Consumer Inflation Expectations: Daily Dynamics*

Carola Conces Binder[†] Jeffrey R. Campbell[‡] Jane M. Ryngaert[§]

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Abstract

We use high frequency identification methods to study the response of consumer inflation expectations to many different types of events using data from the Federal Reserve Bank of New York's Survey of Consumer Expectations. We identify the response of expectations to a large set of shocks, including FOMC meetings and macroeconomic data releases. We find that and macroeconomic news and FOMC meetings with a press conference or rate cuts jointly move expectations.

JEL codes: E31, E52, E71

Keywords: Event study, Macroeconomic data releases, Federal Reserve announcements

1 Introduction

In this paper, we use the Federal Reserve Bank of New York's Survey of Consumer Expectations (FRBNY SCE) as a *daily* survey in order to conduct high frequency event studies investigating the response of consumer expectations to monetary policy and macroeconomic data releases. The SCE is a monthly rotating panel, but respondents are surveyed throughout

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[†]Haverford College, Department of Economics. Email: cbinder1@haverford.edu

[‡]University of Notre Dame, Department of Economics; Tilburg University, Department of Econometrics & OR; Federal Reserve Bank of Chicago; and CEPR. Email: jcampb24@nd.edu

[§]University of Notre Dame, Department of Economics. Email: jryngaer@nd.edu

the month and the exact survey date is recorded. We show that respondents are demographically similar throughout the month and argue that the daily feature of the survey provides insights into the daily dynamics of consumer expectations.

We then use the daily data for causal inference about how the regular flow of macroeconomic information from post-meeting FOMC announcements and releases of the Consumer Price Index (CPI) and Nonfarm Payroll (NFP) data influence households' inflation expectations. Our sample period, June 2013 through December 2021, includes 72 such FOMC announcements and 103 releases of each data series. For almost all of these, we conduct an event study in which respondents taking the survey in the two days before the event date serve as the control group and respondents taking the survey on the event date or in the following two days are the treatment group. We use all available data to control for respondent-specific fixed effects.

Estimating a separate treatment effect of each individual news event allows for events of the same type to affect expectations differently. Indeed, we find that FOMC meetings with target rate cuts may have large positive, large negative, or near zero treatment effects on inflation expectations. Additionally, the treatment effects' magnitudes have changed over time. Specifically, the largest treatment effects on expectations have occurred since the start of the COVID-19 pandemic. Consumers in these recent years may be particularly attuned to news and its potential inflationary impacts. Similarly, household expectations do not always respond predictably to data news as determined from the data releases and real-time professional forecasts. To assess empirically household attention to macroeconomic news events, we conduct tests of the null hypothesis that *all* of the treatment effects within a given class (e.g. CPI releases) equal zero. The data firmly reject this hypothesis for all FOMC meetings, all CPI releases, and all NFP releases.

Our identification strategy resembles that of Lamla and Vinogradov (2019), who survey consumers in the days before and after the first 12 FOMC press conferences following the departure from the zero lower bound in December 2015. They find that more respondents report hearing news about the Federal Reserve in the days following an announcement, but inflation and interest rate expectations are not significantly changed. Rast (2022) also exploits the timing of a survey of German consumers to assess the causal effects of ECB meetings on inflation expectations. Our paper examines a broader set of events and utilizes the rotating panel nature of the data—participants remain in the SCE for up to 12 months—allowing us to include individual fixed effects in the regressions.

In another closely related paper, Fiore, Lombardi and Schuffels (2019) also use the SCE data and an identification strategy similar to that of Lamla and Vinogradov (2019) to study the effects on monetary policy announcements on expectations. They modify Lamla and Vinogradov's approach by interacting the post-event dummy variable with seven monetary policy measures associated with each meeting, such as the change in the shadow federal funds rate and measures of financial market surprises. They find that announcements affect interest rate expectations, especially for highly numerate or financially literature respondents, but barely affect inflation expectations. They also consider the effects of several key FOMC meetings in 2013 associated with the "Taper Tantrum" on expectations, and find no significant effects. The baseline event window we use, from two days before to two days after each event, is much narrower than that of Fiore, Lombardi and Schuffels (2019), who use a window of 21 days before to 21 days after. Their wider window increases the number of observations surrounding each event, and allows for the possibility that expectations respond with a delay. Our narrower window allows us to identify separately the treatment effects of macroeconomic data releases, which usually occur within three weeks of an FOMC meeting.

Our paper is also closely related to a few other papers using daily data or new surveys to study expectations in the Covid era. Armantier, Kosar, Pomerantz, Skandalis, Smith, Topa and van der Klaauw (2021) use the SCE to study inflation expectations in the first six months of the Covid-19 pandemic. They regress inflation expectations measures on dummy variables corresponding to five stages of the pandemic and fixed effects for individuals, month, and survey tenure. Detmers, Ho and Karagedikli (2022) also use the daily SCE data to study inflation expectations in the pandemic, but their main focus is on public-health responses to the pandemic. Restrictive state-level containment policies were associated with higher inflation expectations. In March 2020, Dietrich, Kuester, Muller and Schoenle (2021) began conducting a daily survey of consumers' expectations about how the Covid-19 pandemic would affect the economy, including inflation. In a large survey experiment in April 2020, Coibion, Gorodnichenko and Weber (2022) randomly provided US consumers with information treatments about the spread and deadliness of Covid, and about fiscal, monetary, and health policy. Respondents who learned that the Fed lowered interest rates in response to the pandemic had lower inflation expectations. These focused examinations of an exceptional macroeconomic period complement our investigation of how household expectations respond to more routine macroeconomic news. Binder and Makridis (2022) and Lewis, Makridis and Mertens (2019) study the responses of consumer sentiment to gas prices and monetary policy announcements (respectively) using daily Gallup survey data. Sentiment declines with gas prices and with a surprise increase in the federal funds target rate. The Gallup data does not ask about inflation expectations, but rather about sentiment (optimism or pessimism) about overall economic conditions. Nevertheless, evidence suggests that Gallup sentiment and the SCE's inflation expectations might move together.[1]

The paper proceeds as follows. Section 2 describes SCE's inflation expectations data and its daily sampling structure. Section 3 describes our event-study methodology and results. Section 4 concludes.

2 Daily Consumer Inflation Expectations

We build our measures of daily inflation expectations using data from the FRBNY Survey of Consumer Expectations (SCE), an online survey which began in June 2013. The Demand Institute, operated by the Conference Board and Nielsen, administers the survey on behalf of the FRBNY. The Demand Institute recruits SCE participants from respondents to the Conference Board's monthly Consumer Confidence Survey (CCS). In turn, the CCS draws its participants from the population of US postal addresses, and it seeks responses from *household heads*, defined as those who own or rent a housing unit in their own names. Although the Demand Institute collects the SCE responses online, the CCS is a mail-in survey. Armantier, Topa, van der Klaauw and Zafar (2017) note that CCS respondents tend to be older than typical household heads, as measured with the American Community Survey (ACS). However, the selection associated with an internet-based survey offsets this bias towards older households and leaves the SCE's age distribution similar to that of the ACS.[2]

The SCE surveys a rotating panel of household heads monthly, and respondents can participate for up to 12 months in a row. We use the version of the data released in 2022. After removing records that appear to included erroneously, the data contains 134,060 survey responses from 18,599 distinct households.[3] On average, a participating household completed

[1]See Andre et al. (2022), who find that some U.S. households believe that increasing the federal funds target rate raises inflation due to a "good-bad heuristic."

[2]Section 4 of Armantier, Topa, van der Klaauw and Zafar (2017) describes the recruitment of the SCE's sample in more detail.

[3]The original data set contains 134,278 records from 18,599 households. We drop some records because either (i) they are date-stamped after 31 December 2021 , (ii) a household made multiple reports in the same month, or (iii) the household's records spanned a time period exceeding 12 months. In total, this data cleaning removed 218 records. All of these problematic records appear to arise from clerical errors in data collection, and most of them corresponded to survey invitations for early 2021 extended to households who already completed their 12-month spell in the sample. These screens removed no household from the data. The original data contain no records date stamped before the survey start date of 1 June 2013 . We looked for evidence that multiple households were assigned the same user identification number, but we found none.

the survey 7.21 times. The distribution of responses across households has two modes, at one and at twelve. These two values account for 17.6 percent and 29.1 percent of households. The corresponding fractions of survey responses equal 2.4 percent and 48.4 percent. The sample period, from 1 June 2013 to 31 December 2021 , contains 103 months. In an average month, 1302 households complete the survey. Of these, 168 do so for the first time.[4]

2.1 The SCE's Measures of Inflation Expectations

The SCE solicits inflation expectations at two horizons—one year ahead and 2-3 years ahead.[5] For each horizon, the questionnaire asks for respondents' *point forecasts* and *density forecasts.* The point forecast question for the shorter horizon asks,

> What do you expect the rate of [inflation/deflation] to be over the next 12 months? Please give your best guess.

The respondent can answer with any number. The same horizon's density forecast question asks,

> Now we would like you to think about the different things that may happen to inflation over the next 12 months. We realize that this question may take a little more effort. In your view, what would you say is the percent chance that, over the next 12 months...

The respondent answers by entering numbers to indicate the probability that "the rate of inflation will be 12% or higher," "the rate of inflation will be between 8% and 12%," ... "the rate of deflation (opposite of inflation) will be 12% or higher." That is, they enter percentage probabilities into ten bins, two of which are open-ended, four of which have width 4%, and four of which have width 2%. The computer aided response system requires the percentage probabilities to sum to 100.[6] The questions about the 12-month period between 24 months and 36 months from the survey date are analogous.

Armantier et al. (2017) create inflation expectations for each survey response by first fitting a flexible-but-parametric distribution to the density forecasts and then calculating its

[4]Most of the SCE's repondants in June 2013 had experience in survey completion from a pilot program. The only sample month with an unusually large number of first-time respondents was August 2013 , which had 740 first-time participants and 1769 total responses.

[5]The SCE began questioning panelists about their 5-year-ahead inflation forecasts in January 2022.

