_t && (7)
\end{aligned}
$$

Where $\delta()$ is a function that maps observables, x_t, to central bank objectives, inflation and output, using parameter vector β_t. $\gamma()$ is a function that maps these objectives to the central bank's control variable, the interest rate.

Why partition $f()$ into the two sequential functions? Purely for explanatory purposes. None of the implications of the paper are changed if one thinks of $f()$ mapping observables to the interest rate, and this function (optimally) varying over time and causing market surprises. In Section 3, when investigating how market participants (or those close to markets) interpret Federal Reserve decisions, we find it much easier to interpret perceived changes in the function $f()$ as either coming from (i) "assessment", i.e. the mapping from observables to objectives has changed unexpectedly and so the participant's estimate of $\delta(;\beta_t)$ was incorrect, or (ii) "preferences", i.e. the mapping from the projected objectives of the Federal Reserve to the interest rate had changed, either because the policymakers re-evaluate how effective their instruments are, or because they change their weighting between achieving different objectives, and so the participant's estimate of $\gamma(;\theta_t)$ was incorrect. Given that both of these types of news represent reaction function changes and *surprises*, it should be clear that these will be more prevalent than reaction function *shocks*.

The nature of reaction function changes are also different from classical monetary policy shocks. The impulse responses for reaction function shocks have an 'anything goes' characteristic. At steady state, an exogenous shock to the reaction function has no (immediate) effect on the economy. Far away from steady state, when inflation is not on target, a shock that makes the Fed more sensitive to inflation can have large effects on the economy. But the ambiguity of a what a reaction function shock "should" look like does not stop there. A reaction function shock in which the Fed becomes more sensitive to inflation may lead to either an increase or decrease in the interest rate (depending on the state of inflation relative to target). And, if it is persistent, will have a differential effect on the economy based on forecasted inflation. If the Fed becomes more sensitive to inflation, and inflation is currently above target, but it is forecasted to fall below target, then the reaction function shock is initially dovish, but becomes hawkish over time. The effect on the macroeconomy of this shock is therefore unclear, particularly if these longer term effects are priced into long-dated asset classes, even if one can correctly ascertain the extent of reaction function variation that has taken place. The subsequent effect on empirical impulse responses can therefore be material. Where the change in interest rate owes to a classical monetary policy shock, the resulting effect on the economy is clear. This is less so the case when dealing with the mix of effects that may accompany a reaction function surprise.

Furthermore, reaction function shocks change the impulse responses of other shocks as pointed out in McMahon and Munday (2022). This is true in a general sense of most macroeconomic models, since a change in reaction function alters the way in which the control variable (typically the interest rate) reacts to other shocks. For example, in the textbook three equation New Keynesian model of Gali (2015) the impulse response of a technology shock (a) on inflation (π) is:

$$\pi_t = \frac{-\sigma\psi_{ya}^{n}(1-\rho_a)\kappa a_t}{(1-\beta\rho_a)\left(\sigma\left(1-\rho_a\right)+\phi_y\right)+\kappa\left(\phi_\pi-\rho_a\right)} \tag{8}$$

Without delving too much into the different parameters here (they are all defined in Chapter 3 of Gali (2015)), the important part is the appearance of ϕ_π and ϕ_y, the parameters which govern the reaction function of the central bank. Any shock to them changes the impulses of current technology shocks passing through the economy, and to the extent that the parameter shocks are persistent, future technology shocks as well.

This time varying nature of reaction function shocks will not be captured in most standard econometric frameworks. The use of time-varying parameter structural VAR models, as in for example Baumeister and Benati (2013) who allow for the time-varying nature of shocks, is one possible future avenue that the literature could pursue to the study any exogenous reaction function variation. Or perhaps the approach in Lewis (2019), who also allows for time variation in the effect of surprises on the economy. Nonetheless, the reaction function variation would have to be exogenous in both of these frameworks, which, as we will argue fits neither the financial market evidence, the evidence of a forecasting team nor the macroeconomic evidence.

In Section 4, we discuss the challenges of trying to clean surprises of the effect of reaction function surprises. This stands in contrast to the various ways in which information effects are typically cleaned out of monetary policy surprises.

3. Private sector interpretation of surprises

Our central idea: that monetary surprises could be related to endogenous changes in the reaction function (and as a result cannot be used to construct shocks) whilst relatively novel in the academic literature, will seem obvious to those who study central banks outside of the academy. In this section we read the reports of a bulge bracket bank, who have a team dedicated to forecasting the US economy. We examine the reaction to their own "surprises", i.e. FOMC meetings where their forecast of either the announcement or accompanying action was incorrect. In the majority of cases, an explanation is given, and the lion's share of those explanations relate to a misspecification of the reaction function from the forecasters side.

This is important for two reasons. First, it shows that those people whose livelihoods are closely linked to how well they forecast the Federal Reserve decision see most of the surprises as resulting from reaction function variation, not monetary policy "shocks" (or even information effects). Second, as we mentioned previously, a change in reaction function alters the *equilibrium* of the economy (in model speak), which is one reason why it should not be confused with a monetary policy shock. For it to change the equilibrium path of the economy, the agents in the economy must realise that there is a new reaction function and act accordingly. Indeed Fed Chairman Ben Bernanke said in 2003 that "A given [monetary] policy action... can have very different effects on the economy, depending (for example) on what the private sector infers... about the information that may have induced the policymaker to act, about the policymaker's objectives in taking the action." The fact that our forecasters regularly update their view of the reaction function and publish their new view is evidence for this.

The data we examine from the forecaster runs from 1999 to 2019. We examine reports surrounding 180 different FOMC announcements. Of these, we find 98 documents that discuss the recent the FOMC meeting in detail. Unfortunately we have no data for 2009 or 2010.

We categorise the reports based on a simple mechanism. First we read the report published after the FOMC meeting discussing the meeting, and if available, the preview of the FOMC which contains the expectations of the forecaster. We decide whether or not any part of the FOMC announcement was a surprise to the forecaster, and provide a quote to explain this decision. For example, a quote that suggests there was no surprise from December 2019 reads "The December meeting was broadly in line with our expectations." A quote that suggests there was an element of surprise from January 2019 reads "We viewed both the January statement and press conference as dovish and have reduced our subjective odds of a March hike to less than 5% (from 10% previously) and our Q2 hike probability to 25% (from 55% previously)." This quote shows the forecasters were surprised because following the meeting they updated their probabilities of future monetary policy movements, suggesting they received new information from the announcement.

Then, we categorise the reason (if any) that the authors give for their failure to accurately predict the announcement. We have five categories of reasons: assessment, preferences, information, shock, and no explanation. Assessment is defined as a perceived unforecasted change in $\delta()$, the function that maps observables to objectives. An explanatory quote for assessment could be one that argues that the FOMC's action was unexpected because they seem to be placing a higher weight on core inflation when evaluating the inflation outlook than the forecaster expected. Preference surprises are defined as a perceived unforecasted change in $\gamma()$, the function that maps the central banks forecasted objectives to their actions. An explanatory quote could be a sentence that argues that the FOMC's action was unexpected because they are weighting inflation outcomes more heavily that output (within the dual mandate) than the forecaster expected. Information surprises are those that we attribute to the explanation of Nakamura and Steinsson (2018). These are surprises that the forecaster attributes to the Federal Reserve having private information about the state of the economy, that the forecaster themselves cannot observe. An explanatory quote could be a sentence that ascribed the unexpected action by the FOMC to potential private information regarding the state of systematically important bank balance sheets that are not publicly available. Shocks are surprises that are attributed by the forecaster as being truly exogenous changes in the interest rate, or ϵ's in our previous notation. Finally, we leave an option for the forecaster to not give a reason for the surprise. These categories are not mutually exclusive and the forecaster can give multiple reasons for the surprise.

To give an example, in January 2019, after having classified the meeting as surprising to our forecasters, we then classified the surprise as stemming both from assessment and preferences. On assessment, the forecasters wrote that "Powell explained that increased downside risks from slowing growth abroad, unresolved government policy issues, tighter financial conditions, and weaker survey data warrant the committee's new patient, wait-and-see approach to future policy changes." This quote shows that the indicators that the FOMC (or in this case Chairman Powell) are using to forecast their objective functions were the reason behind the "new patient...approach" which caught the forecasters by surprise.[6] This is a form of surprise regarding the assessment function we defined earlier. The forecasters then go on to also ascribe part of the surprise to an preference surprise, stating that "the increased emphasis on inflation [has]... raised the bar for hiking in the first half of this year", suggesting that the relative weight of inflation versus output has changed relative to their expectations as well.

Figures 1 and 2 show the results of this manual classification process. Two points are immediately obvious. First, even with the incentive to claim that most announcements were in line with their forecast, the forecasters still admit that there was new information in the FOMC announcement in around half of meetings. (And other forecasters may be surprised in different, and even more, meetings.) Second, of those surprising meetings, there are no cases in which the forecasters ascribe the surprises to private information of the FOMC, or mention monetary policy "shocks". Of course, the lack of an explanation could be construed as a shock — but nonetheless it is not something that professional forecasters view as a natural explanation for a forecast error. The lack of "information effect" is even more surprising. We found only one mention of the information effect, discussed as a reason for surprise interest rate cut, but it was dismissed: "The FOMC may have private information about the health of the financial system suggesting a more adverse outlook. We have no reason to believe that this is the case."

Of the surprises that are given explanations, most fall into the category of "assessment".

[6]Note that these are not information effects, since all of these series are publicly available. What has been revealed is which series the Fed regards as important to make its decision in this particular meeting.

That is, the forecaster is surprised at how the data is mapping into an assessment of the state of the economy. This means that explanations of surprises by this particular forecasting team are predominantly based on reaction function variation. Furthermore this reaction function variation seems to be *endogenous* to the macro cycle. In other words, the assessment quotes often point to new data sources that the Fed is considering, or alterations to the Fed's structural view of the model of the economy, both of which are endogenous. This will motivate our methodological approach in later sections, where we allow a structural parameter in the economy to switch regimes, resulting in a time varying reaction function.

Table 1 shows the FOMC dates from 2019 and the quotes that motivated our decision whether or not to categorise the meetings as surprises (to the forecaster). Table 2 shows, of the meetings that we classified as surprises, the reasons the forecasters gave to those surprises. Appendix Section 7.6 shows these tables for all years where data is available.

Fig. 1. Surprise and non-surprise FOMC meetings

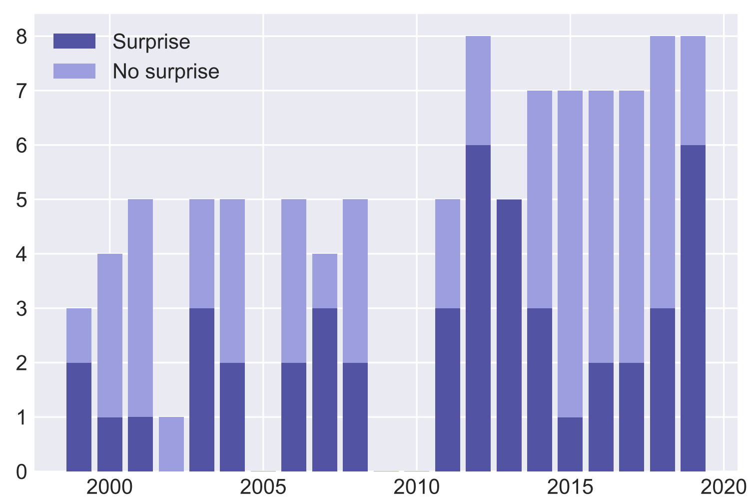


Fig. 2. Categories of surprises

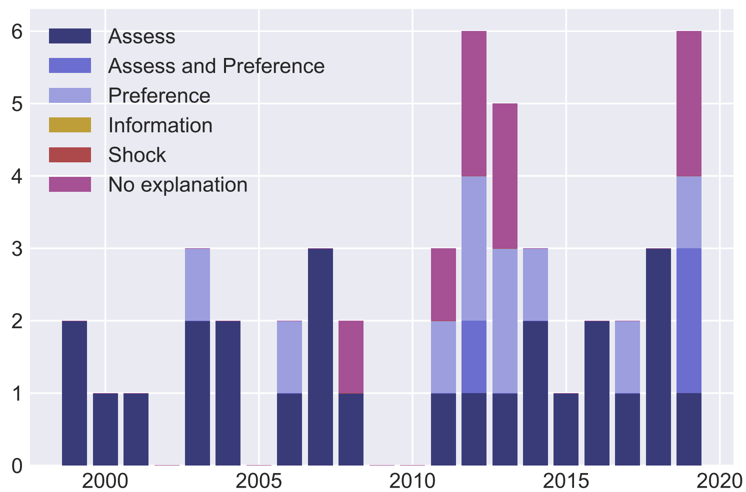


Table 1: Categorisation of 2019 FOMC meetings as surprises

FOMC Date	Surprise	Quote
30/01/2019	✓	We viewed both the January statement and press conference as dovish and have reduced our subjective odds of a March hike to less than 5% (from 10% previously) and our Q2 hike probability to 25% (from 55% previously).
20/03/2019	✓	In light of the stronger than expected consensus for no hikes in 2019, we now expect the next rate hike to come in 2020Q1, instead of 2019Q4. We have reduced our probabilities of a rate hike in 2019H2 and boosted our probabilities of a rate hike in 2020H1, as shown in Exhibit 2.
01/05/2019	✓	Today's meeting further reduced the odds of a rate cut in response to low inflation, which we already saw as quite unlikely.
19/06/2019	✓	The Fed left the funds rate unchanged but delivered a dovish message, even relative to market expectations. Seven of the 17 participants projected 50bp of easing this year, and the statement provided an unqualified "will act as appropriate" signal that cuts are now likely...We now expect cuts in July and September, as well as an end to balance sheet runoff in July.
31/07/2019	✗	We see the results of today's meeting as consistent with our baseline expectation that easing will end with a second 25bp cut, for a total funds rate recalibration of 50bp.
18/09/2019	✓	In light of the strength of the opposition to the cut at today's meeting, we have shaved our odds of an October cut slightly. We now see a 65% chance of a 25bp cut, a 5% chance of a 50bp cut, and a 30% chance of no change at the October FOMC meeting (vs. 70%/10%/20% previously).
30/10/2019	✓	We had expected the FOMC to use today's meeting to clarify that it does not anticipate further easing, and the messages from the statement and the press conference were even firmer than we had anticipated.
11/12/2019	✗	The December meeting was broadly in line with our expectations.

Table 2: Categorisation of 2019 FOMC meetings by explanation type

FOMC Date	Explanation	Assessment Quote	Preference Quote
30/01/2019	✓	Powell explained that increased downside risks from slowing growth abroad, unresolved government policy issues, tighter financial conditions, and weaker survey data warrant the committee's new patient, wait-and-see approach to future policy changes.	The removal of the hiking bias from the statement and the increased emphasis on inflation have raised the bar for hiking in the first half of this year.
20/03/2019	✗	N/A	N/A
01/05/2019	✓	Second, on inflation, Powell emphasized that core inflation "actually ran pretty close to 2 percent for much of 2018" and attributed the recent decline largely to "transitory factors" influencing categories such as portfolio management and apparel, as we have also emphasized. He pointed as an example to the case of cell phone services in 2017, when Fed officials forecasted that the drop in inflation would be temporary and were proven correct. To help look through these transitory factors, Powell pointed to the Dallas Fed trimmed mean measure, which has continued to run at roughly 2%.	N/A
19/06/2019	✓	Second, the tone of the June press conference was much more dovish relative to the May press conference, at which Powell refused to discuss cases in which the Fed might cut rates and did not express immediate concern about downside risks to inflation expectations. Powell also offered a list of uncertainties that could warrant accommodative policy, ranging from global growth and trade policy to relatively minor headwinds such as the grounding of the Boeing 737 MAX and the drop in oil prices (-$10 since the May meeting).	Our reading of the meeting suggests that growth concerns are the primary justification, with low inflation lowering the hurdle required for Fed action. After all, Powell kicked off the press conference by emphasizing the Committee's "overarching goal" of sustaining the expansion.
18/09/2019	✗	N/A	N/A

30/10/2019	✓	N/A	The bar that Powell set for additional cuts—developments "that cause a material reassessment of our outlook"—appears to be quite high. In practice, we think this would likely mean a few pieces of very weak data or a combination of trade war escalation, an adverse market reaction, and fairly bad data. We therefore see just a 15% chance of a cut at the December meeting.

4. Existing Approaches to Monetary Surprises

The last section shows that reaction function surprises are not, as is often assumed, very rare and discrete events associated with new FOMC chairs or changes to the monetary framework. Moreover, we show that at least some of these surprises are endogenous to the economy; this is crucial for some, but not all, of the implications we discuss. As we have argued, these types of changes have been ignored in the existing literature. In this section we first use the framework outlined above to show how such reaction function surprises are consistent with the stylized facts of monetary policy surprises documented in the major papers in the literature. We then show that each of the literature's attempts to isolate monetary policy shocks from monetary policy surprises fail in the presence of reaction functions surprises.

4.1. Information Effects

Information effects were initially introduced by C. Romer and D. Romer (2000). The idea is that the market learns economic news from the monetary policy decision. In our decomposition, information effects are denoted by $\psi_t e_t^x$. The focus of the literature on monetary policy surprises has recently been on information effects (Nakamura and Steinsson 2018; Cieslak 2018; Miranda-Agrippino and Ricco 2021; Bauer and Swanson 2020; Bauer and Swanson 2022, for example).

Nakamura and Steinsson (2018) argue that if one uses Δ_t as a measure of a monetary policy shock, ϵ_t, then the contamination by the information component will lead to incorrect conclusions about the directional effect monetary policy has on the economy, since if interest rates are increased unexpectedly due to stronger-than-expected growth, then the correlation between interest rate surprises and future growth is likely to be positive. This may lead the researcher to incorrectly conclude that monetary policy shocks have positive effects on future growth. (This is essentially the same form of argument made in this paper, but we are concerned with a new form of shock – reaction function shocks – in addition to information effect shocks.)

