Fed Tails:
FOMC Announcements and Stock Market Uncertainty[*]

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Abstract

Uncertainty around FOMC announcements builds up days ahead of the meeting and fully resolves once the policy decision is announced. Disentangling tail uncertainty shows that the perception of bad economic states is the primary driver of this pattern, albeit policy operations are meant to be stabilizing. Investors are afraid of the revelation of bad states and are willing to pay a hedging premium of approx. 9% per meeting. FOMC announcements are special as uncertainty around other macroeconomic news releases is not driven by tail uncertainty. Not only does tail uncertainty predict pre-announcement stock market returns but also changes in the fed fund target rate for horizons up to one year. Our results indicate that policy makers closely monitor downside uncertainty and use this information as part of their decision-making process.

Keywords: Monetary Policy Decisions, FOMC, Macroeconomic News Announcements, Stock Market Uncertainty, Jump Risks, High-Frequency Options Data, Target Rate Predictability

JEL: E44, E52, G12, G18

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I. Introduction

The Federal reserve states the stabilization of financial markets as a central objective to comply with its mandate of promoting a strong and healthy U.S. economy. Yet, the fact that the FOMC meets on a predefined schedule seems to move stock markets in a puzzling manner. Lucca and Moench (2015) show that the average return on the S&P 500 over the 24-hour window before a meeting accounts for most of the equity risk premium, but traditional measures do not indicate a period of unusually high risk. A recent attempt at rationalizing the pre-announcement drift argues the VIX, a gauge for economic uncertainty, to increase in the three days leading up to a meeting with a decline in the 24-hour window before the actual announcement (Hu, Pan, Wang, and Zhu, 2020), which renders the drift a premium for the resolution of heightened uncertainty.

This paper answers the questions how and why uncertainty moves around FOMC meetings. We focus in particular on how uncertainty about different states of the economy relates to monetary policy meetings in the U.S. and how these dynamics are transmitted to the stock market through rate decisions. From this we draw important implications about the role of uncertainty in FOMC decisions. We show that the dynamics of uncertainty around FOMC announcements are primarily driven by changes in the perception of downside risks, or more precisely, tail uncertainty. Tail uncertainty can explain both the increase of uncertainty ahead of the meeting, as well as the resolution at the announcement time. We consider the underlying mechanism of the cross-reaction of financial markets and FOMC decisions, by using tail uncertainty to predict both stock market returns and target rate changes up to one year, indicating that the Fed actively monitors and considers tail risk as part of its internal decision-making process.

Our analysis starts by documenting the behavior of VIX-type uncertainty around FOMC announcements. Overall uncertainty increases in the week ahead of FOMC announcements before it sharply drops at the announcement time. Purging overall uncertainty from the impact of expected tail events, we reject the finding of a significant increase ahead of the meeting but rather uncover a steady downward trend. Furthermore, the announcement resolution of this purged uncertainty estimate is practically zero. FOMC announcements, which may bring about a change in the target rate, provide a gloomy economic outlook in the form of forward guidance, or a tampering of quantitative easing programs, induce uncertainty into the market. The fact that tail uncertainty explains the increase ahead of the meeting as well as the sudden resolution at announcement time speak in favor of this idea. From a short-term perspective, the Fed's effect on total economic uncertainty is rather marginal when taking the uncertainty buildup into account.

A natural question to ask is whether the observed pattern also exists for other pre-scheduled macroeconomic announcements. We find this not to be the case. More specifically, we first condition on differences of FOMC announcements with or without an additional macroeconomic announcement during the blackout period. The dynamics in both cases are similar, with a small shift in the level. Constructing pseudo blackout periods around a large set of macroeconomic announcements, we then show that the pattern is vastly different from the one observed for monetary policy announcements. Once we take the impact of tails into account, we find that tail uncertainty decreases relative to overall uncertainty as we move closer to the announcement, which contrasts the significantly positive impact of tail uncertainty we find for FOMC announcements. Monetary policy meetings are special in that they command a sizable tail premium, as there is a small, but real possibility of revealing a bad economic state (Wachter and Zhu, 2019).

To quantify the uncertainty premium associated with FOMC meetings, we approximate the payoffs to variance swaps using continuously delta-hedged straddle and strangle returns (Coval and Shumway, 2001). Straddles pick up the premium for all variation in returns, while strangles focus on larger movements. This way we can separately identify the insurance premium awarded for tail uncertainty. Changes in both premia are large and negative over the observed time span from the start of the blackout period to a day after the announcement. Buying insurance against total and tail uncertainty costs an average of -9% per meeting, as measured by capital used. While tail insurance is more expensive on most days, it does pay off positively on the day after announcements, as expected tail uncertainty subsides, corroborating the existence of a large premium to hedge monetary policy announcement risk.

To understand the pattern we document, we condition on various meeting characteristics that have previously been found to enhance or outright drive the results of FOMC announcements on uncertainty. We show a slightly elevated, but generally comparable impact of tail uncertainty for meetings with a press conference (Boguth, Gregoire, and Martineau, 2019). Following Gürkaynak, Sack, and Swanson (2005) and Kuttner (2001) to quantify the change in the target rate not expected by market participants, we again find a comparable pattern. Interestingly, however, levels of uncertainty are significantly elevated across the entire blackout period, in contrast to the unconditional analysis, for which the elevation is significant only for the day before the announcement. We provide two possible explanations for this phenomenon: 1) rate changes occur in turbulent times, for which coming up with an expectation of where the Fed will set the target rate is generally more difficult or 2) higher tail uncertainty significantly relates to surprising future target rate changes.

We test this and use tail uncertainty to understand changes in the target rate and the reaction of stock markets around FOMC announcements. Tail uncertainty significantly predicts the pre-FOMC announcement drift and the overall meeting return. A one standard deviation increase in tail uncertainty is associated with a return of 61 bps from 24 hours before the meeting until the end of the FOMC announcement day. To give an economic interpretation for this, we predict future target rate changes, which are known to be a substantial driver for the stock market (Bernanke and Kuttner, 2005). Not only does higher tail uncertainty significantly predict the likelihood of a target rate cut, it also predicts the magnitude of rate changes up to one year in the future. A one standard deviation increase significantly predicts a rate cut of 13 bps in the meeting that follows 24 hours later and a cumulative cut of 53 bps one year later. This effect remains sizable after accounting for signed intermeeting returns introduced in Cieslak and Vissing-Jorgensen (2020), and holds for different subsamples.

These results show that tail uncertainty provides complementary information to stock market performance in predicting the future path of monetary policy. A potential explanation to this is that the Fed not only monitors the stock market on its own but also incorporates forward-looking downside uncertainty in its decision-making process. For instance, the Fed actively gave guidance on tail risk in that it would accommodate if financial markets and economic conditions worsened ("whatever it takes"). Vice Chair Janet L. Yellen relates the purpose of the FOMC directly to tail risk in her speech on March 4, 2013.[1] Minutes of the Federal Open Market Committee point in a similar direction and show that committee members frequently discuss uncertainty measures and tail risk.[2]

We are the first to tackle the empirical identification problems of FOMC meetings using a large and liquid panel of high-frequency option quotes. The prices of options depend on forward-looking information and can be used to extract the aggregate perception about the future course of the economy. We compare the intraday dynamics of uncertainty around FOMC meetings with a control group of thirty days before the blackout period, which is the one week before FOMC announcements. During this week, members are not allowed to publicly discuss the content and possible decisions of the upcoming meeting. The implications of this "Purdah" have been studied by Ehrmann and Fratzscher (2009), with the reasoning that abstaining from public communication should lower uncertainty in times of heightened sensitivity to monetary policy.

We add to the literature analyzing the impact of monetary policy decisions on financial markets. Hu, Pan, Wang, and Zhu (2020) rationalize pre-announcement market returns with a resolution of uncertainty. We find that the buildup and most of the resolution of uncertainty is tail uncertainty entering and leaving market. Next, we find perceived downside risks to be an important driver of Fed decision-making, by showing that the federal fund target rate is predictable up to a year into the future. Our results complement existing evidence that stock market information predicts Fed decisions (Cieslak and Vissing-Jorgensen, 2020). We further contribute to the identification of monetary policy shocks. We show that a focus on high-frequency changes in uncertainty disregards the increase during the blackout period. The tail premium building up during this period would be discarded, overestimating the Fed's ability to resolve, and disregarding its role in elevating uncertainty. In a similar vein, Brooks, Katz, and Lustig (2019) find that the reaction to FOMC announcements for long-term bond yields takes longer than the standard 30-minute window.

[1] Janet L. Yellen, March 4, 2013, at the National Association for Business Economics Policy Conference, Washington, D.C.: *"Even in the aftermath of the crisis, businesses, banks, and investors have been exceptionally cautious, presumably reflecting their concern about future business conditions, uncertainty about economic policy, and the perception of pronounced tail risks relating, for example, to stresses in global financial markets. I see one purpose of the Committee's accommodative policies as promoting a return to prudent risk-taking."*

[2] See the Minutes from April 28-29, 2009 or September 25-26, 2018.

II. Related Literature

Measuring Effects of Monetary Policy. The primary objective of the Fed is to create a suitable environment for economic stability. A dual mandate of simultaneously targeting a certain level of unemployment and inflation is at the heart of this.[3] The main tool to achieve economic stability is changing the target rate, through which the Federal Reserve controls the short-end of the yield curve. An expansionary downward shift in the target rate should be conducted if inflation is lower than its target rate, or unemployment above its natural rate (Taylor, 1993), to spur economic growth. Since the real effects of policy changes are observed only with a lag (Olivei and Tenreyro, 2007), researchers have turned to the prices of traded assets to understand how policy intervention affects economic expectations in near real-time. Zooming in on the release of information by the Fed resembles a controlled experiment setting, if the considered time frame is small enough, such that no other material information is released, and the time frame is large enough for all released information to be processed (Gürkaynak and Wright, 2013).

A major contribution to effectively measure monetary policy shocks has been made by Kuttner (2001), who uses the unanticipated movement in the Federal Fund Futures Rate (FFR) to capture target rate shocks. Gürkaynak, Sack, and Swanson (2005) use this measure to gauge the high-frequency impact of monetary policy announcements on short- to long-term forward rates. They find that short-term forward rates react positively to a contractionary target rate shift, while long-term rates decrease. More generally, Neuhierl and Weber (2019) find that a slope factor constructed from FFR across multiple horizons can forecast stock returns at the weekly frequency. Expectations of sooner policy easing positively predicts stock returns, and conveys information about the speed of future monetary policy intervention. Faust and Wright (2018) stress the signaling effects of monetary policy, by showing that bond return predictability is concentrated around announcement times, while the expectation hypothesis cannot be rejected on other days. Commenting on the effectiveness of monetary policy, Hanson and Stein (2015) document strong effects on distant short-term forward rates, which they attribute to changes in term premia, driven by yield-seeking investors.

[3]See the Federal Reserve Act of 1977 `https://fraser.stlouisfed.org/title/1040`.

Seeking to understand the policy reaction to overall stock market development, Rigobon and Sack (2003) introduce a heteroskedasticity-based estimator, using the fact that policy announcements almost surely release new information to the market. A 5% drop in the S&P 500 increases the likelihood of a 25 basis point (bps) target rate cut by half. Using the high-frequency measure by Gürkaynak, Sack, and Swanson (2005) as input to a VAR model, D'Amico and Farka (2011) analyze the joint dependency between policy changes and stock market development. They find that a surprise tightening in the target rate by 1% leads to a 4.9% stock market decline on average, while a 5% stock rise led the Fed to raise rates by 10bps in their sample. Evidence that the Fed closely watches the inter-meeting (stock) market development is also given in Cieslak and Vissing-Jorgensen (2020), who uncover an asymmetric response to market returns, with an easing of monetary policy after particularly bad stock market performance, but no similar tightening after rallies. On a related note, Cieslak (2018) find that most variation in short term interest rates is due to forecasting errors by investors, which concentrate around periods of monetary easing, in which the Fed historically surprised participants by easing more aggressively than anticipated. Bernanke and Kuttner (2005) find that an unanticipated 25bps target rate cut leads to a 1% stock market price increase, with subsequently abnormally low returns. Lucca and Moench (2015) show that most compensation for equity risk is awarded in a 24-hour window before FOMC announcements, a puzzling finding as traditional risk measures are unusually calm during this period. Cieslak, Morse, and Vissing-Jorgensen (2019) show that this finding extends to a bi-weekly pattern, which coincides with public appearances of Fed governors. Savor and Wilson (2013) find large and significant returns on days of scheduled news announcements, and Kroencke, Schmeling, and Schrimpf (2019) find substantial fund flows on FOMC announcement days. The authors show that a large share of these announcement returns is related to how investors perceive risks.

