Consumer Inflation Expectations: Daily Dynamics

Conces Binder, Carola and Campbell, Jeffrey and Ryngaert, Jane

Haverford College, Department of Economics, University of Notre Dame, Department of Economics; Tilburg University, Department of Econometrics OR; Federal Reserve Bank of Chicago; and CEPR., University of Notre Dame, Department of Economics

15 December 2022

Consumer Inflation Expectations: Daily Dynamics*

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

December 15, 2022

Abstract

We use high frequency identification methods to study the response of consumer inflation expectations to many different types of events. We use 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 announcements, macroeconomic data releases, and news related to the Covid-19 pandemic. The majority of FOMC meetings have no detectable effects on consumer inflation expectations, though certain especially salient announcements have short-lived effects. Good news about the pandemic tends to reduce inflation expectations.

JEL codes: E31, E52, E71

Keywords: inflation expectations, monetary policy, consumer surveys

Introduction

In recent years, central banks and researchers have ramped up efforts to measure and study household inflation expectations. Understanding how households form their inflation expectations, and how policymakers might be able to influence these expectations, is of critical interest to monetary policymakers. Despite a wealth of new survey evidence, identifying the effects of economic conditions and policies on consumer expectations remains challenging. Households' inflation expectations are highly heterogeneous and likely driven by a range of

*We thank our two discussants, Fiorella DeFiore and Emanuel Moench as well as participants at the 2022 JME-SNB-SCG Conference.

†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

different factors, making it difficult to pinpoint the effect of, for example, a central bank announcement or economic news. Endogeneity concerns also plague such efforts.

Two types of approaches have attempted to address this challenge. The first approach utilizes randomized control trials, or “information experiments,” that randomize respondents’ exposure to one or more information treatments and measure the effect of the information on respondents’ expectations (Armantier et al., 2016a; Coibion et al., 2020; Binder and Rodrigue, 2018; Binder, 2020a, 2021a). Consumers may, however, respond differently to these information treatments that they would to “real world” announcements. A second approach, which alleviates this external validity concern, involves high frequency event studies in which researchers survey respondents in a small window of days surrounding events or announcements of interest. If the window is sufficiently narrow, differences in expectations in the pre- and post-event groups can be attributed to the event itself. For example, Dräger et al. (2022) survey German economics professors a few days before and after the Russian invasion of Ukraine, and find that the respondents surveyed after the invasion have higher inflation expectations. These surveys are typically only conducted over a relatively small number of pre-selected days and are therefore limited by researcher foresight.

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 consumer expectations response to monetary policy and news. The SCE is a monthly rotating panel, but respondents are surveyed throughout 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.

First, we describe the properties of consumer expectations at higher frequency, and compare several time series measures constructed from the daily SCE inflation point forecasts and density forecasts to each other and to more recent surveys launched by Federal Reserve Bank of Cleveland researchers in 2020 and 2021. We also show that despite high noise in the SCE daily inflation expectations time series, they are positively correlated with measures of inflation compensation from the Treasury Inflation Protected Securities (TIPS) market and with daily gas prices.

We then use the daily frequency of the data to facilitate causal inference about potential drivers of inflation expectations. We identify a large set of event dates from June 2013 through December 2021, including 70 FOMC announcements, 102 consumer price index (CPI) releases, and 93 nonfarm payroll (NFP) releases. For each announcement or data release, we conduct an event study in which we estimate the difference in expectations between the two days following an event and the two days before the event as well as the event date. We use all available data from the survey to control for fixed effects. The respondents who take the survey in the few days before a particular event serve as a control group for the respondents who take the survey immediately after that event allowing for causal interpretation of our estimates.

An important feature of our approach is that we estimate a *separate* effect of each event, rather than an average effect of the pooled events. This allows for the possibility that different events affect expectations in different ways, which may not necessarily be correlated with the events' effects on market expectations or even with the magnitude or direction of the change in policy rate. Indeed, we find that FOMC meetings with target rate cuts sometimes have large positive effects and sometimes large negative effects on inflation expectations, for example. Likewise, strong jobs reports sometimes increase and sometimes reduce inflation expectations, depending on the news coverage surrounding the release.

We show that particularly newsworthy FOMC announcements and macroeconomic data releases can have significant effects on consumer inflation expectations. For example, unscheduled emergency FOMC meetings, and certain meetings with policy rate changes, are more likely to affect inflation expectations. The effects of events on medium-run inflation expectations are similar to those on short-run expectations and the effects on inflation uncertainty are mildly positively correlated with effects on inflation expectations.

Many of the events in our sample with the largest effects on expectations have ocurred since the start of the Covid-19 pandemic. Consumers in these recent years may be particularly attuned to news and its potential inflationary impacts. To explore this further, we extend our analysis to study the effect of news about the COVID-19 pandemic on consumer expectations. We find that several key dates associated with the pandemic had large effects on expectations. For example, of all of the event dates in our study, the day that Moderna revealed vaccine efficacy results had the largest negative effects on consumer inflation expectations, reducing them by 2.2%. This could reflect a simple association of "good times" with low inflation (Binder, 2020b; Kamdar, 2018; Candia et al., 2020), or consumers might have anticipated that the vaccine would help relieve supply restrictions. The two major Covid-related fiscal stimulus packages also had significant positive effects on inflation expectations. We also consider the two presidential election dates in our sample, and find that the Trump election lowered expectations and the Biden election raised expectations, though neither effect was statistically significant.

Our identification strategy is similar to that of Lamla and Vinogradov (2019), who survey consumers in the days before and after a set of Federal Open Market Committee (FOMC) announcements. 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 different. Another closely related paper by Rast (2022) exploits the timing of a survey of German consumers. Some respondents were surveyed about their qualitative inflation expectations before European Central Bank (ECB) announcements and others after. ECB announcements about changes in the target interest rate have a significant effect on qualitative inflation expectations, while announcements about forward guidance and QE do not. Announcements that increase the target rate reduce inflation expectations.

In the paper most closely related to ours, Fiore et al. (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 on inflation expectations. The baseline event window we use, from two days before to two days after each event, is much shorter than that of Fiore et al. (2019), who use a window of 21 days before to 21 days after, and this may explain some of the differences in our results. There are, of course, tradeoffs involved in selecting the window width. A wider window increases the number of observations surrounding each event, and allows for the possibility that expectations respond with a delay. A narrower window only captures the very short-run effect of an event, but with cleaner identification. Narrower windows reduce the threat to identification that arises when other events that affect expectations occur in the same window. In particular, macroeconomic data releases and salient political events could potentially affect inflation expectations, and often occur within days or weeks of an FOMC meeting.

Our paper is also closely related to a few other papers ussing daily data or new surveys to study expectations in the Covid era. Armantier et al. (2021) use the SCE to study inflation expectations, uncertainty, and disagreement in the first six months of the Covid-19 pandemic. They regress inflation expectations measures on dummy variables corresponding to five periods of 2020—pre-pandemic (January 1 to March 10), initial period (March 11 to March 26, 2020), lockdown (March 27 to May 15, 2020), and reopening (May 16 to June 30)—and on a post-2018 dummy and fixed effects for individuals, month, and survey tenure. Uncertainty rose quickly in the initial period, while expectations rose moderately in the lockdown period and more notably in the reopening period. Detmers et al. (2022) also use the daily SCE data to study inflation expectations in the pandemic, but their main focus is on state-level government responses to the pandemic. Containment policies aimed at mitigating the pandemic were associated with higher inflation expectations and uncertainty. In March 2020, Dietrich et al. (2021) began conducting a daily survey of consumers' expectations about how the Covid-19 pandemic would affect the economy, including inflation. The difference between our paper and these is that we use a high-frequency identification strategy to study the effects of a wide variety of shocks over a longer time period.

Nagel and Yan (2021) study the response of retail flows into TIPS in response to inflation news and announcements. Retail investors' inflation expectations do not respond to typical Fed announcements, but major TIPS flows are associated with the 2016 Presidential election and the March 2020 Covid-19 crisis. Binder and Makridis (2022) and Lewis et al. (2019) study the response of consumer sentiment to gas prices and monetary policy announcements, respectively, using daily Gallup survey data. The Gallup data does not ask about inflation expectations, but rather about sentiment (optimism or pessimism) about overall economic conditions. Sentiment declines with gas prices and with a surprise increase in the federal funds target rate. In a large survey experiment in April 2020, Coibion et al. (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. In another experiment, Andre et al. (2022) find that some U.S. households believe that increasing the federal funds target rate raises inflation due to a "good-bad heuristic."

The paper proceeds as follows. Section 1 describes properties of a daily time series constructed with the SCE data and describes why, in analyzing the daily dynamics of consumer data, it is useful to use the panel feature of the data rather than a raw time series. Section 2 describes our events and methodology. Section 3

1 Daily Consumer Survey Data

We build our measures of daily inflation expectations using data from the FRBNY Survey of Consumer Expectations, which began in June 2013. A nationally representative sample of approximately 1300 household heads participate in the online survey each month, and respondents can participate for up to 12 months in a row. The Demand Institute, operated by the Conference Board and Nielsen, operates the survey on behalf of the FRBNY.

We are able to use this monthly survey to calculate *daily* inflation forecasts because respondents take the survey throughout the month and the public data set includes each response's calendar date. Our sample spans 3,140 days, from 1 June 2013, and it ends on 4 January 2022. The average number of respondents per day over this period is a bit over 42, the median equals 35, and the 25th and 75th percentiles are 22.5 and 56. The maximum number of respondents on a single day is 172 (which occurred on 14 November 2019), and there are 111 days in the sample with zero respondents. Appendix Figure A.1 displays how responses are distributed across the days of the week, weeks of the month, and weeks of the year. Responses are more frequent on Mondays and decline through the week, with around 58 responses on an average Monday and 33 on an average Saturday. Binder (2021b) shows that on a popular survey platform, Amazon Mechanical Turk, respondent demographic characteristics differ by the day of the week that they take the survey. In the SCE, however, respondent characteristics are consistent across days of the week and month. Appendix Figure A.2 shows that the share of college-educated, low-income, and female respondents are stable over the days of the week. In summary, the number of respondents varies somewhat systematically across time, but respondents' demographic characteristics do not.

1.1 Respondents' Forecasts

The FRBNY SCE solicits point forecasts and density forecasts at two horizons—one year ahead and 2-3 years ahead. 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 enter any number. The corresponding 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 then enters 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 probabilities into ten bins, two of which are open-ended, four of which have width 4%, and four of which have width 2%. Analogous questions are asked about the 12-month period between 24 months and 36 months from the survey date.

We use the mean implied by the subjective distribution fit according to Ryngaert (2022). The Ryngaert measure combines the point and density forecasts to form a subjective probability distribution.[1] We also consider two additional measures of inflation expectations derived from the density forecasts: the probability that the respondent assigns to high inflation (above 4%) and the probability that the respondent assigns to near-target inflation (between 0% and 4%).

The inflation expectations data display thick tails in the cross section. The interquartile range of one-year-ahead inflation expectations equals 4 percent. A normal distribution with the same range would have a standard deviation of 2.96, which is much less than the actual standard deviation reported in Appendix Table A.1, 5.08. The interquartile range for the two-to-three year ahead expectations equals 4.1 percent, and the analogous predicted standard deviation is 3.05 percent. If we Winsorized the top and bottom 5% of forecasts *by day*, the standard deviations fall to 3.97 and 3.91 percent. In spite of this lower cross-sectional standard deviation, we choose *not* to remove outliers from our data by Winsorization or by any other means, because we believe (for reasons we document below) that Winsorization removes economically relevant information from the time series. This hypothesis is consistent with Reis (2021)'s findings that inflation expectations typically become unanchored first through movement out of and into the tails of the cross-sectional distribution.