[6]For more details on the SCE's elicitation of point and density forecasts, see Sections 2.1 and 2.3 of Armantier, Topa, van der Klaauw and Zafar (2017).

	One Year Ahead		Two-Three Years Ahead	
	Standard Deviation	Percentage of Variance	Standard Deviation	Percentage of Variance
Total	3.85	100	3.91	100
Without Time Effects	3.71	93	3.82	95
Without Individual or Time Effects	2.44	40	2.55	42

Table 1: Decomposition of Variance for Measured Inflation Expectations

mean.[7] So that our analysis incorporates both the panelists' density forecasts and their point forecasts, we instead measure inflation expectations of the distribution fit following Ryngaert (2023).[8] To reduce the influence of outliers on our results, we Winsorized the data.[9]

Table 1 provides a decomposition of variance for both horizons' expectations. Its first row reports sample standard deviations, which greatly exceed the analogous moments from any measure of overall inflation. Its second row reports the sample standard deviations after removing time-specific means. These equal zero under the Full Information Rational Expectations baseline. In fact, common movement of the expectations accounts for only 5 to 7 percent of their overall variance. The final row reports standard deviations after removing time-specific and panelist-specific means. Together, these "saturated" effects account for about 60 percent of the expectations' variances. The remaining 40 percent of variance reflects idiosyncratic changes within households over time. No empirically-grounded econometric forecast of inflation can reproduce the size of these within-panelist changes of expectations. Nevertheless, these expectations might reveal *some* macroeconomic information after a suitable scale transformation.

[7] Their Section 5.2 contains more information on their density forecast construction.

[8] In the SCE, the majority of consumers (nearly 80%) give point forecasts that are within the bin with highest probability. Therefore, she uses the point forecast to identify the *mode* of the distribution underlying the density forecast. Combining this with the respondent's reported density forecasts and mild distributional assumptions, she calculates the underlying continuous probability density function. She then measures each respondent's expected inflation with that distribution's mean. Ryngaert (2023) describes this measure in considerably more detail.

[9] More specifically, on days with 20 or more records, we replaced the smallest and largest 5 percent of the observations with that day's 5th and 95th percentiles. On days with fewer than 20 observations, we replaced the smallest and largest 10 percent of the observations with that day's 10th and 90th percentiles.

2.2 The SCE's Daily Structure

We are able to use this monthly survey to create a *daily* series of inflation forecasts because the Demand Institute solicits responses throughout each month and because the public data set includes each response's calendar date. In a typical month, the Demand Institute contacts panelists in three approximately equally-sized batches.[10] The batches' e-mails inviting survey responses usually go out on the 2nd, 11th, and 20th days of the calendar month. Panelists assigned to one batch receive up to two e-mail reminders before either the next batch begins or (for the third batch) before the end of the month. Figure 1 displays the sample histogram of survey responses across days of the month. As Armantier et al. (2017) note, this distribution has three modes, which coincide with the days after the three typical survey invitation days. Relatively few panelists responded on the 1st and 31st days of the month.[11]

This surveying scheme produces an informative sample of responses for most days in our sample period, the 3,136 days, from 1 June 2013 through 31 December 2021 . The average number of respondents per day approximately equals 43 , the corresponding median equals 35 , and the 25th and 75th percentiles are 23 and 56 . The maximum number of respondents on a single day is 178 , which occurred on 14 November 2019 . There are 111 days with zero respondents. The vast majority of these occurred on the first or second days of the month.

The initial random assignment to the three survey invitation batches supports the hope that household demographic characteristics do not vary substantially across days of the month. Figure 2 shows that this is so for the respondent's sex, college attainment, and household income status. Because 7 does not divide evenly into either 30 or 31, fixed survey invitation dates should promote uniformity of survey responses across days of the week. Figure 3 displays the sample histogram of survey responses across days of the week. Response frequencies are highest on Mondays and decline through the week, but all of the frequencies exceed 10 percent. Binder (2021) shows that on Amazon Mechanical Turk, respondent demographic characteristics differ by the day of the week. Figure 4, which is the day-of-week analogue of Figure 2, demonstrates that the same is *not* true for the SCE.

Apparently, panelists' observable demographic characteristics do not influence their choices

[10] The Demand Institute assigns new panelists and experienced panelists who failed to respond in the previous month to the three batches randomly. Experienced panelists who completed the previous month's survey were assigned non randomly to the batches with the goal of increasing the time between responses subject to the constraint of the three batches having approximately equal numbers of panelists.

[11] If the Demand Institute followed the "typical" survey solicitation to the letter, then there should be no survey responses on the first of the month. About 50 percent of these day-1 responses come from the five shorter calendar months, in which the Demand institute might adjust its survey solicitation. This does not seem disproportionately high to us, so we cannot claim to understand the reasons for these early responses.

of *when* to complete the SCE questionnaire in a given month or week. To learn something about the possibility that their *unobservable* characteristics do so, we investigated the predictability of panelists' survey completion dates. Using all observations of panelists completing the survey in two consecutive months, we calculated the sample frequency that a panelist completed the survey on day j in one month given her survey completion on day i of the previous month, where both i and j run from 1 through 31.[12] With this, we created a Markov chain for the random variable equal to the date of survey completion. Its largest eigenvector equals one by construction, and the corresponding eigenvector is proportional to the chain's ergodic distribution. The chain's second-largest eigenvector gives the *slowest* geometric rate of decay for any initial deviation from this ergodic distribution. We find that this equals 0.57. The corresponding *maximum* half life for an initial deviation equals 1.2 months. This shows that the history of a panelist's response dates becomes irrelevant for predicting future response dates very quickly; and this finding is incompatible with persistent unobserved heterogeneity dominating panelists' response dates. We also completed the analogous exercise for the day of the week, and we found almost no predictability.

Apparently, selection does not create predictable within-month or within-week variation in daily reports of inflation expectations. Because we wish to focus on changes in these data around the times of monetary policy announcements and macroeconomic data releases, we next examine the survey responses within five-day windows centered on the macroeconomic events of interest, FOMC announcements, CPI releases, and NFP releases. We begin by assessing whether panelists disproportionately choose to complete their survey responses within the windows around these events. For this, we estimated negative-binomial regressions of the number of responses per day with calendar-month indicators, day-of-month indicators, and indicators for membership in a five-day event window. The estimated percentage effects on the number of participants within the FOMC, CPI, and NFP windows are -6.8 percent, -7.5 percent and 6.8 percent. The first-two estimated effects are statistically significant at the 5 percent level, and the last is significant at the 10 percent level.[13]

The possibility that panelists condition their survey completion on regular macroeconomic news reports motivates close inspection of self-selection into the event windows based on observable or unobservable persistent characteristics. Figure 5 plots averages for the same demographic characteristics examined above across the FOMC, CPI, and NFP windows. These vary little across days of the windows, and they are close to their unconditional

[12]Our calculations ignore the fact that it is sometimes impossible for j to equal 29, 30, or 31.

[13]The relevant t-statistics equal -2.02 , -2.39 , and 1.83 .

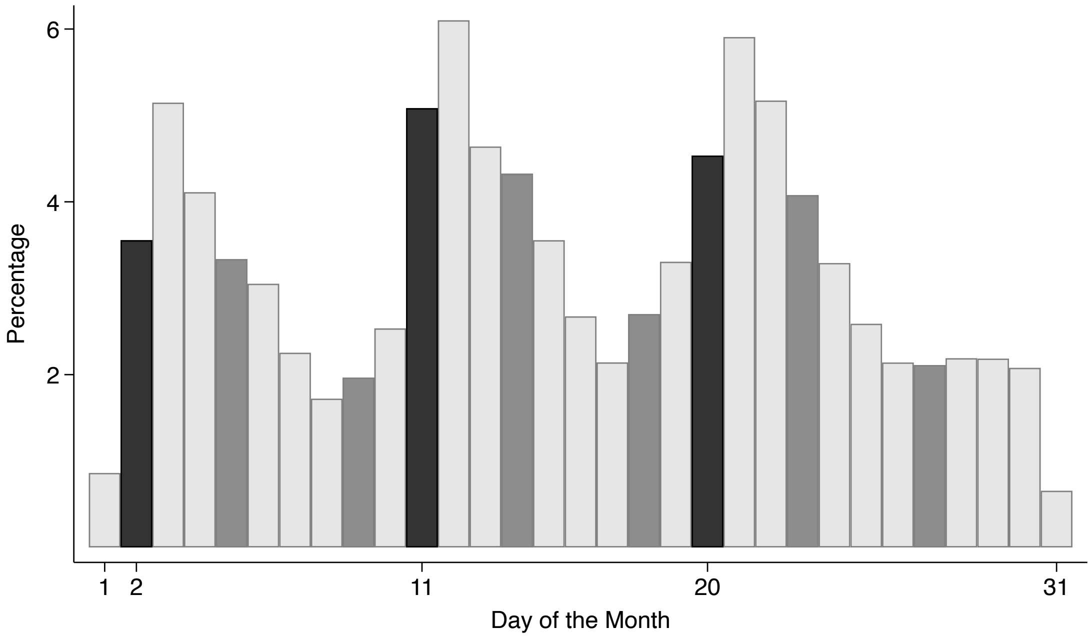


Figure 1: Distribution of SCE Responses Across Days of the Month

Note: We calculated this sample distribution using observations from all months, including those with less than 31 days. Armantier, Topa, van der Klaauw and Zafar (2017) report that in a typical month panelists receive survey invitations by e-mail on the 2nd, 11th, and 20th of the month (shaded black), and that these panelists receive reminders 3 and 7 days after their invitations (in dark grey). This figure's design mimics that of Chart 1 in Armantier, Topa, van der Klaauw and Zafar (2017).

sample means. Therefore, there is no evidence of self-selection based on these observable characteristics. To check for self-selection based on unobservable persistent characteristics, we estimated Markov chains for response during an event window analogous to those reported above for reporting on a particular day of the month or day of the week. The second-largest eigenvalues' magnitudes equal 0.06 , 0.13 and 0.18 for the FOMC, CPI, and NFP windows. Their corresponding half-lives are all much less than one month, so we find no evidence to support panelists' self-selection based on persistent unobserved characteristics.

