FOMC Event Risk*

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ABSTRACT

This paper examines FOMC event risk, the volatility generated by regularly scheduled FOMC announcements, using S&P 500 index options. To isolate FOMC event risk from factors like time-varying volatility and crash risks, we calibrate structural models using intraday index option data. FOMC event risk is economically large, time-varying, and highly predictive of realized event risk. We find evidence for early uncertainty resolution in the hours and days before an FOMC announcement, as well as economically large FOMC event risk volatility risk premia. We analyze event risk for major macroeconomic announcements like GDP, CPI, and employment.

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Every six weeks, the Federal Reserve's Federal Open Market Committee (FOMC) announces monetary policy decisions and financial markets quickly respond to the new information. As Bernanke and Kuttner (2005) note, the direct effects of monetary policy on financial markets create valuable shocks linking policy and the real economy through financial markets.[1] Recent research documents the importance of these shocks around FOMC and macroeconomic announcements.[2]

This paper analyzes these shocks from a new perspective, using SPX index options to estimate ex-ante FOMC event risk, the market volatility generated by the FOMC's disclosures. We do this using a novel estimation procedure that estimates FOMC event risk prior to each meeting while controlling for other factors impacting option prices. Empirically, FOMC event risk is large and significant; it varies dramatically over time; it predicts to a high degree subsequent realized index volatility; and it carries a significant volatility risk premium. We also estimate our model in the days and hours prior to FOMC meetings and find strong evidence for a significant uncertainty resolution prior to FOMC meetings, consistent with Hu et al. (2022) and Ai et al. (2022). We also analyze risk pricing of employment, inflation, and GDP macroeconomic announcements.

Options are the natural source of information about market expectations of future scheduled events, as first explained by Patell and Wolfson (1979). Predictable events induce clear patterns in option prices: Black-Scholes implied volatility (IV) generally increases prior to important events, falling ex-post as asset prices adjust to the news and event uncertainty resolves. Dubinsky et al. (2019) show that predictable events also induce a declining IV term structure prior to the events. These effects are most easily seen for earnings announcements given their large impact,[3] but are also present for FOMC events, macroeconomic

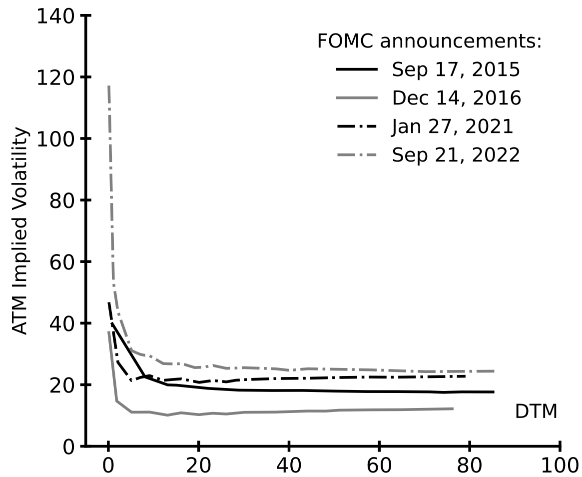
[1] Bernanke and Kuttner (2005) note that: "*The most direct and immediate effects of monetary policy actions, such as changes in the Federal funds rate, are on the financial markets; by affecting asset prices and returns, policymakers try to modify economic behavior in ways that will help to achieve their ultimate objectives. Understanding the links between monetary policy and asset prices is thus crucially important for understanding the policy transmission mechanism.*" (p. 1221). See also Rudebusch (1998), Cochrane and Piazzesi (2002) or Gürkaynak et al. (2005) for discussions of how high-frequency asset prices provide "clean" measures of monetary policy shocks.

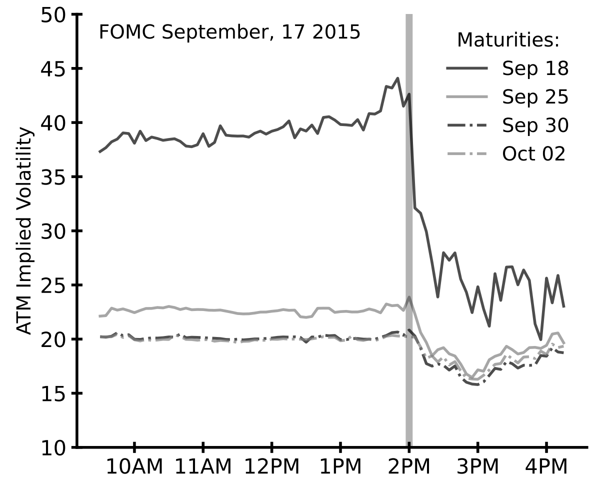
[2] See, e.g., Savor and Wilson (2013), Lucca and Moench (2015), Wachter and Zhu (2022), Hu et al. (2022), Ai and Bansal (2018), Savor and Wilson (2014), Ai et al. (2022), Gürkaynak et al. (2022), and Caballero and Simsek (2024).

[3] See, e.g., the initial work of Patell and Wolfson (1979, 1981), Isakov and Pérignon (2001), Donders and Vorst (1996) and more recently Dubinsky et al. (2019).

Figure 1. ATM Implied Volatility Around FOMC Announcements

The left plot provides the at-the-money (ATM) term structure of implied volatility (x-axis: days to maturity (DTM), y-axis: ATM IV) at 1 pm ET, one hour before the FOMC announcements on September 17, 2015, on December 14, 2016, on January 27, 2021 and on September 21, 2022. The right plot provides the intraday ATM IVs for various short-dated S&P 500 spot index option maturities (option maturities are September 18, 2015, September 25, 2015, September 30, 2015 and October 2, 2015) around the September 17, 2015 FOMC meeting (x-axis: ET trading hours, y-axis: ATM IV). The underlying of the option contracts is the S&P 500 spot index.





announcements, and political events.[4]

To see the effects quantitatively, Figure 1 plots SPX index at-the-money (ATM) IVs around FOMC announcements. The left panel shows the extremely downward-sloping term structure of IV one hour prior to the announcement in four different volatility environments. The right panel shows abrupt drops in IVs after the announcement. These figures also highlight that event risk effects are strongest for short-dated maturities, an effect that is also clear in event risk models (see Dubinsky et al. (2019)).

This paper provides an empirical approach to estimating FOMC event risk from SPX options, combining the predictable timing of FOMC announcements with three ingredients: (1) the introduction of additional option expiries, starting with weekly Friday expiries that became liquid in 2011, (2) high-quality intraday quote data, and (3) structural stochastic volatility (SV) models augmented with predictable events. This approach allows us to es-

[4]See, e.g., Nikkinen and Sahlström (2004) and Carr and Wu (2006) for the FOMC, Ederington and Lee (1996) for macroeconomic announcements, and Kelly et al. (2016) for political events.

timate and analyze the pricing of FOMC event risk as well as for other macroeconomic announcements while controlling for other important shocks that affect option prices.

The first ingredient, the rich maturity structure of options, allows us to separately identify event risks both from SV and crash components as well as confounding macroeconomic announcements. This is feasible initially due to the introduction of weekly option expiries. Friday expiries were introduced in 2005 and became actively traded in 2011 and additional weekday expiries were launched in 2016 and 2022, which improve identification. Intuitively, options of different maturities load differently on underlying risk factors, allowing separate identification of FOMC event risk. Very short-dated options are highly informative about event risks, as in Figure 1.

The second ingredient is high-quality intraday quote data for the period 2012-2023. As argued by Andersen et al. (2021), high-quality intraday option quote data avoids well-known problems with commonly used close price data,[5] but more importantly provides clean mid-point price data during the day. Intraday quotes allow us to estimate FOMC event risk not only just before an FOMC announcement but also in the hours and days leading up to the announcement. This, in turn, allows us to analyze the temporal resolution of FOMC event risk, an issue highlighted by Hu et al. (2022) and Ai et al. (2022). Additionally, intraday quotes allow a clean calculation of variance risk premia via narrow-window straddle returns around FOMC announcements.

Third, we estimate FOMC (and macroeconomic) event risk in a structural model combining pre-scheduled event risk with time-varying volatility and crash risks. These models allow us to control for non-event risks and, in particular, other factors driving the term structure of volatility, which can create problems for event risk estimation (see, e.g., Dubinsky et al. (2019)). We estimate event risk by calibrating the structural SV models prior to FOMC releases using option prices from a broad range of strikes and maturities. These models control for other factors and allow us to investigate the robustness of event risk estimates to different SV and crash specifications. We also develop a simple regression-based event risk estimator using ATM Black-Scholes IVs, extending an approach developed in Dubinsky et al. (2019) to incorporate additional maturities.

On the empirical side, we have a number of new findings. First, we find significant FOMC event risk with an average FOMC event volatility of 0.88% and substantial time variation.

[5] See, e.g., Goyenko and Zhang (2019).

The 5% and 95% observed percentiles of FOMC event risk over our sample period are 0.29% and 1.87%, respectively. This range of variation, a factor of almost six, is significantly higher than that observed for measures of overall market volatility like the VIX.[6] This variation is important for understanding event uncertainty and is informative for theories like Ai et al. (2023) that show the importance of time-varying event risk for understanding preferences. These ex-ante estimates confirm the time-variation documented with the ex-post estimates in Ai et al. (2023) based on the drop in VIX-like indices post-event.

The FOMC event risk estimates are separately identified from SV factors, permitting a comparison of FOMC event risk to traditional volatility proxies such as option implied spot volatility, the VIX index, or realized volatility. We find a significant, though modest, correlation between FOMC event risk and the VIX, about 50%, higher (lower) in periods of low (high) market volatility. The extant literature often quantifies FOMC event risk via the post-FOMC VIX decline. This proxy is noisier, as the negative correlation between FOMC event risk and the ex-post drop in the VIX is smaller, about 20%. The correlation is lower in high volatility regimes, consistent with a greater role for SV and crash risks in the VIX. These results are not surprising as the VIX measures 30-day average volatility.[7] Similar levels of correlation exist between FOMC event risk and diffusive spot volatility, as well as short-dated indices like the 9-day VIX. These results show the FOMC event risk estimates capture new information.

FOMC event risk estimates are under the risk-neutral measure $\mathbb{Q}$, and we evaluate the predictive ability of ex-ante event risk estimates for post-event $\mathbb{P}$-measure realized volatility. FOMC event risk estimates are highly predictive of subsequent S&P 500 futures realized volatility, with predictive R^2 values well above 50%. Thus, option-based estimates capture $\mathbb{P}$-measure realized return volatility, as option markets efficiently impound information about future event risk. Additionally, using data on realized volatility in Eurodollar, Fed Funds, and

[6] From 1990 through 2022, the (5%, 95%) range for the VIX is approximately (11.3%, 33.6%), a factor of less than three.

[7] The VIX is a constant-maturity 30-day volatility index, which mechanically downweights short-dated options as calendar time passes, placing greater weight on longer-dated options as time passes. This calendar time treatment also induces predictable calendar effects, including a general downward drift during the week and large increases over weekends (see Fernandez-Perez et al. (2016)). The VIX also 'rolls' underlying contracts frequently, generating additional variation due to the term structure of IV. See, e.g., Mixon (2007) and Fernandez-Perez et al. (2016). See Fernandez-Perez et al. (2017) for a high-frequency study of the ex-post behavior of the VIX.

2, 5, 10, and 30y Treasury futures, we find that our S&P 500 index FOMC event risk estimates significantly predict realized bond market volatility after the FOMC announcement, although (as expected) to a lesser degree than for S&P 500 futures.

A number of important new asset pricing theories study announcement asset pricing and argue that an early resolution of event risk prior to an FOMC announcement can explain the anomalous "FOMC return drift," positive stock index returns prior to the FOMC, documented by Lucca and Moench (2015). In Hu et al. (2022), there is uncertainty over both price impact and FOMC shock volatility, and uncertainty resolves in the days prior to the FOMC, leading to a reduction in risk and price drifts. Using the VIX, they find supporting evidence, with similar mechanisms and findings in Ai and Bansal (2018) and Ai et al. (2022).

Our approach provides direct estimates of FOMC event risk in the hours and days before an FOMC meeting. Consistent with their theories, we find a substantial and largely smooth downward drift in event risk estimates prior to FOMC announcements of about 30%, direct validation of theories of uncertainty resolution. Combined with Ai et al. (2023), these results provide additional direct option-based evidence for a preference for early resolution of uncertainty.[8] Although event risk does increase prior to some FOMC meetings, changes in FOMC event risk estimates are significantly negatively correlated with S&P 500 futures returns over the same ex-ante period, a strong supporting test of uncertainty resolution based theories of FOMC drift.[9] These conditional effects can be present in a sample even with no average drifts, as price drifts for events with decreasing uncertainty average out those with increased uncertainty and negative drifts.

Our approach permits the comparison of effects from FOMC statements, typically released at 2:00 pm ET, and press conferences, which typically occur from 2:30 pm to about 3:00 pm ET. Press conferences were introduced post-financial crisis in order to enhance communication. These press conferences have occurred at every other meeting since 2011 and at every meeting since 2019.[10] To analyze uncertainty resolution, we estimate FOMC event risk just prior to the FOMC statement, and then again just prior to the press conference. Press conference FOMC announcements have higher ex-ante total event risk, consistent with

[8]The theory of Ai et al. (2023) requires identification of a period of "resolution of information quality," identified as five days prior to the FOMC via news articles.

[9]This effect is stronger for "clean" FOMC announcements, those without any confounding macroeconomic announcements in the days before the FOMC.

[10]https://www.federalreserve.gov/newsevents/pressreleases/monetary20110324a.htm

greater information content and/or market sensitivity. For press conference meetings, a large fraction of the total FOMC event risk volatility remains after the initial statement, only to be resolved after the press conference.

Prior research finds significant volatility and/or jump risk premiums in index options. We investigate FOMC event risk premiums via straddle returns and compare them to other short-horizon risk premia. To do this, we compute ATM straddle returns in narrow windows around the FOMC meetings, avoiding confounding factors to provide a clean return measure. We find strong evidence for an FOMC event risk premium: short-dated ATM straddles fall about 4% to 5% during a 30-45 minute window around the FOMC announcement, effects that are highly statistically significant.[11] In terms of magnitudes, these FOMC event risk premia are larger than overnight and weekend average straddle returns, see Jones and Shemesh (2018) and Muravyev and Ni (2020), respectively.

We also analyze event risk for Jackson Hole speeches by the Federal Reserve chair as well as CPI, Core PCE, GDP, and employment reports. These events are used as controls in our FOMC event estimates above, but we can estimate the ex-ante event risk using the same approach used for the FOMC. Like FOMC event risks, option-implied macroeconomic event risks are large and time-varying. For the full sample, magnitudes are similar across announcements, ranging from an average of roughly 0.6% for GDP and core PCE to roughly 0.80% for CPI, Jackson Hole speeches, and monthly payrolls. Identification of these announcements is somewhat noisier, as estimates are zero for a small fraction of announcements. Time variation is even more variable than for the FOMC, with spring 2020 Covid macroeconomic announcements showing much larger event risks than other observations. For example, March 2020 payrolls (announced in April) were more than 4%, compared to a median estimate of 0.68%.

Finally, we also develop easy-to-compute estimates of FOMC event risk based on ATM Black-Scholes IVs, extending the approach of Dubinsky et al. (2019). The Dubinsky et al. (2019) approach uses only two maturities, can be noisy due to SV and crash factors, and often doesn't directly apply due to confounding scheduled events. To do this, we develop a regression-based extension of the approach in Dubinsky et al. (2019) using ATM IVs for many option maturities, which generates event risk estimates controlling for other macroeconomic events. These simple estimators generally work well, even better after 2016 and 2022, with

[11] Dim et al. (2024) confirm these results using VIX-like variance risk premiums and similar intraday data.

the introduction of additional weekly maturities.

I. Related Literature

Numerous papers in economics, finance, and accounting examine event risk. Investor behavior and market pricing before and after the events provide valuable shocks and insights, which have been analyzed both empirically and theoretically for various markets. Our approach connects to and builds on this prior work.

Event risk was first widely studied in the context of earnings announcements. Starting with Ball and Brown (1968), stock prices respond strongly to earnings announcements, as realized returns around earnings are abnormally volatile, correlated with earnings news, and on average positive, consistent with an event risk premium (see, e.g., Ball and Kothari (1991) or more recently Frazzini and Lamont (2007)). Investors tend to underreact, generating post-earnings announcement drift (see, e.g., Fink (2021)). Starting with Kim and Verrecchia (1991a, 1991b, 1997), a large literature analyzes asset pricing theory around earnings events.

Patell and Wolfson (1979, 1981) show that earnings event risk is priced in stock options and identify the key 'signatures' of priced event risk: IV increases prior to and then drops after the event as uncertainty resolves. Dubinsky et al. (2019) develop an alternative event risk model and ex-ante and ex-post estimators of earnings event risk, documenting these estimates are robust to SV and crash risk and highly predictive of ex-post realized stock return volatility. Their time series estimators are closely related to the patterns identified in Patell and Wolfson (1981), but the ex-ante term-structure estimators are less noisy than the time series estimators as IVs can increase or decrease prior to events for many reasons.

Macroeconomic and policy announcements also generate abnormal volatility and anomalous return patterns. Early research documented that aggregate market returns have abnormally high volatility around macroeconomic announcements (e.g., Ederington and Lee (1993)), effects more easily identified via intraday data (e.g., Andersen and Bollerslev (1997, 1998)). Macroeconomists have utilized market returns of macroeconomic announcements, and especially FOMC announcements, to identify macroeconomic shocks to understand monetary policy (see, e.g., Bernanke and Kuttner (2005) and Gürkaynak and Wright (2013) for a review). There is a recent focus on intraday shocks measured by futures price changes in narrow windows around FOMC announcements (e.g., Nakamura and Steinsson (2018) identify monetary policy shocks using 30-minute returns around FOMC announcements).