Nakamura and Steinsson (2018) argued that monetary policy surprises are positively correlated with professional forecasters updating their growth outlook, and concluded that positive monetary policy surprises must include positive information about the economy previously unknown to professional forecasters.

This evidence has come under some scrutiny in Bauer and Swanson (2020). They set out several reasons to doubt the "information effect" hypothesis as a source of monetary policy surprises (as measured as high frequency changes in asset prices around Fed announcements). One of these is that monetary policy surprises are (positively) correlated with news that occurs close to, but before, the FOMC meeting. The authors argue that: (i) the market under-reacts to this news, relative to the Fed, thus creating market surprises, and (ii) once this news is accounted for in Nakamura and Steinsson's regressions showing that professional forecasters update following a positive monetary policy surprise, that the information effect disappears.

They interpret this as a "Fed reacts to news" effect — similar to a reaction function effect that we propose, but specific to pieces of news that occur close to the Fed's announcements. We don't preclude information effects from existing within our framework. But we will show that even after "cleaning" the surprise for information effects, the residual measure will still be contaminated by reaction function effects.

4.2. Reaction function surprises and stylised facts of asset surprises

In the information effects literature, a sign-restrictions identification assumption is often used to separate monetary shocks from information effects. Specifically, Jarociński and Karadi (2020) use the co-movement of interest rates and equities in tight windows around monetary policy announcements; they argue that information effects will drive both the interest rate surprise, Δ_t, and the equity response in the same direction, while monetary shocks push these news variables in the opposite directions.

In addition, there are a number stylised facts that are prominent in the monetary surprises literature:

Fact 1 Surprises are larger when policy rates deviate from a traditional Taylor rule (Schmeling, Schrimpf, and Steffensen 2020)

Fact 2 Surprises are positively correlated with news that occurs prior to the FOMC announcement (Bauer and Swanson 2020)

Fact 3 Surprises are systematically negative in downturns (Cieslak 2018; Schmeling, Schrimpf, and Steffensen 2020)

Fact 4 Surprises are predictable based on past macro data (Miranda-Agrippino 2016).

Fact 5 Surprises are serially correlated (Ramey 2016; Miranda-Agrippino and Ricco 2021)

Fact 6 Surprises are correlated with central banks' private forecasts (Barakchian and Crowe 2013; Gertler and Karadi 2015).

The existing literature claims that these facts are driven by the presence of information effects. Are reaction function surprises consistent with these facts? If not, these feature provide a case against the presence, or even dominance, of reaction function surprises. However, as we now outline, each fact can be shown to be consistent with a role for reaction function surprises.

4.2.1. ***Fact*** *1*

Fact 1 is most clearly related. Deviations from a standard, fixed-coefficient Taylor rule could be picking up either exogenous shifts in the reaction function that come as a surprise to market participants (e^{ϵ_t}), or changes in coefficients that are captured the residual (e^{ψ_t}) that the fixed-coefficient estimation push into the residual. However, while Schmeling, Schrimpf, and Steffensen (2020) emphasise the role of financial conditions in explaining the surprise and the deviation from the "normal" reaction, we argue that the cause can be much more general. And, in the unlikely even that the deviation could be deemed exogenous, the interpretation of the effect of that deviation is different from a typical monetary policy shock.

4.2.2. ***Fact*** *2 and* ***Fact*** *3*

Fact 2 and **Fact** 3 both relate to a co-movement between the business cycle and monetary policy surprises. Bauer and Swanson (2020) argue that the market under-reacts to pre-FOMC meeting news, relative to the Fed, thus creating market surprises, and that the information effect disappears once this news is accounted for in Nakamura and Steinnson's regressions showing that professional forecasters update following a positive monetary policy surprise. Cieslak (2018) documents that investors' expectations of short dated interest rates are too positive when entering recessions (both market expectations and survey based measures). In other words, investors systematically underestimate the easing cycle of the Federal Reserve.[7]

To see how reaction function surprises can account for these facts, consider the general framework in Equation (5) but to simplify matters, consistent with Bauer and Swanson (2020), keep the market expectation of ψ_t and x_t independent, and remove information effects from the analysis. Thus surprises can be written as:

$$\Delta_t = \underbrace{e_t^{\psi} x_t}_{\text{reaction function surprise}} + \underbrace{\epsilon_t}_{\text{monetary policy shock}} \tag{9}$$

Furthermore, we decompose the forecast error of the reaction function e_t^{ψ} into three components: a time-invariant mean $\bar{e}$ which captures the average error across the whole sample, a time-varying zero mean rational forecast error w_t which captures random deviations from expected reaction, and a time-varying forecast error related to the market's *systematic* misunderstanding of the switches in the central bank's reaction function u_t.

$$\Delta_t = (\bar{e} + w_t + u_t)\, x_t + \epsilon_t \tag{10}$$

It is this u_t term which is endogenous to the state of the economy, a feature we provided some motivation for in Section 3, and one will provide evidence for using a macro model in Section 5. Therefore we can write u_t as $u_t(x_t)$. The $u_t(x_t)$ component is the component that leads to correlations between monetary policy surprises and other state variables. For now, we can be general about the form that $u_t(x_t)$ takes, both in terms of the functional form, and which members of x_t matter for u_t. However, on the latter point, there are suggestions from the literature that can guide our thinking. For example, Schmeling, Schrimpf, and Stef-

[7] Schmeling, Schrimpf, and Steffensen (2020) corroborate the findings of Cieslak (2018), stating that "market participants have, over the past 30 years, underestimated how aggressively the Federal Reserve (Fed) was going to cut interest rates."

fensen (2020) argue that financial variables drive deviations from standard monetary policy responses, McMahon and Munday (2022) show that uncertainty leads to endogenous reaction function variation, and Cieslak (2018) points towards recession indicators as an important correlate for reaction function changes.

To see a specific correlation between market surprises and a given variable, y_t, you can run a regression of the form:

$$\Delta_t = \beta_0 + \beta_1 y_t + v_t \tag{11}$$

For instance, Bauer and Swanson (2020) document that market surprises are (positively) correlated with non-farm payrolls news that occurs prior to the FOMC announcement. And, as mentioned before, in the case of Cieslak (2018), y_t is a recession indicator. For Schmeling, Schrimpf, and Steffensen (2020), y_t is linked to deteriorating financial conditions. The logic is the same if y has multiple constituent series.

The finding that $\hat{\beta}_1$ is greater than 0 is surprising if one thinks that the coefficients of the reaction function are rationally forecastable by the market, as this implies that $\left(\bar{\psi}_t - E_{M,t-1}\left(\psi_t\right)\right)$ should be, on average, 0. But the result that $\hat{\beta}_1$ is significantly larger than zero is not surprising if one entertains the mechanism of endogenous reaction function surprises outlined in this paper. Comparing the estimated Equation 11 with the posited data generating process Equation 10 we can see there are several omitted variables in Bauer and Swanson (2020)'s regression. First, any members of x not contained in y will end up in the error term (multiplied by the reaction function surprise). Secondly, $u_t\left(x_t\right) x_t$ will also be an omitted variable, even if y_t completely spans x_t.

Therefore, if $u_t x_t$ exists in the true data generating process, one source of omitted variable bias for the estimated coefficient $\hat{\beta}_1$ is the same direction as the sign of the covariance term: $cov(x_t, u_t x_t)$. Empirically, if u_t is a function of a parameter in the economy which feeds into the policymakers reaction function, and is correlated with the state x_t, then this covariance is positive.

For example, if Fed concerns about the state of the economy, or how well anchored are inflation expectations, lead to shifts in their reaction function, these are plausibly correlated with Non-farm payrolls causing $cov(x_t, u_t x_t) > 0$ which helps to explain Bauer and Swanson's result. If these reaction shifts are correlated with the recession indicator, the correlation that Cieslak observes can be explained by reaction function surprises. Thus, a "Fed reacts to news" effect is similar to a reaction function effect that we propose, but specific to pieces of news that occur close to the Fed's announcements. As is the idea that investors, forecasting in real time, struggle to predict the state of the economy and hence underestimate response of the Fed.

Our framework differs from these in that we will propose an optimal policy reason for reaction function variation in Section 5. We show that a candidate parameter is the persistence of inflation dynamics. An advantage is that this explanation is not limited to news that occurs close to Fed announcements, nor does the difficulty of predictability have to be centred around recession periods.

4.2.3. ***Fact*** *4,* ***Fact*** *5 and* ***Fact*** *6*

Miranda-Agrippino and Ricco (2021) focus on **Fact** 4 and **Fact** 5 and **Fact** 6. They propose a noisy asymmetric information environment that justifies these facts. Noise enters their model because both the market agents and the central bank receive noisy signals about the state of the economy, and then filter these to estimate the true state. Imperfect information enters the model because the market and the central bank receive separate signals, so only via the central bank's action does the market learn the central bank's signal. This model fits the stylized facts they are concerned with.[8]

Our framework is simpler than Miranda-Agrippino and Ricco (2021), and hinges on a more obvious information asymmetry: that agents mispercieve reaction function changes. Nonetheless, these stylized facts are also consistent with our time-varying reaction function interpretation of surprises. Using our formulation of a surprise in Equation 10, we can write the previous three facts in terms of covariances that need to be non-zero across the sample, and show that they are likely to hold in an environment in which there are only reaction

[8]This model does not address why the errors are not getting smaller over time as the filtering process improves, or why the volatility of errors is so high in certain periods.

function surprises (we will omit information effects or monetary policy shock surprises).

For **Fact** 4, the covariance of the surprises and past data should be non-zero:

$$\begin{aligned} Cov\left(\Delta_t, x_{t-1}\right) &= Cov\left(\left(\bar{e} + w_t + u_t\right) x_t, x_{t-1}\right) \\ &= Cov\left(u_t x_t, x_{t-1}\right) \\ &\neq 0 \end{aligned} \tag{12}$$

where the second line holds as a result of the assumptions on $\bar{e}$, w_t and u_t. This non-equality is likely to hold if there is any persistence in the macro time series x_t, combined with the market misunderstanding, u_t, and how this feeds into reaction function variation. For instance, this would be the case if the market takes a while to learn about the extent of the Fed's concerns about the risks of rising inflation.

For **Fact** 5, the autocovariance of surprises should be non-zero:

$$\begin{aligned} Cov\left(\Delta_t, \Delta_{t-1}\right) &= Cov\left(\left(\bar{e} + w_t + u_t\right) x_t + \epsilon_t, \left(\bar{e} + w_{t-1} + u_{t-1}\right) x_{t-1} + \epsilon_{t-1}\right) \\ &= Cov\left(u_t x_t, u_{t-1} x_{t-1}\right) \\ &\neq 0 \end{aligned} \tag{13}$$

This is likely to be the case if there is persistence in the systematic misunderstanding of the parameter which causes reaction function changes, u_t, or the state of the economy, x_t, or their products.

For **Fact** 6, denoting the central banks' private forecast of x_{t+1} as $F_{cb}\left(x_{t+1}\right)$, the following covariance should be non-zero:

$$\begin{aligned} Cov\left(\Delta_t, F_{cb}\left(x_{t+1}\right)\right) &= Cov\left(\left(\bar{e} + w_t + u_t\right) x_t + \epsilon_t, F_{cb}\left(x_{t+1}\right)\right) \\ &= Cov\left(u_t x_t, F_{cb}\left(x_{t+1}\right)\right) \\ &\neq 0 \end{aligned} \tag{14}$$

This non-equality is harder to interpret at first glance under our framework. But it essentially asks whether there is covariance between the systematic reaction function change surprise, and the forecast. The answer is yes, if, as we posit in Section 5, that the reaction function changes owing to the state of the economy.

One clear implication of these stylised facts, if they are to fit a reaction function explanation, is that a substantial portion of reaction function variation needs to be endogenous to the cycle (via u_t). We make the case for this via (i) interpreting a forecast team's opinions in Section 3 and (ii) estimating a macro model in Section 5.

4.3. Cleaning out of reaction function surprises?

The stylized facts of monetary policy surprises do not rule out a that reaction function surprises are an important part of surprise variation. We will now show that attempts to clean the surprises of information effects will not remove reaction function surprises.

4.3.1. Jarociński and Karadi (2020)

Jarociński and Karadi (2020) use the co-movement of interest rates and equities in tight windows around monetary policy announcements to try to separate monetary policy shocks from information effects in a sign-restrictions set up. They rely on the (implicit) assumption of a fixed reaction function, thereby reducing Equation 5 to only the information effect and monetary policy shock components. The authors then posit that if Δ_t is positive and the movement in equities over the same period is positive, then the driving force behind the surprise is likely to be an information effect, and if the change in equities is negative then the effect of the monetary policy shock dominates.

If, however, the full set of potential causes of surprises are included, as in Equation 5, then this methodology breaks down.

In 2.3 we explained that reaction function surprises have an 'anything goes' nature. This means that the sign of the co-movement between interest rates and equities is not pinned down when one considers reaction function surprises being an element of monetary policy surprises. A hawkish interest rate surprise caused by a reaction function shock can have a positive or negative effect on equities depending on the forecasted path of the macro-variables to which the reaction function surprise pertained.

This is similar to the argument in Faust, Rogers, Wang, and Wright (2007). In that paper, the authors argue that the relationship between shocks and asset prices varies between announcements. And so any attempt to map an average effect on asset prices of a monetary policy surprise will not categorise the surprises accurately. Moreover, they also argue that the source of the shock matters — in their case, whether it is supply or demand driven — thus making the ultimate effect on the economy difficult to discern.

All that said, the reaction function component is likely to contribute to what Jarociński and Karadi (2020) would denote a monetary policy shock. Imagine a scenario in which inflation becomes more persistent, the reaction function optimally becomes more sensitive to inflation, and this is revealed in the monetary policy announcement. Interest rates rise unexpectedly, because $e_t^{\psi} x_t$ is positive. This is likely to be accompanied by a fall in equity prices during the high frequency window, since the more aggressive reaction function will now be priced in by market participants, including conditionally higher interest rates for all future states. Without explicitly accounting for a variable reaction function, the sign restrictions methodology of Jarociński and Karadi (2020) will likely incorrectly categorise reaction function surprises as monetary policy shocks.

4.3.2. Miranda-Agrippino and Ricco (2021)

Miranda-Agrippino and Ricco (2021) also attempt to purge information effects from monetary policy surprises. Their approach is to orthogonalise the surprise by regressing Δ_t on Greenbook forecasts and previous surprises, and then extracting the residual. This approach, as in Jarociński and Karadi (2020), assumes that the reaction function is fixed. There is also an assumption that the only new information is contained in the Greenbook forecast information and that this information is transmitted in the decision even though the Greenbook is not released for 5 years. Ideally, any purging would identify the information that is new to the market, e_t^x. Our analysis of the investor responses suggested there is little actual new information.

Notwithstanding this, does such a procedure remove the reaction function surprise and leave the surprise as a monetary policy shock? To see it does not, assume that there is no information effect or monetary policy shock, and that the market believes that ψ_t and x_t are independent (note this does not preclude them from being dependent in reality). So Equation 5 is becomes:

$$\Delta_t = e_t^{\psi} x_t = (\bar{e} + w_t + u_t)\, x_t \tag{15}$$

Miranda-Agrippino and Ricco (2021) run a regression of Δ_t on x_t and extract the residual.[9] There are three potential issues with this:

1. If the reaction function surprises are systematic, $u_t(x_t)x_t$, exists. Even if we assume, generously, that the Greenbook forecasts and lagged surprises completely span x_t, then the endogeneity of the u_t term to the state of the economy means the functional form of the regression is wrong.

   For instance, imagine that $u_t = \alpha + \gamma x_t$ and this is known, then the correct regression to purge the effect of the reaction function surprises is $\Delta_t = \alpha + \gamma(x_t)^2$. Using a linear regression in x_t only removes a (linear) part of the reaction function surprise.
2. The random reaction function surprises, $w_t x_t$, will not be cleaned. Imagine that there are only reaction function surprises that happen randomly each period – the estimated coefficient on x_t will be zero, and the residual will contain all the reaction function surprise variance which will be classified as clean monetary policy shocks. These are exogenous movements in the interest rate, but ones that change the equilibrium solution of the economy, and so have a different empirical impulse response, and economic interpretation, to those of a classical monetary policy shock.
3. If the variable that drives the reaction function changes is not included in the Greenbook controls and lagged surprises, then the regression does not even purge a linear part. For instance, imagine, as in Cieslak, Hansen, McMahon, and Xiao (2022), there is an effect

[9] More accurately, they assume that the set of variables from the Greenbook span x_t.

of policymakers uncertainty which is only revealed in their FOMC meeting deliberations. Of course, if there is a latent variable that is driving reaction function changes, controlling for lagged surprises (or indeed Greenbook information) does no harm, and may indeed soak up some of the latent variable variation, but without the correct functional form and the exact data on the variable, it will be impossible to completely purge the endogenous variation out.

There have been attempts by others to expand the set of information used for orthogonalisation, particularly with the use of text analysis, for example Ochs (2021). Nonetheless, as we argued before a linear orthogonalisation procedure necessarily produces "shocks", if the reaction function is a function of the states of the economy. Raising the dimensionality of the states to which the surprises are orthogonalised is welcome for sure, but it is no silver bullet. Without controlling for all possible quantitative and qualitative data sources, in a non-linear and time-varying manner, cleaning using regression techniques is likely to fail.

4.3.3. Bauer and Swanson (2020)

Bauer and Swanson (2020) argue that controlling for news that occurs close to Federal Reserve meetings eliminates both the information effect and their "Fed reacts to news effect". Our argument is not with whether there is an information effect or not, only that any cleaning of the information effect will not remove reaction function effects.