2.3 Daily Average Inflation Expectations

Overall, the above results suggest that panelists' choices of when to complete the SCE within a month are as-good-as-random for the purposes of creating from them a daily time series. Figure 6 displays the two daily average inflation expectations series with the 12-month expectation in the top panel and the 24-36 month expectation in the bottom. Both panels

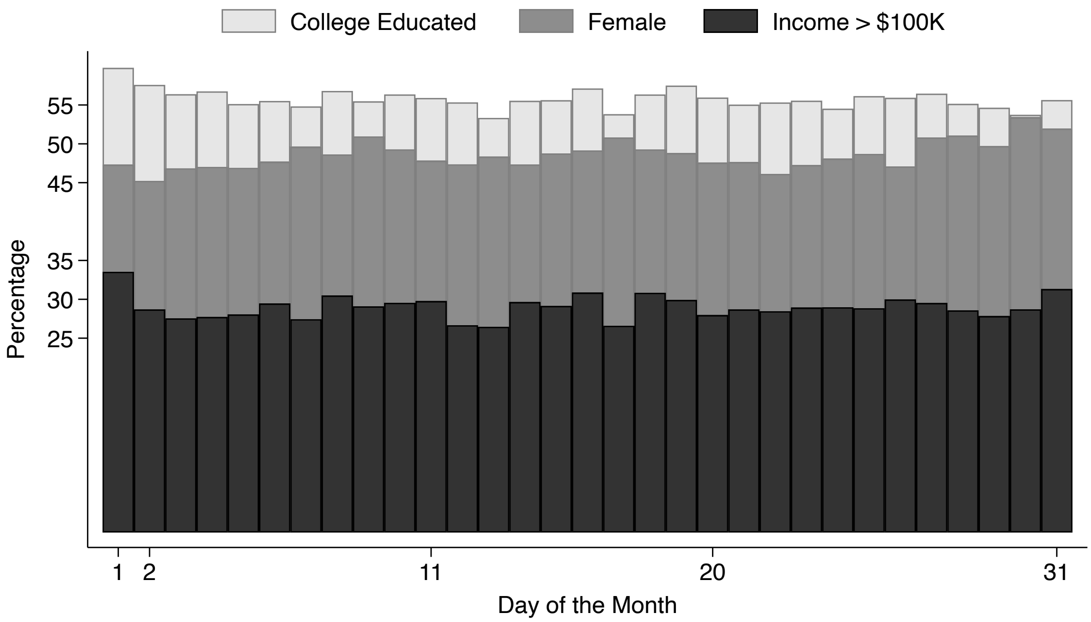


Figure 2: SCE Respondents' Demographic Characteristics Across Days of the Month

Note: We calculated the shares of respondents with these three characteristics using observations from all months, including those with less than 31 days.

also display market-based five-year inflation expectations from TIPS prices[14] The Figure only displays prices for business days, but our full analysis also uses panelist reports from weekends and holidays.

The plots show that daily average inflation expectation series contain much transitory noise. This follows at least in part from the small daily samples.[15] To quantify the contribution of sampling variance to the daily time series, we express each day's sample mean as the population mean (which we would calculate by surveying every US household head on that day) and sampling error. Then, we estimate the variance of each sampling error using the conventional feasible estimate of a sample mean's variance. Averaging these across days measures the contribution of sampling variance to a series' total variance.[16] The sample

[14]This equals the difference between the market yield on U.S. Treasury securities at 5-year constant maturity (FRED series DGS5) and the market yield on inflation-indexed U.S. Treasury securities at 5-year constant maturity (FRED series DFII5).

[15]There are 2,148 business days in the sample period. Of these, 61 had no respondents. The average and median numbers of respondents on business days are 45 and 38 . The 25th and 75th percentiles for the number of respondents equal 25 and 59 . These differ little from the analogous statistics reported above for all sample days.

[16]This estimate does not account for a handful of business days in our sample with exactly one response

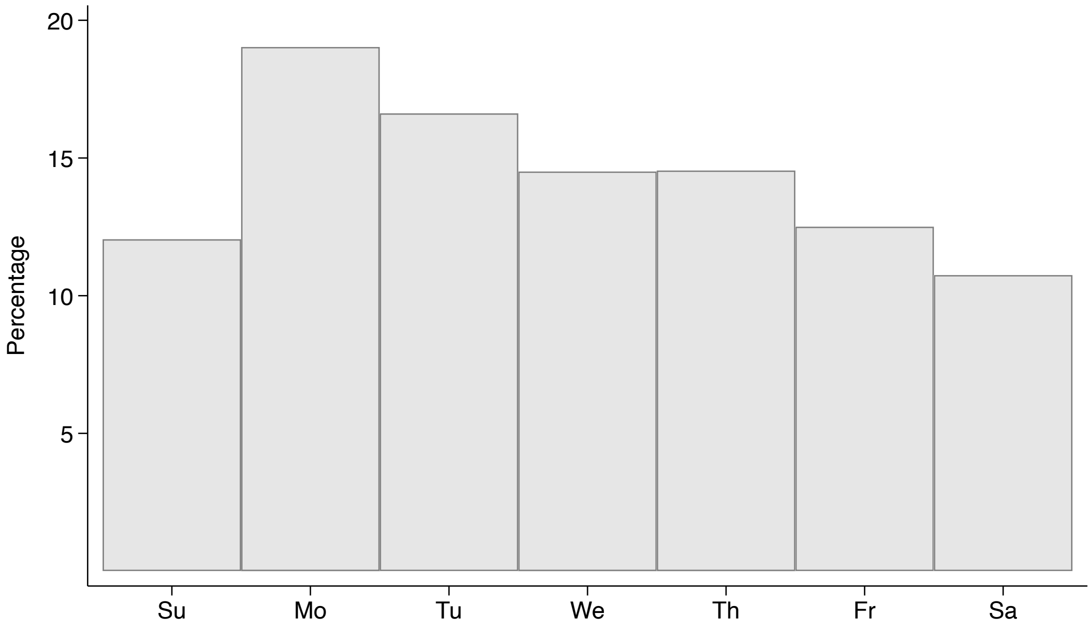


Figure 3: Distribution of SCE Responses Across Days of the Week

variances for the two inflation expectation series equal 1.32 percent and 0.97 percent. The corresponding average sampling-error variances equal 0.50 percent and 0.52 percent.

Secondly, the plots verify that the SCE's reported inflation expectations greatly exceed market expectations, as is the case for other consumer surveys in the United States, such as the Michigan Survey (Binder and Kamdar, 2022). The two series averages (calculated over the whole sample period) equal 3.98 percent and 3.82 percent. The 5-year TIPS inflation expectation's analogous average equals 1.72 percent. Nevertheless, the SCE and TIPS expectations move together. This is particularly evident during the expectations unanchoring of 2021. To determine whether this single event is responsible for *all* of the comovement between the SCE and TIPS expectations, we estimated a descriptive regression explaining the SCE series with the TIPS series and a fifth-order polynomial of calendar time,

$$\hat{\pi}_t^S = \gamma \hat{\pi}_t^M + \sum_{l=0}^{t} \alpha_i p_i(2t/T - 1) + u_t.$$

Here, $\hat{\pi}_t^S$ and $\hat{pi}_t^M$ are the Survey -based and Market-based inflation expectations for business day t, the first and last business days of the sample are $t = 0$ and $t - T$, and $p_i(2t/T - 1)$ is the

and therefore no information about sampling variance.

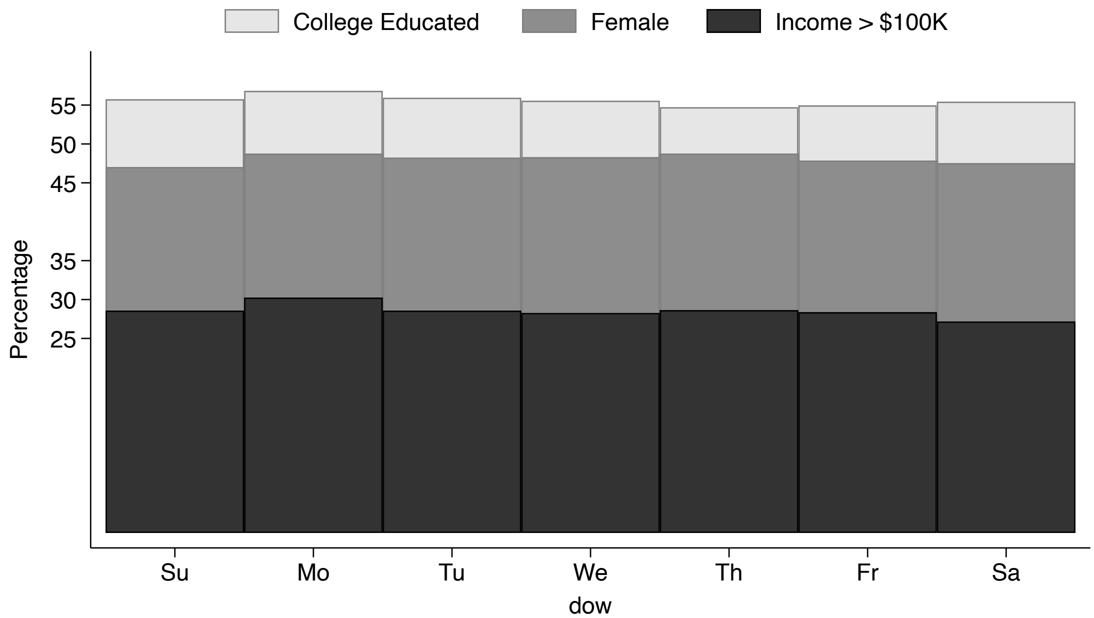


Figure 4: SCE Respondents' Demographic Characteristics Across Days of the Week

$i^t h$ order Chebychev polynomial evaluated at $2t/T - 1$.[17] The polynomial terms capture the expectations' gradual decline until the COVID outbreak in March 2020 and their sharp rise thereafter, so the estimate of γ embodies the covariance between $\hat{\pi}_t^S$ and $\hat{\pi}_t^M$ after accounting for those well-understood movements. The OLS estimates of γ are 0.38 and 0.35 , and their robust standard errors equal 0.09 and 0.08 . Evidently, the daily SCE and TIPS inflation expectations move together at higher frequencies.