On the asset pricing side, Savor and Wilson (2013) find significant excess aggregate stock market returns on macroeconomic announcement days over a long historical period. Lucca and Moench (2015) document a strong drift in equity returns prior to the FOMC meeting. Ai and Bansal (2018) provide a theory of announcement event risk premia and uncertainty resolution timing (see also Wachter and Zhu (2022)).

FOMC event risk is priced in SPX index options. Carr and Wu (2006) document an increase in index option IV prior to and a decline after FOMC events (see also Fernandez-Perez et al. (2017)). Andersen et al. (2017) document strong shifts in option prices, and in particular, index option tails, around a number of FOMC meetings in 2012 and 2013 using short-dated S&P 500 futures options. They highlight the high sensitivity of short-dated options to FOMC event risk and tail risk more generally. Dim et al. (2024) document high trading volumes in very short-dated index options around FOMC announcements.

Hu et al. (2022) discovered that the VIX declines prior to FOMC meetings (and other macroeconomic announcements) and provide a theory of event risk uncertainty resolution, likely due to information acquisition. Ying (2020) also documents a VIX decline prior to the FOMC and argues that ex-post VIX decline magnitudes are useful for understanding ex-ante SPX index drifts. Liu et al. (2022) use index options to estimate the FOMC risk premium and quantify drift effects. Ai et al. (2023) use SPX index options and the VIX to analyze a preference for the timing of uncertainty resolution around FOMC events (see also Ai et al. (2022)). Our results extend the results in these papers, providing direct option market-based estimates of FOMC event risk without using the relatively long-dated and noisy VIX.

Wright (2020), Beckmeyer et al. (2021), and Londono and Samadi (2023) study macroeconomic event risks using short-dated options. Wright (2020) examines unemployment and FOMC event risk in Treasury futures options, using weekly Friday expiries introduced in 2011 as well as Wednesday expiries introduced in 2017. Using close price data, he documents an increase in IVs into macroeconomic events. Using full samples of event and non-event days, Wright (2020) uses the abnormal increase into events in a regression-based approach to identify event risk, similar to Patell and Wolfson (1981). Wright (2020) finds bond variance risk premia on FOMC days. This approach doesn't separately treat multiple announcements and only quantifies FOMC event risk post-2017. In subsequent research to this paper, Dim et al. (2024) confirm our findings that a substantial FOMC event risk volatility premium is realized post-announcement. They use VIX-like variance risk-premium estimates based on short-dated options sampled intradaily around FOMC events.

Beckmeyer et al. (2021) analyze option pricing around FOMC meetings using high-frequency data and find left-tails are important for understanding the resolution of uncertainty and risk premia around FOMC announcements (compared to non-FOMC days). They also document increases in pre-FOMC uncertainty and drops in post-FOMC uncertainty. In contemporaneous work, Londono and Samadi (2023) analyze macroeconomic events using closing prices on SPX index options from 2017. Conceptually, they identify event risk by comparing options expiring prior to and spanning the event, in both cases using relatively long dated maturities from 7 to 21 days, fundamentally different from our approach. They document risk and risk premium measures are higher for options spanning macroeconomic events. Forward-looking equity and realized variance risk premiums calculated as in Gandhi et al. (2023), Gao and Martin (2021), and Kelly et al. (2016) time-vary and are correlated with measures of risk aversion and economic uncertainty. Their econometric approach does not apply in the immediate week prior to an event release, as they use only options with more than one week to expiry and also do not use the short-dated options spanning events.

FOMC event risk also appears in the cross-section of equity returns. Gürkaynak et al. (2022) identify a cash flow conduit for FOMC shocks in the cross-section, with shocks measured using principal components from bond market returns. Ai et al. (2022) estimate an FOMC risk premium in the cross-section using the decrease in the VIX on FOMC days. We also use event risk estimates around the FOMC and other announcements to create a market-based macroeconomic risk index, similar in spirit to those created by Baker et al. (2016).

II. Model, Data and Estimation Approach

A. A Simple Option Pricing Model with Events

For intuition, consider the Dubinsky et al. (2019) model extension of Black-Scholes to incorporate predictable events. M_t counts the number of macroeconomic events prior to time t that occur at predictable times τ_j. The jump size, $Z_j^{\mathbb{Q}}$, captures the price impact of a macroeconomic announcement at time τ_j on the underlying (log) stock price index, effectively a reduced-form asset pricing model translating news into asset returns.

The stock index value, S_t, evolves under the risk-neutral measure $\mathbb{Q}$ via

$$dS_t = rS_t dt + \sigma S_t dW_t^{\mathbb{Q}} + d\Big(\sum_{j=1}^{M_t} S_{\tau_j -} \left[e^{Z_j^{\mathbb{Q}}} - 1 \right] \Big), \tag{1}$$

where $W_t^{\mathbb{Q}}$ is a Brownian motion and jump sizes at event times are i.i.d. normal:

$$Z_j^{\mathbb{Q}} \sim \mathcal{N}\left(-\frac{1}{2} \left(\sigma_j^{\mathbb{Q}}\right)^2, \left(\sigma_j^{\mathbb{Q}}\right)^2 \right).$$

The jump size distribution embeds the martingale restriction at predictable jump times (see Piazzesi (2000)), requiring that price jumps at predictable times are conditionally mean zero. Although diffusive volatility is constant, event risk can vary both over time and by the type of event (e.g., FOMC vs. CPI).

In this model, S_t is log-normal, which implies that European options are priced by a version of the Black-Scholes formula with a modified volatility input. The annualized Black-Scholes implied variance at time t of an option expiring at time T is given by

$$\sigma_{t,T}^2 = \sigma^2 + (T-t)^{-1} \sum_{j=M_t+1}^{M_{t+T}} \left(\sigma_j^{\mathbb{Q}}\right)^2.$$

Implied variance is linear in event risk and diffusive variance, though event risk imparts a key time dependence as it is scaled by time-to-maturity.

As an example, assume the current time t is prior to a normal 2:00 pm ET Wednesday FOMC announcement, with the option's expiry, T, after the announcement. The option-implied variance at time t is given by

$$\sigma_{t,T}^2 = \sigma^2 + \frac{\left(\sigma_{FOMC}^{\mathbb{Q}}\right)^2}{T-t},$$

where $\sigma_{FOMC}^{\mathbb{Q}}$ is the event risks for the FOMC. This simple model captures the main effects of event risk on option prices:

- Event risk scales inversely to the time to maturity, implying that implied variance increases into the event at rate $(T-t)^{-1}$.

- The IV term structure slopes downward prior to the event (see Figure 1).
- IV drops ex-post as uncertainty is resolved (see Figure 1).
- Event risk has a quantitatively much greater impact on short-dated maturities, as $(T-t)^{-1}$ is large, magnifying event risks.

This model is conceptually useful for thinking about event risk identification and estimation. Dubinsky et al. (2019) develop event risk estimators for earnings announcements using option IVs. Their ex-ante "term structure" estimators use the IVs of two ATM options for different maturities spanning the events, and "time series" estimators based on the post-event IV decline.[12] Dubinsky et al. (2019) find that the term structure estimators are more accurate than time series estimators, as event risk estimators based on realizations tend to be noisier than those based on a single point in time.

The simple estimators developed in Dubinsky et al. (2019) apply in principle for FOMC and macroeconomic events, but in practice have a number of pitfalls. One problem arises from low signal strength due to omitted factors like SV and crash risks. Even with only one event, the simple estimators tend to be less accurate because FOMC event risk is smaller than earnings event risks relative to background risks. For example, daily realized volatility is approximately 1% for the S&P 500 index, similar in magnitude to FOMC event risks. Earnings volatility is often five or even ten times higher than daily volatility for individual stocks, which implies that FOMC event risk has a much lower 'signal-to-noise' ratio relative to background risks. This is exacerbated by SV, which impacts IV term structures, as seen in Figure 1, as well as leverage effects between stock returns and volatility, which drive ATM IVs. Together, these non-event background factors create noise and potentially large directional biases when estimating FOMC event risks from S&P index options.

Confounding events such as other macroeconomic announcements are another challenge for these simple estimators.[13] An example is an FOMC announcement with other major announcements (e.g., CPI or GDP) earlier on the same day. It is not possible to separately identify these confounded events with closing option price data. They can be separately estimated using intraday data option prices sampled prior to the FOMC but after earlier

[12] It is also possible to estimate event risk based on the increase in IVs prior to events, as used by Patell and Wolfson (1981) and Wright (2020). Kelly et al. (2016) use an alternative term structure approach based on IV for options expiring before and after the event.

[13] This is also the case for the approaches in Londono and Samadi (2023) and Wright (2020).

events. Another confounding situation can occur with multiple events prior to expiration. For example, in the case of a Wednesday FOMC event with a CPI announcement the following week and the shortest option maturity is the following Friday, ten days later. In this case, it is generally not possible to separately identify the two event risks based on options spanning both events. This latter situation is attenuated recently after the introduction of additional daily expiries.

Due to these factors, we estimate FOMC (and macroeconomic) event risk from a general model with SV and crash risk. This allows us not only to use more option prices (OTM options and many expiries) and account for macroeconomic announcements, but also to analyze the sensitivity of event risk estimates to the model specification. We also develop a new regression-based event risk estimation approach using the cross-section of all ATM IVs spanning the event, extending Dubinsky et al. (2019). We compare the structural model estimates to these regression-based estimates, and the simple regression-based estimators work well in recent samples with multiple weekly expiries using intraday quote data.

B. A General Announcement Model

To estimate event risks, we embed event risks into standard SV models. The general model assumes that the log value of the stock index evolves under the $\mathbb{Q}$-measure via

$$d\log(S_t) = dx_t + d\left(\sum_{j=1}^{M_t} Z_j^{\mathbb{Q}}\right),$$

a sum of a traditional SV model with jumps, x_t, and macroeconomic event risks. The main benchmark for x_t is the SVJ model of Bates (1996):

$$\begin{aligned} dx_t &= \left(r - \tfrac{1}{2}v_t - \lambda(\psi_Y(1) - 1)\right) dt + \sqrt{v_t} dW_{1t}^{\mathbb{Q}} + d\left(\sum_{j=1}^{N_t^{\mathbb{Q}}} Y_j^{\mathbb{Q}}\right) \\ dv_t &= \kappa(\theta - v_t)dt + \sigma_v \sqrt{v_t} dW_{2,t}^{\mathbb{Q}}, \end{aligned}$$

where ψ_Y is the moment generating function of the jump size $Y_j^{\mathbb{Q}} \sim \mathcal{N}\left(\mu_y^{\mathbb{Q}}, \left(\sigma_y^{\mathbb{Q}}\right)^2\right)$, $\lambda^{\mathbb{Q}}$ is the $N_t^{\mathbb{Q}}$ intensity, and the Brownian motions are correlated.[14]

Option prices are easy to compute using now standard Fourier inversion methods based on the conditional characteristic function of x:

$$\Psi_x(t, T, u) = \mathbb{E}_t^{\mathbb{Q}}\left[e^{ux_T}\right].$$

For Bates (1996), the generalized conditional characteristic function is known analytically:

$$\Psi_x(t, T, u) \quad = \quad e^{\alpha(t,T,u)+\beta(t,T,u)v_t+ux_t},$$

where the coefficients $\beta(t, T, u)$ and $\alpha(t, T, u)$ are analytic functions of the parameters and time, and $u \in \mathbb{C}$.

Provided the event risk component has a known or easily computable characteristic function, option pricing proceeds via standard characteristic function methods. This "components" modeling approach is quite flexible, permitting both general non-announcement dynamics and announcement/event effects. For example, it is easy to incorporate more general SV specifications with known characteristic functions. We consider a number of these extensions below to establish robustness, allowing for non-normal crash risk. This approach also permits non-normal event risk jumps and even jump sizes that are state-dependent.

We assume normally distributed event jump sizes, allowing event risk volatility to vary across time (for a given announcement type) and also announcement types. We focus on the FOMC and four commonly analyzed macroeconomic announcements mentioned above: quarterly GDP growth, monthly employment (first Friday of the month), monthly CPI inflation, and Core PCE inflation. We also analyze Jackson Hole speeches made by the Federal Reserve chairs. When reporting FOMC estimates, the other macroeconomic events can be viewed as controls.

[14]The interpretation of the model parameters is standard: r is the risk-free interest rate, κ is the mean reversion speed of the latent variance v_t, θ is the long-run variance, σ_v is the volatility of volatility and the two standard Brownian motions $W_{1,t}^{\mathbb{Q}}$ and $W_{2,t}^{\mathbb{Q}}$ have a correlation coefficient of ρ.

C. Data

We use intraday options and futures data to estimate event risk using two main data sets. The first is S&P 500 (SPX) index option and futures data, the former from Refinitiv's consolidated OPRA records from the CBOE. The option data is similar to intraday data used previously and described in Andersen et al. (2021). We construct best bid/ask spread midpoints for each strike/maturity at a 5-minute intervals. Quote data avoids bid/ask bounce and stale prices, which is important for short-dated and out-of-the-money (OTM) options.

Intraday sampling frequencies are particularly important for isolating event risk, tracking event risk variation, and analyzing option returns around announcements. As noted earlier, FOMC announcement days often have important economic announcements either at 8:30 or 10:00 am ET prior to the FOMC announcements at 2:00 pm ET. Intraday quote data provides price data after these other announcements, avoiding the confounding that is present when using close price data. Internet Appendix IA.A provides further details on the data and filters. As short-term options are crucial for identification, the sample starts in 2012 as trading volume and liquidity in weekly Friday expiries increased dramatically in 2011 (see, e.g., Andersen et al. (2017) and Rhoads (2014)). The sample ends on March 25, 2023.

In addition to option data, we use 5-minute S&P 500 futures prices from Refinitiv to calculate realized volatility measures. Futures are traded almost around the clock, which is useful, especially for premarket announcements that often occur at 8:30 am ET prior to the regular market opening. We construct a single futures return time series using the shortest available contract, rolling prior to expiration (depending on volume). We also obtain futures data for 2, 5, 10, and 30-year bonds, federal funds, and Eurodollar, with returns calculated in a similar manner.

We collect macroeconomic announcement dates and timestamps from 2012 to March 2023.[15] We focus on FOMC announcements and the Consumer Price Index (CPI), Core PCE, Gross Domestic Product (GDP), Jackson Hole speeches by the Federal Reserve chair, and Employment Situation (Monthly Payrolls). Precise announcement times are important and hand-collected from original sources (e.g., the Bureau of Labor Statistics). In case of any ambiguity in the original data source, announcement times are verified from LexisNexis reporting on the precise event time. Table I provides a summary of the announcements,

[15] We also collect macroeconomic announcement dates and times beyond March 2023 as we use option prices that mature after March 2023.

including the number of observations and their most common announcement times. The March 2020 FOMC meeting during the COVID outbreak was canceled, as the FOMC held an emergency meeting days earlier.

Major political events have similar effects on option prices as scheduled macroeconomic events, as noted by Kelly et al. (2016). We account for the 2016 and 2020 US presidential elections and the Brexit referendum in June 2016, treating them as additional priced predictable events occurring after the close of markets on the event day. FOMC meetings normally occur from Tuesday to Wednesday but are moved one day later if they overlap with the presidential election date. Indeed, for the 2016 US presidential election as well as the 2016 Brexit referendum, the IV term structure prior to the FOMC announcement was not downward sloping, because the election/Brexit events were much larger than the FOMC event. Accounting for these additional events corrects for any potential downward bias in our event risk estimates.

Table I
Announcements

This table summarizes the different announcements used in this paper, as well as the number of observations and the most frequent announcement time (Eastern Time). We include CPI, Core PCE, FOMC, GDP, Jackson Hole, and Monthly Payroll announcements. Our sample is from January 2012 to March 2023. Abbreviations for data sources: BEA: Bureau of Economic Analysis, BLS: Bureau of Labor Statistics, Fed: Federal Reserve Board of Governors.

Announcement	Obs	Most frequent announcement times (high frequency to low)	Source
CPI	135	Wed 08:30, Tue 08:30, Thu 08:30, Fri 08:30	BLS
Core PCE	133	Fri 08:30, Mon 08:30, Thu 08:30, Wed 08:30, Tue 08:30	BEA
FOMC	89	Wed 14:00, Wed 12:30, Wed 14:15, Thu 14:00, Tue 14:15	Fed
GDP	134	Thu 08:30, Fri 08:30, Wed 08:30, Tue 08:30	BEA
Jackson Hole	9	Fri 10:00, Thu 09:10	Fed
Monthly Payrolls	135	Fri 08:30, Thu 08:30, Tue 08:30	BLS

D. Estimation Approach

Given the data, we estimate event risk by calibrating the components model in Section II.B with SV, crash, and macroeconomic event risks. To estimate the model prior to an FOMC announcement, which most often takes place at 2 pm ET, we use SPX option mid-quotes one hour prior to the announcement in the base results. We use options with expiries less than 60 days and with log-moneyness between -3 and 3.[16] We use OTM options as these are usually more liquid and because put and call IVs for the same strike and maturity are similar by put-call parity. We have experimented with alternative filters, such as longer maturities or broader cross-sections, and the results are similar.