As in the case above, where the reaction coefficient depends linearly on the macroeconomy, a researcher who then runs the regression of market surprises on x and takes the residual is fitting a linear function to a quadratic. Even if there are no "shocks" in the true relationship, the researcher will find some but they will be the gap between the quadratic data surprise generating process and the linear approximation to that. This is even in the case where we have assumed x is known and well defined, and the function is non-time varying. And, of course, reaction coefficients may depend non-linearly on the state of the economy or, even on variables that are latent to the market.[10]

[10]Hansen, McMahon, and Tong (2019) argue that Bank of England Inflation Report releases communicate new information on risks and uncertainty that lead to yield curve changes, particularly through risk premiums.

In a later paper, Bauer and Swanson (2022) extend their argument with a richer model. We discuss this new paper in Appendix Section 7.1. We show that (i) monetary policy surprises are contaminated by reaction function surprises, and (ii) that within their model, the theoretical impulse responses for a reaction function shock and a monetary policy shock are different. In this model, they assume that reaction function surprises are exogenous (which we disagree with, based on the stylised facts presented previously, and our argument in Section 5). Nonetheless, there is no econometric issue if one continues under this assumption of exogeneity. The issue is one of mixing two forms of shocks and interpreting the resulting impulse responses correctly, whilst allowing for the fact that one changes the solution of the model, whilst the other does not.

4.3.4. Summary of cleaning

Categorising reaction function surprises as monetary policy shocks is not innocuous. Approaches to purge the reaction function shocks applied using the methods of the major papers of the information effects literature will likely fail to remove reaction function variation.

Monetary policy surprises, therefore, potentially combine two different forms of surprise in the 'cleaned' measures. These surprises are sufficiently distinct in their effects (and economic interpretations) for this to be an important issue. Reaction function surprises change the *equilibrium solution* of the model, and are likely endogenous, and so are fundamentally different from a monetary policy "shock".

Even if the endogenous part of reaction function surprises could be cleaned, the resulting residual would still violate Ramey's point (2), in that monetary policy surprises would contain both monetary policy shocks and reaction function shocks. This is not a problem of endogeneity bias (as both shocks are exogenous), but a problem of interpretation. The resulting impulse responses will answer a different question to which the economist is usually asking. They will not show the answer to "what is the effect of a one-off exogenous 25bp increase in the interest rate in a given period", i.e. the empirical analogue to the model-based shock, rather they will show "what is the average effect of a one-off 25bp increase in the interest rate either due to an exogenous shock, or due to the central bank becoming more aggressive with respect to an unspecified state variable, the weights of which depend on the relative prominence of these two forces in the data." This mixing of shocks means that the empirical output is difficult to interpret cleanly.

5. A Markov-Switching Framework

Having argued that including reaction function effects in monetary policy surprises makes the surprises untenable as exogenous instruments for monetary policy shocks, we then showed that both the high frequency surprise data and the text from a major forecaster support the view that reaction function variation could be driving monetary policy surprises. In this section we estimate a model in which the reaction function of the policymaker changes over time, and then show that this is (i) supported by the data in an estimation exercise, and (ii) plausible behaviour in an optimal policy exercise, and (iii) optimally endogenous to the cycle. We find that periods in which the policymakers' reaction function is changing (as signalled by our estimated macro model) coincide with periods of large monetary policy surprises. This corroborates our earlier evidence that the monetary policy surprises used in the literature are likely contaminated with endogenous reaction function surprises.

Further, we show that if one removes the monetary policy surprises from these reaction-function-variation-heavy periods, and re-calculates the impulse responses of macroeconomic variables to a monetary policy surprise, the resulting IRFs are vastly different. This is in line with the theoretical prediction that the effects of reaction function shocks can be starkly different from monetary policy shocks, and underlines the empirical effect that including reaction function shocks in monetary policy surprises can have on the researchers' conclusions.

Why would the coefficients of the central bank's reaction function change? Fixed coefficient reaction functions are common in many macro models, with some values of the coefficients even becoming famous, as in Taylor's eponymous rule (Taylor 1993).

Nevertheless, it is far from a new idea to suggest that the coefficients of the reaction function change. For example, uncertainty of policy may, in certain environments, alter optimal policy. Most famously, Brainard (1967) suggests uncertainty should result in caution: coefficients of the classic Taylor-rule type reaction function should attenuate when uncertainty regarding the sensitivity of inflation to the interest rate is higher.[11] Other reasons

[11] The role of uncertainty on monetary policy is discussed in Cieslak, Hansen, McMahon, and Xiao (2022)

for time-varying parameters in the reaction function could include changing preferences of central bankers, central banks learning the structure of the economy over time and adjusting their optimal reaction function accordingly and time variation in the persistence of shocks or variation in the volatility of the economy (for more on why variable reaction functions are a more accurate description of central banking in practice than the fixed coefficient theoretical construct see Carney (2017)).

Before we discuss the Markov-switching approach we take to reaction function shifts, and its benefits over other, alternative, frameworks, let us briefly consider the empirical evidence regarding variation in reaction functions.

Most of the research studying reaction function variation focuses on empirical exercises of whether structural breaks are pronounced in the data. In a seminal paper, Clarida, Gali, and Gertler (2000) estimated monetary policy reaction functions for the US before and after Paul Volcker's appointment to the Federal Reserve Governorship. They found that their estimated reaction functions suggested a Federal Reserve that was much more sensitive to expected inflation in the post-Volcker era.

In line with the findings of Clarida, Gali, and Gertler (2000), many other papers find evidence for variation in reaction functions over time. Conrad and Eife (2012) find that by empirically estimating a time varying Taylor rule for the US, the observed changes in inflation persistence can be explained. Bianchi (2013) estimates a Markov-Switching DSGE model that permits two regimes in which volatility and reaction function coefficients can differ, and finds good evidence that the variation in reaction function coefficients is necessary to explain macroeconomic dynamics in the US. Fernandez-Villaverde and Rubio-Ramirez (2008) find that the parameters governing monetary policy exhibit substantial drift in an estimated New Keynesian model. And in later work jointly estimate a drifting reaction function and heteroskedastic shocks to in a large scale DSGE model (Fernandez-Villaverde, Guerrón-Quintana, and Rubio-Ramirez 2010). In McMahon and Munday (2022), we provide evidence that there is substantial variation in estimated reaction functions in the US macroeconomic data both

and McMahon and Munday (2022).

from a time varying parameter vector autoregression, and from a small three equation Markov-switching model. Despite this, others have argued against shifting reaction functions. For example, I.-K. Cho and Kasa (2017) devise an environment that encompasses a policymaker who believes the economy may have time varying structural equations when the true underlying economy has fixed coefficient equations. Because of this misunderstanding, the belief in time variation becomes self fulfilling in the reduced form data if the policymaker acts on her beliefs.

Nonetheless, the literature so far has focused on how the shifts in reaction functions should be dealt with when fitting DSGE models to the data. Despite the large literature on reaction function variation, the study of monetary policy surprises has largely been firmly rooted in a fixed coefficient world (with some exceptions). In this paper, we are concerned with how the shifts in reaction functions muddy the waters of monetary policy shock identification.

To determine when a reaction function change has taken place, we will estimate a Markov-switching model in which the parameters of the reaction function will be permitted to vary across regimes (in Appendix Section 7.2 we review some of the alternative explanations for changing reaction functions).

Markov Switching DSGE models (MS-DSGE) are a way of parsimoniously integrating model uncertainty into the environment. That model uncertainty is expressed by the probability that in any period the economy can switch regimes to another model. The forms that this model uncertainty can take are varied. In the Markov Jump Linear Quadratic model, of Svensson and N. Williams (2005), the authors note that: "The forms of model uncertainty our framework encompasses include: simple i.i.d. model deviations; serially correlated model deviations; estimable regime-switching models; more complex structural uncertainty about very different models, for instance, backward- and forward-looking models; time-varying central-bank judgment–information, knowledge, and views outside the scope of a particular model."

We estimate an MS-DSGE model in which reaction functions vary across regimes. We show that these regimes are apparent in the data (from an estimation exercise) and are optimal if they owe to an endogenous response to the structural inflation generating process (from an optimal policy exercise). Furthermore, we will show that the regime shifts are highly correlated with periods in which market surprises are large. This is despite the fact that the MS-DSGE model is estimated on quarterly macroeconomic data, and the surprises are based on a 30 minute high frequency impulse to financial markets around a monetary policy meeting. This leads us to argue that many monetary policy surprises are due to surprises in the reaction function which are endogenous to the macroeconomy.

The literature on MS-DSGE models is large. Following backward looking approaches that tended to be more reduced form (Hamilton 1989; Sims and Zha 2006), the modelling of forward looking rational expectations models that include markov switching components became a more widespread tool in macroeconomic analysis (Lubik and Schorfheide 2004; Farmer, Waggoner, and Zha 2009). This occurred both due to the growing popularity of DSGE models, and also as the methodologies for solving and estimating MS-DSGE models evolved. The evolution of the solution methods ranges from the global methods of, for example, Davig, Leeper, and Walker (2011), the linearised methods of Svensson and N. Williams (2005), S. Cho (2014), and Farmer, Waggoner, and Zha (2011), and the higher order perturbation techniques of Maih (2015) and Foerster, Rubio-Ramirez, Waggoner, and Zha (2016), the former of which we utilise in this paper.

Much of the literature studies models in which reaction functions switch directed by the data, not by an optimal policy problem (Davig and Leeper 2007; Bianchi 2013; Foerster 2016). We will follow this literature in the first part of our investigation. We will then move to show that it is also optimal to change monetary policy between regimes. This part of our paper will follow other optimal policy exercises in MS-DSGE models (Svensson and N. Williams 2008; Svensson and N. Williams 2009; Blake and Zampolli 2011).

5.1. Estimation of a Markov-Switching model

We estimate the three equation New Keynesian model of Lindé (2005) with two regimes using Bayesian methods. In each regime, the coefficients of the Taylor rule and the persistence of inflation dynamics are allowed to vary. All other coefficients are constrained to be equal across regimes. We use a three equation model for simplicity, but show that the results are unchanged if one performs the same estimation exercise with a switching reaction function using the medium scale DSGE model of Smets and Wouters (2007) in Appendix Section 7.5.

We will show that the estimated periods of regime change — when the reaction function is altering according to the macroeconomic data — are the periods where the lion's share of market surprises occur. This is at the heart of our argument for why market surprises are linked to changing reaction functions. There is no reason, ex-ante, or in a full information rational expectations framework, for periods in which the estimated relationship between interest rates and output is changing, for the 30 minute surprise in financial markets to be larger than usual for a monetary policy announcement. Any rational investor knows the optimal policy function and can map its changes either through the same calculation that the central bank does, or by interpreting central bank speech. We show that this view is not consistent with the data: markets do not manage to anticipate reaction function variation.

We choose the persistence of inflation dynamics as a structural parameter to vary across regimes, in addition to the Taylor rule coefficients, for three reasons. First we want to only vary one parameter for parsimony. This keeps our model as simple as possible, and still shows that switches in just a single parameter coincide with market surprises. Models with many more switching parameters (e.g. Svensson and N. Williams (2009)) are also possible to estimate, but would not be as remarkable if they explained market surprises. Second, we wanted the structural parameter to be one that mattered for optimal policy. In a linear quadratic framework with a Bayesian policymaker that rules out changes in the volatilities of shocks as candidates, which are often estimated as switching parameters (Sims and Zha 2006). And finally, inflation dynamics are a common area of interest for central banks. Much of the discussion during the end of 2021 and in to 2022 has been over the properties of current inflation dynamics, and whether they are indeed "transitory".[12] And earlier periods of inflation were also characterised by a Federal Reserve that was preoccupied with how forward or backward looking inflation was (Orphanides and J. C. Williams 2005).

We estimate the model using quarterly US data on the output gap (x_t), inflation (π_t) and interest rates (r_t) between 1985 and 2019. More information on the data can be found in Appendix Section 7.4. The estimation procedure uses the perturbation methodology of Maih (2015).

The model equations are set out below.[13] Parameters with a j superscript are permitted to vary across regimes. The estimated parameters' prior distributions, initial values, posterior modes and the standard deviation of the posterior mode, in brackets, are displayed in tables below. Of note is Table 5 which shows the estimated differences in reaction function coefficients. One can see that the reaction to inflation in Regime 1 is nearly three times that in Regime 2. Clearly, the estimated orders of magnitude of reaction function variation are easily enough to create monetary policy surprises.

$$\pi_t = w_f^j \mathbb{E}\pi_{t+1} + (1 - w_f^j)\pi_{t-1} + \gamma_1 x + \sigma_s \epsilon_s \tag{16}$$

$$x_t = \beta_f \mathbb{E}x_{t+1} + (1 - \beta_f)(\beta_y x_{t-1} + (1 - \beta_y)x_{t-2}) - \beta_r(r - \mathbb{E}\pi t + 1) + \sigma_d \epsilon_d \tag{17}$$

$$r_t = (1 - \rho_1 - \rho_2)(\gamma_\pi^j \pi_t + \gamma_y^j x_t) + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \sigma_r \epsilon_r \tag{18}$$

[12] See, for example, Chairman Powell's comments at the Senate Banking Committee, November 30, 2021

[13] This model, whilst still a three equation New Keynesian model does differ in its equations from the markov switching model in McMahon and Munday (2022). Furthermore, the variances of shocks are fixed in this model, whilst the extent to which inflation dynamics are forward or backward looking are allowed to change. A medium scale estimated MS-DSGE model can be found in Appendix Section 7.5.

Table 3: Priors for estimated parameters

Parameter	Distribution	%90 bands
γ_1	Gamma	0.05, 0.1
σ_d	Weibull	0.05, 1
σ_s	Weibull	0.05, 1
σ_r	Weibull	0.05, 1
β_r	Gamma	0.005, 0.5
β_y	Normal	1.1, 1.2
w_f^1	Gamma	0.4, 0.7
w_f^2	Gamma	0.1, 0.3
$p_{1,2}$	Beta	0.1, 0.25
$p_{1,2}$	Beta	0.1, 0.25
γ_π^1	Gamma	0.5, 5.0
γ_π^2	Gamma	0.5, 5.0
γ_y^1	Gamma	0.05, 3.0
γ_y^2	Gamma	0.05, 3.0

Table 4: Calibrated parameters

Parameter	Value	Reference
β_f	0.99	N/A
ρ_1	0.95	Svensson and N. Williams (2005)
ρ_2	-0.06	Svensson and N. Williams (2005)

Table 5: Estimated Markov Switching parameters

Parameter	Regime 1: Posterior mode	Regime 2: Posterior mode
γ_π^j	2.7	1.1
	(0.35)	(0.65)
γ_y^j	0.15	0.37
	(0.03)	(0.10)
w_f^j	0.37	0.29
	(0.15)	(0.10)

Table 6: Estimated fixed parameters

Parameter	Posterior mode
γ_1	0.001
	(0.001)
σ_d	2.86
	(0.21)
σ_s	0.09
	(0.014)
σ_r	0.07
	(0.02)
β_r	0.016
	(0.024)
β_y	1.15
	(0.036)
$p_{1,2}$	0.097
	(0.083)
$p_{2,1}$	0.15
	(0.12)

$p_{i,j}$ refers to the transition probability for moving from regime i to regime j

5.2. Optimal policy

The estimated markov model does not include an optimal policy element. An obvious question that could be put to our explanation for the odd features of monetary policy surprises is whether central banks should optimally change their reaction functions in the periods we describe. The estimated model shows that empirically they have. Now we turn to an optimal policy markov switching model.

In a series of papers (Svensson and N. Williams 2005; Svensson and N. Williams 2008; Svensson and N. Williams 2009) Svennson and Williams outline the implications for policymakers who live in model environments characterised by different modes linked by markov chains that they name a Markov Jump - Linear Quadratic (MJLQ) approach. Put simply, there are some finite number of linear models of the world (e.g. of the 3 Equation New Keynesian form) each with different parameter values. The policymaker has the (typical) quadratic preferences over state variables. The policymaker has to make optimal policy whilst simultaneously considering a multiplicity of potential models.

As in Svensson and N. Williams (2005), we suppose the policymaker knows the regime they are in.[14] The intuition is simple: if there are different modes the economy can switch between, then different reaction functions are optimal in each of those regimes.

This is straightforward intuitively, but solving, estimating, and doing optimal policy in these frameworks is computationally difficult, hence the predominant use of single regime models in macro. Using the Svensson and N. Williams (2005) methodology, we find the optimal policy in each of the estimated regimes from our three equation New Keynesian model we estimated previously, when the policymaker has quadratic preferences over output and inflation.

Table 7 shows the coefficients from a linear function mapping the states of the economy to the the interest rate. The only variables that are not in the previous model are the λ coefficients, which relate to the lagrange multipliers on each of the equations, which act as constraints when performing optimal policy under commitment. They capture the history dependence that occurs when solving under commitment in the timeless perspective of Woodford (2003).[15] One can see that the response to lagged inflation is nearly three times as large in Regime 1 than in Regime 2, and the immediate response to an inflation shock is much larger too.

Figure 3 shows the difference in responses of the interest rate to a 1 s.d. inflation shock in both regimes. The responses are markedly different. In Regime 1 the policymaker has a much stronger initial reaction to inflation, which wanes over time. In Regime 2, they are slower to respond, and actually let inflation run away, resulting in a rising interest rate at the end of the impulse response.[16]

So not only does the data show that reaction functions vary over time. But optimally, that

[14] The later papers (Svensson and N. Williams 2008; Svensson and N. Williams 2009) deal with the thornier issue of optimal policy when the policy-maker can learn about the mode the economy is in.

[15] Note that the optimal policy is a function of states, not control variables in our exercise. This means that the estimation procedure is not biased as argued in Portier (2022).

