Anchoring long-run inflation expectations in a panel of professional forecasters*

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Abstract

We use panel data from the US Survey of Professional Forecasters to estimate a model of individual forecaster behavior in an environment where inflation follows a trend-cycle stochastic process. Our model allows us to estimate forecasters' allocation of attention when learning about long-run inflation and how sensitive their long-run expectations are to incoming inflation and news about future inflation. We use our model of individual forecasters to study *average* long-run inflation expectations. We find that short term changes in inflation have small effects on average expectations. News about future inflation has larger effects but they are still relatively small. These features of our estimated model provide an explanation for why the anchoring and subsequent de-anchoring of average inflation expectations over the period 1991 to 2020 were long lasting episodes. We use our estimated model to investigate the degree of inflation overshooting necessary to re-anchor average long term inflation expectations going forward from 2021Q3. We find the high inflation readings of mid-2021 must be followed by overshooting generally at the high end of Fed projections to re-anchor average inflation expectations to pre-Great Recession levels.

Keywords: *Inflation anchoring, inflation overshoot, communication, long-run inflation expectations, panel survey data.*

JEL classification: *E31, C83, D84*

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1 Introduction

To assess their progress in maintaining price stability central bankers look at a variety of indicators, including average and median long term expectations from surveys.[1] While survey data on average long-term inflation expectations are plentiful, the information that gets aggregated into them and the factors that can cause them to remain stable or drift away from the central bank's target are not well understood.[2] In this paper, we introduce a method to estimate what forecasters in a panel survey pay attention to when forming expectations about long term inflation (or any other macroeconomic aggregate surveyed) and to study how their inflation expectations respond to the historical behavior of inflation and to news regarding the future path of inflation. We apply our method to panel data from the U.S. Survey of Professional Forecasters (SPF) to address two questions: (1) What were the underlying factors driving the anchoring and de-anchoring of long term average expectations over the last 30 years? and (2) How much must inflation overshoot the Fed's target to move long-term inflation expectations persistently back to the seemingly well-anchored levels that prevailed before the Great Recession?

In our model forecasting occurs within an environment in which inflation follows a standard trend-cycle time series process. Forecasters face a signal extraction problem to track the unobserved trend component of inflation which they use to formulate their long term expectations. We assume forecasters observe two signals. The first signal, which we call the *inflation signal*, is the current inflation rate that updates the forecasters' common knowledge of the history of inflation. This captures everything forecasters can learn about long-run inflation from observing inflation's historical behavior.

The second signal is trend inflation one or more quarters ahead plus noise. This signal captures forward-looking information or *news* about long-run inflation. This signal reflects central bank's communications regarding how it will seek to achieve its inflation objective,

[1]For example, see p. 27 of the January 2015 Tealbook available here: https://www.federalreserve.gov/monetarypolicy/files/FOMC20150128tealbooka20150121.pdf

[2]For example in the U.S. surveys that include longer term inflation expectations include Blue Chip Economic Indicators, Business Inflation Expectations from the Atlanta Fed, Livingston Survey, Michigan Survey of Consumers, Survey of Consumer Expectations from the New York Fed, and the Survey of Professional Forecasters.

but might also include changes in public trust regarding the central bank's ability to stabilize inflation around its target, and animal spirits or sentiment. The noise component of the news signal has two components. The first component is common to all forecasters and has time-varying volatility to capture waves of public attention to long term inflation. The second component is idiosyncratic and has a forecaster-specifc variance. This is to capture the forecasters' heterogeneous attention to long term inflation.

We take this model to the data in two steps. First, we estimate a standard trend-cycle time series model of inflation using core CPI inflation over the sample period 1959 to 2020. We combine this estimated model with the two signals just described to calculate the law of motion of the individual long-run inflation expectations. Second, we estimate this law of motion using the time series of CPI core inflation, trend inflation estimated in the first step, and our panel of SPF CPI 10-year inflation forecasts which covers the sample after 1991.

While we do not observe the second signal, it can be identified by the revisions to forecasters' expectations that cannot be rationalized by the historical behavior of inflation. This is facilitated by our assumption that we observe trend inflation when we estimate the law of motion of forecasters' expectations but forecasters do not. By doing so we can isolate the importance of news about trend inflation that is not yet reflected in historical inflation. The idiosyncratic component of the noise is identified by the cross-section of the SPF.