We estimate the parameters by minimizing the RMSE between market and model IVs:

$$\underset{\Theta}{\operatorname{argmin}} \sum_{d=1,\ldots,n_t} \sum_{i=1,\ldots,N_d} \left(IV_t^{ma}(K_{i,d}, PC_{i,d}) - IV_t^{mo}(V_t, K_{i,d}, PC_{i,d}, \Theta)\right)^2 \tag{2}$$

where n_t is the number of expiries available at time t, N_d is the number of option strikes for maturity d, IV_t^{ma} are the observed market Black-Scholes IVs at time t, IV_t^{mo} are the model-based IVs, and Θ is the parameter vector. $K_{i,d}$ and $PC_{i,d}$ are the strikes and contract types (put or call), respectively.

Minimizing the difference between model and market IVs is now standard for structural SV model estimation (see, e.g., Broadie et al., 2007 or Andersen et al., 2015), as it standardizes option prices in an economically and statistically sensible manner. Raw option prices create problems because longer-dated, ATM, and/or ITM option prices can be orders of magnitude larger than even modestly OTM short-dated options, which are more informative for event risk. IVs place similar weights on all options, with greater weight on OTM options (high IVs), which load more on tail risks.

When estimating FOMC event risk, we include the other announcement categories listed in Table I (CPI, Core PCE, GDP, Jackson Hole, and Monthly Payroll) as control variables and also political events like Brexit and presidential elections as discussed above. Accounting for these other events is crucial for cleanly identifying FOMC event risk. For some announcements and time periods (early in the sample), there are not sufficient maturities to identify each event separately. In this case, we assume that the event risk for the same announcement type on different dates is the same. For example, suppose there is an FOMC announcement on Wednesday and a jobs report on Friday, with only weekly Friday expiries. In this case, we assume this and next month's job reports have the same event volatility, which is then

[16] We define log-moneyness as $m = \log(K/F)/(\sigma_{ATM}\sqrt{T-t})$, where σ_{ATM} is the ATM IV of the options with time to maturity $T-t$, K is the option strike and F is the option-implied forward price for maturity T.

identified as longer-dated options help pin down the employment report event risk.

The estimation procedure generates a sequence of event risk estimates: $\sigma_{i,j}$'s (for i = FOMC, CPI, PCE, GDP, Jackson Hole, and payrolls; and j counts the occurrences of each announcement type). The model and point-in-time estimation allows us to focus on event risk just prior to the event while allowing maximal flexibility to capture other features like SV and crash risks. As such, the Bates (1996) model provides a flexible filter to obtain event risk estimates while accounting for time-varying volatility, volatility mean-reversion, volatility of volatility, longer-run volatility states, leverage effects, and crash risks. It is important to note that this procedure provides *ex-ante* estimates prior to an event.

Our estimation procedure contrasts with the approach in Dubinsky et al. (2019). Their ex-ante term structure estimator uses Black-Scholes IVs for two different expiries, $T_1 < T_2$, just prior to the event:

$$\sigma^2_{event} = \frac{\sigma^2_{t,T_1} - \sigma^2_{t,T_2}}{(T_1 - t)^{-1} - (T_2 - t)^{-1}} \tag{3}$$

As discussed above, these estimators work well when event risk is large relative to diffusive risks, when diffusive SV is close to its long-run mean or very slowly mean-reverting, and/or there is a single large announcement. These estimators don't use information in the full cross-section. We extend these estimators to multiple announcements using a regression approach outlined below, with comparisons estimates using the structural model.

The structural estimates can be contrasted with the approach in Wright (2020), who regresses implied variance on lagged implied variances and an event day dummy variable. These estimates are based on the difference between implied variance and what it would have been if that day were not an event day. This approach uses close prices and can be noisy, as IVs fluctuate prior to events for many reasons unrelated to the announcement. The approach also uses all past and future data in estimation. For FOMC announcements, Wright's approach is only applicable with Wednesday expiries, which doesn't permit FOMC event estimates prior to 2017 or for election years. Our approach also permits multiple announcements prior to expiry, uses a broad cross-section of options (both by strike and maturity), only uses options spanning the target announcement, and can be applied at any point in time up to the announcement (allowing an evaluation time-variation in estimates). Our estimates of σ_{FOMC} also take into account background SV and jump risks.

III. FOMC Announcement Risk

A. Event Risk Estimates

Table II summarizes FOMC event estimates for various samples, estimated one hour prior to the FOMC announcement. For the full sample, the average FOMC event risk is 0.88% (t-statistic 10.95). All but one of the 89 estimated FOMC event volatilities are positive, as indicated by column 7, thus we do not have the 'zeroes' problem that Dubinsky et al. (2019) find occasionally for earnings announcements. The only FOMC meeting for which we estimate a zero event risk is the FOMC which followed the presidential election in November 2020, discussed below. Historical average SPX equity return volatility is about 1% per day, thus ex-ante FOMC event risk is, on average, equivalent to one day's equity volatility.

FOMC event risk varies significantly over time as the 5%/95% percentiles of event risk estimates are 0.29%/1.87%, a ratio of more than six. Sub-sample results indicate an increase in FOMC event risk over the sample, with an average estimate of 1.06% for the FOMC announcements post-2020. To frame the time variation, the VIX's 5%/95% percentiles were 10.85%/30.12%, a ratio of less than three, over the same sample.[17] Thus, FOMC event risk has a higher time series variability than common S&P 500 index risk metrics like the VIX index. To visualize the time-variation, Figure 2 plots FOMC event risk estimates for each meeting as well as a one-year rolling window average of FOMC event risk along with a confidence band at $\pm$ 1.96 times their standard error in shaded red. FOMC announcements with press conferences have gray bars, and those without a press conference have black bars. There are three notables.

First, FOMC event risk is highest at the sample's end in 2022/2023, with values often three to four times higher than in 2018 or even in 2020 during COVID. This highlights the significant differences between overall market risk (as captured by, e.g., the VIX index) and FOMC event risk. While overall market volatility was much higher during the initial COVID outbreak than towards the end of the sample, FOMC event risk was significantly lower. This heightened recent FOMC event risk is likely driven by high policy uncertainty associated with the Federal Reserve's effort to reduce inflation by raising rates and reducing the balance sheet.

[17]Using VIX data back to 1990 doesn't change the conclusion as 5%/95% percentiles are 11.33% and 33.46%, respectively.

Table II
FOMC Announcement Volatility

This table summarizes FOMC announcement volatility estimates for the event risk model of Section II.B using the procedure described in Section II.D. The columns are as follows: *Sample* indicates the sample period, *mean* and *t-stat* are the average FOMC event volatility and its HAC-corrected t-statistic, *median* is the median of the estimates, *perc(5)* and *perc(95)* are the 5th and 95th percentile, respectively, *% ≥ 1bps* is the percentage of estimates larger than 1bp., *Obs* are the number of observations, and *VIX Corr*, Δ *VIX Corr* and *Spot Vol. Corr* are the correlations of the event volatility estimate with the VIX index on the prior day's close, with the change in the VIX from the prior day's close to the close after the announcement and with the spot volatility $\sqrt{v_{\tau_i}}$ of the macroeconomic announcement model, respectively.

Sample	mean	t-stat	median	perc(5)	perc(95)	% ≥ 1bps	Obs	VIX Corr	Δ VIX Corr	Spot Vol. Corr
2012 to 2023	0.88	10.95	0.78	0.29	1.87	99	89	54%	-20%	47%
2012 to 2019	0.81	11.42	0.77	0.28	1.58	100	64	71%	-43%	25%
2020 to 2023	1.06	5.86	0.84	0.43	2.06	96	25	35%	-7%	63%
2014 to 2023	0.87	9.02	0.76	0.29	1.97	99	73	56%	-18%	55%

Second, FOMC meetings with press conferences generally have higher event risk than those without press conferences.[18] Press conferences were initially held every other meeting, but since 2019 after every meeting. In the early part of the sample, there was a clear increase in event risk for most FOMC meetings with press conferences. In terms of magnitudes, the FOMC event risk for meetings with accompanying press conferences can be more than twice as high as neighboring announcements without press conferences.

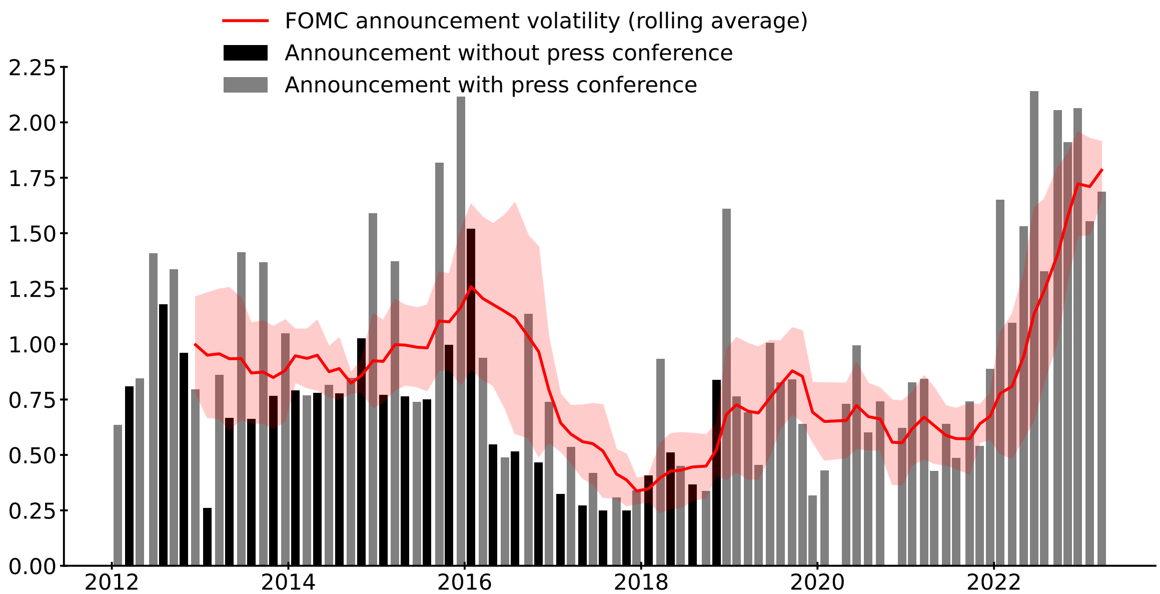
Third, two dates have notable estimates. The estimated FOMC event risk is very low for the January 2013 FOMC meeting, approximately 0.25%, much lower than neighboring meetings. This is likely due to very low anticipated volatility.[19] The second low FOMC volatility estimate is for November 5, 2020, immediately following the presidential election on Tuesday, November 3, 2020. The IV term structure reflected the fact the election was

[18] Boguth et al. (2019) and Narain and Sangani (2023) analyze realized volatility around FOMC meetings with press conferences and also note higher ex-post volatility.

[19] Confounding events may also have contributed. At the time, there was only a weekly Friday expiration, and there were two events prior to the short-term Friday expiry (a Monthly Payroll announcement followed the FOMC announcement). Low volatility is consistent with a lack of expected policy news at this meeting as the FOMC made a major policy announcement in their prior meeting, ending operation twist and announcing a major new bond purchase program and new thresholds for policy exit.

Figure 2. FOMC Announcement Volatility: Time Variation

This figure reports the times series of FOMC event risk, with rolling window estimates in red, using the procedure in Section II.D. Event risk for FOMC announcements without a press conference are in black, while FOMC event risk for announcements with a press conference are in gray. The rolling estimates are simple averages across the last eight announcements with confidence bands based on ± 1.96 times their HAC-corrected standard error.



contested and election uncertainty was not resolved or expected to resolve in the coming days, thus options were clearly pricing events outside our model.

Prior research has used the VIX index level and/or its changes to proxy for FOMC event risk. Indeed, IV does generally increase before and drop after FOMC announcements. To understand the connections, columns 9 and 10 of Table II report correlations between FOMC event risk and levels/changes in the VIX. While the correlations are generally statistically significant, they are somewhat modest in magnitude. The correlation between the VIX and FOMC event risk is 54% for the full sample. The correlation between FOMC event risk and the ex-post change in the VIX is negative, as expected, but smaller in magnitudes, -20%. These modest correlations indicate that the VIX is a noisy proxy for FOMC event risk, in part driven by background volatility and the VIX's longer one-month maturity.

Table III
FOMC Announcement Volatility: Press Conferences

This table summarizes the impact of press conferences on FOMC announcement volatility estimates. Columns 2 to 4 contain estimates for FOMC announcement risk for meetings without a press conference (risk is estimated 10 minutes before the announcement): *mean* is the average estimate, *t-stat* is the HAC-corrected t-statistic and *Obs* is the number of observations. Columns 5 to 7 provide estimates from ten minutes prior to FOMC statement for meetings with a subsequent press conference. Columns 8 to 10 provide estimates from ten minutes before the press conference. The final column (*% median*) is the median of the FOMC announcement variance before the press conference divided by the announcement variance before the FOMC statement (in percentage).

Sample	**FOMC without PC**			**FOMC with PC**						
				Pre-statement			**Press conference**			
	mean	t-stat	Obs	mean	t-stat	Obs	mean	t-stat	Obs	% median
2012 to 2023	0.68	8.55	27	0.98	9.33	62	0.79	8.85	62	62%
2014 to 2023	0.66	6.71	20	0.96	7.90	53	0.77	7.49	53	61%
2020 to 2023	–	–	0	1.09	5.84	25	0.95	6.40	25	68%
2012 to 2018	0.68	8.55	27	0.97	8.48	29	0.73	8.09	29	58%

This is particularly true for estimates based on the ex-post decline.[20] In contrast to the VIX, our estimates utilize the shortest-dated options, which load heavily on event risk. Additionally, the VIX frequently rolls from shorter to longer-dated options, often after the close on Wednesdays after the FOMC, which can create additional variation unrelated to the FOMC at a daily frequency. Idiosyncratic and predictable patterns generated by the VIX's construction have been previously noted; see, e.g., Mixon (2001) and Fernandez-Perez et al. (2017).

Next, consider FOMC press conferences, which raise two issues. First, as mentioned earlier, FOMC meetings with press conferences appear to have higher overall event risk. Over the full sample period, 62 FOMC announcements were followed by a press conference, and 27 were not. Columns 2 to 4 of Table III show that the average ex-ante FOMC event risk for meetings without a press conference is 0.68%, compared to 0.98% for meetings with a subsequent press conference (columns 5 to 7), a meaningful increase. Quantitatively, the

[20] Dubinsky et al. (2019) also found this for earnings announcements.

results are nearly identical for the 2012-2018 period, which indicates this isn't due to COVID and/or the FOMC's response to recent inflation.

Second, FOMC meetings with press conferences have two stages of uncertainty resolution, as total FOMC event risk is resolved both after the FOMC statement, released at 2:00 pm, and after the press conference, which typically runs from about 2:30 pm to 3:00 pm ET. To address this, consider a more granular analysis of FOMC event risk, which estimates total FOMC event risk (statement and press conference risk) ten minutes prior to the FOMC statement release and then re-estimates event risk subsequent to the FOMC statement but before the press conference. High-quality quote data is crucial for this exercise. Columns 8-11 in Table III summarizes the results. Significant FOMC event volatility remains after the initial statement on average (0.79%) and is only resolved after the press conference. The last column reports the median fraction of variance remaining after the statement but before the press conference to the total FOMC event variance is 62%. Thus, about 60% of the total FOMC event risk variance, a majority is resolved by the press conference. The results are similar over sub-samples, though press conferences do play a greater role post-2020. This is also consistent with Figure 2, above, which indicates that the difference is not driven by the fact that press conferences occurred after every meeting since 2019.[21]

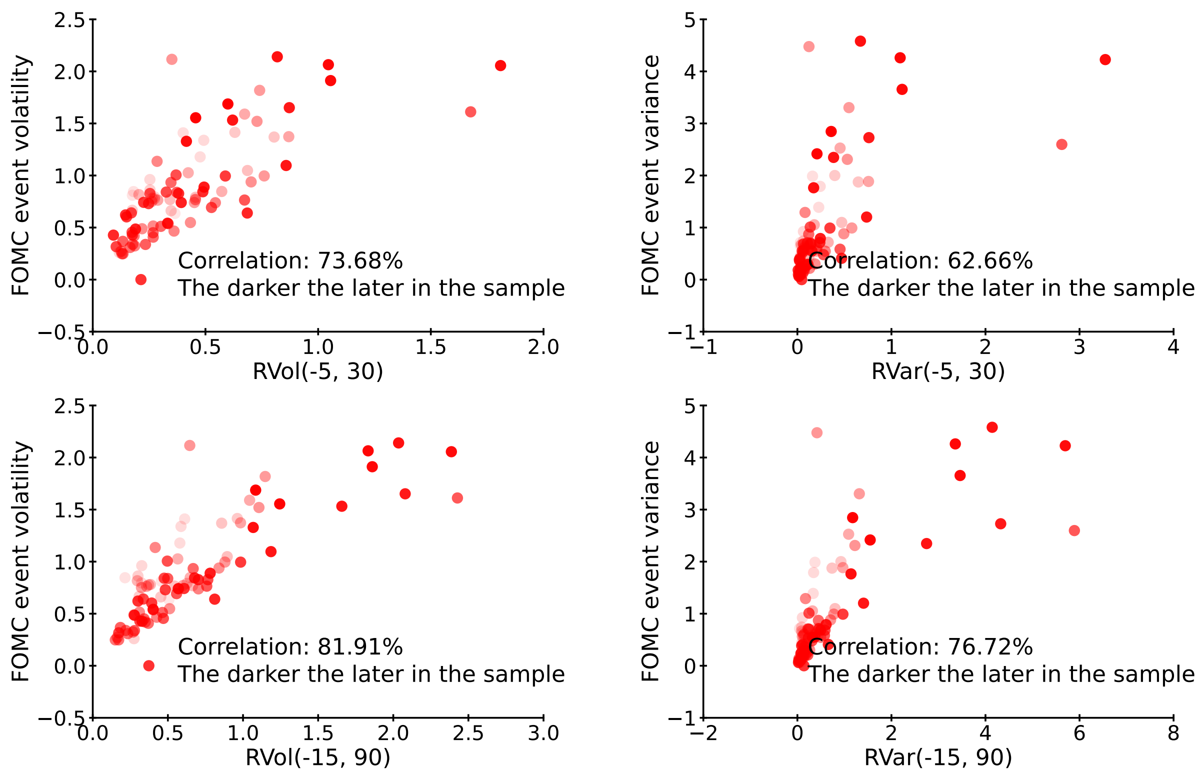
B. Predictability

Next, we quantify the extent to which ex-ante FOMC event risk estimates can predict ex-post stock index volatility. Option-based event risk estimates contain information about both event risk volatility premiums and $\mathbb{P}$-measure volatility. We measure the latter based on multiple common measures based on the realized volatility of high-frequency returns in an announcement window or by simpler (and noisier) measures such as the absolute return. $\text{RVol}(t_1, t_2)$ is the square root of the realized variance of 5-minute log futures returns from t_1 minutes before to t_2 minutes after the FOMC. We consider different windows, including relatively longer ones, in order to capture digestion time and the press conference. $\text{AbsRet}(-5, 15)$ is the absolute value of the log return from 5 minutes before the FOMC statement to 15 minutes after the statement, a measure of the immediate response to the FOMC statement. $\text{RVar}(t_1, t_2)$ denotes the square of the corresponding realized volatility

[21]Tables IA.B1 and IA.B2 in the Internet Appendix show that our results are robust to using other calibration objectives, such as minimizing the differences in prices or in log implied volatilities.