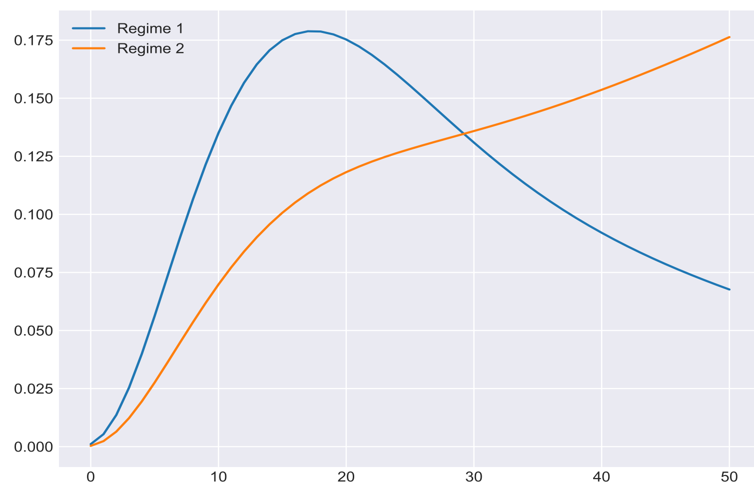
[16] Note that given that one of the impulse responses returns to baseline means that the estimation is still valid if agents believe that there is a substantial enough chance of them returning to Regime 1 in the future. This is similar to the logic of models in which the lower bound is binding, but agents know that in the future it will not be.

the changes in those reaction functions would be large if central banks were solving optimal policy problems. This is true even if the only structural parameter changing between regimes is the persistence of inflation dynamics.

Table 7: Optimal policy coefficients

	π_{t-1}	x_{t-1}	x_{t-2}	i_{t-1}	$\epsilon_{s,t}$	$\epsilon_{d,t}$	$\lambda_{\pi,t-1}$	$\lambda_{x,t-1}$
Regime 1	0.0077	0.0002	-0.0000	0.8667	0.0011	0.7830	0.0001	0.1302
Regime 2	0.0026	0.0002	-0.0000	0.8667	0.0003	0.7830	0.0001	0.1302

Fig. 3. Optimal responses of the interest rate in two regimes to an inflation shock



Of course, allowing other parameters to vary would also result in an optimal policy that varied across regimes. What we have just shown is that only allowing one parameter to vary can induce large changes in optimal policy — easily large enough to account for monetary policy surprises. Allowing further structural parameters to vary across regimes would only reinforce this point. For example, Choi and Foerster (2021) solve a model in which the natural rate of growth switches between regimes. They include a ZLB on monetary policy to force the coefficients of the reaction function to vary when switching regimes. They also find large changes in optimal policy coefficients between regimes.

Fig. 4. Probability of being in Regime 2

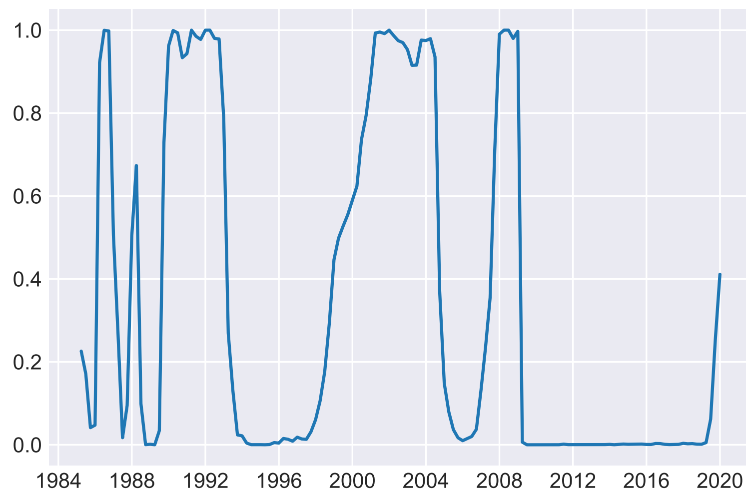


Figure 4 shows the estimated probability that the economy is in Regime 2. Empirically this is a regime in which the weight placed on output versus inflation in the policymaker's reaction function shifts towards output, and inflation becomes a more persistent variable with less of a forward looking component.

5.3. The relationship between surprises and regime change

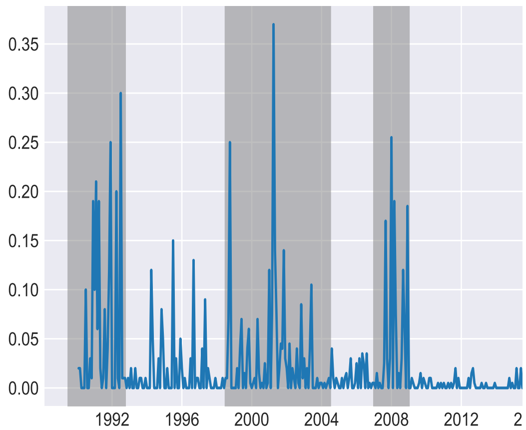
We posit that market surprises result from the market not catching on to regime changes. In the 3-Equation model, the market doesn't catch the switch to Regime 2. We code this as periods where the probability of being in Regime 1 is less than 0.2, or when the probability of being in Regime 1 falls by more than 0.1 in a quarter.

The charts below show these periods in shaded grey. If our hypothesis is correct, in these periods financial market surprises should be large because the market hasn't caught on to the regime change. The blue lines in the charts show different measures of absolute market surprises from the literature. The first two charts show the raw high frequency surprises in interest rates and the equity market 30 minutes each side of FOMC announcements. The second two show the "shocks" derived from a sign restrictions process in Jarociński and

Karadi (2020). The final two show the "shocks" derived from the orthoganlisation process in Miranda-Agrippino and Ricco (2021). In all six of these cases, the periods denoted by our very simple model as being in a regime switching period are highly correlated with the size of the surprises and shocks.

This relationship can also be seen by examining some of the summary statistics regarding the shaded areas:

- For the raw surprise data for interest rates and equities the shaded areas cover 39% of the sample, but they also:
  - Contain for 84% and 80% of the largest 25 observations, respectively
  - Account for 86% and 73% of the variance, respectively
- For the monetary policy and information shocks from Jarociński and Karadi (2020), the shaded areas cover 39% of the sample, but they also:
  - Contain for 80% and 68% of the largest 25 observations, respectively
  - Account for 82% and 72% of the variance, respectively
- For the monetary policy shocks from Miranda-Agrippino and Ricco (2021), calculated in two different ways, the shaded areas cover 50% of the sample, but they also:
  - Contain 72% and 76% of the largest 25 observations
  - Account for 82% and 77% of the variance, respectively



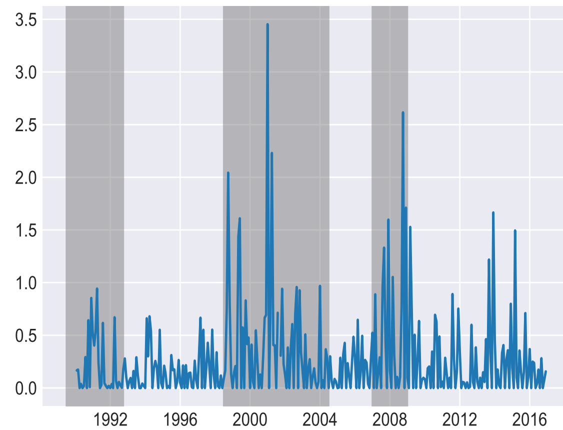
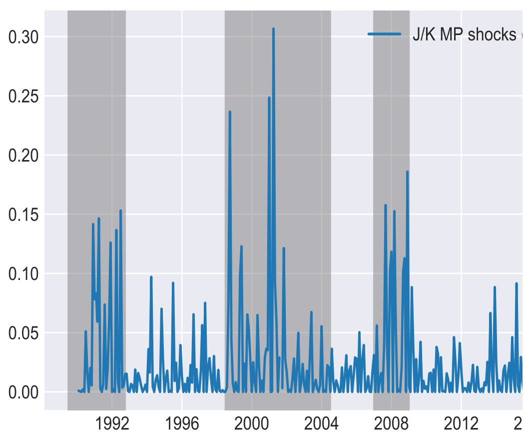


Fig. 5. Absolute HF interest rate surprises

Fig. 6. Absolute HF equity surprises



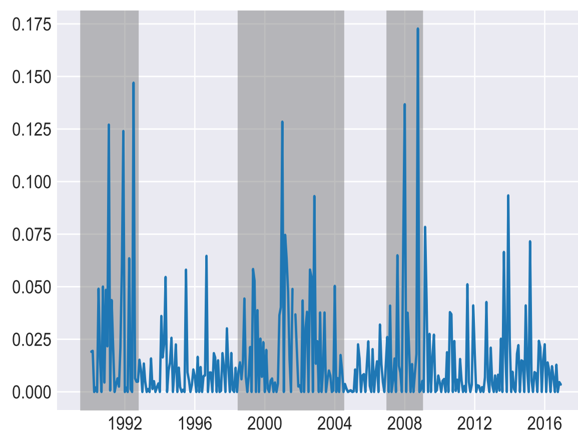
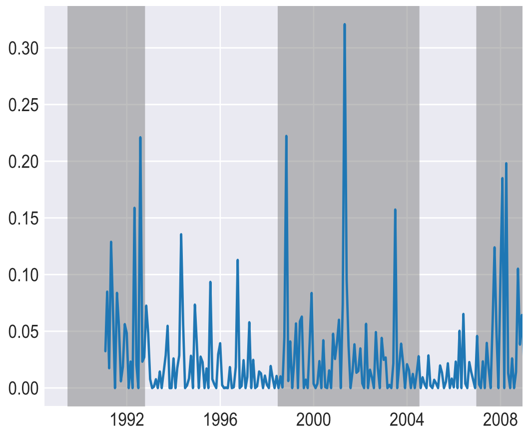


Fig. 7. Absolute HF mon. pol. shocks (Jarociński and Karadi 2020)

Fig. 8. Absolute HF information shocks (Jarociński and Karadi 2020)



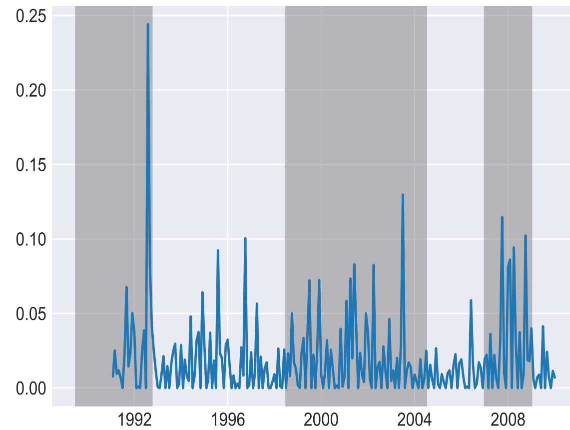


Fig. 9. Absolute HF mon. pol. shocks method 1 (Miranda-Agrippino and Ricco 2021)

Fig. 10. Absolute HF mon. pol. shocks method 2 (Miranda-Agrippino and Ricco 2021)

The evidence from the charts and the summary statistics suggests that the occurrence of monetary policy surprises is heavily skewed towards periods in which the central bank is changing its reaction function. This creates problems for using surprises as instruments for shocks, since the surprises are now likely endogenous, if indeed the reaction function variation owes to endogenous factors.

5.4. Empirical impulse responses across regimes

We investigate these regimes further by calculating the impulse responses to the shocks from both Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021) when using the entire sample of shocks, and then comparing to the impulse responses when only the shocks that occur in one regime are used.

We do this using local projections (Jordà 2005). We use the shocks directly in the local projections as independent variables. Whether the shocks from the previous papers are used directly or as instruments makes little quantitative difference, Appendix Section 7.3 shows the results where the measures are used as instruments.

Figure 11 shows the impulse responses up to 60 months of the monetary policy shocks on industrial production (first row of charts), inflation (second row) and the Effective Federal Funds rate (final row).

The effects are small, except for on the Federal Funds rate. The effect on industrial production is muted for both the Jarociński and Karadi (2020) shocks and the Miranda-Agrippino and Ricco (2021) shocks. For inflation, the Jarociński and Karadi (2020) shocks are insignificant, whilst the Miranda-Agrippino and Ricco (2021) have a significant and negative effect towards the end of the impulse response. Note that we are not directly replicating the work of these papers. We do not place Bayesian priors on these estimates, as in the Bayesian local projections of Miranda-Agrippino and Ricco (2021). Nor do we fit a sign-restrictions VAR as in Jarociński and Karadi (2020).

Figure 12 shows the impulse responses when the samples are split between Regime 1 and Regime 2 as we estimated previously. Regime 2 is where we suspected that the measured "shocks" were actually reaction function innovations. If this were the case we would expect the impulse responses from Regime 1 shocks to look more like the theoretical monetary policy impulse responses: having large (negative) effects on inflation and output in the medium term, and little effect in the short and long term. Shocks from Regime 2 could take any form. Reaction function shocks can have different impulse responses depending on (i) which coefficient of the reaction function has changed, and (ii) the state of the economy, and expected future states, and (iii) the empirical sample of other shocks which are currently passing through the economy, which the reaction function shock will interact with

Remarkably, the data seem to bare this out. The impulse responses of industrial production when confronted with a monetary policy shock take on a negative hump-shape when using data from Regime 1. The case for inflation is not as clear, but with the shocks of Jarociński and Karadi (2020) the impulse response is significantly negative at around 50 months.

Mixing the impulse responses from these two different regimes is the exact issue with using high frequency measures of monetary policy surprises — they combine both monetary policy shocks and reaction function shocks.[17]

[17]Moreover, there is no reason for the IRF using the entire sample to look like a convex combination of the

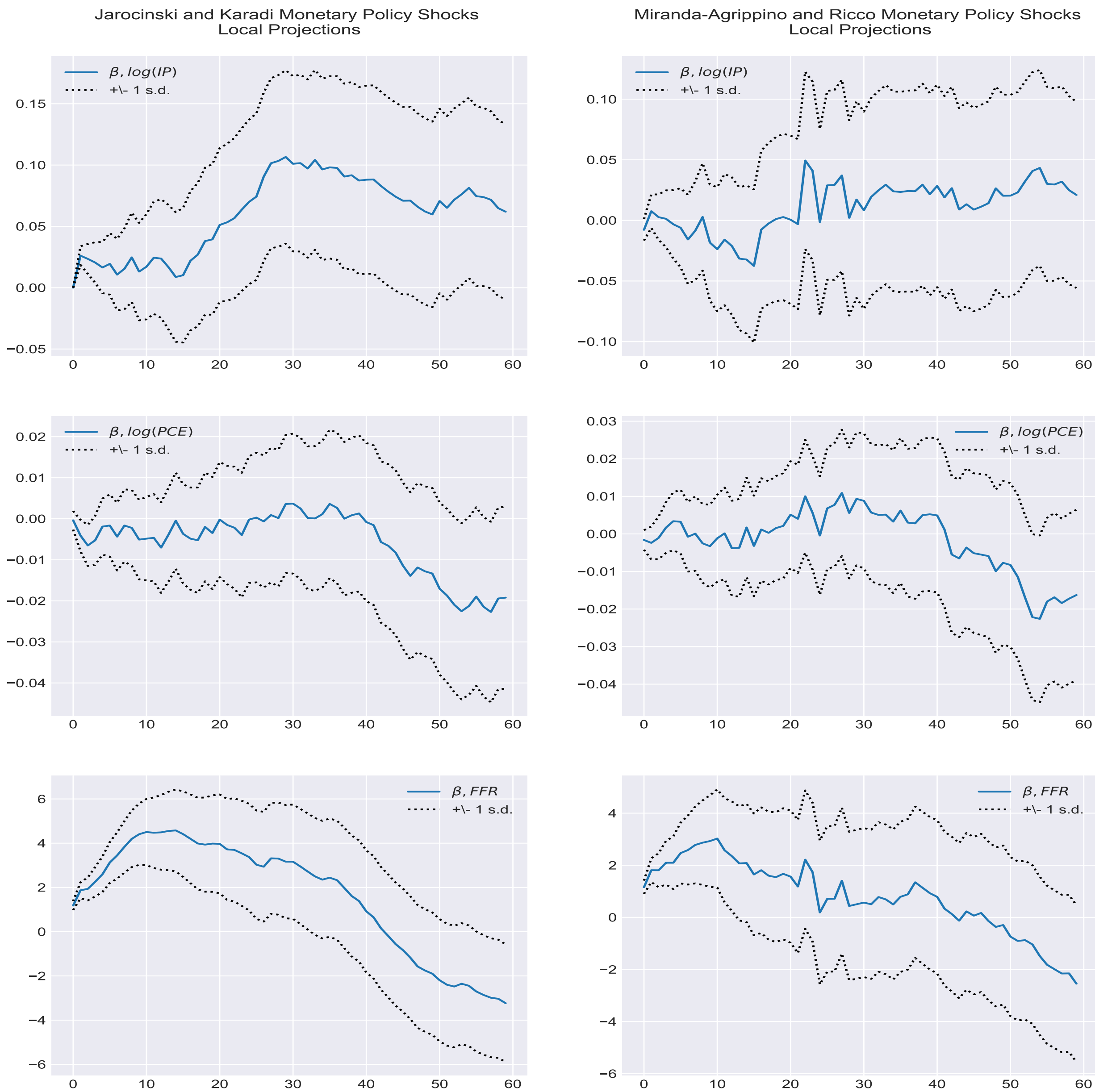


Fig. 11. Local projections of monetary policy shocks on output, inflation and interest rates

IRFs calculated in each regime, so determining the direction of bias is difficult.