Resolution of Uncertainty. Another important channel through which the Fed promotes a stable economy, is by lowering financial and economic uncertainty. Lucca and Moench (2015) have shown that realized risk measures are not agitated before FOMC announcements, which is puzzling, given the high returns during this period. Martello and Ribeiro (2018) come to the same conclusion, but do note that if uncertainty is higher, measured by the CBOE's VIX index, the pre-announcement drift is larger. Bollerslev, Li, and Xue (2018) find that realized volatility is low before announcements, but increases significantly thereafter. Doan, Yang, and Foster (2018) come to the same conclusion, by differentiating between risk and uncertainty. The former jumps suddenly, while the latter declines more gradually. They attribute this to rising trading activity around macroeconomic news announcements, and stress the unique nature of FOMC publications by showing that uncertainty is significantly higher before, and significantly lower after FOMC announcements. Amengual and Xiu (2018) analysis the importance of downward jumps in uncertainty, particularly at the times of macroeconomic releases, in accordance with Fernandez-Perez, Frijns, and Tourani-Rad (2016) who show that uncertainty decreases abruptly at FOMC announcement times, with a continuing 45-minute decline. Bekaert, Hoerova, and Lo Duca (2013), document significant shifts in uncertainty and the variance risk premium (VRP) after monetary easing. Further analyzing how variance risk premia behave, DeSimone and Laux (2018) study straddle and VIX futures returns around FOMC announcements. They find negative payoffs to strategies exposed to uncertainty about jumps in the underlying. Hu, Pan, Wang, and Zhu (2020) show that the pre-announcement return drift is accompanied by a resolution of a premium in economic uncertainty. Measuring uncertainty about future target rate changes from long-term options on short-term rates, Bauer, Lakdawala, and Mueller (2019) find that FOMC announcements significantly depress monetary uncertainty for up to two weeks. Similarly, Beber and Brandt (2006) estimate the state-price density from Treasury options, and find a similar decline in uncertainty after announcements. Husted, Rogers, and Sun (2019) use textual mentions in newspapers relating to monetary policy decisions to gauge uncertainty about future policy decisions. Higher monetary policy uncertainty affects real quantities, leading to lower firm investment. Using a set of derivatives written on the outcome of macro news announcements, Gürkaynak and Wolfers (2006) find significant effects for the surprise news component, beating a benchmark of survey expectations. Using the same data, Beber and Brandt (2009) find that higher uncertainty ahead of releases leads to stronger reductions in the implied volatility of equity and bond options, a reduction in open interest, and increased trading activity. On a related note, Kelly, Pástor, and Veronesi (2016) find that options spanning political events are systematically more expensive due to the uncertain nature of such events.

Theoretical Contributions The importance of monetary policy has been documented in many markets. The pre-FOMC announcement drift by Lucca and Moench (2015) has been of central interest to researchers, as their finding provides a challenge to classical theoretical frameworks. Ai and Bansal (2018) discuss necessary conditions on the preference structure for a pre-announcement drift to emerge, and Cocoma (2018) employs a model of differing opinions, in which two groups of investors process information from news announcements after the fact, and between two meetings. Similarly, in the model of Laarits (2019), investors try to make sense of information already in the market. This way, market participants try to gauge the nature of the upcoming meeting. Through this mechanism, uncertainty is resolved gradually and returns are positive, as predicted by the standard risk-return trade-off. Using the Fed as the sole entity to provide information about the health of the economy, Wachter and Zhu (2019) can match important empirical facts on FOMC announcement days. The small, but very real risk of revealing a disastrous economic state is the primary driver here.

III. Data

A. Option Data

The use of option data allows us to robustly estimate economic uncertainty and focus on the adversity of the expected shock by zooming in on large movements. We isolate tail from overall uncertainty. We rely on high-frequency data, given that intraday patterns around the announcement of monetary policy decisions are from special importance. The use of daily or coarser data might distort inferences.

We obtain minute-by-minute S&P 500 option quote data for the time period from January 2004 to December 2017 from the CBOE datashop. We omit the first two quotes of each trading day to avoid staleness and missing quotes. Our sample consists of 3,524 trading days, with an average of 235 OTM call and 784 OTM put quotes per minute, totaling 410,149 quotes a day.

To remedy the limitation that the S&P 500 is not directly traded and that prices may be poorly recorded especially at higher frequencies, we infer the underlying price S_t from put-call parity and confirm the validity through comparison with traded S&P 500 futures obtained from the CME group.[4] In this, we follow Andersen, Bondarenko, and Gonzalez-Perez (2015).[5] Our data filters follow the same study closely, with slight adaptions as detailed in Appendix A. Throughout our work, we define moneyness as

$$m = log(K/F) \times (IV^{ATM}\sqrt{\tau})^{-1},$$

where K denotes the strike, F the underlying's future price, IV^{ATM} the implied volatility of an ATM option, and τ the time-to-maturity. This measure of moneyness takes the current level of volatility and the maturity of the option into account.

We report average open interest and relative bid-ask spreads per minute for Non-FOMC and FOMC days in Table I. Minute-by-minute open interest is high across the time and moneyness domain. Options are traded actively in our sample, facilitating the extraction of uncertainty measures. We observe a U-shaped pattern in open interest over moneyness, showing that the bulk of outstanding contracts is in OTM put and call options. We find a liquid market for deep-OTM puts ($m < -2.5$), for which we find the highest average open interest numbers. Generally, there is little variation for different times to maturity. Open interest for FOMC and non-FOMC days barely differs, with a slight drop for FOMC announcement days, a finding previously documented by Ying (2020a), which the author attributes to a reduction of investor disagreement following FOMC releases. Relative bid-ask spreads show a similar U-shaped pattern as moneyness varies. Spreads are tightest for ATM contracts and increase significantly as we move further out of the money. The size of bid-ask-spreads on FOMC days are comparable to non-FOMC days, a finding that is somewhat different to Carr and Wu (2006), but may be related to the improving size and liquidity of option markets in recent years. We conclude that high-frequency option quotes are sufficiently liquid also on FOMC announcement days.[6]

[4] We do not use direct futures prices since S&P 500 futures suffered from illiquidity in the earlier sample. A natural choice in our framework is thus to use ATM options to infer the price of the underlying.

[5] The authors provide a detailed analysis of the behavior of option-implied volatility for high frequencies.

[6] High-frequency liquidity measures compare well to measures for the end-of-day option panel.

Table I. Option Sample Characteristics

	Non-FOMC			FOMC		
	≤ 15	≤ 90	≤ 365	≤ 15	≤ 90	≤ 365
Panel A: Open Interest						
$m < -2.5$	567	510	593	511	503	568
$-2.5 \leq m < -1.0$	385	486	404	350	460	393
$-1.0 \leq m < 1.0$	237	330	331	208	312	323
$m > 1.0$	379	355	416	356	350	424
Panel B: Bid-Ask Spread						
$m < -2.5$	0.53	0.39	0.35	0.51	0.41	0.37
$-2.5 \leq m < -1.0$	0.19	0.12	0.09	0.16	0.13	0.10
$-1.0 \leq m < 1.0$	0.10	0.07	0.06	0.09	0.08	0.06
$m > 1.0$	0.60	0.53	0.46	0.57	0.53	0.47

Note. This table shows 1-minute average Open Interest (Panel A) and Bid-Ask-Spread (Panel B) for our option sample on FOMC and Non-FOMC days for different moneyness and maturity buckets. m corresponds to the adjusted log-moneyness $m = log(K/F) \times (IV^{ATM}\sqrt{\tau})^{-1}$ and $15, 90$ and 365 to the options maturity.

B. FOMC News Announcements

The Federal Open Market Committee has scheduled 8 meetings per year since 1994, in which not only monetary policy, but also the economic outlook is discussed. The announcements have typically been released at 2:15 p.m. Since the introduction of press conferences in 2011, dissemination times have varied between 12:30 p.m. and 2:15 p.m.. Currently, the FOMC statements are released at 2:00 p.m. and the press conference is held half an hour later. As we start our analysis in 2004 due to the availability of minute-by-minute option quotes, we are left with a total of 112 meetings, 28 of which have been accompanied by a press conferences. A list of all FOMC meetings considered in our main analysis, as well as an overview of their characteristics, is provided in Appendix C. For purposes of robustness, we also analyze an extended *daily* sample from 1996–2018, comprising 184 meetings.

C. Empirical Design

To isolate the real effects of FOMC announcements on economic uncertainty, we base our analyses on difference-in-difference estimators. These estimators allow us to a) purge our uncertainty measures from deterministic intraday effects, which may skew results (Andersen, Thyrsgaard, and Todorov, 2019), and b) figure out abnormal effects, by a simple comparison with average uncertainty levels ahead of the announcements. The diff-in-diff approach is inspired by Bollerslev, Li, and Xue (2018).

We split our sample into treatment days, which encompasses the day of the FOMC announcement, $\mathcal{F}$, the one week before, and one day thereafter. The remainder is labeled as non-treatment. We use the full week before the actual announcement is held, the so-called *blackout week*, as part of our treatment group. During the blackout week, committee members are officially prohibited to make any public comment about future policy directions. Including the blackout week in our treatment group assures that we condition on news officially provided by the Fed. Deviations from control group levels should thus be a consequence of learning about information that has already been in the market, other macroeconomic news, or even leakage by committee members and close aids.[7] We also include the day following FOMC announcements to identify the persistence of meeting shocks.

We focus on *patterns of uncertainty* around FOMC meetings, and more specifically the impact of tail uncertainty on this pattern.[8]. Therefore, for days d in the set of treatment days $\mathcal{T}_j$ including the jth FOMC announcement $\mathcal{F}_j$, we subtract the 30-day average before the blackout period for each time-of-day from 09:33 to 16:15,

$$\widetilde{\mathcal{U}}_{d\in\mathcal{T}_j}(t) = log\ \left[\mathcal{U}_{d\in\mathcal{T}_j}(t)\right] - \frac{1}{30}\sum_{i=8}^{37} log\ \left[\mathcal{U}_{F_j-i}(t)\right], \tag{1}$$

where $\mathcal{U}$ is the uncertainty level at time t on a given day in the treatment and control groups. For instance, using the most common announcement time of 2:00 pm, we

[7] Vissing-Jorgensen (2019) identifies many instances of inter-meeting leakage to sway the public's opinion. In this study, however, we condition on publicly available news, which makes up the lion share of what is publicized.

[8] When conditioning on unscheduled press conferences, we see little variation around these meetings, but substantially elevated levels of uncertainty.

subtract the 30-day average from 37 to 8 days before the announcement, sampled at 2:00 pm daily to obtain our desired estimator.

We keep the control group constant for the days in each set of treatment days $\mathcal{T}_j$. This approach assures consistent comparisons of pre-meeting uncertainty levels and makes sure that any deterministic intraday patterns are being accounted for. The resulting estimates are convenient, as they assume stationarity, similar to first-differencing in the absence of intraday effects, and can be interpreted as relative changes in uncertainty compared to a predefined pre-announcement control set.

To more formally assess how uncertainty behaves around FOMC announcements, we employ a set of dummy regressions. For this, we use individual dummies corresponding to each day in a set of treatment days $\mathcal{T}_j$. For the announcement day $\mathcal{F}_j$ we define two dummies, PRE and POST, to distinguish between what happens in the run-up to the announcement and dissemination effects.[9] This also allows us to quantify the associated jump in uncertainty measures $\widetilde{\mathcal{U}}$, which we denote as JUMP, as the difference between average effects before, and after the announcement. The regressions take the following form:[10]

$$
\begin{aligned}
\widetilde{\mathcal{U}}_{d\in\mathcal{T}_j}(t) &= \sum_i \beta_i D_{i,t} + \sum_j \delta_j X_{j,t} + \varepsilon_t, \quad \text{with} \\
D_t &= [-5, \ldots, -1, \text{PRE}, \text{POST}, 1]' \quad \text{and} \\
\beta_{JUMP} &= \beta_{POST} - \beta_{PRE},
\end{aligned}
\tag{2}
$$

where βs denote the coefficients to dummies in vector D_t, measuring the average effect across announcements on the respective day. Control variables X_t are assumed to exert a constant effect across all days in the blackout period.

To assess the significance of our results, we employ a bootstrap technique that suits our week-long setup. Simple analytical standard errors are inadequate in this situation, as intraday observations are typically temporally dependent. Therefore, we rely on a simple, yet effective bootstrap technique. Details of this approach are

[9] Lucca and Moench (2015) find significant returns in 24-hours before FOMC announcements. We extend the number of days considered to depict how information is processed that by decree should not have originated from committee members.

[10] Note that we abstain from adding an intercept, as the DID estimates effectively de-mean our sample.

given in Appendix B. We do note that the overall significance of our tests around FOMC announcements is limited. We ask the data whether relative uncertainty levels are, averaged across the 112 meetings in our sample, equal on each blackout period day (except for announcement day where we split the data into PRE and $POST$ meeting levels). This in itself is a fairly conservative statistical test. Our DID estimator tries to circumvent many of these issues, by conditioning on the information available and uncertainty present at the start of the blackout period, but will fail to pick up a rapid change in uncertainty levels that are related to the overall economic condition.

