Beyond the Yield Curve: Understanding the Effect of FOMC Announcements on the Stock Market*

Christoph E. Boehm and T. Niklas Kroner

UT Austin

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Abstract

A large literature uses high-frequency changes in interest rates around FOMC announcements to study monetary policy. These yield changes have puzzlingly low explanatory power for the stock market—even in a narrow 30-minute window. We propose a new approach to test whether the unexplained variation represents monetary policy news or just noise. In particular, we allow for a latent "Fed non-yield curve shock", which we estimate via a heteroskedasticity-based procedure. Using a test for weak identification, we show that our shock is well identified, that is, the unexplained variation is not just noise. We then go on to show that the shock, signed to increase stock prices, leads to sizable declines in the equity and variance premium, an increase in the 10-year term premium, an increase in short-run inflation expectations, as well as a dollar depreciation against multiple non-safe-haven currencies. Hence, the evidence supports the interpretation that the shock affects risk-appetite and leads to a reverse "flight-to-safety" effect. Lastly, using a method from the computational linguistics literature, we show that our shock can be linked to specific topics discussed in FOMC statements, suggesting that it reflects written communication by the Federal Reserve.

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Email: chris.e.boehm@gmail.com and tnkroner@utexas.edu.

1 Introduction

A large literature exploits high-frequency financial data and the lumpy information release of monetary policy news to study the causal effects of monetary policy. Consistent with standard theory, this literature constructs monetary policy shocks from surprise interest rate movements in a narrow window around FOMC announcements, implicitly assuming that any form of monetary policy shocks are captured by movements in the yield curve. While these shocks can, by construction, account for much of the variation in the yield curve around announcements, their explanatory power for the stock market is puzzlingly low. Table 1 illustrates this point for three influential studies by Gürkaynak, Sack, and Swanson (2005), Nakamura and Steinsson (2018), and Swanson (2020). As Swanson's (2020) results show, this phenomenon is stable across different subperiods and even present when one allows for three policy instruments (federal funds rate, forward guidance, and quantitative easing).

One way to rationalize this phenomenon is by introducing what the literature has termed "information effects" whereby central bank communication reveals private information on economic fundamentals (e.g., Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020).[1] Jarociński and Karadi (2020) *assume* that 1) the 30-minute change in the stock market around monetary policy announcements is entirely driven by monetary policy news and 2) there are information shocks in addition to standard monetary policy shocks, which lead stock prices and bond yields to co-move. Adding the information shock allows them to perfectly fit the observed stock market response. However, these two assumptions have been challenged on several grounds. First, it is not clear to what extent the unexplained variation in the stock market reflects noise rather than information effects. Swanson (2020), for instance, attributes the low explanatory power of yield curve changes for the stock market to the "larger idiosyncratic volatility of stocks (...) relative to Treasuries" (Swanson, 2020, p.13). Second, several recent papers argue that information effects are either not existent or at maximum relatively small (Bundick and Smith, 2020; Bauer and Swanson, 2020). Third, even if information effects are present, it is not clear that the positive co-movement of stock prices and bond yields is the right identification assumption (Nakamura and Steinsson, 2018), nor that they can fully account for the unexplained variation in the stock market.[2]

In this paper, we argue that the unexplained variation in the stock market reflects a channel of monetary policy that is independent of any effects on the yield curve. In particular, we use

[1] Other names for information effects in the literature are information shocks, signaling effects or Delphic forward guidance.

[2] Nakamura and Steinsson (2018) develop and estimate a model which includes Fed information effects. In their model stock prices fall after a contractionary monetary policy shock despite the presence of information effects—although they fall by more without information effects. This suggests that information effects may not be strong enough to induce the positive co-movement of stock prices and bond yields assumed by Jarociński and Karadi (2020).

Table 1: Explanatory Power of HF Shocks in 30-minute Window around FOMC announcements

Shocks from	No. of Shocks	R^2—Yields MP1	ED4	2Y	5Y	10Y	R^2—Stocks S&P 500	No. of Obs.	Sample
Gürkaynak, Sack, and Swanson (2005)	2	91%	98%	94%	80%	74%	40%	138	1990–2004
Nakamura and Steinsson (2018)	1	45%	79%	62%	42%	22%	16%	105	2000-2014
Swanson (2020)	3	81%		94%	96%	97%	31%	241	1991-2019
		82%		95%	88%	81%	37%	157	1991-2008
		39%		92%	95%	98%	28%	55	2009-2015
		91%		98%	99%	99%	25%	29	2015-2019

Notes: This table provides an overview of high-frequency identified monetary policy shocks of the literature and their explanatory power in a 30-minute window around FOMC announcements. Abbreviations: *MP1*—Federal funds rate future; *ED4*—One-year ahead Eurodollar future; nY—n-year Treasury yield. Construction: For Gürkaynak, Sack, and Swanson (2005), results are taken from Table 5. For Swanson (2020), results are taken from Table 4 and 5, where results for the 6-month Treasury yield are used as a stand-in for *MP1* and *ED4*. Since Nakamura and Steinsson (2018) do not report responses for 30-minute changes, we take the shocks directly from their supplementary materials, which are provided online, and regress them on our self-constructed 30-minute changes of the adequate series. Please see Appendix B for details on the data construction.

a heteroskedasticity-based procedure to estimate a latent shock that is orthogonal to any yield curve changes. We refer to this shock as the "Fed non-yield-curve shock", or the "non-yield shock" for short, to contrast it to the most common shocks in the literature that all affect the yield curve (henceforth "yield shocks"). We show that the non-yield shock affects a variety of asset prices and it does so at least in part through a change in market participants' risk appetite. Using a latent Dirichlet allocation, a widely-used machine learning algorithm in the computational linguistics literature, we link the non-yield shock to the text contained in FOMC statements, suggesting that the non-yield shock reflects written communication by the central bank.

Our identification scheme builds on the heteroskedasticity-based approach by Gürkaynak, Kısacıkoğlu, and Wright (2020). Intuitively, the procedure first projects stock price changes on yield curve changes in a 30-minute window around FOMC announcements. We show that the residuals of this projection are significantly more volatile than 30-minute stock price changes on non-announcement days. Using the test by Lewis (Forthcoming), we further show that the latent shock is strongly identified, implying that much of the unexplained variation is indeed not just noise but a systematic effect of monetary policy. The identifying assumption is that there is more monetary policy news in the unexplained stock market variation around FOMC announcements than in the stock market on non-announcement days. Importantly, we do not need to take a stance on which and how many shocks drive the yield curve.

We subsequently explore the effects of the non-yield shock on various asset prices. First, we show that it can explain much of the remaining variation in the stock market within the 30-minute window. Second, its effect on asset prices points towards a risk-appetite/risk-preference shock interpretation. In particular, a positive shock, signed to increase stock prices, leads to a decrease in the equity premium measure by Martin (2017), as well as the VIX. Using the decomposition by Bekaert and Hoerova (2014), we show that the response of the VIX is driven by the risk aversion (variance premium) and not the uncertainty (conditional variance) component. Further, a positive non-yield shock leads to a depreciation of the US dollar relative to several other currencies including the Euro, the British Pound, and the Canadian Dollar. The non-yield shock also raises short-term inflation expectations and long-term term premia.

To show that the non-yield shock indeed reflects a dimension of US monetary policy, we employ a latent Dirichlet allocation (LDA) (Blei, Ng, and Jordan, 2003), a machine learning algorithm for topic modeling, to link the text contained in FOMC statements to our non-yield shock. For a given FOMC statement, the LDA provides a distribution over the estimated topics. We show that time variation in the topic distribution robustly predicts our shock. This suggests that central bank communication has important effects on asset prices—independent of any yield curve changes. In a second step, we inspect the topics with the greatest predictive power to understand what types of content may trigger the observed market responses. The themes of these topics range from inflation expectations to large-scale asset purchases and appear to be broadly consistent with our interpretation of the non-yield shock as primarily affecting financial markets through an effect on risk appetite.

We further discuss several checks that confirm that our series of non-yield shocks is robust. While our baseline analysis purifies stock price using nine distinct surprises to the yield curve, we first show that our findings are almost unchanged when we use three yield shocks estimated via principal components as done by Swanson (2020). Second, we extract our non-yield shock separately for three sub-samples—before, while, and after the nominal interest rate was constrained by the zero lower bound (ZLB). For all three sub-periods, the non-yield shock is very similar to our baseline series. Third, we estimate our non-yield shock on the two sub-periods from February 2000 to June 2003 and from August 2003 to May 2006, for which the Federal Reserve used consistent forward guidance language (Lunsford, 2020). Although FOMC statements began to include language about future policy inclinations in August 2003, estimates of the non-yield shocks for these two subsamples are nonetheless similar to our baseline series.

Related literature Our paper relates to several strands of the literature in monetary economics. First, our paper relates to a large body of work which uses yield shocks constructed from high-frequency financial market data to understand the transmission of monetary policy. Important early contributions include Cook and Hahn (1989), Kuttner (2001), Cochrane and

Piazzesi (2002), Rigobon and Sack (2004), Gürkaynak, Sack, and Swanson (2005). Subsequent work uses these shocks either directly in high-frequency event study analyses (e.g., Campbell, Evans, Fisher, and Justiniano, 2012; Hanson and Stein, 2015; Campbell, Fisher, Justiniano, and Melosi, 2017; Nakamura and Steinsson, 2018; Lewis, 2019; Swanson, 2020; Lunsford, 2020) or in combination with lower-frequency times series methods (e.g., Gertler and Karadi, 2015; Lakdawala, 2019; Caldara and Herbst, 2019; Paul, 2020; Bundick and Smith, 2020; Miranda-Agrippino and Ricco, Forthcoming).[3]

Within that literature, two recent papers by Cieslak and Schrimpf (2019) and Jarociński and Karadi (2020) are closely related to ours. Building on prior work by Romer and Romer (2000), both papers use the idea of information effects to rationalize the unexplained stock market variation around FOMC announcements. Both papers start from the premise that the intra-day changes in yields and stocks around FOMC announcements can be fully explained by two (Jarociński and Karadi, 2020) or three (Cieslak and Schrimpf, 2019) shocks. Using sign and monotonicity restrictions, they recover set-identified shocks. Besides the fact that our approach allows for point identification, our paper contributes in at least two ways to the existing literature. First, our framework allows us to test how much of the unexplained variation in the stock market is driven by FOMC announcements rather than noise. Second, we propose a different identification scheme. While Jarociński and Karadi (2020) assume that Fed information shocks necessarily require changes in interest rates, our non-yield shock is by construction orthogonal to interest rate changes at all horizons. This assumption reflects the view that the non-yield shock is a separate policy instrument that can be used independently of interest rate changes—consistent with our text analysis showing that the non-yield shock reflects written communication by the Federal Reserve. We note that our identification scheme is principally consistent with the presence of information effects (Campbell et al., 2012; Nakamura and Steinsson, 2018; Lunsford, 2020). To the extent that changes in interest rates convey private information about economic fundamentals, our non-yield shock will be purified of this effect *on average*. If the Fed in a given FOMC announcement, however, departs from the average information effect by, for instance, revealing significant new information while keeping interest rates unchanged, the effects on the stock market will be captured by our non-yield shock. Our robustness analysis addresses this point by showing that the time-varying information effect does not substantially affect our non-yield shock.

