EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

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The long-run information effect of central bank communication

ECB - Lamfalussy
Fellowship Programme

No 2363 / January 2020

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Abstract

Why do long-run interest rates respond to central bank communication? Whereas existing explanations imply a common set of signals drives short and long-run yields, we show that news on economic uncertainty can have increasingly large effects along the yield curve. To evaluate this channel, we use the publication of the Bank of England's Inflation Report, from which we measure a set of high-dimensional signals. The signals that drive long-run interest rates do not affect short-run rates and operate primarily through the term premium. This suggests communication plays an important role in shaping perceptions of long-run uncertainty.

Keywords: Monetary Policy, Communication, Machine Learning

JEL Codes: E52, E58, C55

Non-technical summary

Central banks communicate a lot nowadays. And they do so in a lot of different ways including via speeches, official reports, announcements with press conferences, research papers, and, increasingly, via social media such as Twitter, YouTube and other new media channels. This a relatively new phenomenon; 25 years ago, many central banks operated with relatively little communication.

There is a growing body of evidence that such communication, at least in the case of the most major forms, give rise to changes in asset prices in financial markets. This suggests that the central bank releases new information that causes the beliefs of the financial market participants to change. However, it is not entirely understood what information released by the central bank is driving such effects.

For example, announcements concerning monetary policy might be expected to affect expectations of monetary policy and the behaviour of the economy over the next year or two. However, studies show that such announcements affect interest rate expectations much further out into the future such as five or ten years.

Some of the existing explanations focus on the following idea. Central banks, when they make these announcements, release information about the most likely short-run developments in the behaviour of the economy and this information changes financial market traders' beliefs about such developments. The effect on the longer-term prices comes when this short-run information also leads to changes in longer-run expectations. This could be because the new information is about something that is very persistent and hence that new information is important when forming beliefs into the more distant future. Or it could be because, in reacting to the short run information, the traders take actions which move the prices of longer horizon assets which makes it appear *as if* beliefs further into the future have reacted. In either case, there should be common information that moves the different asset prices.

We argue that communication about uncertainty can explain the reaction of future expectations more easily. Such uncertainty signals can give rise to relatively small effects on near-term expectations but that grow as we try to form beliefs about a future that is further and further out. This is useful as most macroeconomic developments that the central bank considers are likely not persistent enough to explain the movements of beliefs about ten years into the future.

We examine this idea in the case of the Bank of England's Inflation Report (IR) release. This quarterly report contains the Monetary Policy Committee's (MPC) forecast for the next three years as well as a description of the main stories driving that forecast. And it is an important release of information in that it regularly leads to relatively large updates to beliefs about the future.

The fact that the IR contains such detailed information on what information is released allows us to use techniques from machine-learning to directly test whether the information which drives the different reactions is the same. We find evidence that suggests that *different* information drives the effects at short and long horizons. Moreover, the biggest effects suggest it is related less to beliefs about the most-likely evolution of the economy and more to the risks around that evolution. Taken together, these findings are consistent with, at least in this particular case, the importance of our proposed uncertainty channel.

1 Introduction

For the last two decades, central banks have increasingly used public communication to support their policy goals, and more specifically to manage the expectations that link the policy rates that central banks control to the market interest rates that determine economic decisions (Woodford 2001, Blinder 2008). As nominal policy rates were cut close to the zero lower bound, communication became a policy tool in its own right. Even as the major economies move towards more normal conditions, academics (Blinder 2018) and policymakers (Draghi 2017) expect communication to remain an important instrument. Understanding the effects of communication is therefore a key issue.

While the academic literature has established that central bank communication moves market interest rates at various maturities (Gürkaynak et al. 2005, Boukus and Rosenberg 2006, Blinder et al. 2008, Carvalho et al. 2016, for example), the channels through which this occurs are often unclear. In particular, there is an ongoing debate about why central bank communication moves *long-run* interest rates well outside the window within which central banks seek to obtain their policy goals.[1] Two recent and important contributions present different explanations. First, Nakamura and Steinsson (2018) argue that this is due to monetary policy shocks transmitting information about economic fundamentals that affects long-run market expectations of economic conditions, termed the *information effect* by Romer and Romer (2000).[2] In contrast, Hanson and Stein (2015) argue that news about short-term policy expectations is propagated to longer-maturity bonds by the trading activity of yield-oriented investors. According to their model, decreases (increases) in short rates induce these investors to switch to (from) longer-maturity bonds, driving the yields on such bonds down (up) through changes in the term premium.

Our first contribution is to draw attention to a new channel through which central bank communication affects long-run interest rates: by providing news on risk and uncertainty around economic conditions, and thereby generating a change in the long-run term premium. This channel operates not by changing long-run expectations of economic conditions, but by changing the perceived variance of those conditions. The existing information effect literature focuses on news that changes market expectations of levels (including of highly-persistent fundamentals). Our theoretical framework shows that such signals should move short-run interest rates by at least as much as long-run rates. In contrast, the model shows that uncertainty signals can move long-run interest rates by more than short-run rates. Furthermore, the effect of uncertainty signals comes via the long-run term premium, which can move independently of short-run expectations. The

[1] This is part of a more general comovement of short- and long-term rates in response to other news as in, for example, Gürkaynak et al. (2005).

[2] The information effect channel could also include news about the central bank's typical reaction function and its information set. For example, economic fundamentals can include expectations about the central bank's inflation target (Gürkaynak et al. 2005) though the latter is likely to be less relevant for the UK which we study as it has an explicit (and constant) inflation target (Gürkaynak et al. 2010).

distinguishes the uncertainty channel from Hanson and Stein (2015).

To test for the relevance of these different channels, we use the publication of the Bank of England's Inflation Report (IR) from February 1998 through May 2015. The IR contains information about the Bank of England's economic forecasts, but rarely provides explicit forward guidance on future policy. Moreover, during our sample period, the IR was published according to a fixed, quarterly schedule one week *after* the announcement of the policy decision. It therefore constitutes a policy-free information shock that allows us to directly assess the market impact of news about the Bank's views without having to decompose a policy change into separate information and policy shock components as in Miranda-Agrippino and Ricco (2015) and Jarociński and Karadi (2019).

Our empirical strategy decomposes each IR into a set of relatively high-dimensional numeric and narrative signals, and identifies which signals drive market rate reactions on IR publication days across different rate maturities and rate components (i.e. expectations and term premia). The numeric signals include the Bank's inflation and GDP forecasts, as well as the variance and skew around those forecasts. To obtain narrative signals, we use latent Dirichlet allocation (Blei et al. 2003, and previously applied in monetary economics by Hansen and McMahon 2016 and Hansen et al. 2018) to represent each Report's text as a distribution over a set of topics. To test whether the narrative contains news beyond the numeric forecasts, we employ a permutation test that strongly rejects the null of no news. This allows us to use the richness of the narrative to assess whether different signals drive short-run and long-run market rates.

Our second contribution is to provide robust evidence in favor of the uncertainty channel as an important factor in explaining why long-run rates react to IR publication. First, signals from higher moments of the forecasts explains an increasing proportion of interest rate variation at longer horizons. Second, we use the narrative signals in three ways to show that uncertainty signals drive the change in long-run interest rates:

1. We identify the narrative signals that drive yield movements at each maturity using a bootstrap procedure. There is little overlap between the signals that drive short-run interest rate changes and those that drive long-run changes. Moreover, the narrative signals that explain long-run rates feature words suggestive of uncertainty.

2. We conduct a placebo test in which we replace the key maturity-specific narrative signals with the key signals from other maturities. The key long-run (short-run) signals explain little to none of the residual variance for short-run (long-run) yields.

3. We repeat the analysis splitting the overall yield into expectations and term premium components; the expectations (term premium) component dominates the overall variation for short-maturity (long-maturity) bonds. The key signals that drive expectations are similar across the yield curve, and different to those that

drive term premiums. The key signals for short-run expectations do not explain changes in the long-run term premium.

The results suggest that while the standard information effect appears to operate on long-run level expectations, it does not explain most of the overall long-run market rate reaction to the IR. Instead, the evidence is consistent with an uncertainty communication channel as the primary source of the reaction, via changes in the term premium. Unlike in Hanson and Stein (2015), this term premium effect is the direct result of news rather than an indirect result of trading activity.

Our findings are also related to a growing empirical literature on the effects of monetary policy events on term premiums. For example, Jarociński and Karadi (2019) find no effect of monetary policy surprises on term premiums in the US. By contrast, a growing literature finds important effects. Bundick et al. (2017) show that shocks to uncertainty about future interest rate decisions yield significant moves in long-term term premiums in the US. And Cieslak and Schrimpf (2019) show that monetary events in the US, Euro Area, UK and Japan are associated with risk preference shocks identified off the movement in term premiums across the yield curve. This literature does not emphasise the role of central bank communication about uncertainty as driving the effects. In fact, the findings could be unrelated to information effects as in the risk premium channel of monetary policy in Drechsler et al. (2018). Tang (2015) and Leombroni et al. (2018) link information effects from central bank communication to long-term interest rate movements with an explicit role for uncertainty. Unlike in our paper, the communication is about level expectations which then interact with given uncertainty that prevails at the time of the signal. In our paper, the central bank signals are themselves about uncertainty. Munday (2019) has recently shown that similar IR signals give influence second and third moments of expectations' distributions derived from options prices.

The main implication of our findings is that central bank communication affects market beliefs about long-run uncertainty. In our view, this channel has been underappreciated in the literature on monetary policy, but is something that central banks should take into account as part of their overall communication strategies, especially as there is increasing evidence that uncertainty has macroeconomic effects (Bloom (2009), Fernandez-Villaverde et al. (2011), Jurado et al. (2015), Baker et al. (2016)). Moreover, such a channel may become particularly important when the central bank is confronted with the lower bound on policy interest rates. Carvalho et al. (2016) find communication continued to have effects on longer-maturity bonds even when shorter-maturity bonds stopped responding once US interest rates reached their zero-lower bound.

This is related to the use of forward guidance. Our analysis pertains mostly to so-called 'Delphic' forward guidance, which Campbell et al. (2012) define as communicating a view on future economic conditions and at the same time describing a likely policy response to that view. Our paper shows that market reactions arise from communicating such views about economic conditions even in the absence of new information on policy reactions. Of course, the study of this channel does not rule out an effect from forward guidance that involves more explicit policy commitments ('Odyssean'). However, such forward guidance was not present the UK's Inflation Report. Moreover, temporary deviations from the typical reaction function are unlikely to move longer-term interest rate expectations unless such guidance signalled a persistent change in an economic fundamental such as the real interest rate or inflation target. Even persistent changes in how the central bank will react to economic conditions are unlikely to explain changes in long-run expectations as both deviations of inflation from target and the output gap are typically forecast to be zero sufficiently far out.

Finally, a broader policy implication is the use of narrative as an instrument for managing expectations. Shiller (2017) introduced the notion of Narrative Economics, which emphasizes the role of narratives in spreading beliefs. In monetary policy, central banks have an important role in shaping public narrative (Haldane and McMahon 2018), and our work suggests this includes narratives about economic uncertainty.

From a methodological perspective, we illustrate how to combine event study analysis with a high-dimensional set of regressors that measure signals from unstructured text data. Our framework allows us to distinguish channels based on heterogeneity in the correlation patterns across yields. Given the popularity of event studies in the monetary policy literature, and the preponderance of text that accompanies many central bank communication events, the methods we propose have broad applicability. For example, Gürkaynak et al. (2018) find that the change in interest rates around central bank communication events in the US is only partially captured by headline numeric information. Our approach allows researchers to directly analyze the 'missing' information not accounted for in traditional analysis.

The paper is organized as follow. Section 2 describes the Inflation Report and the yield curve data; Section 3 introduces a framework that incorporates information effects on levels and uncertainty; and Section 4 explains how we measure the numeric and narrative information in the IR. Section 5 presents our core empirical findings, and Section 6 presents robustness results. Section 7 concludes.

2 IR Communication and the Yield Curve

In this section we motivate the focus on the IR and the information it delivers. We then discuss the interest rate data we use and show using an event study that the Report's publication has an impact on market rates at a range of maturities.

2.1 The Inflation Report

Following the adoption of inflation targeting in the UK in 1993, the IR has been published quarterly by the Bank of England. When the Bank of England was granted operational independence for monetary policy in May 1997, a nine-person Monetary Policy Committee (MPC) was established to set policy on a monthly basis in a way consistent with meeting its inflation target remit. Since independence, the IR is the quarterly communication vehicle for the MPC and contains the Committee's forecasts for GDP growth and inflation. In its own words, the IR "sets out the economic analysis and inflation projections that the Monetary Policy Committee uses to make its interest rate decisions."

Our sample comprises 70 IR publications. It starts in February 1998 when the MPC began publishing forecasts on a consistent basis. During our sample, the IR was published one week after the announcement of the policy rate decision but before the publication of the minutes that explained the decision. Our sample ends in May 2015, after which the Bank moved to a new schedule where the IR is published at the same time as the policy rate and minutes, which makes isolating the impact of communication difficult.

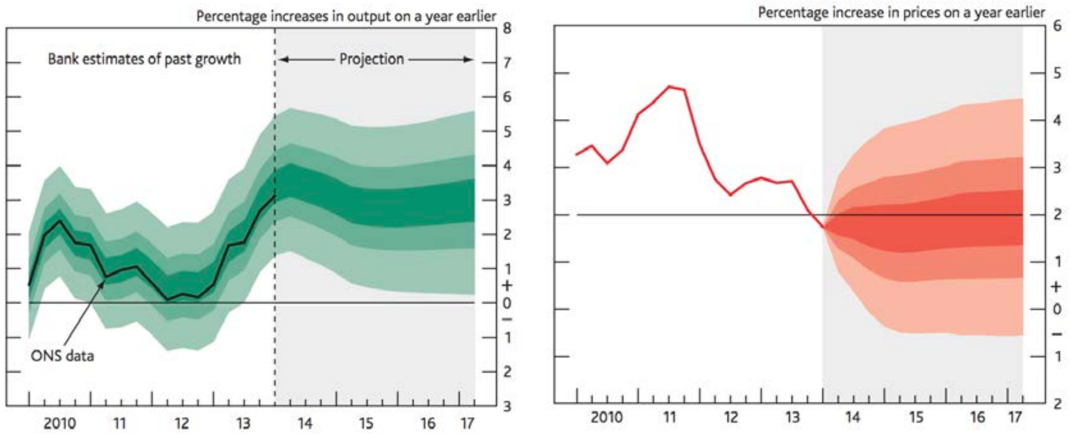


Figure 1: Numeric Information: Fan Charts

Notes: The left-hand figure shows the May 2014 Inflation Report fan chart for the GDP growth projection based on market interest rate expectations and other policy measures as announced. The right-hand figure shows the analagous fan chart associated with the CPI inflation forecast. Source: Bank of England.

The Inflation Report is a rich source of information. Its headline information is modal forecasts for GDP and inflation over the following two years (and from August 2004 onwards for the following three years), as well as distributional information around those modes in the form of a variance and skew. It presents these projections in the form of fan charts, as illustrated in Figure 1.[3] The IR also contains extensive narrative

[3]The numeric values for forecast distributions are made publically available on the IR website alongside the graphical representation as fan charts.

information in the form of written text. In Section 4 we describe how we quantify both the numeric and narrative information in the IR.

The IR report is also important for what it does *not* contain, i.e. formal forward guidance. It is primarily a vehicle for delivering the MPC's views on the development of economic conditions, and it does not provide explicit signals about how it will react to those developments. Two exceptions are August 2013 and February 2014 when the MPC discussed their forward guidance thresholds in the IR. We nonetheless view it as an ideal setting to study how a central bank transmitting information about economic conditions can generate market news.[4] Such an exercise would, for example, not be possible in the US since the Federal Reserve does not publish contemporaneous Greenbook forecasts.[5]

In summary, the IR has several advantages. Its publication schedule is exogenously set; there is no policy rate announcement on the same day as IR publication that could confound its market impact; it contains news just on the outlook; and it has a rich set of potential signals that allow one to dig deeply into the information it conveys.

2.2 Event study description and yield curve data

In order to study the impact of IR publication on market interest rates, we use an event study approach that has now become quite standard in the literature (Cook and Hahn (1989), Kuttner (2001), Bernanke and Kuttner (2005), among many others).[6] Suppose the IR is published on day t in month $m(t)$. Figure 2 depicts the timeline of events. The month $m(t)$ policy rate $i_{m(t)}$ is announced seven days prior to IR publication. At the close of market trading on day $t-1$, the market information set is I_{t-1}^{MK} and we observe some market interest rate. At the close of trade on day t, the market information set is I_t^{MK} and we observe a new market interest rate. The assumption in the event study literature is that $I_t^{\text{MK}} \setminus I_{t-1}^{\text{MK}}$ is generated entirely by the IR's publication, and that this additional information in turn generates the observed change in market interest rates on day t. During our sample, the MPC also engaged in other forms of communication like member speeches, but these do not systematically fall on IR publication days. However, on a number of days in our sample there is also the release of labour market data but we show in Section 6 that this information is orthogonal to the IR and does not affect our results. We, therefore, use the observed change in market interest rates on day t to

[4] Of course, as pointed out in Hansen and McMahon (2018), information about economic conditions can help market participants identify other drivers of the monetary policy decisions and thus may provide information on fundamentals beyond those conditions.

[5] We take a broader view of what Romer and Romer (2000) call the information effect. In their sample, the observed policy rate change was one of the main means by which markets could infer Fed forecasts. In this paper, the "information effect" includes any systematic market reaction to communication about economic fundamentals via any medium.

[6] Reeves and Sawicki (2007) conducted an event study on the effect of IR publication on market rates, and find significant effects. Here we extend their analysis with a longer sample and different market rates.

assess the news contained in IR publication. While the literature increasingly uses tight, intra-day windows around communication events,[7] we use daily changes since it may take markets longer to incorporate the length and complexity of the IR.

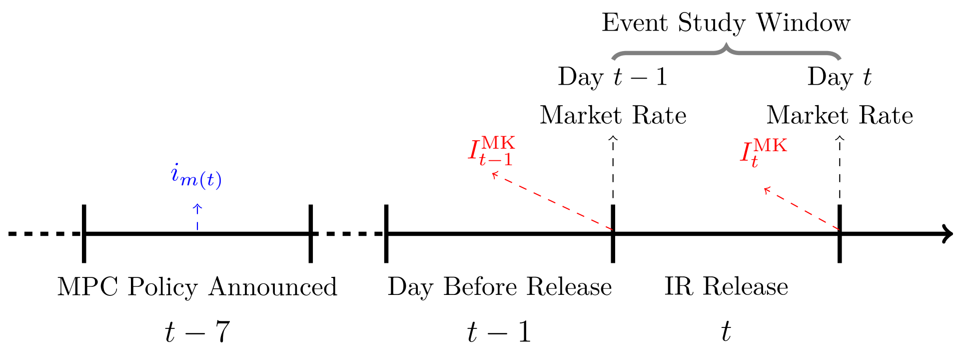


Figure 2: Event Study Time Line for IR Publication on Day t

For our analysis, we use daily data during the period January 1998 to July 2015 on market rates at four different maturities derived from UK government bond prices: the one-year spot rate; the three-year forward rate; the five-year forward rate; and the five-year ahead, five year forward rate (equivalent to the average forward rate five to ten years ahead). We use nominal rather than real rates because obtaining reliable short-run real rates during our sample in the UK is difficult. In Section 6.3 we repeat the anlaysis on medium- and long-run real rates, and show results that are very similar to those with nominal rates.

Under standard asset pricing theory, we can write forward interest rates as a combination of an expectation and term premium. If investors were unconcerned about the risks around future interest rates, the term structure of interest rates —the 'yield curve' —should equal the expected path for short-term interest rates. This is often called the 'pure expectations hypothesis' and arises from the ability of investors to choose between buying a long-term bond or investing in a series of short-term bonds. In practice, however, market interest rates deviate from the pure expectations hypothesis, with the difference referred to as the 'term premium', which we denote by TP.

A general expression for the k-month ahead forward rate on day t is therefore

$$f_{k,t} = \mathbb{E}\left[\, i_{m(t)+k} \;\middle|\; I_t^{\text{MK}} \right] + \text{TP}_k(I_t^{\text{MK}}), \tag{1}$$

and our four particular market rates can be expressed as[8]

[7] Gürkaynak et al. (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018) and Jarociński and Karadi (2019) all use high-frequency identification relying on news about monetary policy in a 30-minute window surrounding scheduled Federal Reserve announcements.

[8] Here we have expressed nominal rates in terms of expectations formed at a monthly frequency for notational convenience; in practice, the forward rates are computed from a fitted curve of instantaneous interest rates, and the 1-year spot and 5-year, 5-year rates are integrals under the curve.