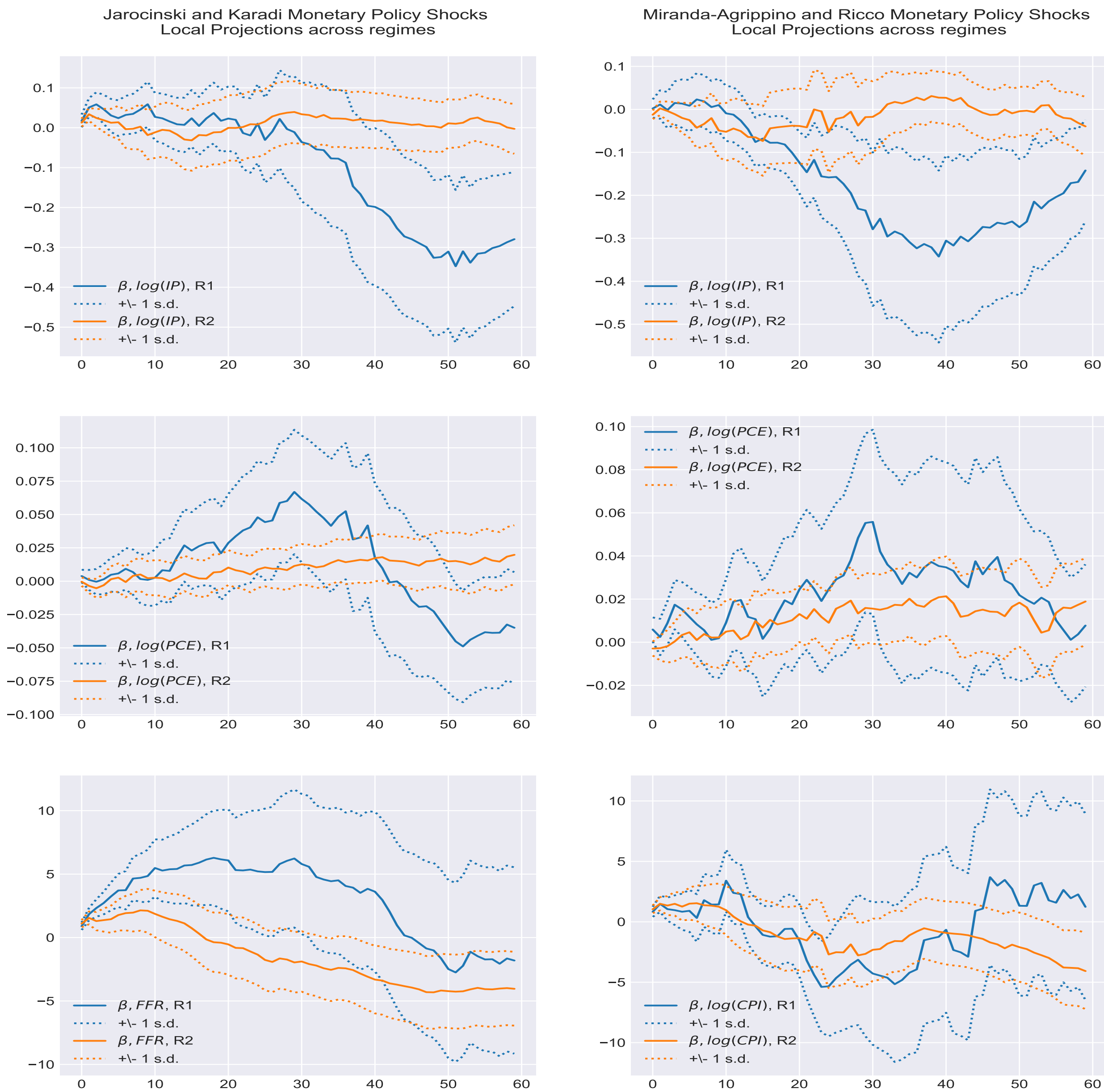


Fig. 12. Local projections of monetary policy shocks on output, inflation and interest rates across regimes

6. Conclusion

Reaction function variation is empirically well supported in the macro data. Surprises in reaction functions are common explanations of market participants. And, endogenous reaction function surprises fit the stylized facts of high frequency monetary policy surprises that have been documented elsewhere in the literature.

If reaction function surprises do contaminate monetary policy surprises then that is a problem for the identification of monetary policy shocks. Even if reaction function variation is exogenous, reaction function shocks can have different impulse responses to monetary policy shocks, and can therefore lead the researcher astray. But more importantly than that, variation in reaction function is likely to be endogenous to the state of the economy. We find evidence for this by estimating a DSGE model with a Markov-switching component in the structural parameters of the economy, and in the reaction function, and then finding that periods of endogenous reaction function variation coincide with periods of monetary policy surprise variation.

Of course, the use of monetary policy surprises remains a useful tool for understanding the information that moves financial markets. Decomposition of the surprises into constituent drivers as in Gürkaynak, Sack, and Swanson (2004) or Swanson (2021) still contain valuable information for scholars.

Is there a way of cleaning both information effects and reaction function effects out of monetary policy surprises? We are sceptical. Given that the relationship between the reaction function and the economy is time-varying and extremely high-dimensional, attempts to orthogonalise the problem away will likely fail. Economists may be better off searching for examples of exogenous monetary policy decisions, rather than increasing the list of control variables to try to clean the surprises of all endogenous variation.

The negative interpretation to the arguments made in this paper is that the effect of monetary policy on the economy is not particularly well identified, and perhaps much of the variation in current attempts at identification is endogenous. But the positive interpretation is that policy should not be exogenous. We do not expect, or indeed want, policymakers to be delivering “shocks” to the economy. We would prefer them to have considered decisions, based on reacting to the state of the economy in order to achieve their objectives. Perhaps our argument that monetary surprises are actually based on reaction function changes is a argument in favour of the capable nature of modern monetary policymakers.

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7. Appendix

7.1. Bauer and Swanson 2022

In Bauer and Swanson (2022), the authors argue that even if monetary policy surprises are driven by reaction function changes that they can still be used as instruments for shocks.

We do not quarrel with the authors that the full scope of monetary policy shocks acts through monetary policy surprises. Where we disagree is Bauer and Swanson (2022) believe that the surprises themselves are not contaminated by the reaction function changes, and can then be used as instruments for shocks.

In essence our argument is similar to Nakamura and Steinsson (2018): monetary policy surprises contain multiple shocks and so thinking of them as only containing one (monetary policy shocks) creates difficulties. Bauer and Swanson set up a simple model, and then use it to argue their above point. They write that output, x_t, and the interest rate, i_t, are governed by the equations below (η_t, ϵ_t and u_t are all gaussian zero mean shocks). In their framework, the market updates slowly on the parameter α (because they are Bayesian with priors over α), learning the reaction function of the central bank over time.

Below we take their model and show that reaction function shocks in their model are represented in monetary policy surprises. Furthermore, we show that, again in their model, reaction function shocks have real effects on the state of the economy. This violates a claim the authors make, that " To be a valid external instrument for a monetary policy shock, [a monetary policy surprise] must be exogenous with respect to the other structural shocks and the lagged variables of the VAR [in question]". As a result, we disagree with the authors that using monetary policy surprises as instruments for shocks is a valid methodology.

This is all under the assumption that reaction function surprises are themselves exogenous and random, and so can be labelled as shocks. We doubt that this is true, and document indicative evidence of optimal endogenous reaction function variation driving monetary policy surprises in the main text.

The economy is modelled by the following three equations:

$$x_t = \rho x_{t-1} - \theta i_{t-1} + \eta_t \tag{19}$$

$$i_t = \alpha_t x_t + \epsilon_t \tag{20}$$

$$\alpha_t = \alpha_{t-1} + u_t \tag{21}$$

Rolling this economy forward and writing output as a function of parameters, initial conditions and shocks that occur in period 1 gives:

$$\begin{aligned}
x_0 &= x_0 \\
x_1 &= (\rho - \theta\alpha_0)\, x_0 + \eta_1 \\
&\vdots \\
x_N &= (\rho - \theta\,(\alpha_0 + u_1))^{N-1}\,((\rho - \theta\alpha_0)\, x_0 + \eta_1) - (\rho - \theta\,(\alpha_0 + u_1))^{N-2}\,\theta\epsilon_1
\end{aligned} \tag{22}$$

Similarly, interest rates as a function of parameters, initial conditions and shocks that occur in period 1 are:

$$\begin{aligned}
i_0 &= \alpha_0 x_0 \\
i_1 &= (\alpha_0 + u_1)\,((\rho - \theta\alpha_0)\, x_0 + \eta_1) + \epsilon_1 \\
&\vdots \\
i_N &= (\alpha_0 + u_1)\left((\rho - \theta\,(\alpha_0 + u_1))^{N-1}\,((\rho - \theta\alpha_0)\, x_0 + \eta_1) - (\rho - \theta\,(\alpha_0 + u_1))^{N-2}\,\theta\epsilon_1\right)
\end{aligned} \tag{23}$$

First, we imagine a monetary policy shock, ϵ, that occurs in period 1. The path for output is:

$$\begin{aligned} x_0 &= x_0 \\ x_1 &= (\rho - \theta\alpha_0)\, x_0 \\ &\vdots \\ x_N &= (\rho - \theta\alpha_0)^N x_0 - \theta\,(\rho - \theta\alpha_0)^{N-2}\,\epsilon_1 \end{aligned} \tag{24}$$

and for the interest rate:

$$\begin{aligned} i_0 &= \alpha_0 x_0 \\ i_1 &= \alpha_0\,(\rho - \theta\alpha_0)\, x_0 + \epsilon_1 \\ &\vdots \\ i_N &= \alpha_0 \left((\rho - \theta\alpha_0)^N x_0 - \theta\,(\rho - \theta\alpha_0)^{N-2}\,\epsilon_1 \right) \end{aligned} \tag{25}$$

Then, imagine a reaction function shock, u, that occurs in period 1. The path for output is:

$$\begin{aligned} x_0 &= x_0 \\ x_1 &= (\rho - \theta\alpha_0)\, x_0 \\ &\vdots \\ x_N &= (\rho - \theta\,(\alpha_0 + u_1))^{N-1}\,(\rho - \theta\alpha_0)\, x_0 \end{aligned} \tag{26}$$

and for the interest rate:

$$\begin{aligned} i_0 &= \alpha_0 x_0 \\ i_1 &= (\alpha_0 + u_1)\,((\rho - \theta\alpha_0)\, x_0) \\ &\vdots \\ i_N &= (\alpha_0 + u_1) \left((\rho - \theta\,(\alpha_0 + u_1))^{N-1}\,(\rho - \theta\alpha_0)\, x_0 \right) \end{aligned} \tag{27}$$

There is no reason for these impulse response functions to coincide. Indeed if the economy starts at steady state with x_0 at zero, then reaction function shocks have no effect, but monetary policy shocks do have an effect.

Moreover, in the case that both shocks cause identical dislocations in i in the first period, the effects are still different. This is because the reaction function shock changes future reactions of the central bank to x, which leads to a feedback loop that is not apparent in the classical monetary policy shock.

Furthermore, they say that "it may be problematic to use monetary policy surprises for estimation of the dynamic effects of monetary policy on macroeconomic variables in a structural VAR or local projections framework. To be a valid external instrument for a monetary policy shock, mps_t [their notation for a monetary surprise] must be exogenous with respect to the other structural shocks and the lagged variables of the VAR."

Even if their framework is correct, a monetary policy surprise is not a valid instrument for a monetary policy shock. It is the same reason that others have argued that they cannot be used owing to information effects. That monetary policy surprises are the combination of multiple shocks.

To use their framework again, a monetary policy surprise that occurs in period 1 is:

$$\begin{aligned} mps_1 &= i_1 - E_{m,t_1}(i_1) \\ &= (\alpha_0 + u_1)\left((\rho - \theta\alpha_0)\, x_0 + \eta_1\right) + \epsilon_1 - \alpha_0\left((\rho - \theta\alpha_0)\, x_0\right) \\ &= u_1\,(\rho - \theta\alpha_0)\, x_0 + (\alpha_0 + u_1)\,\eta_1 + \epsilon_1 \end{aligned} \tag{28}$$

Just as Nakamura and Steinsson (2018) argued that mps_1 could not be used as an instrument for ϵ_1 because of the existence of η_1, which is a shock that affects the endogenous variables of the economy, we make the same argument that the existence of u_1 also makes the use of mps untenable.

This goes to an argument we make in the main text. That mixing monetary policy shocks and reaction function shocks is not a problem *per se* econometrically (if one assumes they are exogenous) but the impulses responses will answer a different question to which the econometrician is usually asking. They will not show the answer to "what is the effect of a one-off exogenous 25bp increase in the interest rate in a given period", rather they will show "what is the average effect of a one-off 25bp increase in the interest rate either due to an exogenous shock, or due to the central bank becoming more aggressive with respect to an unspecified state variable, the weights of which depend on the relative prominence of these two forces in the data." Furthermore, the impulse responses for each of these two driving forces may be different, so confusing them is not an innocuous mistake.

That is before considering the idea that u_1 is itself endogenous to the state of the economy (as we argue it likely is), then the usefulness of *mps* as an instrument is dealt a further blow.

After Nakamura and Steinsson (2018) the idea, as taken up by, for example Miranda-Agrippino and Ricco (2021), was that if some set of data spans the private information set of the central bank, then othorgonalising with respect to this might be enough to rid the monetary policy surprise of η_1.

But that is more difficult in the case of u_1. u_1 could be a function of any number of variables, both exogenous (a change in voting committee) and endogenous (a change of structure in the economy that requires a different reaction function). Orthoganlising with respect to a set of variables is a difficult way of achieving identification. It relies on the set of orthogonalising variables to completely span the possible space — which, given the discussions of different pieces of evidence by the forecaster in Section 3, both quantitative and qualitative, is likely not possible (although some attempts have been made, e.g. in Ochs (2021)). Further, it relies on the relationship between these state variables and the monetary policy surprise to be fixed over time, and known by the researcher, rather than constantly varying in their relative importance to the outlook.

Bauer and Swanson's attempt to orthognalise away the reaction function surprises is valiant but ultimately, we believe, flawed. Indeed, their strategy could be applied to many other macro-econometric problems: to find exogenous variation in some variable of interest, control for enough other variables that might also cause variation, and look at the residual which is now assumed to be exogenous. We are more pessimistic about this “selection on observables” method: reaction function surprises may not be possible to clean out by running regressions on state variables.

7.2. Alternative explanations of changing reaction functions

In this (sub)section we briefly outline the alternative frameworks to the markov switching one we will adopt.

The first is a robust control framework. We explore this particular framework in McMahon and Munday (2022). In that paper, we outline a model in which a robust control policymaker is faced with stochastic volatility. In this world, the policymaker *optimally* changes the coefficients of their reaction function in response to volatility shocks.

This is an attractive framework because stochastic volatility shocks are increasingly viewed as important for determining the main dynamics of the macroeconomy (Christiano, Motto, and Rostagno 2014; Baker, Bloom, and Davis 2016). Furthermore, as we document in McMahon and Munday (2022), the empirical evidence suggests that volatility shocks coincide with observed changes in reaction functions.

However, the changes in volatility needed to cause the observed alterations in reaction functions are too large to be plausible. Moreover, for volatility shocks to be at fault for monetary policy surprises, market participants would have to be less informed specifically regarding second moment shocks than the central bank. Whilst this is technically plausible, it is less intuitive compared to the framework we adapt in this paper which is far more general in what the information asymmetry between the market and the central bank is.

An alternative, but similar framework, is a Bayesian central banker that reacts to uncertainty shocks in a Brainard (1967) type manner. This approach has some issues, particularly if one considers that the effect on the reaction function can differ markedly depending on which parameter uncertainty is applied to (Söderström 2002). Moreover, it falls into the same trap as the robust control set up: it requires the information asymmetry between investors and the central bank to be confined to second moment shocks, an odd assumption to make.

The previous two alternative frameworks have involved the central bank reaction function optimally changing in response to some external factor. A different framework would be to say that preferences of central bankers shift (exogenously) over time, and cause reaction function variation. This is clearest when there are changes in the Fed Chairperson, or voting members of the policy committee, but could occur for other reasons.

We cannot rule this out. But it is an unsatisfactory explanation for variation in reaction functions, and one that does not fit the fact that monetary policy surprises seem to be highly correlated with the macro cycle.