Figure 3. FOMC Announcement Event Risk vs Realized Volatility

This figure provides scatter plots of FOMC announcement risk and measures of realized volatility/variance. FOMC event risk volatility is the FOMC announcement volatility estimate for the macroeconomic announcement model of Section II.B (y-axis, first column). We use two realized volatility measures on the x-axis (first column): RVol(-5,30) and RVol(-15,90), which are the square root of the realized variance of 5-minute log (percentage) futures returns from 5 (15) minutes before the scheduled announcement to 30 (90) minutes after the announcement. Each marker represents one event volatility/realized volatility observation, where darker marker colors indicate that the observation is later in the sample. The second column provides corresponding plots in variance units, squaring both the FOMC event volatility (denoted FOMC event variance) and the realized volatility measures (denoted RVar(-5,30) and RVar(-15,90)).



measure.

Figure 3 graphs FOMC event risk estimates versus subsequent realized volatility in S&P 500 futures returns. The two left plots show FOMC event risk versus realized volatility for two different event windows (RVol$(-5, 30)$ and RVol$(-15, 90)$). We find a very high correlation between the ex-ante estimates of event risk and subsequent stock market volatility, with the correlation for the longer event window reaching almost 82%. The plots in the right column also show a strong relationship if both variables are measured in variance units, although the volatility association is stronger. There appears to be no evidence that the estimates before the additional Wednesday maturities were introduced in 2016 are biased. To see sample period effects, observations are shaded darker for later in the sample.

To formalize this, we report the Mincer-Zarnowitz volatility prediction regressions:

$$RV_i = \alpha + \beta_1 \times \sigma^{\mathbb{Q}}_{FOMC,\, i} + \beta_2 \times Vol_i + \varepsilon_i$$

where RV_i is the i^{th} FOMC announcement's realized volatility, $\sigma^{\mathbb{Q}}_{FOMC,\, i}$ is the ex-ante option-implied FOMC event risk, and Vol_i is a measure of diffusive spot volatility. We include two alternative controls for non-event "background" volatility Vol_i,: a rolling window GARCH estimates of the daily volatility on the announcement day and also the calibrated spot volatility state variable from the SV model prior to the event, $\sqrt{v_{\tau_i -}}$.[22]

[22]We use daily data for S&P 500 index returns and a GJR model with t-distributed error terms, using a rolling window to fit the model to five years of return data. We have used other specifications, but our conclusions are the same, and to economize on space, we do not report other estimation results.

Table IV
FOMC Volatility: Predictive Regressions

This table summarizes predictive regressions where the dependent variable is a measure of realized volatility around the FOMC announcement, and the independent variables include daily volatility measures and the FOMC event risk estimates from the model in Section II.B as follows: RVol(t_1, t_2) is the square root of the realized variance of 5-minute log futures returns from t_1 minutes pre-event to t_2 minutes post-event and AbsRet(-5,15) is the absolute value of the log futures return from 5 minutes pre-event to 15 minutes post-event. The columns are as follows: *const* reports the regression constant α, *Spot Vol (Options)* is the regression coefficient on $\sqrt{v_{\tau_i}}$ as a measure of spot volatility, *Spot Vol (GARCH)* is the coefficient on t-GARCH spot volatility, *Event Risk* is the coefficient on FOMC event risk, *R2* is the R^2 of the regression and *Obs* is the number of observations. t-statistics are reported in parenthesis and are HAC corrected.

Independent Variable	const	Spot Vol (Options)	Spot Vol (GARCH)	Event Risk	R2	Obs
RVol(-15, 90)	-0.08			0.83	0.67	89
	(-0.89)			(6.47)		
RVol(-15, 90)	-0.18		0.28	0.66	0.72	89
	(-2.09)		(3.65)	(5.89)		
RVol(-15, 90)	-0.23	0.43		0.68	0.75	89
	(-3.33)	(4.43)		(7.13)		
RVol(-5, 30)	0.02			0.47	0.54	89
	(0.34)			(6.49)		
RVol(-5, 30)	-0.00		0.05	0.43	0.55	89
	(-0.04)		(1.02)	(6.91)		
RVol(-5, 30)	-0.04	0.15		0.41	0.57	89
	(-0.68)	(2.11)		(6.13)		
AbsRet(-5, 15)	-0.02			0.36	0.28	89
	(-0.26)			(4.08)		
AbsRet(-5, 15)	-0.02		0.00	0.35	0.28	89
	(-0.25)		(0.07)	(4.09)		
AbsRet(-5, 15)	-0.07	0.15		0.30	0.30	89
	(-1.08)	(1.57)		(3.17)		

Table IV reports the regression results. For all combinations of realized and spot volatility measures, the option-implied FOMC event risk measure is a highly significant predictor of realized FOMC announcement volatility. With RVol$(-15, 90)$ as the dependent variable and controlling for option-implied spot volatility, the β-coefficient on $\sigma^{\mathbb{Q}}_{FOMC,\,i}$ is 0.68 with a t-statistic of more than seven. Option-implied diffusive spot volatility, $\sqrt{v_{\tau_i}}$, is also significant, though less so with a smaller coefficient and lower t-statistic. In regressions with FOMC event risk and a GARCH measure of spot volatility, the coefficient and significance are similar for FOMC event risk, but coefficients and t-statistics are somewhat lower for GARCH volatility. In the longer time windows, both event risk and diffusive spot volatility are significant, though event risk is more important, as these windows contain both event and diffusive risk. As expected, diffusive volatility is less important in short windows, as measured by RVol$(-5, 30)$ or AbsRet$(-5, 15)$, but event risk is still highly significant.

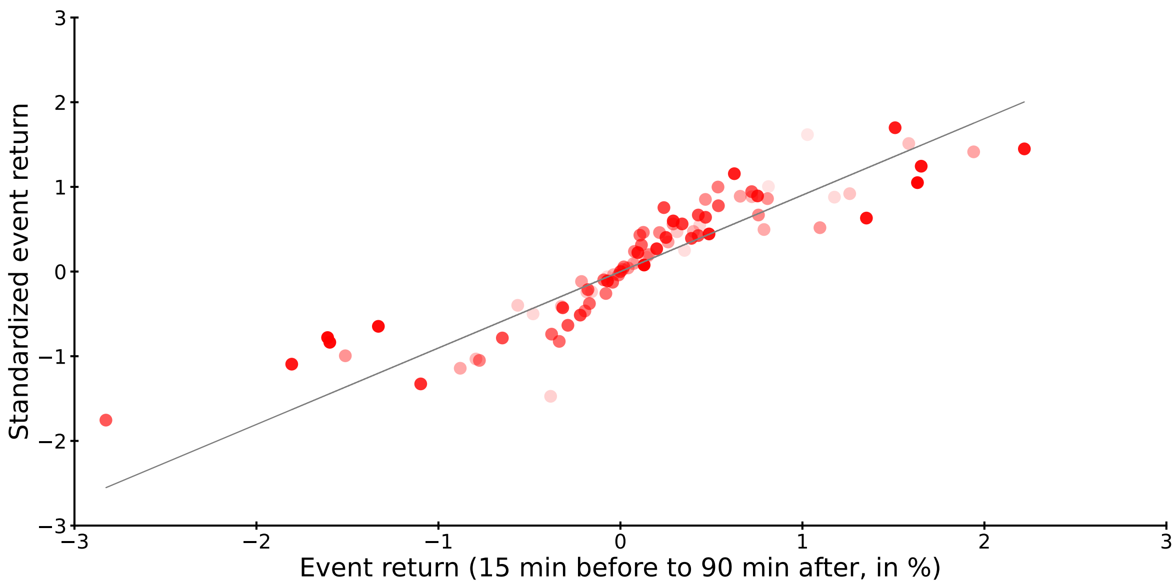
These results are consistent with the general model given earlier and prior research for several reasons. First, the FOMC event risk volatility is highly significant, as expected. R^2 values of 70% are extremely high for predicting realized volatility, much higher than is normally found in studies predicting, for example, daily volatility or earnings announcement volatility.[23] Second, markets do take some time to fully digest the FOMC announcement, especially with press conferences, which provide an additional role for other measures of secular volatility. It is well known in the literature that option-implied spot volatility has strong predictive power for non-event realized volatility. As expected the influence of spot or GARCH volatility decreases (and becomes less significant) when the announcement window is shortened, however, FOMC event risk remain highly significant. This is even true for a very noisy estimate of realized volatility such as AbsRet$(-5, 15)$ where $\sigma^{\mathbb{Q}}_{FOMC,\,i}$ is still highly significant in all specifications. The results are also robust in short sub-samples, for samples that only include observations for which the FOMC event is not the only announcement before the first option maturity, and when using a different objective function in the calibration (see Internet Appendix Tables IA.B3, IA.B4, IA.B5 and IA.B6).

These results document that ex-ante option implied information is highly predictive of subsequent realized volatility around FOMC events, indicating that $\mathbb{Q}$-measure information

[23] Asai et al. (2012) find maximal R^2 values around 50% for daily forecasts of S&P 500 index realized volatility. Dubinsky et al. (2019) find lower values predicting earnings announcements realized volatility from options.

Figure 4. FOMC Announcement Volatility: Standardized Return Shocks

This figure provides standardized and un-standardized returns around the FOMC announcements. The sample period is from 1/2012 to 3/2023 and excludes the FOMC announcement in November 2020 (presidential election).



is closely related to $\mathbb{P}$ realizations. This does not rule out risk premia, a topic we explore in detail below using straddles in narrow windows around the FOMC events.

The time-variation in event risk and realized volatility has implications for commonly used monetary policy shocks extracted from S&P 500 futures returns. The above results imply that the volatility of commonly used announcement shocks is highly predictable. This suggests that a better measure of an FOMC "shock" would be to standardize the futures returns around the FOMC announcement by our ex-ante measure of volatility.[24] Figure 4 plots the raw returns standardized by our measure of ex-ante event volatility. The figure shows a noticeable "S"-shaped pattern, as large positive and negative returns are down-weighted as they typically occur in high volatility environments. As argued first by Rosenberg (1972), time-varying volatility generates outliers and non-normalities, which can, in principle, explain the extreme non-normalities in monetary policy shocks documented by Jarocinski (2023).

[24]See Johannes et al. (2022) for a similar analysis in crude futures markets.

Monetary policy shocks effect not only aggregate equity markets but also bond markets given their systematic nature. To supplement our predictability results, we analyze the ability of our equity index FOMC event volatilities to predict bond market realized volatility. In general, FOMC event risk captures two components: the volatility of monetary policy shock to fundamentals as well as the sensitivity of the S&P 500 index to those fundamentals, similar to the model of Hu et al. (2022). Formally, we can intuitively decompose S&P 500 index FOMC event risk as: $\beta_{S\&P}\sigma^{\mathbb{Q}}_{FOMC}$, where $\sigma^{\mathbb{Q}}_{FOMC}$ is the monetary policy shock and $\beta_{S\&P}$ captures the impact of this shock on the S&P 500 index. Our option implied estimators capture the product of the two, and it is straightforward to evaluate the extent to which the S&P 500 index event risk captures time-variation that is correlated with the same quantities in the bond market.

Table V and Figure 5 summarize the results for Federal Fund, Eurodollar 2, 5, 10, and 30-year bond futures.[25] For Federal Fund and Eurodollar futures, we construct constant maturity futures with targeted maturities close to six months and one year, respectively. For Treasuries, we use front-month futures rolling based on daily trading volumes. Figure 5 shows that shorter-dated Fed Fund Futures and Eurodollar returns around FOMC events are relatively small, consistent with clear Fed communication on short-term decisions. In fact, these short-dated contracts have zero realized volatility for many FOMC events.

Figure 5 shows a significant relationship for longer-dated bond futures, with correlations above 50%. Table V runs predictive regressions for bond market realized volatility on FOMC event risk extracted from S&P 500 index options as well a measure of bond market spot volatility based on a GJR-GARCH model. For all markets and specifications, S&P 500 extracted FOMC event risk is significant on its own or when GARCH volatility is included, indicating that our index option event risk measure is capturing broad monetary policy shocks. The coefficient on bond market spot volatility is typically larger in size and has higher t-statistics, consistent with different loadings on FOMC shocks. This isn't surprising as aggregate equities have cash flow risks that aren't present in bond markets.

[25] The 30-year bond futures are the regular bond futures, not the longer term, "ultra" bond futures.

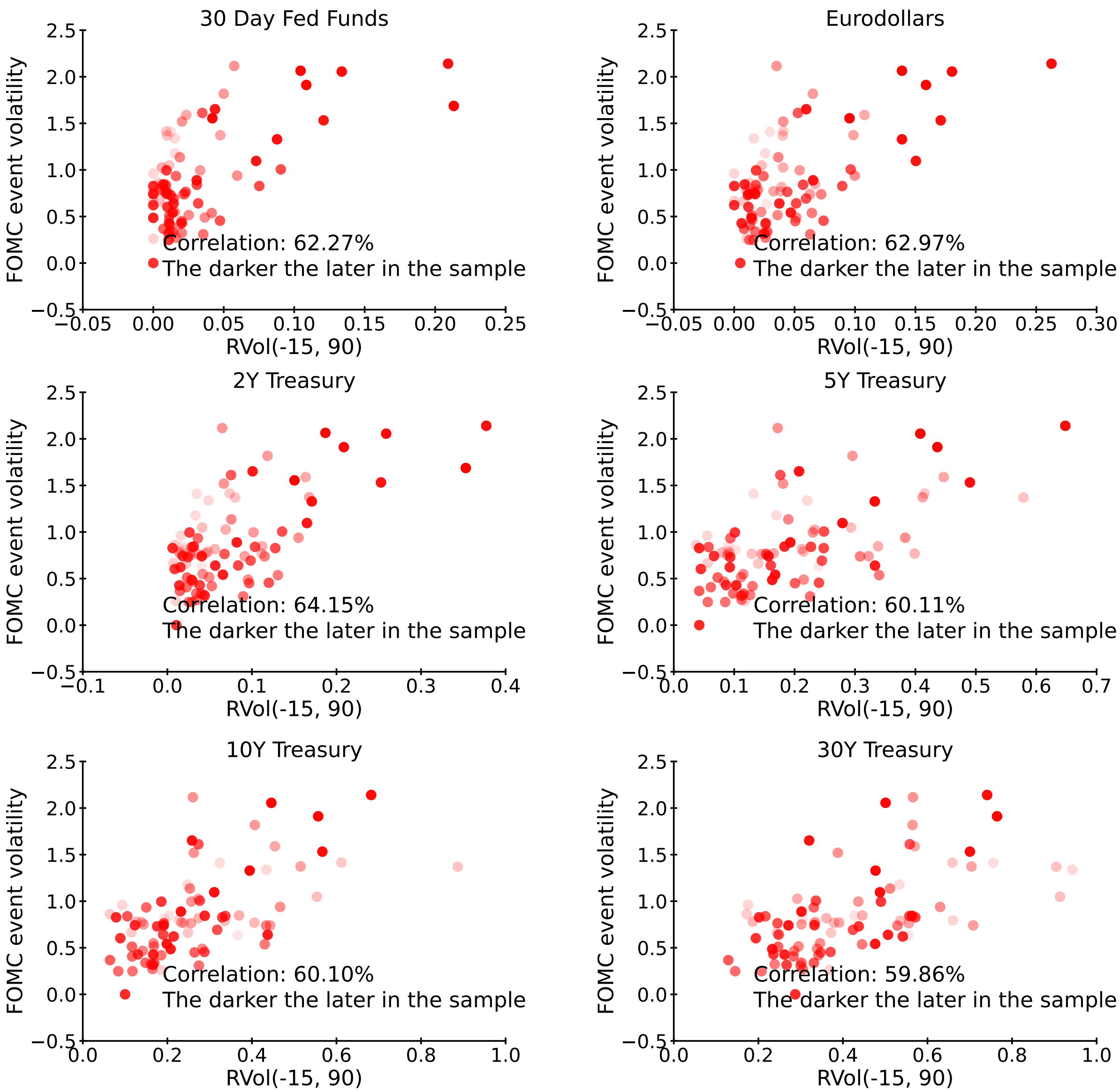
Table V
FOMC Volatility: Bond Market Predictive Regressions

This table summarizes predictive regressions where the dependent variable is the realized bond market volatility from 15 minutes before to 90 minutes after the FOMC announcement (RVol(-15,90)), and the independent variables include a daily bond-market volatility forecast for the day of the FOMC announcement (using a GJR-GARCH model) and the FOMC event risk estimates from the model in Section II.B. The columns are as follows: *Instrument* provides details on the futures contract, *const* reports the regression constant α and the corresponding HAC-corrected t-statistic in parenthesis, *Spot Volatility* is the coefficient and t-statistic on the bond-market GJR-GARCH spot volatility, *Event Risk* are the coefficient and t-statistic on FOMC event risk, *R2* is the R^2 of the regression, *Obs* are the number of observations and *Avg Mat* is the average maturity of the Instrument (in days). The sample period for 30-Day Fed Fund Futures, Eurodollars, and 2Y Treasury Futures is from 1/2012 to 3/2023. The sample period for 5Y Treasury Futures, 10Y Treasury Futures, and 30Y Treasury Futures is from 1/2012 to 12/2022.