1. 1-year spot rate:

$$i_{0:12,t} = \frac{i_{m(t)} + \sum_{i=1}^{11} \mathbb{E}\left[\, i_{m(t)+i} \;\middle|\; I_t^{MK} \right]}{12} + \mathrm{TP}_{0:12}\left(I_t^{MK}\right) \tag{2}$$

2. 3-year forward rate:

$$f_{36,t} = \mathbb{E}\left[\, i_{m(t)+36} \;\middle|\; I_t^{MK} \right] + \mathrm{TP}_{36}\left(I_t^{MK}\right) \tag{3}$$

3. 5-year forward rates:

$$f_{60,t} = \mathbb{E}\left[\, i_{m(t)+60} \;\middle|\; I_t^{MK} \right] + \mathrm{TP}_{60}\left(I_t^{MK}\right) \tag{4}$$

4. 5-year, 5-year rates:

$$f_{60:120,t} = \frac{\sum_{i=60}^{119} \mathbb{E}\left[\, i_{m(t)+i} \;\middle|\; I_t^{MK} \right]}{60} + \mathrm{TP}_{60:120}\left(I_t^{MK}\right) \tag{5}$$

In some of the analysis, we distinguish between the effect that IR publication has on expectations and term premiums separately. One common way to perform an empirical decomposition of the yield curve into these two components is to use an affine term structure model. Some of these models use only the past behavior of the market yield curve to estimate the decomposition, whereas others supplement that with survey or other additional data on expectations. The specification of the model can lead to quite large differences in the estimates. In our analysis we use an average of four differently-specified models, two of which supplement the yield curve data with survey information.[9]

Table 1 shows the contribution of each component to explaining the overall variance in yields on IR publication days in our sample. The term premium plays an increasingly important role in accounting for movements in interest rates at longer horizons, and is the primary driver of changes in the five-year, five-year forward rate.[10]

[9]Specifically we use the benchmark and survey models in Malik and Meldrum (2016), the model in Vlieghe (2016), and the model in Andreasen and Meldrum (2015).

[10]One reason for the relatively low variance of the 1-year spot rate is that our sample includes a period in which short-maturity interest rates were at the effective lower bound.

Table 1: Variance Decomposition of Market Interest Rate Changes

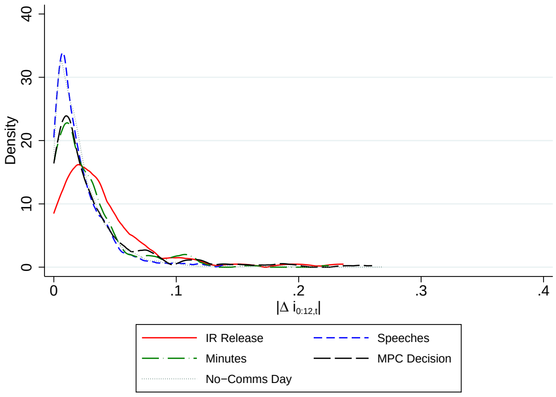
	Total Var	Var(Exp)	Var(TP)	2 x Cov
1 Year Spot	0.0032	0.0024	0.0001	0.0007
	100	75	3	22
3 Year Forward	0.0066	0.0037	0.0009	0.0020
	100	56	14	30
5 Year Forward	0.0050	0.0026	0.0015	0.0009
	100	52	29	19
5 Year, 5 Year Forward	0.0039	0.0018	0.0023	-0.0002
	100	47	59	-6

Notes: This table reports the variance decomposition of different yields by expectation and term premium components on our 70 IR release days. Var(Exp) is the variance explained by expectations; Var(TP) is the variance explained by term premiums; and Cov is the covariance between the components.

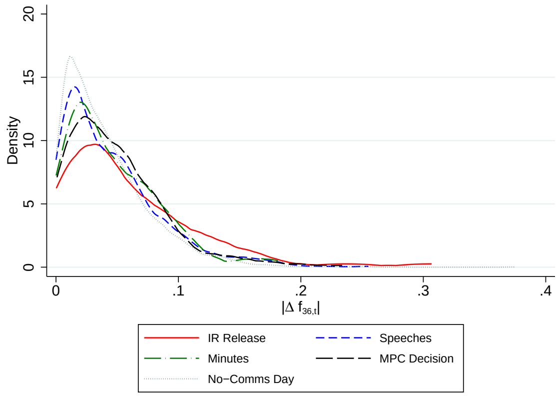
2.3 Event study results

For the event study, we classify each day in our sample of market interest rates according to whether (1) an IR is released; (2) a policy decision from the MPC is announced; (3) an MPC member makes a public speech; (4) minutes from MPC meetings are released; or (5) none of the above. We plot kernel densities of the news (absolute value of the change) in the four yields for each of these five categories in Figures 3a-3d. For one-year spot and three-year forward rates, the IR release dates appear to generate a consistently large amount of news relative to other forms of communication. For longer-horizon rates there is more similarity in the impact across communication events, but there is a mass of large tail moves in interest rates on IR publication dates not present for other communication events. In Appendix B, we conduct a more formal assessment of the relative market impact of the IR using regression analysis which is consistent with these patterns.

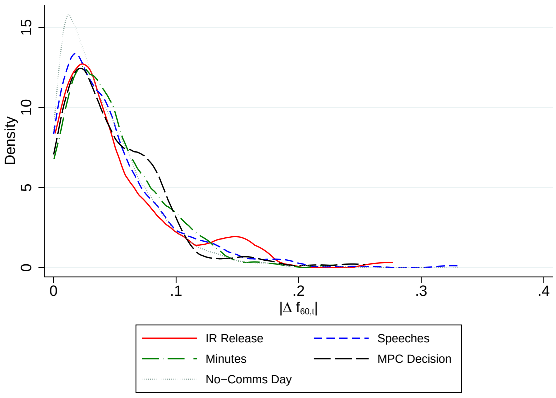
One concern might be that long-run rate movements on IR dates are too small to have policy relevance, so that explaining them is not of first-order importance. One way of assessing the importance of long-run rate moves is by examining the fractions of IR publication dates on which there are large yield moves, as shown in Table 2. For all yields, and despite revealing no policy actions, a quarter or more of IR publication dates lead to at least a five-basis point change, with the proportion growing to nearly a half for three-year forward rates. Moreover, movements of ten basis points are also not uncommon, and there are even occasional twenty basis point moves. All of which suggests that there is indeed meaningful variation in longer maturity rates in our sample.



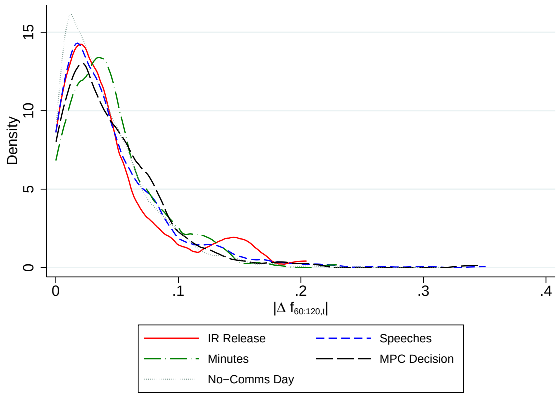
(a) Kernel Density of $|\Delta i_{0:12,t}|$.



(b) Kernel Density of $|\Delta f_{36,t}|$.



(c) Kernel Density of $|\Delta f_{60,t}|$.



(d) Kernel Density of $|\Delta f_{60:120,t}|$.

Figure 3: Kernel Densities of Yield Changes by Type of Communication

Notes: These figures show the kernel-density distribution of changes in expected interest rates at different maturities. We use the Epanechnikov kernel, and set the half-width to the value that would minimize the mean integrated squared error if the underlying distribution were Gaussian.

Table 2: Magnitude of Rate Moves on IR Days

Asset	Days	$\geq$ 5 bps	$\geq$ 10 bps	$\geq$ 20 bps
$\lvert\Delta i_{0:12,t}\rvert$	IR	0.24	0.09	0.01
$\lvert\Delta f_{36,t}\rvert$	IR	0.46	0.20	0.03
$\lvert\Delta f_{60,t}\rvert$	IR	0.36	0.13	0.01
$\lvert\Delta f_{60:120,t}\rvert$	IR	0.27	0.11	0.01

Notes: This table shows the fraction of IR publication dates in our sample on which there are yield moves of at least 5bps, 10bps and 20bps.

3 Theoretical Channels for the Information Effect

An important question is *which* information in the IR might generates market news, especially at longer maturities. In this section we present a simple model of how news about the outlook for economic conditions from the central bank can affect market interest rates. In particular, we include a stochastic form of uncertainty and show that central bank signals about uncertainty shocks can have an increasing impact on rates at greater maturities under a sufficiently high persistence of the underlying volatility. The formal proofs are contained in Appendix A.

This theoretical framework enables us to distinguish between three potential channels through which central bank communication could affect interest rates. We model two information effect channels; one concerning level expectations and the other concerning signals about uncertainty. The third channel, unmodelled here, is an investor demand channel as in Hanson and Stein (2015). The uncertainty channel is distinguished by the correlation structure it induces between signals across yields and their components.

3.1 Model Environment

As in macroeconomic models with forward-looking monetary policy, the central bank is assumed to set nominal interest rates as a function of forecasts of future economic conditions. For simplicity, we denote month-m economic conditions as $\omega_m \in \mathbb{R}$, $\mathbb{E}\left[\, \omega_{m+h} \;\middle|\; I_m^{\text{CB}} \,\right]$ as the central bank's h-period-ahead forecast of economic conditions given its month m information set I_m^{CB}, and ϕ as the central bank's reaction coefficient. The short-term nominal interest rate in month m is therefore

$$i_m = \phi \mathbb{E}\left[\, \omega_{m+h} \;\middle|\; I_m^{\text{CB}} \,\right] + \epsilon_m \tag{6}$$

where the monetary policy shock is assumed to be $\epsilon_m \sim \mathcal{N}(0, \sigma_\epsilon^2)$ and uncorrelated across months. This could be expanded to a vector of state variables $\boldsymbol{\omega}_m$ that included, for example, the expected output gap, expected inflation, and the equilibrium real interest rate, along with an associated vector of reaction coefficients $\boldsymbol{\phi}$. The analysis below would then apply to each component separately, with the overall effect of central bank communication then being the sum over the effect on each component. We also ignore the effective lower bound on interest rates but return to this in Section 6.

We assume economic conditions ω_m evolve according to an AR(1) process

$$\omega_m = \rho \omega_{m-1} + \underbrace{\mu_m + \varepsilon_m}_{= \, v_m} \text{ where } 0 < \rho \leq 1. \tag{7}$$

The shock to economic activity in month m, which we denote v_m, is comprised of two components. The first is μ_m which is drawn independently every month from $\mu_m \sim$

$\mathcal{N}(0, s^2)$. We assume the central bank obtains information that allows it to forecast the level of μ_m (details below). We therefore view uncertainty in μ_m as reducible with improvements in forecasting ability or new information. If the central bank's forecasting ability is high enough, we can even treat μ_m as fully observable.

In contrast, the central bank cannot forecast the level of the second component of the shock, ε_m. This represents the fundamental, or irreducible, uncertainty in the economy. We assume it is drawn independently each month from $\varepsilon_m \sim \mathcal{N}(0, \sigma_m^2)$, where the amount of fundamental uncertainty in the economy σ_m^2 is stochastic.

We follow much of the finance literature and model σ_m^2 as

$$\log \sigma_m^2 = \rho_\sigma \log \sigma_{m-1}^2 + (1 - \rho_\sigma) \log \sigma_0^2 + u_m \text{ where } 0 < \rho_\sigma \leq 1. \tag{8}$$

Here σ_0^2 is some baseline level of uncertainty and we assume $u_m \sim \mathcal{N}(0, \sigma_u^2)$. This assumption generates a lognormal distribution for σ_m^2. It is important to note that, while the level of ε_m is not forecastable, the level of uncertainty σ_m^2 *is* forecastable given information about shocks $u_{m'}$ for $m' < m$. This is an important mechanism that will lead to changes in long-run interest rates in the model.

Central Bank Information Set. In every month m, we assume that the central bank observes ω_m perfectly. In addition, it observes some collection of signals correlated with the means of the forecastable shocks over the forecast horizon $\mu_{m+1}, \ldots, \mu_{m+h}$. Moreover, these signals accumulate every month. So, for example, suppose in month m the central bank observes a first signal about μ_{m+h}. Then, in month $m+1$, it may observe a second signal about μ_{m+h} that it combines with its first signal to form a new, more precise, forecast, and so on through month $m+h$, when we assume that the shock v_{m+h} is fully revealed through observation of ω_{m+h}. This is consistent with the idea that the central bank revises both its mean forecast of future conditions, as well as the forecast uncertainty around that mean, as time proceeds. Rather than model the precise details of the signal structure, we summarize the signals the central bank observes in terms of the updated belief on μ_{m+j} that they induce. More specifically, we assume that

$$\mu_{m+j} \mid I_m^{\text{CB}} \sim \mathcal{N}\left(\widehat{\mu}_{m+j,m}^{\text{CB}}, \left(s_{m+j,m}^{\text{CB}}\right)^2\right) \text{ for } j = 1, \ldots, h. \tag{9}$$

where $\widehat{\mu}_{m+j,m}^{\text{CB}}$ is the central bank's point estimate of μ_{m+j} in month m, and $s_{m+j,m}^{\text{CB}}$ captures the forecast uncertainty around that mean.[11] We assume that the central bank forms more precise forecasts as it accumulates additional signals over time, so $s_{m+j,m+1}^{\text{CB}} \leq s_{m+j,m}^{\text{CB}}$. We also assume the central bank is Bayesian, so $\mathbb{E}[\,\widehat{\mu}_{m+j,m+k} \mid \widehat{\mu}_{m+j,m}\,] = \widehat{\mu}_{m+j,m}$ for all $j > k > 1$.

While the central bank does not receive information that improves its forecast of the

[11] Since μ_{m+j} is assumed to be drawn from a normal distribution, we can assume that the central bank observes normally distributed signals to arrive at normally distributed posterior beliefs.

level of the second component of economic shocks ε_m, we assume that in every month m the central bank observes time-varying fundamental uncertainty σ^2_{m+h} perfectly. This is clearly a strong assumption, as it implies that in every month m the central bank knows perfectly the sequence $u_{m+1}, \dots, u_{m+h}$. We could relax this assumption and instead allow the central bank to receive noisy signals of the future shocks to fundamental uncertainty. However, this increases notational clutter without leading to any fundamental new insights.

In summary, the central bank's information set I^{CB}_m consists of:

1. ω_m or, equivalently, the entire history of shocks v up to month m.
2. Signals for each μ over the forecast horizon that leads to beliefs as specified in (9).
3. σ^2_{m+h} or, equivalently, the sequence of fundamental uncertainty shocks u up to month $m+h$.

Market Information Set. Suppose the inflation report (IR) is published on day t, and let $m = m(t)$ be the month in which day t falls. I^{MK}_t is defined as the market's information set on day t, and we assume that $I^{\text{CB}}_m = I^{\text{MK}}_t$, so that the information contained in the IR is a sufficient statistic for whatever else the market knows about the economy on day t. On day $t-1$, we assume the market has observed ω_m, as well as signals on the values of μ within the forecast horizon that lead to beliefs

$$\mu_{m+j} \mid I^{\text{MK}}_{t-1} \sim \mathcal{N}\left(\widehat{\mu}^{\text{MK}}_{m+j,t-1}, \left(s^{\text{MK}}_{m+j,t-1}\right)^2\right) \text{ for } j = 1, \dots, h. \tag{10}$$

These signals may have come from the previous IR publication, or from independent market forecasts. In any case, we assume that the IR contains relevant additional information in the sense that $s^{\text{MK}}_{m+j,t-1} > s^{\text{MK}}_{m+j,t} = s^{\text{CB}}_{m+j,m}$: after IR publication, the market updates its beliefs from $\widehat{\mu}^{\text{MK}}_{m+j,t-1}$ to $\widehat{\mu}^{\text{MK}}_{m+j,t} = \widehat{\mu}^{\text{CB}}_{m+j,m}$ and has lower forecast uncertainty about the value of μ_{m+j} for all $j = 1, \dots, h$.

On day $t-1$, we assume that the market has observed the sequence of shocks to fundamental uncertainty u up to month $m+h-1$ only. Thus IR publication reveals u_{m+h}, which gives the market a new source of information for predicting σ^2_{m+j} for all $j > h$. This is one particular way of modeling the idea that the IR contains news on fundamental uncertainty shocks. In a more complex model, the market would hold signals on day $t-1$ about $u_{m+1}, \dots, u_{m+h}$ that IR publication then added to, as we have assumed for the μ terms, but the basic idea would be the same as in this setup.[12]

In summary, the markets's day $t-1$ information set I^{MK}_{t-1} consists of:

[12] Another channel we do not consider is that the IR could deliver indirect information about ϵ_m, which is itself persistent. This variable in the interest rate rule can be thought of as capturing the central bank's preferences. However this is unlikely to be very persistent five to ten years ahead, when the membership of the MPC is likely to have changed completely.

1. ω_m.

2. i_m, the month m policy rate published one week prior to the IR.

3. Signals for each μ in the forecast horizon that leads to beliefs as specified in (10).

4. σ^2_{m+h-1} or, equivalently, the sequence of fundamental uncertainty shocks u up to month $m+h-1$.

3.2 Expectations Channel

To assess the impact of information in the IR publication on interest rates, we distinguish between two separate channels. Recall that the k-month-ahead forward rate is given in (1) by

$$f_{k,t} = \mathbb{E}\left[\, i_{m+k} \mid I_t^{\text{MK}} \,\right] + \text{TP}_k\left(I_t^{\text{MK}}\right).$$

Any observed change in $f_{k,t}$ must arise from a change in either expected future nominal rates or the term premium. We refer to the *expectations channel* as the effect of IR publication on expected future interest rates, and define

$$\text{EXP}_m(k) \equiv \mathbb{E}\left[\, i_{m+k} \mid I_t^{\text{MK}} \,\right] - \mathbb{E}\left[\, i_{m+k} \mid I_{t-1}^{\text{MK}} \,\right].$$

Using the policy rule in (6), we can express the k-month-ahead policy rate as

$$i_{m+k}\left(I_{m+k}^{\text{CB}}\right) = \phi\mathbb{E}\left[\,\omega_{m+k+h} \mid I_{m+k}^{\text{CB}}\,\right] + \epsilon_{m+k}. \tag{11}$$

We can expand the ω_{m+k+h} term as

$$\omega_{m+k+h} = \rho^{k+h}\omega_m + \sum_{j=1}^{k+h} \rho^{k+h-j} v_{m+j} \tag{12}$$

and so

$$\mathbb{E}\left[\,\omega_{m+k+h} \mid I_{m+k}^{\text{CB}}\,\right] = \underbrace{\rho^{k+h}\omega_m + \sum_{j=1}^{k} \rho^{k+h-j} v_{m+j}}_{=\,\omega_{m+k}} + \sum_{j=k+1}^{k+h} \rho^{k+h-j}\widehat{\mu}^{\text{CB}}_{m+j,m+k}. \tag{13}$$

In month $m+k$, the central bank observes ω_{m+k} by assumption. The final term in (13) is the central bank's forecasts for the shocks that will hit the economy within the month $m+k$ forecasting horizon.

While the market in month m can observe ω_m, IR publication provides news in two senses. First, it provides signals on the v terms within the month-m forecasting horizon, which will feed into the market expectations for ω_{m+k} for all k due to the autoregressive process specified in (7). Second, it provides indirect signals on $\widehat{\mu}^{\text{CB}}_{m+j,m+k}$ for $j = 1, \ldots, h$. Because the central bank is Bayesian, the market's best guess for $\widehat{\mu}^{\text{CB}}_{m+j,m+k}$ after observing the IR is $\widehat{\mu}^{\text{CB}}_{m+j,m}$. The overall effect is described in the following result.

Proposition 1 *The impact of IR publication in month m on interest rates through the expectations channel is*

$$EXP_m(k) = \phi\rho^k \sum_{j=1}^{h} \rho^{h-j} \left(\widehat{\mu}^{CB}_{m+j,m} - \mathbb{E}\left[\, \widehat{\mu}^{CB}_{m+j,m} \mid \widehat{\mu}^{MK}_{m+j,t-1}, i_m \,\right]\right)$$

Moreover, if $\rho < 1$ then $EXP_m(k)$ is strictly decreasing in k and $\lim_{k\to\infty} EXP_m(k) = 0$, while if $\rho = 1$ then $EXP_m(k)$ is independent of k.

On day $t-1$ the market has its own forecasts of future conditions $\widehat{\mu}^{\text{MK}}_{m+j,t-1}$ and the current policy rate i_m as relevant indicators of $\widehat{\mu}^{\text{CB}}_{m+j,m}$ for $j = 1, \ldots, h$,[13] which are in turn the best predictors of (13) following IR publication. The size of the expectations channel effect on market interest rates depends on the degree to which the market's views on $\widehat{\mu}^{\text{CB}}_{m+j,m}$ change after observing the IR.

For our purposes, more relevant is how the expectations channel operates at different points on the forward yield curve. Proposition 1 distinguishes between two cases. The first is when $\rho < 1$ and (7) is a stationary process, as is plausible for macro variables like inflation and GDP growth. Here the size of the expectations channel effect is declining in maturity of the forward rate. The reason is simply that the influence of current shocks on ω_{m+k} is declining in k due to mean reversion in the autoregressive process.