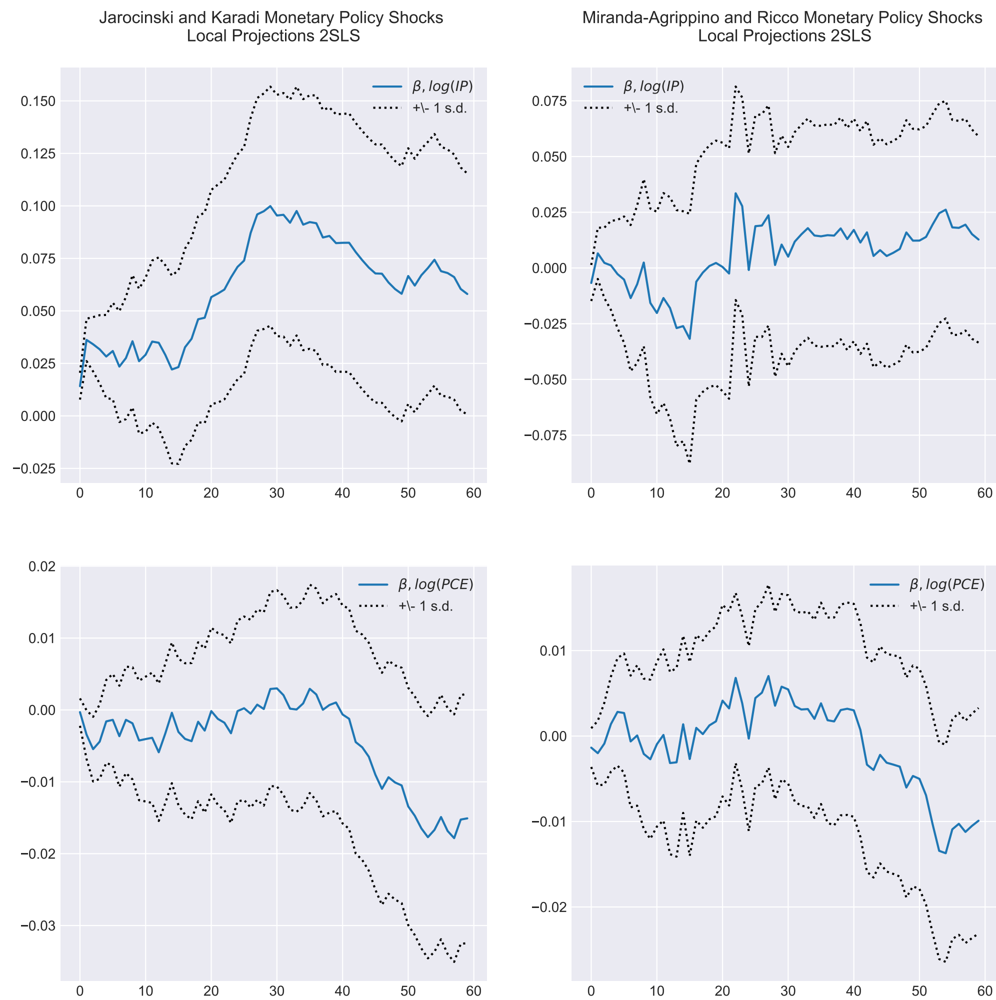


Fig. 13. 2SLS local projections of monetary policy shocks on output, inflation and interest rates

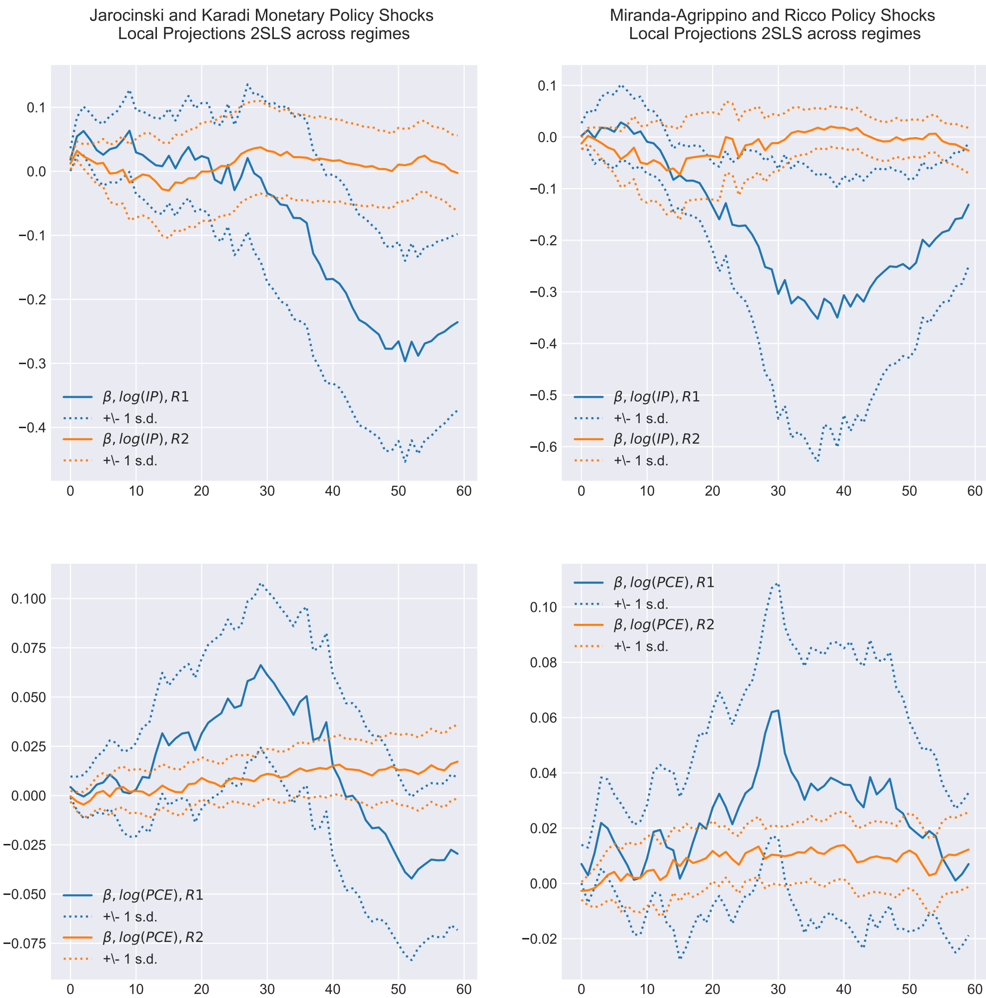


Fig. 14. 2SLS local projections of monetary policy shocks on output, inflation and interest rates across regimes

7.4. Data

The three data series we use to estimate the Lindé (2005) model are the output gap, core inflation and the effective Federal Funds rate.

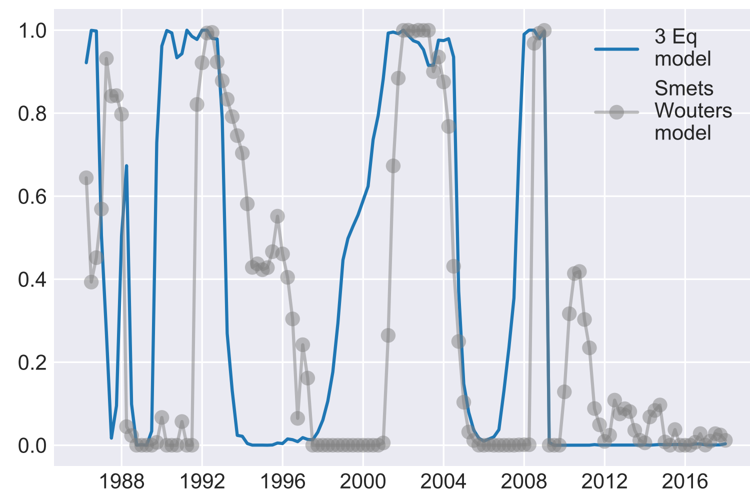
The seven data series we use to estimate the Smets Wouters model are as close as possible to the original series used in Smets and Wouters (2007), with the only changes occurring due to statistical revisions by the authorities. The series are : quarterly change in real consumption per person, quarterly change in real investment per person, quarterly change in real GDP per person, average hours per person, quarterly inflation (GDP deflator), change in hourly real wages and the effective quarterly federal funds rate. The codes needed to obtain the data needed to construct these series from FRED, or the BLS, are: GDPC, GDPDEF, PCEC, FPI, CE16OV, FEDFUNDS, CNP16OV, PRS85006023, PRS85006103.

7.5. Smets Wouters Estimation

In the main text we kept the model simple. A potential criticism of our methodology is that the regime switches that we estimate are only applicable in the case of the three equation New Keynesian model, and would not occur if we estimated a richer model.

To address this, we estimate the Smets and Wouters (2007) model, with two regimes, in which the persistence of inflation dynamics and the coefficients of the reaction function are permitted to vary across regimes. Figure 15 shows the probability of being in Regime 2 in both the three equation model, and the richer model. The results are highly correlated, suggesting it is not simply a feature of the simplicity of the model that the regime switches occur at the same time as large monetary policy surprises.

Fig. 15. Probability of being in Regime 2



We use as initial values the estimated parameters from Lindé, Smets, and Wouters (2016), which updates the estimation of Smets and Wouters (2007) until 2014, thus including some of the zero lower bound period. After confirming with our priors and no regime switching that we have results that are similar to both Lindé, Smets, and Wouters (2016) and Smets and Wouters (2007), we update the data sample used in both of those papers until Q4 2019. To match the exercise of the three equation model, we then estimate based on a sample that runs from Q1 1985 to Q4 2019.

For an explanation of the equations present in the model see the aformentioned papers. Below we provide our priors, the posterior modes and standard deviations. To the extent possible, we use the same parameter notation as in Lindé, Smets, and Wouters (2016). As a result, we don't include the set of equations that define an equilibrium in the Smets Wouters model, since they are identical to those in Appendix Section A in Lindé, Smets, and Wouters (2016).

Table 8: Estimated Parameters

Parameter	Description	90% prior bands	Distribution	Init. val	Mode	Std.dev
r_π^1	Taylor rule inflation weight	1,2	Normal	1.6	1.39	0.198
r_π^2	Taylor rule inflation weight	0,1	Normal	0.488	0.101	0.218
r_y^1	Taylor rule output weight	0.025,0.225	Normal	0.05	0.0270	0.243
r_y^2	Taylor rule output weight	0.025,0.225	Normal	0.15	0.172	0.128
ρ_p^1	Price markup shock persistence	0.2,0.6	Beta	0.5	0.319	0.0720
ρ_p^2	Price markup shock persistence	0.5,0.9	Beta	0.92	0.799	0.0979
$p_{1,2}$	Transition probability	0.05,0.1	Beta	0.05	0.139	0.0258
$p_{2,1}$	Transition probability	0.05,0.1	Beta	0.05	0.121	0.0491
σ_a	Stationary tech shock var.	0.01,2	Inv. Gamma	0.46	1.50	0.153
σ_b	Risk premium shock var.	0.01,2	Inv. Gamma	0.19	0.151	0.027
σ_g	Gov cons shock var.	0.01,2	Inv. Gamma	0.609	0.387	0.113
σ_i	Investment specific tech shock var.	0.01,2	Inv. Gamma	0.36	0.272	0.0527
σ_r	Mon. pol. shock var.	0.01,2	Inv. Gamma	0.23	0.0813	0.00561
σ_p	Price markup shock var.	0.01,2	Inv. Gamma	0.12	0.129	0.0213
σ_w	Wage markup shock var.	0.01,2	Inv. Gamma	0.37	0.440	0.0386
α	Capital production share	0.2,0.4	Normal	0.19	0.170	0.0843
σ_c	Inv subs. elast. of cons.	0.75,2.25	Normal	1.49	1.823	0.363
ϕ_p	Gross price markup	1,1.5	Normal	1.6	1.494	0.289
ρ_{ga}	Response of g to ϵ^a	0.1,1.5	Normal	0.51	0.0305	0.0583
ϕ	Investment adjustment cost	1,7	Normal	4.58	9.21	0.99
χ	Habit formation	0.3,0.7	Beta	0.62	0.726	0.112
ϵ_w	Calvo prob. wages	0.3,0.7	Beta	0.83	0.805	0.0324
σ_l	Labour supply elasticity	0.5,3.5	Normal	1.81	0.550	0.339
ϵ_p	Calvo prob. prices	0.3,0.7	Beta	0.75	0.972	0.00447
i_w	Indexation of wages	0.3,0.7	Beta	0.69	0.455	0.105
i_p	Indexation of prices	0.3,0.7	Beta	0.22	0.246	0.0540
ψ	Capital utilization cost	0.3,0.7	Beta	0.8	0.871	0.0441
ρ_R	Taylor rule interest rate smoothing weight	0.3,0.7	Beta	0.8	0.680	0.0333
$r_{\Delta y}$	Taylor rule weight on change in output	0.025,0.225	Normal	0.24	0.0300	0.0618
ρ_a	Stationary tech shock persistence	0.2,0.8	Beta	0.96	0.989	0.00350
ρ_b	Risk premium shock persistence	0.3,0.7	Beta	0.4	0.380	0.105
ρ_g	Gov. cons. shock persistence	0.2,0.8	Beta	0.49	0.929	0.0304
ρ_i	Investment specific tech shock persistence	0.3,0.7	Beta	0.84	0.779	0.0442
ρ_r	Mon. pol. shock persistence	0.3,0.7	Beta	0.21	0.867	0.0336
ρ_w	Wage markup shock persistence	0.3,0.7	Beta	0.97	0.486	0.0975
θ_p	MA(1) price markup shock	0.3,0.7	Beta	0.8	0.723	0.245
θ_w	MA(1) wage markup shock	0.3,0.7	Beta	0.96	0.497	0.0829
$100(\beta^{-1}-1)$	Discount factor	0.05,0.8	Gamma	0.1	0.067	0.0656
$\bar{\gamma}$	Growth in s.s.	0.2,0.6	Normal	0.41	0.168	0.0459
$\bar{\pi}$	Inflation in s.s.	0.425,0.825	Gamma	0.7	0.568	0.438
$\bar{l}$	Hours worked in s.s.	-4,4	Normal	-0.4	-0.684	0.335

Table 9: Categorisation of FOMC meetings as surprises

FOMC Date	Surprise	Quote
30/06/1999	✓	The FOMC Surprises by its Words
24/08/1999	✓	The statement that accompanied the action, however, was a bit friendlier than expected, implying that Fed officials believe that the steps they have taken this summer will be sufficient to prevent a rise in inflationary pressures.
21/12/1999	✗	This posture reinforces our view that another 25-basis-point rate hike is likely sometime during the first quarter. We continue to believe that Fed officials will boost short-term rates by another 25 basis points sometime in the first quarter, with the probabilities for timing split roughly evenly between early February and late March.
02/02/2000	✓	The only surprise in the Federal Open Market Committee's decision to boost interest rates by 25 basis points and to voice concern about inflation risks was the moderate tone of its statement given recent labor cost acceleration.
28/06/2000	✗	As widely expected, the FOMC kept monetarypolicy on hold.
15/11/2000	✗	As we had expected, the FOMC decided to keep both the federal funds rate target and the 'bias' toward inflation risks unchanged.
19/12/2000	✗	We continue to believe that the cumulative easing will be 50-100 basis points, concentrated toward the beginning of the year,when growth is likely to be weakest.With respect to the timing, we would reiterate that the first quarter is likely to be the weakest period, as noted in the previous daily comment and in the latest issues of the U.S. Economics Analyst (December 15) and Pocket Chartroom(December/January).
18/04/2001	✗	The FOMC's action to reduce interest rates another half-percent on Wednesday signals that senior Fed officials share our deep concerns about the fundamental outlook for business and consumer spending in 2001,
15/05/2001	✗	The 50-basis-point cuts in the federal funds and discount rates announced by the FOMC on May 15 were not surprising, nor was the retention of the bias toward economic weakness. We continue to expect 50 basis points of additional easing by the end of the summer. At this moment, we would be inclined to expect at least part of this at the June 26/27 meeting, although the size and timing of future rate cuts are heavily dependent on the data.
27/06/2001	✓	US central bankers this week adopted a more cautious easing strategy, apparently on a view that the cumulative weight of past rate reductions soon will revive domestic demand and incomes.
21/08/2001	✗	As we had expected, Fed officials sounded a bit less gloomy in explaining their – widely anticipated – 25-basis-point rate cut than they had either in the most recent 'beige book' or in justifying their previous move on June 27.
02/10/2001	✗	As widely anticipated, the FOMC cuts its federal funds rate and discount rate by 50 basis points to $2\frac{1}{2}$% and 2%,respectively.
07/05/2002	✗	The FOMC meeting outcome was completely predictable—policy is stable, the accompanying statement was virtually unchanged from the March 19 statement.
18/03/2003	✓	However, that was the easy part, as the Committee's decision to suspend its assessment of risks to the economic outlook took everyone by surprise.
06/05/2003	✗	*No short quote to support but there is no surprise*
25/06/2003	✓	The Federal Open Market Committee opted to reduce its federal funds rate target by only 25 basis points on Wednesday. The decision was contrary to our expectation of a 50-basis-point cut

28/10/2003	✗	Today's FOMC decision was no surprise to market participants. However, the FOMC is sending a strong message, through its comment about maintaining policy accommodation for a 'considerable period,' that a tightening is not yet on the horizon. Were affirm our view that monetary tightening is unlikely to occur before mid-2005 and believe this to be true even if the consensus outlook for growth (slightly less than 4% from now through the end of 2004) proves to be right.
09/12/2003	✓	The FOMC's decision to downgrade the risk of deflation while maintaining the 'considerable period' language was both surprising and sensible.
16/03/2004	✗	There was nothing to cause us to change our forecast for no Fed tightening until the middle of 2005.
04/05/2004	✓	the committee removed the ambiguous term 'patient' in favor of the notion that tightening can proceed at a 'measured' pace when it does start, both the relaxed tone of the statement and the fact that there were no dissenters suggest that the hurdle for a June move is high.
30/06/2004	✗	Wednesday's FOMC action was extremely close to expectations. The committee raised its federal funds rate target by 25 basis points and retained the 'measured' language in reference to the speed of tightening.
10/08/2004	✓	The Fed's decision to raise its funds rate target by another 25 basis points was no surprise, but the tone of the statement was more hawkish than expected in two ways.
10/11/2004	✗	As expected, the Federal Open Market Committee increased the fed funds rate to 2% today. We expect another 25 basis point increase at the December 14 meeting, but as always the data will drive the decision.
28/03/2006	✓	Although the statement was largely in line with expectations, it implied that (1) inflation data are likely to become more important in coming months,
10/05/2006	✗	Today's statement from the Federal Open Market Committee (FOMC) was largely as expected.
29/06/2006	✗	The committee recognized both the weaker growth and higher core inflation data, as expected.
08/08/2006	✓	Today's action—more accurately, the lack thereof—was not what we had expected. As discussed more fully in last week's issues of the US Economics Analysis and US Views, we thought the FOMC would decide to boost its federal funds rate target one more time.
25/10/2006	✗	Today's FOMC statement confirms that the committee is firmly locked on hold for the time being.
21/03/2007	✓	the committee recognized more explicitly than before that the next policy move might not be a rate hike, which says implicitly that economic weakness can quickly develop to the point of requiring a policy response.
18/09/2007	✗	*No short quote to support but there is no surprise*
31/10/2007	✓	However, the statement was more hawkish than anticipated as the committee indicated that it views the risks of higher inflation and weaker growth as "roughly balanced."
11/12/2007	✓	This afternoon, the FOMC cut the fed funds rate by 25 basis points, as we had expected. However, the decision as a whole tilted toward the more hawkish side.
22/01/2008	✓	A key question in this regard is what motivated the timing of the rate cut.
30/01/2008	✗	The Federal Open Market Committee took another decisive easing step today, lowering the Fed funds rate target 50 basis points, as we had expected, and keeping its policy statement clearly focused on downside risks to growth.
18/03/2008	✓	Following today's 75-basis point funds rate cut—less than the 100bp we and the market had expected
30/04/2008	✗	Today the Federal Open Market Committee (FOMC) delivered pretty much what we had expected since the last meeting in mid-March, which gradually became the consensus view as well.
16/09/2008	✗	The FOMC kept the funds rate target unchanged at 2%, as we and most other economists had expected.