Instrument	const		Spot Volatility		Event Risk		R2	Obs	Avg Mat
30 Day Fed Funds	-0.02	(-1.66)			0.05	(3.54)	0.39	89	169
	-0.01	(-1.46)	0.35	(4.42)	0.04	(3.21)	0.69		
Eurodollars	-0.01	(-0.66)			0.06	(3.26)	0.40	88	323
	-0.02	(-2.66)	1.34	(10.34)	0.03	(2.73)	0.75		
2Y Treasury	-0.01	(-0.54)			0.10	(3.93)	0.41	89	79
	-0.01	(-1.29)	0.77	(4.07)	0.05	(3.56)	0.74		
5Y Treasury	0.05	(1.77)			0.17	(4.42)	0.36	86	79
	-0.08	(-2.94)	1.10	(5.76)	0.09	(3.31)	0.54		
10Y Treasury	0.10	(3.73)			0.20	(5.38)	0.36	86	69
	-0.11	(-2.23)	0.93	(4.62)	0.13	(4.10)	0.48		
30Y Treasury	0.22	(8.68)			0.24	(6.88)	0.36	86	69
	0.03	(0.43)	0.40	(3.31)	0.20	(4.95)	0.41		

Figure 5. FOMC Announcement Event Risk vs Realized Bond Volatility

This figure provides scatter plots of FOMC announcement risk and measures of realized bond-market volatility. FOMC event risk volatility is the FOMC announcement volatility estimate for the macroeconomic announcement model of Section II.B (y-axis). Realized volatility is the square root of the realized variance of 5-minute log (percentage) futures returns from 15 minutes before the scheduled announcement to 90 minutes after the announcement (x-axis). The realized volatility is given for various different bond market instruments: 30-day Fed Funds, Eurodollars, 2Y Treasury Futures, 5Y Treasury Futures, 10Y Treasury Futures and 30Y Treasury Futures. Each marker represents one event volatility/realized volatility observation, where darker marker colors indicate that the observation is later in the sample. The full sample period is from 1/2012 to 3/2023.



C. Resolution of FOMC Uncertainty

Lucca and Moench (2015) document a striking pattern of large upward drifts in stock index returns in the days and hours prior to FOMC meetings. To explain this, a number of authors have posited risk-based stories, see, e.g., Ai et al. (2022) and Hu et al. (2022). In these models, event risk in FOMC and other macroeconomic announcements is priced and significantly resolved in the days and hours leading up to the announcements. At the core of these models is a quantitative reduction in perceptions of ex-ante event risk volatility due to attention, learning, or even potentially information leaks.

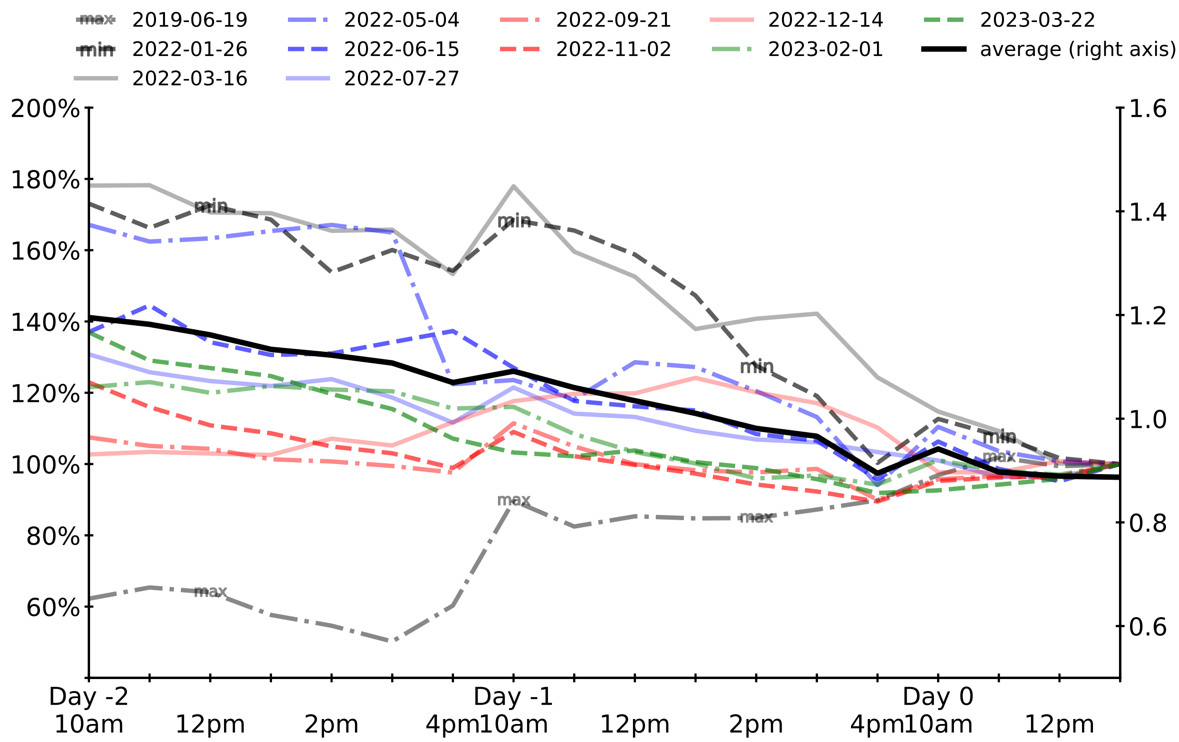
Our approach is well-suited to evaluating these uncertainty dynamics, as it is feasible to directly estimate FOMC event risk in the days/hours leading up to an FOMC meeting and avoid noisy proxies for event risk like the VIX.[26] We estimate FOMC event risk starting two full business days prior to the announcement day using the same approach as described in Section II.D. For example, we start estimating FOMC event risk on Monday morning for a Wednesday FOMC meeting (denoted Day -2). At every full hour during the trading day, we re-estimate the event volatility. This provides seven estimates for each of the two trading days before the announcement (sampled hourly from 10 am ET to 4 pm ET) and four estimates on the announcement day (10 am, 11 am, 12 pm and 1 pm, which are denoted Day 0), for a total of 18 time-series estimates. In an economy without any pre-event resolution of uncertainty, FOMC event risk estimates should be roughly constant in the days prior to the announcement, with any variation driven by sampling noise. Estimates of event risk evolution in the days prior to the FOMC meeting are particularly clean for meetings without other confounding macroeconomic announcements in the days leading up to the FOMC. For this reason, we report results for two samples: the full sample, including all FOMC announcements, and a second sample, which contains the 48 meetings without confounding announcements in the two trading days before the meeting.

Figure 6 provides the average FOMC event volatilities for the 18 hourly time periods prior to the FOMC for this second sample (bold black line on the right axis), as well as the evolution for recent individual FOMC meetings and the meetings with the largest increase

[26]Calendar time indices like the VIX have additional problems in that they tend to fall into weekends, spike over the weekend, and then decrease during the week. For example, for a Tuesday FOMC meeting, three days prior is a Friday, which mechanically induces a large drop over the weekend, a spike higher on Monday, followed by a slow decline during the week. See, e.g., Mixon (2001).

Figure 6. FOMC Announcement Volatility: Resolution of Uncertainty

This figure provides estimates of average FOMC announcement volatility using options data at different points before the announcement. We report the average of all FOMC announcements without a confounding macroeconomic announcement (black line, right axis), as well as FOMC event risk estimates for the last eight announcements in this sample, as well as the announcements with the highest and lowest absolute drift in FOMC announcement volatility (which occurred in June 2019, labeled *max*, and January 2022, labeled *min*). The individual announcement volatility drifts are given as percentages of their final FOMC announcement volatility at 1 pm ET on Day 0 (left axis). Day -2 is two trading days before the announcement date, Day -1 is the trading day before the announcement, and Day 0 is the announcement day. The sample period is from 1/2012 to 3/2023.



and decrease. Note that the estimates trend down in the days prior to the FOMC announcement, with very small upward increments during the overnight periods. Overall, the average FOMC event risk decreases from roughly 1.20% to 0.87%, a substantial risk reduction. Note that changes in our announcement volatility estimates are very smooth, which suggests that our effects are robust and that our procedure accurately captures these declines. The time series standard errors are of the order of 0.1%, largely due to the large time-series variation in levels over time.

Event risk estimates for the last eight FOMC announcements in the sample are also in Figure 6, as a percentage of their final FOMC event volatility. Most announcements show a significant resolution of uncertainty, with estimates in some cases dropping by more than 50%. Only the FOMC announcement in September 2022 shows almost no ex-ante volatility resolution. By contrast, the FOMC announcement in June 2019 shows a marked increase of about 40% and is the largest absolute increase in announcement volatility in our sample. Although uncertainty resolution explanations generally posit a decline in event risk, there is no reason that a similar learning mechanism couldn't generate increases in announcements, which is observed for some FOMC meetings.

To evaluate statistical significance, Table VI documents that the downward drift in FOMC announcement event risk is statistically significant. Panel A reports results for the full sample, for which the average drift, defined as the difference between event risk of Day 0 (1 pm ET) and Day -2 (10 am ET) is -0.14% with a t-statistic of -2.39. For FOMC meetings without confounding macroeconomic events, the effects are stronger with a drift of more than 30bps (t-statistic: -4.95).

The precise estimates of event risk allow a direct evaluation of the relationship between FOMC event risk and S&P 500 index futures returns. To do this, we calculate the correlation between changes in event risk estimates and S&P 500 futures returns. Table VI reports a statistically significant negative correlation: -34.54% for all announcements but even more negative for FOMC announcements without confounding macroeconomic announcements (Panel B), -50.01%, both statistically significant. Thus, not only is there resolution of uncertainty, but index returns are negatively correlated with ex-ante FOMC event risk changes. This decline is consistent with theoretical models previously offered in the literature and consistent with the decline in the VIX index previously documented. Hu et al. (2022) argue in a two-stage model that investors acquire information allowing them to more accurately estimate the FOMC event risk in the period prior to the FOMC announcement. The decline in FOMC event risk we document corresponds to their 'impact uncertainty,' the volatility of event shocks. Ai et al. (2022) have a similar argument about information acquisition in a continuous-time model prior to the FOMC announcement. This is also consistent with information leakage, as argued in Mano (2021).

Table VI
FOMC Volatility: Statistics of Uncertainty Resolution

This table provides statistics related to the drift in the FOMC announcement volatility. Panel A reports statistics over all FOMC announcements in the sample period from 1/2012 to 3/2023. Panel B reports statistics for a sub-sample that includes only FOMC announcements without a confounding announcement in the two days prior to the FOMC. The first row in each panel provides the average change of the estimate of the FOMC announcement volatility from two days before the announcement to the announcement day (Difference between Day 0 (1 pm ET) and Day -2 (10 am ET) FOMC event risk estimate). The second row in each panel provides the correlation between the change in estimated FOMC announcement volatilities and the S&P 500 futures log return during the same pre-announcement time period. The columns *t-stat* and *p-value* provide the corresponding t-statistic or p-value.

Variable	Statistic	t-stat	p-value
Panel A: All FOMC Announcements (89 observations)			
Average difference between Day 0 (13 pm) and Day -2 (10 am) estimates of FOMC announcement volatility (in %)	-0.14	-2.39	
Correlation (in %) between the drift (difference between Day 0 (13 pm) and Day -2 (10 am) FOMC announcement volatility) and log return of S&P 500 futures over same time period	-34.54		0.00
Panel B: No Confounding Announcements Prior to FOMC (48 observations)			
Average difference between Day 0 (13 pm) and Day -2 (10 am) estimates of FOMC announcement volatility (in %)	-0.31	-4.95	
Correlation (in %) between the drift (difference between Day 0 (13 pm) and Day -2 (10 am) FOMC announcement volatility) and log return of S&P 500 futures over same time period	-52.01		0.00

These results are even more striking given that Kurov et al. (2021) argue that FOMC price drifts have largely disappeared since 2015. It is important to note, though not previously recognized, that even if average drifts are insignificant, the correlation between FOMC event risk and S&P 500 futures returns could still be significant, as drifts upward for meetings with uncertainty resolution are offset by index return drifts downward for FOMC meetings for which uncertainty increases prior to the FOMC announcement. The absence of average drifts may only reflect the fact that uncertainty increases into some FOMC events and does not imply that index returns are unrelated to FOMC event risk changes. Overall, our estimates find both strong declines in FOMC event risk prior to the FOMC as well as a significant negative correlation with index returns, consistent with risk-based theories.

D. Straddle Returns and Event Risk Premia

In models with jumps, randomly arriving or prescheduled jumps cannot be perfectly hedged using standard Merton-style hedging arguments with continuously distributed sizes. This, and the systematic nature of crash risks, is consistent with widely documented jump-risk premiums for index returns (see, e.g., Pan (2002) or Broadie et al. (2007)). Given the systematic nature of FOMC shocks and the unhedgeable nature of jumps at FOMC events, this section evaluates the variance risk premium associated with FOMC events.

In this section, we focus on straddle returns around FOMC announcements. ATM straddles are useful for understanding volatility risk premia, given their high sensitivity to volatility and event risk.[27] With intraday quote data, straddle returns can be cleanly measured in a narrow window around the FOMC event, mitigating confounding factors and cleanly measuring event volatility risk premia from option prices. These estimates don't require estimates of realized volatility.

To do this, for each FOMC announcement, we collect mid quotes for ATM straddles 15 minutes before the FOMC announcement and match them with mid quotes for the same strike straddle post-event to calculate finite holding period returns. Consistent with our earlier definition, a strike level is defined ATM if the price difference between the put and call is the smallest of all other put/call strike pairs with the same maturity. With this construction, ATM straddles are approximately delta-neutral. We report straddle returns for windows of lengths 30m, 45m, 75m, and 105m, in part because some FOMC announcements have press conferences. Since our construction yields a single straddle return per option maturity, we calculate equally weighted averages for different days-to-maturity (DTM) buckets.

Table VII summarizes the results. Overall, FOMC announcements generate significantly negative straddle returns, consistent with a significant FOMC event risk premium. In the announcement window from 15 minutes before to 15 minutes after the FOMC announcement, short-term options (DTM $\leq$ 7) have an average return of -4.01% (t-statistic: -4.05) and longer-term straddles (DTM $\leq$ 60) have an average return of -1.48% (t-statistic: -4.40). As expected, short-term straddles have greater exposure to FOMC event risk, but their returns

[27]We provide more details on delta-hedged returns in the Internet Appendix.

Table VII
Straddle Returns around FOMC Announcements

This table presents at-the-money (ATM) straddles holding period returns realized by holding the straddle from before an FOMC announcement to after the announcement. We work with different event windows provided in Column 1 to account for the fact that announcements may have different digestion times. The window [-15, 15] indicates that the straddle is held from 15 minutes before the announcement to 15 minutes after the announcement, and similarly for other event windows. Since our construction yields one straddle return per option maturity, we calculate equally weighted straddle returns for different days-to-maturity (DTM) buckets (provided in Column 2). The remaining columns are as follows: *mean* is the average straddle return, *t-stat* is the HAC-corrected t-statistic and *Obs* is the number of FOMC announcements in the sample.

Window	DTM	mean	t-stat	Obs
[-15, 15]	0 to 7	-4.01	-4.05	89
	0 to 60	-1.48	-4.40	89
[-15, 30]	0 to 7	-5.02	-4.89	89
	0 to 60	-1.71	-4.91	89
[-15, 60]	0 to 7	-4.46	-2.81	89
	0 to 60	-1.45	-2.71	89
[-15, 90]	0 to 7	-4.48	-2.37	89
	0 to 60	-1.29	-2.09	89

are also more volatile. Straddle returns for other event windows are comparable in size and remain significant throughout.