The other case is when $\rho = 1$ and (7) is a unit-root process. For example, there is evidence that shocks to the natural rate of interest are highly persistent (Laubach and Williams 2003). In this case, long-run expectations of ω_{m+k} would react to updated beliefs of those shocks. Such information in the IR publication would, therefore, induce a one-for-one movement at all maturities in the forward yield curve. This observation in turn leads to the result

Corollary 1 *Any move in long-run forward rates due to the expectations channel must generate at least an equivalent move in short-run forward rates. The impact of the expectations channel on long-run rates is maximal when $\rho = 1$, in which case the impact on short-run rates is identical.*

This implication is important for empirically evaluating theories of long-run yield curve movements that rely on central bank communication's shifting market expectations of some economic fundamental. This mechanism is plausible only when the fundamental

[13] i_m provides information since it is a function of $\widehat{\mu}^{\text{CB}}_{m+j,m}$ for $j = 1, \ldots, h$. It does not perfectly reveal the central bank's information set since it also depends on the stochastic shock ϵ_m.

is highly persistent. Moreover, in this case the same signals that move long-run expectations must necessarily also move short-run expectations, and by essentially the same magnitude.[14]

3.3 Uncertainty Channel

The effect on forward nominal interest rates that information on uncertainty contained in the IR publication —the *uncertainty channel* —defined as

$$\mathrm{UNC}_m(k) \equiv \mathrm{Var}\big[\, i_{m+k} \,\big|\, I_t^{\mathrm{MK}} \,\big] - \mathrm{Var}\big[\, i_{m+k} \,\big|\, I_{t-1}^{\mathrm{MK}} \,\big].$$

While we do not explicitly model it, any news contained in the IR that only affects $\mathrm{UNC}_m(k)$ and not $\mathrm{EXP}_m(k)$ must by definition affect only the term premium. Moreover, a large macrofinance literature provides theoretical foundations for why uncertainty about economic conditions indeed affects the term premium (e.g. Bansal and Shaliastovich 2013, Martin 2013).

In our model there is an important distinction between short- and long-run effects of the uncertainty channel, so we analyse each in turn.

3.3.1 Short-run effects

By short-run effects, we mean the effect on forward rates within the central bank's forecast horizon, i.e. $k < h$. The relevant quantity that IR publication could affect here is the market's perceived variance of the central bank's month $m + k$ expectation of economic conditions in month $m + k + h$, as in equation (13) above.[15] There are two relevant sources of news in the IR. First, the market receives additional signals about the shocks that will hit economic conditions, which reduces variance in the forecasts of v_{m+j} for $j \leq k$. Second, since the market learns $\widehat{\mu}^{\mathrm{CB}}_{m+j,m}$ from the IR, it can also better predict $\widehat{\mu}^{\mathrm{CB}}_{m+j,m+k}$ for $k < j \leq h$ since the signals that go into forming $\widehat{\mu}^{\mathrm{CB}}_{m+j,m}$ also enter $\widehat{\mu}^{\mathrm{CB}}_{m+j,m+k}$. The uncertainty channel for $k < h$ is therefore quite straightforward to derive, and we state the following without proof.

Proposition 2 *Suppose that $k < h$. Then the uncertainty channel is*

$$UNC_m(k) = \phi^2 \left\{ \begin{array}{c} \sum_{j=1}^{k} \rho^{2(k+h-j)} \left(\left(s^{MK}_{m+j,t}\right)^2 - \left(s^{MK}_{m+j,t-1}\right)^2 \right) + \\ \sum_{j=k+1}^{h} \rho^{2(k+h-j)} \left(Var\big[\, \widehat{\mu}^{CB}_{m+j,m+k} \,\big|\, I_t^{MK} \big] - Var\big[\, \widehat{\mu}^{CB}_{m+j,m+k} \,\big|\, I_{t-1}^{MK} \big] \right) \end{array} \right\}.$$

Both sources of news serve to reduce the variance of future interest rates, and so

[14] Another possibility is that the central bank could send separate short- and long-maturity-specific information that led market participants to update their views on each end of the yield curve independently, but this is not the case in the Inflation Report.

[15] We ignore the variance in future rates arising from ϵ_m since IR publication does not affect this.

$\text{UNC}_m(k) < 0$. However, the dependence of $\text{UNC}_m(k)$ on k is difficult to pin down at this level of abstraction. Characterizing this requires determining conditions under which the reduction in variance in future cyclical shocks can be compared to the reduction in variance in the central bank's future beliefs about cyclical shocks. Rather than provide such results, we interpret Proposition 2 as saying that the publication of the IR impacts the short-run term premium due to a reduction in uncertainty about short-run nominal interest rates, but that the effect need not have a clear relationship with the maturity of forward rates within the central bank's forecasting horizon.

3.3.2 Long-run effects

We next consider the impact of uncertainty news on forward rates outside of the forecast horizon, i.e. $k \geq h$. The crucial difference in this case is that the variance of future nominal rates now depends on the variance of ε_{m+j} for $j \in \{h, \ldots, k\}$, which the market does not know on day $t-1$. Instead, it forms a forecast of these terms with variance σ^2_{m+h-1}, which is in I^{MK}_{t-1}. IR publication then reveals σ^2_{m+h} (or, equivalently, u_{m+h}), which leads the market to update its forecast on future fundamental uncertainty and thus its view on future nominal rate volatility. This effect is absent in the short run ($k < h$) since the short-run fundamental uncertainty in the economy is known prior to IR publication.

The extent to which learning σ^2_{m+h} affects market forecasts of long-run fundamental uncertainty depends on ρ_σ, the persistence of shocks to fundamental uncertainty in the model defined in (8). With low persistence, the effect of u_{m+h} dies away quickly and forecasts of the variance of ε_{m+j} are relatively unaffected as j grows past h. With high persistence, the opposite is true. In our next result, we characterize an upper bound on the uncertainty channel in the long run by considering the limiting behavior as ρ_σ approaches 1 and (8) becomes a unit-root process.

Proposition 3 *Suppose that $k \geq h$. Then the uncertainty channel satisfies*

$$\lim_{\rho_\sigma \to 1} UNC_m(k) = \phi^2 \left\{ \begin{array}{c} \sum_{j=1}^{h} \rho^{2(k+h-j)} \left(\left(s^{MK}_{m+j,t}\right)^2 - \left(s^{MK}_{m+j,t-1}\right)^2 \right) + \\ \sum_{j=h}^{k} \rho^{2(k+h-j)} \exp\left(\frac{(j-h)\sigma_u^2}{2}\right) \left[\sigma^2_{m+h} - \sigma^2_{m+h-1} \exp\left(\frac{\sigma_u^2}{2}\right)\right] \end{array} \right\}.$$

Moreover,

$$\lim_{k \to \infty} \lim_{\rho_\sigma \to 1} |UNC_m(k)| = \infty.$$

whenever $\sigma^2_{m+h} \neq \sigma^2_{m+h-1} \exp\left(\frac{\sigma_u^2}{2}\right)$.

The effect in the first line of the expression for $\text{UNC}_m(k)$ is also present in the short run, and represents a reduction in uncertainty due to additional signals on the cyclical shocks that will hit economic conditions over the next h months. Its value is declining in k whenever $\rho < 1$ because, as with the expectations channel, the impact of short-run shocks fades away in the long run in a stationary autoregressive process.[16]

The effect in the second line is specific to the long run, and reflects the impact of revised forecasts of future fundamental uncertainty. It can be positive or negative depending on the sign of $\sigma^2_{m+h} - \sigma^2_{m+h-1} \exp\left(\frac{\sigma^2_u}{2}\right)$, which captures whether IR publication increases or decreases the expected value of σ^2_{m+j} for $j > h$.[17] As k grows, the absolute value of this effect also grows. This is because the number of shocks to fundamental uncertainty between months $m+h$ and $m+k$ increases in k. So fundamental uncertainty, and therefore the impact of forecast revisions, accumulates as one moves further out in the yield curve. In the limit as k grows very large, IR publication induces an unboundedly large absolute change in the expected variance of the policy rate outside of the measure zero event $\sigma^2_{m+h} \neq \sigma^2_{m+h-1} \exp\left(\frac{\sigma^2_u}{2}\right)$. While we have not modeled the precise mapping between the uncertainty channel and changes in the term premium, our model strongly suggests that news contained in central bank communication relevant for forecasting fundamental uncertainty can have a large impact on long-run term premiums.[18]

The case of high ρ_σ is an empirically plausible assumption; Bansal and Shaliastovich (2013) estimate a stochastic volatility model similar to ours, and find the persistence in uncertainty shocks to be well above 0.9. We expect a similar mechanism to operate at the long run, and similar results to arise, in situations with a low value of ρ_σ if the central bank alternatively provides signals on the baseline uncertainty (σ^2_0) rather than the innovations to uncertainty.

3.4 Distinguishing theories of long-run rate movements

The model analysis presented above enables us to distinguish in the data between competing theories of why central bank communication moves long-run interest rates.

Expectations channel. In this channel central bank communication changes modal expectations of long-run economic conditions. This is the channel emphasized in Nakamura and Steinsson (2018), and is plausible only when the central bank transmits information about shocks to highly persistent variables like the equilibrium real interest rate. Proposition 1 shows that such information should change short-run expectations at least as much as it does long-run expectations.

[16]The short-run uncertainty channel also depended on the change in the variance of the central bank's future beliefs on economic conditions. This effect is absent in the long run because IR publication provides no news on $\widehat{\mu}^{\text{CB}}_{m+i,m+k}$ for $k > h$.

[17]The change in future expected value does not depend simply on $\sigma^2_{m+h} - \sigma^2_{m+h-1}$ because σ^2_{m+j} is lognormally distributed.

[18]Martin and Ross (2019) present a non-Gaussian bond-pricing framework in which a similar effect could arise if signals altered transition probabilities between persistent states of the world. Cieslak and Schrimpf (2019) discuss a similar channel (without formally modeling it), and the idea is also consistent with Bansal and Shaliastovich (2013) and Ellison and Tischbirek (2018).

Uncertainty channel. In this channel central bank communication changes the perceived variance of interest rates by transmitting information on persistent uncertainty. As in Proposition 3, this information should have its largest effect on long-run rates and we expect this channel to operate through the term premium.

Investor Demand channel. This channel is not present in our model, but is modelled by Hanson and Stein (2015). In that model, the effect on long-run rates comes from a change in demand from yield-oriented investors who react to monetary news that affects short-run expectations by trading longer-term debt to maximize the yield in their portfolios. The main impact on long rates comes via the term premium but is driven by identical information to that driving the change in short-run rates.

The first two channels rely on the central bank providing direct information relevant for long-run beliefs. While the first is present in the literature, the uncertainty channel is novel. The demand channel instead relies on information relevant for short-run beliefs that then propagates to the long run through trading activity.

While not explicitly included in the model, each Inflation Report event can be thought of as the central bank sending a vector of signals to the market, and in the next section we will explicitly construct an empirical proxy for this vector. In fact the model is silent about which signals are responsible for generating which channels, and on whether the same signal could simultaneously convey information on the level and variance of future economic conditions. For example, one signal contained in each IR is the change in the inflation forecast at the forecast horizon relative to the previous IR. From this signal, market participants may update their expectations for the inflationary state of the economy, but they may also, as a result of a large change (or non-change), update their views of uncertainty going forward. More generally, we view the total effect of any given signal the central bank sends as potentially coming from all three channels, and our empirical exercise does not attempt to argue that some channels are present while others are not. Instead, the goal is to identify which channel appears most responsible for the long-run rate reactions we observe after IR publication.

4 Measuring Inflation Report Signals

Using our theoretical framework to interpret interest rates moves on IR publication days requires us to measure the vector of signals that the IR contains. Our approach is to be as flexible as possible and build a high-dimensional set of measures from both the numeric and narrative data in the IR, each of which in principle can convey news to markets. Here the richness of the information in the Report is crucial, as it allows us to study with a great deal of granularity the information that drives different maturities in the market data and the different components (expectation and term premium) of the asset price response.

4.1 Numeric information

As described in Section 2.1, the numeric forecast information in the IR on day t is the forecasts for GDP growth and inflation, which form part of $\mathbb{E}\left[\omega_{m+h} \mid I_m^{\text{CB}}\right]$, and distributional information around them. In our analysis we use a set of 15 core numeric signals contained in each IR published in month m.

We take the modal growth and inflation projections, denoted g_m^{CB} and π_m^{CB} respectively. We also include the variances, $\text{Var}(g_m^{\text{CB}})$ and $\text{Var}(\pi_m^{\text{CB}})$, and skews, $\text{Skew}(g_m^{\text{CB}})$ and $\text{Skew}(\pi_m^{\text{CB}})$. Since 1998, these forecasts have been consistently conditioned on the path for the policy rate (called 'Bank Rate') implied by market interest rates. While projections are provided for each quarter over the forecast period, in our anlaysis we focus our attention on the projections at the two-year horizon as that is the horizon that has tended to be focused on in the Bank's monetary policy communication as the one most relevant for the current stance of policy.

Rather than the rate of GDP growth g_m^{CB}, the potentially more relevant variable for interest rate expectations is the MPC's view of the h-month ahead output gap $\tilde{y}_{m,h}^{\text{CB}}$. It may be that investors infer the MPC's view of the future output gap from its GDP growth forecast. To measure this, we construct an implied modal output gap using the MPC's growth forecasts together with private-sector estimates of long-run potential growth.[19]

It is also important to capture not just the IR forecast levels but also how much these deviate from market expectations of the IR forecast, since the surprise component in the forecast should be the driver of any change in market interest rates. Ideally we would compare each of the MPC's forecast measures to equivalent expectations from the private sector. The Bank of England collects equivalent market forecasts ahead of each IR publication, and we denote the difference between g_m^{CB} and its expected value as $\text{Surp}(g_m^{\text{CB}})$, and similarly $\text{Surp}(\pi_m^{\text{CB}})$. For the variance and skew variables, we do not have measures of private-sector expectations, and we define surprise as the difference between the current and previous value of the variable.

For the output gap surprises, we include the deviation of the two-year-ahead implied output gap from the two-year-ahead implied output gap in the previous IR forecast, i.e. $\tilde{y}_{m,24}^{CB} - \tilde{y}_{m-1,24}^{CB}$. We also control for a like-for-like comparison by comparing the two-year-ahead (8 quarters) output gap forecast from the last IR with the 7-quarter-ahead output gap in the current forecast, i.e. $\tilde{y}_{m,21}^{CB} - \tilde{y}_{m-1,24}^{CB}$.

[19] Specifically, we grow the real GDP series implied by the forecast at the rate of long-run growth from Consensus Economics. We then pass the resulting series through a Baxter-King Bandpass filter to isolate movements between 2 and 36 quarters. The output gap estimate for the IR release in month m, $\tilde{y}_{m,h}^{\text{CB}}$, is the percentage deviation of the forecast level of real GDP from the BK-filtered trend series.

In total we obtain 15 variables associated with the numeric information in the IR communication published on day t, which we label $\mathbf{q}_t$. We divide these into two groups. The first contains seven variables that directly represent the level or news on the expectational component of the forecast: the modal growth and inflation forecasts; the surprise in these forecasts relative to market expectations; the output gap; and the two measures of the evolution of the output gap from the previous IR. We denote these variables $\mathbf{q}_t^{\text{EXP}}$. The remaining eight variables represent information on the distributions around these forecasts, and broadly measure uncertainty. We label these $\mathbf{q}_t^{\text{UNC}}$. Of course, the same set of signals can operate through multiple channels if they convey, either directly or indirectly, information on both the level and uncertainty around future economic conditions.

4.2 Narrative information

The narrative information in the IR consists of text broadly organized into two parts. A set of economics sections assess the current state of the economy, covering recent developments in and the near-term outlook for financial conditions, demand, supply, costs and prices. A forecast section describes the MPC's forecasts, the risks around those forecasts, and the potential trade-offs for policy. The IR does not contain explicit forward guidance, understood as an explicit commitment to a future policy rule, or even a suggested response as to how future interest rates may evolve.

The narrative information can have important effects on future expectations and uncertainty for several reasons. First, there are many hundreds of hard and soft indicators of economic activity that the MPC regularly monitors, including surveys, disaggregate activity and inflation series, and information from regional agents. These indicators are all (potentially) endogenously related to each other and to the inflation and output forecasts contained in the fan charts. The narrative in the IR provides the Bank of England's views about the nature of these endogenous relationships, as well as what are the key drivers of the current forecasts. This can influence market views of likely future MPC forecasts. For example, the IR can reveal whether the inflation forecast is driven by persistent or transitory price movements.

Additionally, monetary policymakers in general, and the MPC specifically, do not publish quantitative views on the value of latent macroeconomic variables such as the equilibrium real interest rate. While an important driver of the policy action, the equilibrium real rate is an inherently elusive variable that depends on quantities such as the unobserved productive capacity of the economy about which there may be significant disagreement. In this context, the narrative may be the *only* way the MPC can signal its view of, and uncertainty about, the level of the real rate.

Another advantage of using narrative information is that it is inherently much richer than the numeric forecasts. This allows us to capture much more precisely the different signals that central banks send to markets. However this advantage also presents several statistical challenges that we must address. These include the issue of how to quantitatively represent the text for statistical analysis, as discussed in the rest of this section. It also includes the issues of the endogeneity of text to economic conditions and forecasts, and how to determine which topics are driving interest rate changes when the topic space is high dimensional, both of which are discussed in Section 5.

In the 70 Reports in our sample, there are 15,023 paragraphs. We first pre-process the text by removing all non-alphabetic terms, as well as extremely common words that are uninformative about the content such as ‘the’, ‘and’, and so on —so-called *stopwords*. We then stem each remaining term into its linguistic root using the Porter stemmer. Stems need not be an English word: for example, the stem of ‘inflation’ is ‘inflat’. Following these steps gives us 754,884 total terms in the dataset and 4,382 unique terms.

In order to reduce the dimensionality of the dataset we represent the text using a probabilistic topic model called Latent Dirichlet Allocation (LDA), first used in the economics literature by Hansen et al. (2018). Here we provide a high-level overview of the concept. Our estimation follows the same Markov Chain Monte Carlo procedure described in Hansen et al. (2018) and introduced by Griffiths and Steyvers (2004); we refer interested readers to those papers for full details.[20]

LDA is a Bayesian factor model for discrete data. Suppose there are D documents (we treat each paragraph as a document, so $D = 15,023$) that comprise a corpus of texts with V unique terms (so here $V = 4,382$). LDA identifies K *topics* (i.e. factors), each of which is a probability vector $\boldsymbol{\beta}_k \in \Delta^{V-1}$ over the V unique terms in the data. The use of probability distributions allows the same term to appear in different topics with potentially different weights. Informally, one can think of a topic as a weighted word list that groups together those words that express the same underlying theme.

Each document can belong to multiple topics. Formally, each document d has its own distribution over topics given by $\boldsymbol{\theta}_d$ (i.e. factor loadings). Informally, θ_d^k is topic k's “share” of document d. The probability that any given word in document d is equal to the vth term is therefore $p_{dv} \equiv \sum_k \beta_k^v \theta_d^k$ and the overall likelihood is $\prod_d \prod_v p_{d,v}^{n_{d,v}}$ where $n_{d,v}$ is the number of times terms v appears in document d.

Importantly, LDA reduces the dimensionality of each document substantially. In the document-term matrix, documents live in a V-dimensional space. After estimating LDA, one obtains a representation of each document in terms of the (estimated) θ_d, which lives in the $K - 1$ simplex, and in general $K \ll V$. Importantly, though, LDA does not ignore any dimensions of variation in the raw term counts since the underlying topics are free

[20] A precursor to LDA is Latent Semantic Analysis (LSA), a non-probabilistic model that applies a singular value decomposition to the matrix of term counts in a corpus. Boukus and Rosenberg (2006) and Hendry and Madeley (2010) use LSA to assess the market impact of Fed and Bank of Canada communications, respectively, but do not propose tests for the information effect.

to lie anywhere in the $V - 1$ simplex.

LDA places Dirichlet priors over the $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ probability vectors, and the inference problem is to approximate their posterior distributions. The main model selection choice is the number of topics K. We use a model with $K = 30$, which provides a generally interpretable set of topics.[21]

Figure 4 represents the 30 topics that LDA estimates in our data and demonstrates that they are indeed interpretable. Topic 6, for example, appears to capture discussion of commodity prices; Topic 14 of the forecast; Topic 24 of financial markets; and so on. Since topics have no natural ordering, we define our own based on whether an IR is published during a cycle of rate increases (i.e. the previous rate change was an increase) or rate decreases (i.e. the previous rate change was a decrease). For each topic, we compute its average share of time in the IR during both cycle, and order topics based on the difference. Topic 0, about the pace of wage and labour cost growth, is most associated with an increasing rate cycle. While Topic 29, financial market conditions, which were of primary concern during the crisis, is most associated with a decreasing cycle.

While we estimate LDA at the paragraph level to exploit variation across thousands of examples of text, we are ultimately interested in the content of each IR in its entirety. We follow the procedure detailed in Hansen et al. (2018) to obtain the distribution over topics in the IR published on day t, which we denote $\boldsymbol{\theta}_t$. Since changes in topic coverage can also have potentially important market effects, we also include $\boldsymbol{\delta}_t \equiv \boldsymbol{\theta}_t - \boldsymbol{\theta}_{t-1}$ to obtain a 60-dimensional representation of the text information in each IR —the 30 topic levels (later denoted 'L') and the 30 changes (denoted 'D').

To illustrate LDA output, Figure 5 plots two representative topic shares within the Inflation Report as well as an alternative representation of these topics in terms of word clouds. Topic 15 reflects discussion of labor markets. This was fairly stable until 2014, when the Bank started increasing its analysis of the labor market in response to the puzzle that domestic inflationary pressure had remained subdued even as unemployment fell. Topic 26 about demand had a marked increase at the onset of the financial crisis, and has remained high reflecting the MPC's concerns about the pace of the recovery.

Since LDA is an unsupervised learning algorithm, the topics have no objective labels. While the most frequent words in topics are certainly strongly suggestive of a concrete meaning, one should proceed with caution when using these in any evaluation of economic mechanisms. Although we comment on which topics drive which market interest rates below, we also provide several tests that do not rely on any specific interpretation.

A final point is that LDA topics do not necessarily have a directional interpretation. When discussing inflation, the IR could be refering to increasing or decreasing inflation.