[17]The Chebychev polynomials' domain is $[-1, 1]$. We use these instead of ordinary polynomials to avoid colinearity.

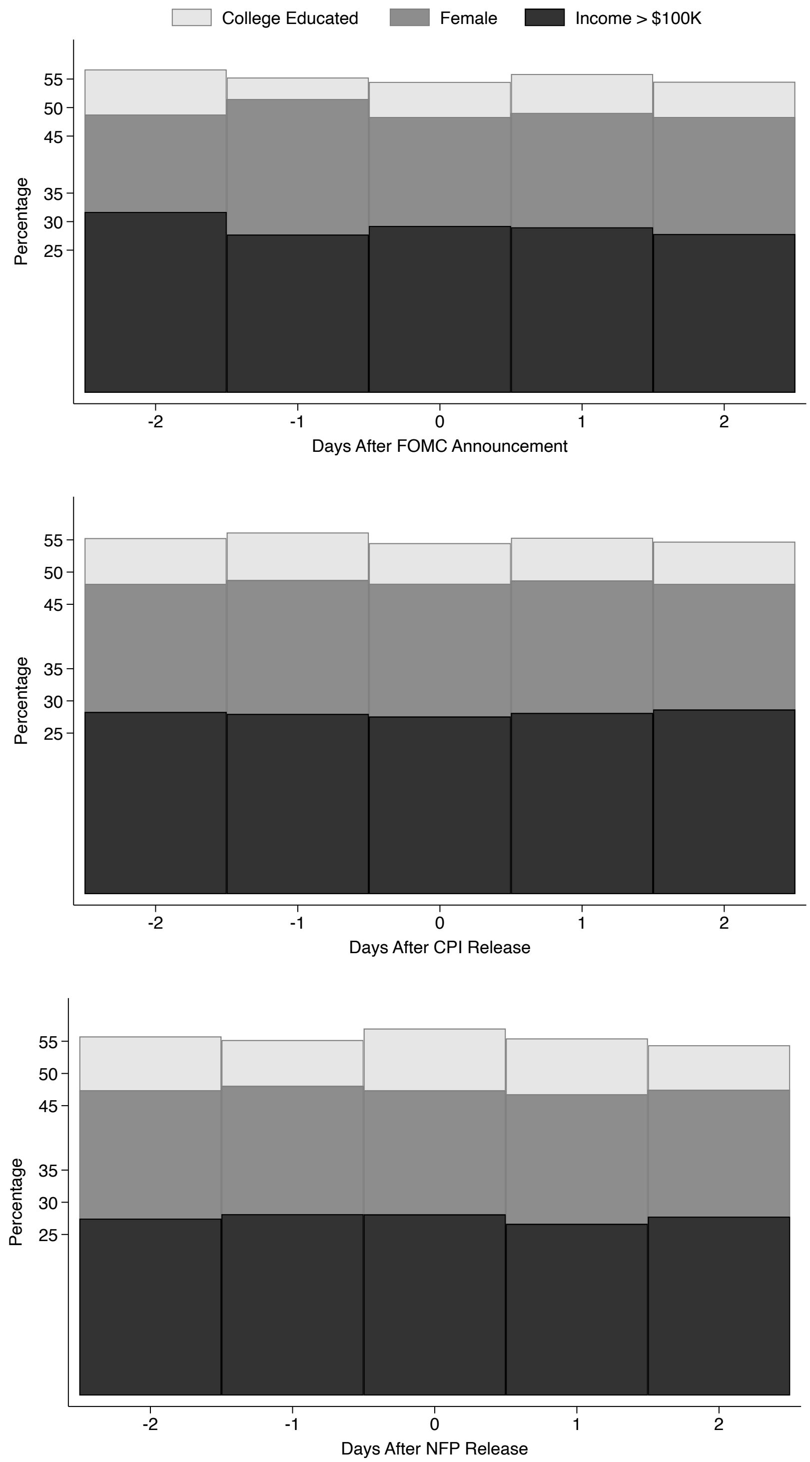
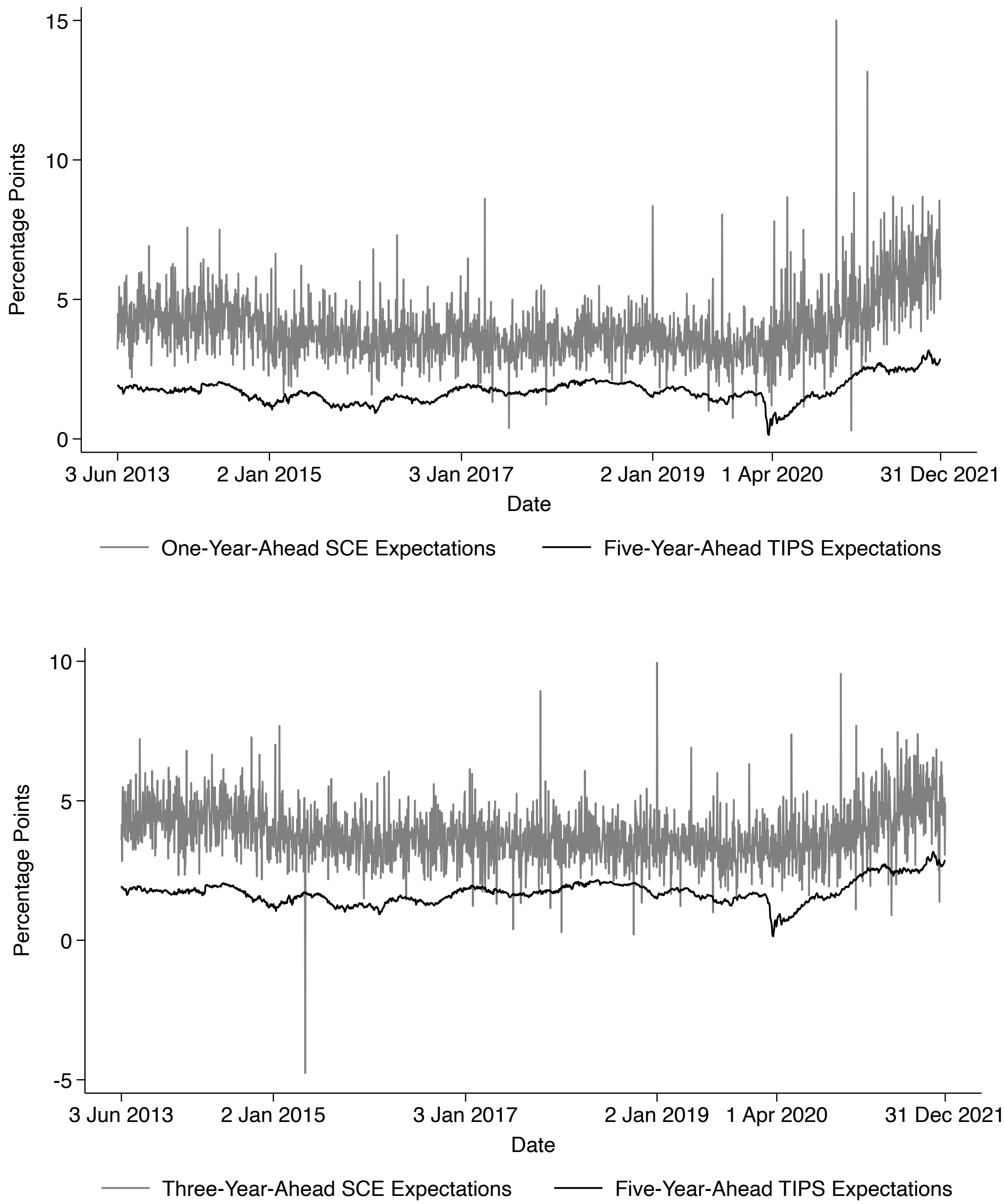


Figure 5: SCE Respondents' Demographic Characteristics Within Event Windows

Figure 6: Daily Inflation Expectations



Notes: Survey of Consumer Expectations data from June 2013 through December 2021. The panels display daily means and medians of expected inflation at the one-year horizon. Household expectations calculated following Ryngaert (2023).