In order to understand these returns better, to account for other well-known risk premia/anomalous returns (see Jones and Shemesh, 2018 and Muravyev and Ni, 2020), and to benchmark magnitudes, we compute straddle returns for otherwise similar time periods. To do this, we construct ATM straddles in hourly intervals from 9:45 am to 3:45 pm. This implies that each FOMC announcement falls into an hourly interval during the trading day. The overnight category starts at 3:45 pm on the previous trading day. The construction is very similar to the delta-hedged returns of Muravyev and Ni (2020) and ensures that the resulting straddle time series remains ATM. Most importantly, this procedure generates returns for each hourly interval in our sample in order to compare the effects of FOMC events from other periodic option return patterns. With these hourly returns, we estimate a regression model for straddle returns, including dummy variables for each hourly period (Mon 9:45 am, Mon 10:45 am, ..., to Friday 3:45 pm) and a dummy variable for the FOMC announcements.

Table VIII
Straddles and Delta-Hedged Returns: Hourly Returns

This table provides regression results for an at-the-money (ATM) straddle time series of hourly returns and for hourly delta-hedged returns. The coefficients reported in column *Coefficient* are for the regression coefficient of the dummy variable that controls for the occurrence of FOMC announcements and can be interpreted as the return in addition to any seasonal return. We also control for time of the day and weekday effects using dummy variables, but these controls are not reported. *DTM* denotes days-to-maturity and *t-stat* is the HAC-corrected t-statistic of the FOMC dummy variable. The sample period is from 1/2012 to 3/2023.

Variable	DTM	Coefficient	t-stat
FOMC straddle dummy variable	0 to 7	-4.47	-3.63
FOMC straddle dummy variable	0 to 60	-1.55	-3.70
FOMC delta-hedged return dummy variable	0 to 7	-4.71	-5.97
FOMC delta-hedged return dummy variable	0 to 60	-2.28	-5.38

Table VIII reports regression coefficients for the FOMC dummy variable, interpreted as the excess return relative to any periodic returns in the same time interval. For the shortest maturity bucket, FOMC straddle returns average -4.47%, controlling for other factors, while longer-term straddles average -1.55%, both highly statistically significant. While the construction and holding periods are slightly different, the results are consistent with those reported in Table VII. In Table VIII, we also report results for a similar regression exercise where we replace the hourly ATM straddle returns with hourly delta-hedged returns, closely following the methodology outlined in Muravyev and Ni (2020). For these, the statistical significance is even stronger. This implies that the raw straddle returns were not related to any periodic components.

To compare the FOMC announcement results to previously documented seasonalities in Jones and Shemesh (2018) and Muravyev and Ni (2020), we consider another regression exercise with an FOMC dummy variable and additional dummy variables for (a) intraday periods (i.e. all trading periods except the ones starting at 3:45 pm ET) (b) overnight periods (i.e. all trading period starting at 3:45 pm ET) and (c) weekends (i.e. the Friday trading period starting at 3:45 pm ET). Table IX reports the results, with two notable results. First, we confirm the strong intraday/overnight and weekend effects previously reported. Second, FOMC event risk magnitudes are economically large, and despite the much smaller sample,

Table IX
Straddles: Comparison with Overnight and Weekend Effects

This table summarizes regressions for hourly at-the-money (ATM) straddle returns. We include dummies for (a) intraday periods (i.e. all hours except those starting at 15:45:00), (b) overnight periods (i.e. all trading periods starting at 15:45:00), and (c) weekends (i.e. the Friday trading period starting at 15:45:00). The coefficients in column *Coefficient* are on the dummy variable capturing FOMC announcements and can be interpreted as the return in addition to any seasonal return. *DTM* denotes days-to-maturity and *t-stat* is the HAC-corrected t-statistic of the FOMC dummy variable. The sample period is from 1/2012 to 3/2023.

Variable	DTM	Coefficient	t-stat
intraday dummy variable	0 to 7	-0.39	-6.00
overnight dummy variable	0 to 7	-1.38	-3.77
weekend dummy variable	0 to 7	-1.89	-2.17
FOMC dummy variable	0 to 7	-4.19	-3.56
intraday dummy variable	0 to 60	-0.10	-4.29
overnight dummy variable	0 to 60	-0.45	-3.56
weekend dummy variable	0 to 60	-0.99	-3.17
FOMC dummy variable	0 to 60	-1.44	-3.57

the significance is similar to the other two effects. The same exercise for delta-hedged returns (unreported) has similar conclusions, although the effect for the overnight premium increase and the weekend effect weakens compared to the straddle results. Together, these results suggest the FOMC volatility risk premium is quantitatively larger than previously identified volatility risk premiums/anomalies at intraday frequencies.

IV. Macroeconomic Announcements

In addition to FOMC announcements, other macroeconomic announcements generate event risk. In this section, we summarize event risk embedded in employment, CPI, Core PCE, and GDP reports, as well as the annual Jackson Hole Federal Reserve conference speech given by the Federal Reserve chair.

A. Announcement Volatility Estimates

Like FOMC meetings, major macroeconomic announcements occur at predictable times and generate large and significant asset price movements as shocks to important macroeconomic announcements are priced in financial markets. Our models and estimation methodology apply not only to FOMC announcements but, more generally, to other macroeconomic announcements. In this section, we apply our estimation procedure to extract estimates of GDP, CPI, Core PCE, Jackson Hole, and Monthly Payrolls event risk just prior to these events. As most macroeconomic announcements occur at 8:30 am ET, prior to March 9, 2015, we use options data at 3:50 pm ET on the trading day before the announcements. After this date, SPX options quotes are available for the pre-market trading session, and we use option data one hour before the announcement.

Table X provides macroeconomic announcement volatility estimates for the full sample and subsamples. For the full sample, FOMC announcements have the largest event risk with an average of 0.88% (t-statistic is 10.95, reported in Table II) whereas CPI (0.80%), core PCE (0.60%), GDP (0.58%), Jackson Hole speeches (0.78%) and monthly payrolls (0.78%) are somewhat smaller though all highly significant. Similar to the FOMC results, estimates in the first part of the sample from 2012 to 2019 are lower than those from 2020 to 2023. The increase in CPI and GDP announcement volatility is particularly pronounced (from 0.64% to 1.18% for CPI and from 0.48% to 0.83% for GDP). Despite the small subsample sizes (in particular for the second subsample), the announcement volatilities remain highly significant.

Our results imply that the vast majority of event risk estimates are bounded away from zero, though there are some events with zero estimated event risk. As discussed earlier, this can occur if there are unaccounted events (other macroeconomic or policy announcements) and/or heightened non-event SV, and it occurs more frequently for smaller announcements and earlier in the sample when identification is more difficult due to fewer expiries. Payrolls, Jackson Hole speeches, and CPI are least likely to have zeros, consistent with their overall importance and size. Like FOMC event risk, macroeconomic event risk estimates are also time-varying and persistent, as shown in Figure 7. Compared to FOMC announcements, macroeconomic event risk is more variable and there is a sharper increase in macroeconomic event risk at the onset of the pandemic in 2020. In particular, CPI event risk post-Covid is about three times larger in 2022 than pre-Covid.

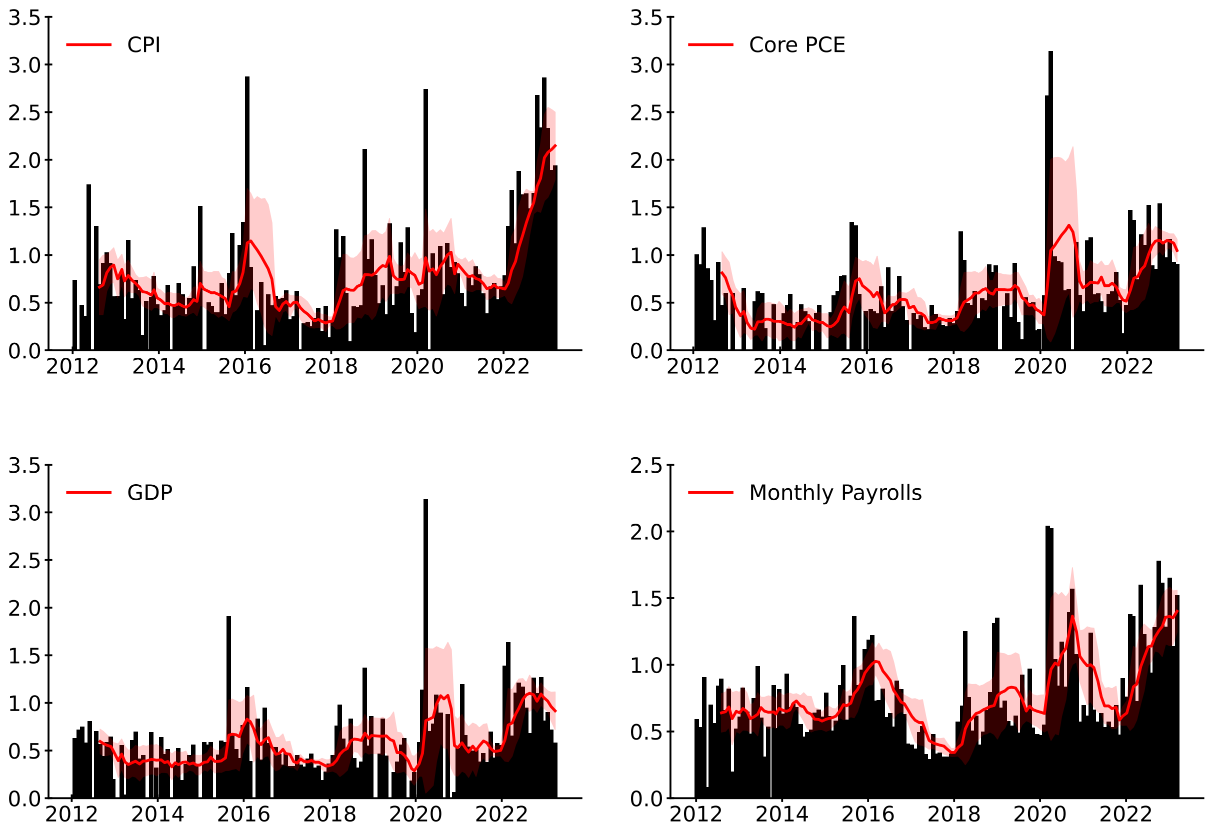
Table X
Macroeconomic Announcement Volatility

This table summarizes the announcement volatility estimates for the macroeconomic announcement model of Section II.B. For each CPI, Core PCE, GDP, Jackson Hole, and Monthly Payroll announcement, the volatility is estimated by minimizing Equation (2). We use option data at 3:50 pm prior to March 9, 2015, and option data one hour before the announcement after March 9, 2015. We include all announcement categories (CPI, Core PCE, FOMC, GDP, Jackson Hole, and Monthly Payroll) as control variables and also control for political events. Standard errors (and hence t-statistics) use the HAC correction. The remaining columns are as follows: *median* is the median of the estimates, *perc(5)* and *perc(95)* are the 5th and 95th percentile, respectively, *% ≥ 1bps* is the percentage of estimates larger than one basis point, *Obs* are the number of observations, and *VIX Corr*, Δ *VIX Corr* and *Spot Vol. Corr* are the correlations of the announcement volatility estimate with the VIX index on the close prior to the announcement, with the change in the VIX from the close prior to the announcement to the close after the announcement, and with the spot volatility of the macroeconomic announcement model $\sqrt{v_{\tau_i}}$, respectively. The sample period is from 1/2012 to 3/2023.

Announcement	Sample	mean	t-stat	median	perc(5)	perc(95)	% ≥ 1bps	Obs	VIX Corr	Δ VIX Corr	Spot Vol. Corr
CPI	2012 to 2023	0.80	9.67	0.63	0.04	1.99	94	135	62%	-2%	52%
	2012 to 2019	0.64	11.96	0.55	0.00	1.33	93	96	59%	-7%	28%
	2020 to 2023	1.18	6.46	0.88	0.45	2.68	97	39	43%	-4%	49%
Core PCE	2012 to 2023	0.60	9.75	0.51	0.00	1.32	87	133	79%	19%	75%
	2012 to 2019	0.46	11.08	0.43	0.00	0.96	84	95	52%	19%	28%
	2020 to 2023	0.95	7.83	0.90	0.36	1.71	97	38	84%	27%	91%
GDP	2012 to 2023	0.58	11.88	0.53	0.00	1.23	90	134	73%	-17%	70%
	2012 to 2019	0.48	14.07	0.46	0.00	0.89	88	95	64%	-33%	47%
	2020 to 2023	0.83	8.03	0.71	0.06	1.42	94	39	72%	-11%	75%
Jackson Hole	2012 to 2023	0.78	6.87	0.70	0.37	1.27	100	9	85%	80%	81%
	2012 to 2019	0.64	8.78	0.64	0.37	0.97	100	6	82%	80%	90%
	2020 to 2023	1.05	9.79	1.15	0.69	1.33	100	3	82%	99%	66%
Monthly Payrolls	2012 to 2023	0.78	14.96	0.66	0.33	1.54	100	135	81%	-7%	74%
	2012 to 2019	0.66	18.29	0.62	0.31	1.20	100	96	66%	-6%	50%
	2020 to 2023	1.05	10.91	1.04	0.53	1.81	100	39	79%	-2%	85%

Figure 7. Other Announcement Volatility: Time Variation

This figure provides rolling window estimates of CPI, Core PCE, GDP, and Monthly Payroll announcement volatility (red) for our macro-announcement model introduced in Section II.B. The estimates are the averages across the last eight announcements (hence, they span one calendar year, with ± 1.96 times their standard error). The black bars are the individual announcement volatilities estimated by the model.



The relationship between the VIX and macroeconomic event risk is less clear than it was for FOMC announcements. The correlation with VIX spot levels tends to be higher, consistent with greater market risk in many of these announcements. This is especially true for Core PCE, payrolls, and Jackson Hole speeches. This could, in part, be due to the fact that clusters of correlated macroeconomic announcements have a combined larger effect on the VIX. The correlation with the ex-post decline in the VIX is quite varied: largely insignificant for the CPI and payrolls, positive for Core PCE and Jackson Hole (very small sample size), and moderately negative for GDP.

We also investigate predictability, by regressing realized futures returns around events on volatility measures including macroeconomic event risk. These tests are important in part to validate our ability to estimate the event risk accurately and to understand the relationship between option-implied and realized measures of event risk. Our design of this exercise is similar to Section III.B with the exception that we run a multivariate regression to account for the fact that some announcements occur at the same time and that some event windows overlap. Another important difference between FOMC and GDP, Core PCE, CPI, and Monthly payrolls is that the latter are not reported during the ordinary trading day. While futures are traded around the clock one expects the digestion of information in macroeconomic announcements may be more rapid during ordinary trading hours.

Table XI shows that our macroeconomic event risk estimates are highly predictive of future realized volatility of the S&P 500 index, for every measure of realized volatility and independent of which spot volatility controls. As before, the strongest results are obtained for $\text{RVol}(-15, 90)$ where t-statistics for all major announcement types consistently exceed 5, with R^2 of 61%-63%. An advantage of the longer announcement window is that the 90-minute window includes the market open and hence accounts for any lagged price adjustments that are incorporated at the start of the ordinary trading session. The results for $\text{RVol}(-5, 30)$ and $\text{AbsRet}(-5, 15)$ confirm the predictive power of our macro-announcement volatility estimates for shorter announcement windows, with t-statistics of more than 3.

Table XI
Macroeconomic Announcement Volatility: Predictive Regressions

This table summarizes the results from the predictive regressions where the independent variable is a measure of realized volatility around the macroeconomic announcement, and the dependent variables include daily volatility measures and the macro announcement volatility estimates from the macro announcement model in Section II.B. The independent variables are as follows: RVol(-5,30) is the square root of the realized variance of 5-minute log returns from 5 minutes before the scheduled announcement to 30 minutes after, RVol(-15,90) is defined similarly but using a longer announcement window starting 15 minutes before the announcement and ending 90 minutes after the announcement, AbsRet(-5,15) is the absolute value of the log return between 5 minutes before the announcement to 15 minutes after. The following columns are: *const* is an estimate of the regression constant α, *Spot Vol* is the β_2-coefficient if the spot volatility $\sqrt{v_{\tau_i}}$ from the macroeconomic announcement model is used, *Ann Vol* is the estimate of the β_1-coefficient, *R2* is the R^2 of the regression and *Obs* are the number of observations. The sample period is from January 2012 to March 2023. t-statistics are reported in parenthesis and are HAC corrected.

Variable	RVol(-15, 90)		RVol(-15, 90)		RVol(-5, 30)		RVol(-5, 30)		AbsRet(-5, 15)		AbsRet(-5, 15)	
const	-0.00	(-0.05)	-0.01	(-0.34)	-0.02	(-0.66)	-0.02	(-0.73)	-0.02	(-0.71)	-0.03	(-0.91)
Spot Vol (GARCH)	0.12	(3.04)	–	–	0.05	(1.92)	–	–	0.00	(0.01)	–	–
Spot Vol (Options)	–	–	0.22	(3.41)	–	–	0.10	(1.96)	–	–	0.04	(0.72)
CPI	0.45	(5.30)	0.40	(5.06)	0.37	(3.98)	0.35	(3.95)	0.40	(3.59)	0.38	(3.42)
Core PCE	0.31	(5.46)	0.25	(4.87)	0.19	(3.76)	0.16	(3.35)	0.17	(3.23)	0.14	(2.69)
FOMC	0.65	(9.88)	0.63	(10.24)	0.45	(8.54)	0.43	(8.38)	0.36	(5.64)	0.34	(5.26)
GDP	0.35	(5.83)	0.31	(5.60)	0.20	(3.81)	0.18	(3.27)	0.22	(3.74)	0.19	(3.05)
Jackson Hole	0.38	(2.40)	0.38	(2.45)	0.58	(3.55)	0.57	(3.50)	0.29	(3.99)	0.27	(3.84)
Monthly Payrolls	0.49	(10.36)	0.45	(10.34)	0.40	(8.15)	0.38	(8.39)	0.35	(5.93)	0.32	(5.52)
Obs	616		616		620		620		620		620	
R2	0.60		0.63		0.45		0.46		0.31		0.31	

V. Additional Empirical Results

This section reports additional empirical results, robustness checks of results, and extensions.