IV. Empirical Analysis

We focus our empirical analysis on understanding how economic uncertainty behaves around monetary policy announcements. To this end, we rely on VIX-like measures to approximate uncertainty in reference to Bloom (2009). Formally, uncertainty about future states of the economy may be extracted from option prices as the expected quadratic variation for the S&P 500 U.S. market index:

$$\mathbb{E}_t^{\mathbb{Q}}\left[\mathrm{QV}_t^{t+\tau}\right] = 2e^{\int_t^{t+\tau} r_s ds}\left(\int_0^{\infty} \frac{O_t^{\tau}(K)}{K^2} dK\right), \tag{3}$$

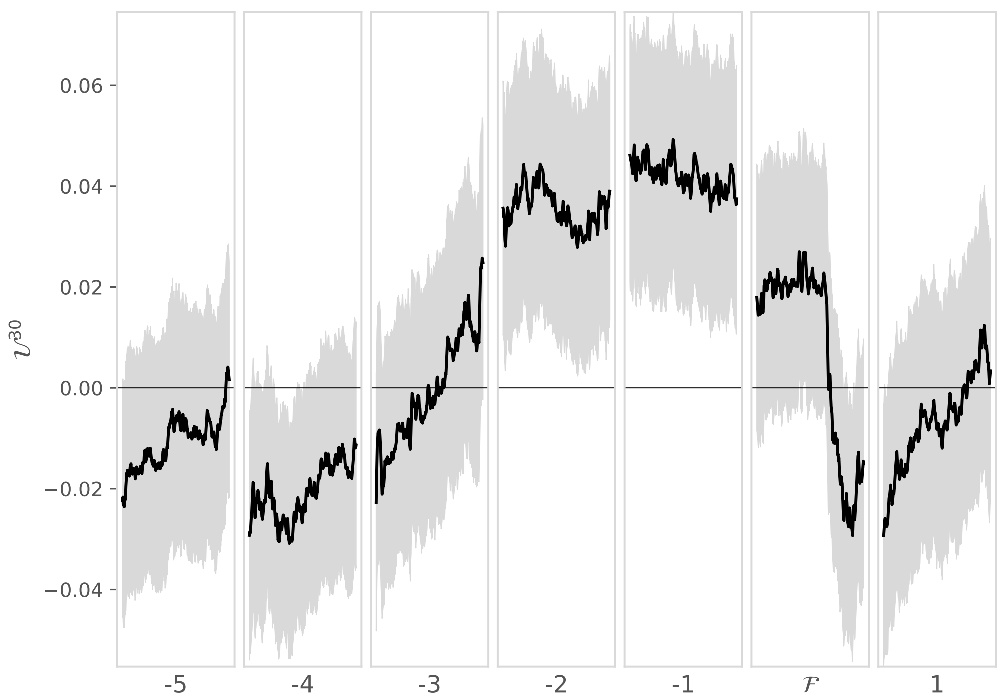
with risk-free rate r, option prices O at strike K and time horizon τ. We abstract from the calculation methodology proposed by the CBOE as its cutoff rule may lead to random biases in the estimation.[11] Instead, we construct a granular grid of minute-by-minute option quotes by employing a Gaussian-kernel smoothing technique across adjusted log-moneyness, time to maturity and a put-call identifier. Note that we do not extrapolate outside the observed strike range to refrain from making any statement about the underlying distribution in unknown regions.

[11] The CBOE cuts off options once two consecutive strikes have zero bid quotes. Andersen, Bondarenko, and Gonzalez-Perez (2015) uncover that the random truncation of the strike range leads to artificial jumps in the VIX and, thus, an incoherent uncertainty measure.

A. Uncertainty around FOMC Announcements

The first part of our analysis will focus on a measure of short-term economic uncertainty. Specifically, we extract uncertainty about the future economic trajectory as in Equation (3) for a horizon of one month. Our instrument in this is the S&P 500 index, which covers a large fraction of publicly traded U.S. companies. This measure is similar to, but more robust than the CBOE's VIX, a measure that has been used in numerous studies to identify the real effects of FOMC announcements on uncertainty.[12] Figure 1 shows the average evolution of our diff-in-diff estimate of uncertainty ($\widetilde{\mathcal{U}}^{30}$) over all FOMC announcements from 2004 through 2017. The vertical axis displays deviations from the control group and the horizontal axis days surrounding the FOMC announcement $\mathcal{F}$.

Figure 1. Evolution of Economic Uncertainty over Blackout Period



Note. The figure shows the evolution of $\widetilde{\mathcal{U}}^{30}$, 30-day economic uncertainty differenced against its control, and averaged across all announcement days. Measures are shown as 5-minute averages. 95% confidence intervals are calculated from bootstrapped standard errors, randomly shuffling realizations of relative uncertainty across the 112 FOMC announcements considered.

[12]For example in Bekaert, Hoerova, and Lo Duca (2013) or Hu, Pan, Wang, and Zhu (2020).

We identify four phases of a consistent pattern in the seven days considered in our analysis: On the first days of the blackout period, $\mathcal{F}-5$ through $\mathcal{F}-3$, we see a pronounced increase in uncertainty levels. $\widetilde{\mathcal{U}}^{30}$ rises significantly from about 2% *below* the control group on days $\mathcal{F}-5$ and $\mathcal{F}-4$ to 4% *above* the control group at the start of day $\mathcal{F}-2$. This phase usually encompasses a weekend given that FOMC announcements often fall on a Wednesday. We observe an increase in uncertainty of approx. 1 percentage points while markets are closed. The second phase from $\mathcal{F}-2$ up to the time of the announcement replicates the findings by Hu, Pan, Wang, and Zhu (2020), who document a reduction of uncertainty *before* FOMC announcements. Compared to the 30-day control group, uncertainty drops from +4% to +2% at the start of the announcement day $\mathcal{F}$, and remains relatively stable. At the actual announcement, we observe a significant drop from +2% to about −2% compared to control group levels. The drop of 4 percentage points is the direct average effect of monetary policy decisions on aggregate uncertainty. However, the resolution of uncertainty is short-lived. Once the meeting concludes, levels revert back to control group levels (approx. 0%) on the next trading day. Incorporating pre-meeting uncertainty levels and intraday effects, we show that uncertainty is elevated before announcements and that the announcement jump is statistically significant. We do find no evidence of a significant resolution of uncertainty ahead of the announcement time, nor any evidence of persistence in lowered uncertainty.

We cannot confirm many of the recent findings in the literature that the FOMC resolves uncertainty. Our results indicate that the mere presence of pre-scheduled FOMC announcements induces uncertainty. It builds up by roughly 5 percentage points in the days before the announcement. Once the FOMC's decision is announced, the pre-meeting buildup is resolved again. The fact that uncertainty levels revert back to the control group average speaks in favor of this interpretation. Therefore, we conclude that zooming out and looking at a broader picture is necessary when the impact of FOMC meetings on uncertainty is analyzed. A mere consideration of high-frequency shocks, for example in the common 30 minute window around meetings, is ill-advised and picks up spurious effects in the form of the pre-meeting buildup documented here. These findings are reminiscent of Brooks, Katz, and Lustig (2019) who argue that monetary policy effects on bond yields take longer to unfold, as investors are only slowly adjusting their expectations.

Table II. Economic Uncertainty around FOMC Announcements - Dummy Regressions.

	-5	-4	-3	-2	-1	PRE	$POST$	1	$JUMP$
					Panel A				
Base	-0.011	-0.021	-0.001	0.036	0.042	0.025	-0.028	-0.007	-0.053
	$[-0.047, 0.021]$	$[-0.055, 0.011]$	$[-0.038, 0.037]$	$[-0.002, 0.072]$	$[0.009, 0.077]$	$[-0.012, 0.058]$	$[-0.061, 0.005]$	$[-0.043, 0.031]$	$[-0.066, -0.039]$
PC	0.034	0.008	0.044	0.071	0.067	0.022	-0.056	-0.048	-0.077
	$[-0.036, 0.102]$	$[-0.061, 0.080]$	$[-0.033, 0.125]$	$[0.001, 0.148]$	$[-0.001, 0.131]$	$[-0.046, 0.082]$	$[-0.114, 0.001]$	$[-0.117, 0.012]$	$[-0.099, -0.054]$
no PC	-0.011	-0.021	-0.001	0.036	0.042	0.025	-0.028	-0.007	-0.053
	$[-0.045, 0.023]$	$[-0.053, 0.012]$	$[-0.038, 0.036]$	$[-0.000, 0.071]$	$[0.007, 0.079]$	$[-0.012, 0.060]$	$[-0.062, 0.006]$	$[-0.044, 0.031]$	$[-0.066, -0.040]$
Sur	0.075	0.060	0.064	0.100	0.097	0.063	0.004	0.014	-0.059
	$[0.028, 0.121]$	$[0.007, 0.109]$	$[0.002, 0.122]$	$[0.047, 0.153]$	$[0.045, 0.150]$	$[0.003, 0.113]$	$[-0.047, 0.048]$	$[-0.043, 0.068]$	$[-0.078, -0.042]$
no Sur	-0.070	-0.076	-0.047	-0.008	0.004	-0.002	-0.049	-0.021	-0.047
	$[-0.116, -0.024]$	$[-0.118, -0.037]$	$[-0.091, -0.001]$	$[-0.055, 0.038]$	$[-0.044, 0.050]$	$[-0.048, 0.043]$	$[-0.091, -0.003]$	$[-0.071, 0.026]$	$[-0.064, -0.029]$
					Panel B – Less Tail Impact				
Base	-0.013	-0.007	-0.004	-0.017	-0.033	-0.042	-0.044	-0.026	-0.003
	$[-0.024, -0.001]$	$[-0.019, 0.005]$	$[-0.016, 0.007]$	$[-0.029, -0.005]$	$[-0.045, -0.020]$	$[-0.054, -0.027]$	$[-0.055, -0.029]$	$[-0.038, -0.013]$	$[-0.009, 0.002]$
PC	-0.021	-0.009	-0.015	-0.039	-0.033	-0.052	-0.046	-0.020	0.006
	$[-0.045, -0.007]$	$[-0.027, 0.004]$	$[-0.036, -0.001]$	$[-0.068, -0.032]$	$[-0.064, -0.025]$	$[-0.080, -0.045]$	$[-0.067, -0.028]$	$[-0.034, 0.000]$	$[0.003, 0.022]$
no PC	-0.010	-0.006	-0.000	-0.009	-0.032	-0.040	-0.039	-0.028	-0.001
	$[-0.026, 0.005]$	$[-0.021, 0.008]$	$[-0.016, 0.012]$	$[-0.023, 0.005]$	$[-0.046, -0.016]$	$[-0.054, -0.022]$	$[-0.055, -0.022]$	$[-0.044, -0.011]$	$[-0.006, 0.004]$
Sur	0.013	0.020	0.019	-0.000	-0.027	-0.028	-0.033	-0.022	-0.005
	$[-0.003, 0.036]$	$[0.004, 0.040]$	$[0.000, 0.038]$	$[-0.019, 0.020]$	$[-0.045, -0.001]$	$[-0.044, 0.000]$	$[-0.050, -0.007]$	$[-0.042, 0.004]$	$[-0.015, 0.002]$
no Sur	-0.031	-0.025	-0.020	-0.028	-0.036	-0.051	-0.051	-0.029	-0.001
	$[-0.045, -0.016]$	$[-0.038, -0.011]$	$[-0.033, -0.005]$	$[-0.044, -0.014]$	$[-0.049, -0.023]$	$[-0.067, -0.036]$	$[-0.066, -0.037]$	$[-0.043, -0.013]$	$[-0.009, 0.005]$

Note. Dummy regressions (Equation 2) from 2004 through 2017 of economic uncertainty $\mathcal{U}^{30}$ on dummies for each day of blackout period. PRE and $POST$ are dummies for the hours before / after the announcement and $JUMP$ is the difference between both. Base includes all FOMC meetings in our sample, PC only FOMC meetings with a subsequent press conference, and Sur all FOMC meetings with a unexpected interest rate decision. 95% confidence intervals are given in brackets below and are calculated from bootstrapped standard errors.

B. The Source of FOMC Uncertainty

Our result that uncertainty levels build up significantly ahead of monetary policy announcements seems odd as a central objective of the Fed is to calm markets and thus lower uncertainty. Yet, the fact that important information is to be disclosed at pre-scheduled times could explain the above documented pattern. A natural question to ask is where the sources of the elevation in uncertainty lie. Therefore, we separately identify the portion of uncertainty stemming from the possibility of very bad and good future economic states. More formally, we follow Bollerslev, Todorov, and Xu (2015) and estimate left (LU) and right (RU) tail uncertainty as

$$LU_t = \int_t^{t+\tau} \int_{-\infty}^{-k_t} x^2 \nu_s(dx) ds, \qquad RU_t = \int_t^{t+\tau} \int_{k_t}^{\infty} x^2 \nu_s(dx) ds, \tag{4}$$

by assuming the jump compensator $\nu_s(dx)$,

$$\nu_t(dx) = \left(\phi_t^+ \times e^{-\alpha_t^+ x} \mathbf{1}_{\{x>0\}} + \phi_t^- \times e^{\alpha_t^- x} \mathbf{1}_{\{x<0\}} \right). \tag{5}$$

where $\phi^{\pm}$ governs the level of tail uncertainty, $\alpha^{\pm}$ the decay of the tail, and x the jump-size. Bollerslev and Todorov (2014) show how, given that log-prices of deep-OTM put (call) options increase (decrease) linearly in the log-moneyness as time to maturity approaches zero, both parameters can be consistently estimated through least absolute deviation. As we are interested in the impact of very large asset price movements on uncertainty, we only consider jumps that are larger than a time-varying cutoff $k_t = 7 \times IV^{ATM}\sqrt{\tau}$.[13] We exclude options for which $-2.5 < m < 1$ in the parameter estimation. We include the information from options with $\tau \leq 45$ days, explicitly incorporating very short-term options. Those options have often

[13] Note that the absolute cutoff depends on the current level of volatility and on the maturity of the option. For a hypothetical option with 30 days to maturity at an ATM IV level of 20%, our choice corresponds to expecting annualized minute-by-minute jumps of around 40%. We follow Andersen, Todorov, and Ubukata (2020) for the cutoff rule. The procedure proposed by Bollerslev, Todorov, and Xu (2015) sorts the options by m regardless of their time to maturity, while demanding strict convexity in option mid prices. This effectively discards otherwise valid option quotes from the sample and mixes the inherently unique information from options maturing at different points in time to come up with single values for $\alpha_t^{\pm}$ and $\phi_t^{\pm}$ at time t. In contrast, we seek to retain as much information on the tails as possible and estimate the parameters for each time to maturity τ individually. In the next step, we calculate LU and RU for each τ and take the median at time t to obtain robust minutely tail uncertainty proxies.