Our paper also relates to prior work emphasizing the empirical link between monetary policy and risk premia. Bernanke and Kuttner (2005) show that shocks to the federal funds

[3] Eberly, Stock, and Wright (2019) provide a recent summary of the empirical evidence on the transmission of U.S. monetary policy. Researchers have also used similar methods to study monetary policy in the Euro Area (e.g., Brand, Buncic, and Turunen, 2010; Altavilla, Brugnolini, Gürkaynak, Motto, and Ragusa, 2019; Andrade and Ferroni, 2021), as well as in the U.K. (e.g., Gerko and Rey, 2017; Cesa-Bianchi, Thwaites, and Vicondoa, 2020).

rate affect the stock market mostly through the equity premium. Bekaert, Hoerova, and Lo Duca (2013) show for similar shocks substantial effects on the variance premium. Hanson and Stein (2015) and Gertler and Karadi (2015) report monetary policy effects on term premia and credit spreads. Our paper contributes to this literature by showing that monetary policy affects risk premia not only through the yield curve, but also directly, which is crucial for understanding the stock market response around FOMC announcements. The latter point is consistent with findings by Cieslak and Pang (2020). Similar to Cieslak and Schrimpf (2019), they use sign and monotonicity restrictions to decompose daily changes in stock prices and yields into different shocks. They find that risk-premium shocks account for a large portion of the daily stock return on FOMC announcements days. Our paper also relates to a recent strand of theoretical work which models the effects of monetary policy on risk premia (e.g., Drechsler, Savov, and Schnabl, 2018; Kekre and Lenel, 2020; Bhandari, Evans, and Golosov, 2019; Pflueger and Rinaldi, 2020). Although none of these papers allow for a non-yield shock, several mechanisms emphasized in this literature are useful to rationalize our findings, most notably a "flight-to-safety"-type effect.

Lastly, our paper builds on a growing literature which applies computational linguistics methods to study U.S. monetary policy. Using a variety of tools, prior work has analyzed FOMC minutes and transcripts (e.g. Boukus and Rosenberg, 2006; Acosta, 2015; Hansen, McMahon, and Prat, 2018), FOMC press conferences (e.g. Gorodnichenko, Pham, and Talavera, 2021), as well as FOMC statements as in this paper (e.g. Lucca and Trebbi, 2009; Acosta and Meade, 2015; Hansen and McMahon, 2016; Doh, Song, and Yang, 2020; Handlan, 2020).[4]

Roadmap The remainder of the paper is structured as follows. The next section presents our empirical framework and discusses how we identify the non-yield shock. Section 3 shows how the non-yield shock affects various asset prices. This section also helps interpret the non-yield shock. We subsequently link the shock to language contained in FOMC statements in Section 4. Lastly, Section 5 concludes.

2 The Fed Non-Yield-Curve Shock

2.1 Framework

We start with reviewing the conventional high-frequency event-study design employed in the literature and then extend it to include the Fed non-yield curve shock. The estimating equation in the standard setup is

$$\Delta p_t = \beta' s_t^y + \varepsilon_t, \qquad \text{for } t \in F, \tag{1}$$

[4]Similar methods are also used to analysis monetary policy in other countries (e.g. Hansen, McMahon, and Tong, 2019; Ehrmann and Talmi, 2020).

where Δp_t is the daily or intraday change in a stock market index around the time-t FOMC announcement and F denotes the set of dates/times of FOMC announcements. Further, s_t^y is a vector of monetary policy shocks that pass through the yield curve (henceforth, "yield shocks"). Following Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005), a large literature constructs s_t^y using 30-minute changes in interest rate futures. Consistent with conventional economic theory, the underlying assumption is that monetary policy only transmits through its effect on interest rates, that is, the yield curve.

However, as noted in the introduction, the low explanatory power is puzzling and potentially indicative of an unobserved dimension of monetary policy. Thus, instead of (1), we consider the following specification in our analysis

$$\Delta p_t = \beta' s_t^y + \gamma s_t^{ny} + \varepsilon_t, \qquad \text{for } t \in F, \tag{2}$$

where s_t^{ny} denotes the latent non-yield shock thus allowing for the possibility that information released during the FOMC announcement has an effect on the stock market independent of its effect on interest rates. To recover s_t^{ny}, we use the facts that (i) we can directly measure s_t^y from interest rate futures following the previous literature, and (ii) that we know that s_t^{ny} is not present during non-FOMC announcement times. These two facts allow us to identify the non-yield shock from heightened stock market volatility relative to non-announcement days, i.e. a heteroskedasiticty-based approach (Rigobon, 2003). The underlying idea is that on trading days, on which there is no announcement, 30-minute stock price changes at similar times as FOMC announcements should neither include s_t^y nor s_t^{ny}, but be otherwise comparable. Formally,

$$\Delta p_t = \varepsilon_t, \qquad \text{for } t \in NF, \tag{3}$$

where NF denotes the set of non-announcement dates/times.

We estimate s_t^{ny} using the Kalman filter.[5] The observation equation combines equations (2) and (3) and is given by

$$\Delta p_t = \beta' s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t. \tag{4}$$

Here, $d_t = 1\,(t \in F)$ is an announcement indicator, and s_t^{ny} is independently and identically normally distributed with zero mean and unit variance. The variance is normalized to one since γ is otherwise only identified up to scale.[6] We provide details on the estimation in Appendix A.

We next describe the construction of the data we employ in the estimation. Before turning

[5]We apply the procedure by Gürkaynak, Kısacıkoğlu, and Wright (2020).

[6]Note that our baseline model has no intercept following Gürkaynak, Kısacıkoğlu, and Wright (2020) as we assume that our employed 30-minute changes are mean-zero in population which is true in our sample. In Appendix Table C1, we check this assumption by estimating our non-yield shock with demeaned data. The results are almost identical.

to the estimation results, we also discuss the identification assumptions we make in our analysis. We further test for the strength of our identification using the F-test proposed by Lewis (Forthcoming) thereby addressing concerns that our estimation might pick up noise rather than an announcement-related shock.

2.2 Data

For our empirical analysis, we construct 30-minute changes in various asset prices using a window from 10 minutes prior to 20 minutes after a given timestamp. Such a tight window circumvents econometric issues arising from other news releases (Gürkaynak, Sack, and Swanson, 2005) and strengthens the identification of the heteroskedasticity approach (Lewis, Forthcoming). All high-frequency data are obtained from the *Thomson Reuters Tick History* database.

In order to adequately estimate our non-yield shock s_t^{ny}, we need to soak up all variation arising from yield shocks s_t^y. As shown by, e.g., Gürkaynak, Sack, and Swanson (2005) and Swanson (2020), FOMC announcements potentially affect the yield curve through different channels leading to complex and multidimensional effects. To capture these effects, we construct the vector s_t^y from the following nine 30-minute surprises across different yields,

$$s_t^y = \begin{bmatrix} MP1_t & MP2_t & ED2_t & ED3_t & ED4_t & T2Y_t & T5Y_t & T10_t & T30_t \end{bmatrix}'. \tag{5}$$

In this expression $MP1_t$ and $MP2_t$ are surprises in the expected federal funds rate after the current and subsequent FOMC meeting. Both are constructed from federal funds futures contracts. Further, $ED2_t$, $ED3_t$, and $ED4_t$ are surprises in the implied rates from Eurodollar futures capturing revisions of the expected 3-month US Dollar LIBOR from two to four quarters out. All five measures ($MP1_t$, $MP2_t$, $ED2_t$, $ED3_t$, and $ED4_t$) are standard in the literature (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018), and cover surprises in the yield curve of maturities up to 14 months. For longer horizons, we use implied rates from Treasury futures of horizons two ($T2Y_t$), five ($T5Y_t$), ten ($T10Y_t$), and thirty years ($T30Y_t$) (see, among others, Gorodnichenko and Ray, 2017; Gürkaynak, Kısacıkoğlu, and Wright, 2020). In Appendix B, we provide more details on the construction and show that all our constructed surprises closely match those of previous studies.

Note that we could alternatively allow for noise in each of the nine surprises by estimating a factor model via principal components as done in previous work (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Swanson, 2020). However, we prefer to use all raw surprises as our baseline for two reasons. First, it is a more conservative approach that makes sure that our non-yield shock does not pick up any information captured in the yield curve (this will be confirmed in our robustness analysis below). Second, we do not need to take a stance on how many shocks adequately capture the effects of monetary policy shocks on the yield curve. That being said, we show in the robustness section below that our non-yield shock is almost identical when estimated with three principal components—consistent with the findings by Swanson (2020).

Another key part of our estimation are the 30-minute changes in the stock market indicators Δp_t, the outcome variables of interest. Although we could use the log-change in the S&P 500 (ΔSPX_t) alone, we also add the log-change in the first and second closest contract of the E-mini S&P 500 futures ($\Delta ES1_t$, $\Delta ES2_t$). Hence, Δp_t is given by

$$\Delta p_t = \begin{bmatrix} \Delta SPX_t & \Delta ES1_t & \Delta ES2_t \end{bmatrix}'. \tag{6}$$

While all three series are very highly correlated, using them jointly in our estimation helps us capture systematic changes in the stock market, thereby mitigating risks that our non-yield shock picks up idiosyncratic price movements present only in one series.

Our sample period ranges from January 1, 1996 to December 31, 2019. In our analysis, we focus on scheduled FOMC announcements since unscheduled announcements often occur during periods of higher stock market volatility. Announcements associated with unscheduled meetings are also frequently released at different times. Both of these issues could potentially add noise to our estimation. We obtain dates and times of FOMC announcements from *Bloomberg* and cross-check them with information from the Federal Reserve website. With very few exceptions, the FOMC announcements are released at 2:15 pm eastern time (ET) until January 2013 and after that at 2:00 pm ET. We have a total of 190 observations in our announcement sample F. For the non-announcement days, we use a timestamp of 2:15 pm ET on regular trading days where we exclude both scheduled and unscheduled FOMC announcements days, as well as days for which trading closed early (e.g. July 3 or December 24). In total, the non-announcement sample NF comprises 5,617 observations. Appendix B provides more details on the sample construction.

2.3 Identification

We now summarize the identification assumptions that allow us to estimate the non-yield shock s_t^{ny} based on equation (4): i) the 30-minute changes in the stock market around 2:15 pm ET on non-FOMC announcements days do not include monetary policy news but are otherwise comparable to changes on announcement days, ii) the 30-minute change of the yield curve around FOMC announcements is entirely driven by monetary policy shocks, and vector s_t^y is able to capture all these shocks, iii) the relationship between the yield curve and the stock market is roughly stable over the sample period.

Assumptions i) and ii) are standard in the literature. We provide evidence on the strength of the identifying variation momentarily. We further verify in Section 3 that our non-yield shock has no effect on Treasury yields. Without a regime change, assumption iii) is always satisfied up to a first order. As mentioned in the introduction, however, some prior work indicates that the relationship between the yield curve and stock prices potentially varies over time. We therefore show in our robustness analysis below that, to the extent that assumption iii) is violated, the consequences for our estimation are relatively inconsequential—in line with findings by Swanson (2020).