We estimate time-varying attention to inflation and news about future inflation and find that forecasters typically pay little attention to incoming inflation when trying to learn about long-term inflation. Averaging over the panel, forecasters adjust their long-term expectations by only 10 basis points in response to an observed change in the inflation signal of 100 basis points. On the one hand, this finding suggests that it takes a long period of high or low inflation for average inflation expectations to move away from target. On the other hand, if average inflation expectations become de-anchored, the central bank will be required to engineer a prolonged period of inflation above or below target to correct this situation.

Forecasters pay more attention to news about long term inflation but the elasticity of expectations to news is still relatively small; averaging over the panel a 100 basis point increase in the news signal leads to an immediate 25 basis point increase in long term expectations. This greater sensitivity to news than to actual inflation suggests that effective communications about the central bank's commitment to keep inflation at or near target is a less expensive tool to keep inflation expectations anchored in the face of rising inflation than actually engineering a recession with persistently lower inflation. We also find that attention to news about long-term inflation can change quickly. For example in the Great Recession the expectations elasticity for the news signal shot up from under 20% to 35% within a year.

Before the pandemic, CPI inflation ran below average inflation expectations for the most part of two decades. Yet from the late 1990s to the cusp of the Great Recession average long term expectations were remarkably stable, or anchored, at about 2.5%.[3] But in the face of inflation running below target for so long, at the onset of the Covid recession, average inflation expectations had drifted down to be close to our sub-target estimate of the trend level of inflation. Our estimates suggest the Fed's forward-looking communications slowed down the fall in SPF average inflation expectations but could not prevent it from happening eventually with inflation continuing to run below target.

What would have to happen to inflation to re-anchor expectations to their pre-Great Recession level? In our model, expectations can be re-anchored if inflation runs for some time above the Fed's average inflation target and the Fed communicates that it will use policy to ensure this outcome. We can use our model to investigate for how long and by how much inflation must overshoot the Fed's inflation target to bring average inflation expectations from the SPF back to their pre-Great Recession level on a persistent basis. Our estimated model is ideally suited to such an investigation because it provides an empirical grounding to how quickly individual SPF forecasters respond to incoming inflation and news about future inflation.

Following inflation's sharp rise in mid-2021 SPF long term expectations have returned to (nearly) 2.5%. How much of an overshooting would be required to keep long term expectations at this level? To address this question we consider an experiment where trend inflation

[3] CPI inflation runs higher than inflation in the personal consumption expenditures prices index from the National Income and Product Accounts which is the inflation measure targeted by the Fed.

is assumed to rise gradually to 2.5% by the end of 2024 and then solve for the path of inflation and news that is necessary to keep long term expectations at 2.5%. We find that the overshoot would have to far exceed the top end of the SEP projections unless there is strong communication. By signalling that inflation will come in higher than warranted by the underlying trend the central bank does not need as much of an overshoot to keep expectations anchored.

The remainder of the paper proceeds as follows. In the next section we discuss the related literature. After this we describe our model of individual forecasters, how we estimate this model, and the data we use. We then examine the history of inflation expectations through the lens of our estimated model. In the penultimate section we discuss our overshooting experiments, and then we conclude.

2 Relation to the literature

Our paper contributes to a large literature on the anchoring of inflation expectations. Broadly speaking the literature focuses on three concepts of anchoring. The first is the one we employ that considers expectations to be anchored when average inflation forecasts at long horizons remain stable and close to the inflation target. Ball and Mazumber (2018) and Kurmar, Afrouzi, Coibion and Gorodnichenko (2015) are two papers that also use this concept. The papers in this literature that are closest to ours study representative agents learning about the central bank's inflation objective. Some key work in this area includes Carvalho, Eusepi, Moench and Preston (2020), Beechey, Johannsen and Levin (2011), and Orphanides and Williams (2005). These papers consider signal extraction problems where agents seek to understand the central bank's inflation target using past data. Since they focus on the representative agent these papers consider mean or median of inflation expectations from surveys and ignore the cross-section information that is central to our study.