A. Alternative Pricing Models

The event risk estimates relied on the Bates (1996) SVJ model as the structural benchmark model. This model, especially when calibrated daily, is highly flexible and can accurately fit the cross-section of SPX index options data well on ordinary trading days (i.e. days not affected by announcements). Intuitively, the SVJ model can generate a wide range of IV smiles and term structures. The goal was to combine a flexible SV model with crash risks to capture the non-event components with parsimonious event risk specifications.

To quantify the robustness of our event risk estimates to the non-event model, we re-estimate event risk parameters with alternative option pricing models. To do this, we focus on jump models driven by CGMY model dynamics of Carr et al. (2003), a highly flexible and commonly used extension of Bates (1996). In this model, the non-event index dynamics under the risk-neutral measure are given by

$$\begin{aligned} dx_t &= \left(r - \tfrac{1}{2}v_t\right) dt + \rho\sqrt{v_t}dW^{\mathbb{Q}}_{1t} + \sqrt{1-\rho^2}\sqrt{v_t}\, dL_t, \\ dv_t &= \kappa(\theta - v_t)dt + \sigma_v\sqrt{v_t}dW^{\mathbb{Q}}_{2,t}, \end{aligned}$$

where dL_t is the increment of a compensated CMGY process. The logarithm of the generalized characteristic function of the generalized CMGY process is given by

$$\ln \Psi_L(t,T,u) = -\omega u(T-t) + (T-t)V\left[w_n \frac{(G+u)^{Y_n} - G^{Y_n}}{Y_n(Y_n-1)G^{Y_n-2}} + (1-w_n)\frac{(M-u)^{Y_p} - M^{Y_p}}{Y_p(Y_p-1)M^{Y_p-2}}\right]$$

where ω is a normalizing constant, V is the variance per unit time and w_n is the fraction of downward jumps, and $u \in \mathbb{C}$.

The parameter range of this process is given by $G, M > 0$ and $Y_p, Y_n < 2$. For $Y_p, Y_n < 0$ the process has finite activity, for $Y_p, Y_n < 1$ the process has finite variation. Setting $Y_n = Y_p = 1$ yields a time-changed version of the double exponential jump model of Kou (2002), denoted SV-DEXP, and setting $Y_n = Y_p = 0$ provides a time-changed variance gamma model

Table XII
Effect of Pricing Model on Announcement Volatilities

This table provides estimates for the announcement volatilities for different baseline models for x_t over the sample period from January 2012 to March 2023. SV is the pure stochastic volatility of Heston (1993), SVJ is the stochastic volatility model with normal jump sizes of Bates (1996), SV-DEXP is the stochastic volatility model with time-changed double-exponentially distributed return jumps and SV-VG uses variance-gamma distributed jumps. The last two models are versions of the general Levy model studied in Bates (2012). We report HAC-corrected t-statistics.

Model	SV (mean)	SV (t-val)	SV-DEXP (mean)	SV-DEXP (t-val)	SV-VG (mean)	SV-VG (t-val)	SVJ (mean)	SVJ (t-val)
CPI	0.78	(9.64)	0.79	(9.77)	0.78	(9.43)	0.80	(9.67)
Core PCE	0.60	(10.08)	0.58	(9.32)	0.59	(9.69)	0.60	(9.88)
FOMC	0.85	(10.60)	0.87	(11.01)	0.87	(10.95)	0.88	(10.95)
GDP	0.58	(12.35)	0.57	(11.66)	0.58	(12.08)	0.58	(11.92)
Jackson Hole	0.80	(5.76)	0.80	(5.71)	0.76	(6.03)	0.80	(5.79)
Monthly Payrolls	0.78	(14.89)	0.77	(14.61)	0.77	(15.08)	0.78	(15.00)

(Madan and Seneta, 1990), denoted SV-VG. These models are nested in the model presented in Bates (2012), to which we refer to the reader for further details, including option pricing.

Table XII provides event risk estimates for both the FOMC and macroeconomic announcements for the various models of the non-announcement-related dynamics x_t: SVJ, SV-DEXP and SV-VG. We also include the Heston (1993) pure diffusion model, denoted SV, to include a model with well-known difficulties fitting very short-term S&P 500 index volatility smiles. For the FOMC, the three jump models have an almost identical average FOMC event risk size: as previously reported in Table II, the estimate for SVJ is 0.88%, whereas SV-VG and SV-DEXP yield average volatilities of 0.87%. The differences are, as expected, generally quite small, even for the SV model, which implies that the baseline non-event model has at most a minor impact on our average estimates. The same conclusions apply to the three other announcements (CPI, GDP and Monthly Payrolls) where the estimates for the three jumps models are also mostly within 1-2 bps.

To go one step further, Table XIII provides the Pearson and Spearman correlations between the SVJ event risk estimates and those in alternative benchmark SV models. For the FOMC, the correlations between SVJ and the two alternative price jumps models are in excess of 98%, and even the relatively poorly fitting SV model still has only slightly lower

Table XIII
Correlation Between Announcement Volatilities of Different Pricing Models

This table provides Spearman and Pearson correlation coefficients between the announcement volatilities of SVJ and alternative baseline models for x_t over the sample period from January 2012 to March 2023. The alternative models are (a) SV, the stochastic volatility model of Heston (1993), (b) SV-DEXP, the stochastic volatility model with time-changed double-exponentially distributed return jumps, and (c) SV-VG, a stochastic volatility model with variance-gamma distributed jumps. The last two models are versions of the general Levy model studied in Bates (2012).

Model	SV (Pearson)	SV (Spearman)	SV-DEXP (Pearson)	SV-DEXP (Spearman)	SV-VG (Pearson)	SV-VG (Spearman)
CPI	0.97	0.93	0.99	0.98	0.95	0.94
Core PCE	0.98	0.95	0.98	0.96	0.97	0.94
FOMC	0.97	0.95	0.99	0.98	0.99	0.98
GDP	0.94	0.88	0.94	0.91	0.92	0.86
Jackson Hole	1.00	1.00	1.00	1.00	0.98	0.93
Monthly Payrolls	0.97	0.96	0.96	0.96	0.99	0.99

correlations. High correlation coefficients are also observed for the other macroeconomic announcements. This confirms that our estimates are not only similar on average but highly correlated across announcements for alternative reasonable choices for the dynamics of x_t. This also confirms that the "signatures" of event risk are quite different from those of SV and crash risk, as discussed earlier.

The list of alternative models tested here is, of course, not exhaustive, but similar arguments apply to other models. Multi-factor variance models, for instance, allow for some additional flexibility to model the mean reversion of volatility. This is not expected to be an important feature for our data set as we are focusing on short-term options that are sensitive to announcements. In contrast, multi-factor variance specifications generally feature one very slowly moving variance factor that cannot be identified from short-term options. Overall, the results indicate event risk estimates are robust to SV components.

B. Simple Announcement Volatility Estimates

To estimate FOMC event risk, we calibtrate a structural SV model to account for time-varying volatility, price jumps as well as other macroeconomic announcements. In this section, we compare these structural estimates to relatively simple and easy-to-compute regression-based estimates based only on ATM Black-Scholes IVs. This procedure can be viewed as an extension of the term structure estimator in Dubinsky et al. (2019).

As discussed earlier, estimating event risk for all of the macroeconomic announcements is difficult for two reasons. First, this model assumes diffusive volatility is constant, and there are no leverage effects or price jumps, both of which can and do impact ATM IVs. Second, and more importantly, there are typically multiple maturities that are informative about event risks, though longer-dated options have a lesser sensitivity. In order to combine the information in all of the maturities, we use a simple cross-section least squares approach, regressing IVs on maturity variables, with the regression coefficients capturing the event risk. To understand the approach, recall that in a constant volatility model with normally distributed event jump sizes, Black-Scholes IV is given by:

$$\sigma_{t,T_i}^2 = \sigma^2 + \frac{\sum_{j=M_t+1}^{M_{t+T_i}} \left(\sigma_j^{\mathbb{Q}}\right)^2}{T_i - t}.$$

This regression approach estimates the following model

$$\sigma_{t,T_i}^2 = \sigma^2 + \frac{N^{FOMC}(t,T_i)}{T_i - t} \times \sigma_{FOMC}^2 + \sum_{c \in \{CPI, PCE, Jobs, GDP\}} \frac{N^c(t,T_i)}{T_i - t} \times \sigma_c^2 \quad + \; \varepsilon_i \tag{4}$$

where σ_{t,T_i} is the ATM IV of SPX options as time t with maturity T_i and $N^{FOMC}(t, T_i)$ is the number of FOMC announcements prior to maturity (and similarly for the other announcement types). The constant in the regression model is the annualized diffusive variance σ^2. The regression coefficients are the variances of the macroeconomic events. Rather than using unrestricted OLS, we impose the restriction that all regression parameters are non-negative, as they are variances. If multiple announcements of the same announcement type occur prior to the longest-dated maturity, they are included, though the magnitudes are assumed to be the same. Non-FOMC announcements are included as control variables, though our primary interest is FOMC event risk. The regression model is estimated using the same data as was used for the structural estimation. It is important to note that t is fixed in this regression and the data points are from the ATM IV term structures at a single time point before the announcement, thus it is a point-in-time cross-sectional regression.

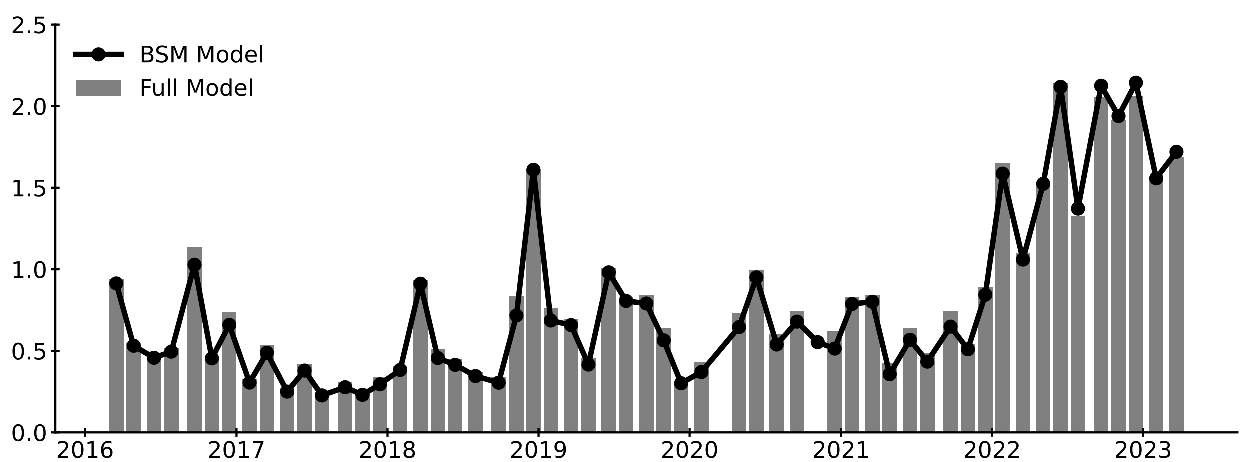
Table XIV
Simple FOMC Announcement Volatility Estimates

This table provides a comparison of FOMC announcement event risk estimates for the full structural model (Bates (1996)) and simple Black-Scholes-based estimates. *All (Bates Model)* provides results for the full sample from 2012 to 2023 when the Bates model is used. *All (BS Model)* provides results for the full sample from 2012 to 2023 when the Black-Scholes model is used, and the estimates are obtained by regression (4). *Full identification* restricts the sample to 2016 to 2023 when Wednesday option expiries became available. The remaining columns are as follows: *mean* is the average of the FOMC announcement volatility estimates, and *t-stat* is the corresponding HAC-corrected t-statistic. *median* is the median of the estimates, *perc(5)* and *perc(95)* are the 5th and 95th percentile, respectively, *% ≥ 1bps* is the percentage of estimates larger than one basis point, *Obs* are the number of observations.

Sample	mean	t-stat	median	perc(5)	perc(95)	% ≥ 1bps	Obs
All (Full Model)	0.88	10.95	0.78	0.29	1.87	99	89
All (BSM Model)	0.80	9.18	0.66	0.00	1.87	93	89
Full identification (Full Model)	0.80	6.98	0.67	0.27	1.95	98	56
Full identification (BSM Model)	0.78	6.52	0.61	0.27	1.98	100	56

Figure 8. Simple FOMC Announcement Volatility Estimates: Time Series

This figure provides a comparison of FOMC announcement event risk estimates for the full structural model (Bates (1996), *Full Model*) and simple Black-Scholes-based estimates (*BSM Model*). We restrict the sample to January 2016 to March 2023, as Wednesday option expiries became available in 2016.



The estimation results are presented in Table XIV and Figure 8. For the entire sample, the first row reports the full structural model for comparison. The second row provides our simple estimates using Black-Scholes IVs. Note first that the simple estimates are somewhat smaller and downward biased, with an average of 0.80% compared to 0.88% for the full structural model. In particular, there are also now additional events with zero estimates. All of these zero estimates occurred in the first parts of the sample when there were much fewer expiries available. With additional maturities in the latter parts of the sample, the discrepancies shrink. With short-term options expiring almost every day, SV and jump factors have only a minor impact on FOMC event risk as short-dated options are given greater weight in the regression, diffusive volatility is persistent, and the term-structure impact on options with maturities differing by only a few days is minor.

To analyze this empirically, we provide a second sample (called full identification), which starts in March 2016. At this point, Wednesday expiries are available and provide clean identification of the FOMC announcement risk. For this sub-sample, the estimate from the simple BSM model and the full structural model are even closer with 0.78% and 0.80% average FOMC announcement volatility. We plot the time series of these two estimations in Figure 8: apart from one observation (which follows the presidential election in 2020), the models closely correspond. These results suggest that the simple model estimates are useful and highly robust alternatives once short-term options became available.

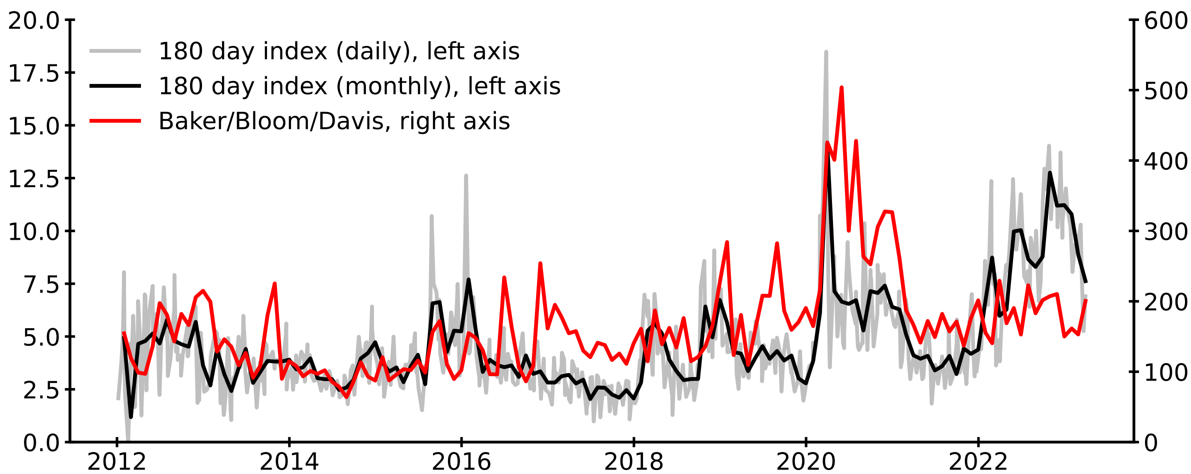
C. Macro Risk Index

The rolling window estimates presented in Figure 2 document that FOMC event risk changes over time. In this section, we construct a forward-looking index of event risk as follows. On each day of a macro announcement (either CPI, Core PCE, FOMC, GDP, Jackson Hole, or Monthly Payroll), we estimate all the macro announcement volatilities from our model in Section II.B (denoted $\sigma_{c,0}$ where c is the announcement category) and use the volatilities to predict the macro risk forward. To do so, we select a horizon D (usually 180 days) and count the number of all upcoming announcements in the six announcement categories until the end of the chosen horizon. For the FOMC announcements, these are denoted $N^{FOMC}(t,T)$ as before. The announcement risk index is then calculated as follows:

$$\text{MacroRisk(D days)} = \sqrt{\frac{365}{D} \times \sum_{c \in I} N^c(t, D/365) \times \sigma_{c,0}^2},$$

Figure 9. Macro Risk Index

This figure provides a time series of the forward-looking macro-announcement risk index MacroRisk(180 days), both at daily and monthly levels. For the daily index, we update the index before each announcement in our sample and predict macro risks at different horizons. For the monthly index, we average the index per calendar month and compare the index to the news-based policy uncertainty index of Baker et al. (2016).



where I collects the six different announcement categories. The index can be interpreted as the annualized volatility that originates from macroeconomic announcements over the next D days.