[21] There is a well-known trade-off between interpretability and goodness-of-fit in the machine learning literature (Chang et al. 2009). While objective measures of goodness-of-fit can be used to determine a choice for K, our goal is to obtain an interpretable description of IR content, for which defining objective criteria is challenging.

													Pro-cyclicality
Topic0	growth	wage	cost	earn	pay	pressur	labour	sector	real	privat	higher	rise	0.013
Topic1	measur	chang	use	differ	can	weight	indic	rel	provid	movement	base	tend	0.013
Topic2	rate	interest	market	offici	expect	impli	point	chart	rise	path	unchang	forward	0.013
Topic3	growth	quarter	gdp	slow	output	weaker	slowdown	strong	stronger	trend	grew	pick	0.01
Topic4	survey	sector	output	servic	suggest	manufactur	indic	report	evid	busi	agent	region	0.01
Topic5	invest	capit	busi	money	financi	deposit	compani	sector	corpor	broad	increas	privat	0.009
Topic6	price	oil	energi	rise	increas	cost	commod	higher	import	food	futur	ga	0.009
Topic7	month	year	rose	annual	fell	point	percentag	earlier	chart	around	increas	januari	0.007
Topic8	import	uk	export	trade	good	net	demand	domest	servic	sterl	account	world	0.006
Topic9	report	sterl	februari	exchang	august	rate	novemb	start	lower	time	point	averag	0.006
Topic10	estim	data	revis	gdp	suggest	account	recent	output	previous	past	inform	current	0.005
Topic11	household	spend	hous	consumpt	incom	consum	real	increas	save	rise	wealth	ratio	0.005
Topic12	may	recent	retail	level	year	sale	stock	reflect	time	underli	trend	inventori	0.004
Topic13	remain	year	past	recent	level	although	low	continu	littl	broadli	appear	risen	0.003
Topic14	project	period	forecast	central	mpc	assum	assumpt	path	around	next	report	profil	0.002
Topic15	employ	labour	unemploy	work	number	hour	market	job	peopl	increas	time	rise	0.0
Topic16	may	could	reduc	might	exampl	increas	possibl	adjust	lead	greater	addit	becom	-0.001
Topic17	chart	year	averag	tabl	probabl	show	around	forecast	distribut	rang	outturn	time	-0.001
Topic18	risk	committe	uncertainti	outlook	balanc	judg	view	central	downsid	prospect	overal	consider	-0.004
Topic19	effect	will	govern	impact	increas	public	plan	fiscal	year	nomin	chang	budget	-0.004
Topic20	inflat	target	cpi	pressur	price	rpix	higher	vat	inflationari	rise	contribut	downward	-0.004
Topic21	expect	term	near	littl	month	medium	short	outlook	rise	next	longer	fall	-0.006
Topic22	will	section	factor	depend	discuss	develop	extent	suppli	box	affect	impact	demand	-0.007
Topic23	economi	unit	euro	area	global	world	kingdom	activ	state	countri	prospect	econom	-0.008
Topic24	market	equiti	financi	asset	bond	yield	corpor	share	may	increas	return	reflect	-0.008
Topic25	fall	reflect	declin	chart	part	fallen	sharpli	larg	past	lower	fell	much	-0.008
Topic26	demand	continu	growth	recoveri	remain	domest	weak	activ	support	pace	gradual	eas	-0.011
Topic27	bank	polici	committe	purchas	mpc	meet	asset	monetari	rate	maintain	billion	econom	-0.015
Topic28	product	compani	capac	margin	suppli	recess	spare	demand	weak	economi	output	slack	-0.018
Topic29	bank	credit	condit	lend	fund	borrow	mortgag	loan	avail	compani	secur	cost	-0.02

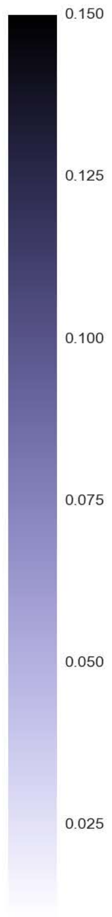


Figure 4: Topics Ranked by Pro-Cyclicality; Terms within Topics Ranked by Probability

Notes: This table summarizes the 30 separate distributions over vocabulary terms that LDA estimates to represent topics. We order these distributions from 0 to 29 based on a pro-cyclicality index that computes the difference in average time the IR spends discussing the corresponding topic when interest rates are in tightening and loosening cycles, respectively. (There are limited cycles on which to base the cyclicality, but it is only for labelling purposes.) Within each row, terms are ordered left to right by the probability they appear in each topic, with differential shading indicating approximate probability values.

(a) Topic 15 ‘Labor Market’ **(b)** Topic 26 ‘Demand’

Figure 5: Illustrative Topic Variation across Inflation Reports

Notes: These figures plot the prevalence of two illustrative topics in the Inflation Reports in our sample. Recession periods are shaded in gray. The distributions over terms that each topic induces are represented as word clouds, where the size of term is approximately proprtional to its probability.

In the baseline analysis below, we sign the topics following the procedure used in Hansen and McMahon (2016) and Thorsrud (2018). Essentially we identify the main topic of each paragraph and then count the contractionary and expansionary sentiment in that paragraph for that topic using dictionaries specific to monetary policy as in Apel and Blix Grimaldi (2012) and Hansen and McMahon (2016). We then aggregate expansionary and contractionary topic counts across paragraphs and use the resulting measures ($n^{+}_{k,t}$ and $n^{-}_{k,t}$) to an form IR-specific, topic level sentiment balance measure (and its first difference $\delta^{\pm}_{t,k}$):

$$\theta^{\pm}_{k,t} = \frac{n^{+}_{k,t} - n^{-}_{k,t}}{n^{+}_{k,t} + n^{-}_{k,t}}. \tag{14}$$

5 Market Impact of Inflation Report Signals

This section presents the main empirical results. It identifies which of the IR signals extracted in Section 4 are most responsible for generating the observed rate movements and hence shed light on which channels decribed in Section 3 may be responsible. A key prediction of that theoretical framework is that the signals that generate an effect through the uncertainty channel can have independent effects on long-run interest rates that do not move short-run interest rates, and we organize much of what follows around the evidence for this. For this, we first use the signed market news (e.g. $\Delta f_{36;t}$) with the signed narrative signals, but show in Section 6 that the results are robust to using the absolute value of the news (e.g. $|\Delta f_{36;t}|$).

From a statistical viewpoint, this is a high-dimensional regression problem since there are more signals in the IR (the 15 numeric signals and the 60 narrative signals) than there are IR publication days (70 in total, but only 69 used for analysis due to differencing across IRs to generate some signals). We therefore use regularization methods below for estimation, but we do not treat numeric and narrative information symmetrically. The numeric variables are, almost by definition, viewed by the Bank of England as informative about future economic conditions and so, while one may not be sure of the exact channels they enter, there is a strong argument for including them in the set of signals that generate any overall information effect. The narrative signals, by contrast, may or may not provide market news. For this reason, we include the numeric variables as regressors throughout the analysis, and only regularize the narrative signals.

5.1 Numeric news signals

We begin the analysis by estimating a regression model that explains yield curve news using just the news in the numeric information in the IR as captured by the variables in $\mathbf{q}_t$ described in Section 4.1. The model is

$$\Delta Y_{k,t} = \beta_{0k} + \boldsymbol{\beta}_{1k}^T \mathbf{q}_t + \varepsilon_t^k, \tag{15}$$

where ΔY_t is the change in the market interest rates (1-year spot, 3-year forward, etc.) observed on IR publication date t. We use the pre-defined split between forecast expectations and uncertainty forecast information to separate $\mathbf{q}_t$ into $\mathbf{q}_t^{\text{EXP}}$ and $\mathbf{q}_t^{\text{UNC}}$.

We are not particularly interested in the coefficients on individual quantitative measures (in particular, because some of the measures are highly correlated), but rather the overall (joint) explanatory power as measured by the R^2 (R-Squared) statistic for each of the four interest rate horizons. As such, we summarise the results in the first columns of Table 3 and report the full regression analysis in Tables D.1-D.3 in the appendix.

The first key result is that the forecast variables, and especially the central expectation variables, are an important driver of variance at the short-end of the yield curve, as measured by changes in the 1-year spot rate, with an R^2 statistic of over 0.5. But the impact declines in maturity, with quite weak effects on market rates at five-years ahead and beyond. The split between expectation and uncertainty signals allows us to show

Table 3: Effect of Forecast Variables on Market Yields: Split by Component

		Overall		Exp		TP	
		$\mathbf{q}_t^{\text{EXP}}$	Add $\mathbf{q}_t^{\text{UNC}}$	$\mathbf{q}_t^{\text{EXP}}$	Add $\mathbf{q}_t^{\text{UNC}}$	$\mathbf{q}_t^{\text{EXP}}$	Add $\mathbf{q}_t^{\text{UNC}}$
$\Delta i_{0:12;t}$	R^2	0.45	0.56	0.45	0.57	0.26	0.37
	Additional R^2		0.11**		0.11**		0.11***
	Proportion of R^2		0.2		0.2		0.3
$\Delta f_{36;t}$	R^2	0.26	0.36	0.33	0.41	0.06	0.24
	Additional R^2		0.10**		0.08		0.18***
	Proportion of R^2		0.28		0.19		0.75
$\Delta f_{60;t}$	R^2	0.17	0.33	0.3	0.39	0.03	0.28
	Additional R^2		0.17***		0.09*		0.24***
	Proportion of R^2		0.5		0.22		0.88
$\Delta f_{60:120;t}$	R^2	0.16	0.37	0.33	0.41	0.05	0.32
	Additional R^2		0.22***		0.08		0.26***
	Proportion of R^2		0.58		0.18		0.83

Notes: This table summarises estimates from regressing absolute changes in market yields on the numeric forecast variables defined in Section 4.1. The Additional R^2 captures the additional R^2 from introducing the new regressors; */**/*** denote joint significance of these regressors at the 10/5/1% significance level according to a joint F-test. The Proportion of R^2 expresses this additional explanatory power as a proportion of the total variation captured by including all the regressors.

that the declining explanatory power of the forecast variables is driven by a declining role of $\mathbf{q}_t^{\text{EXP}}$. When economic conditions follow a stationary AR(1) process (as is natural for GDP growth and inflation) and signals operate through the expectations channel, we showed in Proposition 1 that central bank communication would have its largest effect on short-run rates with a monotonically declining effect in horizon. The empirical results on the market impact of $\mathbf{q}_t^{\text{EXP}}$ are consistent with this view.

The second key result is that, consistent with an effect through the uncertainty channel in our model, the uncertainty signals are increasingly important as we move along the yield curve. The additional R^2 from including $\mathbf{q}_t^{\text{UNC}}$ variables is significant using an F-test. And the relative explanatory power of the $\mathbf{q}_t^{\text{UNC}}$ variables, measured by the proportion of R^2 explained – i.e. the proportion of the total explained variance that is captured by adding those additional variables – grows with maturity of the interest rate.

We next estimate (15) separately for the two comonents of the change in market rates: the change in the expectations and the change in the term premiums (described in Section 2.2). The relative impact of the $\mathbf{q}_t^{\text{EXP}}$ variables on expectations is not greater at the long than the short end of the yield curve, whereas the relative impact on long-run term premiums is greater than that on the short run. This result is again consistent with the uncertainty channel, which should have its largest impact via the long-run term premium. Although, one should be careful in over-interpreting the R^2 from these estimates as the overall amount of variation in term premiums at the short end of the yield curve is very small (as discussed earlier); the R^2 in column 2 of panel (b) tells us that the overall regression is explaining about half of very little variation.

These results provide preliminary evidence that central bank communication operates through multiple channels, and that long-run interest rates appear to react to signals on uncertainty that are distinct from the signals that move short-run interest rates.

5.2 Narrative news signals

The analysis of the numeric forecast information is consistent with the uncertainty channel being a primary driver of longer-maturity yields. We now use the narrative signals to explore this idea more specifically, as its dimensionality provides a means to explore the different communication channels that can drive the long-run information effect (expectations, uncertainty, investor demand) in more detail.

5.2.1 Is there news in narrative?

Before analyzing the market impact of narrative signals, one needs to establish that they contain news at all over and above the information in the numeric forecasts. The first step is to purge variation in the signed narrative variables $(\theta^{\pm}_{k,t}, \delta^{\pm}_{k,t})$ that is endogenous to the numerical forecast information. For example, an increase signed inflation topic may be associated with a deviation of inflation from target in the modal forecast.

We fit the models

$$\theta^{\pm}_{k,t} = \alpha_{0k} + \boldsymbol{\alpha}^T_{1k}\mathbf{q}_t + \alpha_{2k}\text{VIX}_t + v^k_{Lt} \tag{16}$$

$$\delta^{\pm}_{k,t} = \beta_{0k} + \boldsymbol{\beta}^T_{1k}\mathbf{q}_t + \beta_{2k}\text{VIX}_t + v^k_{Dt} \tag{17}$$

The estimated residuals $\widehat{v}^k_{Lt}$ and $\widehat{v}^k_{Dt}$ represent the variation in signed topic k, and its change from the previous IR, not explained by the forecasts.

Our construction is similar to that in Romer and Romer (2004) and Cloyne and Hürtgen (2016), who construct monetary policy shocks by regressing interest rate decisions on numerical forecast variables for the Federal Reserve and the Bank of England, respectively. Here we construct 'narrative shocks' by extracting the exogenous component of the Inflation Report text. This yields 60 narrative shocks that we denote $\widehat{\mathbf{v}}_t = (\widehat{\mathbf{v}}_{Lt}, \widehat{\mathbf{v}}_{Dt})$.[22]

Statistically, establishing whether narrative shocks contain news is equivalent to determining whether the narrative shocks explain the residuals from equation (15), that part of the overall market news not explained by numerical forecasts. As explained above, ordinary least squares is not feasible in this setting since there are more narrative shock

[22] One concern in high-dimensional regressions is that correlation among regressors can impede the ability to identify variables with a 'true' relationship with the outcome. In fact, our narrative shocks display little correlation on average.

variables than degrees of freedom in the model. Instead, we use an elastic net regression as in Zou and Hastie (2005) and solve

$$\min_{\gamma_Y} \sum_t \left(\widehat{\varepsilon}_t^k - \boldsymbol{\gamma}_Y^T \widehat{\mathbf{v}}_t\right)^2 + \lambda \left[\alpha \|\boldsymbol{\gamma}_Y\|_1 + (1-\alpha)\|\boldsymbol{\gamma}_Y\|_2^2\right]. \tag{18}$$

The first term is the objective function of an OLS regression of the yield-k residuals on the narrative shock variables. The second term is a penalty on non-zero values of the regression coefficients $\boldsymbol{\gamma}_Y$. The parameter α can range from 0, equivalent to a ridge regression, to 1, equivalent to the least absolute shrinkage and selection operator (LASSO). The $\alpha = 1$ LASSO specification is useful because it induces sparse solutions but when two or more covariates are significantly correlated it typically only generates a non-zero coefficient for one of them. We set $\alpha = 0.99$ to induce a degree of sparsity akin to the LASSO, while maintaining robustness to the (relatively few) high correlations in the narrative shocks (Friedman et al. 2010).

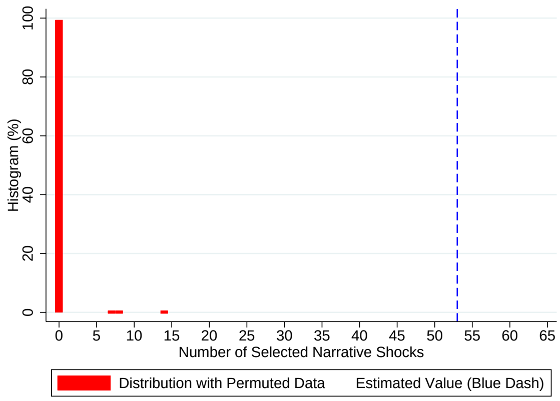
Before estimating (18), one must choose a value for the penalty parameter λ. We use the common approach of selecting λ using cross validation based on out-of-sample predictive performance. We describe this procedure in detail in Appendix C and here focus on the results. We find that a large number of narrative shocks are selected at each maturity, as displayed in Table 4.

Table 4: Number of Selected Narrative Shocks in Baseline

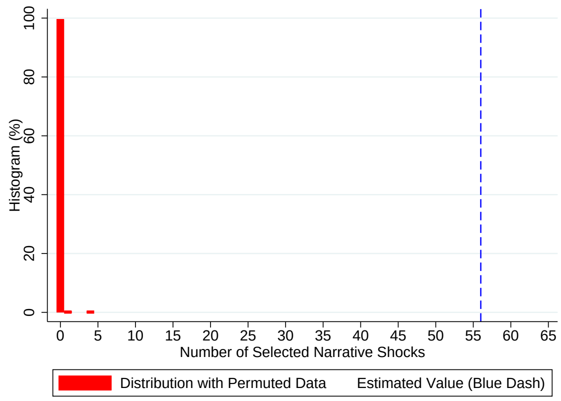
	$\Delta i_{0:12,t}$	$\Delta f_{36,t}$	$\Delta f_{60,t}$	$\Delta f_{60:120,t}$
# selected narrative shocks	53	56	56	55

Notes: This table displays the number of selected covariates arising from the estimation of (18) for four market rates by leave-one-out cross validation.

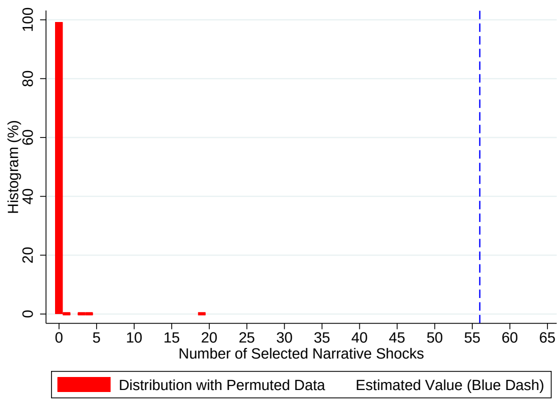
That a large number of narrative shocks is selected for each maturity suggests that they are indeed important in explaining the yield residuals. To test that this result is not spurious, we need to compare it to the distribution of the number of selected variables under the null hypothesis that narrative shocks are independent of yield residuals. To approximate this hypothesis test, we use a simple permutation test. In each of 500 simulations for each interest rate, we randomly permute the residuals, re-estimate (18), and record the number of selected narrative shock variables. We then compare the values in Table 4 against these simulated distributions. The results are shown in Figure 6, where the red-shaded histogram is the distribution of the number of selected narrative shocks generated by the simulations, and the blue dashed line is the number of narrative shocks we select in our actual data. At all interest rate maturities we strongly reject the null hypothesis that the correlations we find are spurious. In the vast majority of permuted draws, the elastic net selects no narrative shocks, and in no draw is the number of selected shocks greater than the number we select with the non-permuted data. We conclude that there indeed appears to be genuine explanatory power contained in the IR narrative that is orthogonal to that in the numerical forecast variables.[23]



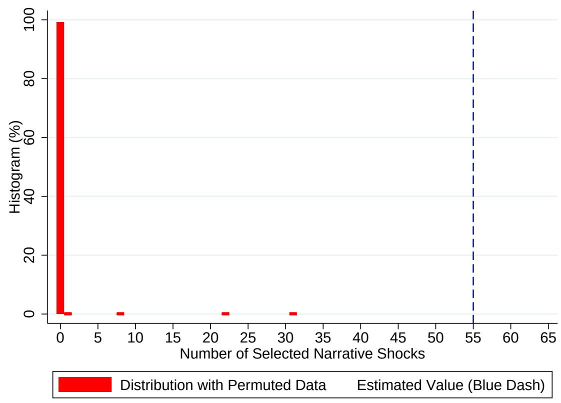
(a) 1-year Spot



(b) 3-year Forward



(c) 5-year Forward



(d) 5-year, 5-year Forward

Figure 6: Permutation Test for Narrative News

Notes: These figures describe a permutation test for narrative news. The blue, dashed vertical lines for each yield plot the number of selected text variables from Table 4. The red histograms describe the distribution of selected features in 500 different random permutations of yield residuals for which we used the same cross validation procedure as on the original data. In no permutation do we select as many features as with the true order.

The finding that there is market news in the narrative of central bank communication is of independent interest and another contribution of the paper. Most studies of central bank communication that analyze their content focus on numerical information, but there is evidence that some other factor is needed to explain the full market reaction around communication events (Gürkaynak et al. 2018). We find it natural to view narrative as an important aspect of this 'missing' information in event studies, and the approaches

[23]Repeating these tests by component (expectations and term premiums), we continue to find strong evidence for an important role for narrative information at all maturities for each component.

we develop are more broadly relevant to the literature.

5.2.2 Testing distinct long-run information I: key narrative signals

While we have established that narrative shocks are a source of news, we do not know which are most important for explaining market rates, nor whether these differ by maturity. The baseline elastic net regression selects nearly every shock at every maturity,[24] so we need some way of discriminating among signals according to their information content. To do this, we adopt a bootstrap procedure suggested by Hastie et al. (2015). In each of 500 simulations we draw a bootstrap sample with replacement from our original data, compute coefficient estimates using the same cross validation procedure as in the baseline, and record whether each topic variable is selected. Across all the bootstrap draws, we can compute the fraction of times that each topic variable is selected, and use this as an indicator of which variables are key in driving the market response to the IR.[25]

Table 5 lists the top four topic variables for each yield based on the bootstrap draws, and reports the fraction of draws in which they appear. This reveals that the topics that are most likely to drive short and long rates differ considerably: the top topics for 1-year spot rates and 5-year, 5-year forward rates contain no overlap. We formalize this below.