3 Measuring Expectation Changes with Event Studies

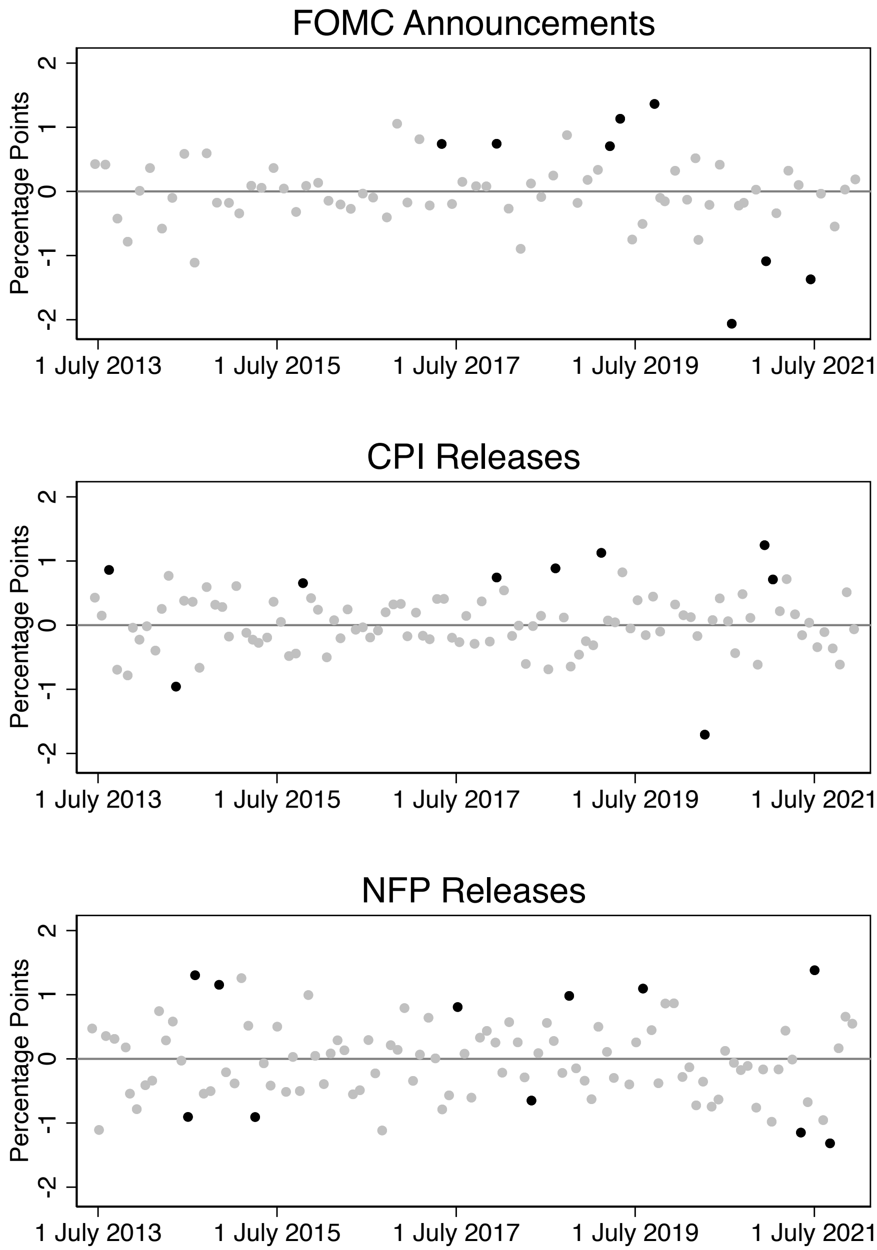
The daily SCE data facilitates measuring the responses of households' reported inflation expectations to specific data releases and policy announcements. Our sample period contains 72 post-meeting FOMC announcements and 103 CPI and NFP data releases, and we refer to these collectively as "information events." Appendix Table A provides a complete list of event dates and descriptions of their policy or data surprises. For each of these, we conduct an event study based on the following regression specification.

$$Y_{it} = \alpha_i + \gamma E_{it}^s + \beta A_{it}^s + \theta Z_{it} + \epsilon_{it} \tag{1}$$

Here, s represents a particular event (e.g. the FOMC announcement on 30 January 2019). The dependent variable Y_{it} is the short-run inflation expectation for household i on day t. The dummy variable E_{it}^s indicates whether or not respondent i's date t response occurred in a five-day window centered on event s, and the dummy variable A_{it}^s indicates that respondent took the survey either on the day of event s or in the following two days. Observations with $E_{it}^s = A_{it}^s = 1$ are the event study's treatment group, while those with $E_{it}^s = 1$ and $A_{it}^s = 0$ are its control group. The vector Z_{it} contains control variables for day t's day of the week and household i's survey tenure at date t. The household-specific fixed effects α_i control for time-invariant demographic characteristics. We use *all* data from June 2013 through December 2021 for each event study's estimation. This enables estimation of the fixed effects and the control variables' coefficients.[18] The effectively-random sorting of respondents into the treatment and control groups allows us to event s's treatment effect, β, could be estimated without controlling for individual fixed effects or for the control variables in Z_{it}. We choose to account for these influences on expectations (i) as a precaution against an undetected (by us) failure of random sorting and (ii) to reduce the error variance and thereby increase our estimates' precision. Thirteen CPI releases coincide with FOMC announcements, and the SCE contains no observations in the control group for two data releases (one for CPI and another for NFP). Therefore, we estimate 263 distinct event studies.

[18]We include day-of-the-week fixed effects since our events often occur on fixed days of the week, e.g. FOMC meetings on Wednesdays and NFP releases on Fridays. Binder (2021) shows that on Amazon Mechanical Turk, features of respondents' inflation expectations differ by day of the week. Inflation expectations are slightly lower on Thursdays in our sample, and we don't want to misattribute this to FOMC meetings. The tenure fixed effects control for "learning-through-survey" effects (Kim and Binder, 2023). The respondent fixed effects control for both observable and unobservable heterogeneity between respondents and help improve the precision of our estimates.

Figure 7: Estimated Treatment Effects



Note: This plots the estimated treatment effects associated with FOMC announcements, NFP releases, and CPI releases on one-year-ahead inflation expectations over time. Solid black points represent estimates with associated t-statistics exceeding 1.9645 in absolute value.

3.1 Estimated Treatment Effects

Figure 7 plots over time the estimated treatment effects on inflation expectations for the next 12 months for the three event classes. Each black dot marks an estimate with an accompanying t-statistic exceeding 1.9645 in absolute value. The gray dots mark the other estimated treatment effects.

Consider first the top panel, which contains the FOMC announcements' estimated effects. Eight of the 72 estimates have t-statistics that exceed the conventional 5 percent critical value, and all of these occurred after 2016. Of these, the estimated effect for the FOMC announcement of July 29, 2020, -2.0 percentage points, stands out. Chair Powell pledged during the post-meeting press conference to extend the Fed's emergency lending programs through the end of the year, and the *New York Times* reported that Powell said he was "not even thinking about thinking about thinking about" raising rates from the effective lower bound.[19] Two of the other FOMC announcements with statistically-significant effects also came during the pandemic. The estimated treatment effect for the December 16, 2020 meeting equals -1.1 percentage points. After that meeting, CNBC quoted Chair Powell; " There are significant disinflationary pressures around the world. And there have been for a while... It's not going to be easy to have inflation move up."[20] At the June 16, 2021 meeting, the Fed " considerably raised its expectations for inflation this year and brought forward the time frame on when it will next raise interest rates,"[21]. Nevertheless, consumers' expectations fell. The FOMC announcement with the largest *positive* effect on inflation expectations (1.4 percentage points) was before the pandemic, on September 18, 2019. That day, the *New York Times* wrote that " the latest economic headlines feature an uncanny tonal resemblance to those of the early 1970s. General Motors workers are on strike, seeking more of the spoils of their employer's successes. The president of the United States is pressuring the Federal Reserve to lower interest rates, hoping for a booming economy as he seeks re-election. And now, violence in the Middle East is pushing up global oil prices."[22] Though the Fed cut interest rates by a quarter basis point, President Trump publicly berated Powell on Twitter after the announcement for not doing more to stimulate the economy.[23]

[19]Jeanna Smialek, "Stocks Rise as Fed Reiterates Support for the Economy," *New York Times*, July 29, 2020.

[20]Thomas Franck, "Fed chief says it could be a while before higher inflation levels," CNBC, December 16, 2020.

[21]Jeff Cox, " The Fed moves up its timeline for rate hikes as inflation rises," CNBC, June 16, 2021.

[22]Neil Irwin, " A Rerun From the 1970s? This Economic Episode Has Different Risks," September 18, 2019, *New York Times*.

[23]Jeanna Smialek, " Fed Cuts Interest Rates by Another Quarter Point," September 18, 2019, *New York*

Although our estimates contain *some* statistically-significant treatment effects of FOMC communications, we find no discernible effects of other historically-notable policy episodes. The June, September, and December 2013 FOMC meetings associated with the "Taper Tantrum" have estimated treatment effects of statistically-insignificant estimates of 0.4, −0.4, and 0.0 percentage points. Fiore et al. (2019) also found no effects of these meetings on SCE respondents' inflation expectations. We also measure no significant response to the August 27, 2020 "Statement on Longer-Run Goals and Monetary Policy Strategy." With this announcement, the FOMC changed its inflation targeting strategy to an average inflation targeting strategy and also noted that "the maximum level of employment is a broad-based and inclusive goal." Eurodollar market participants interpreted this announcement as expansionary. Our estimated treatment effect for that meeting equals −0.2 percentage points and is statistically insignificant. This conforms to the results of Coibion et al. (2021), whose survey evidence revealed only a small rise in the share of households who reported hearing news about monetary policy after that announcement. These examples demonstrate that events of interest to financial markets and other Fed watchers are not necessarily salient for consumers.

Figure 7's middle panel presents the estimates for the CPI data releases. Nine of these 102 estimates have t-statistics exceeding 1.9645 in absolute value. An event early in the Coronavirus pandemic also stands out here. The April 10, 2020 CPI report was unexpectedly low and reduced expectations by 1.7 percentage points. A *Reuters* piece, "U.S. consumer prices post largest drop in five years amid coronavirus disruptions," noted that "economists are predicting the disinflationary trend will persist for a while or even a short period of outright deflation."[24] The CPI release with the largest positive impact on inflation expectations also came during the pandemic, in December 2020, when an unexpectedly high CPI reading raised expectations by 1.2 percentage points. The subsequent release in January 2021 also raised expectations by a statistically significant 0.7 percentage points. The *Financial Times* reported then on "concern that inflation might prove to be a 'black swan' event, with a low-probability but high-impact risk."[25] News coverage of inflation was especially high then because of high-profile debates about whether the Biden administration's proposed coronavirus relief act would lead to excessive inflation.[26] The figure's bottom panel displays the

Times.

[24]Lucia Mutikani, "U.S. consumer prices post largest drop in five years amid coronavirus disruptions," *Reuters*, April 10, 2020.

[25]Gillian Tett, "The US inflation pressure cooker may be steaming," Financial Times, January 14, 2021.

[26]Hillary Hoffower and Juliana Kaplan, "High-profile economists want to shut down Biden's stimulus over fears it could cause a damaging inflation spike. But recent history suggests otherwise," *Business Insider*,

analogous estimates for NFP releases. Eleven of these are statistically significant at the 5 percent level. The largest treatment effect of an NPF release (1.4 percentage points) also occurred post-COVID, associated with an unexpectedly high NFP report on July 2, 2021. By this time, inflation was already elevated, so reporting on the jobs report focused on how the labor market recovery was raising wages, and whether the wage increases would contribute to inflation.[27] Similarly, unexpectedly weak jobs reports in September and May 2021 reduced inflation expectations by 1.3 and 1.1 percentage points, respectively.