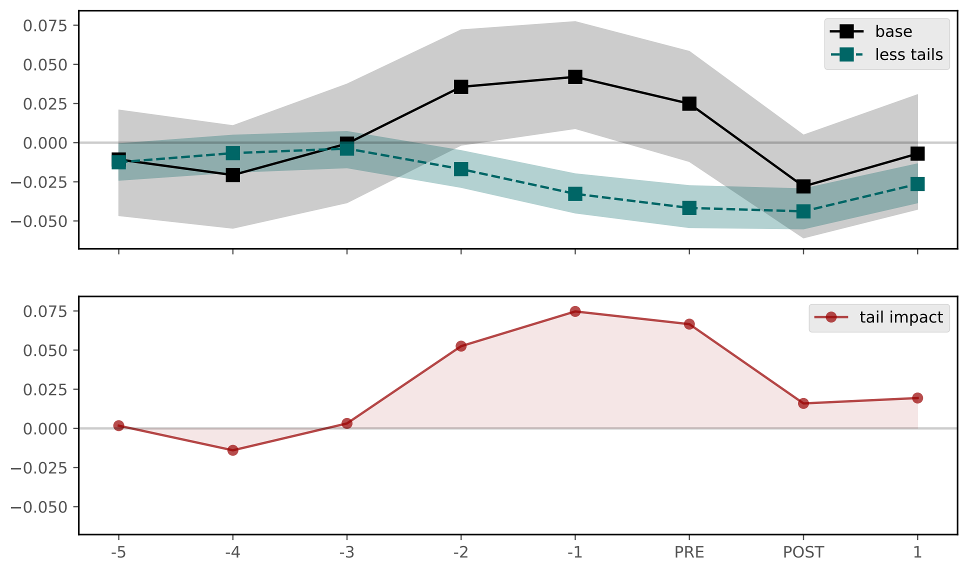
been discarded in previous studies although they are particularly informative about tail uncertainty and liquid enough to gain meaningful inference.

The first row of Panel B in Table II shows the results for our dummy regression when using $\widetilde{\mathcal{U}}^{30}$ as the dependent variable and $\widetilde{LU}_t$ and $\widetilde{RU}_t$ as additional controls. Our results are also visualized in Figure 2. Three major differences to our base analysis are immediately apparent. First, the whole buildup of uncertainty from $\mathcal{F}-5$ until $\mathcal{F}-2$ is exclusively driven by tail uncertainty. In contrast to the significant increase from -2% to 3.5% in the our base case (black line), levels purged from tail uncertainty (green line) stay at around 0%. In fact, once uncertainty is purged from tail impact, we observe levels that are significantly below the control group. This is in sharp contrast to overall uncertainty levels that are significantly above the control group. Second, the large resolution of uncertainty at the day of the announcement vanishes almost completely when we control for tail uncertainty. Comparing the base case to levels purged from tail uncertainty from PRE to $POST$ shows that there is almost no change. Table **??** reveals that the change ($JUMP$ coefficient) is only -0.3% and statistically indistinguishable from 0. This indicates that the full resolution of uncertainty at FOMC meetings is attributable to tail uncertainty leaving the market. Last, without the impact of the tails, levels of uncertainty stay significantly below their control group the day after the FOMC announcement.

The coefficient for $\widetilde{LU}_t$ is 0.66, significant at the 1% level, while the coefficient for $\widetilde{RU}_t$ is only 0.001 and insignificant. This indicates that the possibility of large *negative* stock price movements, or bad economic states, is the sole driver of the buildup and resolution of uncertainty around FOMC meetings. Markets find it likely that bad economic states are either (i) revealed at the FOMC announcement or (ii) possibly caused by unfavorable monetary policy decisions. Given that information about the state of the economy is to be released at FOMC announcements, uncertainty builds up days ahead of the meetings. The mere fact that the FOMC meets at pre-scheduled times does not add to calm markets at all.

The data tells that investors fear the revelation of bad economic states around FOMC announcements, else $\widetilde{LU}_t$ should not be the explanatory driver of uncertainty. This very real, but small, chance of the revelation of a serve economic downturn is what warrants a return premium when invested around news releases. Using our relative measures, we find empirical support for the idea by Wachter and Zhu (2019). In their

Figure 2. Economic Uncertainty purged from Tail Impact



Note. The figure shows regression coefficients of Equation 2 averaged across all announcement days. The solid black line in the upper panel corresponds to the base specification in which dummies are set for different days of the blackout period. The dashed green lined includes tail uncertainty as a control variable and thus shows the evolution of $\mathcal{U}^{30}$ purged from tail impact. The lower panel depicts the impact of tail uncertainty, calculated as the difference between the black and green line. 95% confidence intervals are calculated from bootstrapped standard errors.

setting, the central bank is the sole provider of economic news, which consequently leads to the resolution of all uncertainty about bad states once the announcement is made.

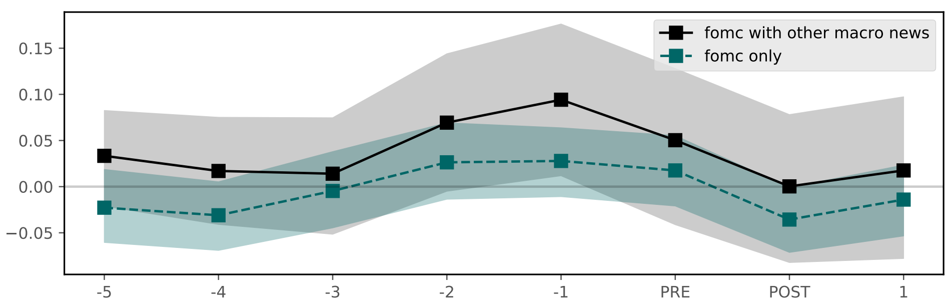
C. *Other News Releases*

We assess the robustness of our results and explore whether the behavior of uncertainty is (i) driven by other macro news releases falling in the FOMC blackout period (i.e. the one week ahead of the meeting) and (ii) similar around other macro releases or unique to FOMC announcements. We follow Cieslak, Morse, and Vissing-Jorgensen (2019) and use macro releases with the highest relevance according to Bloomberg's news alert. These include GDP growth, initial jobless claims, and nonfarm payrolls. We collect all announcement dates for our sample period of 2004 to 2017. After accounting for Saturday and holiday releases, as well as multiple releases on the same day, we are left with 221 *other macro news* in total. From these

221 announcement, xxx do not coincide with a previously defined FOMC blackout period and are used in this analysis.

To rule out the possibility that our results are driven by other market-moving news releases, we split our FOMC sample by whether another macro announcement was made during the blackout period. 88 of our 112 FOMC meetings are without an additional macro release during the week before the announcement time, and 24 are. Figure 3 compares the behavior of uncertainty for both samples. Albeit the average uncertainty level for other macro news is higher, driven by the fact that many of these FOMC meetings took place between 2007–2012, the dynamics over the blackout period are very similar. We observe that uncertainty levels increase ahead of the FOMC meeting and start to decline a day before the announcement is made. We find no substantial effect of other macro news to the behavior of uncertainty around FOMC announcements.[14]

Figure 3. FOMC Announcements with and without other Macro News Releases



Note. The figure shows regression coefficients of Equation 2 averaged across all announcement days for FOMC meetings with other macro news releases during the blackout period (black line) and without (green line). 95% confidence intervals are calculated from bootstrapped standard errors.

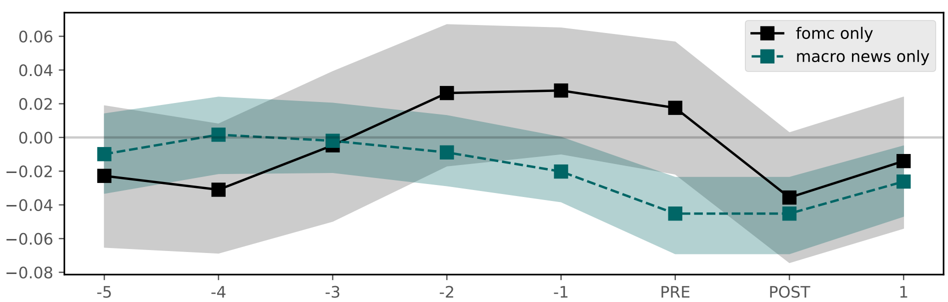
The above exercise compares FOMC meetings that have additional macro news releases during the blackout period to FOMC meetings that do not. It is, however, also interesting to compare FOMC announcements to other macro news releases more generally. Therefore, we compare the blackout week pattern of uncertainty around FOMC meetings to the pattern around other macro news. We use all other macro news announcements and construct artificial blackout weeks around each. As for regular FOMC announcements, if the day count between two announcements is

[14] A consideration of the tail impact for both meeting types yields similar results.

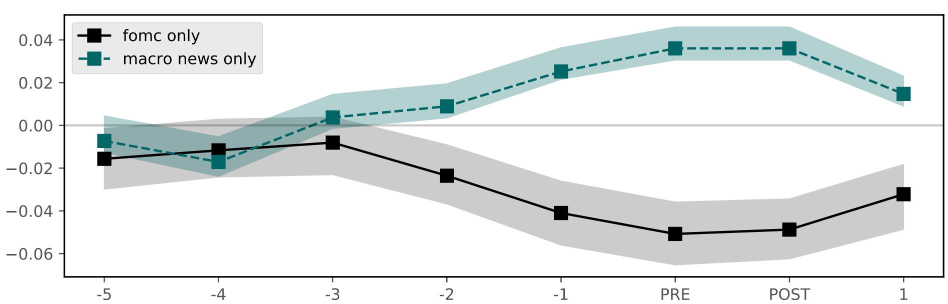
less than 15, we choose the same control group for both meetings. This is necessary, as other macroeconomic announcements are typically not evenly spaced out.[15] This way, we implicitly assume that two announcements that are close in calendar time relate to the same pre-announcement level of uncertainty, and are perceived as joint uncertainty-moving events. If the day count is ≥ 15, we choose the number of control days $N_{\mathcal{C}}$ such that $N_{\mathcal{C}} = min(30, \text{day count})$. We report the dynamics of uncertainty with (Panel A) and without (Panel B) the impact of tails for FOMC and other macro news releases in Figure 4.

Figure 4. Blackout Week Pattern of FOMC and Other Macro News Releases

Panel A: Evolution of Uncertainty



Panel B: Evolution of Uncertainty less Impact of Tails



Note. In Panel A, the figure shows regression coefficients of Equation 2 averaged across all announcement days for 112 FOMC meetings (black line) and for 221 other macro news releases (green line). In Panel B, we include tail uncertainty as a control variable and thus shows the evolution of $\mathcal{U}^{30}$ purged from tail impact. 95% confidence intervals are calculated from bootstrapped standard errors.

In sharp contrast to its behavior around FOMC announcements, uncertainty around other macro news is on average never above its control group, gradually decreases

[15]We also consider many more macro announcements than FOMC announcements.

before the actual announcement, and stays significantly below its control group after the announcement.[16] Interestingly, the pattern is very similar to our purged uncertainty measure from Figure 2, granting suggestive evidence that the dominant behavior of left-tail uncertainty is not present around other macro news. We explore this notion by extracting the tail impact, reported in Panel B of Figure 4. Surprisingly, the picture for uncertainty flips once we control for the impact of the tails. While we find a downward trend for tail-purged uncertainty around FOMC meetings, it actually increases for other macro news releases. This suggests that control group levels of tail uncertainty were higher than levels around other macro news. Furthermore, it highlights that the documented behavior of tail uncertainty is unique to FOMC meetings.

D. Economic Significance: Meeting Cost

The previous sections has shown that the impact of tail uncertainty is large and unique to FOMC meetings. Investors care about possibly negative news revealed at monetary policy announcements and consequently may seek to hedge against this source of uncertainty. In this section, we quantify the economic costs of the previously documented findings.

The hedging cost can be studied using delta-neutral straddle and strangle returns. A straddle is a portfolio of at-the-money put and call options, weighted such that the delta of the portfolio is zero. Effectively, a straddle has no stock price risk but loads on changes in variance (Coval and Shumway, 2001). A strangle, on the other hand, is constructed in a similar fashion but consists of buying an otm call and put closest to $\pm 2\sigma$. The strategy profits from large movements in volatility, and hence approximates changes in tail uncertainty (Bakshi and Kapadia, 2003). Explicitly, delta-neutral straddles will depend on changes in spot volatility, and changes in perceived jump risks, assuming that the stock price follows a jump-diffusion process.

[16]Note that the news releases we consider take place outside of regular trading hours. Hence, the impact of the meeting is the change from -1 to PRE. Coefficients PRE and $POST$ are consequently identical.

Straddle and strangle returns will follow:

$$dSTR = \frac{\partial STR}{\partial V}\left(dV_t - \mathbb{E}_t^{\mathbb{Q}}\left[dV_t\right]\right) + \left(\Delta STR_{i,t} - \mathbb{E}_t^{\mathbb{Q}}\left[\Delta STR_{i,t}\right]\right), \qquad (6)$$

with

$$\Delta STR_{i,t} = STR(S_{i,t-} + \Delta S_{i,t}) - STR(S_{i,t-}),$$

with underlying S, portfolio price STR, spot variance V, and jump size ΔS. From the Black-Scholes model we know that strangles load less on spot volatility, as $\frac{\partial STR}{\partial V}$ peaks at-the-money and decreases in the tails. This way we approximate the premium for tail uncertainty.[17]

Strangles are cheaper compared to straddles given that the portfolio is constructed with out-of-the-money options. Our trading strategy sells straddles and strangles at the start of the blackout week (-5) and buys back the options one day after the FOMC announcement. We rebalance the position each minute to focus on changes in the assessment of volatility.[18] Since we do not have continuous access to options at our desired adjusted moneyness, we use a leeway of $\pm 0.25\sigma$ for straddles, and $\pm 0.5\sigma$ for options forming the strangle portfolio. Through a linear weighting scheme,

$$w_c = \frac{\Delta_p}{\Delta_c - \Delta_p},$$

we assure approximate neutrality to movements of the underlying.