27/04/2011	✗	Taken together, Bernanke's remarks were consistent with our forecast for no rate hikes for a long time to come.
22/06/2011	✗	Today's events brought no major surprises but a number of tweaks in light of recent news. Finally, there were no substantive changes to the policy-related language and no hints about further easing. Taken together the Chairman's remarks were consistent with our view that the FOMC remains well within a "zone of inaction."
09/08/2011	✓	We have changed our call because today's statement suggests that the committee's reaction function to incoming economic news is more dovish than we had previously thought.
21/09/2011	✓	Although the broad thrust of the statement and action were consistent with our expectations, the overall easing move was larger than we anticipated, for several reasons:
02/11/2011	✓	The one surprise in the November 2 FOMC statement, forecasts, and press conference was that Chicago Fed President Evans decided to dissent in favor of additional monetary easing, while Presidents Fisher, Kocherlakota, and Plosser opted to vote with the majority for an unchanged policy. On the surface, this looks like a shift that brings the Federal Reserve closer to renewed policy easing. After all, we have found statistical evidence that dissents help predict changes in monetary policy at short horizons (see Sven Jari Stehn, "The Likelihood of Additional Fed Easing," US Economics Analyst, 11/36, September 9, 2011). Moreover, Chairman Bernanke did say that renewed easing including a return to purchases of mortgage-backed securities remains on the table. However, other observations suggest that significant additional policy easing is not yet imminent.
25/01/2012	✓	The message is that the core of the FOMC is at least as dovish, perhaps even more dovish, than we had thought previously.
13/03/2012	✗	On net the FOMC statement is very close to our expectations
25/04/2012	✓	a moderately more hawkish than expected FOMC meeting. The post-meeting statement was close to our expectations but a few changes added a more upbeat tone
20/06/2012	✓	While the announcement represents a "substantive" easing step (in Chairman Bernanke's words), it was less aggressive than our baseline expectation of renewed balance sheet expansion. The FOMC's communication was dovish. First, changes to the committee's economic outlook were larger than expected, with significant downgrades to real GDP growth and employment. Second, the FOMC put in place a more explicit easing bias in the statement, saying that it "is prepared to take further action" should the recovery–and the job market in particular–continue to disappoint.
01/08/2012	✓	The Federal Open Market Committee took no action at its latest policy meeting, a modest disappointment to markets (and us). However, it did strengthen the "easing bias" in its statement.
13/09/2012	✓	Meanwhile, the description of the economic outlook was actually upgraded in a couple of places from the August statement.
24/10/2012	✗	The FOMC meeting delivered no surprises as all policy parameters remained unchanged and the committee made minimal changes to the description of the outlook.
12/12/2012	✓	Change to outcome-based forward guidance. Although we expected a shift to outcomes-based forward guidance in early 2013 (based largely on the strong endorsement from Vice Chair Yellen in a recent speech), we did not expect the Committee to introduce new guidance at this meeting. In the event, the new guidance states that the Committee expects to maintain an exceptionally low level of the federal funds rate at least as long as: (1) the unemployment rate remains above 6.5%, (2) inflation one- to two-years ahead is projected to be no more than 2.5%, and (3) longer-term inflation expectations continue to be well anchored.
19/06/2013	✓	The FOMC was more hawkish than we had expected.

31/07/2013	✓	included a small dovish tweak to the language describing its expectation for the stance of monetary policy in the future...The Committee chose to "reaffirm 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," a slightly stronger statement than the previous language in which the Committee simply "expected" that this would be the case.
18/09/2013	✓	The FOMC unexpectedly decided to leave its monthly rate of asset purchases unchanged for both Treasuries ($45bn) and MBS ($40bn) at today's meeting.
30/10/2013	✓	The October FOMC statement was just a bit more hawkish than expected.
18/12/2013	✓	FOMC Unexpectedly Tapers
29/01/2014	✗	There were no major surprises in the January FOMC statement.
30/04/2014	✗	The April FOMC statement was very close to expectations, containing only modest changes to the economic assessment.
18/06/2014	✓	Today's FOMC meeting was a touch more dovish than we expected.
30/07/2014	✓	The July FOMC statement showed more of an acknowledgement of firming inflation and reduction in downside risks to inflation than we had expected.
17/09/2014	✗	As overwhelmingly expected, the monthly pace of asset purchases was reduced by a further $10bn, to a level of $15bn, taking effect at the start of October....The Committee released updated exit principles, which were in line with guidance provided in the last two sets of meeting minutes, as well as our expectations.
29/10/2014	✓	On net, the October FOMC statement was a modest hawkish surprise
17/12/2014	✗	Taken together, the December FOMC statement, Summary of Economic Projections (SEP), and Chair's press conference were fairly close to expectations.
28/01/2015	✗	January FOMC Statement Close to Expectations
18/03/2015	✓	The March FOMC statement and the updated "dot plot" were more dovish than expected.
29/04/2015	✗	The April FOMC statement was roughly in line with expectations.
29/07/2015	✗	the new language is a small tweak and does not suggest, in our view, that Fed officials are reading recent labor market developments in a wholly different way....In our view these changes are neutral for the policy outlook.
17/09/2015	✗	The bottom line from the meeting was a more definitive shift to a December baseline for liftoff—where we have assumed Chair Yellen was already—but few signals of a lengthier delay at this point.
28/10/2015	✗	We continue to expect the committee to follow through with a rate hike in December.
16/12/2015	✗	The FOMC raised the funds rate to 0.25-0.50%, as widely expected.
27/01/2016	✗	*No short quote to support but there is no surprise*
16/03/2016	✓	The March FOMC statement indicated that Fed officials remain concerned about the global economic and market backdrop, despite the easing in financial conditions over the last month. The statement noted that "global economic and financial developments continue to pose risks"—a more cautious assessment than we had anticipated.
27/04/2016	✗	*No short quote to support but there is no surprise*
15/06/2016	✗	Much of today's FOMC meeting was close to expectations.
27/07/2016	✓	Accordingly, we modestly raised our subjective odds of a rate hike at the September FOMC meeting to 30% from 25% previously.
02/11/2016	✗	We interpret the small revisions to the statement as moving the committee incrementally closer to a December rate increase, and still see a 75% chance of a hike next month.
14/12/2016	✗	The FOMC raised the funds rate range today, as widely expected....We continue to expect the committee to raise the funds rate three times over the course of 2017.
01/02/2017	✗	We see limited implications for the near-term policy outlook, and continue to assign a 35% chance that the committee raises rates as soon as the March 14-15 meeting.
15/03/2017	✗	The FOMC raised the funds rate target range, as widely expected.

03/05/2017	✗	The FOMC left the target range for the funds rate unchanged at its May meeting, as widely expected.
14/06/2017	✓	In light of these hints, we now think that there is only a 10% probability that the next rate hike will come in September, a 10% probability that it will come in November, and a 50% probability that it will come in December. Cumulatively, this implies a 70% probability of at least three hikes this year....We have updated our balance sheet runoff projections to reflect the newly announced series of caps. The changes relative to our earlier projections are minor, with the balance sheet shrinking a bit more slowly than we previously expected and reaching its terminal size in late-2020 instead of mid-2020.
26/07/2017	✗	The FOMC left the target range for the funds rate unchanged at its July meeting, as widely expected.
01/11/2017	✓	The main surprise was the upgrade of the growth assessment to "solid" for the first time since January 2015. The statement made no changes to the balance of risks ("roughly balanced") or to the inflation assessment ("below 2 percent"), but it did add that core inflation "remained soft." We view the statement as broadly consistent with a December hike, provided that economic conditions do not worsen appreciably. Based on this as well as the strong recent data, we increased our subjective odds of a December hike to 85% (from 75% previously).
13/12/2017	✗	we continue to expect a total of four hikes in 2018....The FOMC raised the funds rate target range, as widely expected. ...Overall, the statement was broadly similar to our expectations, and we still expect rate hikes to continue at a quarterly pace next year.
31/01/2018	✓	The failure to upgrade the balance of risks was a somewhat dovish surprise relative to our expectations. Offsetting this, we would highlight the more upbeat inflation outlook, as well as the addition of the word "further" to describe expected rate increases. Taken together, we continue to expect four rate hikes this year, and we are increasing our subjective odds of a March hike to 90% (from 85% previously).
21/03/2018	✓	The economic projections were slightly more hawkish than we expected, with a 0.5% boost to the median level of 2020 GDP, lower unemployment in 2018-2020, and—for the first time—a modest core inflation overshoot in 2019-2020.
02/05/2018	✗	As widely expected, the FOMC left the funds rate target range unchanged at 1.50-1.75% at its May meeting. The key change in the post-meeting statement was the recognition that headline and core inflation have "moved close to 2 percent," an upgrade that was widely expected but important nonetheless. We left our subjective odds of a June hike unchanged at 90%.
13/06/2018	✗	The outcome of today's meeting was close to our expectations but hawkish relative to market expectations, evidenced by the sell-off in the bond market after the release of the FOMC statement and Summary of Economic Projections at 2pm. Each piece of today's meeting leaned somewhat hawkish.
01/08/2018	✗	We do not believe today's statement has major implications for near-term policy, and we continue to expect a hike at the September meeting, with subjective odds of 85%.
26/09/2018	✗	The FOMC raised the target range for the funds rate to 2-2.25% at its September meeting today. The widely expected rate hike is the eighth in the cycle that began in December 2015....We continue to expect 4 rate hikes in total in 2018 and 4 more in 2019 for a terminal rate of 3.25-3.5%, with the risks skewed to the upside. Our subjective odds of a hike at the December meeting are 85%.
08/11/2018	✗	The FOMC left the funds rate target range unchanged, as universally expected. The changes to the post-meeting statement were minimal and broadly in line with our expectations.

19/12/2018	✓	the meeting was a bit more dovish overall than we expected. Chairman Powell attributed the shift largely to the tightening in financial conditions and softer-than-expected inflation numbers....We have lowered our probabilities of rate hikes to 30% (down 15pp) in 2019Q1, 65% (down 10pp) in Q2, 55% (down 15pp) in Q3, and 55% (down 5pp) in Q4. The expected value of the number of net hikes in 2019—which considers the probability of hikes as well as a small chance of cuts—is now 1.6, down from 2.0.
30/01/2019	✓	We viewed both the January statement and press conference as dovish and have reduced our subjective odds of a March hike to less than 5% (from 10% previously) and our Q2 hike probability to 25% (from 55% previously).
20/03/2019	✓	In light of the stronger than expected consensus for no hikes in 2019, we now expect the next rate hike to come in 2020Q1, instead of 2019Q4. We have reduced our probabilities of a rate hike in 2019H2 and boosted our probabilities of a rate hike in 2020H1, as shown in Exhibit 2.
01/05/2019	✓	Today's meeting further reduced the odds of a rate cut in response to low inflation, which we already saw as quite unlikely.
19/06/2019	✓	The Fed left the funds rate unchanged but delivered a dovish message, even relative to market expectations. Seven of the 17 participants projected 50bp of easing this year, and the statement provided an unqualified "will act as appropriate" signal that cuts are now likely....We now expect cuts in July and September, as well as an end to balance sheet runoff in July.
31/07/2019	✗	We see the results of today's meeting as consistent with our baseline expectation that easing will end with a second 25bp cut, for a total funds rate recalibration of 50bp.
18/09/2019	✓	But the biggest surprise of the meeting was the forceful pushback not just to potential future cuts but even to today's cut. ...In light of the strength of the opposition to the cut at today's meeting, we have shaved our odds of an October cut slightly. We now see a 65% chance of a 25bp cut, a 5% chance of a 50bp cut, and a 30% chance of no change at the October FOMC meeting (vs. 70%/10%/20% previously).
30/10/2019	✓	We had expected the FOMC to use today's meeting to clarify that it does not anticipate further easing, and the messages from the statement and the press conference were even firmer than we had anticipated.
11/12/2019	✗	The December meeting was broadly in line with our expectations.

Table 10: Categorisation of FOMC meetings surprises

FOMC Date	Explanation	Assessment Quote	Preference Quote
30/06/1999	✓	Despite the tone of the statement and the lack of a bias, we continue to expect that Fed officials will tighten again later this year...Third, the current environment of above-trend growth and growing pressure on labor supplies is apt to persist. Thus, the FOMC is likely to conclude that one 25-basis-point move is not a sufficient antidote against the risk of over heating.	NaN
24/08/1999	✓	The statement that accompanied the action, however, was a bit friendlier than expected, implying that Fed officials believe that the steps they have taken this summer will be sufficient to prevent a rise in inflationary pressures.	NaN
02/02/2000	✓	The only surprise in the Federal Open Market Committee's decision to boost interest rates by 25 basis points and to voice concern about inflation risks was the moderate tone of its statement given recent labor cost acceleration. Although this statement reinforced our belief that Fed officials would prefer to move slowly, persistent signs of strength in the economy will probably convince them to tighten again by 25 basis points at the March 21 FOMC meeting.	NaN
27/06/2001	✓	US central bankers this week adopted a more cautious easing strategy, apparently on a view thatthe cumulative weight of past rate reductions soon will revive domestic demand and incomes.	NaN
18/03/2003	✓	However, nobody expected the Committee to suspend the balance of risks statement that has been a fixture in its statements since early 2000....Our interpretation of the Fed's statement, reprinted in full below, is as follows:...Against this baseline view, labor market weakness is what most disturbs the Committee. Disappointments in the labor market were the only ones singled out in the statement, as if to imply that signs of stagnation in manufacturing, sharp drops in consumer confidence, and shaky retail sales were more easily explained as the result of geopolitical uncertainty and possibly poor weather.	NaN

25/06/2003	✓	The decision to cut rates only modestly may be understandable given the widespread expectation that growth will improve incoming quarters—which we share—and likely concerns among FOMC members that conventional monetary policy might run out of room to cut further.	NaN
09/12/2003	✓	NaN	They recognized the better growth outlook but reiterated their intention to keep interest rates low until the excess slack in the economy has been used up and inflation has risen. On our forecasts, this is unlikely to happen until 2005. The statement underscores that the Fed has moved to a more 'reactive' policy regime. Although the markets gave a thumbs-down to this shift, we believe it is, in fact, appropriate when core inflation is running below target.
04/05/2004	✓	In addition to the change in the 'patient' part of the statement – the main focus of market interest prior to today – we found three points noteworthy: 1. Little inflation anxiety. The committee appears to be fairly relaxed regarding the inflation outlook. Although the statement notes the higher recent inflation numbers, it also says that long-term inflation expectations 'appear to have remained well-contained.' Incidentally, this suggests that the Fed is putting more weight on consumer inflation expectations than on break-even inflation between nominal and indexed Treasuries. Using the University of Michigan's 5-year median measure, the former currently stand at 2.7%, in the lower part of the 2.5% to 3.1% range seen over the past five years. Meanwhile, break-even inflation in the 10-year sector has trended up to about 2.3% from an average of less than 2% in prior years.	NaN

10/08/2004	✓	but the tone of the statement was more hawkish than expected in two ways. First, its appeal to energy prices as the main reason for recent softness in the economic data may leave the central bank between a rock and a hard place. If energy prices keep rising, does the FOMC really stop tightening in the face of a rising threat to inflation, and if they fall does that not also assure further tightening by removing the cause of recent weakening—unless, of course, it isn't the cause. Which brings up the second point: In evaluating incoming information, the central bank continued to stress its obligation to assure price stability, leaving in place the implication that departures from a 'measured pace' are more likely to occur on the side of faster tightening. The bottom line—25 basis points per meeting is the path of least resistance, at least as the FOMC now sees it.	NaN
28/03/2006	✓	NaN	Although the statement was largely in line with expectations, it implied that (1) inflation data are likely to become more important in coming months, (2) the detailed minutes from this meeting may contain more information (and thus have a bigger impact) than usual, (3) the next FOMC statement is more likely to be a positive market event. We continue to expect the next Fed hike to be the last for this cycle. ...We draw three broader implications from the FOMC statement: 1. The focus on inflation data is likely to increase in coming months. Numerous FOMC members, including the Chairman himself, have already noted that policy is becoming more data-driven as the fed funds rate normalizes. Following first quarter real GDP growth that we expect to be in the range of $4\frac{1}{2}\%$ (annualized), some moderation is highly likely, as the statement implies (our forecast is that real GDP will expand at a 4% pace in Q2). If growth slows...