Before we turn to the estimation, we perform pre-tests to assess the strength of our identification. To do so, we use the equivalence result, shown by Gürkaynak, Kısacıkoğlu, and Wright (2020), between the one-step Kalman filter estimation of (4) and a two-step procedure, which applies the Rigobon (2003) heteroskedasticity estimator to the error term ϕ_t, where ϕ_t is given by

$$\phi_t \equiv \Delta p_t - \beta s_t^y = \gamma s_t^{ny} + \varepsilon_t \quad \text{for } t \in F,$$

after estimating β by OLS, and

$$\phi_t \equiv \Delta p_t = \varepsilon_t \quad \text{for } t \in NF.$$ [7]

Figure 1 shows kernel density estimates of ϕ_t for $t \in F$ and $t \in NF$ separately for the S&P 500 and the first and second futures contract. Clearly, the distribution of ϕ_t on announcement days differs substantially from that on non-announcement days. In particular, the variance of ϕ_t on announcement days is approximately three times as large as on non-announcement days (0.150 versus 0.052 for the S&P 500) and they are significantly different from one another ($p < 0.0001$).

Further, with this alternative formulation we can use a more robust test for weak identification, as proposed by Lewis (Forthcoming), which is based on the idea that a heteroskedasticity estimator can be rewritten as an instrumental variable problem (Rigobon and Sack, 2004). In particular, we construct for each series in Δp_t, the following F-statistic

$$F = \frac{\hat{\Pi}^2 \left(\sum_{t=1}^{T} z_t^2 \right)^2}{\sum_{t=1}^{T} z_t^2 \hat{v}_t^2}, \tag{7}$$

[7] As shown by Gürkaynak, Kısacıkoğlu, and Wright (2020), both approaches lead to slightly different results when more than one series is included in Δp_t. The reason for that is that the Kalman filter takes the covariance of the assets in Δp_t into account while the two-step procedure can only be implemented for a single asset at a time.

where $\hat{\Pi}$ and $\hat{v}_t$ are OLS estimates from the first stage

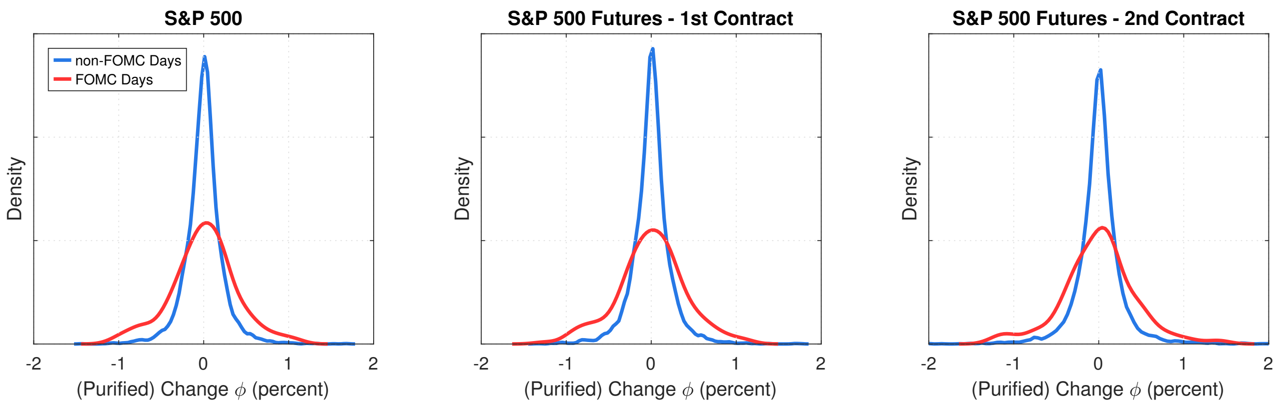
$$\phi_t = \Pi z_t + v_t,$$

with the instrumental variable z_t, satisfying

$$z_t = \left[1 \left(t \in F \right) \times \frac{T}{T_F} - 1 \left(t \in NF \right) \times \frac{T}{T_{NF}} \right] \phi_t.$$

Here, T is the total number of observations, T_F is the number of observations in the announcement sample F, and T_{NF} is the number of observations in the non-announcement sample NF.

Figure 1: Distribution of (purified) 30-minute Stock Price Changes



Notes: This figure displays kernel density estimates of ϕ_t separately for $t \in F$ and $t \in NF$. For all density estimates we use a normal smoothing kernel and the default bandwidth, which is optimal for normal densities.

Table 2 shows the results for each of the three series included in Δp_t: the S&P 500 (ΔSPX_t), the S&P 500 Futures 1st Contract ($\Delta ES1_t$), and the S&P 500 Futures 2nd Contract ($\Delta ES2_t$). As the table shows, we can easily reject weak identification in our setting. Hence, the variation in the stock market during FOMC announcements, which changes in the yield curve do not explain, is indeed a systematic response to monetary policy news rather than noise. Note that the sample sizes shown in Table 2 for the S&P 500 futures are slightly smaller since they were only introduced in 1997. The estimation procedure can handle these missing observations, as long as we have non-missing observations for at least one of the three series. Overall, the results of these tests show that our non-yield shock estimated from specification (4) is well identified.

Table 2: Tests of Weak Identification

	F-Statistic	Above Critical Value			Observations	
		Bias = 20%	Bias = 10%	Bias = 5%	FOMC	Non-FOMC
S&P 500	166.06	Yes	Yes	Yes	190	5617
S&P 500 Futures 1st Contract	171.67	Yes	Yes	Yes	177	5227
S&P 500 Futures 2nd Contract	77.82	Yes	Yes	Yes	177	5218

Notes: This table shows the results of the first-stage F-tests for each of the three series in Δp_t: S&P 500 (ΔSPX_t), S&P 500 Futures 1st Contract ($\Delta ES1_t$), and S&P 500 Futures 2nd Contract ($\Delta ES2_t$). The F-statistic is constructed as in (7). Robust critical values are calculated as in Montiel Olea and Pflueger (2013). *Observations* refers to number of days in the set of FOMC announcements and non-FOMC announcements.

2.4 Results

We now turn to the estimation results of specification (4), which are shown in Table 3. We emphasize the following points: First, the non-yield shock is able to explain almost the entire unexplained variation in the stock market. Combined with our pre-tests in the previous subsection, this means that almost the entire stock market response can be directly linked to FOMC announcements. Second, a one standard deviation non-yield shock raises the S&P 500 by 35 basis points. This effect is quite sizable. Comparing it to the estimates by Swanson (2020), the 0.35% effect on the S&P 500 is similar in size to the effect of a one standard deviation federal funds rate shock, about twice as large as the effect of a one standard deviation forward guidance shock, and an order of magnitude larger than a one standard deviation large-scale asset purchases shock. Third, the explanatory power of our nine yield surprises, i.e. the R^2 without the non-yield shock, is somewhat greater than in previous studies. This suggests that our non-yield shock is conservatively estimated in the sense that we likely take out too much rather than too little variation potentially attributable to yield changes. We return to this point in the next subsection, where we re-estimate our non-yield shocks with the first three principal components of the nine surprises used here.

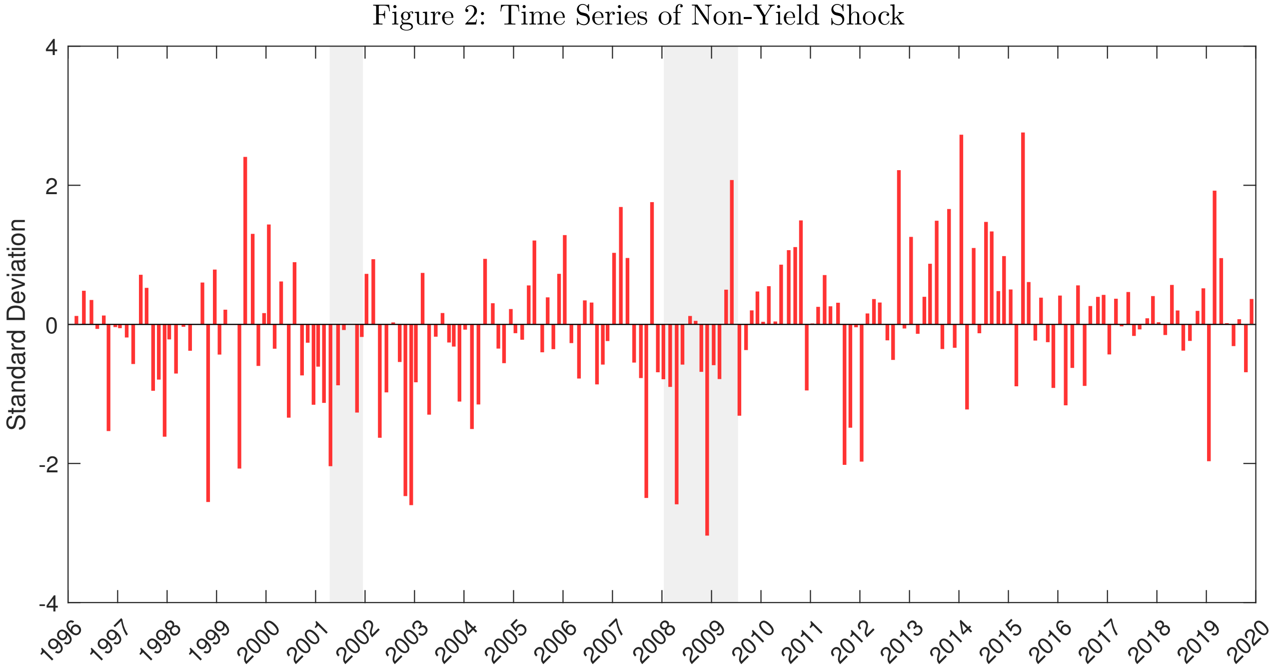
Figure 2 shows the time series of the estimated non-yield shock. As is clear from the figure, the series displays substantial variation throughout our sample period indicating that our results below are unlikely to be driven by recession periods or certain other sub-periods. Further, there are no extreme outliers. All observations are within three standard deviations, and we have roughly an equal number of positive (91) and negative (99) observations.

Table 3: Estimation Results

	S&P 500	S&P 500 Futures 1st Contract	S&P 500 Futures 2nd Contract
Non-yield shock	0.35***	0.37***	0.37***
	(0.01)	(0.01)	(0.01)
R^2 without shock	0.41	0.40	0.38
R^2 with shock	0.98	0.99	0.90

Notes: This table shows the results of specification (4), $\Delta p_t = \beta' s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$, estimated via the Kalman filter. The first row displays coefficient vector γ, i.e. the effect of non-yield shock s_t^{ny} on each of the three series in Δp_t. Coefficients are in percentage change, and standard errors are in parentheses. The R^2 values are obtained from announcement day regressions of the respective independent variable on (i) yield shocks s_t^y, and (ii) yield shocks s_t^y and non-yield shock s_t^{ny}. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level. See text above or Appendix A for details on the estimation and inference.

Figure 2: Time Series of Non-Yield Shock



Notes: This figure displays the time series of non-yield shock over the sample period. Grey bars indicate NBER recession periods. The series is normalized to be in terms of standard deviations.

2.5 Robustness

In this section, we analyze the robustness of our baseline series of non-yield shocks by re-estimating it under alternate specifications of (4). In particular, we aim to address three questions in this section: First, how does our choice of using the raw interest rate surprises rather than estimating principal components from them affect our results? Second, does the episode at the zero lower bound (ZLB) and its effect on the conduct of US monetary policy during this period potentially jeopardize our results? Third, can the existence of information effects be an alternative explanation for our non-yield shock? Table 4 summarizes the results of all robustness analyses, which we discuss now in more detail. Note that the left-hand side variables are always the same three series as in the baseline version but we only report results for the S&P 500 since the information content is very similar across all three series.