Figure 5 reports average returns for the days in the blackout period, the day after the announcement, as well as split for the periods before and after the time of the announcement on the announcement day. Straddle returns are depicted in the panel on the left. Straddles have earned substantially negative returns on many of the days considered. Most strinkingly, the payoffs to straddles have been negative on the announcement day, as well as on the day thereafter. On average, buying insur-

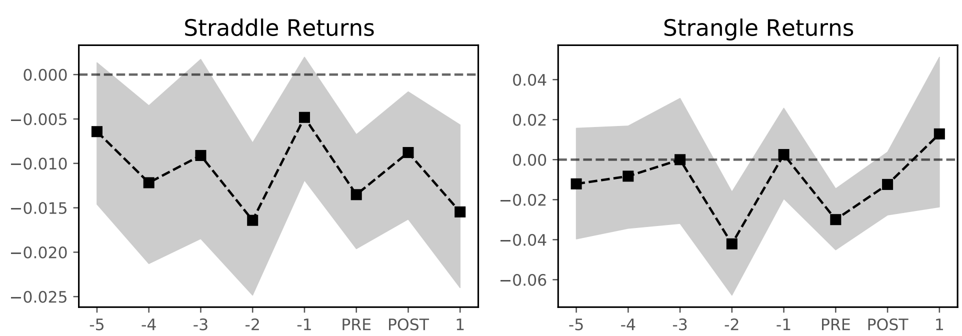
[17] A similar decomposition is done in Cremers, Halling, and Weinbaum (2015). The authors isolate jump exposure by comparing straddle portfolios over time, not by focusing on further out-of-the-money strikes, as these options are typically not liquidly traded for individual equities.

[18] This of course disregards transaction costs fully, which would be large in this setting. We focus on the changes in variance premia embedded in index options and not on payoffs of investable trading strategies. While these strategies also allow for exposure to the dynamics of variance and tail uncertainty, the movement of the underlying, which at times is large around FOMC announcements, obscures inference when the position is not continuously delta-hedged.

ance against volatile movements during the blackout period would have resulted in net returns of approximately -9% per meeting. These returns relate to the payoff of hypothetical variance swaps and highlight substantial costs for hedging volatility exposure around FOMC announcements. Especially closely around the announcement are straddle returns significantly negative. This may be driven by consistently less volatile reactions to monetary policy announcements, or an FOMC uncertainty premium set by financial intermediaries providing insurance. Either way, insuring against the uncertainty brought on by FOMC meetings is costly to investors.

The panel on the right of Figure 5 shows strangle returns in an attempt to better capture the costs to hedging *very large* movements around FOMC announcements. The magnitude of strangle returns is on average higher than for straddles. Since deep out-of-the-money options have higher embedded leverage than those at-the-money, this is expected. We also note that strangle returns are more volatile, such that average period returns are only statistically significant on day -2, the weekend gap, as well as in the hours before the announcement time. This coincides with the period in which the impact of tail uncertainty increases substantially as seen in Figure 2. Thus, the price of insurance against tail uncertainty in the market increases, simply due to the possibility of material policy stance changes. As the tail premium is resolved after the announcement, strangle returns turn positive, albeit insignificant statistically. As for the returns to straddle positions, strangle returns also amount to around -9% per meeting, again highlighting the importance of the assessment of very large movements around FOMC announcements.

Figure 5. Strangle and Straddle Returns Around FOMC Announcements



Note. This figure plots cumulative returns of minute-by-minute rebalanced straddle (black) and strangle (grey) portfolios around FOMC announcements.

E. Meeting Classification

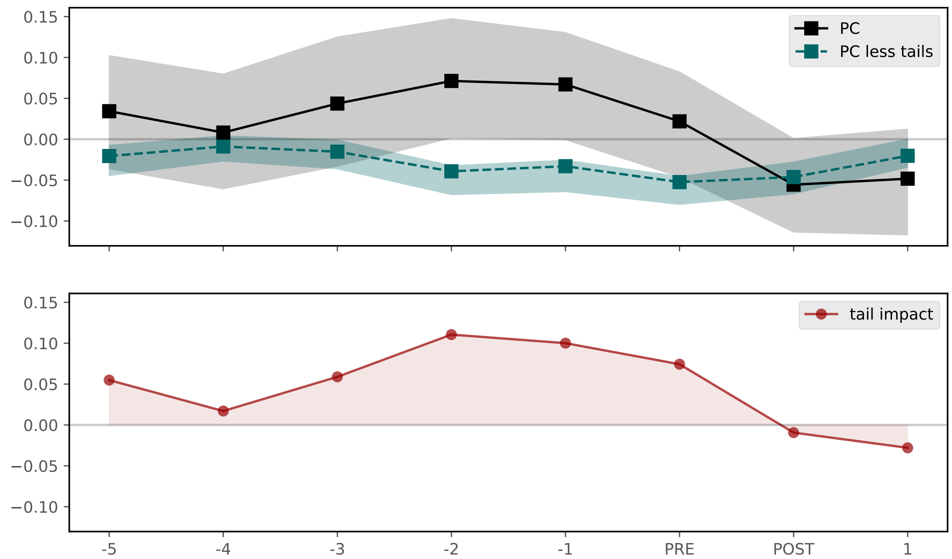
As robustness, and to further highlight the role tail uncertainty plays around FOMC announcements, we condition on various meeting characteristics, which have previously been found to play a substantial role in asset price reactions to monetary policy.

Press Conferences. We first condition on whether a press conference was held after an announcement. Since 2011 the FOMC has scheduled press conferences after every other FOMC announcement to explain their decisions. This in turn has led to a belief that only announcements with scheduled press conferences are important, as they grant the committee a platform to explain steps taken.[19] In Figure 6 we repeat our analysis for the 28 FOMC meeting that were followed by a press conference. The solid line depicts the evolution of uncertainty including the influence of tails and the dashed line without the influence of tails. Generally, both evolve in a similar fashion as in our base analysis. Uncertainty exhibits the usual increase ahead of FOMC announcements and a sharp decline at the announcement day and purged uncertainty has a decreasing trend. Looking at the impact of tail uncertainty, we find a large difference in the level of 7-9 percentage points when tail uncertainty is at its peak ($\mathcal{F} - 2$). Since announcement days with press conferences almost surely hold valuable information provided by the Fed, tail uncertainty levels are significantly elevated in advance and fully resolved at the announcement. The overall uncertainty reduction is again little more than the premium for tail uncertainty leaving the market.

Policy Surprises. Many researchers have argued that days on which the Fed announces decisions unexpected by the market represent a monetary policy shock. We therefore wish to understand how uncertainty behaves on these days. We measure surprises with the methodology proposed in Kuttner (2001) by taking the unexpected changes in federal fund futures rates on announcement days. Out of 112 meetings, 46 FOMC announcements are considered to be surprising. Uncertainty is elevated significantly at the start of the blackout period for surprising policy decisions (see Figure 7). On average, relative levels are 7 percentage points higher. Again, we see an increase in uncertainty ahead of FOMC announcements to almost

[19] See Boguth, Gregoire, and Martineau (2019). Eventually, this led to a policy shift to always hold press conferences after meetings starting in 2019.

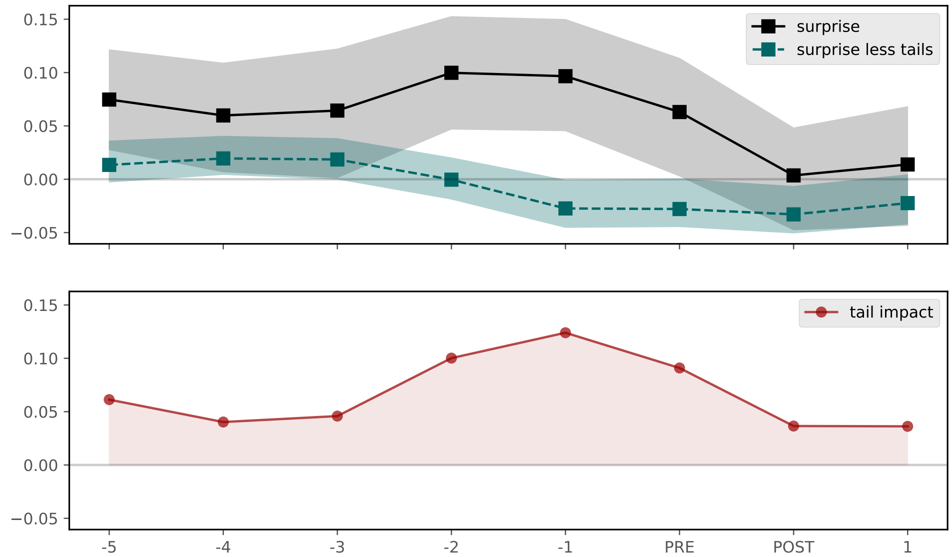
Figure 6. FOMC Meetings With a Subsequent Press Conference



Note. The figure shows regression coefficients of Equation 2 averaged across all FOMC announcements with a press conference. The solid black line in the upper panel corresponds to the base specification in which dummies are set for different days of the blackout period. The dashed green lined includes tail uncertainty as a control variable and thus shows the evolution of $\mathcal{U}^{30}$ purged from tail impact. The lower panel depicts the impact of tail uncertainty, calculated as the difference between the black and green line. 95% confidence intervals are calculated from bootstrapped standard errors.

10%. In this setup we find significantly elevated levels of overall uncertainty when compared to the control group. This is in contrast to the base case, where significant elevation occurs only a day before the announcement. A possible explanation for this phenomenon is that (surprising) rate changes occur in turbulent times, during which it is harder to form an expectation as to where the Fed may set the target rate. Alternatively, higher levels of (tail) uncertainty may be directly related to these rate decisions, and would imply that tail risks are used as an input in Fed decision-making. Regarding the first explanation, Table C in the Appendix shows that many surprise decisions indeed happened during the financial and sovereign debt crises. Accounting for the impact of tail uncertainty we confirm that surprise decisions occur primarily in turbulent market phases, with a tail impact on overall uncertainty as large as 12 percentage points. Following the second explanation, a higher level of tail uncertainty should have predictive power over future target rate changes. We will further analyze this idea in the next section.

Figure 7. FOMC Announcements with Surprising Decisions.



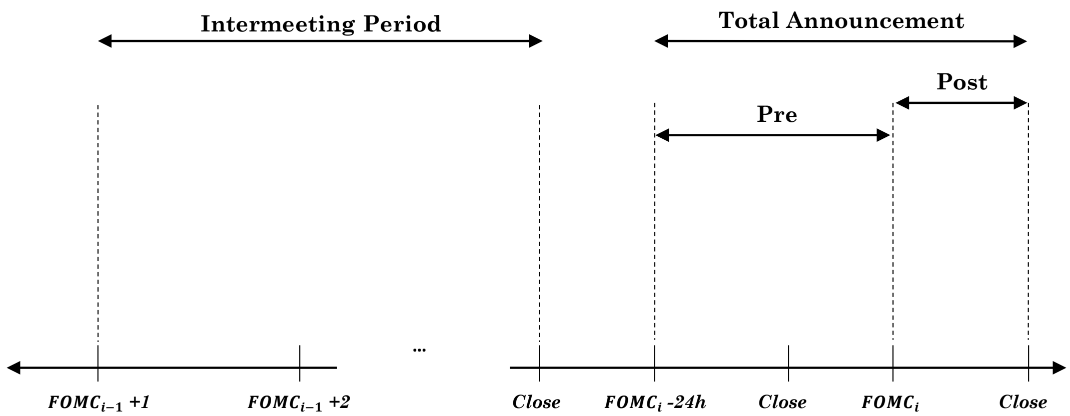
Note. The figure shows regression coefficients of Equation 2 averaged across all FOMC announcements with a surprising interest rate decision. The solid black line in the upper panel corresponds to the base specification in which dummies are set for different days of the blackout period. The dashed green lined includes tail uncertainty as a control variable and thus shows the evolution of $\mathcal{U}^{30}$ purged from tail impact. The lower panel depicts the impact of tail uncertainty, calculated as the difference between the black and green line. 95% confidence intervals are calculated from bootstrapped standard errors.

The tail impact is particularly large for surprise rate decisions, between 5 and 12%. Accounting for the impact of tail uncertainty, we find the residual to vary little over time. Arguably it is tail uncertainty that is of importance when rate decisions surprised investors.

V. Predictive Power of Tail Uncertainty

Our previous results indicate that left tail uncertainty (LU) is the dominating part of uncertainty around FOMC announcements. This section uses LU as a signal and provides evidence about its predictive power for stock returns and fed fund target rate changes around FOMC meetings to shed light on whether expected downside risks are used as an input for accommodating policy changes.

Figure 8. Time Line



Note. This figure gives an overview of the time line considered. Intermeeting period is defined as one day after the last to two days before the current announcement $FOMC_i$, Pre as 24 hours before $FOMC_i$, Post as the trading hours after $FOMC_i$, and total announcement as 24 hours before $FOMC_i$ until end of the trading day.