3.2 Summary Statistics

Overall, Figure 7 leaves several qualitative impressions. First, the estimated treatment effects average about zero. This makes sense, since a given treatment effect should equal the product of the signal revealed during an event with household's average sensitivity to that signal. Second, the estimated treatment effects have a great deal of dispersion relative to the changes in any relevant econometric inflation forecast. Third, the vast majority of the estimated treatment effects cannot be statistically-distinguished from zero. Table 2 formalizes these impressions with summary statistics. Its columns report the estimates' means, standard deviations, percentages statistically-significant (at the 5 percent level), and average squared t-statistics, while each of its rows corresponds to a subset of the estimates. The first four rows distinguish between event classes, while the remaining rows give statistics by calendar year.

For all event classes and both forecast horizons, the average estimated treatment effects are within a few basis points of zero. These vary more substantially across years, from a low of -0.25 percentage points to a high of 0.26 percentage points. For the shorter forecast horizon, the standard deviations lie between 0.42 and 0.63 percentage points. They are substantially larger for the longer horizon. The percentages of statistically-significant estimates are much higher in 2019, 2020, and 2021 than they were earlier in the sample. The one fact from Table 2 that is not visually evident in Figure 7 concerns the squared t-statistics. If households paid no attention to the FOMC announcements and data releases, then these should have a sample average close to one. In fact, most of the reported averages substantially exceed one. We return to this point below.

January 13, 2021. Note that Presidents receive substantially more news coverage than monetary policymakers (Binder, 2017).

[27] Lucia Mutikani, "U.S. jobs gain largest in 10 months; employers raise wages, sweeten perks," Reuters, July 2, 2021.

	Next 12 Months				24-36 Months Ahead				
Subset	Mean	Std Dev	% $p < 0.05$	Mean t^2	Mean	Std Dev	% $p < 0.05$	Mean t^2	N
ALL	-0.01	0.55	10.27	1.43	0.01	0.63	11.41	1.64	263
FOMC	-0.03	0.57	11.11	1.41	-0.01	0.64	8.33	1.54	72
CPI	0.04	0.46	8.82	1.27	0.03	0.52	8.82	1.35	102
NFP	-0.03	0.60	10.78	1.56	-0.00	0.73	14.71	1.96	102
2013	-0.05	0.55	5.56	1.30	-0.22	0.80	11.11	2.07	18
2014	0.03	0.61	13.33	1.70	0.04	0.69	13.33	1.88	30
2015	0.03	0.48	6.45	1.09	0.02	0.37	0.00	0.64	31
2016	-0.03	0.42	0.00	0.63	-0.07	0.72	13.79	1.64	29
2017	0.11	0.43	10.34	1.39	0.26	0.52	10.34	1.99	29
2018	-0.01	0.47	9.38	1.64	0.12	0.57	12.50	1.87	32
2019	0.25	0.58	17.24	2.23	0.25	0.56	17.24	1.80	29
2020	-0.25	0.62	12.12	1.19	-0.19	0.59	12.12	1.37	33
2021	-0.09	0.63	15.62	1.68	-0.19	0.74	12.50	1.78	32

Table 2: Summary Statistics for Estimated Treatment Effects

Note: The columns labelled "%$p < 0.05$" report the percentage of estimated treatment effects with absolute t statistics exceeding 1.9645, and the columns labelled "Mean t^2" report the average of the estimated treatment effects' squared t statistics.

3.3 Treatment Effect Predictability

Campbell, Evans, Fisher and Justiniano (2012) found that professional inflation forecasts responded little on average to unanticipated monetary policy changes, and they conjectured that this reflected heterogeneous policy surprises. Sometimes, policy unexpectedly tightened exogenously, and sometimes proclamations of heightened inflation concerns accompanied unexpected tightening. The former should reduce inflation expectations, while the latter could actually raise them.

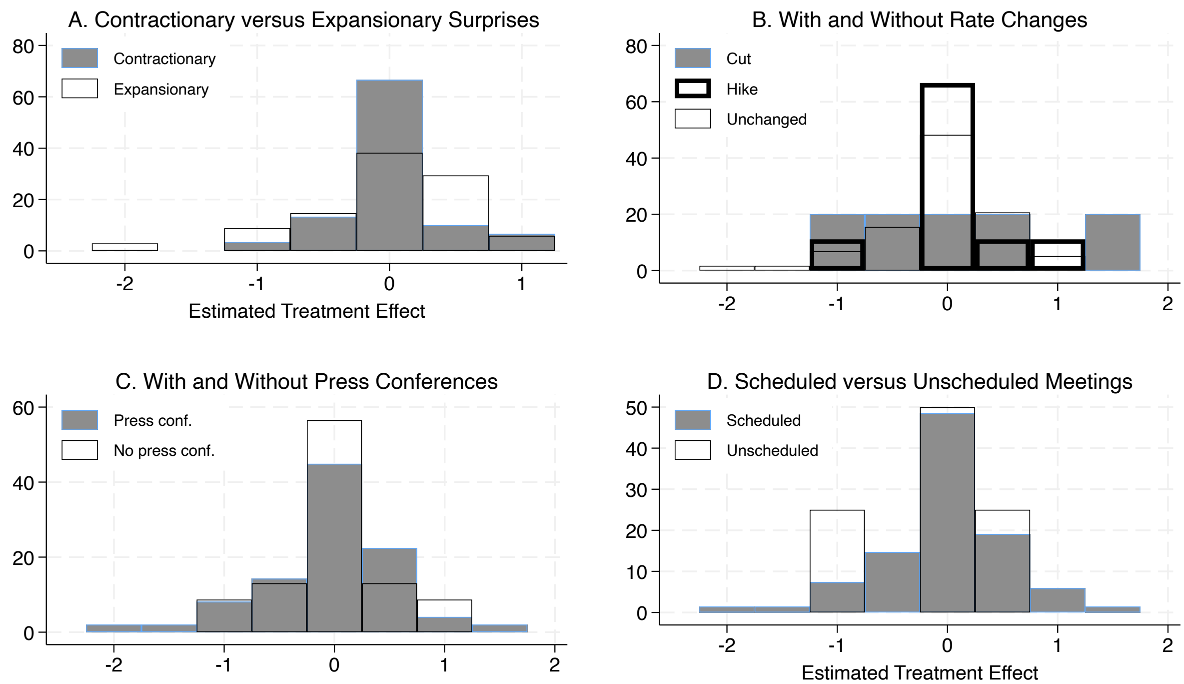
These prior characterizations of professional forecasts motivate us to investigate the predictability of the estimated treatment effects following FOMC meetings. Specifically, we measure an FOMC announcement's monetary policy surprise with the change in the four-quarter ahead Eurodollar rate on day of the announcement. With this, we can classify an announcement's surprise component as expansionary or contractionary. Figure 8 provides histograms of the estimated treatment effects from FOMC announcements distinguished by characteristics of the meeting and its outcome. Its northwest panel gives separate histograms for announcements with expansionary and contractionary surprises. Two results immediately stand out. First, whether or not a meeting is contractionary has little if any impact on the treatment effect's sign. This is as the characterization of professional forecasts from Campbell, Evans, Fisher and Justiniano (2012) leads us to expect. Second, expansionary surprises treatment effects display much more dispersion. The figure's northeast panel gives analogous histograms for meetings with rate cuts and with rate hikes. The results from this different measure of a meeting's policy stance are similar. Policy rate changes have no measurable effect on treatment effects' signs, but policy rate cuts raise their dispersion.

Figure 8 bottom two panels give histograms after distinguishing between FOMC announcements with more or less public visibility. Its southwest panel gives histograms for meetings with and without press conferences.[28] The treatment effects associated with press conferences have substantially more dispersion. The figure's southeast panel shows the histograms after breaking FOMC meetings into scheduled (68 meetings) and unscheduled (4 meetings). One of the four unscheduled meetings, that on March 15, 2020 had an exceptional and negative treatment effect.

Responses of forecasts to data release surprises have received relatively little prior attention. Figure 9 teaches us something about this by presenting histograms of the treatment effects for CPI and NFP releases separated into positive and negative data surprises relative to the releases' Bloomberg consensus forecasts. The histograms for both surprise directions have similar shapes and somewhat different locations. Just as with the FOMC announcements, data surprises of either sign can and do have oppositely-signed treatment effects on inflation expectations. However, there is some evidence that the content of the data release surprise influences the estimated treatment effect. For the CPI releases, the difference between the average (across releases) treatment effects for positive and negative surprises equals 0.17 percentage points, and the accompanying standard error equals 0.095. The analogous difference and standard error for the NFP releases equal 0.10 and 0.12 percentage points.

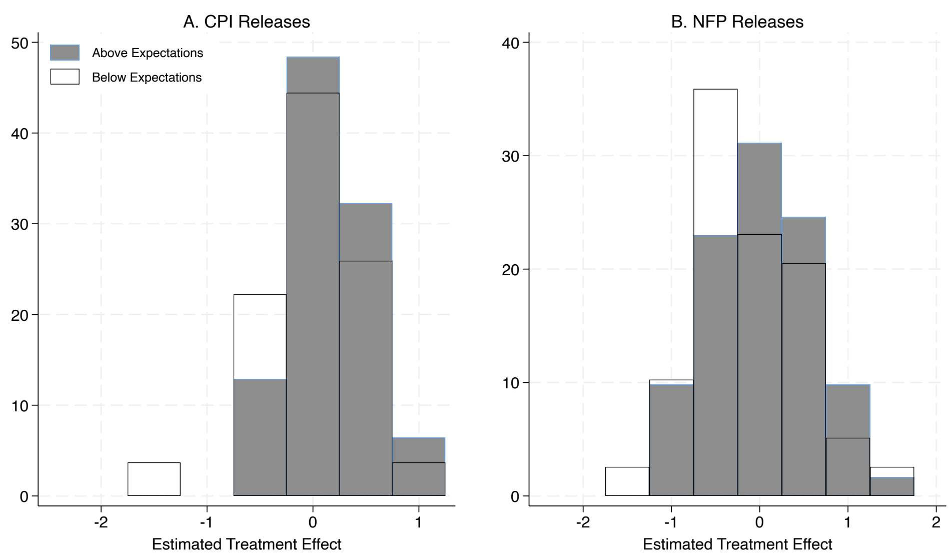
[28] From the beginning of our sample through 2018, the Chair held a press conference following every other scheduled FOMC meeting. Since then, a press conference follows every meeting.