1.2 The Daily Time Series

Figure 1 shows two time series measures of daily inflation expectations using the Ryngaert measure at the one-year horizon. Panel A is the interpolated median, which is the preferred measure that the FRBNY uses to summarize the monthly data.[2] Panel B shows the mean.

[1] 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 (2022) describes this measure in considerably more detail. We use this measure, but we examine our results' robustness to instead using the the New York Fed's preferred methodology.

[2] Armantier et al. (2016b, p. 21) note that "almost all respondents appear to round to the nearest integer value. Accordingly, when tracking changes in survey responses over time, it would be common to see either no change in the computed raw median or a sudden abrupt change of one or more percentage points...

Inflation expectations at both horizons begin the sample (in June 2013) at about 4.4 percent. They fall in 2015 to about 3.7 percent, and fluctuate between 3.4 and 3.7 percent through 2020. In 2021, they rise substantially to 5.7 percent and 4.7 percent.

Appendix Figure A.3 shows the centered seven-day moving average of the mean Ryngaert measures of inflation expectations and uncertainty at the one-year and two- to three-year horizons. The longer- and shorter-horizon series have similar properties and are highly correlated. Appendix Tables A.2, A.3 and A.4 provide summary statistics and correlations between median and mean inflation expectations and uncertainty measures at both horizons, using point or density forecasts.

The daily time series are quite noisy due to the relatively small sample size per day. In our regression analysis in the next sections, we will use the daily microdata, which pools observations in the days surrounding events and allows us to control for individual heterogeneity, thereby mitigating this noisiness. Response heterogeneity creates sampling error in the time series. Here, we begin our characterization of the daily time series' dynamics by quantifying this sampling error's contribution to their variances.

For this, define π_t^e as the population mean inflation expectation on day t, and let $\hat{\pi}_t^e$ be the average calculated from the finite SCE sample for the same day. If we had an infinite sample for each day in hand, then we would estimate the unconditional variance of π_t^e using

$$\hat{\mathbb{V}} = \frac{1}{T}\sum_{t=1}^{T}\left(\pi_t^e - \bar{\pi}_t\right)^2,$$

where $\bar{\pi}_t \equiv \frac{1}{T}\sum_{t=1}^{T}\pi_t^e$ is the sample mean (across days) of the daily inflation expectations. If we replace the unobserved values of π_t^e with their estimates, we get

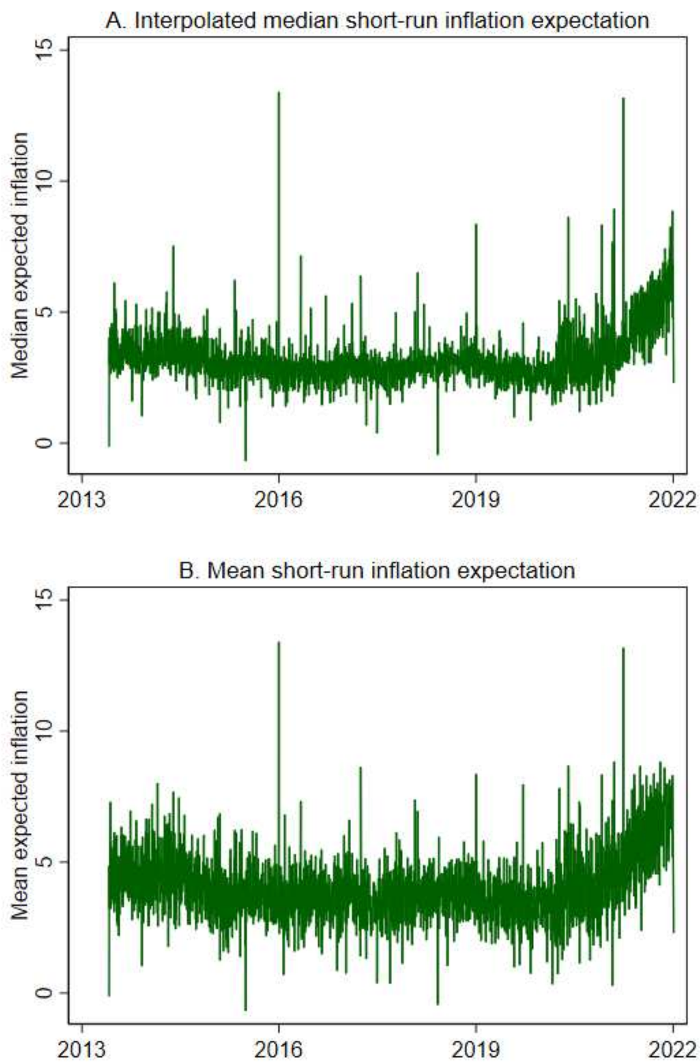
$$\hat{\hat{\mathbb{V}}} = \frac{1}{T}\sum_{t=1}^{T}\left(\hat{\pi}_t^e - \bar{\hat{\pi}}_t\right)^2,$$

where $\bar{\hat{\pi}}_t \equiv \frac{1}{T}\sum_{t=1}^{T}\hat{\pi}_t^e$ equals the average of the observed inflation expectations. To characterize the relationship between $\hat{\mathbb{V}}$ and $\hat{\hat{\mathbb{V}}}$, take expectations of the later across possible finite samples of respondents. (This holds the time series π_t^e fixed.) Straightforward calculations yield

$$\mathbb{E}\left[\hat{\hat{\mathbb{V}}}\right] = \hat{\mathbb{V}} + (1+3/T)\,\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}\left[(\hat{\pi}_t^e - \pi_t^e)^2\right].$$

Interpolated medians will better capture shifts in the frequencies of responses around the median."

Figure 1: Daily short-run inflation expectations



Notes: Survey of Consumer Expectations data from June 2013 through December 2021. Figure shows the mean Ryngaert measure of expected inflation at the one-year horizon by day.

Since T greatly exceeds 3, the second term approximately equals the average (across days) sampling variances of the daily inflation estimates. if we calculate this average instead with the standard unbiased estimates of these sampling variances and subtract the result from $\hat{\hat{\mathbb{V}}}$, we get

$$\hat{\mathbb{V}}^C \equiv \hat{\hat{\mathbb{V}}} - (1 + 3/T)\frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\frac{1}{N_t - 1}\sum_{i=1}^{N_t}\left(\pi_{it}^e - \hat{\pi}_t^e\right)^2,$$

where N_t is the number of observations on date t and π_{it}^e is the response of individual i at date t. By construction $\mathbb{E}\left[\hat{\mathbb{V}}^C\right] = \hat{\mathbb{V}}$. Furthermore, applying a standard law of large numbers to the second term (with appropriate regularity conditions on the fourth moments of π_{it}^e) shows that $\hat{\mathbb{V}}^C$ consistently estimates $\hat{\mathbb{V}}$ as T becomes large.

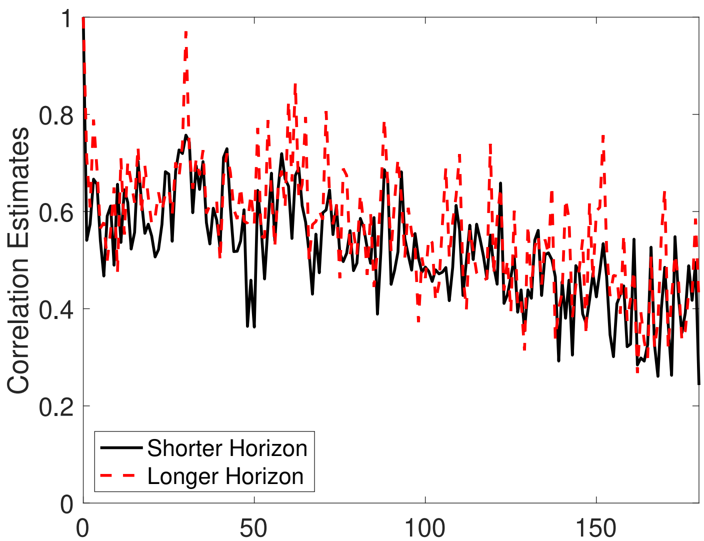
We apply this result to our entire sample and to two subsamples, before and after December 1, 2019. We chose this break date so that our earlier sample is free of the effects of Covid-19. For the pre-Covid-19 sample, the raw variance estimates ($\hat{\hat{\mathbb{V}}}$) equal 1.43 and 1.15 percentage points squared at the short and longer horizons, respectively. The estimates corrected for sampling variance ($\hat{\mathbb{V}}^C$) equal 0.58 and 0.25 percentage points squared. That is, the majority of the time-series variance in our daily estimates arises from sampling error.

With a consistent estimate of the variance of π_t^e in hand, we proceed to estimate the time series' autocorrelations. When each day's sample is entirely independent of any other day's, then the two days' sampling errors are also independent, which implies that $\mathrm{Cov}(\pi_t^e, \pi_{t-j}^e) = \mathrm{Cov}(\hat{\pi}_t^e, \hat{\pi}_{t-j}^e)$. To estimate the autocorrelations, we assume that the panel structure of the SCE data does not lead to a substantial violation of this equality. Based on this, our estimate of the autocorrelation at lag j is the sample covariance between $\hat{\pi}_t^e$ and $\hat{\pi}_{t-j}^e$ divided by the consistent estimator of $\hat{V}$ as calculated above.

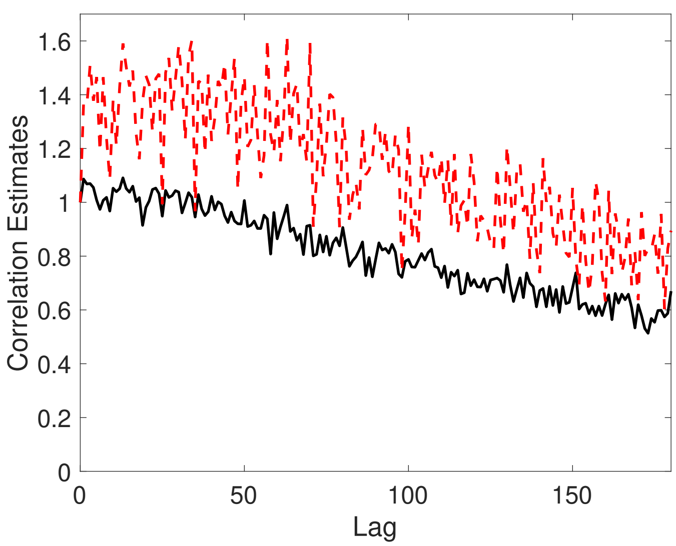
The top panel of Figure 2 plots the resulting autocorrelation estimates for both the one-year-ahead and two-to-three-year expectations for the pre-Covid sample. The analogous autocorrelations for the post-Covid sample are in the bottom panel. Both panels give the autocorrelations from zero through 180 lags, and we set the contemporaneous autocorrelation equal to its true value of one. The other autocorrelation estimates are noisy, which is not surprising since we have used almost no econometric structure to estimate them. Nevertheless, the estimates reveal some basic time-series properties of the daily inflation expectations. For both forecast horizons, the first autocorrelation, that is the correlation between any day's expectation and that of an adjoining day, is substantially below one. For the one-year horizon, this equals 0.54, while for the longer horizon it equals 0.71. As the lag length increases, both autocorrelation functions fall slowly. At 180 days, they equal 0.24

Figure 2: Daily Inflation Expectations' Estimated Autocorrelations

a. Pre-Covid Sample



b. Post-Covid sample



Notes: Survey of Consumer Expectations data from June 2013 through December 2021. Panel a shows estimated autocorrelations before December 1, 2019, at shorter and longer horizons. Panel b shows analogous results since December 1, 2019.

and 0.42, respectively.[3] This figure suggests that some shocks have a transitory influence on respondents' inflation expectations. The post-Covid autocorrelations in the bottom panel both start out *above* one. Although our estimation procedure does not mechanically rule out such estimates, they obviously exceed their population counterparts. These autocorrelations also decline slowly with the lag length. At 180 days, they equal 0.67 and 0.89 respectively.