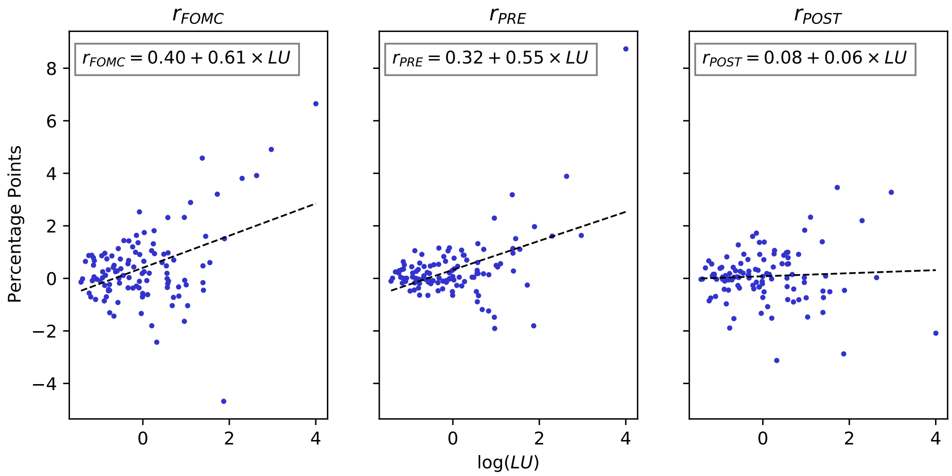
A. Results for 2004 – 2017.

For the period of 2004−2017, we start by assessing whether our tail uncertainty has predictive power over returns to holding the S&P 500 from 24 hours before the meeting until the end of the FOMC announcement day. With this time window we include the pre-announcement drift (Lucca and Moench, 2015) and any after-meeting effects, which comprise surprise reactions to the meeting's outcome. We consider three periods individually in the regression analyses: total announcement, pre-announcement, and post-announcement. Figure 8 gives an overview.

We regress the excess return on the average level of *LU* during the blackout period up until 24 hours before the announcement time, that is to say, we use the average level of *LU* from -5 days until -24 hours before the meeting. The predictors are thus known at the beginning of the interval over which we measure the subsequent returns. We standardize and logarithmize uncertainty measures across all 112 meetings in the sample to ease interpretation and facilitate linear regression analysis.

Figure 9 shows scatter plots for the total announcement returns, as well as returns for the two sub-periods considered. Average announcement returns amount to 40 bps between 2004 and 2017, of which 32 bps are earned in the 24 hours leading up to the announcement time. The relation between blackout-period tail uncertainty and subsequent meeting returns is positive and significant. This is primarily driven by a strong relation between the pre-announcement drift and LU, while the predictive power over returns after the announcement is insignificant. Higher tail uncertainty before FOMC announcements leads to a positive reaction in the market.

Figure 9. Scatter Plot of LU and Meeting Returns



Note. This scatter plot shows the linear relationship between the natural logarithm of LU and meeting returns for three different return specifications: r_{FOMC} denotes the total announcement return from -24 hours before an announcement until the end of the announcement day, r_{PRE} the pre-announcement return from -24 hours before an announcement until the announcement, and r_{POST} the post-announcement return from the announcement until the end of the trading day.

We add additional predictors in the subsequent regressions. In Model 1 we include the portion of blackout-period total uncertainty not already explained by LU. This way we can distinguish between expectations of small and large moves realizing around the announcement time. To obtain this orthogonalized measure, $U^{\perp}$, we use the following regression setup for the 112 blackout-period observations:

$$\log(U) = a + b \times \log(LU) + U^{\perp}.$$

Regression results are reported in column 1 of Table III. The t-statistics are HAC estimators and given in brackets below the coefficients. For a one standard deviation increase of LU, realized excess meeting returns increase by unchanged 61 bps. Higher levels of left tail uncertainty ahead of the meeting lead to positive announcement returns. The impact of the orthogonal portion of total uncertainty is

Table III. Predictive Regressions: Stock Market Returns

	Model 1			Model 2		
	r_{FOMC}	r_{PRE}	r_{POST}	r_F	r_{PRE}	r_{POST}
LU	0.611	0.552	0.058	0.661	0.642	0.020
	[2.847]	[2.257]	[0.371]	[2.792]	[2.315]	[0.117]
$U^{\perp}$	−0.007	0.086	−0.093			
	[−0.057]	[1.168]	[−0.754]			
r^-				0.032	0.047	−0.016
				[1.287]	[1.372]	[−0.436]
r^+				−0.038	−0.076	0.039
				[−0.584]	[−1.170]	[0.697]
$const$	0.404	0.324	0.080	0.536	0.565	−0.029
	[3.320]	[3.455]	[0.868]	[2.526]	[2.478]	[−0.169]
Adj. R^2	0.168	0.226	−0.006	0.167	0.245	−0.016
N	112	112	112	112	112	112

Note. Predictive regressions of three announcement return specifications on different predictors from 2004 through 2017. r_{FOMC} denotes the total announcement return from -24 hours before an announcement until the end of the announcement day, r_{PRE} the pre-announcement return from -24 hours before an announcement until the announcement, and r_{POST} the post-announcement return from the announcement until the end of the trading day. Model 1 includes LU as well as total uncertainty $U^{\perp}$ orthogonalized w.r.t LU as predictors. Model 2 uses LU as well as signed intermeeting returns as predictors. T-statistics are HAC estimators and given in brackets below.

insignificant. Columns 2 and 3 provide the same analysis separately for pre- and post-announcement returns. The pre-announcement drift is again well explained by tail uncertainty. A one standard deviation increase in LU during the blackout period translates to an average return increase of 0.552%. This is statistically significant with a t-statistic of 2.257. The adjusted R^2 of 22.6% confirms the idea that left tail uncertainty adequately explains returns leading up to U.S. monetary policy announcements. Additionally, the orthogonal component of total uncertainty is again insignificant. The same is true for the post-announcement period, spanning the trading phase after the announcement is made until the market closes. Here, however, we also find insignificant results for LU and an R^2 that is close to zero. The returns during this period are quite low, however, averaging only 8 bps with little variation.

To understand whether *realized* or *expected* information better explains meeting stock market returns, we add the two intermeeting semi-returns r^- and r^+ defined in Cieslak and Vissing-Jorgensen (2020) to the regression.[20] Stock market news in-between meetings has significant explanatory power for monetary policy decisions and the Fed's growth expectations. Columns 4–6 redo the above analysis using LU and both intermeeting returns as predictors. Results change little from our baseline results using Model 1. Neither negative nor positive intermeeting returns predict any of the return specifications in our sample. Results for LU are close to unchanged, with similar magnitudes of coefficients and levels of significance. Negative and positive intermeeting returns show no significance in our test specifications. The small changes in R^2 from Model 1 to Model 2 confirm this interpretation.

Mechanically speaking, these results point towards the existence of a resolution of (tail) uncertainty around FOMC meetings, for which index prices increase and consequently positive returns realize . Table IV formally assesses this idea by regressing the percentage changes in economic uncertainty following the announcement on pre-meeting levels of tail uncertainty. We again consider three different periods of changes in economic uncertainty (pre, post, and total). The results to this exercise mirror Section IV. in that a higher share of tail uncertainty leads to a more pronounced reduction in economic uncertainty. This line of argument suggests that the central bank may intervene after a particularly bad stock market performance. Tail uncertainty explains both the pre- and total FOMC resolution of uncertainty to a satisfactorily high extent.

Our findings above imply that a higher level of meeting uncertainty corresponds to greater resolution of uncertainty and in turn higher realized announcement returns. While this interpretation tells us *what* happens, it lacks a story for *why* things happen. A plausible economic explanation is that high levels of LU lead the Fed to cut the target rate, using an estimate of adverse economic uncertainty as an input to their decision rule, which in turn raises stock prices. To formally assess this mechanism, we repeat the exercise of Cieslak and Vissing-Jorgensen (2020) and regress cumulative changes in the fed fund rate, $FFR_{t+n} - FFR_{t-1}$ on pre-meeting LU. More precisely, we determine the contemporaneous and future changes in the fed fund rate, cumulate them for different horizons, and use our predictor LU to find out whether it can explain current as well as cumulative future rate changes.

[20]Intermeeting returns are defined as the excess stock market return from one day after the last to two days before the current meeting. r^- captures negatives movements and is defined as $\min(0, rx)$. r^+ corresponds to positive stock market movements and is defined as $\max(0, rx)$.

Table IV. Predictive Regressions: Economic Uncertainty

	$\mathcal{U}_F$	$\mathcal{U}_{PRE}$	$\mathcal{U}_{POST}$
LU	-0.181	-0.162	-0.089
	[-2.243]	[-1.935]	[-1.103]
$const$	-0.000	0.000	-0.000
	[-0.000]	[0.000]	[-0.000]
Adj. R^2	0.024	0.018	-0.001
N	112	112	112

Note. Predictive regressions of economic uncertainty resolutions on LU from 2004 through 2017. Column 1 predicts the resolution of uncertainty from -24 hours before an announcement until the announcement ($\mathcal{U}_{FOMC}$), column 2 and 3 split the resolution of uncertainty into pre- and post-announcement. T-statistics are HAC estimators and given in brackets below.

We report the results of our analysis in Table V. HAC t-statistics with lag n are in brackets below. The coefficient for $n = 0$ is -0.127 with a t-stat of -4.252. A one standard deviation increase in LU significantly predicts a rate cut of 13 bps in the meeting that follows 24 hours later. Taking the next ($n = 1$) and three additional ($n = 3$) meetings into account, the coefficients decrease even further, while staying significant at the 1% level. A one standard deviation increase in LU predicts a cumulative rate cut of 41 bps over the next 4 meetings, or half a year later. For the one year horizon the effect remains strong (53 bps) and is also statistically highly significant. The R^2 we find in our analysis is sizable, e.g. at 0.316 for the current meeting and 0.312 for two meetings.[21] We again run comparative regressions, differentiating the informational content of realized intermeeting returns and uncertainty on target rate changes. Results are in Panel B of Table V. We observe two major results: First and strikingly, neither the coefficients nor the significance level of LU change much after including realized intermeeting stock market returns. Higher LU still remarkably predicts target rate cuts for up to a year. Second, negative stock market movements in-between meetings also have predictive power for cumulative target rate changes for two to eight meetings in the future, which complements the already high explanatory power of LU alone. The relatively moderate increase in R^2 from Panel A to Panel B again verifies the idea that LU is the main driver in

[21] We note that interest rates are close to the zero-lower bound for most of our sample, and hence redo our analysis for an extended sample in Section *B.* below.

Table V. Predictive Regressions: Fed Fund Rate Changes

	Dependent Variable: $FFR_{t+n} - FFR_{t-1}$			
	$n = 0$	$n = 1$	$n = 3$	$n = 7$
LU	-0.127	-0.227	-0.411	-0.530
	[-4.252]	[-3.929]	[-3.704]	[-2.747]
$U^{\perp}$	-0.009	-0.020	-0.029	0.012
	[-0.680]	[-0.527]	[-0.315]	[0.085]
$const$	0.004	0.009	0.029	0.040
	[0.260]	[0.219]	[0.228]	[0.149]
$Adj.R^2$	0.316	0.312	0.230	0.166
N	112	112	112	112
LU	-0.141	-0.225	-0.421	-0.537
	[-4.488]	[-4.124]	[-3.483]	[-2.680]
r^-	-0.004	0.021	0.032	0.041
	[-1.284]	[2.622]	[2.707]	[2.925]
r^+	0.016	0.021	0.051	0.057
	[1.526]	[1.667]	[2.004]	[1.852]
$const$	-0.035	-0.006	-0.034	-0.023
	[-1.126]	[-0.127]	[-0.215]	[-0.079]
$Adj.R^2$	0.332	0.384	0.286	0.201
N	112	112	112	112
Logit Model ($n = 0$)				
LU	1.269	[3.329]		
$const$	-3.274	[-5.844]		

Note. Predictive regressions of fed fund rate changes on different predictors from 2004 through 2017. $n = 0$ are contemporaneous changes in the fed fund rate and $n > 0$ are cumulative contemporaneous and future changes. The first model includes LU as well as total uncertainty $U^{\perp}$ orthogonalized w.r.t LU as predictors. The second Model uses LU as well as signed intermeeting returns as predictors. The third model estimates a logit model in which rate cut dummies are the dependent variable. T-statistics are HAC estimators with lag n and given in brackets below.

predicting future target rate changes. Positive stock market performance is unsurprisingly barely significant for all forecast horizons. The Fed is concerned with bad economic states and asymmetrically pays attention to avoiding them. Panel C of Table V estimates a Logit model of target rate cuts on LU. It show that a higher LU ahead of FOMC announcements corresponds to a larger likelihood of a rate cut.

B. Results for 1996–2019.

A natural way to test for robustness of our results is to extend the sample. Our baseline sample from 2004 through 2017 is characterized by an effort to help the U.S. economy overcome the fallout from the financial crisis. The monetary policy intervention came in the form of QE and target rate cuts. We redo our predictive analyses using a daily sample of option quotes from OptionMetrics for the time period from 1996 through 2018.[22] Returns are still measured at the minute-by-minute frequency to split announcement returns between post-surprises and the pre-drift of Lucca and Moench (2015), but uncertainty measures are estimated end-of-day and averaged across the blackout period up until two days before the pre-scheduled announcement day. Looking at our results in Table VI for predicting returns in this extended sample, we find somewhat smaller, but still very significant coefficient estimates for LU. A one standard deviation increase in LU led to a 38 bps increase in announcement returns, and an increase in the pre-announcement drift of 39 bps. Both estimates are highly significant at the 5% level. We find no predictive power for post announcement returns. The orthogonal component of total uncertainty is again not significantly driving FOMC returns. Turning to Model 2 in Columns 3–6, which includes LU and intermeeting signed returns, we can confirm that our measure of tail expectations better explains index announcement returns than intermeeting signed returns. In fact, intermeeting returns are insignificant for all return specifications.[23] The impact of LU on returns is left virtually unchanged from analyses in Model 1. Two possible explanations come to mind: one, that option-

[22]We also confirm that our results hold for a sample from 1996 through 2008 to exclude the long period of zero interest rates. Results are available upon request.