Table 4: Results of Robustness Analyses

	3 Yield Curve	Subsamples			FG Regimes of Lunsford (2020)	
	Factors	pre-ZLB	ZLB	post-ZLB	Regime I	Regime II
S&P 500						
R^2 without shock	0.26	0.46	0.46	0.45	0.52	0.53
R^2 with shock	0.98	0.97	1.00	1.00	0.91	1.00
Correlation with Baseline Shock	0.89	0.99	0.92	0.88	0.60	0.85
Announcements						
Observations	190	102	55	33	27	23
Sample	01/96–12/19	01/96–12/08	01/09–11/15	12/15–12/19	02/00–06/03	08/03–05/06

Notes: This table shows the results of our robustness analyzes discussed in the text. We re-estimate alternate versions of baseline specification (4), $\Delta p_t = \beta' s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$, using the Kalman filter. While the left-hand side variables are always the same three variables used in the baseline analysis, we only report R^2 values for the S&P 500 since the information content of all three series is very similar. The R^2 values are obtained from announcement day regressions of the respective independent variable on (i) yield shocks s_t^y, and (ii) yield shocks s_t^y and non-yield shock s_t^{ny}. Further, we report the correlation of our re-estimated series with our baseline one for the overlapping sample period. The set of announcement and non-announcement days is always unchanged compared to the baseline estimation.

In our first exercise, we change the data series used for s_t^y in our estimation. While we use nine interest rate surprises in the baseline version, we now employ three factors instead. These factors are extracted from the nine series via principal components analysis. The remainder of the estimation is unchanged. The first column of Table 4 shows the results of this exercise. The estimated shock his very highly correlated (89%) with our baseline series. The explanatory power of the three factors for the stock market drops to 26%, while the explanatory power including the non-yield shocks is 98%—just as in the baseline estimation. This may indicate that the non-yield shock in this alternative specification is contaminated with changes in the yield curve that are not captured accurately by the three principal components. The high correlation also suggests that our baseline version is robust to allowing for noise in the yield curve surprises by using the first three principal components instead.

We next analyze the stability of our analysis over our sample period with particular emphasis on the impact of the ZLB. To do so, we first split our sample into three periods (pre-ZLB, ZLB, and post-ZLB), and then re-estimate our non-yield shock for each period separately. As columns two to four of Table 4 show, the results are very similar for each subperiod. Further, each of the re-estimated shock series are very highly correlated with the baseline series. Overall, these results suggest that around FOMC announcements, the relationship between the yield curve and the stock market are mostly stable throughout our sample consistent with the findings in Swanson (2020).

Lastly, we take a closer look at the role of information effects in our estimation. To do so, we focus on two short periods with a consistent forward guidance language. As shown by Lunsford (2020), FOMC statements only contained forward guidance about economic outlook risks from February 2000 to June 2003 (regime I), whereas forward guidance about future policy inclinations was added to the statements from August 2003 to May 2006 (regime II). Further, Lunsford (2020) provides evidence that information effects were stronger during regime I compared to regime II. We next re-estimate our non-yield shocks separately for both regimes. The results in columns five and six of Table 4 indicate that despite a small increase in the explanatory power of the yield curve surprises, there is substantial variation left which is explained by the re-estimated non-yield shock. Further, the correlation with the baseline series is still high in both cases. The somewhat lower correlation for regime I is consistent with the evidence by Lunsford (2020). We conclude that while there seems to be evidence of a slightly changed relationship between yield curve and stock market in regime I, our results in columns two to six indicate that information effects are not a major driving force of the non-yield shock.

3 The Effects on Asset Prices

In this section, we study the effects of the non-yield shock on various asset prices. We do so with two objectives in mind. The first objective is to improve our understanding of the nature of the shock. By construction, it moves equity prices and is orthogonal to current changes in interest rate futures. We show in this section that the non-yield shock affects equity prices at least in part through an affect on investor risk appetite. Our second objective is to study the economic impact of the non-yield shock at high-frequencies. We show that the non-yield shock affects exchange rates, short-run inflation expectations, as well as long-term term premia. It does not seem to drive treasury yields at any horizon, longer-run inflation expectations, or corporate bond yields to an economically meaningful degree.

We estimate event study regressions of the following form

$$\Delta x_t = \alpha + \delta^x s_t^{ny} + \eta_t, \qquad \text{for } t \in F, \tag{8}$$

where Δx_t is the change in a variable of interest around the FOMC announcement at time t. We estimate specification (8) by OLS for a variety of asset classes. Whenever intraday data is available to us, Δx_t is constructed from a 30-minute window around the announcement. If intraday data is not available to us, we use a daily window ranging from previous day's closing value to the announcement day's closing value.

Note that we do not exclude any announcements during periods of financial market stress. However, some of our daily series display extremely large changes in episodes of high market volatility, which are unrelated to the news release itself. To mitigate the influence of such extreme values, we winsorize series for which we only have daily data at the top and bottom 1%.

3.1 Stock Market

As discussed earlier and shown in Table 3, a positive value of the non-yield shock raises equity prices. The first column in Panel A of Table 5 further demonstrates that the non-yield shock also affects the VIX, a commonly used measure of risk aversion and uncertainty. A one standard deviation positive non-yield shock reduces the VIX by 1.88 percent. This effect indicates that monetary policy can affect equity prices through effects on risk aversion and/or uncertainty that do not pass through the yield curve.

We next decompose this effect and analyze the impact on commonly used measures of risk aversion and uncertainty separately. The second column of Panel A in Table 5 shows the effect on a proxy for the equity premium as constructed by Martin (2017).[8] A one standard deviation shock in the non-yield shock reduces the equity premium by 0.39 percent. This estimate is significantly different from zero at the 10 percent level, thus suggesting that at least part of the effect of the non-yield shock on equity markets works through investor risk appetite.

The third and fourth columns of Panel A in Table 5 show the effects of the Fed non-yield shock on the conditional variance of stock returns and the equity variance premium as defined by Bekaert and Hoerova (2014).[9] The conditional variance is often interpreted as a measure of uncertainty and the variance premium as a measure of risk aversion. As Panel A of Table

[8] In particular, we use the 12-month SVIX series. For details on this series and its construction, see Martin (2017). We would like to thank Ian Martin for sharing with us an updated series ending in August 2014. This updated series is also used in Martin and Wagner (2019).

[9] We use an updated series available from Marie Hoerova's website, http://mariehoerova.net/.

Table 5: The Effect of the Fed Non-Yield Shock on Asset Prices

Panel A: Stock Market (%)	VIX	Equity Premium	Conditional Variance	Variance Premium	
Non-yield shock	-1.88***	-0.39*	-0.47	-34.96**	
	(0.24)	(0.23)	(0.95)	(13.71)	
R^2	0.36	0.04	0.00	0.09	
Observations	190	147	190	190	
Window	30-min	Daily	Daily	Daily	
Panel B: Treasury Yields (bp)	6 Month	2 Year	5 Year	10 Year	30 Year
Non-yield shock	-0.04	-0.35	-0.30	-0.06	0.17
	(0.31)	(0.40)	(0.46)	(0.35)	(0.30)
R^2	0.00	0.00	0.00	0.00	0.00
Observations	180	180	180	180	180
Window	30-min	30-min	30-min	30-min	30-min
Panel C: Inflation Expectations (bp)	2 Year	3 Year	5 Year	10 Year	20 Year
Non-yield shock	2.05*	0.21	-0.15	0.24	0.36
	(1.15)	(0.60)	(0.46)	(0.31)	(0.30)
R^2	0.02	0.00	0.00	0.01	0.01
Observations	167	167	167	167	167
Window	Daily	Daily	Daily	Daily	Daily
Panel D: Term Premia (bp)	1 Year	2 Year	5 Year	7 Year	10 Year
Non-yield shock	-0.12	-0.14	0.30	0.57	0.84*
	(0.18)	(0.22)	(0.33)	(0.39)	(0.45)
R^2	0.00	0.00	0.01	0.02	0.03
Observations	190	190	190	190	190
Window	Daily	Daily	Daily	Daily	Daily
Panel E: Exchange Rates (%)	Canadian Dollar	Swiss Franc	Euro	British Pound	Japenese Yen
Non-yield shock	0.09***	0.03	0.09***	0.07***	-0.01
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
R^2	0.09	0.00	0.05	0.05	0.00
Observations	190	190	172	190	190
Window	30-min	30-min	30-min	30-min	30-min
Panel F: Corporate Bond Yields (bp)	Aaa	Baa			
Non-yield shock	-0.05	0.15			
	(0.35)	(0.35)			
R^2	0.00	0.00			
Observations	190	190			
Window	Daily	Daily			

Notes: This table presents estimates of δ^x from (8), $\Delta x_t = \alpha + \delta^x s_t^{ny} + \eta_t$, where the left-hand side is varies for each regression. Units are in percentage change *(%)* or basis points *(bp)* per a one-standard deviation shock. *Exchange rates* are expressed in US dollars so that an increase reflects a depreciation of the US dollar relative to the foreign currency. *Window* refers to the window size of the left-hand side variable around the FOMC announcement. We winsorize the top and bottom 1% of each left-hand variable for which we only have daily changes. Heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

5 shows, the non-yield shock reduces the variance premium while having no significant effect on the conditional variance. These estimates thus corroborate the interpretation that the non-yield shock affects equity prices through an effect on risk aversion.

3.2 Treasury Yields, Inflation Expectations, and Term Premia

We next turn to the effects on treasury yields and inflation expectations. Our non-yield shock is constructed to be orthogonal to changes in various interest rates futures around FOMC announcements. We confirm in Panel B of Table 5 that this property extends to treasury yields with maturities between 6 months and 30 years. For all maturities the estimated coefficients are less than one standard deviation away from zero.

Panel C of Table 5 shows the effects on inflation expectations. We use as our measures of inflation expectations the breakeven inflation rates from Gürkaynak, Sack, and Wright (2010), which are constructed from data on Treasury Inflation-Protected Securities (TIPS).[10] The estimates in the table show that 2-year inflation expectations increase by approximately 2 basis points after a one standard deviation shock. This effect, which is significant at the 10 percent level, may indicate that market participants expect that the non-yield shock has a short-run stimulative effect on the economy and thus increases inflationary pressure. Inflation expectations at longer time horizons are largely unresponsive.

Panel D of Table 5 shows the effects on term premia at different maturities, which we measure using the series from Adrian, Crump, and Moench (2013).[11] The estimates suggest a small effect that is increasing with the maturity and which becomes significant for the 10-year term premium at the 10 percent level. This pattern is consistent with a flight-to-safety-type effect where risk premia on bonds increase while risk premia on stocks decrease.

3.3 Exchange Rates

Panel E of Table 5 shows the effects of the non-yield shock on various exchange rates. All exchange rates are expressed in US dollars per foreign currency so that an increase reflects a depreciation of the dollar. The estimates show that the Canadian dollar, the Euro, and the British Pound appreciate against the dollar by between 7 and 9 basis points in response to a positive one-standard deviation non-yield shock. In contrast, the Swiss Franc and the Japanese Yen appear to be largely unaffected.

These findings are consistent with a growing literature documenting that the dollar is weak when measures of risk appetite are high (e.g., Lilley, Maggiori, Neiman, and Schreger, 2019),

[10] We use an updated series available from the Federal Reserve Board's website, `https://www.federalreserve.gov/data/tips-yield-curve-and-inflation-compensation.htm`.