The second concept of anchoring that the literature has focused on is the one emphasized by Bernanke (2007). He described inflation expectations as being anchored when long-run expectations do not respond very much to incoming data. Corsello, Neri and Tagliabracci

(2021), Dräger and Lamla (2014), and Barlevy, Fisher and Tysinger (2021) have this concept in mind when they use panel data from surveys to estimate the time-varying elasticity of changes in long-run expectations with respect to changes in short-run expectations. Gürkaynak, Levin, Marder and Swanson (2007), Binder, Janson and Verbrugge (2019) and others analyze the response of inflation compensation in financial data to incoming macroeconomic news. We relate revisions of long-term inflation expectations to incoming inflation and news about future inflation using data on inflation and long term expectations of individual forecasters facing a signal extraction problem.

The third strand of the anchoring literature emphasizes higher order moments of inflation expectations from surveys and financial market data. Reis (2021) relates inflation anchoring to changes in the cross-sectional variance and skewness of survey measures of inflation expectations. Grishchenko, Mouabbi and Renne (2019) use a trend-cycle model with time-varying volatility to relate anchoring to the probability of future inflation as measured by survey expectations being in a certain range of the inflation target. While we focus on a narrower notion of expectations anchoring resting only on first moments, our methodology leverages the entire distribution of individuals' long-run inflation expectations to measure the sensitivity of average inflation expectations to news. Our approach has several advantages. First, it allows us to distinguish between changes in the aggregate attention to news concerning long-run inflation from the fixed amount of attention paid by an individual forecaster to news compared to that paid by other forecasters. Second, estimating these fixed effects allows us to control for compositional effects in the distribution of attention. Nechio (2015) studies the role of composition in the SPF in terms of the distribution of forecasters' root mean inflation forecast error. Accounting for compositional effects is particularly important in light of the critique of conditional mean forecasts highlighted by Engelberg, Manski and Williams (2010).

We also contribute to the large literature that has sought to identify the role of central bank communications in aggregate dynamics, including the literature on the Fed information effect and forward guidance that builds on Nakamura and Steinsson (2018), Gürkaynak, Sack and Swanson (2005), and Campbell, Evans, Fisher and Justiniano (2012). We identify central bank communications as the news received by forecasters about the long-run dynamics of inflation that are not reflected in the historical dynamics of inflation. Central bank communications may not be understood or listened to by the public. Indeed Coibion, Gorodnichenko, Kumar and Pedemonte (2020) show using survey data that, at least in a low inflation environment, households and firms pay little attention to monetary policy communications. This suggests that central bank communication does not flow directly through these channels. It seems more likely that professional forecasters pay attention to central bank communications and our framework allows us to measure that attention.

3 The Model

This section describes the stochastic environment confronting a collection of forecasters and how they forecast long-run inflation within that environment. We finish up by discussing our notion of inflation anchoring within this set up.

3.1 The forecasting environment

We assume forecasters form their long-term inflation expectations in an economy where inflation outcomes are driven by a trend-cycle autoregressive process.[4] This process is as follows:

$$\pi_t = (1-\rho)\bar{\pi}_t + \rho\pi_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \phi\varepsilon_{t-1} + \eta_t, \quad \eta_t \backsim \mathcal{N}\left(0, \sigma_\eta^2\right) \tag{2}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \lambda_t, \quad \lambda_t \backsim \mathcal{N}\left(0, \sigma_\lambda^2\right) \tag{3}$$

where π_t denotes inflation, ε_t denotes the cyclical component of inflation, and $\bar{\pi}_t$ denotes the trend or drift component of inflation. Cyclical inflation reflects transitory deviations of inflation from its long-run trend. Trend inflation reflects the long-run drivers of inflation that

[4]The idea to model inflation with a trend-cycle model builds on a large literature including Stock and Watson (2007) and Harvey (1985). In this draft, we use a homoscedastic trend-cycle model of inflation even though Stock and Watson (2007) show that relaxing this assumption would help the model fit the US postwar data. Recent papers studying trend-cycle models with stochastic volatility include Mertens (2016) and Stock and Watson (2016). We are currently working on expanding the model to allow for heteroscedasticity.

are already incorporated in the historical behavior of inflation. According to this process the expected value of inflation at long horizons equals the trend, $\bar{\pi}_t$. In a New Keynesian model trend inflation would be determined by perceptions of the behavior of the central bank and would be incorporated into long-run inflation expectations of price setters, $E_t\pi_\infty$, as described by Hazell, no, Nakamura and Steinson (2020).