08/08/2006	✓	Although we expect significant slowing in US growth, we thought the FOMC's outlook for growth—essentially at trend over the next year and a half—coupled with recent evidence that labor costs have accelerated more than previously thought, pointed to another rate hike....In our view, the tightening in monetary policy has probably ended. This may seem like an odd statement, coming from the guys who held out the longest for the rate hike that didn't happen. However, as already noted, this expectation was predicated on how we thought Fed officials would read the situation, not on our forecast. Our own view is that the economy will lose momentum significantly over the remainder of 2006 and grow at a below-trend pace through 2007. Given this outlook, and the FOMC's apparent willingness to live with the current constellation of inflation data, we would need to see significant upside surprises to forecast another tightening in the funds rate. Accordingly, we expect the...	NaN
21/03/2007	✓	The committee did not mention problems in the subprime mortgage market, either because they are seen as contained or because they have not yet become convinced that a policy response is in order on this account. ...While retaining its concern that inflation is the "predominant policy risk," the committee recognized more explicitly than before that the next policy move might not be a rate hike, which says implicitly that economic weakness can quickly develop to the point of requiring a policy response. ...	NaN

31/10/2007	✓	The Federal Open Market Committee cut its federal funds rate target to $4\frac{1}{2}$%, as we had long been expecting. However, the statement was more hawkish than anticipated in several respects: First, Kansas City Fed President Hoenig's dissented from the rate cut decision in favor of unchanged rates. Second, the committee chose to restore the balance of risks statement by saying that, "after this action, the upside risks to inflation roughly balance the downside risks to growth." Third, in the inflation paragraph they noted that while core inflation had improved during the year "recent increases in energy and commodity prices, among other factors, may put renewed upward pressure on inflation." Fourth, they characterized growth in recent quarters "solid" rather than moderate. This is obviously justifiable in light of this morning's stronger-than-expected GDP report, which produced a second consecutive ...	NaN
11/12/2007	✓	The statement can be best described as stingy—moving away from explicitly describing the risks as "balanced" but not willing to tilt the risk assessment toward noting that the downside risks to growth are the main threat to the economy. This was despite their acknowledgment that "economic growth is slowing" and "strains in the financial market have increased in recent weeks". Instead, the FOMC noted that the recent events have "increase[d] the uncertainty surrounding the outlook for economic growth and inflation." This phrasing looks like an attempt to split the difference between a "roughly balanced" and a weak-growth risk assessment. However, at this point the risks appear clearly tilted toward slower growth. Remaining concerns about inflation on the committee seem to be preventing a more explicit recognition of the growth risks. Specifically, the statement continues to worry that "elevated energy and commodity prices ... may put upward pressure on inflation"	NaN

22/01/2008	✓	A key question in this regard is what motivated the timing of the rate cut. With less new information on the economy now than earlier in the month, the possibilities include either heightened concern about financial stability or, more likely, the latest sell-off in global equities....But with only eight days to go until the scheduled decision and in the absence of much new information about the real economy, the FOMC decided to cut by 75 basis points at 8.20 this morning. There are three possible reasons for this decision: 1. The FOMC may have reacted to new, publicly available information pointing to a more adverse economic outlook...2. The FOMC may have private information about the health of the financial system suggesting a more adverse outlook. We have no reason to believe that this is the case...3. Finally, the FOMC may simply have reacted to the plunge in foreign stock markets yesterday, and indications that US markets would open sharply lower. In our view, this is by far the most likely explanation.	NaN
18/03/2008	✗	NaN	NaN
09/08/2011	✓	NaN	We have changed our call because today's statement suggests that the committee's reaction function to incoming economic news is more dovish than we had previously thought.
21/09/2011	✗	NaN	NaN

02/11/2011	✓	The Fed upgraded its language about the economy's performance a touch, indicating that "economic growth strengthened somewhat in the third quarter." This presumably moves the committee a tad further away from renewed easing. Bernanke also cautioned that in weighing the pros and cons of additional easing, the FOMC would need to consider whether "those tools [are] likely to be sufficiently effective, or [whether] they bear costs and risks that would make them less effective." Finally, Bernanke promised only that "we will take action to make sure the recovery continues, and that we have stable prices in the US." Although we are somewhat unsure how high the bar is for saying that "the recovery continues"–in particular, whether this means only that real GDP growth needs to be positive or whether the recovery needs to be strong enough to push down the unemployment rate–to us this does not sound like a statement that the Fed is about to embark on a concerted effort to speed up the pace of economic growth in the absence of a renewed meaningful slowdown.	NaN
25/01/2012	✓	NaN	The message is that the core of the FOMC is at least as dovish, perhaps even more dovish, than we had thought previously....The easing action did not come in response to a deteriorating economic outlook. On the contrary, "central tendency" forecasts for growth and inflation were little changed from November and those for the unemployment rate were moved down slightly (see Exhibit 1)....This is probably a good time to point out that as a group, the FOMC voting membership has shifted in a more dovish direction in 2012, as three noted hawks–President Plosser of Philadelphia, President Fisher of Dallas, and President Kocherlakota of Minneapolis–have rotated off the voting membership and only one of the new members–President Lacker of Richmond–is generally perceived as hawkish....The rate commitment implies a more dovish reaction function than the Fed has followed historically. Exhibit 2 below shows the funds rate prescribed by a "Taylor rule" ... This exhibit shows that if the FOMC reacted to the data in the same way that it did historically, it would likely hike in early 2014 under its forecasts.

25/04/2012	✓	Fed officials revised up their forecast for core inflation and down their forecasts for unemployment, in both cases by larger amounts than we expected. Likely as a result, some participants also lifted their forecasts for the federal funds rate. ...the committee noted “some signs of improvement” in the housing market, and said that it expects growth to “pick up gradually”. Both phrases reflect known information, but the additions give the statement a slightly more upbeat tone than we had anticipated....Likely as a result of the lower unemployment rate trajectory and higher core inflation forecast, several officials also revised up their projections for the federal funds rate.	NaN
20/06/2012	✓	changes to the committee’s economic outlook were larger than expected, with significant downgrades to real GDP growth and employment....The FOMC shaved its real GDP growth numbers and pushed up its unemployment rate forecasts even more than we had expected....	second, the FOMC put in place a more explicit easing bias in the statement, saying that it ”is prepared to take further action” should the recovery–and the job market in particular–continue to disappoint....Fed officials also added that promoting a ”sustained improvement in labor market conditions” could be justification for easing (in addition to promoting ”a stronger economic recovery”)
01/08/2012	✗	NaN	NaN
13/09/2012	✓	NaN	Today’s statement–which reveals aggressive action paired with a somewhat improved description of the current state of the economy–clearly represents a dovish shift in the committee’s reaction function....Today’s policy action signals a dovish shift in the committee’s reaction function, and on net is more aggressive than consensus expectations prior to the report.
12/12/2012	✗	NaN	NaN

19/06/2013	✓	Second, the committee moved down its unemployment rate forecasts by about 0.2 percentage points throughout the forecast horizon. Third, the committee noted that downside risks had "diminished" since last fall; while that is obvious at some level, it is noteworthy that they chose to emphasize it. Fourth, although inflation projections moved down, the chairman was somewhat dismissive of the recent inflation drop, attributing much of it to special factors....the mid-point of the central tendency for the unemployment rate was lowered by 0.15 percentage point to 7.25% at the end of 2013, 0.2 point to 6.65% at end-2014 and 0.25 point to 6% at end-2015. In our view this upgrade of the labor market outlook is surprisingly large given that the unemployment rate has only declined 0.1 point since the last economic projections at the March meeting.	NaN
31/07/2013	✗	NaN	NaN
18/09/2013	✗	NaN	NaN
30/10/2013	✓	NaN	The FOMC's overall assessment of the economy was only marginally changed in the face of recent events, tighter financial conditions were no longer listed as an explicit worry, and there was no shift in language to more directly indicate a later expected date of the first reduction in asset purchases....1. Despite disappointing labor market data in recent months, the language around labor market conditions was tweaked only slightly. Also, in spite of the October government shutdown and debt ceiling fight, the Committee left its statement unchanged that "fiscal policy is restraining economic growth."
18/12/2013	✓	NaN	The FOMC decided to cut the pace of its asset purchases to $75bn/mo, but offset this with a qualitative enhancement to the forward guidance. The Committee's assessment of the economic outlook was somewhat more upbeat. We see today's statement as slightly hawkish relative to expectations. The fact that President Rosengren dissented and President George did not is consistent with that.

18/06/2014	✓	NaN	Chair Yellen downplayed the recent firmer inflation data and signaled some willingness to let inflation overshoot the 2% target if the employment side of the mandate continues to disappoint....In particular, Yellen signaled some willingness to let inflation overshoot the 2% target if the employment side of the mandate continues to disappoint by citing the "balanced approach" to the Fed's dual mandate. These remarks differed slightly in tone from her April 16 remarks at the Economic Club of New York. Yellen also appeared to downplay the recent firmer inflation data, by stating that "the data we are seeing is noisy" and that "broadly speaking, inflation is evolving in line with the Committee's expectations." She also stressed that wage inflation remains very low "at 2%." Finally, the changes to the Committee's economic assessment were slightly more dovish than we expected, with the recovery in the housing sector still described as remaining slow.
30/07/2014	✓	The July FOMC statement showed more of an acknowledgement of firming inflation and reduction in downside risks to inflation than we had expected.	NaN
29/10/2014	✓	On net, the October FOMC statement was a modest hawkish surprise, as the Committee sees "gradually diminishing" rather than "significant" underutilization in the labor market....The Committee adjusted its assessment of the labor market, noting that "underutilization of labor resources is gradually diminishing." This replaces prior language referring to "significant underutilization," which we view as a modest hawkish shift. In addition, job gains were described as "solid." The assessment of household spending was not downgraded, despite the disappointing September retail sales report. Also, there was no reference made to slower global growth.	NaN

18/03/2015	✓	Overall, we see the March FOMC statement, the new Summary of Economic Projections (SEP), and the Chair's press conference as more dovish than expected. In particular, the combination of a substantial reduction in the dots and a broadly dovish set of economic projections suggests that liftoff is considerably more likely in September than in June....But several details gave the statement a dovish tilt. First, the Committee downgraded its assessment that growth was "solid" to note that it had "moderated somewhat." Second, the statement noted that export growth had weakened, giving new prominence to the expected drag from net trade. Third, the guidance indicated that a hike would be appropriate when the FOMC is reasonably confident that inflation will move back "to" instead of "toward" its 2 percent objective, a subtly higher bar than the language Yellen had previously used. Fourth, the statement noted that the Committee had not yet decided on the timing of the first hike and Yellen clarified that removing "patient" did not indicate that the Committee would be "impatient"	NaN
16/03/2016	✓	Fed officials indicated a more cautious approach to the near-term policy outlook at today's meeting....Comments from Fed Chair Yellen at the post-meeting press conference suggest the shift relates to: (1) concern about the transmission of policy changes through financial markets after the volatility earlier this year; and (2) a more dovish take on the recent turn higher in core inflation. We are keeping our funds rate forecasts unchanged—we still expect three rate increases this year—mostly because we are more confident that the inflation pickup is for real. However, the risks to our funds rate call tilt clearly to the downside....The revisions to the funds rate projection in the SEP were therefore larger than can be explained with a standard policy rule. Does this imply a change in the committee's reaction function? Not with regards to the FOMC's goals, in our view. ... We take these comments to mean that policymakers' goals have not changed, but they now see them as more difficult to achieve—in other words, the shift in the SEP was about "headwinds" not "running hot".	NaN

27/07/2016	✓	The FOMC indicated that "near-term risks to the economic outlook have diminished" in its post-meeting statement, likely reflecting the improvement in incoming data and the easing in financial conditions in recent months. We see this phrase as a half step toward the "nearly balanced" language the committee used to describe the outlook late last year, and an effective way to keep its options open for action as early as the September meeting. As a result, we have raised our subjective odds of a hike at the September meeting to 30% from 25% previously; we continue to see a 40% chance that the next hike will come in December—implying a roughly 70% probability of at least one rate increase this year.	NaN
14/06/2017	✓	NaN	Today's FOMC meeting delivered a hawkish surprise to markets that appeared to expect the Fed to react more strongly to a string of three consecutive soft CPI reports. Instead, the FOMC signaled surprising confidence in the inflation outlook, Chair Yellen reiterated the Committee's desire to forestall excessive labor market overheating, and the dots were largely stable....Several hints also strengthened our confidence that the Committee will announce balance sheet normalization in September. First, the FOMC statement said that normalization would begin this year as long as the economy evolves as expected, dropping the requirement from the May minutes that the path of the funds rate also evolves as expected. Second, the release of additional operational details suggests that the start is not far off. Third, Yellen said that the beginning would come "relatively soon." We expect the July statement to include an even more explicit nod to a September announcement..

01/11/2017	✓	The main surprise was the upgrade of the growth assessment to "solid" for the first time since January 2015. The statement made no changes to the balance of risks ("roughly balanced") or to the inflation assessment ("below 2 percent"), but it did add that core inflation "remained soft." We view the statement as broadly consistent with a December hike, provided that economic conditions do not worsen appreciably. Based on this as well as the strong recent data, we increased our subjective odds of a December hike to 85% (from 75% previously)....The main surprise was the upgrade of the growth assessment to "a solid rate" from "rising moderately." The statement noted that this growth occurred "despite" disruptions from the hurricanes, and it explicitly attributed the decline in September payroll employment to the storms. This return to a "solid" pace of growth—last referenced in the January 2015 statement—underscores the Committee's more positive view on real activity, following softness in parts of the economy over the last two years.	NaN
31/01/2018	✓	The failure to upgrade the balance of risks was a somewhat dovish surprise relative to our expectations. Offsetting this, we would highlight the more upbeat inflation outlook, as well as the addition of the word "further" to describe expected rate increases. Taken together, we continue to expect four rate hikes this year, and we are increasing our subjective odds of a March hike to 90% (from 85% previously).	NaN
21/03/2018	✓	The economic projections were slightly more hawkish than we expected, with a 0.5% boost to the median level of 2020 GDP, lower unemployment in 2018-2020, and—for the first time—a modest core inflation overshoot in 2019-2020.	NaN
19/12/2018	✓	But there were also dovish changes we did not expect, such as lowering the peak rate of core inflation to 2%, adding a second reference to global economic and financial developments, and suggesting a bit more "room to run" with slightly higher potential growth.	NaN
30/01/2019	✓	Powell explained that increased downside risks from slowing growth abroad, unresolved government policy issues, tighter financial conditions, and weaker survey data warrant the committee's new patient, wait-and-see approach to future policy changes.	The removal of the hiking bias from the statement and the increased emphasis on inflation have raised the bar for hiking in the first half of this year.
20/03/2019	✗	NaN	NaN

01/05/2019	✓	Second, on inflation, Powell emphasized that core inflation “actually ran pretty close to 2 percent for much of 2018” and attributed the recent decline largely to “transitory factors” influencing categories such as portfolio management and apparel, as we have also emphasized. He pointed as an example to the case of cell phone services in 2017, when Fed officials forecasted that the drop in inflation would be temporary and were proven correct. To help look through these transitory factors, Powell pointed to the Dallas Fed trimmed mean measure, which has continued to run at roughly 2%.	NaN
19/06/2019	✓	Second, the tone of the June press conference was much more dovish relative to the May press conference, at which Powell refused to discuss cases in which the Fed might cut rates and did not express immediate concern about downside risks to inflation expectations....Powell also offered a list of uncertainties that could warrant accommodative policy, ranging from global growth and trade policy to relatively minor headwinds such as the grounding of the Boeing 737 MAX and the drop in oil prices (-$10 since the May meeting).	Our reading of the meeting suggests that growth concerns are the primary justification, with low inflation lowering the hurdle required for Fed action. After all, Powell kicked off the press conference by emphasizing the Committee’s “overarching goal” of sustaining the expansion.
18/09/2019	✗	NaN	NaN
30/10/2019	✓	NaN	The bar that Powell set for additional cuts—developments “that cause a material reassessment of our outlook”—appears to be quite high. In practice, we think this would likely mean a few pieces of very weak data or a combination of trade war escalation, an adverse market reaction, and fairly bad data. We therefore see just a 15% chance of a cut at the December meeting.

Conclusion

This section briefly concludes the thesis.

Monetary policy is important for the economy. Even more so in an era in which central banks have been given sole *de facto*, if not *de jure*, responsibility for managing the business cycle. In this thesis, I have examined two major aspects of monetary policy.

The first, monetary policy communication, was dealt with by the first two chapters. In the first chapter, I investigated which parts of central bank communication affect the higher moments of expectations embedded in financial market pricing, and found that the relevant communication in the case of the Bank of England is primarily confined to the information contained in the Q&A and Statement, rather than the longer Inflation Report. In the second chapter, I answered a narrower policy question: how can central banks change their communication in order to receive greater newspaper coverage, if that is indeed an objective of theirs. Using computational techniques, I found several aspects of writing style could be associated with greater news coverage for central bank communication.

The second aspect of monetary policy, reaction functions, was examined in chapters three and four. In chapter three I tried to match the comovement of volatility and central bank aggressiveness apparent in the US data using a variety of approaches concerning monetary policy under uncertainty. The failure of these approaches to match the magnitude of reaction function variation led me to speculate on alternative sources of uncertainty that I believe should be more prevalent in the literature on monetary policy. In chapter four, I examined the implications for monetary policy shock identification of reaction function variation. I showed that reaction function surprises are fundamentally different from monetary policy shocks in their effect on the economy, are likely endogenous to the state, and unable to removed using current orthogonalisation procedures. As a result monetary policy surprises should not be used to measure the effect of a monetary policy "shock" to the economy.

What does this analysis have to say about current policy? This paper is, unfortunately, timely. Many central banks are facing significant above-target inflation for the first time in 30 years. Moreover, many central banks have been accused of miscalculating the state of the economy and the shocks that have hit it. There remains, of course, uncertainty about the correct course of action, but the balance of opinion among policymakers suggests tightening, perhaps aggressively, is the necessary course of action. Policymakers appear to be shifting very quickly into a more-hawkish, anti-inflation mode.

This thesis can only hope to offer some (very) small pieces of advice to policymakers navigating the current economic environment. Communicate your intentions clearly (Chapter 2), being aware that communications can move the entire distribution of beliefs, particularly in Q & A's (Chapter 1). When deciding your policy, know that the estimates you have for how your instruments affect the economy are uncertain and may be based on endogenous variation (Chapter 4), so fine-tuning your response is not likely to be possible. Moreover, be aware that the economy has a structure that shifts, meaning your reaction to inflation today may need to be different than it was in the past, and that the credibility you have earned can be used to avoid undue volatility when fighting inflation (Chapter 3).