[11] We use an updated series available from the New York Fed's website, `https://www.newyorkfed.org/research/data_indicators/term_premia.html`.

thus supporting our interpretation of the non-yield shock as primarily working through an effect on risk premia. Further, the differential behavior of the Swiss Franc and the Japanese Yen likely reflects the safe-haven status that is often attributed to these two currencies (Ranaldo and Söderlind, 2010). Lilley et al. (2019) show that the co-movement of the Franc and the Yen with measures of global risk appetite differs from that of other currencies (see, in particular, their Figure 4).

3.4 Corporate Bonds

Panel F in Table 5 reports the estimated effects of the non-yield shock on corporate bond yields. Daily corporate yields are Moody's Aaa and Baa seasoned corporate bond yields and are obtained from FRED. The estimates for both Aaa- and Baa-rated corporate bond yields are economically small and insignificantly different from zero. Corporate bond spreads and related measures are often studied for their predictive content for economic activity (see, e.g., Gilchrist and Zakrajšek, 2012, and the references cited therein).

Summary The evidence in this section suggests that the Fed non-yield shock affects equity prices at least in part through an effect on the equity risk premium. Hence, we interpret our shock as a Fed-induced change in risk appetite. The increase in the 10-year term premium may indicate that the non-yield shock triggers flight-to-safety-type effect. This shock also affects exchange rates of non-safe-haven currencies, and short-run inflation expectations. In contrast, the Fed non-yield shock does not affect treasury yields, longer-run inflation expectations, or corporate bond yields to an economically meaningful degree.

4 The Role of the FOMC Statement Language

In this section, we turn to the question of how the Federal Reserve can affect the non-yield shock through its choice of words. To do so, we analyze FOMC statements through the lens of a latent Dirichlet allocation (LDA) (Blei, Ng, and Jordan, 2003), a widely-used machine learning algorithm for topic modeling in the field of natural language processing. We first describe the LDA and its estimated topics, and then study the relationship between topics and the non-yield shock.

4.1 Estimation of Topics in FOMC Statements

The LDA is an algorithm that is designed to summarize text in terms of unobserved topics. The broad idea is that the text of interest arises as a mixture of different topics, where a topic is a distribution over a vocabulary of words. The LDA is a mixed-membership model which means that text can be assigned to different topics at varying degrees. Further, the LDA is an unsupervised learning algorithm, that is, topics are estimated endogenously, and hence the researcher does not need to define topics (sets of words) as is necessary for word-counting approaches. This feature is attractive for our application since we want to stay agnostic on which topics, if any, drive the non-yield shock.

For a formal exposition, we introduce some terminology and notation, where reused letters are unrelated to those in previous sections.[12] The set of texts employed to estimate the LDA is called the (text) corpus. It is a collection of D documents and N words. Each document $d \in \{1, ..., D\}$ consists of N_d words, where $w_{d,n}$ is word $n \in \{1, 2, ..., \max_d \{N_d\}\}$ in document d. Further, the corpus consists of V unique words called the vocabulary, where each unique word is indexed by $v \in \{1, ..., V\}$. A topic $k \in \{1, ..., K\}$ is defined as a probability vector β_k over the V unique words, θ_d is a vector of the proportions of words in document d over the K topics, and $z_{d,n}$ is the topic assignment of word $w_{d,n}$.

In our setting, document d is a sentence in a FOMC statement, and the corpus includes all sentences of FOMC statements in our sample. Overall, we have 2050 sentences contained in scheduled FOMC statements ($D = 2050$). Note that our choice of treating a sentence as a document follows Hansen and McMahon (2016), and is motivated by the observation that in FOMC statements, individual topics are discussed at the sentence-level rather than the paragraph or statement level. Before we can analyze our raw text, we perform multiple pre-processing steps. Following Hansen, McMahon, and Prat (2018), we account for two and three-word sequences, remove common stopwords, reduce words to their stems, and remove highly uninformative words. Appendix D describes these steps in detail. We end up with a corpus of 26170 stemmed words ($N = 26170$), and 718 unique stems ($V = 718$). In the rest of this section, we refer to the stemmed words simply as words.

Given our text corpus at hand, we next turn to the topic estimation. To understand the estimation problem, it is helpful to briefly describe the corpus' data generating process assumed by the LDA.

1. For each topic k, draw a distribution over words $\beta_k \sim Dirichlet\,(\eta)$
2. For each document d
   (a) Draw a vector of topic proportions $\theta_d \sim Dirichlet\,(\alpha)$
   (b) Each word $w_{d,n}$
      i. Draw topic assignment $z_{d,n}$ from topic proportions θ_d of document d ($z_{d,n} \sim Multinomial\,(\theta_d)$).
      ii. Draw $w_{d,n}$ from word distribution $\beta_{z_{d,n}}$ of the assigned topic $z_{d,n}$ ($w_{d,n} \sim Multinomial\left(\beta_{z_{d,n}}\right)$).

[12] The brief description and notation in this section closely follows Blei, Ng, and Jordan (2003), Blei and Lafferty (2009), Hansen, McMahon, and Prat (2018), and Nimark and Pitschner (2019). See these papers for more details.

For compact notation, we define the matrices $w = \left\{ \underset{N_1 \times 1}{w_1}, ..., \underset{N_D \times 1}{w_D} \right\}$, $\beta = \left\{ \underset{K \times 1}{\beta_1}, ..., \underset{K \times 1}{\beta_V} \right\}$, $\theta = \left\{ \underset{K \times 1}{\theta_1}, ..., \underset{K \times 1}{\theta_D} \right\}$, and $z = \left\{ \underset{N_1 \times 1}{z_1}, ..., \underset{N_D \times 1}{z_D} \right\}$. Then the estimation problem is to recover β, θ, and z given words in the corpus w, the hyperparameters η, α, and the number of topics K. To do so, we approximate the posterior distribution

$$p\left(\beta, \theta, z | w; \eta, \alpha, K\right) = \frac{p\left(\beta, \theta, z, w | \eta, \alpha, K\right)}{p\left(w | \eta, \alpha, K\right)}, \tag{9}$$

which is achieved via the collapsed Gibbs sampling algorithm of Griffiths and Steyvers (2004). Following Hansen, McMahon, and Prat (2018), we set the hyperparameters, $\alpha = \frac{50}{K}$, $\eta = \frac{200}{V}$, and choose the number of topics to be $K = 23$, using a formal model selection procedure described in Appendix D. Lastly, we are interested in the topic distribution at the statement level, i.e. on a more aggregate level. Keeping the topic estimates β fixed, we re-estimate θ again at the statement level. Appendix D provides more details on the estimation. Appendix Figure C1 shows word clouds of all 23 estimated topics, and Appendix Figure C2 shows each topics proportion over the FOMC statements in our sample.

4.2 Link between Statement Topics and Non-Yield Shock

With the estimated topics at hand, we now study their relation to the non-yield shock. To do so, we estimate the following specification

$$s_t^{ny} = \delta_0 + \delta_1' \theta_t + \nu_t, \tag{10}$$

where θ_t is the vector of each topics' proportion in the FOMC statement on date t and s_t^{ny} is the non-yield shock. It should be noted at this point that the estimated topics might be directional or not. However, it turns out that most estimated topics are directional, and hence the linear specification (10) is a reasonable starting point. That being said, there might be topics which are important for our non-yield but are not uncovered in our simple specification. With that caveat in mind, we proceed with estimating specification (10).

In the first step, we test if there is a link between the statement's distribution across topics, θ_t, and the non-yield shock. Hence, we run a joint hypothesis test of all coefficients in δ_1 via OLS estimation.[13] The left column of Table 6 shows the results of this exercise. We can easily reject the null that the topic choice of a statement does not affect the non-yield shock.

In the second step, we want to understand which of the 23 estimated topics are important for understanding the non-yield shock. In essence, we face a variable selection problem, which

[13]Due to perfect multicollinearity, we need to drop one topic in the OLS analysis which we choose to be last one (Topic 23). This choice has (almost) no effect on our results, and does not change any of our conclusions.

Table 6: Link between Non-Yield Shock and Topics of FOMC Statement

Specification: $s_t^{ny} = \delta_0 + \delta_1' \theta_t + \nu_t$		
Question	Does topic choice matter?	Which topics are important?
Estimation	OLS	LASSO
Results	P-value of Joint F-test = 0.0021	Selected Topics = 7
	$R^2 = 0.23$	$R^2 = 0.14$

Notes: This table shows the results of regressing our non-yield shock on the estimated topic proportions. The sample size is 169 observations. The left column shows results of the OLS estimation, where we conduct a joint hypothesis test of all δ_1 coefficients being equal to zero. The right column presents the results of the LASSO estimation, where the penalty weight is chosen by 10-fold cross-validations. To account for the randomness of the folds, we conduct 100000 iterations, and report results for the average penalty weight chosen. Finally, the table reports the number of topics which are selected at least 50 times, and the average R^2 over all iterations.

we solve by applying the least absolute shrinkage and selection operator (LASSO) introduced by Tibshirani (1996), and which Hansen, McMahon, and Prat (2018) also apply for topic selection. Note that a selection based on the statistical significance of OLS coefficient estimates is generally problematic in our setting due to the combination of a small sample size, a large number of regressors, and highly correlated regressors (e.g., Greene, 2018, Ch. 4).

The LASSO selects a subset of regressors by setting certain coefficients to zero. This is achieved by adding a penalty term to the OLS objective function—which consists of the sum of the absolute value of regression coefficients.[14] In our estimation, we employ the optimization procedure by Friedman, Hastie, and Tibshirani (2010) where the penalty weight is chosen by 10-fold cross-validations.[15] For more details on the estimation, see notes to Table 6. The right column of Table 6 reports the number of selected topics, as well as the corresponding R^2 of the model. The results indicate that the LASSO picks 7 out of the 23 topics which explain 15% of the variation compared to 23% explained by all topics.