Forecasters make their forecast in each period with an information set that includes knowledge of the trend-cycle model and its parameters, the history of inflation, and two signals. The two signals include one that updates the history of inflation to include its current value and another consisting of news about inflation's long-run dynamics.[5] The two signals are given by:

$$\pi_t - \rho\pi_{t-1} = (1-\rho)\bar{\pi}_t + \varepsilon_t \tag{4}$$

$$y_t(i) = \bar{\pi}_{t+h} + u_t(i), \quad h > 0. \tag{5}$$

The first signal is received by all the forecasters. Since it updates the history of inflation we refer to it as the *inflation signal*. The second signal is private as it depends on the identity of the forecaster, denoted i. The dependence on the identity of the forecasters reflects the noise, $u_t(i)$. This noise includes an idiosyncratic forecaster-specific component and a common component that applies to all forecasters. In particular, $u_t(i) \equiv z_t(i) + v_t$. The forecaster-specific component is $z_t(i) \backsim \mathcal{N}\left(0, \sigma_z^2(i)\right)$ and the aggregate component v_t is driven by

$$v_t = \rho_v v_{t-1} + \nu_t \tag{6}$$

with $\nu_t \backsim \mathcal{N}\left(0, \sigma_{\nu,t}^2\right)$. The shocks $z_t(i)$ are orthogonal to each other and ν_t.[6] Since the private signal provides news about the future long-run dynamics of inflation we refer to it as the *news*

[5]The forecasters in the SPF do not know the current value of inflation because they submit their forecasts in the second month of each quarter. We will use a timing assumption to take this issue into account when we estimate the model.

[6]In principle the forecast-specific component of noise could be also modelled as serially correlated. We follow the above approach since for the majority of forecasters in our estimation we do not find evidence of serial correlation in the forecast-specific component of noise.

signal.

The news signal $y_t(i)$ is designed to gauge the importance of news or forward-looking information about long-term inflation in forecasters' inflation expectations. This signal reflects the central bank's communications regarding how it will seek to achieve its inflation objective, but might also include changes in public trust regarding the central bank's ability to stabilize inflation around its target, and animal spirits or sentiment. To see how the private signal reflects news about long-term inflation, use equation (3) to decompose the first term on the right-hand side equation (5) as follows:

$$\bar{\pi}_{t+h} = \bar{\pi}_t + \sum_{j=1}^{h} \lambda_{t+j}. \tag{7}$$

The first term of this decomposition captures all forward-looking factors that affect the current value of the drift, and therefore are already reflected in the historical dynamics of prices. The second term captures the news received by forecasters about the long-run dynamics of inflation that are not yet known by agents in the economy and, therefore, are not reflected in historical inflation. It should be noted that this specification does not imply that forecasters know more about trend inflation than other agents in the economy. Indeed trend inflation likely also reflects news received by other agents in the economy, for example by price-setters, that is not observed by the forecasters.

The second term in equation (5), $u_t(i)$, captures both pure noise as well as news about future inflation that ultimately does not come to pass. Either way, the volatility of $u_t(i)$ determines how much attention forecasters pay to news about trend inflation. If the volatility of $u_t(i)$ is zero, a forecaster knows the inflation drift $\bar{\pi}_{t+h}$ perfectly and their long-term expectations will be equal to the drift. If the volatility of $u_t(i)$ is very high, the news signal is close to useless. This can be interpreted as the situation in which forecasters rely only on the historical behavior of inflation to form their long-term inflation expectations.

Note that the standard deviation of the innovations to the aggregate component of the noise, $\sigma_{\nu,t}$, is time-varying and the same across forecasters whereas the standard deviation of the idiosyncratic component of the noise, $\sigma_z(i)$, is constant and specific to each forecaster.