Figure 9 shows the index for a horizon of 180 days. The daily index is updated before every new macro announcement and is ex-ante. The monthly index aggregates the index over a monthly horizon by averaging the daily index values in each calendar month. This means the index is an average index, not an end-of-the-month index. We also compare our index to the macroeconomic uncertainty index developed in Baker et al. (2016) (right axis). While there is a moderate correlation between the different indices, we find that macroeconomic uncertainty, as measured by the reaction of the stock market, is much more pronounced post-COVID.

VI. Conclusion

This paper provides a methodology to estimate FOMC and macroeconomic announcement event risk from high-frequency option data on the S&P 500 index. Options are a natural source of information about event risks, given their forward-looking nature. On the methodological side, our approach combines the predictable timing of FOMC announcements with three ingredients: (1) additional daily option expiries that became actively traded in 2011, (2) high-quality intraday quote data, and (3) structural stochastic volatility (SV) models augmented with predictable events. This approach allows us to estimate and analyze the pricing of FOMC announcement event risk (as well as other macroeconomic announcements).

Empirically, we find evidence for significant FOMC and macroeconomic event risk, with additional evidence that these risks vary significantly over time. We decompose FOMC event risk into statement risk and press conference risk, with evidence indicating that the meetings with press conferences have higher event risk and that the vast majority is related to risks associated with the press conference. Option implied FOMC event risk strongly predicts not only S&P 500 futures realized volatility but also fixed income futures. FOMC event risk carries an economically large and statistically significant event risk premium, as straddle returns in windows spanning FOMC announcements are negative. We also investigate uncertainty resolution and find both that FOMC event risk falls or resolves in the days prior to the FOMC meeting and that FOMC event risk variation is significantly negatively correlated with S&P 500 futures returns, strong evidence in favor of risk-based explanations for the FOMC drift.

A number of extensions are left for future research. The first is to analyze the FOMC information effect of Nakamura and Steinsson (2018), whereby FOMC meetings resolve additional macroeconomic uncertainty. This can be analyzed in our setting by characterizing variation in future macroeconomic risks (e.g., jobs reports) around FOMC events. Second, given our forward-looking measures of event risk and the modest correlation between event risk and other standard risk measures such as the VIX, it would be interesting to investigate the informativeness of the forward-looking macro-risk index estimated from options.

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Internet Appendix to “FOMC Event Risk”

Appendix IA.A. Further Details on the Option Dataset

We process the raw data as follows. First, we discard options where the bid price is not smaller than the ask price. We then calculate the mid-price using the average of the bid and ask quotes and discard options that have a negative time to maturity recorded. Second, for each timestamp and option maturity on each trading day in the sample, we calculate the at-the-money strike price by choosing the strike for which the put and call option mid prices are closest to each other. We use this call and put pair to calculate the implied forward price using put-call parity and the one-month treasury yield from FRED (St. Louis Fed) as a substitute for the risk-free rate. Using the implied forward price, we calculate implied volatilities using the Black model, as well as option Greeks. We require at least ten valid option prices per maturity. The combination of option price, strike, implied forward price, risk-free rate, maturity, and implied volatility serves as input to various calculations, such as model-based option prices or straddles.

Appendix IA.B. Additional Results

The following tables provide additional robustness checks mentioned in the main paper.

Table IA.B1
FOMC Announcement Volatility (Log-IV Objective Function)

This table summarizes the FOMC announcement volatility estimates for the macroeconomic announcement model of Section II.B. For each FOMC announcement, the volatility is estimated by minimizing the RMSE based on the differences of log implied-volatilities one hour before the FOMC announcement. We include the other announcement categories (CPI, Core PCE, GDP, Jackson Hole, and Monthly Payroll) as control variables and also control for political events. The columns are as follows: *Sample* indicates the sample years, *mean* and *t-stat* are the average announcement volatility and its corresponding HAC-corrected t-statistic, *median* is the median of the estimates, *perc(5)* and *perc(95)* are the 5th and 95th percentile, respectively, *% ≥ 1bps* is the percentage of estimates larger than one basis point, *Obs* are the number of observations, and *VIX Corr*, Δ *VIX Corr* and *Spot Vol. Corr* are the correlations of the announcement volatility estimate with the VIX index on the close prior to the announcement, with the change in the VIX from the close prior to the announcement to the close after the announcement, and with the spot volatility $\sqrt{v_{\tau_i}}$ of the macroeconomic announcement model, respectively. The full sample is from 1/2012 to 3/2023.

Sample	mean	t-stat	median	perc(5)	perc(95)	% ≥ 1bps	Obs	VIX Corr	Δ VIX Corr	Spot Vol. Corr
2012 to 2023	0.89	10.49	0.77	0.28	1.97	98	89	55%	-21%	49%
2012 to 2019	0.80	12.02	0.75	0.27	1.46	98	64	69%	-47%	36%
2020 to 2023	1.12	5.59	0.91	0.42	2.34	96	25	33%	-8%	49%
2014 to 2023	0.88	8.69	0.74	0.29	2.05	99	73	57%	-19%	55%

Table IA.B2
Announcement Volatility (Price Objective Function)

This table summarizes the FOMC announcement volatility estimates for the macroeconomic announcement model of Section II.B. For each FOMC announcement, the volatility is estimated by minimizing the RMSE based on the differences in market and model prices one hour before the FOMC announcement. We include the other announcement categories (CPI, Core PCE, GDP, Jackson Hole, and Monthly Payroll) as control variables and also control for political events. The columns are as follows: *Sample* indicates the sample years, *mean* and *t-stat* are the average announcement volatility and its corresponding HAC-corrected t-statistic, *median* is the median of the estimates, *perc(5)* and *perc(95)* are the 5th and 95th percentile, respectively, *% ≥ 1bps* is the percentage of estimates larger than one basis point, *Obs* are the number of observations, and *VIX Corr*, Δ *VIX Corr* and *Spot Vol. Corr* are the correlations of the announcement volatility estimate with the VIX index on the close prior to the announcement, with the change in the VIX from the close prior to the announcement to the close after the announcement, and with the spot volatility $\sqrt{v_{\tau_i}}$ of the macroeconomic announcement model, respectively. The full sample is from 1/2012 to 3/2023.

Sample	mean	t-stat	median	perc(5)	perc(95)	% ≥ 1bps	Obs	VIX Corr	Δ VIX Corr	Spot Vol. Corr
2012 to 2023	0.93	10.48	0.79	0.29	2.07	99	89	57%	-21%	55%
2012 to 2019	0.82	12.93	0.75	0.29	1.48	98	64	66%	-44%	53%
2020 to 2023	1.20	5.63	1.04	0.36	2.48	100	25	37%	-9%	42%
2014 to 2023	0.94	8.90	0.76	0.34	2.11	100	73	58%	-19%	58%

Table IA.B3
FOMC Volatility: Predictive Regressions (2020-2023)

This table summarizes the results from the predictive regressions where the independent variable is a measure of realized volatility around the macroeconomic announcement, and the dependent variables include daily volatility measures and the macro announcement volatility estimates from the macro announcement model in Section II.B. The independent variables are as follows: RVol(-5,30) is the square root of the realized variance of 5-minute log returns from 5 minutes before the scheduled announcement to 30 minutes after, RVol(-15,90) is defined similarly but using a longer announcement window starting 15 minutes before the announcement and ending 90 minutes after the announcement, AbsRet(-5,15) is the absolute value of the log return between 5 minutes before the announcement to 15 minutes after. The following columns are: *const* is an estimate of the regression constant α, *Spot Vol (Options)* is the β_2-coefficient if the spot volatility $\sqrt{v_{\tau_i}}$ from the macroeconomic announcement model is used, *Spot Vol (GARCH)* is the β_2-coefficient if spot volatility is proxied by a GARCH estimate, *Event Risk* is the estimate of the β_1-coefficient, *R2* is the R^2 of the regression and *Obs* is the number of observations. t-statistics are reported in parenthesis and are HAC corrected. The sample is from 1/2020 to 3/2023.

Independent Variable	const	Spot Vol (Options)	Spot Vol (GARCH)	Event Risk	R2	Obs
RVol(-15, 90)	-0.09			1.00	0.87	25
	(-1.09)			(10.85)		
RVol(-15, 90)	-0.22		0.18	0.92	0.90	25
	(-3.24)		(2.78)	(11.31)		
RVol(-15, 90)	-0.27	0.27		0.89	0.89	25
	(-2.90)	(1.80)		(7.66)		
RVol(-5, 30)	-0.01			0.51	0.63	25
	(-0.14)			(5.33)		
RVol(-5, 30)	-0.03		0.03	0.50	0.64	25
	(-0.30)		(0.43)	(5.69)		
RVol(-5, 30)	-0.09	0.12		0.47	0.64	25
	(-0.69)	(0.99)		(4.87)		
AbsRet(-5, 15)	0.01			0.36	0.31	25
	(0.12)			(2.92)		
AbsRet(-5, 15)	0.03		-0.03	0.38	0.31	25
	(0.23)		(-0.31)	(3.51)		
AbsRet(-5, 15)	-0.10	0.16		0.30	0.32	25
	(-0.60)	(1.09)		(2.21)		

Table IA.B4
FOMC Volatility: Predictive Regressions with Confounding Events

This table summarizes predictive regressions where the dependent variable is a measure of realized volatility around the FOMC announcement, and the independent variables include daily volatility measures and the FOMC event risk estimates from the model in Section II.B as follows: RVol(t_1, t_2) is the square root of the realized variance of 5-minute log futures returns from t_1 minutes pre-event to t_2 minutes post event and AbsRet(-5,15) is the absolute value of the log futures return from 5 minutes pre-event to 15 minutes post-event. The columns are as follows: *const* reports the regression constant α, *Spot Vol (Options)* is the regression coefficient on $\sqrt{v_{\tau_i}}$ as a measure of spot volatility, *Spot Vol (GARCH)* is the coefficient on t-GARCH spot volatility, *Event Risk* is the coefficient on FOMC event risk, *R2* is the R^2 of the regression and *Obs* is the number of observations. The sample period is from 1/2012 to 3/2023 and includes only FOMC announcements that have a confounding macroeconomic announcement. t-statistics are reported in parenthesis and are HAC corrected.

Independent Variable	const	Spot Vol (Options)	Spot Vol (GARCH)	Event Risk	R2	Obs
RVol(-15, 90)	0.15			0.43	0.38	22
	(1.91)			(3.82)		
RVol(-15, 90)	-0.02		0.16	0.46	0.43	22
	(-0.16)		(1.81)	(4.50)		
RVol(-15, 90)	-0.01	0.23		0.47	0.45	22
	(-0.12)	(2.04)		(4.28)		
RVol(-5, 30)	0.06			0.38	0.43	22
	(1.07)			(5.50)		
RVol(-5, 30)	0.00		0.06	0.38	0.44	22
	(0.04)		(0.86)	(7.23)		
RVol(-5, 30)	-0.07	0.19		0.40	0.50	22
	(-1.63)	(3.18)		(8.37)		
AbsRet(-5, 15)	-0.09			0.41	0.31	22
	(-1.82)			(4.86)		
AbsRet(-5, 15)	-0.02		-0.07	0.40	0.32	22
	(-0.18)		(-0.66)	(4.37)		
AbsRet(-5, 15)	-0.16	0.10		0.42	0.33	22
	(-1.83)	(0.98)		(5.00)		

Table IA.B5
FOMC Volatility: Predictive Regressions: Log IV Objective Function

This table summarizes the results from the predictive regressions where the independent variable is a measure of realized volatility around the FOMC announcement, and the dependent variables include daily volatility measures and the FOMC volatility estimates from the macro announcement model in Section II.B. The FOMC announcement volatilities are obtained by minimizing the RMSE based on the differences in log market and model implied volatilities. The independent variables are as follows: RVol(-5,30) is the square root of the realized variance of 5-minute log returns from 5 minutes before the scheduled announcement to 30 minutes after, RVol(-15,90) is defined similarly but using a longer announcement window starting 15 minutes before the announcement and ending 90 minutes after the announcement, AbsRet(-5,15) is the absolute value of the log return between 5 minutes before the announcement to 15 minutes after. The following columns are: *const* is an estimate of the regression constant α, *Spot Vol (Options)* is the β_2-coefficient if the spot volatility $\sqrt{v_{\tau_i}}$ from the macroeconomic announcement model is used, *Spot Vol (GARCH)* is the β_2-coefficient if spot volatility is proxied by a GARCH estimate, *Event Risk* is the estimate of the β_1-coefficient, *R2* is the R^2 of the regression and *Obs* is the number of observations. t-statistics are reported in parenthesis and are HAC corrected. The full sample is from 1/2012 to 3/2023.

Independent Variable	const	Spot Vol (Options)	Spot Vol (GARCH)	Event Risk	R2	Obs
RVol(-15, 90)	-0.05			0.80	0.69	89
	(-0.80)			(7.79)		
RVol(-15, 90)	-0.16		0.27	0.65	0.74	89
	(-2.25)		(3.68)	(7.40)		
RVol(-15, 90)	-0.24	0.43		0.66	0.76	89
	(-3.59)	(4.56)		(8.02)		
RVol(-5, 30)	0.03			0.44	0.55	89
	(0.75)			(7.22)		
RVol(-5, 30)	0.01		0.05	0.41	0.56	89
	(0.20)		(0.99)	(7.66)		
RVol(-5, 30)	-0.02	0.12		0.40	0.57	89
	(-0.41)	(1.90)		(6.40)		
AbsRet(-5, 15)	-0.01			0.34	0.29	89
	(-0.17)			(4.43)		
AbsRet(-5, 15)	-0.01		-0.00	0.35	0.29	89
	(-0.13)		(-0.03)	(4.63)		
AbsRet(-5, 15)	-0.06	0.12		0.30	0.31	89
	(-1.07)	(1.47)		(3.39)		

Table IA.B6
FOMC Volatility: Predictive Regressions: Price Objective Function

This table summarizes the results from the predictive regressions where the independent variable is a measure of realized volatility around the FOMC announcement, and the dependent variables include daily volatility measures and the FOMC volatility estimates from the macro announcement model in Section II.B. The FOMC announcement volatilities are obtained by minimizing the RMSE based on the differences in market and model prices. The independent variables are as follows: RVol(-5,30) is the square root of the realized variance of 5-minute log returns from 5 minutes before the scheduled announcement to 30 minutes after, RVol(-15,90) is defined similarly but using a longer announcement window starting 15 minutes before the announcement and ending 90 minutes after the announcement, AbsRet(-5,15) is the absolute value of the log return between 5 minutes before the announcement to 15 minutes after. The following columns are: *const* is an estimate of the regression constant α, *Spot Vol (Options)* is the β_2-coefficient if the spot volatility $\sqrt{v_{\tau_i}}$ from the macroeconomic announcement model is used, *Spot Vol (GARCH)* is the β_2-coefficient if spot volatility is proxied by a GARCH estimate, *Event Risk* is the estimate of the β_1-coefficient, *R2* is the R^2 of the regression and *Obs* is the number of observations. t-statistics are reported in parenthesis and are HAC corrected. The full sample is from 1/2012 to 3/2023.

Independent Variable	const	Spot Vol (Options)	Spot Vol (GARCH)	Event Risk	R2	Obs
RVol(-15, 90)	-0.05			0.76	0.70	89
	(-0.76)			(8.42)		
RVol(-15, 90)	-0.14		0.25	0.62	0.74	89
	(-2.22)		(3.18)	(7.43)		
RVol(-15, 90)	-0.23	0.42		0.62	0.75	89
	(-3.52)	(3.89)		(7.15)		
RVol(-5, 30)	0.04			0.42	0.56	89
	(0.83)			(7.43)		
RVol(-5, 30)	0.02		0.04	0.40	0.56	89
	(0.36)		(0.65)	(7.77)		
RVol(-5, 30)	-0.00	0.09		0.39	0.57	89
	(-0.09)	(1.18)		(5.96)		
AbsRet(-5, 15)	-0.01			0.34	0.31	89
	(-0.27)			(4.61)		
AbsRet(-5, 15)	-0.01		-0.02	0.35	0.31	89
	(-0.08)		(-0.42)	(5.06)		
AbsRet(-5, 15)	-0.05	0.08		0.31	0.32	89
	(-0.84)	(0.80)		(3.49)		

Table IA.B7
Delta-Hedged Returns: Comparison with Overnight and Weekend Effects

This table provides regression results for a delta-hedged option return time series of hourly returns. We include dummies for (a) intraday periods (i.e. all trading periods except the ones starting at 15:45:00) (b) overnight periods (i.e. all trading periods starting at 15:45:00), and (c) weekends (i.e. the Friday trading period starting at 15:45:00). The coefficients reported in column *Coefficient* are for the regression coefficient of the dummy variable that controls for the occurrence of FOMC announcements and can be interpreted as the return in addition to any seasonal return. *DTM* denotes days-to-maturity and *t-stat* is the HAC-corrected t-statistic of the FOMC dummy variable. The sample period is from 1/2012 to 3/2023.

Variable	DTM	Coefficient	t-stat
intraday dummy variable	0 to 7	-0.35	-6.43
overnight dummy variable	0 to 7	-2.71	-8.61
weekend dummy variable	0 to 7	-3.04	-3.05
FOMC dummy variable	0 to 7	-4.40	-5.92
intraday dummy variable	0 to 60	-0.07	-2.58
overnight dummy variable	0 to 60	-1.19	-7.95
weekend dummy variable	0 to 60	-1.64	-2.75
FOMC dummy variable	0 to 60	-2.17	-5.38