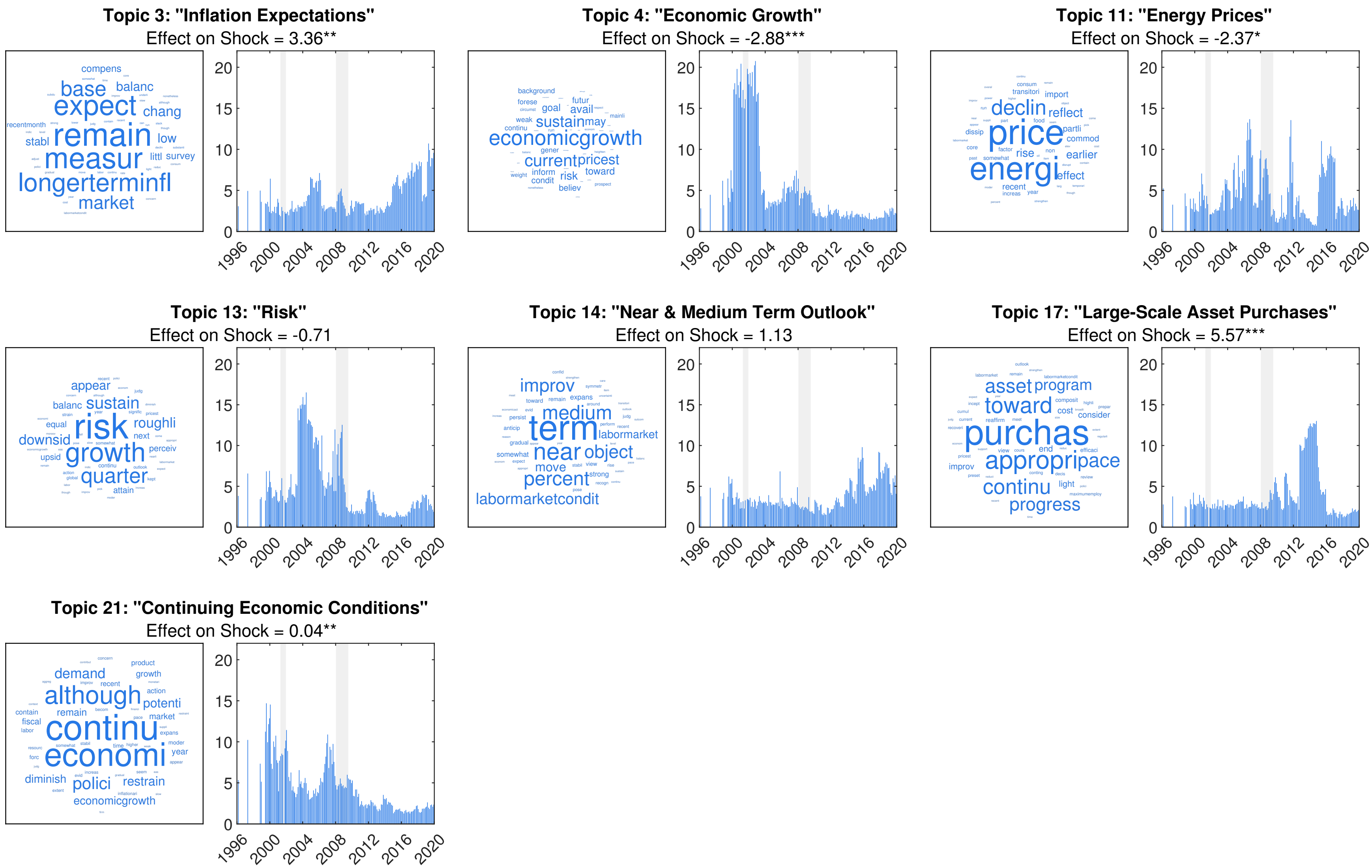
We now take a closer look at the selected topics. For each topic, Figure 3 shows the distribution over words illustrated as a word cloud, and its proportion in FOMC statements over the sample. It also shows the coefficient estimate from the LASSO as well as the significance level, where confidence intervals are constructed using the LASSO bootstrap procedure by Liu, Xu, and Li (2017) with 100000 simulations.[16] Note that the LASSO coefficients are generally biased towards zero. The topic titles are chosen based on the words in the cloud, and our reading of sentences in FOMC statements with high topic proportions.

[14]See Hastie, Tibshirani, and Wainwright (2015) for a textbook treatment on the LASSO, and Belloni, Chernozhukov, and Hansen (2014) for an economics-focused introduction.

[15]This is implemented via the *glmnet* package in R.

[16]This is implemented via the *HDCI* package in R.

Figure 3: Overview of Selected Topics



Notes: This figure illustrates the 7 selected topics by the LASSO estimation of (10), where the coefficient estimate is also reported in units of standard deviation change per 100 percent increase of topic proportion. For each topic, the word cloud shows the 50 most important words, where the size of the word indicates the topic weight on the word. Further, the figure shows each topic's proportion in FOMC statements over our sample, where the unit is percentage. ***, **, and * indicate significance at the 1, 5, and 10 percent level, where confidence intervals are calculated using the bootstrap procedure by Liu, Xu, and Li (2017) with 10000 simulations.

As Figure 3 shows, Topic 3, Topic 4, and Topic 17 have the largest and most significant coefficients. Upon further inspection, Topic 3 relates to discussions of market-based and survey-based measures of inflation, in particular a focus on longer-term horizons. Words such as "low" and "littl" indicate that the topic refers to inflation expectations below target. The rise in its proportion towards the end of our sample confirms this interpretation. The coefficient estimate seems to suggest that this is seen as a positive signal, i.e. an increase in risk appetite, consistent with the view that no tightening is to be expected soon. Topic 4 is about the discussion of economic growth. Its high proportion from 2000 to 2003 aligns with the analysis of Lunsford (2020). Further, words such as "weak" and "risk" indicate a pessimistic connotation in line with the negative coefficient estimate. Regarding Topic 17, both word cloud and time series match the discussion of the Federal Reserve's Large-Scale Asset Purchase (LSAP) programs. The positive coefficient suggests that the program or a continuation of it leads to an increase in risk appetite. Lastly, Topic 11 is about declining energy prices where the negative coefficient is consistent with a negative economic signal. Topic 21 is about continuing economic conditions which has a small but significant coefficient. Topic 13 and Topic 14, while selected by the LASSO, seem to neither have a substantial nor significant effect.

Overall, our analysis illustrates that 1) there is a clear link between our non-yield shock and the words in FOMC statements, and 2) multiple topics are able to substantially affect our shock.

5 Conclusion

In this paper we argue that monetary policy affects asset prices through channels other than the yield curve. We apply a heteroskedasticity-based procedure to estimate a latent shock that is by construction orthogonal to yield curve changes around FOMC announcements. This shock explains much of the variation of stock price changes around announcements and impacts other asset prices such as exchange rates. Its effects also suggest that the Fed non-yield shock affects asset prices at least in part through a change in investor risk appetite.

Using methods from the computational linguistics literature, we have linked the non-yield shock to text contained in FOMC statements and our findings suggest that the content communicated in FOMC statements drives the non-yield shock. As a next step, it is then natural to ask whether central banks can systematically choose topics and/or language to affect investor risk appetite and thus asset prices. We view this as a promising question for future research.

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A Estimation Appendix

This appendix provides details on the estimation of our "non-yield shock". Our estimation and code is adapted from Gürkaynak, Kısacıkoğlu, and Wright (2020).

A.1 Setup

Our estimation framework can be written as a standard state-space representation. The estimation equation (4) is the *measurement equation*

$$y_t = \beta' s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t, \tag{A1}$$

where ε_t is i.i.d. with a diagonal variance-covariance matrix Σ_ε. The (degenerate) *transition equation* is given by

$$s_t^{ny} \sim \text{iid } N(0,1). \tag{A2}$$

The parameters of the system can be summarized by the parameter vector $\theta = \begin{bmatrix} \beta & \gamma & \Sigma_\varepsilon \end{bmatrix}$. The goal is to estimate the unobserved factor s_t^{ny}, given a set of parameters $\hat{\theta}$ which we choose such that they maximize the likelihood function of the model.

For the to be identified, Note that γ is only identified up to scale

A.2 Estimation Algorithm

We estimate s_t^{ny} by using the Kalman filter to obtain the log-likelihood function of the model,

$$\begin{aligned} l(\theta) = -\frac{1}{2}\sum_{t=1}^{T} \Big\{ & 1(d_t = 1)\left[\left(y_t - \beta' s_t^y\right)' \left(\Sigma_\varepsilon + \gamma\gamma'\right)^{-1} \left(y_t - \beta' s_t^y\right) + \log\left(\left|\Sigma_\varepsilon + \gamma\gamma'\right|\right)\right] \\ & + 1(d_t = 0)\left[y_t' \Sigma_\varepsilon^{-1} y_t + \log\left(\left|\Sigma_\varepsilon\right|\right)\right] \Big\} \end{aligned} \tag{A3}$$

and then maximize it via the following EM algorithm:

1. Start with initial guess for the parameters $\theta^{(0)}$, where

$$\beta^{(0)} = \beta^{OLS} = \left(s_t^{y\prime} s_t^y\right)^{-1} s_t^{y\prime} y_t$$

$$\Sigma_\varepsilon^{(0)} = diag\left(E_t\left[\left(y_t - \beta^{(0)} s_t^y\right)^2\right]\right)$$

$$\gamma^{(0)} = \begin{bmatrix} 0.01 & 0.01 & 0.01 \end{bmatrix}.$$

2. Run Kalman filter: The updating equations are given by

$$s_{t|t}^{ny(j)} = \gamma^{(j-1)\prime} F_t^{-1} v_t d_t,$$

$$p_{t|t}^{(j)} = 1 - \gamma^{(j-1)\prime} F_t^{-1} \gamma^{(j-1)} d_t,$$

where

$$F_t = \left(\gamma\gamma' d_t + \Sigma_\varepsilon^{(j-1)}\right),$$

$$v_t = y_t - \beta^{(j-1)\prime} s_t^y,$$

and $p_{t|t}^{(j)}$ is the MSE of $s_{t|t}^{ny(j)}$, i.e. $p_{t|t}^{(j)} = E\left[\left(s_t^{ny} - s_{t|t}^{ny(j)}\right)\left(s_t^{ny} - s_{t|t}^{ny(j)}\right)'\right]$. The log-likelihood (A3) can then be written as

$$\begin{aligned} l(\theta)^{(j)} &= \sum_{t=1}^{T} l_t(\theta)^{(j)} \\ &= \sum_{t=1}^{T}\left(-\frac{1}{2}\right)\left[\log(2\pi) + \log|F_t| + v_t' F_t^{-1} v_t\right] \\ &= -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log|F_t| - \frac{1}{2}\sum_{t=1}^{T} v_t' F_t^{-1} v_t. \end{aligned}$$

3. Run Kalman smoother: Due to the non-degenerate form of the transition equation, the smoothed estimates are equal to the filtered ones:

$$\begin{aligned} s_{t|T}^{ny(j)} &= s_{t|t}^{ny(j)}, \\ p_{t|T}^{(j)} &= p_{t|t}^{(j)}. \end{aligned}$$

4. Calculate $\theta^{(1)}$: Let us define $\omega = \left[\begin{array}{cc} \beta & \gamma \end{array}\right]$ such that the measurement equation (A1) can be written as $y_t = \omega' x_t + \varepsilon_t$. Further, let $x_{t|T}^{(j)} = \left[\begin{array}{cc} s_t^y & s_{t|T}^{ny(j)} \end{array}\right]$ and $P_{t|T}^{(j)} = diag\left(\begin{array}{cc} 0 & p_{t|T}^{(j)} \end{array}\right)$, then $\theta^{(1)}$ is given by

$$\begin{aligned} \omega^{(j)} &= \left(\sum_{t=1}^{T}\left(E_T\left(x_t x_t'\right)\right)\right)^{-1}\sum_{t=1}^{T} E_T\left(x_t' y_t\right) \\ &= \left(\sum_{t=1}^{T}\left(x_{t|T} x_{t|T}' + P_{t|T}^{(j)}\right)\right)^{-1}\sum_{t=1}^{T} x_{t|T}' y_t, \end{aligned}$$

and

$$\begin{aligned} \Sigma_\varepsilon^{(j)} &= diag\left(\frac{1}{T}\sum_{t=1}^{T} E_T\left(y_t - \omega^{(j)\prime} Z_t\right)^2\right) \\ &= diag\left(\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \omega^{(j)\prime} Z_{t|T}\right)^2 + \omega^{(j)\prime}\sum_{t=1}^{T} P_{t|T}^{(j)}\omega^{(j)}\right). \end{aligned}$$

5. Repeat step 2-4 until the improvement in the log-likelihood is below a certain threshold. Let j^* denote the final iteration of the algorithm. Then the final parameter estimates are given by $\hat{\theta} = \theta^{(j^*)}$ with $\hat{\gamma} = \gamma^{(j^*)}$ being reported in Table 3. The non-yield shock series is given by $\hat{s}_t^{ny} = s_{t|T}^{ny(j^*)}$.