The first component captures waves of attention that are common to all or a large share of forecasters. The second component captures the forecaster-specific attention to long-term inflation.[7]

3.2 Forecasters' long-run inflation expectations

The environment confronted by forecaster i has a state-space representation given by

$$\xi_t = \mathbf{\Phi}\xi_{t-1} + \mathbf{R_t} e_t \tag{8}$$

$$s_t(i) = \mathbf{D}\xi_t + \Psi(i) z_t(i) \tag{9}$$

where

$$\begin{aligned} \xi_t &= [\pi_t, \varepsilon_t, \bar{\pi}_{t+h}, \bar{\pi}_{t+h-1} \cdots, \bar{\pi}_{t+1}, v_t]' \\ e_t &= [\eta_t, \lambda_{t+h}, \nu_t]' \\ s_t(i) &= [\pi_t, y_t(i)]'. \end{aligned}$$

Here $\mathbf{\Phi}$ is a $k \times k$ matrix which depends on ρ, ϕ, and ρ_v, where $k = h + 3$ is the number of state variables; $\mathbf{R_t}$ is $k \times 3$ and depends on σ_η, σ_λ and $\sigma_{\nu,t}$; $\mathbf{D}$ is a $2 \times k$ matrix of zeros and ones; and $\Psi(i)$ is 2×1 and depends on $\sigma_z(i)$. These matrices are defined in Appendix A.

At each date t forecasters observe the signals with knowledge of the history of inflation. They use this information to update their expectations about ξ_t using Bayes rule. The Gaussian structure of the shocks implies that it is optimal for forecasters to update their expectations using the Kalman filter. Specifically, expectations of forecaster i following the date t signals are updated as follows:

$$\xi_{t|t}(i) = \left(\mathbf{I}_k - \mathbf{K}_t(i)\mathbf{D}\right)\xi_{t|t-1}(i) + \mathbf{K}_t(i)\, s_t(i), \tag{10}$$

where $\xi_{t|t}(i) \equiv \mathbb{E}\left(\xi_t | s_t(i), \pi^{t-1}\right)$ denotes forecaster i's expectations conditional on their signals

[7] We think this dichotomy is natural to assume. It is corroborated by the fact that for the majority of forecasters in our data the null hypothesis of homoskedasticity for $z_t(i)$ is not rejected.

and the history of inflation π^{t-1}; $\mathbf{I}_k$ denotes the $k \times k$ identity matrix; and the $k \times 2$ matrix $\mathbf{K}_t(i)$ denotes forecaster i's Kalman gain at date t, which is defined in Appendix B. The third element of the vector $\xi_{t|t}(i)$ is forecaster i's long-run inflation expectation. Correspondingly, the two elements of the third row of $\mathbf{K}_t(i)$ are the i'th forecaster's Kalman gains for the inflation and news signals that are associated with their long-run inflation expectations.

3.3 Inflation anchoring in the model

Forecasters' inflation expectations are considered anchored when their average long-term expectations do not drift away from the central bank's inflation target. Conversely, de-anchoring occurs when average long-term inflation expectations do drift away from the target. Note that the inflation drift $\bar{\pi}_t$, which is central to long term inflation expectations, is different from the concept of an inflation target.

One way in which de-anchoring could occur in our model is when the central bank lets inflation run persistently away from its target. Sooner or later the inflation drift will start diverging from the target and de-anchoring occurs as forecasters learn that the inflation drift is changing. The role played by the inflation and news signals in this type of de-anchoring is quite different. As the inflation drift keeps deviating from the the central bank's target, the inflation signal reveals a persistent deviation of inflation from the central bank's target, leading to a progressive de-anchoring of inflation expectations. This de-anchoring is typically slow as the cyclical component of inflation, ε_t, is generally more volatile than the trend component, $\bar{\pi}_t$.

The role of the news signal is more nuanced and depends on the volatility of the common component, v_t, which captures the average forecasters' attention to long-term inflation. If the volatility of this component is large so that forecasters are inattentive, the news signal plays essentially no role and forecasters' expectations are updated at a pace consistent with observing the historical behavior of inflation.

If the volatility of the aggregate component is smaller, long-run inflation expectations move more autonomously from the observed dynamics of inflation (encoded in the inflation signal). As a result, the news signal can either accelerate or decelerate de-anchoring depending on the news the forecasters receive regarding the long-run behavior of inflation. For instance, even though inflation has been running high for a period of time, de-anchoring might not occur because forecasters remain confident that the central bank will soon tighten monetary policy ($\sum_{j=1}^{h} \lambda_{t+j} + v_t < 0$). However, if forecasters' trust in the central bank's ability or willingness to quash the rising inflation is waning ($\sum_{j=1}^{h} \lambda_{t+j} + v_t > 0$), the news signal can even accelerate the de-anchoring.