Table 5: Top Topics for Different Yields (L=Level; D=Change)

$\Delta i_{0:12,t}$		$\Delta f_{36,t}$		$\Delta f_{60,t}$		$\Delta f_{60:120,t}$	
Var	Selection %	Var	Selection %	Var	Selection %	Var	Selection %
D1	0.962	D9	0.932	D9	0.94	L16	0.946
L11	0.942	D18	0.836	L16	0.89	D18	0.92
D9	0.936	L11	0.824	D18	0.878	L12	0.844
L19	0.92	D13	0.814	D13	0.87	D13	0.802

Notes: This table lists the top four topics for each yield according to fraction of times they are selected across 500 bootstrap draws. An L indicates the topic variable corresponds to a residual in levels, while a D indicates a residuals in the absolute change in the topic level.

The most likely words within the key topics for the shortest- and longest-maturity assets, listed above in Table 5, are presented graphically as word clouds in Figures 7 and 8. While these topics do not come with labels and interpreting them is a subjective exercise, the key topics that drive the different yields are suggestive of the channels from the theoretical model. On the one hand, those that drive the 1-year spot rates appear to relate to current economic conditions and include those that vary most with the interest rate cycle (see Figure 5). On the other hand, the key topics for the five-year ahead,

[24] This is not surprising. Meinshausen and Bühlmann (2006) show that the number of selected features from an elastic net regression estimated via cross validation may be a superset of the relevant variables.

[25] The elastic net regression we estimate is very similar to the LASSO, which has a probabilistic formulation as a Bayesian regression model with Laplace priors on the coefficients. The bootstrap procedure can be thought of as a shortcut for doing a full posterior simulation exercise.

five-year forward rate appear to relate to the forecasts and their uncertainty and are less cyclical. This is consistent with a model in which the central bank sends signals about the levels of mean-reverting economic conditions that affect short-run rates, and signals about economic uncertainty that affects long-run rates.

Table 6 formalizes the finding that different narrative signals drive different rate maturities. It reports the Pearson correlation coefficients between narrative shocks based on the fraction of bootstrap draws in which they are selected. The selection percentages for 1-year spot rates are in fact uncorrelated with those for the longest rates, while the selection percentages associated with all other rates are significantly correlated. Importantly, this finding casts doubt on either the expectations channel or the investor demand channel being the primary driver of long-run rate movements in response to the IR. Both channels require the signals that move short-run rates to also move long-run rates.

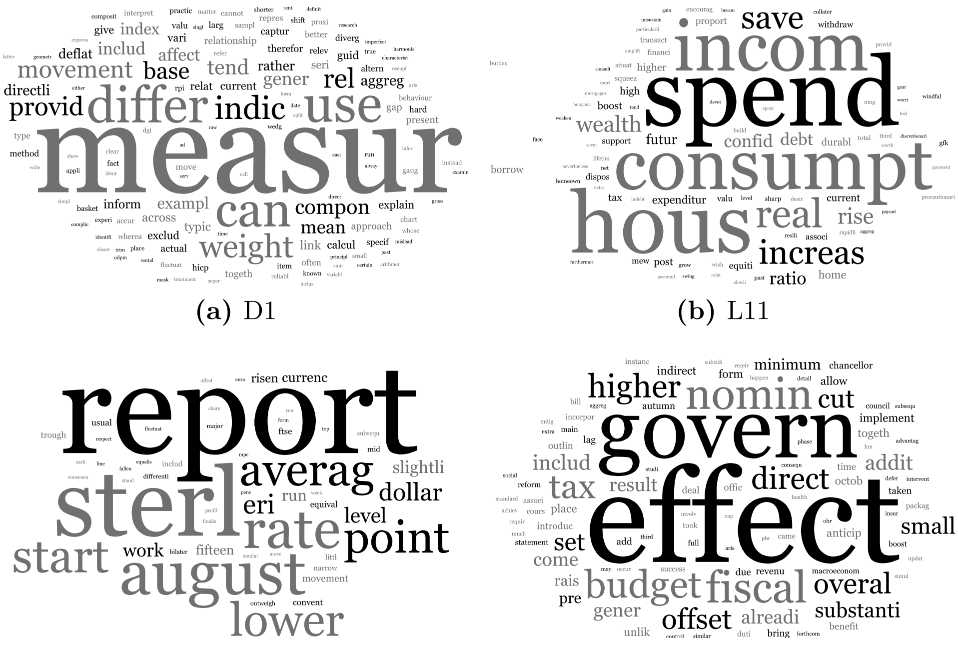
Table 6: Pearson Correlations of Narrative Signals' Selection Percentage Across Yields

	$\Delta i_{0:12,t}$	$\Delta f_{36,t}$	$\Delta f_{60,t}$	$\Delta f_{60:120,t}$
$\Delta i_{0:12,t}$	1.00			
$\Delta f_{36,t}$	0.22*	1.00		
$\Delta f_{60,t}$	0.06	0.75***	1.00	
$\Delta f_{60:120,t}$	0.07	0.52***	0.87***	1.00

Notes: This table reports the Pearson correlation coefficient of the topics' selection percentages across 500 bootstrap draws for different yields. */**/*** denote significance at the 10/5/1% significance level.

If the uncertainty channel drives long-run interest rates, we expect it to do so through the term premium rather than expectations, while the reverse is true of the expectations channel. We repeat the bootstrap procedure on each separate yield component, Table 7 shows the results. There is substantial overlap between the narrative signals that drive short-run movements in the overall yield change and the signals that drive the short-run expectations component. In contrast, there is an overlap between the top long-run overall and term premium signals. Relatedly, the key signals for explaining long-run term premiums are not the key signals for explaining the overall change in short-run yields. This is further evidence that long-run rate movements do not arise solely from trading activity in response to signals driving the short end, as would be the case in the investor demand channel.

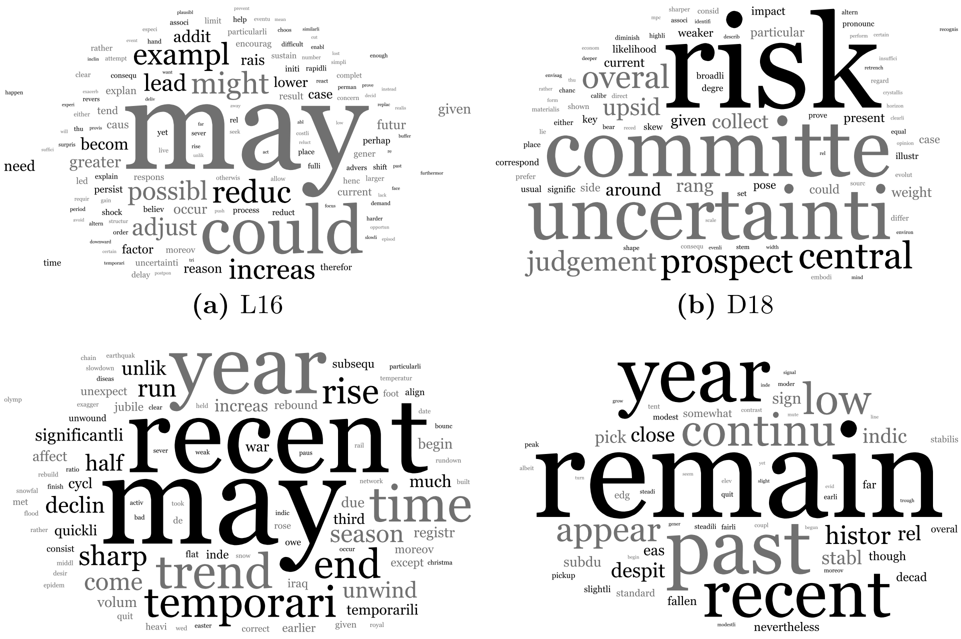
Table 8 is the analogue of Table 6 by yield component. Here we find an interesting distinction between expectation and term premium signals: the topic selection percentages for expectations are much more correlated across maturities than that of term premiums. This suggests that the results on the overall change potentially mask an underlying expectations component that reflects a rather persistent set of common signals driving short- and long-run expectations. However, this is not the dominant source of variation



(a) D1 (b) L11

(c) D9 (d) L19

Figure 7: Key Topics for Market Reaction to Narrative: 1-Year Spot Rate



(a) L16 (b) D18

(c) L12 (d) D13

Figure 8: Key Topics for Market Reaction to Narrative: 5-Year, 5-Year Forward Rate

Table 7: Top Narrative Signals for Different Yields (L=Level; D=Change)

(a) Expectations

$\Delta i_{0:12,t}$		$\Delta f_{36,t}$		$\Delta f_{60,t}$		$\Delta f_{60:120,t}$	
Var	Selection %	Var	Selection %	Var	Selection %	Var	Selection %
D1	0.97	D9	0.93	D9	0.938	D9	0.938
L19	0.93	L11	0.868	L11	0.802	L11	0.85
L11	0.92	L24	0.736	D13	0.758	D18	0.802
L28	0.908	D18	0.714	D18	0.726	D13	0.762

(b) Term Premiums

$\Delta i_{0:12,t}$		$\Delta f_{36,t}$		$\Delta f_{60,t}$		$\Delta f_{60:120,t}$	
Var	Selection %	Var	Selection %	Var	Selection %	Var	Selection %
D13	0.944	D9	0.854	L16	0.896	D29	0.88
L11	0.91	L16	0.838	D29	0.816	L16	0.858
D9	0.882	D18	0.838	L12	0.776	L12	0.85
D1	0.864	D13	0.828	D11	0.774	D11	0.81

Notes: This table lists the top four topics for each yield and component according to fraction of times they are selected across 500 bootstrap draws. An L indicates the topic variable corresponds to a residual in levels, while a D indicates a residuals in the absolute change in the topic level.

Table 8: Pearson Correlations of Topic Variables' Selection Percentage Across Yields

(a) Expectations

	$\Delta i_{0:12,t}$	$\Delta f_{36,t}$	$\Delta f_{60,t}$	$\Delta f_{60:120,t}$
$\Delta i_{0:12,t}$	1.00			
$\Delta f_{36,t}$	0.44***	1.00		
$\Delta f_{60,t}$	0.28**	0.91***	1.00	
$\Delta f_{60:120,t}$	0.34***	0.89***	0.92***	1.00

(b) Term Premiums

	$\Delta i_{0:12,t}$	$\Delta f_{36,t}$	$\Delta f_{60,t}$	$\Delta f_{60:120,t}$
$\Delta i_{0:12,t}$	1.00			
$\Delta f_{36,t}$	0.10	1.00		
$\Delta f_{60,t}$	-0.06	0.68***	1.00	
$\Delta f_{60:120,t}$	-0.19	0.40***	0.86***	1.00

Notes: This table reports the Pearson correlation coefficient of the topics' selection percentages across 500 bootstrap draws for different yields and for different components of the yield curve. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

in long-run interest rates and suggests that, while the uncertainty channel is not the only factor driving the long-run information effect, it is the primary one.

5.2.3 Testing distinct long-run information II: Placebo regressions

Although we have found distinct narrative signals in the bootstrap test, one might still question whether these actually explain different amounts of movement in yield residuals. Our final test of distinct long-run information assesses to what extent the key narrative signals associated with each maturity actually explain more of the yield residual at that maturity than the key narrative signals associated with other maturities.

In Table 9 we replicate the overall regressions in Table 3 and then compute the R^2 impact associated with adding in the top four narrative signals from Table 5. (Appendix Tables D.4 and D.5 display more details of the regressions on which Table 9 is based.)

Table 9: Summary of R^2 Statistics from Yield Regressions

		$\mathbf{q}_t^{\text{EXP}}$	Add $\mathbf{q}_t^{\text{UNC}}$	Add Key Narrative Signals
$\Delta i_{0:12;t}$	R^2	0.45	0.56	0.69
	Additional R^2	-	0.12**	0.13**
	Proportion of R^2	-	0.17	0.18
$\Delta f_{36;t}$	R^2	0.26	0.36	0.56
	Additional R^2	-	0.10**	0.20**
	Proportion of R^2	-	0.18	0.35
$\Delta f_{60;t}$	R^2	0.17	0.33	0.5
	Additional R^2	-	0.17***	0.17**
	Proportion of R^2	-	0.34	0.33
$\Delta f_{60:120;t}$	R^2	0.16	0.37	0.52
	Additional R^2	-	0.21***	0.15**
	Proportion of R^2	-	0.42	0.29

Notes: This table reports the R^2 statistics from regressing changes in market yields on $\mathbf{q}_t^{\text{EXP}}$ (column 3), $\mathbf{q}_t^{\text{EXP}}$ and $\mathbf{q}_t^{\text{UNC}}$ (column 4), and the numeric forecast variables and also the top 4 topic shocks for each yield (column 5). The Additional R^2 captures the additional R^2 from introducing the new regressors; */**/*** denote joint significance of these regressors at the 10/5/1% significance level according to a joint F-test. The Proportion of R^2 expresses this additional explanatory power as a proportion of the total variation captured by including all the regressors.

To test whether the key narrative signals at each maturity explain more yield residual variance at that maturity, we replace them with key narrative signals at other maturities, and record the additional R^2 reported as a proportion of the total variance explained by the regression. Table 10 displays the results and indicates the significance level of an F-test on the joint significance of the narrative shocks given the inclusion of $\mathbf{q}_t$. Here we have not accounted for the post-selection inference problem of how to conduct hypothesis tests on the significance of selected regressors from an elastic net regression. Our question of interest is not whether the selected signals at each maturity are significant in a statistical sense, but how their explanatory power compares to other narrative signals selected at other maturities. This is another way of asking whether we have selected independent signals to explain long-run rate movements.

The answer is clear from Table 10. The top narrative signals for short-run rates do not improve the overall fit for longer maturity rates; for five-year, five-year forward rates, the short-rate top topics add 0.04 to the R^2 (10% of the total R^2) but the additional variables are not statistically significant. Likewise, the top narrative signals for long-run rates do not significantly add to the regression for one-year spot rate. The effects of the top narrative signals for the five-year forward rate and the five-year, five-year rate are similar for both maturities, which is not surprising given there is overlap in the selected topics. The bottom line is that the selected narrative signals for the long-run are not an indirect proxy for signals that move short-run rates, but distinct information. This reinforces the plausibility of the uncertainty channel.

Table 10: Placebo Regressions

Asset News	Narrative Shocks			
	$\Delta i_{0:12;t}$ Overall	$\Delta f_{36;t}$ Overall	$\Delta f_{60;t}$ Overall	$\Delta f_{60:120;t}$ Overall
$\Delta i_{0:12;t}$	0.18**	0.10	0.05	0.03
Δ EXP$(i_{0:12;t})$	0.15**	0.08	0.05	0.01
Δ TP$(i_{0:12;t})$	0.29*	0.29	0.21	0.14
$\Delta f_{36;t}$	0.27	0.35**	0.31**	0.18
Δ EXP$(f_{36;t}$	0.26*	0.30*	0.23	0.10
Δ TP$(f_{36;t})$	0.17	0.34	0.39**	0.34*
$\Delta f_{60;t}$	0.20	0.31*	0.32**	0.26**
Δ EXP$(f_{60;t})$	0.27	0.33*	0.27*	0.13
Δ TP$(f_{60;t})$	0.02	0.12	0.28*	0.30*
$\Delta f_{60:120;t}$	0.10	0.20	0.30**	0.28**
Δ EXP$(f_{60:120;t})$	0.25*	0.31**	0.25*	0.13
Δ TP$(f_{60:120;t})$	0.04	0.10	0.26*	0.25*

Notes: This table reports the proportion of R^2 gained from adding the top four narrative signals to a regression of changes in market yields on the numeric forecast variables ($\mathbf{q}_t$). Each row reports the results for a different yield. Each column indicates the yields from which the top narrative shocks are estimated. For example, the cell in the bottom right of the top panel indicates the additional R^2 from adding the top four narrative shocks estimated from the 5y-5y forward rates on 5y-5y forward rate news; it is the same result as in Table 9. Stars (***, **, and *) indicate the significance level (1%, 5% and 10%) of an F-test on the joint significance of the narrative shocks given the inclusion of $\mathbf{q}_t$.

The table also shows the effect of the top topics on the separate components of the overall yield curve. This allows us to explore in more detail the impact of the expectations and investor demand channels. The narrative signals that explain the one-year spot rate, which is predominantly driven by variation in the expectations component, do not significantly explain variation overall for all other yields but they do explain the expectations component at all maturities (for the five-year forward, the additional R^2 has a p-value of 0.12). While this is consistent with a longer-run expectations channel, it is not the main driver of the overall movement in long-run rates.

The investor demand channel requires that the information that moves short-run expectations also moves the long-run term premiums. Instead, the top signals for the one-year spot rate, and particularly the expectations component, add only 4% (2%) of the variation in the five-year, five-year (five-year forward) term premium. Moreover, the top signals for explaining the long-run term premium explain almost nothing about short-run expectations (1% for the one-year spot expectations component and 3% overall).

Together, the results show that the expectations channel may indeed operate, but there is little evidence of the investor demand channel. In any case, the main driver of long-run interest rates is narrative signals that explain the long run independently of any impact on short- or medium-term expectations. This long-run impact comes largely via the term premium. All of these facts point to the uncertainty channel as the primary mechanism through which the Inflation Report operates on long-run interest rates.

6 Robustness

In this section we explore the robustness of the baseline results to a number of potential concerns. These include robustness of the main results to measuring news using the absolute value of asset price changes, excluding the ZLB period, the effect on real rates and measuring the effect of other news on the IR event day.

6.1 News as the absolute value of asset price changes

An alternative measure of asset price news used in the literature on central bank communication takes the absolute value of asset price changes. This is necessary when the anaylsis is using only dummy variables as the event indicator (since news can be either positive or negative). Using absolute values has the advantage of not needing to assign a tone to the topics. We have, therefore, repeated our analysis using this alternative measure of the news and using the raw topic allocations rather than the signed ones.

The first-stage model replaces the dependent variable in (15) with $|Y_t^k|$, the absolute value of the change in the market interest rates observed on IR publication date t and uses the absolute value of the surprise and difference regressors in $\mathbf{q}_t$. We also include the VIX volatility index as a control, since bond price news may tend to be more volatile on days with increased levels of general market volatility regardless of the level of news in central bank communication; the key results are unaffected by including VIX.

Table 11: Summary of R^2 Statistics from |Yield| Regressions

		$\mathbf{q}_t^{\mathrm{EXP}}$	Add $\mathbf{q}_t^{\mathrm{UNC}}$	Add Key Narrative Signals
$\lvert\Delta i_{0:12;t}\rvert$	R^2	0.4	0.56	0.69
	Additional R^2	-	0.16	0.13***
	Proportion of R^2	-	0.23	0.18
$\lvert\Delta f_{36;t}\rvert$	R^2	0.25	0.37	0.51
	Additional R^2	-	0.12	0.14
	Proportion of R^2	-	0.23	0.28
$\lvert\Delta f_{60;t}\rvert$	R^2	0.12	0.28	0.5
	Additional R^2	-	0.16**	0.22**
	Proportion of R^2	-	0.31	0.44
$\lvert\Delta f_{60:120;t}\rvert$	R^2	0.11	0.27	0.54
	Additional R^2	-	0.16**	0.27***
	Proportion of R^2	-	0.3	0.49

Notes: This table reports the R^2 statistics from regressing abosolute values of the changes in market yields on VIX and $\mathbf{q}_t^{\mathrm{EXP}}$ (column 3), VIX, $\mathbf{q}_t^{\mathrm{EXP}}$ and $\mathbf{q}_t^{\mathrm{UNC}}$ (column 4), and VIX, the numeric forecast variables and also the top 4 topic shocks for each yield (column 5).

We repeat the tests of the narrative analysis as in Section 5.2. In the interests of space, we simply report the summary regression table (Table 11), the correlations between the asset-specific topic rankings (Table 12) and results of the placebo analysis (Table 13), though the information tests show the same importance of narrative information. The main results are unchanged.

Table 12: Pearson Correlations of Narrative Signals' Selection Percentage Across |Yield|

	$\lvert\Delta i_{0:12,t}\rvert$	$\lvert\Delta f_{36,t}\rvert$	$\lvert\Delta f_{60,t}\rvert$	$\lvert\Delta f_{60:120,t}\rvert$
$\lvert\Delta i_{0:12,t}\rvert$	1.00			
$\lvert\Delta f_{36,t}\rvert$	0.19	1.00		
$\lvert\Delta f_{60,t}\rvert$	0.05	0.68***	1.00	
$\lvert\Delta f_{60:120,t}\rvert$	0.11	0.47***	0.82***	1.00

Notes: This table reports the Pearson correlation coefficient of the topics' selection percentages across 500 bootstrap draws for different yields. */**/*** denote significance at the 10/5/1% significance level.

Table 13: Matrix of Additional R^2 from Placebo Regressions

Asset News	Narrative Shocks			
	$\|\Delta i_{0:12;t}\|$	$\|\Delta f_{36;t}\|$	$\|\Delta f_{60;t}\|$	$\|\Delta f_{60:120;t}\|$
$\|\Delta i_{0:12;t}\|$	0.29***	0.08	0.06	0.01
$\|\Delta f_{36;t}\|$	0.15	0.24***	0.18	0.11
$\|\Delta f_{60;t}\|$	0.14	0.21	0.31**	0.24*
$\|\Delta f_{60:120;t}\|$	0.12	0.13	0.34***	0.37***

Notes: This table reports the Additional R^2 statistic from a regression of the absolute value of changes in market yields on VIX and the numeric forecast variables ($\mathbf{q}_t$) to which four narrative shocks are added. Each row reports the results for a different yield. Each column indicates the yields from which the top narrative shocks are estimated. For example, the cell in the bottom right indicates the additional R^2 from adding the top four narrative shocks estimated from the 5y-5y forward rates on 5y-5y forward rate news; it is the same result as in table 9. Stars (***, **, and *) indicate the significance level (1%, 5% and 10%) of an F-test on the joint significance of the narrative shocks given the inclusion of $\mathbf{q}_t$.