Inflation expectations were stable in the pre-Covid period relative to the post-Covid period, so we expect these two samples' autocorrelations differ substantially. However, we believe that the low values of autocorrelations at very short lags could be informative about the process of expectations formation. Such low short-horizon autocorrelations characterize any process that adds a completely transitory "shock" to a persistent component. To see if inattentive and uninformed respondents raising the variance of inflation expectations accounts for this, we redid our analysis using the Winsorized versions of our data described above. Surprisingly, Winsorizing these data *reduced* these short-lag autocorrelations substantially. For the pre-Covid sample, the first autocorrelations of the two expectations equalled 0.27 and 0.34. The analogous values for the post Covid sample are 0.83 and 0.71. It seems that our sample's "outliers" contain information on inflation forecasts that persists across time. This is our empirical justification for not Winsorizing or removing extreme observations.

Appendix Table A.5 summarizes the correlations of the longer-run daily inflation expectations series with contemporaneous and lagged market-based inflation compensation measures derived from the Treasury Inflation Protected Securities (TIPS) market: a 5-year rate and a 5-year 5-year forward rate,[4]. As should be expected, all correlations are positive. The Ryngaert series have among the highest correlation coefficients with the TIPS measures. Appendix Table A.6 summarize the correlations of the shorter-run daily inflation expectations series with oil prices, lagged oil prices, and consumers' expected gas and food price changes. Again, all correlations are positive, and the Ryngaert series have higher correlation coefficients than the point forecast series. We think that this helps justify our choice of the Ryngaert measure as our preferred measure in the subsequent sections.

On March 10, 2020, the Federal Reserve Bank of Cleveland launched a daily consumer survey to solicit consumers' expectations about how the Covid-19 pandemic would affect the economy (Dietrich et al., 2021). The inflation questions were worded analogously to the point

[3]We have verified that these autocorrelation estimates eventually are in a neighborhood of zero when the lag length is 730 days.

[4]The 5-year inflation expectation rate is computed as 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). The 5-year, 5-year forward inflation expectation rate is the FRED series T5YIFR.

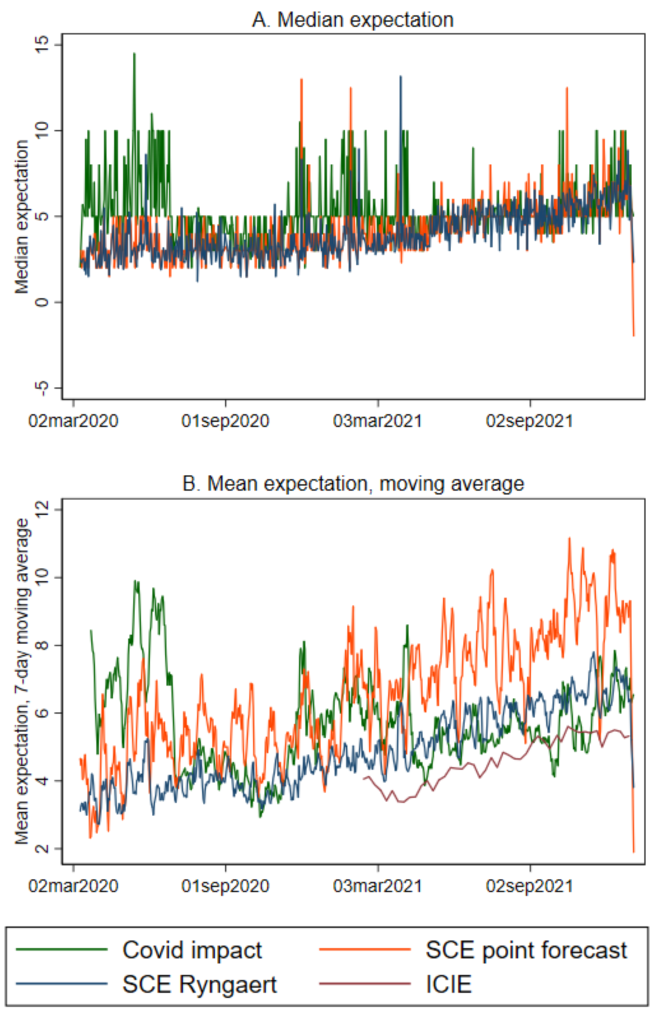
forecast and density forecast questions from the SCE, but asked directly about the impact of coronavirus. For example, the point forecast question asks, "How much [higher/lower] do you expect the rate of inflation to be over the next 12 months because of coronavirus?" They surveyed around 60,000 respondents from March 10, 2020 through July 11, 2021, or around 120 respondents per day. They provide data on the daily (uninterpolated) median point forecast of the Covid impact on inflation, as well as the 7-day moving average mean point forecast. Even more recently, other Cleveland Fed researchers launched a weekly survey of indirect consumer inflation expectations (ICIE), beginning February 13, 2021 (Hajdini et al., 2022).[5]

We construct measures for the SCE point forecasts and Ryngaert forecasts that are comparable to the Cleveland Fed series: the daily uninterpolated median, and the 7-day moving average mean. The daily uninterpolated medians are shown in Panel A of Figure 3. The Covid impact measure is somewhat higher and noisier than the SCE measures over the same time period, with a mean of 5.3% and standard deviation of 1.7%. The SCE point forecast and Ryngaert measures have means of 4.2% and 4.0%, respectively, and standard deviations of 1.5% and 1.4%, respectively. Because of the relatively high noise of these series, the correlation of the Covid impact measure with each of the SCE measures is only about 0.1. Recall that these series are not intended to measure exactly the same thing. Dietrich et al. (2021) interpret the Covid impact measure as capturing "consumers' views about the impulse response of the economy to the pandemic." Appendix Table A.7 shows that the difference between the SCE measures and the Covid impact measure is positively correlated with gas prices–that is, the SCE measures capture movements in inflation expectations related to gas prices, but the Covid impact measure, by construction, does not.

Panel B of Figure 3 shows the 7-day moving average Covid impact, SCE point forecast, and Ryngaert means, and the weekly ICIE. The ICIE measure only overlaps with the others on 47 dates. It is about a percentage point lower than the Ryngaert measure, with which it has a correlation coefficient of 0.8, and three percentage points lower than the point forecast measures, with which it has a correlation coefficient of 0.7.

[5]This survey asks respondents, "Given your expectations about developments in prices of goods and services during the next 12 months, how would your income have to change to make you equally well-off relative to your current situation, such that you can buy the same amount of goods and services as today?"

Figure 3: Comparison of High Frequency Measures of Consumer Expectations



Notes: Data from Survey of Consumer Expectations (SCE) and Federal Reserve Bank of Cleveland. Top panel shows daily medians of consumers' point forecasts of the impact of Covid on inflation, SCE point forecasts of inflation, and the Ryngaert measure. Bottom panel shows seven-day moving average mean of consumers' point forecasts of the impact of Covid on inflation, SCE point forecasts, and the Ryngaert measure, and the weekly ICIE measure.

2 Event Description and Methodology

We measure the response of expectations to 70 FOMC meeting dates, 102 consumer price index (CPI) release dates, and 93 nonfarm payroll (NFP) release dates. These events provide information to markets and consumers about monetary policy and the state of the macroeconomy that may indicate the likely future path of inflation. For FOMC meetings that occur over two days (typically a Tuesday and Wednesday), the event date is defined as the second day of the meeting. The associated "after" dummy thus includes the Thursday and Friday after the Wednesday afternoon FOMC announcement. For each FOMC meeting, we also have data on whether the meeting included a press conference, was unscheduled (i.e. an emergency meeting), and involved a change to the federal funds rate target. We also have measures of the monetary policy shock implied by price changes in the Eurodollar futures market in a narrow window around the FOMC announcement. A shock is defined as the change in the expected interest rate over the next 4 quarters implied by the contract price. We use the eurodollar shocks to classify meetings as expansionary or contractionary (relative to market expectations before the meeting).

We also use macroeconomic data releases from the Bureau of Labor Statistics. Nonfarm payrolls are typically released on the first Friday of the month as a part of the BLS Employment Situation Report. CPI releases typically occur in the second week of the month, though the day of the week varies. To sign the direction of the surprise, we use Bloomberg forecast data to characterize the releases as either higher than expected (positive surprise) or lower than expected (negative surprise). Appendix Table B provides a complete list of event dates and descriptions.

We conduct a separate event study for each FOMC meeting and data release. For each s, our regression takes the form:

$$Y_{it} = \alpha + \beta A^s_{it} + \Gamma Z_{it} + \epsilon_{it} \tag{1}$$

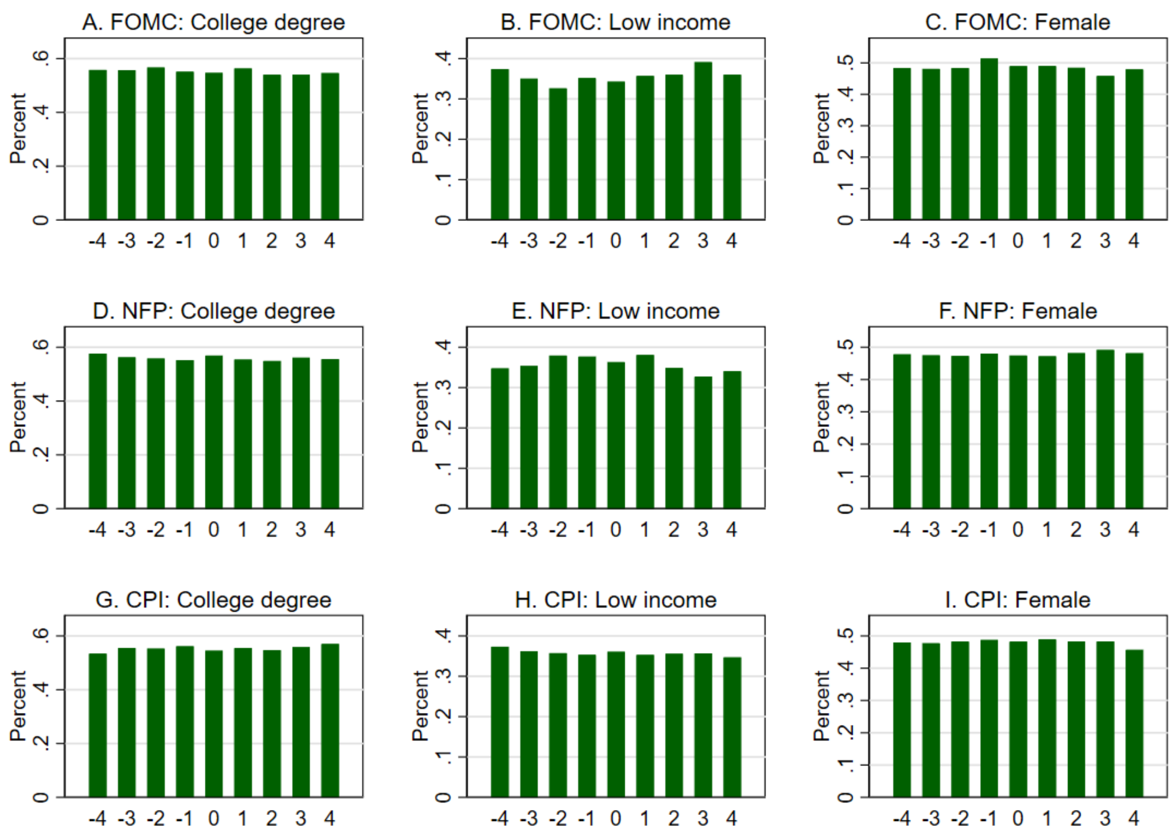
Our primary dependent variable Y_{it} is the Ryngaert short-run inflation expectations measure, though we also estimate the regression with alternative dependent variables, including the point forecast and FRBNY density mean inflation expectations measures and measures of longer-run inflation expectations and inflation uncertainty. Note that we use *all* data from June 2013 through December 2021, not only from windows surrounding event dates. This allows us to add fixed effects for respondent, tenure, day of week.[6]