Figure 8: Histograms of Treatment Effects Associated with FOMC Announcements



Note: This shows histograms of the estimated treatment effects on one-year-ahead inflation expectations.

Figure 9: Histograms of Treatment Effects Associated with Data Releases



Note: This shows histograms of the estimated treatment effects on one-year-ahead inflation expectations.

3.4 Inattention Tests

Overall, the estimated treatment effects' histograms reveal *some* systematic impact of FOMC announcements and data releases on consumers' inflation expectations. However, those impacts seem to be heterogeneous over time. Sometimes, inflation expectations *fall* after highlighting disinflationary pressures announcement (as on December 16, 2020). At other times similar effects fall after an FOMC discussion of *inflationary* pressures (as on July 29, 2020). Furthermore, positive CPI and NFP data surprises can either raise or lower consumers' inflation expectations. Furthermore, different kinds of FOMC meetings seem to induce *dispersion* in the estimated treatment effects. This leaves us with the impression that SCE respondents receive information from FOMC announcements and data releases, but it is difficult to identify exactly what they hear. We formalize that impression in this section.

By definition, an event's treatment effect equals the received signal multiplied by the average household response to it. The average of these treatment effects across events *should* be close to zero in a large sample when the signals have zero means, even when households respond to them. Nevertheless, household responses to news should produce time-series *dispersion* in the estimated treatment effects. Indeed, FOMC press conferences seem to create just such dispersion. Accordingly, we empirically test the proposition that households pay no attention to a class of events (CPI releases, NFP releases, or FOMC meetings) with the joint hypothesis that *all* of that class's treatment effects equal zero. This test has power to detect household attention because then the signals should contribute to the estimated treatment effects' dispersion (over and above ordinary sampling error).

We base our test statistic on the squares of the estimated treatment effects' t-statistics, as reported in Table 2.

For a given event class, we begin by squaring the t-statistics from that class's treatment effect estimates. Under the null hypothesis that a given event's population treatment effect equals zero, the squared t-statistic's mean equals one. When the number of sampled households for the same event is large enough so that the standard normal approximates these t-statistics' distributions well, then their squares have variances equal to two (the variance of a χ^2 random variable with one degree of freedom). Using these results to create a Z-statistic from the sample mean (across events) of these squared t-statistics gives us

$$Z \equiv \frac{\frac{1}{T_{\mathcal{C}}} \sum_{s \in \mathcal{C}} \left(\frac{\hat{\beta}_s}{\hat{\sigma}_s} \right)^2 - 1}{\sqrt{2/T_{\mathcal{C}}}},$$

Table 3: Tests of Inattention

	Next 12 Months		**24-36 Months Ahead**		Number of
Subset	Z-statistic	Placebo	Z-statistic	Placebo	Events
All Events	4.96	-2.24	7.38	0.02	263
CPI Releases	1.96	-0.88	2.53	-0.53	102
NFP Releases	4.02	-1.45	6.83	0.07	102
FOMC Announcements	2.48	-1.95	3.23	0.56	72
Expansionary Surprise	0.87	-1.93	1.54	0.93	34
Contractionary Surprise	0.31	-1.08	2.10	-0.13	30
Rate Cut	3.45	-0.90	1.47	-0.99	5
No Rate Change	1.35	-1.56	2.45	0.73	58
Rate Hike	1.01	-0.90	1.80	0.47	9
Press Conference	3.45	-1.72	3.07	0.92	49
No Press Conference	-0.65	-0.94	1.23	-0.36	23
Scheduled	2.51	-1.93	3.18	0.52	68
Unscheduled	0.15	-0.30	0.60	0.22	4

where $\mathcal{C}$ is the class of events under examination, $T_{\mathcal{C}}$ is the number of events in that class, $\hat{\beta}_s$ is our estimate of β_s, and $\hat{\sigma}_s$ is its feasible standard error. The numerator of Z equals the difference between the sample mean of the squared t-statistics and the population mean under the null hypothesis that *all* of the population treatment effects equal zero, and its denominator equals the sample mean's standard error when the t-statistics are mutually independent. If both $T_{\mathcal{C}}$ is large and the correlations between the events' estimation errors are close to zero, then Z will have a standard normal distribution under the null hypothesis. Under the alternative hypothesis that $\beta_s \neq 0$ for at least one $s \in \mathcal{C}$, the test statistic will approximately equal a normal random variable with a *positive* mean and unit variance. Therefore, we reject the null hypothesis when Z exceeds a critical value. That is, our test is one-sided.

For both forecast horizons, Table 3 shows the Z-statistics for all of the events pooled together, the two sets of data releases, FOMC announcements, and the subsets of FOMC announcements examined above in Figure 8. For each Z statistic except those from events in December 2021, we also calculated a placebo statistic where we replaced the respondent's forecasts with those reported in the *next* calendar month. By that time, respondents in both the treatment and control groups have seen the information revealed in the given event.

The table's top line indicates that SCE respondents' are paying attention to the events we consider. The two forecast horizons' Z-statistics equal 4.96 and 7.38, and their analogous placebo statistics are both well below the 5 percent critical value of 1.645. The same is true for the data releases and FOMC announcements examined separately. If anything, the placebo statistics are somewhat *smaller* than we would expect.

Turning to the subsets of FOMC meetings, the evidence from the shorter-horizon inflation forecasts indicates that households' notice rate cuts. However, the evidence from the longer-horizon forecasts shows that households respond to FOMC announcements and their accompanying press conferences more broadly.

4 Conclusion

In principle, the recorded dates of SCE respondents' reports allow us to learn about the daily dynamics of consumers' inflation expectations. In this paper, we have shown that essentially-random timing of respondents' reports makes this practically feasible. Our event study estimates indicate that households pay attention (at least sometimes) to routine macroeconomic data releases and FOMC post-meeting communications. We believe that our results could be useful for assessing frameworks for monetary policy communications. In particular, monetary policy makers might expand their influence on consumer expectations by routinely discussing the implications of data releases (which already receive public attention) for future macroeconomic outcomes.

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Appendix A List of Event Dates and Descriptions

Date	Description
June 7, 2013	NFP unexpectedly high
June 18, 2013	CPI as expected
June 19, 2013	FOMC leaves rates unchanged with press conference
July 5, 2013	NFP unexpectedly high
July 16, 2013	CPI unexpectedly high
July 31, 2013	FOMC leaves rates unchanged
August 2, 2013	NFP unexpectedly low
August 15, 2013	CPI as expected
September 6, 2013	NFP unexpectedly high
September 17, 2013	CPI unexpectedly low
September 18, 2013	FOMC leaves rates unchanged with press conference
October 22, 2013	NFP unexpectedly high
October 30, 2013	FOMC leaves rates unchanged, CPI as expected
November 8, 2013	NFP unexpectedly high
November 20, 2013	CPI as expected
December 6, 2013	NFP unexpectedly high
December 17, 2013	CPI as expected
December 18, 2013	FOMC leaves rates unchanged with press conference
January 10, 2014	NFP unexpectedly low
January 16, 2014	CPI as expected
January 29, 2014	FOMC leaves rates unchanged
February 7, 2014	NFP unexpectedly low
February 20, 2014	CPI as expected
March 7, 2014	NFP unexpectedly high
March 18, 2014	CPI unexpectedly low
March 19, 2014	FOMC leaves rates unchanged with press conference
April 4, 2014	NFP unexpectedly high
April 15, 2014	CPI as expected
April 30, 2014	FOMC leaves rates unchanged
May 2, 2014	NFP unexpectedly high
May 15, 2014	CPI as expected
June 6, 2014	NFP unexpectedly high
June 17, 2014	CPI unexpectedly high
June 18, 2014	FOMC leaves rates unchanged with press conference
July 3, 2014	NFP unexpectedly high
July 22, 2014	CPI as expected
July 30, 2014	FOMC leaves rates unchanged
August 1, 2014	NFP as expected
August 19, 2014	CPI as expected
September 5, 2014	NFP unexpectedly low
September 17, 2014	FOMC leaves rates unchanged with press conference, CPI unexpectedly low
October 3, 2014	NFP unexpectedly high

October 22, 2014	CPI unexpectedly high
October 29, 2014	FOMC leaves rates unchanged
November 7, 2014	NFP unexpectedly high
November 20, 2014	CPI unexpectedly high
December 5, 2014	NFP unexpectedly high
December 17, 2014	FOMC leaves rates unchanged with press conference, CPI unexpectedly low
January 9, 2015	NFP unexpectedly high
January 16, 2015	CPI unexpectedly high
January 28, 2015	FOMC leaves rates unchanged
February 6, 2015	NFP unexpectedly low
February 26, 2015	CPI as expected
March 6, 2015	NFP unexpectedly high
March 18, 2015	FOMC leaves rates unchanged with press conference
March 24, 2015	CPI unexpectedly high
April 3, 2015	NFP unexpectedly low
April 17, 2015	CPI unexpectedly low
April 29, 2015	FOMC leaves rates unchanged
May 8, 2015	NFP unexpectedly high
May 22, 2015	CPI as expected
June 5, 2015	NFP unexpectedly high
June 17, 2015	FOMC leaves rates unchanged with press conference, CPI as expected
July 2, 2015	NFP unexpectedly low
July 17, 2015	CPI unexpectedly low
July 29, 2015	FOMC leaves rates unchanged
August 7, 2015	NFP unexpectedly high
August 19, 2015	CPI as expected
September 4, 2015	NFP unexpectedly low
September 16, 2015	CPI as expected
September 17, 2015	FOMC leaves rates unchanged with press conference
October 2, 2015	NFP unexpectedly low
October 15, 2015	CPI unexpectedly high
October 28, 2015	FOMC leaves rates unchanged
November 6, 2015	NFP unexpectedly high
November 17, 2015	CPI unexpectedly high
December 4, 2015	NFP unexpectedly high
December 15, 2015	CPI as expected
December 16, 2015	FOMC raises rates with press conference
January 8, 2016	NFP unexpectedly high
January 20, 2016	CPI unexpectedly low
January 27, 2016	FOMC leaves rates unchanged
February 5, 2016	NFP unexpectedly low
February 19, 2016	CPI unexpectedly high
March 4, 2016	NFP unexpectedly high
March 16, 2016	FOMC leaves rates unchanged with press conference, CPI unexpectedly high
April 1, 2016	NFP unexpectedly high