It should be noted that news that keeps expectations anchored may turn out to be just noise, implying that the central bank will eventually fail to tighten (loosen) monetary policy when inflation runs persistently above (below) target. However, this assessment can be done only with the benefit of hindsight, i.e. after having observed or estimated the future shocks to the inflation drift.

4 Estimation

To estimate forecasters' long-term inflation expectations resulting from the signal extraction problem of section 3 we follow a two-step approach. In the first step we estimate the trend-cycle model summarized by equations (1)-(3) using only inflation as an observable to obtain estimates of the drift and cyclical components conditional on all the sample observations using the Kalman smoother.

In the second step, we estimate a panel model assuming that forecasters know their private signals $y_t(i)$, the parameters of the trend-cycle process estimated in the first step, and inflation. We observe inflation, the inflation drift obtained from the first step, and the long term inflation expectations of the forecasters from the SPF, but we do not observe the private signals. Therefore, the model we estimate combines equations (1)-(3) with equation (10) that shows the solution to the signal extraction problem that each forecaster solves. The transition equation we use in our panel estimation therefore reads

$$\begin{bmatrix} \xi_t \\ \overrightarrow{\xi}_{t|t} \end{bmatrix} = \widetilde{\mathbf{\Phi}}_t \begin{bmatrix} \xi_{t-1} \\ \overrightarrow{\xi}_{t-1|t-1} \end{bmatrix} + \widetilde{\mathbf{R}}_t \begin{bmatrix} e_t \\ \overrightarrow{z}_t \end{bmatrix} \tag{11}$$

where $\overrightarrow{\xi}_{t|t}$ and $\overrightarrow{z}_t$ are column vectors stacking $\xi_{t|t}(i)$ and $z_t(i)$ of every forecaster $i \in \{1, ..., N\}$ and the matrices $\widetilde{\mathbf{\Phi}}_t$ and $\widetilde{\mathbf{R}}_t$ are defined in Appendix A. These matrices are constructed from Φ and R_t along with the the matrices describing the evolution of each forecaster's expectations in equation (10).

The measurement equations for our panel estimation are

$$\begin{bmatrix} \pi_t^{cpi} \\ \bar{\pi}_{t+h}^{est} \\ \mathbb{E}_t \pi_t^{long}(1) \\ \mathbb{E}_t \pi_t^{long}(2) \\ \vdots \\ \mathbb{E}_t \pi_t^{long}(N) \end{bmatrix} = \begin{bmatrix} \mathbf{1}_1 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} \\ \mathbf{1}_3 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} \\ \mathbf{0}_{1\times k} & \mathbf{1}_3 & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} \\ \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \mathbf{1}_3 & \dots & \mathbf{0}_{1\times k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{1}_3 \end{bmatrix} \begin{bmatrix} \xi_t \\ \xi_{t|t}(1) \\ \xi_{t|t}(2) \\ \vdots \\ \xi_{t|t}(N) \end{bmatrix}, \tag{12}$$

where $\mathbf{1}_n$ denotes the $1 \times n$ row vector with elements all equal to zero except the n-th one which is equal to one. The observable variables in the vector on the left hand side of (12) include an empirical measure of inflation such as CPI core inflation, π_t^{cpi}, our estimate of the inflation drift, $\bar{\pi}_t^{est}$, and an empirical measure of long-term inflation expectations of forecasters such as the SPF 10 year inflation forecasts, $\pi_t^{long}(i)$. Our inflation drift estimate is explained in detail below. Note that we keep the number of forecasters N fixed over time and we adjust the matrix in equation (12) to take into account the missing forecasts of forecasters, including gaps in their forecast histories.

5 Data

This section describes the inflation and inflation expectation data we use. We use data on CPI core inflation from the U.S. Bureau of Labor Statistics spanning the sample 1959Q1–2021Q3. Our long-term inflation expectations are from the SPF and cover the sample 1991Q4–2021Q3. We use the 10-year average CPI inflation forecasts to measure long-term inflation expectations in our model.[8] This measure does not directly correspond to the long-term inflation expectations

[8] We can use the SPF to construct average inflation expected between 5 and 10 years ahead which might more closely align with the long term concept in our model. However, this requires using the SPF 5-year CPI