The dummy variable A_{it}^s indicates that respondent took the survey one or two days after event s. The set of controls Z_{it} includes a dummy variable $\{E_{it}^s\}_{s=1}^S$ indicating that the respondent took the survey from two days before to two days after event s. The event fixed effects allow for causal interpretation of the coefficient β_s as the effect of event s on Y_{it}, because the respondents in the days before the event serve as a control group for the respondents in the days after the event. Figure 4 shows that the respondents are demographically similar in the days before and after the event. Other events that influence expectations and occur within our event window pose a threat to identification and are omitted variables in this specification. We use small event windows to limit the potential for other events to influence our estimates.

Our approach is similar to that of Lamla and Vinogradov (2019), who estimate the pooled effect of 12 FOMC meetings with press conferences on inflation expectations. We estimate a *separate* effect β_s for each of the an expanded set of meetings and announcement dates. This allows use to identify potentially opposite effects of events on inflation expectations even among events of the same type.

[6]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 (2021b) 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 are important because respondents' inflation expectations and uncertainty tend to decline with their survey tenure, reflecting "learning-through-survey" effects (Kim and Binder, 2022). The respondent fixed effects control for both observable and unobservable heterogeneity between respondents and help improve the precision of our estimates.

Figure 4: Respondent Characteristics around Event Dates



Notes: Share of college educated, low income, and female respondents in the days around FOMC meetings, non-farm payroll and CPI data releases. 0 indicates the event date.

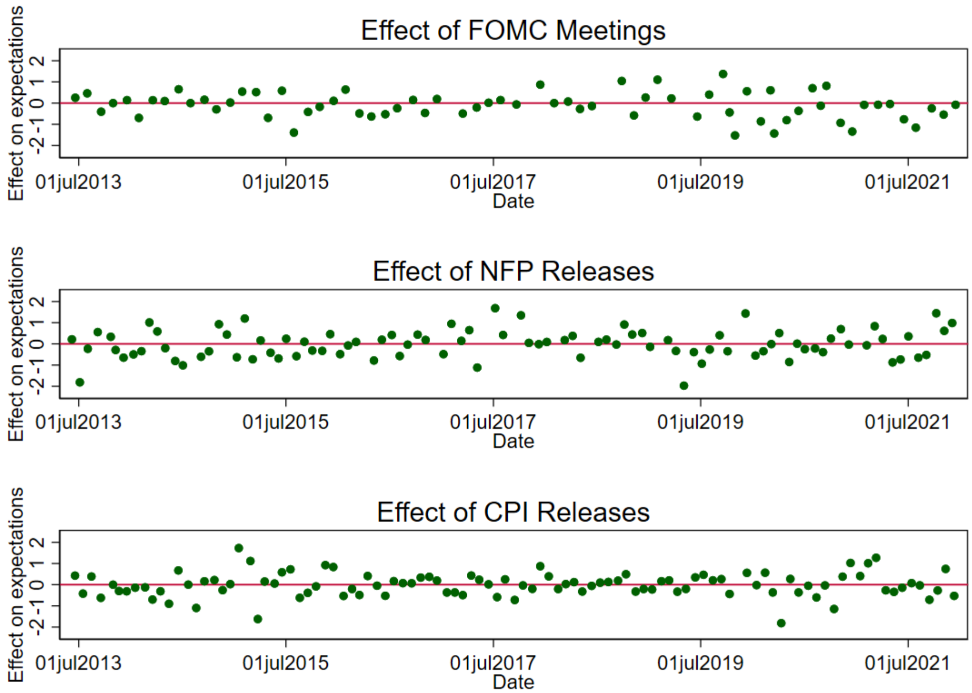
3 Response of Inflation Expectations to Shocks

We estimate Equation 1 separately for each of the shock dates described above, with the Ryngaert measure of short-run inflation expectations as our dependent variable. Figure 5 shows the effects of FOMC meetings and macroeconomic data releases over time.

3.1 Effects of FOMC Announcements on Inflation Expectations

Figure 6 shows histograms of the β_s estimates for different types of FOMC meetings. A notable result, in Panel A, is that meetings with rate cuts sometimes have large positive effects and sometimes have large negative effects. For example, the October 30, 2019 meeting,

Figure 5: Effects of events on inflation expectations



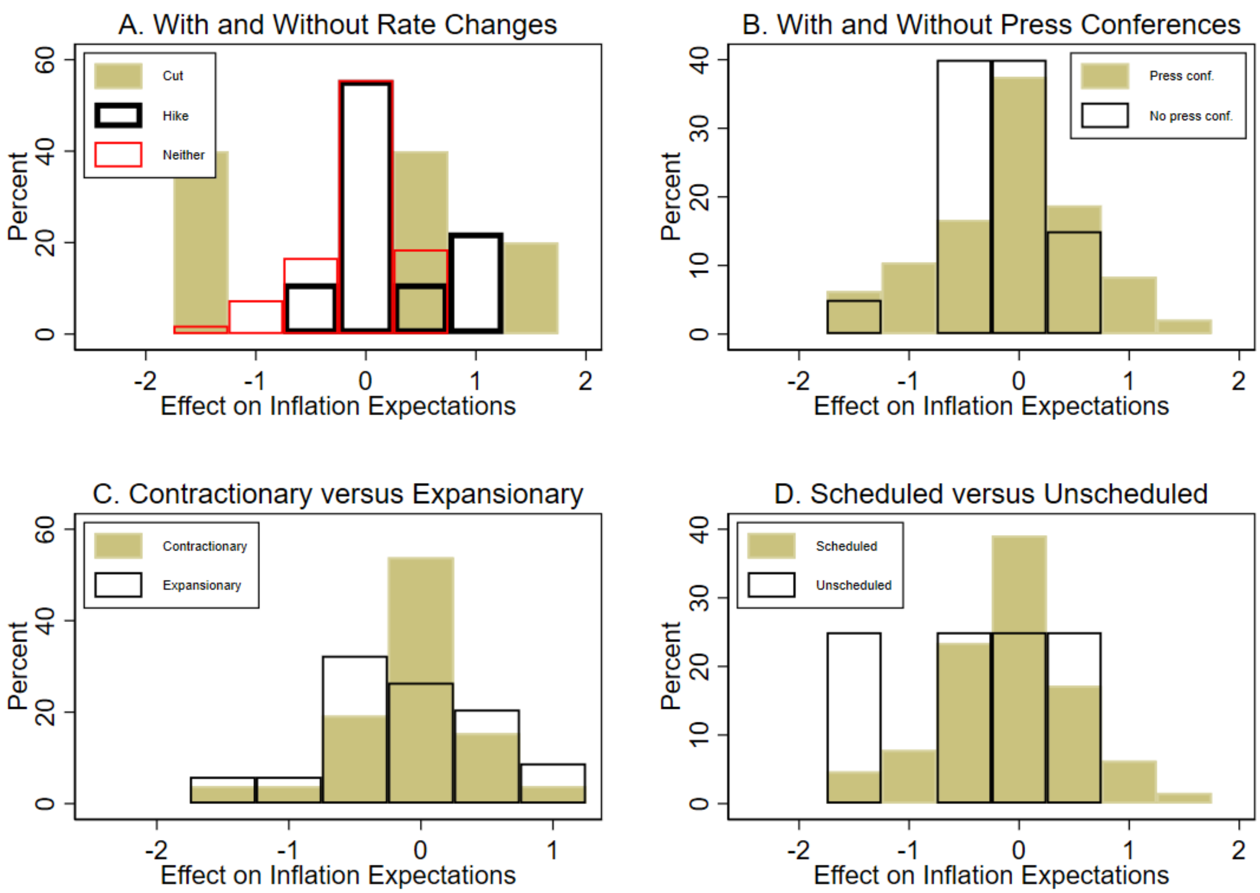
Notes: Figure shows the effects of FOMC meetings, NFP releases, and CPI releases on inflation expectations over time.

which included a rate cut, was associated with a decrease in expectations of 1.5%. CNBC reported that "Fed cuts interest rates, but indicates a pause is ahead"[7] and CNN reported that "Fed cuts rates for the third time as US economy slows."[8] In contrast, the September 18, 2019 FOMC meeting, which also included a rate cut, was associated with an *increase* in expectations by 1.4%. The New York Times reported that "Mr. Powell said that gradual rate increases remained the best way for the Fed to navigate between the danger the economy will overheat and cause inflation, and the danger the economy will falter."[9] This meeting also received a greater-than-usual amount of news coverage because of President Trump's tweets criticizing the Fed for not cutting rates more rapidly.

Still, meetings without rate changes can occasionally have large effects on expectations. For example, the December 16, 2020 meeting was also associated with a significant decline

[7]https://www.cnbc.com/2019/10/30/fed-decision-interest-rates-cut.html.
[8]https://www.cnn.com/2019/10/30/economy/federal-reserve-rate-decision-october/index.html.
[9]https://www.nytimes.com/2018/09/26/us/politics/federal-reserve-raises-interest-rates.html.

Figure 6: Effects of FOMC announcements on inflation expectations



Notes: Figure shows histograms of the estimated effects of FOMC meetings on consumer inflation expectations.

in expectations of 1.3%. Though this meeting did not involve a rate change, CNBC reported that "the Federal Reserve committed to continue buying bonds until the economy reaches full employment and inflation stays at 2%."[10] This may have made some consumers aware that the Fed was concerned about low inflation.

Panel B of Figure 6 shows that meetings with press conferences, which tend to receive more news coverage, are more likely to have large effects on consumer expectations. Panel C shows that meetings that the markets view as contractionary can have either positive

[10]https://www.cnbc.com/2020/12/16/fed-decision-december-2020-fed-commits-to-keep-buying-bonds-until-the-economy-gets-back-to-full-employment.html.

or negative effects on consumer expectations, as can meetings that the markets view as expansionary. Panel D shows that unscheduled or emergency meetings are more likely to have large—and in our sample, negative—effects on expectations. The March 16, 2020 emergency rate cut in response to the Covid-19 pandemic reduced inflation expectations by 1.4%. Newspapers widely reported that the Fed had cut rates to zero.

Fiore et al. (2019) consider the series of 2013 FOMC meetings associated with the "Taper Tantrum," and find that none of these meetings had a statistically significant effect on inflation expectations. The June tapering announcement surprised financial markets and resulted in a substantial stock market decline. Our estimate of β_s associated with that announcement is 0.2% and is not statistically significant. For the September and December announcements, like Fiore et al. (2019), we find no statistically significant effect on inflation expectations, with β estimates of -0.4% and 0.1%, respectively.