April 14, 2016	CPI unexpectedly low
April 27, 2016	FOMC leaves rates unchanged
May 6, 2016	NFP unexpectedly low
May 17, 2016	CPI as expected
June 3, 2016	NFP unexpectedly low
June 15, 2016	FOMC leaves rates unchanged with press conference, CPI as expected
July 8, 2016	NFP unexpectedly high
July 15, 2016	CPI unexpectedly low
July 27, 2016	FOMC leaves rates unchanged
August 5, 2016	NFP unexpectedly high
August 16, 2016	CPI unexpectedly low
September 2, 2016	NFP unexpectedly low
September 16, 2016	CPI unexpectedly high
September 21, 2016	FOMC leaves rates unchanged with press conference
October 7, 2016	NFP unexpectedly high
October 18, 2016	CPI as expected
November 2, 2016	FOMC leaves rates unchanged
November 4, 2016	NFP unexpectedly low
November 17, 2016	CPI as expected
December 2, 2016	NFP unexpectedly low
December 14, 2016	FOMC raises rates with press conference, CPI as expected
January 6, 2017	NFP unexpectedly high
January 18, 2017	CPI as expected
February 1, 2017	FOMC leaves rates unchanged
February 3, 2017	NFP unexpectedly high
February 15, 2017	CPI unexpectedly high
March 10, 2017	NFP unexpectedly low
March 15, 2017	FOMC raises rates with press conference, CPI as expected
April 7, 2017	NFP unexpectedly low
April 14, 2017	CPI unexpectedly low
May 3, 2017	FOMC leaves rates unchanged
May 5, 2017	NFP unexpectedly high
May 12, 2017	CPI unexpectedly low
June 2, 2017	NFP unexpectedly low
June 14, 2017	FOMC raises rates with press conference, CPI unexpectedly low
July 7, 2017	NFP unexpectedly high
July 14, 2017	CPI unexpectedly low
July 26, 2017	FOMC leaves rates unchanged
August 4, 2017	NFP unexpectedly high
August 11, 2017	CPI unexpectedly low
September 1, 2017	NFP unexpectedly high
September 14, 2017	CPI unexpectedly high
September 20, 2017	FOMC leaves rates unchanged with press conference
October 6, 2017	NFP unexpectedly low
October 13, 2017	CPI unexpectedly low

November 1, 2017	FOMC leaves rates unchanged
November 3, 2017	NFP unexpectedly low
November 15, 2017	CPI as expected
December 8, 2017	NFP as expected
December 13, 2017	FOMC raises rates with press conference, CPI as expected
January 5, 2018	NFP unexpectedly low
January 12, 2018	CPI as expected
January 31, 2018	FOMC leaves rates unchanged
February 2, 2018	NFP unexpectedly low
February 14, 2018	CPI unexpectedly high
March 9, 2018	NFP unexpectedly high
March 13, 2018	CPI as expected
March 21, 2018	FOMC raises rates with press conference
April 6, 2018	NFP unexpectedly high
April 11, 2018	CPI as expected
May 2, 2018	FOMC leaves rates unchanged
May 4, 2018	NFP unexpectedly low
May 10, 2018	CPI as expected
June 1, 2018	NFP unexpectedly high
June 12, 2018	CPI as expected
June 13, 2018	FOMC raises rates with press conference
July 6, 2018	US trade war with China escalates, NFP unexpectedly high
July 12, 2018	CPI as expected
August 1, 2018	FOMC leaves rates unchanged
August 3, 2018	NFP unexpectedly low
August 10, 2018	CPI as expected
September 7, 2018	NFP unexpectedly high
September 13, 2018	CPI unexpectedly low
September 26, 2018	FOMC raises rates with press conference
October 5, 2018	NFP unexpectedly low
October 11, 2018	CPI unexpectedly low
November 2, 2018	NFP unexpectedly high
November 8, 2018	FOMC leaves rates unchanged
November 14, 2018	CPI as expected
December 7, 2018	NFP unexpectedly low
December 12, 2018	CPI as expected
December 19, 2018	FOMC raises rates with press conference
January 4, 2019	NFP unexpectedly high
January 11, 2019	CPI as expected
January 30, 2019	FOMC leaves rates unchanged with press conference
February 1, 2019	NFP unexpectedly high
February 13, 2019	CPI unexpectedly high
March 8, 2019	NFP unexpectedly low
March 12, 2019	CPI unexpectedly low
March 20, 2019	FOMC leaves rates unchanged with press conference

April 5, 2019	NFP unexpectedly low
April 10, 2019	CPI unexpectedly high
May 1, 2019	FOMC leaves rates unchanged with press conference
May 10, 2019	CPI unexpectedly low
June 7, 2019	NFP unexpectedly low
June 12, 2019	CPI unexpectedly low
June 19, 2019	FOMC leaves rates unchanged with press conference
July 5, 2019	NFP unexpectedly high
July 11, 2019	CPI as expected
July 31, 2019	FOMC cuts rates with press conference
August 2, 2019	NFP unexpectedly high
August 13, 2019	CPI unexpectedly high
September 6, 2019	NFP unexpectedly high
September 12, 2019	CPI unexpectedly low
September 18, 2019	FOMC cuts rates with press conference
October 4, 2019	NFP unexpectedly high
October 11, 2019	FOMC leaves rates unchanged (unscheduled), CPI as expected
October 30, 2019	FOMC cuts rates with press conference
November 1, 2019	NFP unexpectedly high
December 6, 2019	Pelosi announces plan to impeach Trump, NFP unexpectedly high
December 11, 2019	FOMC leaves rates unchanged with press conference, CPI unexpectedly high
January 10, 2020	NFP unexpectedly low
January 14, 2020	CPI as expected
January 29, 2020	FOMC leaves rates unchanged with press conference
February 7, 2020	NFP unexpectedly high
February 13, 2020	CPI unexpectedly high
March 3, 2020	FOMC cuts rates (unscheduled) with press conference
March 6, 2020	NFP unexpectedly high
March 11, 2020	WHO declares pandemic, CPI unexpectedly high
March 15, 2020	FOMC cuts rates (unscheduled) with press conference
April 3, 2020	NFP unexpectedly low
April 10, 2020	CPI unexpectedly low
April 29, 2020	FOMC leaves rates unchanged with press conference
May 8, 2020	NFP unexpectedly high
May 12, 2020	CPI unexpectedly low
June 5, 2020	NFP unexpectedly high
June 10, 2020	FOMC leaves rates unchanged with press conference, CPI unexpectedly low
July 2, 2020	NFP unexpectedly high
July 14, 2020	Early Moderna data point to efficacy, CPI as expected
July 29, 2020	FOMC leaves rates unchanged with press conference
August 7, 2020	NFP unexpectedly high
August 12, 2020	CPI unexpectedly high
August 27, 2020	FOMC adopts AIT
September 4, 2020	NFP unexpectedly high
September 11, 2020	CPI unexpectedly high

September 16, 2020	FOMC leaves rates unchanged with press conference
October 2, 2020	NFP unexpectedly low
October 13, 2020	CPI as expected
November 5, 2020	FOMC leaves rates unchanged with press conference
November 6, 2020	Biden wins Presidential election, NFP unexpectedly high
November 12, 2020	CPI unexpectedly low
December 4, 2020	NFP unexpectedly low
December 10, 2020	CPI unexpectedly high
December 16, 2020	FOMC leaves rates unchanged with press conference
January 8, 2021	NFP unexpectedly low
January 13, 2021	House impeaches Trump again, CPI unexpectedly high
January 27, 2021	FOMC leaves rates unchanged with press conference
February 5, 2021	NFP unexpectedly high
February 10, 2021	CPI unexpectedly low
March 5, 2021	NFP unexpectedly high
March 10, 2021	House votes on American Rescue Plan, CPI as expected
March 17, 2021	FOMC leaves rates unchanged with press conference
April 2, 2021	NFP unexpectedly high
April 13, 2021	CPI unexpectedly high
April 28, 2021	FOMC leaves rates unchanged with press conference
May 7, 2021	NFP unexpectedly low
May 12, 2021	CPI unexpectedly high
June 4, 2021	NFP unexpectedly low
June 10, 2021	CPI unexpectedly high
June 16, 2021	FOMC leaves rates unchanged with press conference
July 2, 2021	NFP unexpectedly high
July 13, 2021	CPI unexpectedly high
July 28, 2021	FOMC leaves rates unchanged with press conference
August 6, 2021	NFP unexpectedly high
August 11, 2021	CPI unexpectedly high
September 3, 2021	NFP unexpectedly low
September 14, 2021	CPI as expected
September 22, 2021	FOMC leaves rates unchanged with press conference
October 8, 2021	NFP unexpectedly low
October 13, 2021	CPI unexpectedly high
November 3, 2021	FOMC leaves rates unchanged with press conference
November 5, 2021	NFP unexpectedly high
November 10, 2021	CPI unexpectedly high
December 3, 2021	NFP unexpectedly low
December 10, 2021	CPI as expected
December 15, 2021	FOMC leaves rates unchanged with press conference