6.2 The effect of the Zero Lower Bound

Our model does not consider the impact of the Zero Lower Bound (ZLB). One concern is that in a situation where the ZLB is binding, the short-end of the yield is downwardly constrained. This means a signal that economic conditions will be persistently weaker, which would be expected to shift the short- and long-end of the yield curve equally, can only move the yield curve further out. This would be an expectations shock that appeared to only move the long-end. Moreover, to the extent that the persistent weakness of the economy might signal that the economy may have switched into a new regime in which deflation risk is higher, those effects may come through a change in term premiums.

To assess the role that this plays in driving our results, we analyze the effect of removing the ZLB period from our analysis. In our sample, the ZLB was binding from March 2009 and so the pre-ZLB sample is reduced by 25 IR events.

In spite of the small sample, the key results from the whole sample are present in this period. First, the basic pattern of the effect of the numeric forecast information holds; expectational signals have the greater effect at the short end while distributional information is relatively more important further out. In fact, the numeric information explains more of the market reaction at all points on the yield curve to the IR before the ZLB.

Notwithstanding there being a smaller residual left to explain, the narrative continues to continue important information that helps to explain this residual reaction.

Table 14 shows the correlation across the full sample and the pre-ZLB sample of the top topics measured using the topic variables' selection percentage from the bootstrap draws. This table reassures us that it is unlikely to be the ZLB period that drives our results given that the top topics are similar in the pre-ZLB period. Even more reassuringly, the information that explains the residual asset price news at the short-end of the yield curve is different to the signals that explain the residual movements at the longer maturities. This is shown in Table 15.

Table 14: Topic inclusion probabilities: Correlation across Pre-ZLB and Full Sample

Asset	$\Delta i_{0:12,t}$	$\Delta f_{36,t}$	$\Delta f_{60,t}$	$\Delta f_{60:120,t}$
Correlation	0.66***	0.26**	0.53***	0.52***

Notes: This table shows the correlation across the full sample and the pre-ZLB sample of the topic rankings measured using the topic variables' selection percentage from the bootstrap draws.

Table 15: Pre-ZLB Pearson Correlations of Narrative Signals' Selection Probabilities

	$\Delta i_{0:12,t}$	$\Delta f_{36,t}$	$\Delta f_{60,t}$	$\Delta f_{60:120,t}$
$\Delta i_{0:12,t}$	1.00			
$\Delta f_{36,t}$	0.15	1.00		
$\Delta f_{60,t}$	-0.01	0.66***	1.00	
$\Delta f_{60:120,t}$	-0.07	0.33***	0.80***	1.00

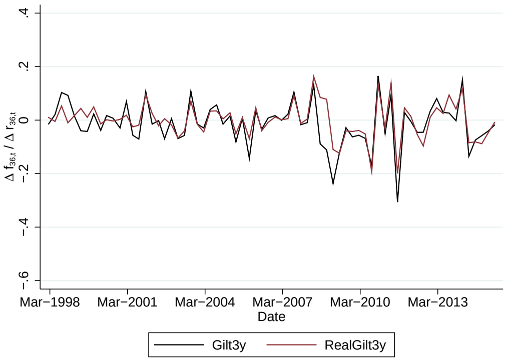
Notes: This table reports the Pearson correlation coefficient of the topics' selection percentages across 500 bootstrap draws for different yields and for different components of the yield curve. *** denotes significance at the 1% significance level.

6.3 Analysis of real interest rates

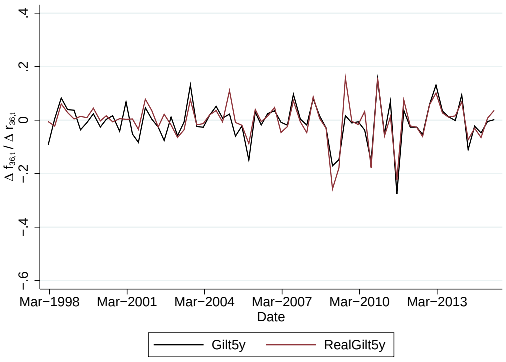
We have thus far focused on nominal rates due to lack of data availability for real rates – in particular, real rates data is not availabile over much of our sample for the 1-year spot interest rate. But it is real rates that should have the biggest impact on real economic decisions such as investment. Therefore, despite the data limitation, we can reassure that the basic analysis also affects the real yields too.

Figure 9 plots the news in equivalent real and nominal yields on IR publication dates in our sample for the three real rates. The most striking observation, consistent with the findings in Nakamura and Steinsson (2018), is that real and nominal yields move closely together. The correlation between the real and nominal market reactions are 0.81, 0.85 and 0.8 for the 3y, 5y and 5y5y-forward rate respectively. All are significant at the 1% significance level. The implication is that inflation expectations, at least at longer maturities, do not react too much in response to the IR.

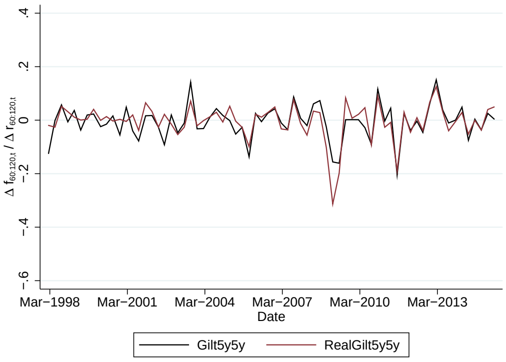
The information test shows that the narrative shocks have explanatory power for the real market news residual (not reported). And the key narrative signals which drive the nominal yield curve are significantly correlated with the key narrative signals driving the real market reaction, as shown in Table 16.



(a) 3-year Forward



(b) 5-year Forward



(c) 5-year, 5-year Forward

Figure 9: Market News in Real and Nominal Yields on IR Days

Table 16: Topic inclusion probabilities: Correlation for Real and Nominal Yields

Asset	$\Delta f_{36,t}$	$\Delta f_{60,t}$	$\Delta f_{60:120,t}$
Correlation	0.63***	0.61***	0.51***

Notes: This table shows the correlation across the real and nominal topic rankings measured using the topic variables' selection percentage from the bootstrap draws.

Finally, although we cannot test the difference of the signals driving the short end and the long end, the 3-year forward, 5-year forward and 5-year, 5-year forward rates correlation structure looks similar to that in the nominals, as shown in Table 17

Table 17: Real Yields: Pearson Correlations of Narrative Signals' Selection Probability

	$\lvert\Delta r_{36,t}\rvert$	$\lvert\Delta r_{60,t}\rvert$	$\lvert\Delta r_{60:120,t}\rvert$
$\lvert\Delta r_{36,t}\rvert$	1	.	.
$\lvert\Delta r_{60,t}\rvert$	0.34***	1	.
$\lvert\Delta r_{60:120,t}\rvert$	-0.01	0.71***	1

Notes: This table reports the Pearson correlation coefficient of the topics' selection percentages across 500 bootstrap draws for different yields and for different components of the yield curve. *** denotes significance at the 1% significance level.

6.4 Interaction effects and labour market releases

One concern may be that the effect of the IR depends on the news from the monetary policy decision a week earlier. Examining specific interactions between topics and earlier news, while potentially interesting, is impossible given our limited data set. However, we show in Table 18 that allowing for a linear effect of the earlier monetary policy shock, in addtion to the numerical $\mathbf{q}_t$ IR data, has no effect.

Another concern mentioned above is that some of the IR publication days coincide with labour market data releases. The IR does not include these data as it includes data only up to close of business on the Wednesday before the monetary policy decision a week earlier. This additional, uncorrelated, news should make it harder to identify an IR effect. Nonetheless, since we have measures of the surprise in the labour market release for unemployment, jobless claims and average earnings, albeit only from 2003 onward, we also show that including these data does not change the analysis (Table 18).

The residual variation left to explain from these regressions is essentially unchanged from the first stage regression without their inclusion; the correlations are between 0.95 and 0.99. This suggests that although some movements in the longer-maturity yields are reacting to the labour release, this is in addition to the variation driven by the IR.

Table 18: The effect of other data on IR news

Main Regressors	(1) $\Delta i_{0:12;t}$	(2) $\Delta f_{36;t}$	(3) $\Delta f_{60;t}$	(4) $\Delta f_{60:120;t}$
Announcement Surprise	-0.026	-0.039	0.013	0.039
	[0.840]	[0.815]	[0.931]	[0.771]
Surp(Claims)	0.0027	0.043**	0.048***	0.038**
	[0.809]	[0.035]	[0.009]	[0.014]
Surp(UE)	0.0087	0.0084	-0.0016	-0.0067
	[0.509]	[0.555]	[0.890]	[0.528]
Surp(Earnings)	0.0035	0.0047	0.0046	4.6e-06
	[0.562]	[0.627]	[0.564]	[0.999]
IR Forward Guidance	0.035**	0.12**	0.064	0.0094
	[0.022]	[0.027]	[0.175]	[0.821]
R-squared	0.577	0.462	0.423	0.431
Includes $\mathbf{q}_t$	Yes	Yes	Yes	Yes
Base R^2	0.562	0.361	0.333	0.371
Partial R^2	0.035	0.158	0.135	0.095
Additional R^2	0.015	0.101	0.090	0.060
Proportion R^2	0.026	0.218	0.213	0.139
F-test p-value	0.302	0.092	0.079	0.219
Component	Total	Total	Total	Total

Notes: This table shows the coefficients on the additional potential drivers of IR release day news when included in (15) in addtion to the numerical $\mathbf{q}_t$ IR data.

7 Conclusion

Communication has offered an additional tool to central banks to move interest rates faced by banks, firms and households face across a variety of different maturities. One mechanism for this is through the central bank conveying information about economic conditions. So far the literature on this information effect has focused on signals about the expectations of the level of economic activity. Our results show that, in addition to this conventional expectations channel, signals about the expected uncertainty around economic conditions can give rise to important effects, especially at the long-run. Using a novel combination of theory, unstructured data and event studies, we find that this uncertainty channel plays a dominant role in moving interest rates at the long-end of the yield curve in response to publication of the Bank of England Inflation Report.

These results suggest that central banks concerned with their influence on long-term interest rates should take seriously the communication of the distribution of risks and uncertainties around economic conditions. Of course, more remains to be done to understand fully the policy implications of this channel of central bank communication and, in particular, how to incorporate this into communication strategies. For instance, earlier work on Delphic forward guidance, an approach adopted by many central banks in the last decade, has stressed the need to combine views on the future evolution of the economy together with a description of how monetary policy will react to these developments whereas our results suggest policy-free guidance can also move long-run interest rates. This may be particularly important for central banks to take into account in periods when it is confronted with an effective lower bound on short-term interest rates and its influence on long-run rates is relatively more important.

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Appendix for Web

A Omitted Proofs

A.1 Proof of Proposition 1

Proof. The first step is to take the expectation of (13) conditional on I_t^{MK}. Observe that

$$\mathbb{E}\left[\, v_{m+i} \mid I_t^{\text{MK}} \,\right] = \widehat{\mu}_{m+i,m}^{\text{CB}} \text{ for } i = 1, \ldots, h.$$

Also, because the central bank is Bayesian, we have

$$\mathbb{E}\left[\, \widehat{\mu}_{m+i,m+k}^{\text{CB}} \mid I_t^{\text{MK}} \,\right] = \widehat{\mu}_{m+i,m}^{\text{CB}} \text{ for } i = 1, \ldots, h; k < i.$$

Outside the current forecast horizon ($i > h$), we have $\mathbb{E}\left[\, v_{m+i} \mid I_t^{\text{MK}} \,\right] = \mathbb{E}\left[\, \widehat{\mu}_{m+i,m+k}^{\text{CB}} \mid I_t^{\text{MK}} \,\right] =$ 0 since the IR in month m contains no relevant news about cyclical shocks more than h months ahead. Expectations over them are therefore computed using the zero-mean prior distribution from which μ is drawn.

Combining these observations gives

$$\mathbb{E}\left[\, \mathbb{E}\left[\, \omega_{m+k+h} \mid I_{m+k}^{\text{CB}} \,\right] \mid I_t^{\text{MK}} \,\right] = \rho^{k+h}\omega_m + \sum_{i=1}^{h} \rho^{k+h-i} \widehat{\mu}_{m+i,m}^{\text{CB}}.$$

By the law of iterated expectations we also obtain

$$\mathbb{E}\left[\, \mathbb{E}\left[\, \omega_{m+k+h} \mid I_{m+k}^{\text{CB}} \,\right] \mid I_{t-1}^{\text{MK}} \,\right] = \rho^{k+h}\omega_m + \sum_{i=1}^{h} \rho^{k+h-i} \mathbb{E}\left[\, \widehat{\mu}_{m+i,m}^{\text{CB}} \mid \widehat{\mu}_{m+i,t-1}^{\text{MK}}, i_m \,\right].$$

The proposition follows immediately. ■

A.2 Proof of Proposition 3

Proof. We begin with basic properties of the lognormal distribution. By expanding the stochastic process for volatility (8), we obtain

$$\log \sigma_{m+h+k}^2 = \rho_\sigma^k \log \sigma_{m+h}^2 + (1 - \rho_\sigma^k) \log \sigma_0^2 + \sum_{i=1}^{k} \rho_\sigma^{k-i} u_{m+h+i}$$

So $\log \sigma_{m+h+k}^2 \mid \sigma_{m+h}^2$ is normally distributed with mean $\rho_\sigma^k \log \sigma_{m+h}^2 + (1 - \rho_\sigma^k) \log \sigma_0^2$ and variance $\sum_{i=1}^{k} \rho_\sigma^{2(k-i)} \sigma_u^2$. Therefore we obtain

$$\mathbb{E}\left[\, \sigma_{m+h+k}^2 \mid \sigma_{m+h}^2 \,\right] = \exp\left[\rho_\sigma^k \log \sigma_{m+h}^2 + (1 - \rho_\sigma^k) \log \sigma_0^2 + \frac{\sigma_u^2}{2} \sum_{i=1}^{k} \rho_\sigma^{2(k-i)}\right]$$

from which we obtain

$$\lim_{\rho_\sigma \to 1} \mathbb{E}\left[\, \sigma_{m+h+k}^2 \mid \sigma_{m+h}^2 \,\right] = \exp\left[\log \sigma_{m+h}^2 + \frac{k\sigma_u^2}{2}\right] = \sigma_{m+h}^2 \exp\left[\frac{k\sigma_u^2}{2}\right].$$

By similar arguments

$$\lim_{\rho_\sigma\to 1} \mathbb{E}\big[\, \sigma^2_{m+h+k} \;\big|\; \sigma^2_{m+h-1} \,\big] = \sigma^2_{m+h-1} \exp\left[\frac{(k+1)\sigma_u^2}{2}\right].$$

We begin by characterizing the variance of (13) conditional on I_t^{MK}. First note that the variance of $\widehat{\mu}^{\mathrm{CB}}_{m+i,m+k}$ does not depend on IR publication whenever $i > k \geq h$ because the IR in month m contains no information on the central bank's forecast more than h months ahead. It is therefore sufficient to compute

$$\mathrm{Var}\left[\sum_{i=1}^{k} \rho^{k+h-i} v_{m+i} \;\middle|\; I_t^{\mathrm{MK}}\right] = \sum_{i=1}^{k} \rho^{2(k+h-i)} \mathrm{Var}\big[\, v_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big]$$

where we can further expand

$$\mathrm{Var}\big[\, v_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big] = \mathrm{Var}\big[\, \mu_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big] + \mathrm{Var}\big[\, \varepsilon_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big].$$

When $i \leq h$ these conditional variances are by assumption $\mathrm{Var}\big[\, \mu_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big] = \big(s^{\mathrm{MK}}_{m+i,t}\big)^2$ and $\mathrm{Var}\big[\, \varepsilon_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big] = \sigma^2_{m+i}$.

When $i > h$, we have $\mathrm{Var}\big[\, \mu_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big] = s^2$ since no information is available on μ_{m+i} beyond the prior distribution, whose variance is s^2. The conditional variance of ε_{m+i} can be decomposed by the law of total variance as

$$\begin{aligned}\mathrm{Var}\big[\, \varepsilon_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big] = \mathbb{E}\big[\, \mathrm{Var}\big[\, \varepsilon_{m+i} \;\big|\; I_t^{\mathrm{MK}}, \sigma^2_{m+i} \,\big] \;\big|\; I_t^{\mathrm{MK}} \,\big] +& \\ \mathrm{Var}\big[\, \mathbb{E}\big[\, \varepsilon_{m+i} \;\big|\; I_t^{\mathrm{MK}}, \sigma^2_{m+i} \,\big] \;\big|\; I_t^{\mathrm{MK}} \,\big].&\end{aligned}$$

The second term is zero since this is the mean of the fundamental uncertainty shock in all periods. For the first term, we can use the results above to obtain

$$\lim_{\rho_\sigma\to 1} \mathrm{Var}\big[\, \varepsilon_{m+i} \;\big|\; I_t^{\mathrm{MK}} \,\big] = \lim_{\rho_\sigma\to 1} \mathbb{E}\big[\, \sigma^2_{m+i} \;\big|\; \sigma^2_{m+h} \,\big] = \sigma^2_{m+h} \exp\left[\frac{(i-h)\sigma_u^2}{2}\right].$$

Combining these results together yields[26]

$$\mathrm{Var}\left[\sum_{i=1}^{k} \rho^{k+h-i} v_{m+i} \;\middle|\; I_t^{\mathrm{MK}}\right] =$$
$$\sum_{i=1}^{h} \rho^{2(k+h-i)} \left(\big(s^{\mathrm{MK}}_{m+i,t}\big)^2 + \sigma^2_{m+i}\right) + \sum_{i=h+1}^{k} \rho^{2(k+h-i)} \left(s^2 + \sigma^2_{m+h} \exp\left[\frac{(i-h)\sigma_u^2}{2}\right]\right).$$

[26]This expression is valid for $k > h$. For $k = h$ the correct expression is simply the first term in the sum.

The equivalent expression for the variance conditional on I_{t-1}^{MK} is

$$\operatorname{Var}\left[\sum_{i=1}^{k}\rho^{k+h-i}v_{m+i}\;\middle|\;I_{t-1}^{\mathrm{MK}}\right]=\sum_{i=1}^{h-1}\rho^{2(k+h-i)}\left(\left(s_{m+i,t-1}^{\mathrm{MK}}\right)^{2}+\sigma_{m+i}^{2}\right)+$$
$$\rho^{2k}\left(\left(s_{m+h,t-1}^{\mathrm{MK}}\right)^{2}+\sigma_{m+h-1}^{2}\exp\left[\frac{\sigma_u^2}{2}\right]\right)+$$
$$\sum_{i=h+1}^{k}\rho^{2(k+h-i)}\left(s^{2}+\sigma_{m+h-1}^{2}\exp\left[\frac{(i-h)\sigma_u^2}{2}\right]\exp\left[\frac{\sigma_u^2}{2}\right]\right).$$

The statement of the proposition then follows directly. ■

B Inflation Report Event Study

In this section, we conduct an event study to assess the average market impact of IR publication and other Bank of England communications. This extends the work of Reeves and Sawicki (2007), who conduct a similar analysis on a shorter sample. See Section B in the main text for related discussion. We define the following events within our sample period: (1) IR publication; (2) policy rate announcement; (3) speech by MPC member; (4) release of minutes of MPC meeting. We define a dummy variable for each event, and estimate the model

$$|\Delta \text{Yield}|_t = \alpha + \beta_1 D(\text{IR})_t + \beta_2 D(\text{Rate})_t + \beta_3 D(\text{Speech})_t + \beta_4 D(\text{Min})_t + \varepsilon_t \qquad \text{(B.1)}$$

for each yield. The estimated coefficients from ordinary least squares (OLS) estimates are in column (1) of Tables B.1a-B.2b. In columns (2)-(5) of these tables we estimate quantile regressions at various points in the distribution.

Confirming the visual evidence from the kernel densities in Section 2.3, at shorter maturities the IR is a dominant mover of market interest rates. The OLS coefficients for the one-year spot and three-year forward rates are both highly significant and approximately twice as large as the coefficient for policy announcements. There is a drop in significance for the five-year forward rate, but the magnitude of the IR coefficient is equivalent to that for policy announcements. This suggests a lack of power given there are three times as many announcements as IR dates over the sample period. However, there is a significant effect of IR releases in the right tail, as seen in column (5). For the five-year ahead, five year forward rate there is a marginally significant coefficient in column (5), and its magnitude is again the largest of any type of communication.