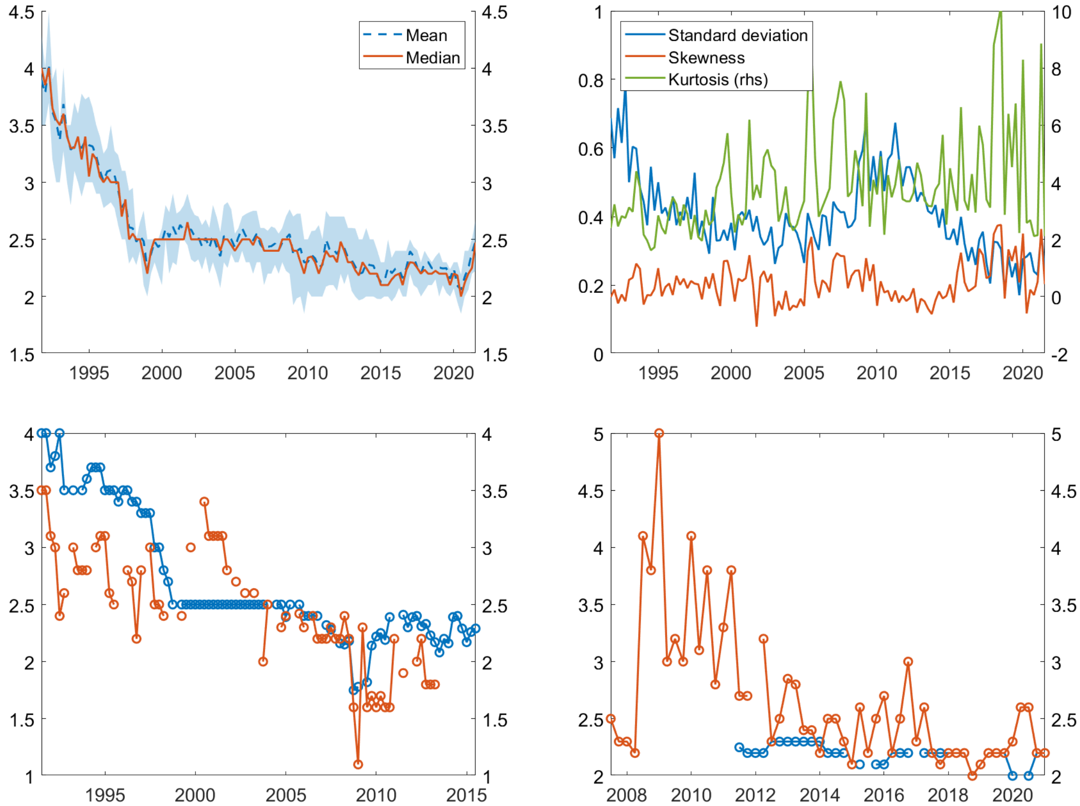

Figure 1: Time series summary of 10-year CPI inflation expectations

Notes: Top left chart shows mean and median together with the interquartile range, top right chart shows higher moments. The two bottom charts show the time series of 4 individual forecasters.

$\bar{\pi}_{t+h}$ in our model, which is the inflation trend 10 years ahead. However, if the cyclical term is sufficiently small and short lived (ϕ and σ_η are small) it should be a good approximation. To have a sufficient number of observations to measure the variances of idiosyncratic noise we consider only those forecasters with at least 32 forecasts (we consider 16 as well and the results are little changed). This leaves us with an unbalanced panel of 48 forecasters. Note that in some cases there are gaps in the time series of forecasts for individual forecasters.[9] In Appendix D we show that average and median long-term expectations in our sample of forecasters corresponds closely to their values in the full SPF sample.

inflation forecasts which are only available starting from 2005.

[9]The Philadelphia Fed must decide whether a forecaster ID should follow a forecaster when they change employer. Information on the Philadelphia Fed's website indicates that such decisions are based on judgments as to whether the forecasts represent the firms or the individual's beliefs. See http://www.phil.frb.org/econ/spf/Caveat.pdf.

The top row in Figure 1 shows how the the distribution of long-term inflation expectations evolved over the sample from 1991Q4 until 2021Q3. Average long-term inflation expectations at the beginning of the 1990s were near 4%. For the first years of the sample there was a steady decline, then from the beginning of the 2000s expectations were stable around 2.5% until the Great Recession after which there was again a downward trend, towards 2%. In the most recent quarter, after several quarters of unusually high inflation, inflation expectations have reached their pre-Great Recession levels again. Generally aggregate expectations have been fairly stable over the last 20 years.