6. Construction of standard errors of $\hat{\theta}$: The formula for the variance-covariance matrix of the parameters is given by

$$Cov\left(\hat{\theta}\right) = \left(HI^{-1}H\right)^{-1},$$

where

$$H = -\sum_{t=1}^{T} \frac{d^2 l_t\left(\hat{\theta}\right)}{d\hat{\theta}d\hat{\theta}'}$$

and

$$I = \sum_{t=1}^{T} \frac{dl_t\left(\hat{\theta}\right)}{d\hat{\theta}} \left(\frac{dl_t\left(\hat{\theta}\right)}{d\hat{\theta}}\right)'.$$

The matrices H and I are computed by plugging in small deviations from $\hat{\theta}$, i.e. $d\hat{\theta}$, into the Kalman filter to obtain $dl_t\left(\hat{\theta}\right)$.

Remarks:

- Gürkaynak, Kısacıkoğlu, and Wright (2020) show that the parameter vector θ is identified. To achieve that, we need to assume that non-yield shock has a variance of one since it is only identified up to scale. Further, we normalize the first element of γ to be positive since it is only identified up to signing convention.

- Note that $\hat{s}_t^{ny} = s_{t|T}^{ny(j^*)}$ has a standard deviation of slightly smaller than one. While the estimates reported in Table 3 account for this smaller variance, we normalize our series to be of standard deviation one in the subsequent analyses.

- The code can handle missing observations in y_t since the updating equations of Kalman filter can be adequately adjusted depending on the available data for period t. Due to missing observations in the futures contracts, in our setting F_t and v_t are scalars for the first couple of periods, and then become matrices of dimensions 3×3 and 3. If there are no missing values, then we have $\hat{\beta} = \beta^{OLS}$ and s_t^y and s_t^{ny} are fully orthogonal.

B Data Appendix

B.1 Construction of Intraday Variables

In the following, we describe the construction of our intraday changes. All Intraday variables are based on 30-minute windows (last trade before 10 minutes and first trade after 20 minutes). All data come from *Thomson Reuters Tick History*, and is obtained via *Refinitiv*.

Monetary Policy Shocks For each FOMC announcement day, we construct nine variables which capture the monetary policy shocks to the yield curve. Table B1 provides a brief overview of the employed data for these variables. The first five variables $MP1$, $MP2$, $ED2$, $ED3$, $ED4$ cover surprises to maturities up to 14 months and are standard measures in the literature following Gürkaynak, Sack, and Swanson (2005). For longer horizons, we employ Treasury futures following Gürkaynak, Kısacıkoğlu, and Wright (2020). Kroner (2021) provides more details and documents the construction of each of these variables.

Table B1: Overview of Intraday Interest Rate Futures Data

Variable in Text	Underlying Instruments	RICs	Sample
$MP1$	Federal Funds Rate Futures	FFc1–FFc2	1/1996–12/2019
$MP2$	Federal Funds Rate Futures	FFc3–FFc4	1/1996–12/2019
$ED2$	Eurodollar Futures	EDcm2	1/1996–12/2019
$ED3$	Eurodollar Futures	EDcm3	1/1996–12/2019
$ED4$	Eurodollar Futures	EDcm4	1/1996–12/2019
$T2$	2-Year Treasury Futures	TUc1,TUc2	1/1996–12/2019
$T5$	5-Year Treasury Futures	FVc1,FVc2	1/1996–12/2019
$T10$	10-Year Treasury Futures	TYc1,TYc2	1/1996–12/2019
$T30$	30-Year Treasury Futures	USc1,USc2	1/1996–12/2019

Notes: This table provides an overview of the intraday data employed to construct the monetary policy surprises to the yield curve. The data comes from *Thomson Reuters Tick History*. *RIC* refers to the Reuters Instrument Code, which uniquely identifies each instrument.

We also compare our constructed variables with the ones of previous papers verifying that these variables are indeed constructed correctly. Table B2 shows that the correlation of each series with the corresponding series. Note that both papers employ different data sources than us.

Table B2:

	NS 2018					GKW 2020			
	MP1	MP2	ED2	ED3	ED4	T2	T5	T10	T30
MP1	0.98								
MP2		0.93							
ED2			0.98						
ED3				0.99					
ED4					0.99				
T2						0.93			
T5							0.89		
T10								0.97	
T30									0.98
Observations	144	144	144	144	144	78	94	93	94

Notes: This table shows the correlation of our constructed interest rate surprises with the ones of Nakamura and Steinsson (2018) (NS 2018) and Gürkaynak, Kısacıkoğlu, and Wright (2020) (GKW 2020) for the overlapping FOMC announcements. For a proper comparison with GKW 2020, we use 20-minute changes instead of the 30-minute changes used throughout our analysis. For both papers, we obtain the data from their online supplementary materials, `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HZOXKN` and `https://www.openicpsr.org/openicpsr/project/119697/version/V1/view`.

Stock Market Variables For both FOMC announcement and non-announcement days, we construct changes of our three stock market variables as described in the main text. Table B3 provides an overview of the employed data.

Table B3: Overview of Intraday Stock Market Data

Variable in Text	Underlying Instruments	RICs	Sample
SPX	S&P 500 Index	.SPX	1/1996–12/2019
$ES1$	E-mini S&P 500 Futures	ESc1	9/1997–12/2019
$ES2$	E-mini S&P 500 Futures	ESc2	9/1997–12/2019

Notes: This table provides an overview of the intraday data employed to construct the stock market changes. The data comes from *Thomson Reuters Tick History*. *RIC* refers to the Reuters Instrument Code, which uniquely identifies each instrument.

Other Variables Table B3 provides an overview of the intraday data employed in Table 5.

B.2 Sample Selection

FOMC announcement days As discussed in the main text, we focus in our analysis on the eight regularly FOMC scheduled announcements per year. Overall, our sample covers 190 announcements. We also exclude the two scheduled FOMC announcements on July 1, 1998, and August 21, 2001. On both days, the entire data provided from *Thomson Reuters Tick History* has large data gaps due to outages leading to irreversible data loss. These outages are more common in the early sample

Table B4: Overview of Intraday Data

Variable	RICs	Sample
VIX (CBOE Volatility Index)	.VIX	1/1996–12/2019
US Dollar Exchange Rates		
Canadian Dollar	CAD=	1/1996–12/2019
Swiss Franc	CHF=	1/1996–12/2019
Euro	EUR=	5/1998–12/2019
British Pound	GBP=	1/1996–12/2019
Japenese Yen	JPY=	1/1996–12/2019
Treasury Yields		
6 Month	US6MT=X	3/1997–12/2019
2 Year	US2YT=X	3/1997–12/2019
5 Year	US5YT=X	3/1997–12/2019
10 Year	US10YT=X	3/1997–12/2019
30 Year	US30YT=X	3/1997–12/2019

Notes: This table provides an overview of the intraday data employed in Table 5. The data comes from *Thomson Reuters Tick History*. *RIC* refers to the Reuters Instrument Code, which uniquely identifies each instrument.

period but otherwise completely random mitigating concerns of sample selection. Lastly, for some of the interest rate futures contracts, the trading is sometimes sparse early in our sample. Similarly to Nakamura and Steinsson (2018), we limit the size of the construction window by setting a price change to zero in the very rare case that there is no trade within 24 hours of the announcement.

FOMC non-announcement days Our sample of FOMC non-announcement days includes all trading days from January 1, 1996 until December 31, 2019 excluding all FOMC announcement days (scheduled and unscheduled). We use 2:15 pm ET as the reference time around which we construct our 30-minute window around since most FOMC announcements in our sample are at that time. Since the estimation can handle missing observations, we set a given series to missing for the couple of trading days for which we do not see a price quote for the series within three hours after 2:15 pm ET. For the E-mini futures contracts, we limit the size of the construction window by setting a price change to zero in the very rare case that there is no trade within 24 hours of the announcement. We drop days for which there is no data for the S&P 500 or the VIX within three hours after 2:15 pm ET. These are either days where trading closed early (e.g. July 3 or December 24) or dates for which the intraday data has large time gaps due to outages from *Thomson Reuters Tick History*. For each series, we account for misquotes by dropping positive 30-minute changes which are more than twice as large as the 99.5 percentile or negative changes which are more than twice as large in size than the 0.5 percentile. Overall, we end up with 5,617 observations.

C Additional Results

Table C1: Allowing for Intercepts in Estimation

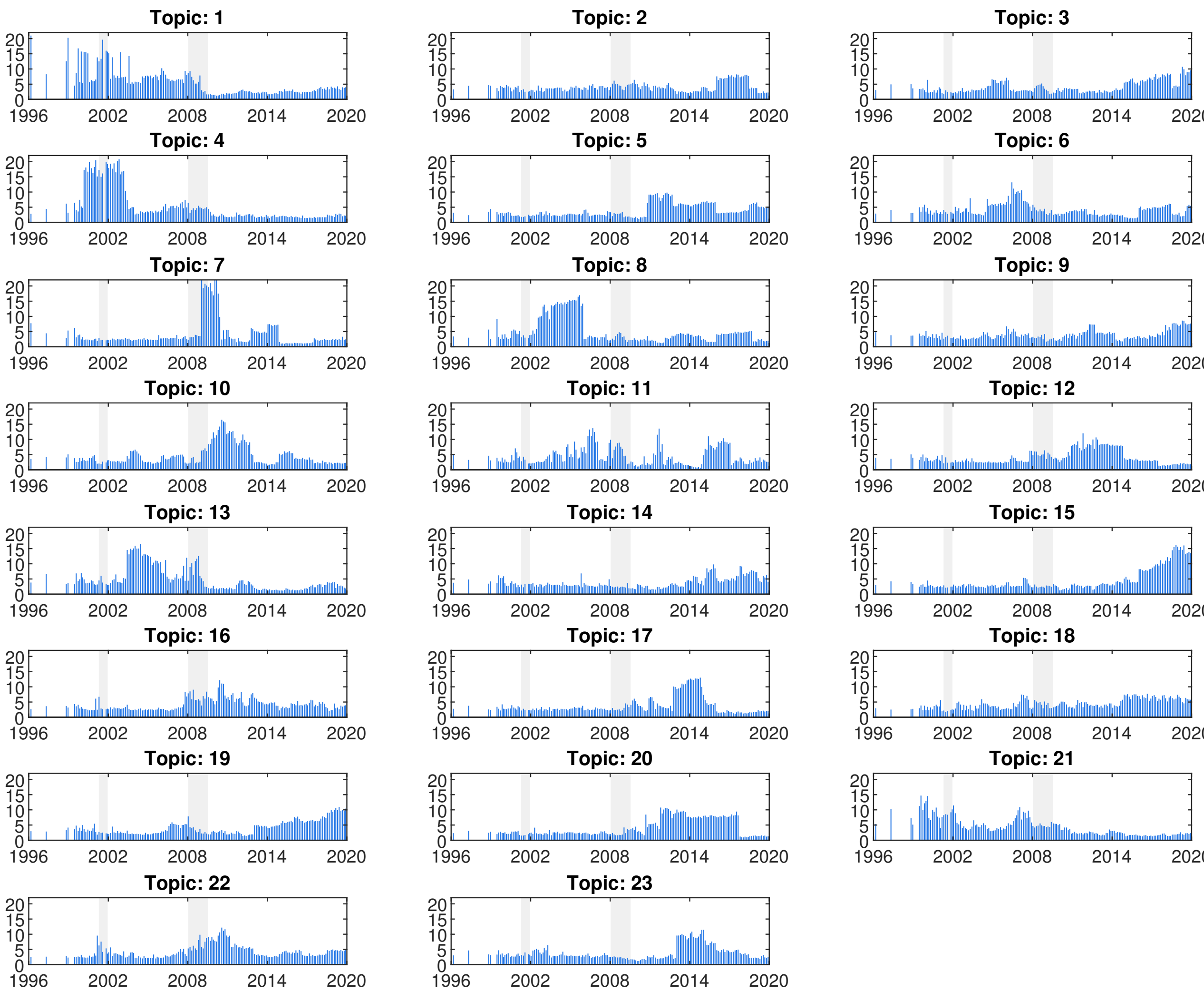
	Intercept	Intercept for each Regime
S&P 500		
R^2 without shock	0.41	0.41
R^2 with shock	0.98	0.98
Correlation with Baseline Shock	1.00	1.00
Announcements		
Observations	190	190
Sample	01/96–12/19	01/96–12/19