Table B.1: Estimated Coefficients of Event-Study Regression

(a) 1-year spot rate

Main Regressors	(1) $\lvert\Delta i_{0:12;t}\rvert$	(2) $\lvert\Delta i_{0:12;t}\rvert$	(3) $\lvert\Delta i_{0:12;t}\rvert$	(4) $\lvert\Delta i_{0:12;t}\rvert$	(5) $\lvert\Delta i_{0:12;t}\rvert$
IR	0.016***	0.0073	0.014***	0.019**	0.031
	[0.000]	[0.317]	[0.002]	[0.013]	[0.151]
Announcement	0.0084***	0.00076	0.0023	0.0033	0.038
	[0.002]	[0.522]	[0.236]	[0.394]	[0.149]
Speech	-0.0022**	-0.0013**	-0.0019**	-0.0024	-0.0034
	[0.033]	[0.039]	[0.030]	[0.108]	[0.396]
Minutes	0.0046**	-0.0011	0.0019	0.0065**	0.024***
	[0.029]	[0.302]	[0.344]	[0.035]	[0.002]
VIX_t	0.00098***	0.00027***	0.00063***	0.0013***	0.0030***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.0024*	0.0022***	0.0039***	0.0040**	0.0022
	[0.093]	[0.001]	[0.000]	[0.015]	[0.664]
R-squared	0.121				
Quantile	OLS	.25	.5	.75	.95
Sample	All	All	All	All	All

(b) 3-year forward rate

Main Regressors	(1) $\lvert\Delta f_{36;t}\rvert$	(2) $\lvert\Delta f_{36;t}\rvert$	(3) $\lvert\Delta f_{36;t}\rvert$	(4) $\lvert\Delta f_{36;t}\rvert$	(5) $\lvert\Delta f_{36;t}\rvert$
IR	0.018***	0.0041	0.011	0.027**	0.061***
	[0.005]	[0.327]	[0.137]	[0.050]	[0.000]
Announcement	0.0071***	0.0027	0.011***	0.0097***	0.0088
	[0.007]	[0.274]	[0.000]	[0.004]	[0.339]
Speech	0.0039**	-0.0016	0.0025	0.0068***	0.022***
	[0.030]	[0.143]	[0.312]	[0.008]	[0.005]
Minutes	0.0042	0.0016	0.0028	0.012**	-0.0027
	[0.109]	[0.404]	[0.464]	[0.031]	[0.591]
VIX_t	0.00092***	0.00025***	0.00091***	0.0013***	0.0030***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.022***	0.0098***	0.014***	0.030***	0.045***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.053				
Quantile	OLS	.25	.5	.75	.95
Sample	All	All	All	All	All

Notes: These tables report quantile regressions to examine the effect on market interest rates according to whether (1) an IR is released, (2) a policy decision from the MPC is announced, (3) an MPC member makes a public speech, (4) minutes from MPC meetings are released, or (5) none of the above. These tables complement the kernel densities in figure 3.

Table B.2: Estimated Coefficients of Event-Study Regression

(a) 5-year forward rate

Main Regressors	(1) $\lvert\Delta f_{60;t}\rvert$	(2) $\lvert\Delta f_{60;t}\rvert$	(3) $\lvert\Delta f_{60;t}\rvert$	(4) $\lvert\Delta f_{60;t}\rvert$	(5) $\lvert\Delta f_{60;t}\rvert$
IR	0.0065	0.0019	-0.0039	0.0069	0.043***
	[0.271]	[0.578]	[0.449]	[0.557]	[0.002]
Announcement	0.0063*	0.0032	0.0059	0.010***	0.0032
	[0.055]	[0.233]	[0.106]	[0.004]	[0.857]
Speech	0.0044**	-0.00041	0.0030	0.0057**	0.025***
	[0.023]	[0.753]	[0.181]	[0.042]	[0.000]
Minutes	0.0037	0.0046	0.0050*	0.0040	-0.0055*
	[0.159]	[0.112]	[0.096]	[0.283]	[0.075]
VIX_t	0.0010***	0.00026***	0.00071***	0.0014***	0.0028***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.021***	0.0097***	0.019***	0.031***	0.052***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.052				
Quantile	OLS	.25	.5	.75	.95
Sample	All	All	All	All	All

(b) 5-year ahead, 5-year forward rate

Main Regressors	(1) $\lvert\Delta f_{60:120;t}\rvert$	(2) $\lvert\Delta f_{60:120;t}\rvert$	(3) $\lvert\Delta f_{60:120;t}\rvert$	(4) $\lvert\Delta f_{60:120;t}\rvert$	(5) $\lvert\Delta f_{60:120;t}\rvert$
IR	0.0021	-0.0015	-0.0014	-0.0014	0.037*
	[0.688]	[0.592]	[0.798]	[0.889]	[0.074]
Announcement	0.0049	0.000084	0.0014	0.0078	0.0046
	[0.154]	[0.978]	[0.641]	[0.179]	[0.669]
Speech	0.0035*	-0.00050	3.7e-06	0.0026	0.021***
	[0.070]	[0.685]	[0.998]	[0.437]	[0.000]
Minutes	0.0036	0.0065*	0.0047*	0.0043	-0.0012
	[0.158]	[0.081]	[0.051]	[0.491]	[0.838]
VIX_t	0.00097***	0.00027***	0.00061***	0.0013***	0.0027***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.021***	0.0094***	0.020***	0.032***	0.051***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.049				
Quantile	OLS	.25	.5	.75	.95
Sample	All	All	All	All	All

Notes: These tables report quantile regressions to examine the effect on market interest rates according to whether (1) an IR is released, (2) a policy decision from the MPC is announced, (3) an MPC member makes a public speech, (4) minutes from MPC meetings are released, or (5) none of the above. These tables complement the kernel densities in figure 3.

C Details of Cross Validation Procedure

Here we detail the cross-validation procedure we use to select λ in our estimation of the elastic net regressions in the paper. Given our small sample size, leave-one-out cross validation is computationally feasible and we adopt it. The specific algorithm is:

1. For each of a sequence of possible λ penalty coefficients:
   (a) For each of the N data points:
      i. Remove the point from the sample.
      ii. Fit (18) on the remaining $N-1$ points.
      iii. Calculate the forecasted value for the held-out point from the fitted model, and compute the squared error.
2. Select the highest value of λ that has a mean squared error (MSE) within one standard deviation of the MSE-minimizing λ across N out-of-sample forecasts.

The model selection rule at stage 2 is sparser than the model with the most accurate out-of-sample predictive power because, as λ increases, the elastic net selects fewer covariates. This increases our confidence that any selected text shock variables have a robust relationship with market interest rates.

Table C.1 reports the value of the penalty weight chosen by LOOCV (λ_{CV}) and the number of text shock variables selected under this model.

It is worthwhile noting that a text shock that is highly correlated with a yield residual in just one IR will, in general, not be selected by this procedure. Instead, we will select shocks whose correlation with yield residuals is robust across at least several different Reports.

Table C.1: Number of Selected Narrative Shocks from LOOCV

	$\lvert\Delta i_{0:12,t}\rvert$	$\lvert\Delta f_{36,t}\rvert$	$\lvert\Delta f_{60,t}\rvert$	$\lvert\Delta f_{60:120,t}\rvert$
λ_{CV}	0.0006	0.001	0.002	0.001
# selected narrative shocks	53	56	56	55

Notes: This table summarizes the estimation of (18) for four market rates by leave-one-out cross validation. At each maturity, a large number of text shock variables are chosen to accurately predict held-out yield residuals.

D Baseline Analysis: Supplementary Tables

D.1 First Stage Regressions

Table D.1: Effect of Forecast Variables on Market Yields

Main Regressors	(1) $\Delta i_{0:12;t}$	(2) $\Delta i_{0:12;t}$	(3) $\Delta f_{36;t}$	(4) $\Delta f_{36;t}$	(5) $\Delta f_{60;t}$	(6) $\Delta f_{60;t}$	(7) $\Delta f_{60:120;t}$	(8) $\Delta f_{60:120;t}$
π_m^{CB}	0.094**	0.080**	0.13*	0.092	0.11	0.079	0.093	0.066
	[0.028]	[0.025]	[0.056]	[0.311]	[0.108]	[0.363]	[0.182]	[0.385]
Surp(π_m^{CB})	0.0040	0.016	-0.012	0.0046	-0.030	-0.014	-0.033	-0.012
	[0.891]	[0.590]	[0.861]	[0.958]	[0.658]	[0.866]	[0.600]	[0.874]
g_m^{CB}	-0.049	-0.053	-0.029	-0.062	-0.032	-0.063	-0.034	-0.057
	[0.122]	[0.162]	[0.402]	[0.201]	[0.369]	[0.127]	[0.353]	[0.160]
Surp(g_m^{CB})	0.031	0.038	0.018	0.053	0.021	0.054	0.019	0.044
	[0.413]	[0.354]	[0.673]	[0.382]	[0.592]	[0.294]	[0.628]	[0.360]
$\tilde{y}_{m;24}^{CB}$	0.36	1.21	0.30	1.25	-0.46	0.33	-0.48	0.059
	[0.704]	[0.483]	[0.833]	[0.672]	[0.741]	[0.898]	[0.707]	[0.979]
$\tilde{y}_{m;24}^{CB} - \tilde{y}_{m-1;24}^{CB}$	6.47***	5.53**	3.69	3.53	2.76	1.89	3.42	1.56
	[0.001]	[0.050]	[0.164]	[0.333]	[0.347]	[0.551]	[0.211]	[0.547]
$\tilde{y}_{m;21}^{CB} - \tilde{y}_{m-1;24}^{CB}$	-4.66**	-4.65**	-5.15	-6.89*	-3.14	-4.85	-1.79	-2.68
	[0.043]	[0.025]	[0.149]	[0.062]	[0.333]	[0.128]	[0.547]	[0.297]
Var(π_m^{CB})		-0.019		-0.016		-0.00077		0.014
		[0.115]		[0.476]		[0.969]		[0.410]
ΔVar(π_m^{CB})		-0.028		0.0043		0.070		0.089**
		[0.606]		[0.940]		[0.138]		[0.044]
Skew(π_m^{CB})		0.099**		0.12		0.096		0.097
		[0.035]		[0.161]		[0.219]		[0.124]
ΔSkew(π_m^{CB})		-0.061		-0.16**		-0.16**		-0.13**
		[0.259]		[0.027]		[0.011]		[0.014]
Var(g_m^{CB})		0.021		-0.0077		-0.023		-0.030
		[0.161]		[0.794]		[0.408]		[0.215]
ΔVar(g_m^{CB})		-0.014		-0.041**		-0.050***		-0.044**
		[0.337]		[0.048]		[0.009]		[0.015]
Skew(g_m^{CB})		0.017		-0.037		-0.044		-0.044
		[0.697]		[0.485]		[0.323]		[0.297]
ΔSkew(g_m^{CB})		0.031		0.031		0.013		0.0031
		[0.310]		[0.486]		[0.738]		[0.928]
Constant	0.11	0.11	0.070	0.17	0.078	0.18	0.085	0.17
	[0.159]	[0.280]	[0.405]	[0.216]	[0.380]	[0.125]	[0.360]	[0.151]
R-squared	0.449	0.562	0.262	0.361	0.166	0.333	0.156	0.371
Additional R^2	-	0.113	-	0.099	-	0.167	-	0.215
Partial R^2	-	0.206	-	0.135	-	0.200	-	0.254
Proportion R^2	-	0.202	-	0.275	-	0.501	-	0.579
F-test p-value	-	0.029	-	0.046	-	0.000	-	0.000
Component	Total	Total	Total	Total	Total	Total	Total	Total

Notes: This table reports estimates from regressing changes in market yields on the numeric forecast variables defined in Section 4.1.

Table D.2: Effect of Forecast Variables on Market Yields: Expectations

Main Regressors	(1) $\Delta i_{0:12;t}$	(2) $\Delta i_{0:12;t}$	(3) $\Delta f_{36;t}$	(4) $\Delta f_{36;t}$	(5) $\Delta f_{60;t}$	(6) $\Delta f_{60;t}$	(7) $\Delta f_{60:120;t}$	(8) $\Delta f_{60:120;t}$
π_m^{CB}	0.080**	0.067**	0.089**	0.065	0.086**	0.059	0.066**	0.046
	[0.041]	[0.041]	[0.027]	[0.251]	[0.015]	[0.250]	[0.026]	[0.276]
Surp(π_m^{CB})	0.0062	0.020	0.0040	0.017	-0.0091	0.0045	-0.0055	0.0087
	[0.819]	[0.475]	[0.921]	[0.743]	[0.807]	[0.925]	[0.857]	[0.830]
g_m^{CB}	-0.044	-0.051	-0.018	-0.038	-0.014	-0.034	-0.0085	-0.022
	[0.109]	[0.140]	[0.525]	[0.326]	[0.527]	[0.276]	[0.656]	[0.428]
Surp(g_m^{CB})	0.028	0.037	0.010	0.032	0.011	0.031	0.0046	0.018
	[0.387]	[0.306]	[0.759]	[0.487]	[0.690]	[0.429]	[0.846]	[0.599]
$\tilde{y}_{m;24}^{CB}$	0.28	0.89	0.57	1.17	0.35	0.77	0.58	0.79
	[0.746]	[0.547]	[0.575]	[0.595]	[0.683]	[0.675]	[0.414]	[0.612]
$\tilde{y}_{m;24}^{CB} - \tilde{y}_{m-1;24}^{CB}$	5.24***	4.70**	3.21*	3.57	2.06	2.39	2.02	2.10
	[0.002]	[0.045]	[0.073]	[0.188]	[0.194]	[0.295]	[0.102]	[0.260]
$\tilde{y}_{m;21}^{CB} - \tilde{y}_{m-1;24}^{CB}$	-3.73*	-3.69**	-4.21	-5.21**	-3.11	-4.27*	-2.60	-3.28*
	[0.058]	[0.044]	[0.107]	[0.045]	[0.159]	[0.060]	[0.155]	[0.079]
Var(π_m^{CB})		-0.014		-0.017		-0.013		-0.0082
		[0.194]		[0.303]		[0.375]		[0.480]
ΔVar(π_m^{CB})		-0.031		-0.040		-0.014		-0.024
		[0.495]		[0.404]		[0.731]		[0.491]
Skew(π_m^{CB})		0.081*		0.085		0.067		0.066
		[0.054]		[0.163]		[0.210]		[0.119]
ΔSkew(π_m^{CB})		-0.048		-0.092*		-0.092**		-0.065*
		[0.313]		[0.075]		[0.038]		[0.081]
Var(g_m^{CB})		0.016		0.0033		-0.0015		-0.00031
		[0.264]		[0.871]		[0.932]		[0.983]
ΔVar(g_m^{CB})		-0.0073		-0.019		-0.025*		-0.017
		[0.605]		[0.249]		[0.056]		[0.112]
Skew(g_m^{CB})		0.014		-0.017		-0.013		-0.0078
		[0.721]		[0.710]		[0.711]		[0.802]
ΔSkew(g_m^{CB})		0.035		0.031		0.017		0.0100
		[0.200]		[0.344]		[0.528]		[0.664]
Constant	0.10	0.11	0.043	0.097	0.035	0.092	0.021	0.056
	[0.132]	[0.239]	[0.523]	[0.364]	[0.521]	[0.287]	[0.642]	[0.449]
R-squared	0.454	0.568	0.334	0.413	0.304	0.391	0.334	0.409
Additional R^2	-	0.114	-	0.079	-	0.087	-	0.075
Partial R^2	-	0.209	-	0.119	-	0.125	-	0.113
Proportion R^2	-	0.201	-	0.192	-	0.223	-	0.183
F-test p-value	-	0.041	-	0.120	-	0.073	-	0.147
Component	Exp	Exp	Exp	Exp	Exp	Exp	Exp	Exp

Notes: This table reports estimates from regressing changes in the expectations component of market yields on the numeric forecast variables defined in Section 4.1.

Table D.3: Effect of Forecast Variables on Market Yields: Term Premiums

Main Regressors	(1) $\Delta i_{0:12;t}$	(2) $\Delta i_{0:12;t}$	(3) $\Delta f_{36;t}$	(4) $\Delta f_{36;t}$	(5) $\Delta f_{60;t}$	(6) $\Delta f_{60;t}$	(7) $\Delta f_{60:120;t}$	(8) $\Delta f_{60:120;t}$
π_m^{CB}	0.014*	0.013	0.037	0.027	0.028	0.021	0.027	0.020
	[0.085]	[0.147]	[0.294]	[0.519]	[0.543]	[0.654]	[0.633]	[0.686]
Surp(π_m^{CB})	-0.0023	-0.0038	-0.016	-0.012	-0.021	-0.018	-0.028	-0.021
	[0.744]	[0.659]	[0.634]	[0.758]	[0.584]	[0.668]	[0.540]	[0.655]
g_m^{CB}	-0.0044	-0.0027	-0.012	-0.024	-0.018	-0.029	-0.026	-0.035
	[0.474]	[0.729]	[0.455]	[0.228]	[0.502]	[0.316]	[0.479]	[0.400]
Surp(g_m^{CB})	0.0030	0.0011	0.0077	0.021	0.0100	0.024	0.014	0.026
	[0.699]	[0.910]	[0.655]	[0.386]	[0.708]	[0.455]	[0.698]	[0.549]
$\tilde{y}_{m;24}^{CB}$	0.078	0.32	-0.27	0.086	-0.81	-0.44	-1.06	-0.73
	[0.655]	[0.340]	[0.676]	[0.938]	[0.326]	[0.755]	[0.298]	[0.673]
$\tilde{y}_{m;24}^{CB} - \tilde{y}_{m-1;24}^{CB}$	1.23***	0.83	0.49	-0.038	0.70	-0.50	1.40	-0.54
	[0.006]	[0.157]	[0.736]	[0.979]	[0.738]	[0.787]	[0.593]	[0.804]
$\tilde{y}_{m;21}^{CB} - \tilde{y}_{m-1;24}^{CB}$	-0.93**	-0.96*	-0.94	-1.68	-0.037	-0.58	0.81	0.60
	[0.049]	[0.066]	[0.525]	[0.244]	[0.985]	[0.711]	[0.756]	[0.742]
Var(π_m^{CB})		-0.0050**		0.0011		0.012		0.023
		[0.046]		[0.899]		[0.295]		[0.122]
ΔVar(π_m^{CB})		0.0033		0.044*		0.084**		0.11**
		[0.781]		[0.077]		[0.023]		[0.021]
Skew(π_m^{CB})		0.017*		0.038		0.029		0.031
		[0.060]		[0.263]		[0.439]		[0.465]
ΔSkew(π_m^{CB})		-0.013		-0.066**		-0.069**		-0.069*
		[0.211]		[0.027]		[0.041]		[0.076]
Var(g_m^{CB})		0.0059**		-0.011		-0.022		-0.030
		[0.032]		[0.380]		[0.166]		[0.118]
ΔVar(g_m^{CB})		-0.0070***		-0.022**		-0.025**		-0.027*
		[0.002]		[0.014]		[0.048]		[0.095]
Skew(g_m^{CB})		0.0037		-0.020		-0.031		-0.036
		[0.670]		[0.349]		[0.353]		[0.416]
ΔSkew(g_m^{CB})		-0.0043		-0.00051		-0.0039		-0.0069
		[0.533]		[0.979]		[0.873]		[0.815]
Constant	0.0065	0.00095	0.028	0.070	0.043	0.091	0.064	0.11
	[0.656]	[0.962]	[0.476]	[0.219]	[0.518]	[0.273]	[0.488]	[0.349]
R-squared	0.261	0.371	0.060	0.244	0.033	0.275	0.054	0.317
Additional R^2	-	0.110	-	0.184	-	0.242	-	0.263
Partial R^2	-	0.149	-	0.195	-	0.251	-	0.278
Proportion R^2	-	0.297	-	0.754	-	0.880	-	0.830
F-test p-value	-	0.009	-	0.001	-	0.001	-	0.000
Component	TP	TP	TP	TP	TP	TP	TP	TP

Notes: This table reports estimates from regressing changes in the term premium component of market yields on the numeric forecast variables defined in Section 4.1.

D.2 Narrative Regressions

Table D.4: Contribution of Numeric vs. Narrative Variables to R^2

Main Regressors	(1) $\Delta i_{0:12;t}$	(2) $\Delta i_{0:12;t}$	(3) $\Delta f_{36;t}$	(4) $\Delta f_{36;t}$
Signed Topic D1		-0.017**		
		[0.02]		
Signed Topic L11		0.034*		0.063**
		[0.05]		[0.04]
Signed Topic D9		-0.010		-0.034***
		[0.15]		[0.01]
Signed Topic L19		-0.024*		
		[0.08]		
Signed Topic D18				0.030**
				[0.02]
Signed Topic D13				-0.026**
				[0.03]
Constant	0.11	0.014	0.17	0.12
	[0.28]	[0.89]	[0.22]	[0.32]
R-squared	0.562	0.694	0.361	0.561
Topics	Own	Own	Own	Own
Include Vix	No	No	No	No
Include $\mathbf{q}_t$	Yes	Yes	Yes	Yes
Additional R^2	-	0.128	-	0.199
Partial R^2	-	0.29	-	0.31
Proportion R^2	-	0.18	-	0.35
F-test p-value	-	0.025	-	0.023

Notes: Columns (1)-(3) ((4)-(6)) show how much market news for $|\Delta i_{0:12;t}|$ ($|\Delta f_{36;t}|$) can be explained by adding numeric in (2) and then, in (3), numeric and narrative information captured by the top 4 topics. This information is reflected in table 9 in the main text.