[23]Cieslak and Vissing-Jorgensen (2020) note that intermeeting returns have performed poorly for the period after 2008 and attribute this to the little variation in the target rate seen thereafter. We extend their sample and observe a few rate hikes after 2016. Our results are still valid for these observations.

Table VI. Predictive Regressions: Stock Market Returns 1996-2019

	Model 1			Model 2		
	r_{FOMC}	r_{PRE}	r_{POST}	r_F	r_{PRE}	r_{POST}
LU	0.379	0.393	-0.015	0.400	0.430	-0.030
	[2.358]	[2.245]	[-0.144]	[2.313]	[2.275]	[-0.280]
$U^{\perp}$	0.055	0.123	-0.068			
	[0.577]	[1.720]	[-0.751]			
r^{-}				0.032	0.025	0.007
				[1.531]	[0.861]	[0.186]
r^{+}				-0.013	-0.044	0.031
				[-0.266]	[-1.028]	[0.757]
$const$	0.352	0.388	-0.037	0.433	0.527	-0.094
	[3.782]	[5.608]	[-0.475]	[2.704]	[3.484]	[-0.640]
Adj. R^2	0.074	0.151	-0.007	0.074	0.143	-0.009
N	184	184	184	184	184	184

Note. Predictive regressions of three announcement return specifications on different predictors from 1996 through 2018. r_{FOMC} denotes the total announcement return from -24 hours before an announcement until the end of the announcement day, r_{PRE} the pre-announcement return from -24 hours before an announcement until the announcement, and r_{POST} the post-announcement return from the announcement until the end of the trading day. Model 1 includes LU as well as total uncertainty $U^{\perp}$ orthogonalized w.r.t LU as predictors. Model 2 uses LU as well as signed intermeeting returns as predictors. T-statistics are HAC estimators and given in brackets below.

implied uncertainty better picks up worry in the market and that the Fed uses this as input to gauge the market's assessment of economic prospects, or two, that the near-term assessment of LU, focusing on just the blackout-period as opposed to the entire period between two meetings, is better suited to forecast meeting decisions in real-time. Either way, option market expectations play an important role in understanding the FOMC decision-making process also for the extended sample.

To follow up on our economic explanation for why returns are predictable by LU around FOMC announcements, we forecast the federal fund target rate for the sample from 1996 through 2018. Overall the impact of LU on future target rate changes is slightly weaker compared to 2004–2017, but still highly significant. Negative intermeeting returns have a larger impact on future target rate changes in this sample. Their impact ranges from a predicted cumulative rate cut of 34 for $n = 1$ to 99 bps for $n = 7$ for a -10% intermeeting return. However, the slight increase in R^2 from Panel A to B again confirms that LU carries valuable information in predicting future rate changes.

Overall, the predictive power of LU for our sample is larger than that of past stock market movements. It seems that forward-looking information about the second moment of the return distribution is more valuable than past information about the first moment. However, both predictors complement one another, given that the predictive power using both signals is generally higher. One should jointly use both sets of information when predicting future rate changes.

Table VII. Predictive Regressions: Fed Fund Rate Changes 1996-2019

	Dependent Variable: $FFR_{t+n} - FFR_{t-1}$			
	$n = 0$	$n = 1$	$n = 3$	$n = 7$
LU	-0.101	-0.187	-0.326	-0.422
	$[-4.415]$	$[-4.629]$	$[-4.358]$	$[-2.991]$
$U^{\perp}$	-0.034	-0.072	-0.195	-0.260
	$[-1.850]$	$[-1.836]$	$[-1.882]$	$[-1.368]$
$const$	-0.016	-0.031	-0.076	-0.129
	$[-1.022]$	$[-0.852]$	$[-0.679]$	$[-0.577]$
$Adj.R^2$	0.186	0.213	0.170	0.133
N	184	184	184	184
LU	-0.099	-0.166	-0.298	-0.383
	$[-3.989]$	$[-3.954]$	$[-3.962]$	$[-2.861]$
r^-	0.007	0.034	0.072	0.099
	[0.909]	[3.241]	[3.080]	[2.418]
r^+	0.002	-0.011	0.005	0.007
	[0.200]	$[-0.907]$	[0.248]	[0.252]
$const$	-0.008	0.050	0.032	0.019
	$[-0.269]$	[1.115]	[0.247]	[0.085]
$Adj.R^2$	0.176	0.259	0.215	0.172
N	184	184	184	184
Logit Model ($n = 0$)				
LU	0.884	[3.767]		
$const$	-2.339	[-8.251]		

Note. Predictive regressions of fed fund rate changes on different predictors from 2004 through 2017. $n = 0$ are contemporaneous changes in the fed fund rate and $n > 0$ are cumulative contemporaneous and future changes. The first model includes LU as well as total uncertainty $U^{\perp}$ orthogonalized w.r.t LU as predictors. The second Model uses LU as well as signed intermeeting returns as predictors. The third model estimates a logit model in which rate cut dummies are the dependent variable. T-statistics are HAC estimators with lag n and given in brackets below.

VI. Conclusion

We use option prices to estimate aggregate expectations about the future course of the economy. Uncertainty increases before FOMC announcements and is largely resolved at the announcement time. These effects are subsumed by the dynamics of tail uncertainty, which focuses on the perception of downside risks in the economy. These results are unique for FOMC announcements and cannot be found around other macroeconomic news releases. We show that changes in uncertainty during the FOMC blackout period carry a significant hedging premium.

We test whether tail uncertainty serves as input in the monetary policy decision process and show that it can significantly predict contemporaneous and future target rate changes. Thereby, tail uncertainty helps to explain the stock market reaction before FOMC announcements. Our empirical analysis corroborates the model intuition of Wachter and Zhu (2019) in that FOMC announcements are important because they reveal information about the likelihood of economic disasters. Empirically, we find that the buildup in tail uncertainty before FOMC announcements and the full resolution at the announcement to be supportive for this theoretical explanation.

We want to acknowledge possible extensions of our empirical analysis. Even after accounting for tail uncertainty, we cannot explain the persistent downward drift in uncertainty starting before the announcement. Ying (2020b) also documents a significant decrease in uncertainty ahead of FOMC announcements and explains this with information leakage. In the model, market makers require compensation for news related to fundamentals but update their beliefs ahead of the actual announcement by observing cumulative trading volumes. This mechanism resolves not only uncertainty but also generates an upward drift in market prices.

In our analysis, we use aggregate signals about tail uncertainty to understand future Fed decisions and argue that it serves as an input in the monetary policy decision-making process. We tie mentions of downside risks by policy makers to evidence of more accommodating monetary policy in periods of higher tail risk. With this we provide evidence that policy makers directly care about these risks. An in-depth textual analysis focusing on tail risk mentions in FOMC publications could more clearly identify that downside risks are an essential input to the Fed decision rule.

References

Ai, Hengjie, and Ravi Bansal, 2018, Risk Preferences and the Macroeconomic Announcement Premium, *Econometrica* 86, 1383–1430.

Amengual, Dante, and Dacheng Xiu, 2018, Resolution of Policy Uncertainty and Sudden Declines in Volatility, *Journal of Econometrics* 203, 297–315.

Andersen, Torben G., Oleg Bondarenko, and Maria T. Gonzalez-Perez, 2015, Exploring Return Dynamics via Corridor Implied Volatility, *Review of Financial Studies* 28, 2902–2945.

Andersen, Torben G., Martin Thyrsgaard, and Viktor Todorov, 2019, Time-Varying Periodicity in Intraday Volatility, *Journal of the American Statistical Association* 114, 1695–1707.

Andersen, Torben G., Viktor Todorov, and Masato Ubukata, 2020, Tail risk and return predictability for the Japanese equity market, *Journal of Econometrics*.

Bakshi, Gurdip, and Nikunj Kapadia, 2003, Delta-Hedged Gains and the Negative Market Volatility Risk Premium, *Review of Financial Studies* 16, 527–566.

Bauer, Michael, Aeimit Lakdawala, and Philippe Mueller, 2019, Market-Based Monetary Policy Uncertainty, *Working Paper*.

Beber, Alessandro, and Michael W. Brandt, 2006, The Effect of Macroeconomic News on Beliefs and Preferences: Evidence from the Options Market, *Journal of Monetary Economics* 53, 1997–2039.

Beber, Alessandro, and Michael W. Brandt, 2009, Resolving Macroeconomic Uncertainty in Stock and Bond Markets, *Review of Finance* 13, 1–45.

Bekaert, Geert, Marie Hoerova, and Marco Lo Duca, 2013, Risk, Uncertainty and Monetary Policy, *Journal of Monetary Economics* 60, 771–788.

Bernanke, Ben S., and Kenneth N. Kuttner, 2005, What Explains the Stock Market's Reaction to Federal Reserve Policy?, *The Journal of Finance* 60, 1221–1257.

Bloom, Nicholas, 2009, The Impact of Uncertainty Shocks, *Econometrica* 77, 623–685.

Boguth, Oliver, Vincent Gregoire, and Charles Martineau, 2019, Shaping Expectations and Coordinating Attention: The Unintended Consequences of FOMC Press Conferences, *Journal of Financial and Quantitative Analysis* 54, 2327—-2353.

Bollerslev, Tim, Jia Li, and Yuan Xue, 2018, Volume, Volatility, and Public News Announcements, *Review of Economic Studies* 85, 2005–2041.

Bollerslev, Tim, and Viktor Todorov, 2014, Time-Varying Jump Tails, *Journal of Econometrics* 183, 168–180.

Bollerslev, Tim, Viktor Todorov, and Lai Xu, 2015, Tail Risk Premia and Return Predictability, *Journal of Financial Economics* 118, 113–134.

Brooks, Jordan, Michael Katz, and Hanno Lustig, 2019, Post-FOMC Announcement Drift in U.S. Bond Markets, *Working Paper*.

Carr, Peter, and Liuren Wu, 2006, A Tale of Two Indices, *The Journal of Derivatives* 13, 13–29.

Cieslak, Anna, 2018, Short-Rate Expectations and Unexpected Returns in Treasury Bonds, *Review of Financial Studies* 31, 3265–3306.

Cieslak, Anna, Adair Morse, and Annette Vissing-Jorgensen, 2019, Stock Returns over the FOMC Cycle, *The Journal of Finance* 74, 2201–2248.

Cieslak, Anna, and Annette Vissing-Jorgensen, 2020, The Economics of the Fed Put, *Review of Financial Studies*.

Cocoma, Paula, 2018, Explaining the Pre-Announcement Drift, *Working Paper*.

Coval, Joshua D., and Tyler Shumway, 2001, Expected Option Returns, *The Journal of Finance* 56, 983–1009.

Cremers, Martijn, Michael Halling, and David Weinbaum, 2015, Aggregate Jump and Volatility Risk in the Cross-Section of Stock Returns: Aggregate Jump and Volatility Risk, *The Journal of Finance* 70, 577–614.

D'Amico, Stefania, and Mira Farka, 2011, The Fed and the Stock Market: An Identification Based on Intraday Futures Data, *Journal of Business & Economic Statistics* 29, 126–137.

DeSimone, Garrett, and Paul A. Laux, 2018, The Timing of Variance Risk Premia around Macroeconomic News Events, *Working Paper*.

Doan, Bao, Li Yang, and Douglas Foster, 2018, Do Investors Differentiate between Uncertainty and Risk: Evidence from Trading around U.S. Macroeconomic News, *Working Paper*.

Ehrmann, Michael, and Marcel Fratzscher, 2009, Purdah-On the Rationale for Central Bank Silence around Policy Meetings, *Journal of Money, Credit and Banking* 41, 517–528.

Faust, Jon, and Jonathan H. Wright, 2018, Risk Premia in the 8:30 Economy, *The Quarterly Journal of Finance* 8, 1–19.

Fernandez-Perez, Adrian, Bart Frijns, and Alireza Tourani-Rad, 2016, When No News Is Good News - The Decrease in Investor Fear after the FOMC Announcement, *Journal of Empirical Finance* 41, 187–199.

Gürkaynak, Refet S., Brian Sack, and Eric Swanson, 2005, The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models, *American Economic Review* 95, 425–436.

Gürkaynak, Refet S., and Justin Wolfers, 2006, Macroeconomic Derivatives: An Initial Analysis of Market-Based Macro Forecasts, Uncertainty, and Risk, *NBER Working Paper No. 11929*.

Gürkaynak, Refet S., and Jonathan H. Wright, 2013, Identification and Inference Using Event Studies: Identification and Inference Using Event Studies, *The Manchester School* 81, 48–65.

Hanson, Samuel G., and Jeremy C. Stein, 2015, Monetary Policy and Long-Term Real Rates, *Journal of Financial Economics* 115, 429–448.

Hu, Grace Xing, Jun Pan, Jiang Wang, and Haoxiang Zhu, 2020, Premium for Heightened Uncertainty: Solving the FOMC Puzzle, *Working Paper*.

Husted, Lucas, John Rogers, and Bo Sun, 2019, Monetary Policy Uncertainty, *Journal of Monetary Economics*.