Notes: This table shows the results of the baseline specification including an intercept, $\Delta p_t = \alpha + \beta' s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$, and an intercept for each regime (i.e. announcement and non-announcement days), $\Delta p_t = \alpha_0 + d_t \alpha_1 + \beta' s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$, estimated via the Kalman filter. Both models are implemented by demeaning each series prior to estimation, where in the first case the mean over both announcement and non-announcement days is taken, and in the second model a separate mean is calculated for announcement and non-announcement days. While the left-hand side variables are the same three variables used in the baseline analysis, we only report R^2 values for the S&P 500 since the information content of all three series is very similar. The R^2 values are obtained from announcement day regressions of the respective independent variable on (i) yield shocks s_t^y, and (ii) yield shocks s_t^y and non-yield shock s_t^{ny}. Further, we report the correlation of our re-estimated series with our baseline one for the overlapping sample period. Lastly, we report the number of announcement days in the estimation with the corresponding sample period. The set of non-announcement days is always unchanged compared to the baseline estimation.

Figure C1: Word Clouds of All Estimated Topics

Notes: This figure shows the word clouds of all 23 estimated topics. For each topic, the word cloud shows the 50 most important words, where the size of the word indicates the topic weight on the word.

Figure C2: Topic Proportions over Sample Period



Notes: This figure shows each topic's proportion in FOMC statements over our sample, where the unit is percentage.

D Details on the Topic Estimation

D.1 Preprocessing

1. Data retrieval: We download all FOMC statements from the Federal Reserve Board's website in PDF format: https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm for more recent announcements or https://www.federalreserve.gov/monetarypolicy/fomc_historical_year.htm for announcements further in the past. Our sample includes all statements of scheduled FOMC announcements from the start of 1996 until the end of 2019. Overall, we have 171 observations. Note here two things: First, the FOMC only started issuing statements for each meeting from May 1999 on. Second, while we estimate our topics using 171 statements, we will only show results for the 169 announcements in the main text which are also used in the construction of our non-yield shock.

2. Data clean-up: First, we remove any time stamps or weblinks created by downloading the file. Second, we remove the generic header of the release, as well as the last paragraph which lists the FOMC members voting in favor of the monetary policy action. Lastly, we split up the statement into sentences.

3. Identification of collocations: As done by Hansen, McMahon, and Prat (2018), we identify collocations (word sequences with specific meanings) in the following way. First, we use the part-of-speech tagger by Toutanova, Klein, Manning, and Singer (2003) to tag every word, and then we use the part-of-speech patterns by Justeson and Katz (1995) to identify two-word (bigrams) and three-word sequences (trigrams). The patterns are defined as: (Noun, Noun), (Adjective, Noun), (Adjective, Adjective, Noun), (Adjective, Noun, Noun), (Noun, Noun, Noun), (Noun, Adjective, Noun), (Noun, Preposition, Noun). We create a single term for bigrams (trigrams) whose frequency is above 100 (50). Lastly, we replace "Federal Open Market Committee" with "committee". This is innocuous since the terms are used synonymously throughout the statements but it is an easy way to account for a very common quadrigram.

4. Remove stopwords: We remove common words in English ("stopwords"), e.g., "the", "are", or "of". Note that if they are part of an identified collocation they are not dropped. Our list of stopwords comes from Hansen, McMahon, and Prat (2018).

5. Stemming: We stem the remaining terms using the Porter (1980) stemmer. For example, "measures" and "measure" both become "measur". However, for example, "economy" becomes "economi", and "economic" becomes "econom".

6. Remove uninformative words: Following Blei and Lafferty (2009) and Hansen, McMahon, and Prat (2018), we rank the remaining terms by their term frequency-inverse document frequency (TF-IDF). The TF-IDF measures the informativeness of a word, where very common and very rare words are both punished. The TF-IDF of term v is calculated as the product of the term frequency

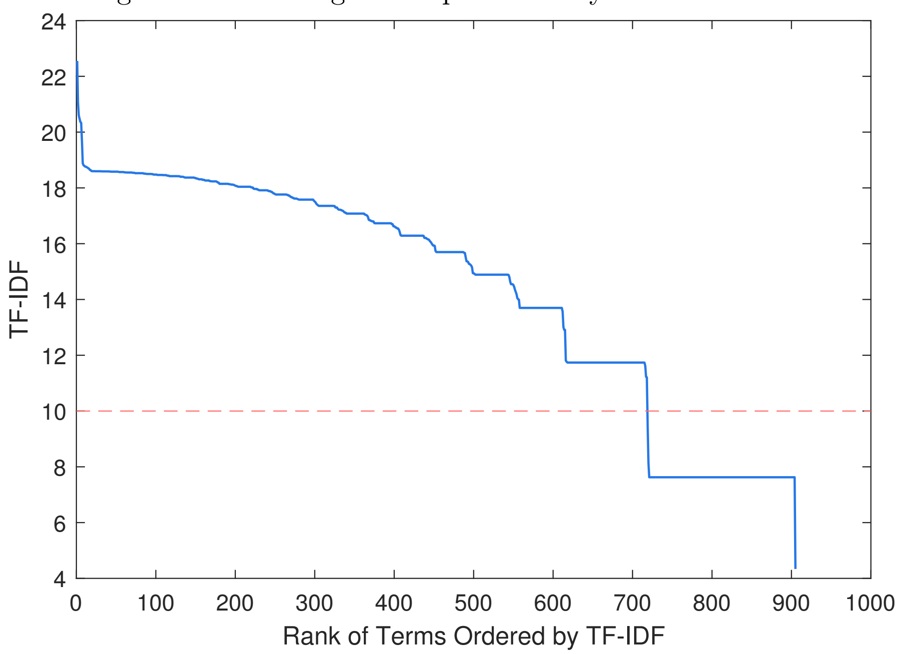
$$tf_v = 1 + \log(n_v),$$

and the inverse document frequency

$$idf_v = \log\left(\frac{D}{D_v}\right),$$

where n_v is the count of term v in the data set, D is the number of documents, and D_v is the number of documents in which term v appears. Figure D2 illustrates the in our sample. Following Hansen, McMahon, and Prat (2018), we decide on a threshold based on inspection of Figure D2, and drop stems with TF-IDF weight of below 10. We end up with 718 unique stems in our dataset.

Figure D1: Ranking of Unique Stems by Informativeness



Notes: This figure shows all unique stems in our dataset by their term frequency-inverse document frequency (TF-IDF), which is calculated as described in the text above. The dotted red line shows the TD-IDF threshold, where we drop stems with a value below it.

D.2 Model Selection

We follow Hansen, McMahon, and Prat (2018) in choosing the number of topics K^*. Precisely, we do the following procedure:

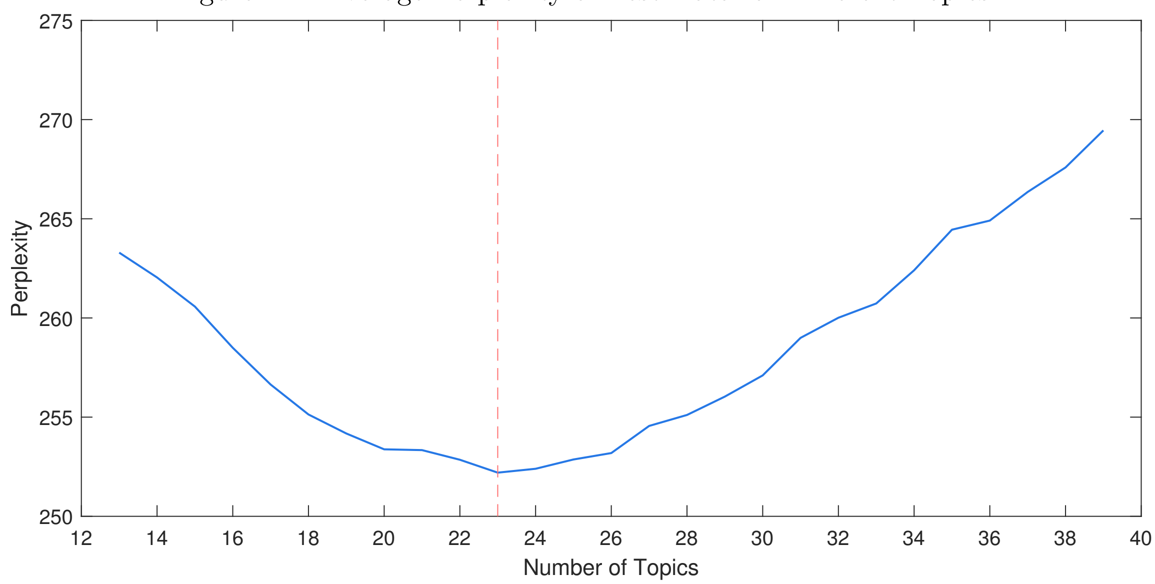
1. We first randomly draw two thirds of our sample ($\lfloor 2050 \times (2/3) \rfloor = 1366$). The remaining third is our test data.

2. Estimate the LDA model for various values of K.

3. Compute the goodness-of-fit for test data (i.e. out-of-sample) using the perplexity measure defined as
$$\exp\left[-\frac{\sum_d \sum_v x_{d,v} \log\left(\sum_k \beta_k^v \theta_d^k\right)}{\sum_d N_d}\right], \tag{D1}$$
where $x_{d,v}$ is the count of term v in document d and N_d is the total number of terms in document d. Note that we keep the estimated topics fixed β_k^v and only estimate the distribution of topics for the out-of-sample documents θ_d^k.

4. Do steps 1.–3. 10 times, and calculate for each value of K the average perplexity across the 10 draws. Choose K^* such that the average perplexity is minimized. Figure D2 shows the results of this exercise.

Figure D2: Average Perplexity of Test Data for Different Topics



Notes: This figure shows the average perplexity, as calculated by (D1), for a given number of topics K. The dotted red line shows the minimum perplexity at $K^* = 23$. See text for details on the calculations.