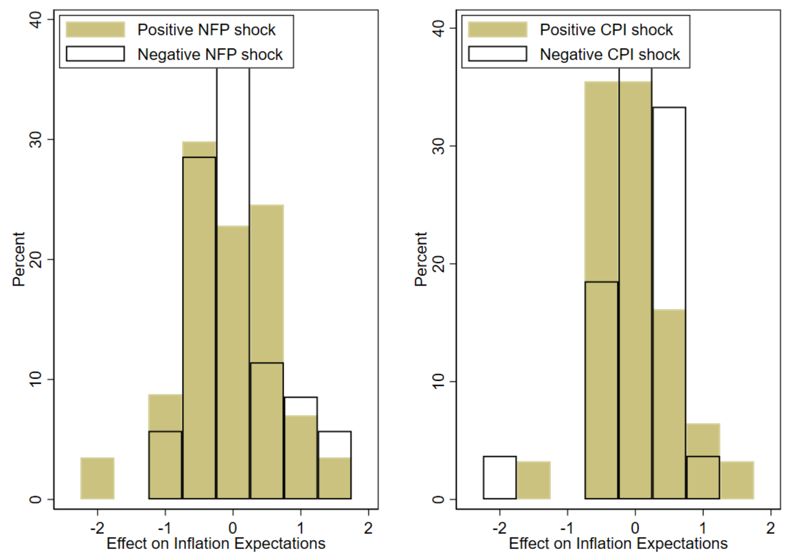
Another important monetary policy announcement in our sample was the August 27, 2020 change to the "Statement on Longer-Run Goals and Monetary Policy Strategy." With this announcement, the FOMC changed its inflation targeting strategy to an average inflation targeting strategy and also noted that "the maximum level of employment is a broad-based and inclusive goal." Based on the eurodollars markets, investors interpreted this announcement as expansionary. For consumers, it had no statistically significant effect on inflation expectations; the β estimate is -0.1%. This is in line with the results of Coibion et al. (2021), whose survey evidence revealed only a small uptick in the share of households who reported hearing news about monetary policy after the announcement compared to before. They also found that information treatments about inflation targeting and about average inflation targeting did not have different effects.

3.2 Response of Expectations to Data Releases

Figure 7 summarizes the response of consumer inflation expectations to CPI and NFP releases. Positive and negative surprises in each of these data releases are similarly likely to reduce or raise inflation expectations. One of the largest positive CPI shocks was in November 2021, when the CPI report came in 0.3% higher than expected and CNBC reported that "U.S. consumer prices jump 6.2% in October, the biggest inflation surge in more than 30 years."[11] Inflation expectations rose 0.7%. The April 2020 CPI announcement had the largest negative effect on expectations, which fell 1.8%. This announcement was particularly newsworthy because, as Reuters reported, "U.S. consumer prices post largest drop in five

[11] https://www.cnbc.com/2021/11/10/consumer-price-index-october.html.

Figure 7: Effect of Data Releases on Inflation Expectations



Notes: Figure shows histograms of the estimated effects of NFP and CPI releases on consumer inflation expectations.

years amid coronavirus disruptions."[12]

Two stronger-than-expected job reports had the opposite effects on inflation expectations. The July 2017 NFP announcement increased inflation expectations by 1.7%, while the May 2019 announcement reduced expectations by 2.0%. Though both of these announcements received significant news coverage, the tone of the coverage differed. Coverage of the July 2017 announcement focused on how the strength of the jobs data alleviated any fear of an economic slowdown.[13] This would have emphasized the strength of aggregate demand. In response to the May 2019 announcement, in contrast, the New York Times and other sources focused on slow wage growth despite strong jobs growth, pointing to "little threat of troublesome inflation or other signs of excess. The length of the average workweek actually fell, while wage growth for the month was slightly below what was expected."[14] The October 2021 NFP announcement, which was weaker than expected, raised inflation expectations by 1.4%. News coverage of this report focused on supply side factors, like the Delta variant and supply chain problems, and also noted that "Rising wages could add to concerns about

[12] https://www.reuters.com/article/us-usa-economy-economy-idUSKCN21S1B7.
[13] https://www.barrons.com/articles/strong-jobs-data-quell-slowdown-fears-1499493604.
[14] https://www.nytimes.com/2019/05/03/business/economy/jobs-report-april.html.

inflation."[15]

3.3 Alternative Dependent Variables

If we use the FRBNY density mean instead of the Ryngaert measure of short-run inflation expectations, results are very similar. The correlation between the β_s estimates using the FRBNY measure and the Ryngaert measure is 0.92 (correlations between t-statistics are similar). Likewise, if we Winsorize the Ryngaert measure, our β_s estimates are highly correlated with our baseline estimates. Correlations with the β_s estimates on inflation uncertainty (the forecast interquartile range) are only mildly positive; using our methodology to study the drivers of inflation uncertainty could be an interesting area of future research.

Table 1: Correlations between β_s estimates for alternative measures of inflation expectations

Variables	Baseline	Wins. Ryngaert	FRBNY	Long-run	Uncertainty
Baseline	1.00				
Wins. Ryngaert	0.91	1.00			
FRBNY	0.92	0.86	1.00		
Long-run	0.54	0.48	0.48	1.00	
Uncertainty	0.08	0.09	0.01	0.01	1.00

3.4 Selection

Our identification strategy requires that the respondents in the days after an event are similar to the respondents in the days before. If certain types of respondents select into the treatment group by observing the event and then deciding to complete the survey on that date, β_s would pick up systematic differences in respondents rather than the effect of the event on expectations. Figure 4 shows that respondent characteristics are similar in the days leading up to and following the three event types. To test for this further, we regress:

$$Y_{it-1} = \alpha + \beta_s^L A_{it}^s + \Gamma Z_{it} + \epsilon_{it} \tag{2}$$

and

[15] https://www.nytimes.com/2021/10/08/business/economy/jobs-report-september-2021.html.

$$Y_{it+1} = \alpha + \beta_s^H A_{it}^s + \Gamma Z_{it} + \epsilon_{it} \tag{3}$$

The dependent variable in Equation 2 is a respondent's inflation expectation from the month before the event s (where s occurs in month t). The treatment and control groups are still determined by the timing of the responses in month t. The online collection of the survey makes it unlikely that a set of respondents responds to the survey with the same relative timing two months in a row. The coefficient, β_s^L, reveals the difference in the expectations of the treatment and control group that existed prior to event s.

The dependent variable in Equation 3 is a respondent's inflation expectation from the month after the event s. β_s^H therefore is the difference in the expectations of the two groups a month after the event. We expect that the effect β_s from Equation 1 will not persist to $t+1$. The identification relies on the timing of the survey; some respondents provide their answers before observing the event and some provide them after. In month $t+1$ all respondents have observed the event in question. Table 2 shows the correlations between the effect of the event on inflation expectations in $t-1$, t and $t+1$. The correlation between β_s^L and β_s is 0.11 and the correlation between β_s^H and β_s is 0.08. The low correlations suggest that the event effect we recover (β_s) are driven by the events themselves rather than selection into the treatment group.

Table 2: Correlations between β_s estimates for inflation expectations at different horizons

Variables	Ryngaert, t-1	Baseline	Ryngaert, t+1
Ryngaert, t-1	1.00		
Baseline	0.11	1.00	
Ryngaert, t+1	0.03	0.08	1.00

4 Pooled Events

We would not expect all events in a category to have the same directional effect on inflation expectations. CPI releases, for example, can come in higher or lower than experts predicted. We therefore use professional forecasts and market-based expectations to classify *direction* within event types. We group CPI release dates as CPI^H if the CPI release comes in higher than predicted by Bluechip forecasters and CPI^L if it comes in lower. We similarly split non-farm payroll releases into NFP^H and NFP^L based on the sign of the surprise to the average Bluechip forecast. We classify FOMC meetings as expansionary ($FOMC^E$) or contractionary ($FOMC^C$) based on interest rate surprise implied by Eurodollar contracts.

Separately for each event type (FOMC, CPI, NFP), we estimate:

$$Y_{it+1} = \alpha + \beta^{type,+} A_{it}^{type,+} + +\beta^{type,-} A_{it}^{type,-} \Gamma Z_{it} + \epsilon_{it} \tag{4}$$

where $A_{it}^{type,+}$ and $A_{it}^{type,-}$ are dummies indicating that a response was submitted in the two days following an event of a given type that surprised markets or forecasters in a given direction. We estimate Equation 4 three times with pooled events NFP^H and NFP^L, CPI^H and CPI^L, and $FOMC^E$ and $FOMC^C$. We include event fixed effects for each individual event to maintain the causal interpretation of our coefficients as well as fixed effects for respondent, day of week, and tenure. The results of the regressions appear in Table 3.

Table 3: Pooled Effect of Shocks

	(1)	(2)	(3)
CPI: Positive Surprise	0.35**		
	(0.17)		
CPI: Negative Surprise	0.49***		
	(0.18)		
NFP: Positive Surprise		0.12	
		(0.34)	
NFP: Negative Surprise		0.07	
		(0.35)	
FOMC: Expansionary			-0.53
			(0.44)
FOMC: Contractionary			-0.55
			(0.48)
Observations	9884	12864	5799

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table shows that, on average, CPI surprises in either direction increase inflation expectations. This means that consumers revise their expectations up when professional forecasters are demonstrated to have underestimated or overestimated inflation. It is possible that CPI releases bring inflation to the forefront of household's minds, regardless of how the release compared to previous professional forecasts. The remaining events do not have a significant effect on expectations on average, though FOMC meetings that induced either contractionary or expansionary surprises in the futures markets have a negative effect on inflation expectations. These results highlight the benefit of our approach. Some events, particularly certain employment surprises, have large effects on consumer inflation expectations even though *on average* these events do not influence inflation expectations. Using the Survey of Consumer Expectations as a daily survey, we are able to identify the events that most move expectations.

5 Extension: Covid-19 News and Elections

We have seen that certain FOMC announcements and macroeconomic releases move consumer inflation expectations. To put the magnitudes of these estimated effects in context, we estimate the response of inflation expectations to certain salient events related to the Covid-19 pandemic and Presidential elections. These events include:

- 11/9/2016 Trump wins Presidential election
- 1/21/2020 CDC confirms first US Covid case
- 1/31/2020 WHO issues global health emergency
- 3/11/2020 WHO declares pandemic
- 3/25/2020 Senate passes CARES Act
- 7/14/2020 Early Moderna data point to efficacy
- 11/6/2020 Biden wins Presidential election
- 11/16/2020 Moderna efficacy results
- 3/10/2021 House votes on American Rescue Plan

We find that early news about the pandemic had little effect on expectations—the WHO declaration of a global health emergency and the CDC confirmation of the first US case had small positive effects. In the early days of the pandemic, consumers may not have known how to interpret potential effects on inflation (Binder, 2020a). The event that had the *largest* negative effect on inflation expectations was the November 2020 news about the efficacy of the Moderna vaccine, which reduced inflation expectations by 2.2%. Announcements of large fiscal stimulus packages in response to the pandemic had statistically significant positive effects on inflation expectations. When the Coronavirus Aid, Relief, and Economic Security Act passed the Senate in March 2020, inflation expectations rose 1.7%, the second largest positive effect of all events we considered. The House vote on the American Rescue Plan in March 2021 raised inflation expectations by 1.3%.