Kelly, Bryan, Ľuboš Pástor, and Pietro Veronesi, 2016, The Price of Political Uncertainty: Theory and Evidence from the Option Market, *The Journal of Finance* 71, 2417–2480.

Kroencke, Tim, Maik Schmeling, and Andreas Schrimpf, 2019, The FOMC Risk Shift, *Working Paper*.

Kuttner, Kenneth N., 2001, Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market, *Journal of Monetary Economics* 47, 523–544.

Laarits, Toomas, 2019, Pre-Announcement Risk, *Working Paper*.

Lucca, David O., and Emanuel Moench, 2015, The Pre-FOMC Announcement Drift, *The Journal of Finance* 70, 329–371.

Martello, Vitor, and Ruy Ribeiro, 2018, Pre-FOMC Announcement Relief, *Working Paper*.

Neuhierl, Andreas, and Michael Weber, 2019, Monetary Policy Communication, Policy Slope, and the Stock Market, *Journal of Monetary Economics* 108, 140–155.

Olivei, Giovanni, and Silvana Tenreyro, 2007, The Timing of Monetary Policy Shocks, *American Economic Review* 97, 29.

Rigobon, R., and B. Sack, 2003, Measuring The Reaction of Monetary Policy to the Stock Market, *The Quarterly Journal of Economics* 118, 639–669.

Savor, Pavel, and Mungo Wilson, 2013, How Much Do Investors Care About Macroeconomic Risk? Evidence from Scheduled Economic Announcements, *Journal of Financial and Quantitative Analysis* 48, 343–375.

Taylor, John B., 1993, Discretion versus Policy Rules in Practice, *Carnegie-Rochester Conference Series on Public Policy* 39, 195–214.

Vissing-Jorgensen, Annette, 2019, Central Banking with Many Voices: The Communications Arms Race, *Working Paper*.

Wachter, Jessica A, and Yicheng Zhu, 2019, A Model of Two Days: Discrete News and Asset Prices, *Working Paper*.

Ying, Chao, 2020a, Heterogeneous Beliefs and the FOMC Announcements, *Working Paper*.

Ying, Chao, 2020b, The Pre-FOMC Announcement Drift and Information Leakage: Kyle Meets Macro-Finance, *Working Paper*.

Appendix

A Data Filter Procedure

To assure a robust inference from our high-frequency options sample, we perform a series of data filters. For our sample from January, 2004 through December, 2017, we are left with a total of 410,149 OTM option quotes per day.

The specific data filters used are the following:

- bid and $ask > 0$.
- $ask > bid$ and $\frac{ask}{bid} \leq 5$.
- Open interest for all contracts is greater than zero.
- Assure standard no-arbitrage bounds.
- The implied volatility can be calculated and is not extreme (we set a cutoff at 400%, which explicitly incorporates very deep OTM short-term options, but discards those with obvious recording flaws).
- The put and call prices are concave, that is, the price difference of two options with consecutive strikes, such that $K_1 < K_2$, is ≥ 0 for calls and ≤ 0 for puts. This is to assure no arbitrage between contracts. If any two contracts violate this condition, the one closer ATM is retained.
- We require at least one quote update per trading day, or trades in the contract to avoid stale quotes.
- For each date-expiry combination for puts and calls, we require three quotes.

B Bootstrap Procedure

To obtain empirical confidence bounds for the dummy coefficients in Equation (2), we follow these steps.

1. Draw randomly, but with replacement, from all days falling into our treatment group of any of the 112 FOMC meetings. We keep the ordering of the days within the treatment days constant $(-5, -4, ..., 1)$. That is, for each individual day of our treatment group, we randomly draw out of the 112 FOMC meetings in our sample.

2. Set the dummies for this pseudo sample and run the regression setup to obtain an estimate of the bootstrapped coefficients $\hat{\beta}$ and $\hat{\delta}$.

3. Repeat this procedure a large number of times. We set n_{trials} to 1,000.

4. The empirical 5 and 95 percentile of $\hat{\beta}$ and $\hat{\delta}$ are used to test the significance of the actual coefficients β and δ.

This procedure alleviates the issues of cross- and autocorrelation, and breaks the correlation *between* days in the blackout periods surrounding any one FOMC announcement. We further apply significance tests that retain this correlation (randomly sampling the entire blackout period) and come to the same conclusions. This suggests that the pattern is independent of temporal ordering across meetings.

C FOMC Meetings

Table B1. Total 112 meetings in our sample with the respective characteristics. "Other Ann." denotes that a secondary macro announcement falls within the respective FOMC meeting's blackout period. "Surprise" follows the definition of Kuttner (2001). Meeting times are taken from Lucca and Moench (2015) until 2011 and from the official meeting calendar thereafter.

Date	Time	Rate	PC?	Surprise?	Other Ann.?	Blackout Start
2004-01-28	14:15:00	0.0100				2004-01-21
2004-03-16	14:15:00	0.0100				2004-03-09
2004-05-04	14:16:00	0.0100		x		2004-04-27
2004-06-30	14:18:00	0.0125		x	x	2004-06-23
2004-08-10	14:15:00	0.0150		x	x	2004-08-03
2004-09-21	14:15:00	0.0175		x		2004-09-14
2004-11-10	14:15:00	0.0200			x	2004-11-02
2004-12-14	14:15:00	0.0225				2004-12-07
2005-02-02	14:17:00	0.0250				2005-01-26
2005-03-22	14:17:00	0.0275				2005-03-15
2005-05-03	14:16:00	0.0300				2005-04-26
2005-06-30	14:15:00	0.0325			x	2005-06-23
2005-08-09	14:17:00	0.0350			x	2005-08-02
2005-09-20	14:17:00	0.0375		x		2005-09-13
2005-11-01	14:18:00	0.0400		x		2005-10-25
2005-12-13	14:13:00	0.0425				2005-12-06
2006-01-31	14:14:00	0.0450				2006-01-24
2006-03-28	14:17:00	0.0475				2006-03-21
2006-05-10	14:17:00	0.0500		x	x	2006-05-03
2006-06-29	14:16:00	0.0525		x	x	2006-06-22
2006-08-08	14:14:00	0.0525		x	x	2006-08-01
2006-09-20	14:13:00	0.0525				2006-09-13
2006-10-25	14:13:00	0.0525				2006-10-18

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Table B1. Total 112 meetings in our sample with the respective characteristics. "Other Ann." denotes that a secondary macro announcement falls within the respective FOMC meeting's blackout period. "Surprise" follows the definition of Kuttner (2001). Meeting times are taken from Lucca and Moench (2015) until 2011 and from the official meeting calendar thereafter.

Date	Time	Rate	PC?	Surprise?	Other Ann.?	Blackout Start
2006-12-12	14:14:00	0.0525			x	2006-12-05
2007-01-31	14:14:00	0.0525				2007-01-24
2007-03-21	14:15:00	0.0525				2007-03-14
2007-05-09	14:15:00	0.0525			x	2007-05-02
2007-06-28	14:14:00	0.0525			x	2007-06-21
2007-08-07	14:14:00	0.0525		x	x	2007-07-31
2007-09-18	14:15:00	0.0475		x		2007-09-11
2007-10-31	14:15:00	0.0450				2007-10-24
2007-12-11	14:15:00	0.0425		x	x	2007-12-04
2008-01-30	14:14:00	0.0300				2008-01-23
2008-03-18	14:14:00	0.0225		x		2008-03-11
2008-04-30	14:15:00	0.0200		x		2008-04-23
2008-06-25	14:19:00	0.0200		x	x	2008-06-18
2008-08-05	14:13:00	0.0200		x	x	2008-07-29
2008-09-16	14:14:00	0.0200		x		2008-09-09
2008-10-29	14:17:00	0.0100		x		2008-10-22
2008-12-16	14:11:00	0.0000		x		2008-12-09
2009-01-28	14:14:00	0.0000				2009-01-21
2009-03-18	14:17:00	0.0000		x		2009-03-11
2009-04-29	14:16:00	0.0000				2009-04-22
2009-06-24	14:18:00	0.0000		x	x	2009-06-17
2009-08-12	14:16:00	0.0000		x	x	2009-08-05
2009-09-23	14:16:00	0.0000				2009-09-16
2009-11-04	14:18:00	0.0000				2009-10-28
2009-12-16	14:15:00	0.0000		x		2009-12-09

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Table B1. Total 112 meetings in our sample with the respective characteristics. "Other Ann." denotes that a secondary macro announcement falls within the respective FOMC meeting's blackout period. "Surprise" follows the definition of Kuttner (2001). Meeting times are taken from Lucca and Moench (2015) until 2011 and from the official meeting calendar thereafter.

Date	Time	Rate	PC?	Surprise?	Other Ann.?	Blackout Start
2010-01-27	14:17:00	0.0000		x		2010-01-20
2010-03-16	14:14:00	0.0000				2010-03-09
2010-04-28	14:14:00	0.0000				2010-04-21
2010-06-23	14:16:00	0.0000				2010-06-16
2010-08-10	14:15:00	0.0000			x	2010-08-03
2010-09-21	14:15:00	0.0000				2010-09-14
2010-11-03	14:16:00	0.0000		x		2010-10-27
2010-12-14	14:15:00	0.0000				2010-12-07
2011-01-26	14:15:00	0.0000				2011-01-19
2011-03-15	14:15:00	0.0000				2011-03-08
2011-04-27	12:30:00	0.0000	x			2011-04-20
2011-06-22	12:30:00	0.0000	x	x		2011-06-15
2011-08-09	14:15:00	0.0000			x	2011-08-02
2011-09-21	14:15:00	0.0000		x		2011-09-14
2011-11-02	12:30:00	0.0000	x			2011-10-26
2011-12-13	14:15:00	0.0000		x		2011-12-06
2012-01-25	12:20:00	0.0000	x			2012-01-18
2012-03-13	14:15:00	0.0000		x	x	2012-03-06
2012-04-25	12:35:00	0.0000	x			2012-04-18
2012-06-20	12:35:00	0.0000	x			2012-06-13
2012-08-01	14:15:00	0.0000		x		2012-07-25
2012-09-13	12:35:00	0.0000	x	x	x	2012-09-06
2012-10-24	14:15:00	0.0000				2012-10-17
2012-12-12	12:30:00	0.0000	x		x	2012-12-05
2013-01-30	14:15:00	0.0000				2013-01-23

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Table B1. Total 112 meetings in our sample with the respective characteristics. "Other Ann." denotes that a secondary macro announcement falls within the respective FOMC meeting's blackout period. "Surprise" follows the definition of Kuttner (2001). Meeting times are taken from Lucca and Moench (2015) until 2011 and from the official meeting calendar thereafter.

Date	Time	Rate	PC?	Surprise?	Other Ann.?	Blackout Start
2013-03-20	14:00:00	0.0000	x			2013-03-13
2013-05-01	14:00:00	0.0000		x		2013-04-24
2013-06-19	14:00:00	0.0000	x	x		2013-06-12
2013-07-31	14:00:00	0.0000				2013-07-24
2013-09-18	14:00:00	0.0000	x			2013-09-11
2013-10-30	14:00:00	0.0000				2013-10-23
2013-12-18	14:00:00	0.0000	x	x		2013-12-11
2014-01-29	14:00:00	0.0000				2014-01-22
2014-03-19	14:00:00	0.0000	x			2014-03-12
2014-04-30	14:00:00	0.0000				2014-04-23
2014-06-18	14:00:00	0.0000	x			2014-06-11
2014-07-30	14:00:00	0.0000				2014-07-23
2014-09-17	14:00:00	0.0000	x			2014-09-10
2014-10-29	14:00:00	0.0000				2014-10-22
2014-12-17	14:00:00	0.0000	x	x		2014-12-10
2015-01-28	14:00:00	0.0000				2015-01-21
2015-03-18	14:00:00	0.0000	x	x		2015-03-11
2015-04-29	14:00:00	0.0000				2015-04-22
2015-06-17	14:00:00	0.0000	x			2015-06-10
2015-07-29	14:00:00	0.0000				2015-07-22
2015-09-17	14:00:00	0.0000	x	x		2015-09-10
2015-10-28	14:00:00	0.0000				2015-10-21
2015-12-16	14:00:00	0.0025	x	x		2015-12-09
2016-01-27	14:00:00	0.0025				2016-01-20
2016-03-16	14:00:00	0.0025	x	x		2016-03-09

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Table B1. Total 112 meetings in our sample with the respective characteristics. "Other Ann." denotes that a secondary macro announcement falls within the respective FOMC meeting's blackout period. "Surprise" follows the definition of Kuttner (2001). Meeting times are taken from Lucca and Moench (2015) until 2011 and from the official meeting calendar thereafter.

Date	Time	Rate	PC?	Surprise?	Other Ann.?	Blackout Start
2016-04-27	14:00:00	0.0025				2016-04-20
2016-06-15	14:00:00	0.0025	x			2016-06-08
2016-07-27	14:00:00	0.0025				2016-07-20
2016-09-21	14:00:00	0.0025	x	x		2016-09-14
2016-11-02	14:00:00	0.0025		x		2016-10-26
2016-12-14	14:00:00	0.0050	x			2016-12-07
2017-02-01	14:00:00	0.0050		x		2017-01-25
2017-03-15	14:00:00	0.0075	x	x	x	2017-03-08
2017-05-03	14:00:00	0.0075				2017-04-26
2017-06-14	14:00:00	0.0100	x	x		2017-06-07
2017-07-26	14:00:00	0.0100				2017-07-19
2017-09-20	14:00:00	0.0100	x			2017-09-13
2017-11-01	14:00:00	0.0100		x		2017-10-25
2017-12-13	14:00:00	0.0125	x	x	x	2017-12-06