Table D.5: Contribution of Numeric vs. Narrative Variables to R^2

Main Regressors	(1) $\Delta f_{60;t}$	(2) $\Delta f_{60;t}$	(3) $\Delta f_{60:120;t}$	(4) $\Delta f_{60:120;t}$
Signed Topic D9		-0.024**		
		[0.05]		
Signed Topic L16		-0.029*		-0.030**
		[0.06]		[0.02]
Signed Topic D18		0.034**		0.031***
		[0.01]		[0.00]
Signed Topic D13		-0.017*		-0.013*
		[0.07]		[0.08]
Signed Topic L12				-0.0076
				[0.47]
Constant	0.18	0.20	0.17	0.20
	[0.12]	[0.16]	[0.15]	[0.14]
R-squared	0.333	0.497	0.371	0.515
Topics	Own	Own	Own	Own
Include Vix	No	No	No	No
Include $\mathbf{q}_t$	Yes	Yes	Yes	Yes
Additional R^2	-	0.167	-	0.149
Partial R^2	-	0.25	-	0.24
Proportion R^2	-	0.33	-	0.29
F-test p-value	-	0.014	-	0.017

Notes: Columns (1)-(3) ((4)-(6)) show how much market news for $|\Delta f_{60;t}|$ ($|\Delta f_{60:120;t}|$) can be explained by adding numeric in (2) and then, in (3), numeric and narrative information captured by the top 4 topics. This information is reflected in table 3 in the main text.

Table D.6: Full Matrix of Partial R^2 from Placebo Regressions including Components of the Asset Response

Asset News	Narrative Shocks											
	$i_{0:12;t}$			$f_{36;t}$			$f_{60;t}$			$f_{60:120;t}$		
	Overall	EXP	TP	Overall	EXP	TP	Overall	EXP	TP	Overall	EXP	TP
$i_{0:12;t}$	0.29***	0.31***	0.11	0.08	0.24***	0.06	0.06	0.08*	0.06	0.01	0.06	0.04
EXP($i_{0:12;t}$)	0.30***	0.32***	0.08	0.08	0.23***	0.06	0.06	0.10*	0.06	0.01	0.06	0.04
TP($i_{0:12;t}$)	0.17*	0.10	0.36***	0.13	0.19	0.02	0.06	0.13	0.02	0.06	0.13	0.04
$f_{36;t}$	0.15	0.11	0.15	0.23*	0.15***	0.15	0.18	0.24***	0.07	0.11	0.16**	0.05
EXP($f_{36;t}$)	0.19***	0.14*	0.14*	0.17	0.25***	0.07	0.08	0.21***	0.05	0.07	0.21***	0.03
TP($f_{36;t}$)	0.11	0.17	0.13	0.17	0.03	0.31**	0.35**	0.15	0.18	0.28*	0.04	0.18
$f_{60;t}$	0.14	0.17	0.12	0.21	0.04	0.26**	0.31**	0.19*	0.14	0.24*	0.04	0.15
EXP($f_{60;t}$)	0.18**	0.12	0.18	0.21*	0.18***	0.11	0.16	0.21***	0.05	0.11	0.18**	0.05
TP($f_{60;t}$)	0.12	0.12	0.08	0.06	0.08	0.38***	0.38***	0.08	0.42***	0.44***	0.09*	0.39***
$f_{60:120;t}$	0.12	0.17	0.08	0.13	0.04	0.28**	0.34***	0.13	0.24*	0.37***	0.04	0.23*
EXP($f_{60:120;t}$)	0.22***	0.14*	0.16	0.22**	0.27***	0.10	0.12	0.24***	0.05	0.09	0.22***	0.05
TP($f_{60:120;t}$)	0.14	0.12	0.04	0.07	0.10	0.29**	0.32***	0.08	0.39***	0.40***	0.11*	0.36***

Notes: This table replicates table 10 reporting the Partial-R^2 statistics from adding four narrative shocks to explain different yields but expands the analysis to include the breakdown by yield components. The top four topics added are indicated by the column and each row reports the results for a different yield or its component. Stars (***, **, and *) indicate the significance level (1%, 5% and 10%) of an F-test on the joint significance of the narrative shocks given the inclusion of VIX and q_t.

E Analysis of Absolute Values

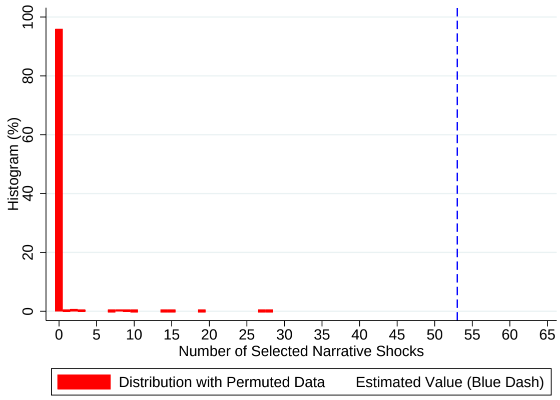
E.1 First Stage Regressions: Absolute Values

Table E.1: Effect of Forecast Variables on Market Yields

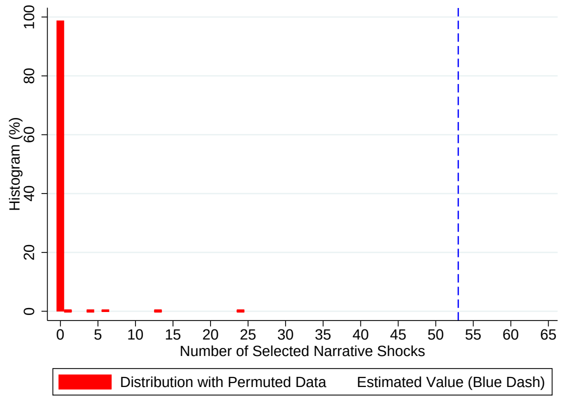
Main Regressors	(1) $\lvert\Delta i_{0:12;t}\rvert$	(2) $\lvert\Delta i_{0:12;t}\rvert$	(3) $\lvert\Delta f_{36;t}\rvert$	(4) $\lvert\Delta f_{36;t}\rvert$	(5) $\lvert\Delta f_{60;t}\rvert$	(6) $\lvert\Delta f_{60;t}\rvert$	(7) $\lvert\Delta f_{60:120;t}\rvert$	(8) $\lvert\Delta f_{60:120;t}\rvert$
VIX_t	0.0016***	0.0013**	0.0015	0.0023	0.0011	0.0018	0.0012	0.0017
	[0.003]	[0.023]	[0.302]	[0.151]	[0.427]	[0.229]	[0.253]	[0.150]
π_m^{CB}	-0.037	-0.016	-0.060**	-0.014	-0.014	0.016	-0.0014	0.025
	[0.207]	[0.535]	[0.025]	[0.698]	[0.612]	[0.645]	[0.963]	[0.432]
$\lvert\text{Supr}(\pi_m^{CB})\rvert$	0.0018	0.034	-0.018	-0.035	-0.0026	-0.042	-0.022	-0.051
	[0.957]	[0.292]	[0.618]	[0.442]	[0.942]	[0.314]	[0.538]	[0.152]
g_m^{CB}	0.018	0.031**	-0.0032	0.00010	-0.015	-0.012	-0.024	-0.015
	[0.127]	[0.038]	[0.848]	[0.995]	[0.388]	[0.476]	[0.165]	[0.381]
$\lvert\text{Supr}(g_m^{CB})\rvert$	-0.0097	-0.048*	0.042*	0.050	0.042	0.053*	0.037	0.024
	[0.704]	[0.063]	[0.099]	[0.140]	[0.114]	[0.084]	[0.196]	[0.373]
$\tilde{y}_{m;24}^{CB}$	1.00	0.41	1.92*	3.35*	0.76	1.68	0.067	-0.50
	[0.310]	[0.722]	[0.087]	[0.097]	[0.541]	[0.369]	[0.961]	[0.747]
$\lvert\tilde{y}_{m;24}^{CB} - \tilde{y}_{m-1;24}^{CB}\rvert$	4.01	4.96**	-0.28	1.41	-2.36	-1.00	-2.05	-1.43
	[0.130]	[0.015]	[0.945]	[0.685]	[0.564]	[0.767]	[0.523]	[0.595]
$\lvert\tilde{y}_{m;21}^{CB} - \tilde{y}_{m-1;24}^{CB}\rvert$	0.25	1.64	1.47	-0.35	2.28	-0.25	1.88	1.31
	[0.899]	[0.430]	[0.647]	[0.925]	[0.503]	[0.944]	[0.548]	[0.652]
$\text{Var}(\pi_m^{CB})$		-0.011		0.025		0.021		0.020
		[0.324]		[0.161]		[0.257]		[0.218]
$\Delta\text{Var}(\pi_m^{CB})$		0.038		-0.057		-0.12**		-0.085*
		[0.455]		[0.240]		[0.011]		[0.084]
$\text{Skew}(\pi_m^{CB})$		0.0045		0.0100		-0.0040		-0.0036
		[0.891]		[0.834]		[0.924]		[0.923]
$\Delta\text{Skew}(\pi_m^{CB})$		0.025		0.065		0.068		0.052
		[0.500]		[0.150]		[0.108]		[0.154]
$\text{Var}(g_m^{CB})$		0.0010		-0.0052		-0.0021		-0.012
		[0.934]		[0.765]		[0.903]		[0.446]
$\Delta\text{Var}(g_m^{CB})$		0.0098		0.019		0.024		0.034*
		[0.539]		[0.236]		[0.153]		[0.058]
$\text{Skew}(g_m^{CB})$		-0.014		-0.071		-0.060		-0.045
		[0.688]		[0.171]		[0.202]		[0.260]
$\Delta\text{Skew}(g_m^{CB})$		-0.063**		-0.00055		0.0031		-0.022
		[0.049]		[0.990]		[0.938]		[0.533]
Constant	-0.053*	-0.070*	0.019	-0.026	0.052	0.014	0.074	0.043
	[0.089]	[0.075]	[0.716]	[0.693]	[0.341]	[0.833]	[0.138]	[0.456]
R-squared	0.403	0.563	0.250	0.368	0.122	0.280	0.114	0.274
Partial R-squared	-	0.269	-	0.157	-	0.180	-	0.181
Proportion R-squared	-	0.285	-	0.320	-	0.564	-	0.584
F-test p-value	-	0.182	-	0.260	-	0.011	-	0.015
R-squared No Vix	0.336	0.336	0.216	0.216	0.099	0.099	0.082	0.082
Component	Total	Total	Total	Total	Total	Total	Total	Total

Notes: This table reports estimates from regressing absolute changes in market yields on the numeric forecast variables defined in Section 4.1.

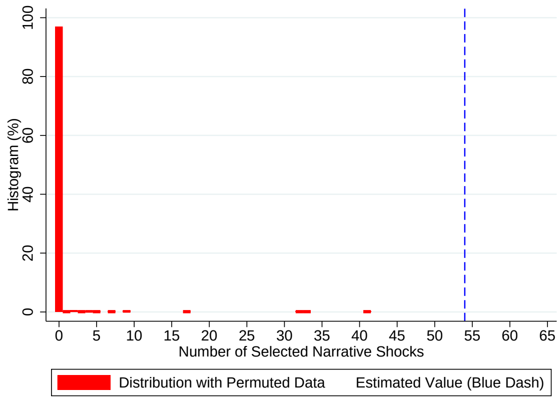
E.2 Information Tests: Absolute Values



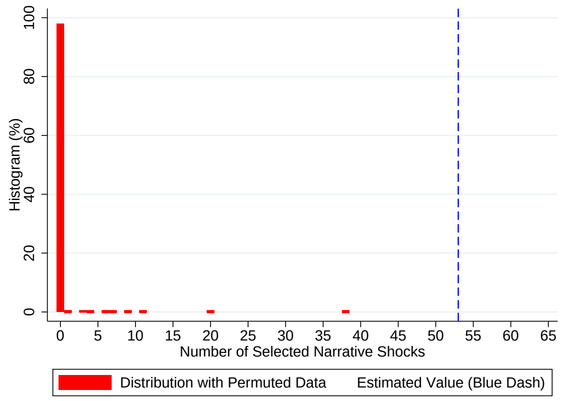
(a) 1-year Spot



(b) 3-year Forward



(c) 5-year Forward



(d) 5-year, 5-year Forward

Figure E.1: Permutation Test for Narrative News

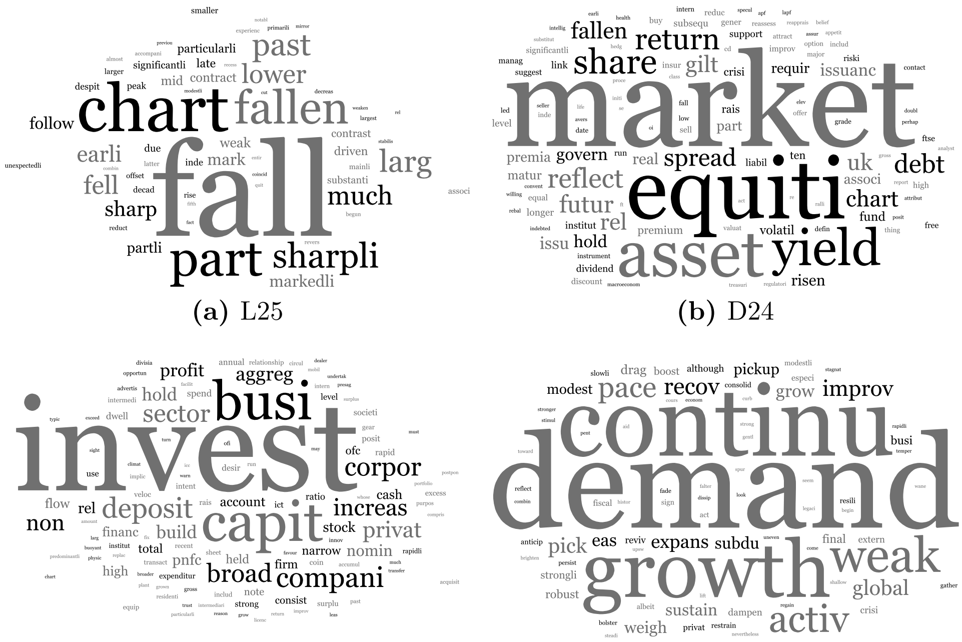
Notes: These figures describe a permutation test for narrative news. The blue, dashed vertical lines for each yield plot the number of selected text variables as in Table 4 in the main text. The red histograms describe the distribution of selected features in 500 different random permutations of yield residuals for which we used the same cross validation procedure as on the original data. In no permutation do we select as many features as with the true order.

E.3 Top Topics: Absolute Values

Table E.2: Top Topics for Different Yields (L=Level; D=Change)

$\lvert\Delta i_{0:12,t}\rvert$		$\lvert\Delta f_{36,t}\rvert$		$\lvert\Delta f_{60,t}\rvert$		$\lvert\Delta f_{60:120,t}\rvert$	
Var	Selection %	Var	Selection %	Var	Selection %	Var	Selection %
L25	0.958	D24	0.858	L28	0.876	D17	0.91
D24	0.954	D25	0.844	D17	0.784	D18	0.896
L5	0.932	L28	0.826	D18	0.772	L20	0.836
L26	0.91	D14	0.76	L20	0.722	D13	0.808

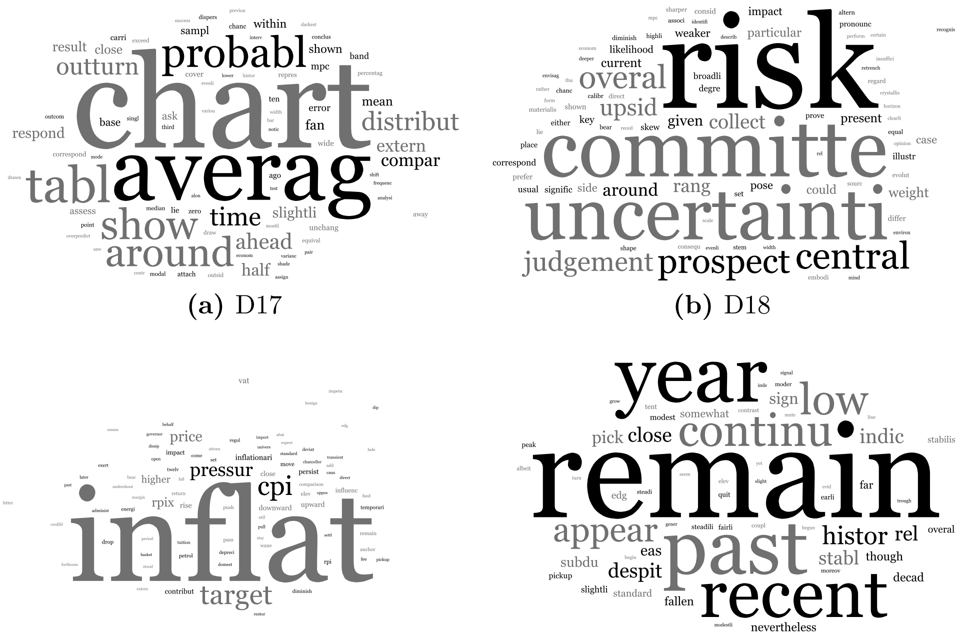
Notes: This table lists the top four topics for each yield according to fraction of times they are selected across 500 bootstrap draws. An L indicates the topic variable corresponds to a residual in levels, while a D indicates a residuals in the absolute change in the topic level.



(a) L25 (b) D24

(c) L5 (d) L26

Figure E.2: Key Topics for Market Reaction to Narrative: 1-Year Spot Rate



(a) D17 (b) D18

(c) L20 (d) D13

Figure E.3: Key Topics for Market Reaction to Narrative: 5-Year, 5-Year Forward Rate

E.4 Narrative Regressions: Absolute Values

Table E.3: Effect of Top Expectations and Term Premium Narrative Shocks on R^2

Main Regressors	(1) $\lvert\Delta i_{0:12;t}\rvert$	(2) $\lvert\Delta i_{0:12;t}\rvert$	(3) $\lvert\Delta f_{36;t}\rvert$	(4) $\lvert\Delta f_{36;t}\rvert$
VIX_t		0.00050		0.0037**
		[0.34]		[0.02]
Topic L25		1.80***		
		[0.01]		
Topic D24		-0.66		-1.42
		[0.13]		[0.11]
Topic L5		-1.32**		
		[0.02]		
Topic L26		-1.34**		
		[0.03]		
Topic D25				-2.91
				[0.14]
Topic L28				1.35*
				[0.05]
Topic D14				2.00
				[0.28]
Constant	-0.070*	0.014	-0.026	-0.058
	[0.08]	[0.81]	[0.69]	[0.35]
R-squared	0.563	0.693	0.368	0.510
Topics	Own	Own	Own	Own
Include Vix	Yes	Yes	Yes	Yes
Include $\mathbf{q}_t$	Yes	Yes	Yes	Yes
Additional R^2	-	0.127	-	0.142
Partial R^2	0.39	0.29	0.26	0.23
Proportion R^2	-	0.18	-	0.28
F-test p-value	-	0.001	-	0.120

Notes: Columns (1)-(3) [(4)-(6)] show how much market news for $\lvert\Delta i_{0:12;t}\rvert$ ($\lvert\Delta f_{36;t}\rvert$) can be explained by the overall yield top narrative shocks in (1) [(4)], the top narrative shocks for the yield expectations component in (2) [(5)], and the top narrative shocks for the term premium component in (3) [(6)].

Table E.4: Effect of Top Expectations and Term Premium Narrative Shocks on R^2

Main Regressors	(1) $\lvert\Delta f_{60;t}\rvert$	(2) $\lvert\Delta f_{60;t}\rvert$	(3) $\lvert\Delta f_{60:120;t}\rvert$	(4) $\lvert\Delta f_{60:120;t}\rvert$
VIX_t		0.0035***		0.0030***
		[0.01]		[0.00]
Topic L28		1.48**		
		[0.02]		
Topic D17		1.41*		1.77**
		[0.08]		[0.01]
Topic D18		-2.39		-3.34*
		[0.23]		[0.06]
Topic L20		1.39*		2.07***
		[0.08]		[0.00]
Topic D13				-3.26***
				[0.01]
Constant	0.014	-0.053	0.043	-0.0070
	[0.83]	[0.44]	[0.46]	[0.89]
R-squared	0.280	0.502	0.274	0.542
Topics	Own	Own	Own	Own
Include Vix	Yes	Yes	Yes	Yes
Include $\mathbf{q}_t$	Yes	Yes	Yes	Yes
Additional R^2	-	0.220	-	0.266
Partial R^2	0.23	0.31	0.23	0.37
Proportion R^2	-	0.44	-	0.49
F-test p-value	-	0.023	-	0.004

Notes: Columns (1)-(3) ((4)-(6)) show how much market news for $\lvert\Delta f_{60;t}\rvert$ ($\lvert\Delta f_{60:120;t}\rvert$) can be explained by the overall yield top narrative shocks in (1) [(4)], the top narrative shocks for the yield expectations component in (2) [(5)], and the top narrative shocks for the term premium component in (3) [(6)].

Acknowledgements

Omiros Papaspiliopoulos and David Rossell provided numerous helpful suggestions on the statistical methodologies used in this paper. We thank our discussants at different conferences – Jan Marc Berk, Jenny Tang (twice) and Jonathan Talmi. We would like to additionally thank, for comments, discussion and suggestions, Michael Ehrmann, Refet Gürkaynak, Emi Nakamura, Alessandro Riboni, and Jon Steinsson, as well as participants at numerous conferences and seminars. This paper has been prepared while McMahon was under the Lamfalussy Fellowship Program sponsored by the ECB. The views expressed here do not necessarily represent the views of the Bank of England, the Monetary Policy Committee, Financial Policy Committee, the ECB, the Eurosystem or anyone else other than the authors. Any errors remain ours alone.

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PDF ISBN 978-92-899-4006-1 ISSN 1725-2806 doi:10.2866/49682 QB-AR-20-015-EN-N