Since Presidential elections tend to be highly salient and newsworthy events, we also estimate the effect of each of the Presidential elections in our sample. We find that Trump's election win reduced inflation expectations by 0.6%, while Biden's raised expectations by 0.7%, though neither of these effects is statistically significant.

6 Discussion and Conclusions

We have used high frequency consumer survey data to study the effects of many different types of events and announcements on consumer inflation expectations outside of a controlled experiment. Previous research has found that consumers are fairly inattentive to monetary policy and central bank communication, and that their inflation expectations differ from a full-information rational inattention benchmark in important ways. Our results are largely in line with these, but add some new insights and nuances.

While consumers are inattentive to monetary policy announcements and macroeconomic data releases on average, *particular* announcements and releases move expectations, perhaps by generating more salient media coverage. In an extension to events related to the Covid-19 pandemic, we show that consumers respond to highly significant developments, such as good news about the vaccine and the passing of large pandemic related spending bills. Future research may use the data and methods described in this paper to investigate the response of inflation expectations to different types of shocks. It may also study the response of other types of expectations and plans to such shocks.

References

Andre, Peter, Carlo Pizzinelli, Christopher Roth, and Johannes Wohlfart (2022) "Subjective Models of the Macroeconomy: Evidence from Experts and a Representative Sample," *Review of Economic Studies*.

Armantier, Olivier, Gizem Kosar, Rachel Pomerantz, Daphne Skandalis, Kyle Smith, Giorgio Topa, and Wilbert van der Klaauw (2021) "How economic crises affect inflation beliefs:

Evidence fromthe Covid-19 pandemic," *Journal of Economic Behavior and Organization*, 189, 443–469.

Armantier, Olivier, Scott Nelson, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar (2016a) "The Price Is Right: Updating Inflation Expectations in a Randomized Price Information Experiment," *Review of Economics and Statistics*, 98 (3), 503–523.

Armantier, Olivier, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar (2016b) "An Overview of the Survey of Consumer Expectations," *Federal Reserve Bank of New York Staff Reports* (800).

Binder, Carola (2020a) "Coronavirus Fears and Macroeconomic Expectations," *Review of Economics and Statistics*.

——— (2020b) "Long-run inflation expectations in the shrinking upper tail," *Economics Letters*, 186 (108867).

——— (2021a) "Presidential Antagonism and Central Bank Credibility," *Economics and Politics*, 33 (2), 244–263.

——— (2021b) "Time-of-day and day-of-week variations in Amazon Mechanical Turk survey responses," *Journal of Macroeconomics*, 71 (103378).

Binder, Carola and Christos Makridis (2022) "Stuck in the Seventies: Gas Prices and Consumer Sentiment," *The Review of Economics and Statistics*.

Binder, Carola and Alex Rodrigue (2018) "Household Informedness and Long-Run Inflation Expectations: Experimental Evidence," *Southern Economic Journal*, 85 (2), 580–598.

Candia, Bernardo, Olivier Coibion, and Yuriy Gorodnichenko (2020) "Communication and the Beliefs of Economic Agents," *NBER Working Paper* (27800).

Coibion, Olivier, Dimitris Georgarakos, Yuriy Gorodnichenko, and Michael Weber (2020) "Forward Guidance and Household Expectations," *Chicago Booth Paper* (20-20).

Coibion, Olivier, Yuriy Gorodnichenko, Edward S. Knotek II, and Raphael Schoenle (2021) "Average Inflation Targeting and Household Expectations," *NBER Working Paper* (27836).

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber (2022) "Does Policy Communication during COVID Work?" *International Journal of Central Banking*.

Detmers, Gunda-Alexandra, Sui-Jade Ho, and Özer Karagedikli (2022) "Understanding Consumer Inflation Expectations during the COVID-19 Pandemic," *The Australian Economic Review*, 55 (1), 141–154.

Dietrich, Alexander M., Keith Kuester, Gernot J. Muller, and Raphael S. Schoenle (2021) “News and uncertainty about COVID-19: Survey evidence and short-run economic impact,” *Federal Reserve Bank of Cleveland Working Paper*.

Dräger, Lena, Klaus Gründler, and Niklas Potrafke (2022) “Political Shocks and Inflation Expectations: Evidence from the 2022 Russian Invasion of Ukraine.”

Fiore, Fiorella De, Marco Lombardi, and Johannes Schuffels (2019) “Are households indifferent to monetary policy announcements?” *BIS Working Paper*.

Hajdini, Ina, Edward Knotek II, Mathieu Pedemonte, Robert Rich, John Leer, and Raphael Schoenle (2022) “Indirect Consumer Inflation Expectations,” *Federal Reserve Bank of Cleveland Economic Commendary* (3).

Kamdar, Rupal (2018) “The Inattentive Consumer: Sentiment and Expectations.”

Kim, GwangMin and Carola Binder (2022) “Learning-Through-Survey in Inflation Expectations,” *American Economic Journal: Macroeconomics*, Conditionally Accepted.

Lamla, Michael J. and Dmitri V. Vinogradov (2019) “Central bank announcements: Big news for little people?” *Journal of Monetary Economics*, 108, 21–38.

Lewis, Daniel, Christos Makridis, and Karel Mertens (2019) “Do Monetary Policy Announcements Shift Household Expectations?” (897).

Nagel, Stefan and Zhen Yan (2021) “Inflation Hedging on Main Street?Evidence from Retail TIPS Fund Flows.”

Rast, Sebastian (2022) “Central Bank Communication with the General Public: Survey Evidence from Germany,” *Working Paper*.

Reis, Ricardo (2021) “Losing the Inflation Anchor,” *Brookings Papers on Economic Activity*, Fall, 307–361.

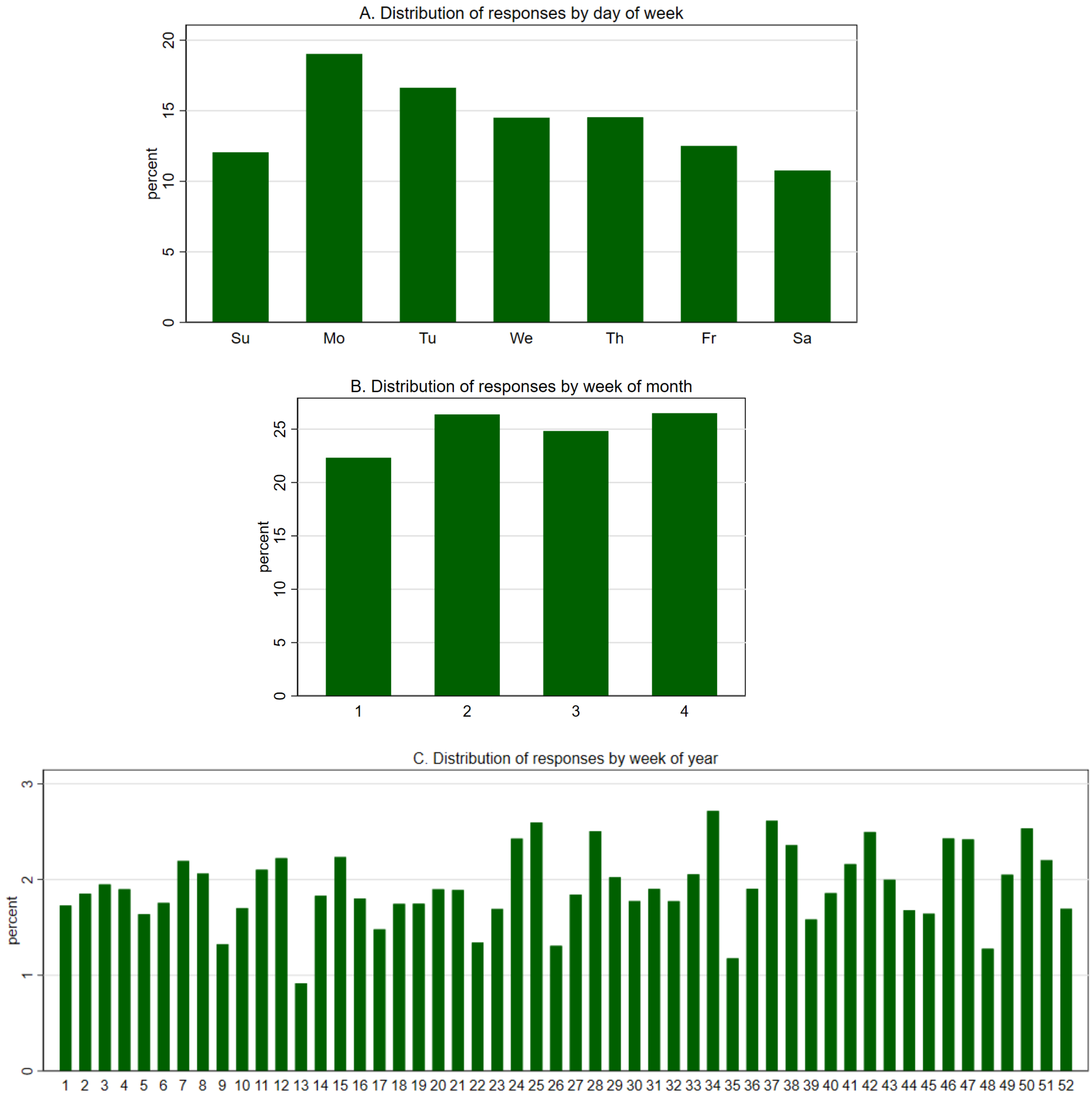
Ryngaert, Jane (2022) “Balance of Risks and the Anchoring of Consumer Inflation Expectations,” *Working Paper*.

Appendix A Appendix

	One Year Ahead			Two-Three Years Ahead		
	Variance	Percentage of Variance	Standard Deviation	Variance	Percentage of Variance	Standard Deviation
Total	24.65	100	4.96	25.84	100	5.08
Without Time Effects	23.50	95.3	4.85	25.02	96.8	5.00
Without Individual or Time Effects	10.76	43.7	3.28	11.70	45.3	3.42

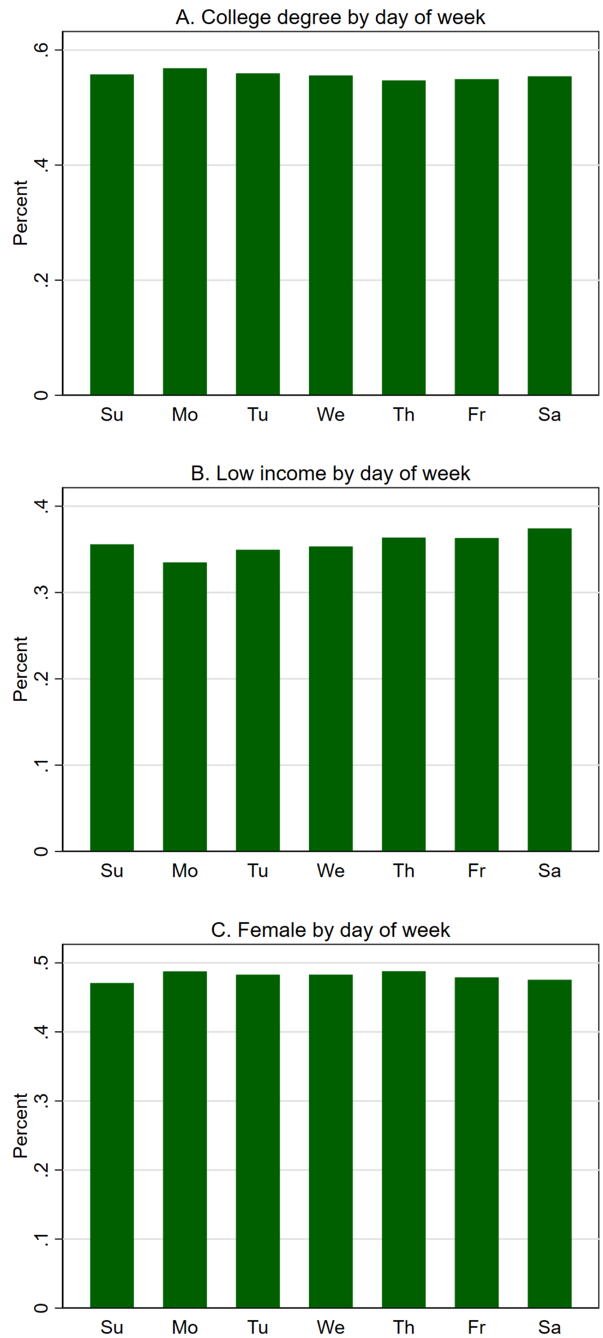
Table A.1: Decomposition of Variance for Reported Inflation Expectations

Figure A.1: Distribution of responses by day of week, week of month, and week of year



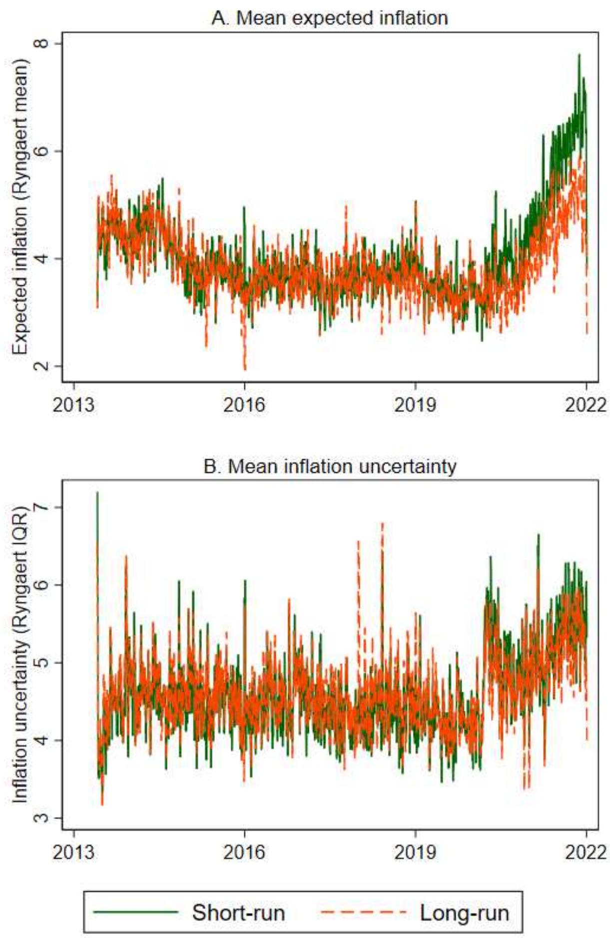
Notes: Survey of Consumer Expectations data from June 2013 through December 2021.

Figure A.2: Respondent characteristics by day of week



Notes: Survey of Consumer Expectations data from June 2013 through December 2021.

Figure A.3: Mean inflation expectations and and uncertainty, seven-day moving average



Notes: Survey of Consumer Expectations data from June 2013 through December 2021. Top panel shows the mean Ryngaert measure of expected inflation at the one-year and five-year horizon by day. Bottom panel shows the mean Ryyngaert measure of inflation uncertainty (density interquartile range) at the one-year and five-year horizon by day. The centered seven-day moving average is shown for each series.

Table A.2: Summary statistics for daily time series of inflation expectations

	Short Horizon		Long Horizon	
Series	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
WinsPF	5.3	2.3	5.1	2.1
MedPF	3.5	1.2	3.5	1.0
Density	3.8	1.2	3.7	1.1
MedDensity	3.0	0.9	2.9	0.7
Ryn	4.0	1.2	3.9	1.1
MedRyn	3.2	0.9	3.2	0.8
High	35.3	9.7	35.4	8.1
NearTarget	51.2	8.1	49.1	8.1

Notes: Survey of Consumer Expectations data from June 2013 to December 2021. Table summarizes daily frequency time series of one-year-ahead and two-to three-year-ahead inflation expectations: winsorized point forecasts, interpolated median point forecasts, density mean, interpolated median density mean, Ryngaert mean, interpolated median Ryngaert mean, density percent above 4%, and density percent between 0% and 4%.

Table A.3: Correlations of daily one-year inflation expectation series

Variables	WinsPF	MedPF	WinsDen.	MedDen.	WinsRyn.	MedRyn.	High
WinsPF	1.00						
MedPF	0.70	1.00					
Density	0.56	0.56	1.00				
MedDensity	0.47	0.61	0.80	1.00			
WinsJRDensity	0.59	0.59	0.97	0.79	1.00		
MedJRDensity	0.50	0.66	0.79	0.93	0.84	1.00	
High	0.54	0.65	0.84	0.84	0.84	0.84	1.00
NearTarget	-0.47	-0.59	-0.61	-0.62	-0.60	-0.63	-0.85

Notes: Survey of Consumer Expectations data from June 2013 to December 2021. Table summarizes correlation coefficients between daily time series of one-year-ahead inflation expectations: winsorized point forecasts, interpolated median point forecasts, density mean, interpolated median density mean, Ryngaert mean, interpolated Ryngaert mean, density percent above 4%, and density percent between 0% and 4%.

Table A.4: Correlations of daily two- to three-year inflation expectation series

Variables	WinsPF	MedPF	WinsDen.	MedDen.	WinsRyn.	MedRyn.	High
WinsPF	1.00						
MedPF	0.63	1.00					
Density	0.51	0.53	1.00				
MedDensity	0.37	0.58	0.74	1.00			
JRDensity	0.55	0.56	0.97	0.71	1.00		
MedJRDensity	0.39	0.64	0.73	0.91	0.77	1.00	
High	0.45	0.65	0.79	0.79	0.80	0.81	1.00
Near Target	-0.28	-0.46	-0.41	-0.42	-0.39	-0.46	-0.75

Notes: Survey of Consumer Expectations data from June 2013 to December 2021. Table summarizes correlation coefficients between daily time series of two- to three-year-ahead inflation expectations: winsorized point forecasts, interpolated median point forecasts, density mean, interpolated median density mean, Ryngaert mean, interpolated Ryngaert mean, density percent above 4%, and density percent between 0% and 4%.

Table A.5: Correlation of long-run daily inflation expectations series with TIPS measures

Variable	WinsPF	MedPF	WinsDen.	MedDen.	WinsRyn.	MedRyn.	High	NearTarg
5y	0.16	0.23	0.30	0.37	0.30	0.37	0.37	-0.30
Lag 5y	0.18	0.28	0.31	0.37	0.32	0.38	0.37	-0.27
5y, 5y	0.14	0.26	0.33	0.35	0.33	0.37	0.40	-0.25
Lag 5y, 5y	0.16	0.31	0.32	0.35	0.33	0.37	0.38	-0.23

Notes: Survey of Consumer Expectations data from June 2013 through December 2021. Table summarizes correlation coefficients between contemporaneous and lagged five-year and five-year, five-year forward Treasury Inflation Protected Securities (TIPS) breakevens and daily time series of two- to three-year-ahead inflation expectations: winsorized point forecasts, interpolated median point forecasts, density mean, interpolated median density mean, Ryngaert mean, interpolated Ryngaert mean, density percent above 4%, and density percent between 0% and 4%.

Table A.6: Correlation of short-run daily inflation expectations series with oil and expected gas and food price measures

Variable	WinsPF	MedPF	Den.	MedDen.	Ryn.	MedRyn.	High
Oil	0.18	0.22	0.30	0.27	0.30	0.28	0.30
Lagged oil	0.20	0.26	0.29	0.27	0.30	0.28	0.29
Gas	0.23	0.29	0.35	0.36	0.36	0.36	0.37
Lagged gas	0.23	0.31	0.36	0.37	0.37	0.37	0.37
WinsExpGas	0.24	0.27	0.26	0.24	0.27	0.26	0.23
MedExpGas	0.24	0.31	0.29	0.28	0.29	0.30	0.27
WinsExpFood	0.39	0.45	0.47	0.46	0.48	0.48	0.49
MedExpFood	0.34	0.48	0.45	0.49	0.46	0.52	0.50

Notes: Survey of Consumer Expectations data from June 2013 through December 2021. Table summarizes correlation coefficients between oil prices, gas prices, winsorized or interpolated median gas price expectations and food price expectations from the SCE, and daily time series of one-year-ahead inflation expectations. Daily gas price data is from OPIS.

Table A.7: Comparison of Daily Covid Inflation Expectations and SCE Inflation Expectations

	(1) Covid Impact	(2) PF	(3) Ryngaert	(4) PF-Covid	(5) Ryngaert-Covid
Mon	0.13	0.14	0.14	-0.03	-0.02
	(0.24)	(0.19)	(0.18)	(0.26)	(0.25)
Tue	0.20	0.14	0.16	-0.12	-0.10
	(0.24)	(0.23)	(0.22)	(0.30)	(0.28)
Wed	0.28	0.21	0.15	-0.15	-0.21
	(0.25)	(0.20)	(0.18)	(0.29)	(0.27)
Thu	0.46	0.06	0.16	-0.42	-0.31
	(0.28)	(0.19)	(0.18)	(0.29)	(0.29)
Fri	0.39	0.13	0.17	-0.31	-0.27
	(0.25)	(0.22)	(0.19)	(0.28)	(0.26)
Sat	-0.01	0.06	0.01	0.02	-0.04
	(0.23)	(0.21)	(0.19)	(0.25)	(0.24)
Gas Price				1.73***	1.76***
				(0.16)	(0.14)
Constant	5.07***	4.08***	3.86***	-5.55***	-5.84***
	(0.17)	(0.13)	(0.12)	(0.46)	(0.43)
N	649	649	649	649	649
R^2	0.01	0.00	0.00	0.18	0.19

Notes: Robust standard errors in parentheses. *** p< 0.01, ** p< 0.05, * p< 0.10. In column 1, dependent variable is the median Covid impact inflation expectation from (Dietrich et al., 2021). In column 2, dependent variable is the median point forecast from the SCE, and in column 3, the median Ryngaert mean from the SCE. Dependent variables in columns 4 and 5 are the difference between the median SCE point forecast or Ryngaert mean and the median Covid impact inflation. Gas price data at daily frequency is from OPIS. Data begins March 10, 2020.

Table A.8: Correlations between β_s estimates using different sets of fixed effects

Variables	All	DOW, ten.	Resp., ten.	Resp., DOW	Resp.	Ten.	DOW
All	1.000						
DOW, ten.	0.749	1.000					
Resp., ten.	0.999	0.752	1.000				
Resp., DOW	0.994	0.761	0.993	1.000			
Resp.	0.996	0.760	0.997	0.996	1.000		
Ten.	0.745	0.999	0.749	0.758	0.757	1.000	
DOW	0.736	0.996	0.739	0.753	0.753	0.996	1.000
None	0.732	0.995	0.736	0.749	0.750	0.996	0.999

Appendix B List of Event Dates and Descriptions

Date	Description
07jun2013	NFP unexpectedly high
18jun2013	CPI as expected
19jun2013	FOMC leaves rates unchanged with press conference
05jul2013	NFP unexpectedly high
16jul2013	CPI unexpectedly high
31jul2013	FOMC leaves rates unchanged
02aug2013	NFP unexpectedly low
15aug2013	CPI as expected
06sep2013	NFP unexpectedly high
17sep2013	CPI unexpectedly low
18sep2013	FOMC leaves rates unchanged with press conference
30sep2013	Government shutdown
22oct2013	NFP unexpectedly high
30oct2013	FOMC leaves rates unchanged, CPI as expected
08nov2013	NFP unexpectedly high
20nov2013	CPI as expected
06dec2013	NFP unexpectedly high
17dec2013	CPI as expected
18dec2013	FOMC leaves rates unchanged with press conference
10jan2014	NFP unexpectedly low
16jan2014	CPI as expected
29jan2014	FOMC leaves rates unchanged
07feb2014	NFP unexpectedly low
20feb2014	CPI as expected
07mar2014	NFP unexpectedly high
18mar2014	CPI unexpectedly low
19mar2014	FOMC leaves rates unchanged with press conference
04apr2014	NFP unexpectedly high
15apr2014	CPI as expected
30apr2014	FOMC leaves rates unchanged
02may2014	NFP unexpectedly high
15may2014	CPI as expected
06jun2014	NFP unexpectedly high
17jun2014	CPI unexpectedly high
18jun2014	FOMC leaves rates unchanged with press conference
03jul2014	NFP unexpectedly high
22jul2014	CPI as expected
30jul2014	FOMC leaves rates unchanged
19aug2014	CPI as expected
05sep2014	NFP unexpectedly low
17sep2014	FOMC leaves rates unchanged with press conference, CPI unexpectedly low
03oct2014	NFP unexpectedly high

22oct2014	CPI unexpectedly high
29oct2014	FOMC leaves rates unchanged
07nov2014	NFP unexpectedly high
20nov2014	CPI unexpectedly high
05dec2014	NFP unexpectedly high
17dec2014	FOMC leaves rates unchanged with press conference, CPI unexpectedly low
09jan2015	NFP unexpectedly high
16jan2015	CPI unexpectedly high
28jan2015	FOMC leaves rates unchanged
06feb2015	NFP unexpectedly low
26feb2015	CPI as expected
06mar2015	NFP unexpectedly high
18mar2015	FOMC leaves rates unchanged with press conference
24mar2015	CPI unexpectedly high
03apr2015	NFP unexpectedly low
17apr2015	CPI unexpectedly low
29apr2015	FOMC leaves rates unchanged
08may2015	NFP unexpectedly high
22may2015	CPI as expected
05jun2015	NFP unexpectedly high
17jun2015	FOMC leaves rates unchanged with press conference, CPI as expected
02jul2015	NFP unexpectedly low
17jul2015	CPI unexpectedly low
29jul2015	FOMC leaves rates unchanged
07aug2015	NFP unexpectedly high
19aug2015	CPI as expected
04sep2015	NFP unexpectedly low
16sep2015	CPI as expected
17sep2015	FOMC leaves rates unchanged with press conference
02oct2015	NFP unexpectedly low
15oct2015	CPI unexpectedly high
28oct2015	FOMC leaves rates unchanged
06nov2015	NFP unexpectedly high
17nov2015	CPI unexpectedly high
04dec2015	NFP unexpectedly high
15dec2015	CPI as expected
16dec2015	FOMC raises rates with press conference
08jan2016	NFP unexpectedly high
20jan2016	CPI unexpectedly low
27jan2016	FOMC leaves rates unchanged
05feb2016	NFP unexpectedly low
19feb2016	CPI unexpectedly high
04mar2016	NFP unexpectedly high
16mar2016	FOMC leaves rates unchanged with press conference, CPI unexpectedly high
14apr2016	CPI unexpectedly low

27apr2016	FOMC leaves rates unchanged
06may2016	NFP unexpectedly low
17may2016	CPI as expected
03jun2016	NFP unexpectedly low
15jun2016	FOMC leaves rates unchanged with press conference, CPI as expected
08jul2016	NFP unexpectedly high
15jul2016	CPI unexpectedly low
27jul2016	FOMC leaves rates unchanged
05aug2016	NFP unexpectedly high
16aug2016	CPI unexpectedly low
02sep2016	NFP unexpectedly low
16sep2016	CPI unexpectedly high
21sep2016	FOMC leaves rates unchanged with press conference
07oct2016	NFP unexpectedly high
18oct2016	CPI as expected
02nov2016	FOMC leaves rates unchanged
04nov2016	NFP unexpectedly low
09nov2016	Trump wins Presidential election
17nov2016	CPI as expected
14dec2016	FOMC raises rates with press conference, CPI as expected
06jan2017	NFP unexpectedly high
18jan2017	CPI as expected
03feb2017	NFP unexpectedly high
15feb2017	CPI unexpectedly high
10mar2017	NFP unexpectedly low
15mar2017	FOMC raises rates with press conference, CPI as expected
07apr2017	NFP unexpectedly low
14apr2017	CPI unexpectedly low
03may2017	FOMC leaves rates unchanged
05may2017	NFP unexpectedly high
12may2017	CPI unexpectedly low
14jun2017	FOMC raises rates with press conference, CPI unexpectedly low
07jul2017	NFP unexpectedly high
14jul2017	CPI unexpectedly low
26jul2017	FOMC leaves rates unchanged
04aug2017	NFP unexpectedly high
11aug2017	CPI unexpectedly low
14sep2017	CPI unexpectedly high
20sep2017	FOMC leaves rates unchanged with press conference
06oct2017	NFP unexpectedly low
13oct2017	CPI unexpectedly low
03nov2017	NFP unexpectedly low
15nov2017	CPI as expected
08dec2017	NFP as expected
13dec2017	FOMC raises rates with press conference, CPI as expected

05jan2018	NFP unexpectedly low
12jan2018	CPI as expected
31jan2018	FOMC leaves rates unchanged
14feb2018	CPI unexpectedly high
09mar2018	NFP unexpectedly high
13mar2018	CPI as expected
21mar2018	FOMC raises rates with press conference
06apr2018	NFP unexpectedly high
11apr2018	CPI as expected
02may2018	FOMC leaves rates unchanged
04may2018	NFP unexpectedly low
10may2018	CPI as expected
12jun2018	CPI as expected
13jun2018	FOMC raises rates with press conference
06jul2018	US trade war with China escalates, NFP unexpectedly high
12jul2018	CPI as expected
03aug2018	NFP unexpectedly low
10aug2018	CPI as expected
07sep2018	NFP unexpectedly high
13sep2018	CPI unexpectedly low
26sep2018	FOMC raises rates with press conference
05oct2018	NFP unexpectedly low
11oct2018	CPI unexpectedly low
02nov2018	NFP unexpectedly high
08nov2018	FOMC leaves rates unchanged
14nov2018	CPI as expected
07dec2018	NFP unexpectedly low
12dec2018	CPI as expected
19dec2018	FOMC raises rates with press conference
04jan2019	NFP unexpectedly high
11jan2019	CPI as expected
30jan2019	FOMC leaves rates unchanged with press conference
13feb2019	CPI unexpectedly high
08mar2019	NFP unexpectedly low
12mar2019	CPI unexpectedly low
20mar2019	FOMC leaves rates unchanged with press conference
05apr2019	NFP unexpectedly low
10apr2019	CPI unexpectedly high
03may2019	NFP unexpectedly high
10may2019	CPI unexpectedly low
07jun2019	NFP unexpectedly low
12jun2019	CPI unexpectedly low
19jun2019	FOMC leaves rates unchanged with press conference
05jul2019	NFP unexpectedly high
11jul2019	CPI as expected

31jul2019	FOMC cuts rates with press conference
02aug2019	NFP unexpectedly high
13aug2019	CPI unexpectedly high
06sep2019	NFP unexpectedly high
12sep2019	CPI unexpectedly low
18sep2019	FOMC cuts rates with press conference
04oct2019	NFP unexpectedly high
11oct2019	FOMC leaves rates unchanged (unscheduled), CPI as expected
30oct2019	FOMC cuts rates with press conference
06dec2019	Pelosi announces plan to impeach Trump, NFP unexpectedly high
11dec2019	FOMC leaves rates unchanged with press conference, CPI unexpectedly high
10jan2020	NFP unexpectedly low
14jan2020	CPI as expected
21jan2020	CDC confirms first US Covid case
29jan2020	FOMC leaves rates unchanged with press conference
31jan2020	WHO issues global health emergency
07feb2020	NFP unexpectedly high
13feb2020	CPI unexpectedly high
03mar2020	FOMC cuts rates (unscheduled) with press conference
06mar2020	NFP unexpectedly high
11mar2020	WHO declares pandemic, CPI unexpectedly high
16mar2020	FOMC cuts rates (unscheduled) with press conference
25mar2020	Senate passes CARES Act
03apr2020	NFP unexpectedly low
10apr2020	CPI unexpectedly low
29apr2020	FOMC leaves rates unchanged with press conference
08may2020	NFP unexpectedly high
12may2020	CPI unexpectedly low
05jun2020	NFP unexpectedly high
10jun2020	FOMC leaves rates unchanged with press conference, CPI unexpectedly low
02jul2020	NFP unexpectedly high
14jul2020	Early Moderna data point to efficacy, CPI as expected
29jul2020	FOMC leaves rates unchanged with press conference
07aug2020	NFP unexpectedly high
12aug2020	CPI unexpectedly high
27aug2020	FOMC adopts AIT
04sep2020	NFP unexpectedly high
11sep2020	CPI unexpectedly high
16sep2020	FOMC leaves rates unchanged with press conference
02oct2020	NFP unexpectedly low
13oct2020	CPI as expected
05nov2020	FOMC leaves rates unchanged with press conference
06nov2020	Biden wins Presidential election, NFP unexpectedly high
12nov2020	CPI unexpectedly low
16nov2020	Moderna efficacy results

04dec2020	NFP unexpectedly low
10dec2020	CPI unexpectedly high
16dec2020	FOMC leaves rates unchanged with press conference
06jan2021	Capitol riots
13jan2021	House impeaches Trump again, CPI unexpectedly high
27jan2021	FOMC leaves rates unchanged with press conference
05feb2021	NFP unexpectedly high
10feb2021	CPI unexpectedly low
05mar2021	NFP unexpectedly high
10mar2021	House votes on American Rescue Plan, CPI as expected
17mar2021	FOMC leaves rates unchanged with press conference
02apr2021	NFP unexpectedly high
13apr2021	CPI unexpectedly high
28apr2021	FOMC leaves rates unchanged with press conference
07may2021	NFP unexpectedly low
12may2021	CPI unexpectedly high
04jun2021	NFP unexpectedly low
10jun2021	CPI unexpectedly high
16jun2021	FOMC leaves rates unchanged with press conference
02jul2021	NFP unexpectedly high
13jul2021	CPI unexpectedly high
28jul2021	FOMC leaves rates unchanged with press conference
06aug2021	NFP unexpectedly high
10aug2021	Senate approves bipartisan infrastructure bill
11aug2021	CPI unexpectedly high
15aug2021	Afghan government falls to Taliban and US evacuates
03sep2021	NFP unexpectedly low
14sep2021	CPI as expected
22sep2021	FOMC leaves rates unchanged with press conference
08oct2021	NFP unexpectedly low
13oct2021	CPI unexpectedly high
03nov2021	FOMC leaves rates unchanged with press conference
05nov2021	NFP unexpectedly high
10nov2021	CPI unexpectedly high
03dec2021	NFP unexpectedly low
10dec2021	CPI as expected
15dec2021	FOMC leaves rates unchanged with press conference