Behind these aggregate dynamics there is substantial heterogeneity across forecasters. The standard deviation is high in the beginning of the sample and around the Great Recession. The distribution is right-skewed and the kurtosis is most of the time above 3 indicating fat-tails. The bottom row in Figure 1 shows the time series of 4 selected forecasters. This highlights two points. First, there can be substantial differences in the level of expected inflation. Second, some forecasters have fairly stable inflation expectations and only adjust smoothly (blue lines) while other forecasters change their expected inflation in nearly every period.

6 Estimates

This section describes our parameter and unobserved component estimates of our time series and panel models. These estimates will be used to measure the factors driving inflation over the last 30 years and to conduct the overshooting experiments.

6.1 Time-series estimates

We estimate the trend-cycle model summarized by equations (1)-(3) using π_t^{cpi} as the observable and the sample period 1959Q1-2020Q3.[10] The initial level of trend inflation, $\bar{\pi}_{t_0}$, is treated as a parameter to be estimated. The priors and estimated posterior modes for all the parameters are shown in Table 1.

Once the model is estimated, we use the Kalman smoother to obtain an estimate of the

[10] We describe how we initialize the state vector of this model in Appendix C.

Parameter	Prior	Posterior mode
ρ	Beta(0.5,0.2)	0.785
ϕ	Beta(0.5,0.2)	0.623
σ_η	Inverse Gamma (0.25,4)	0.427
σ_λ	Inverse Gamma (0.25,4)	0.300
$\bar{\pi}_{t_0}$	Uniform	2.187

Table 1: Parameter estimates for the time series model

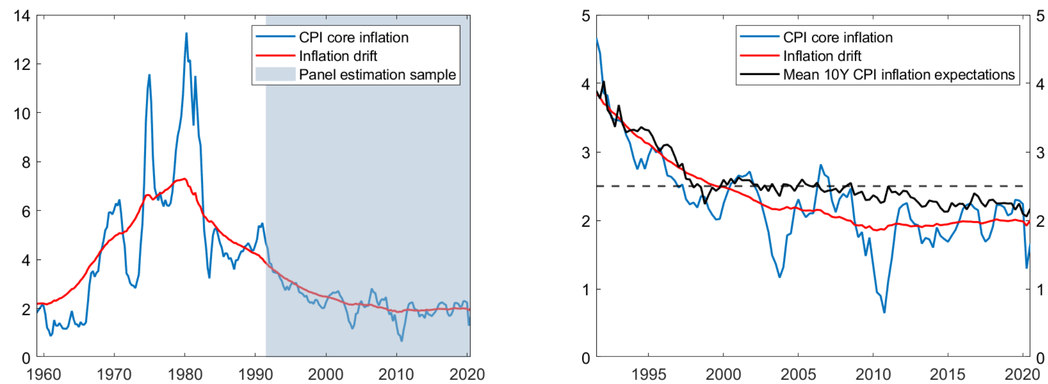

Figure 2: Core inflation, inflation drift and long-term expectations

Notes: The inflation drift is obtained by using the Kalman smoother. The shaded area in the left chart indicates the sample period for the panel estimation.

inflation drift, $\bar{\pi}_t^{est}$. Figure 2 shows the time series of core CPI inflation and our estimate of the inflation drift over the full estimation sample. The gray area shows the sample period we will use to estimate the panel model. The inflation drift reaches its peak of around 7% in 1980 and then declines over the following years. While there is still some downward trend in inflation visible, from an historical perspective the inflation drift has been fairly stable over the last 20 years.

The right chart in Figure 2 shows the mean of long-term CPI inflation expectations from the SPF. It is important to highlight that in the first part the sample the inflation drift and average expectations are very close. From around 2000, the decline of the trend inflation has been faster than that of the long-run inflation expectations, which, in fact, remained anchored to 2.5% from the end of 1990s through to the onset of the Great Recession.

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.384
$\sigma_{\nu,t}$	$\ln\sigma^2_{\nu,t} \backsim \mathcal{N}\left(\ln\sigma^2_{\nu,t-1}, \sigma^2_{\nu,\text{prior}}\right)$	see Figure 3, lhs
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.220
$\sigma_z(i)$	Inverse Gamma (0.5,4)	see Figure 3, rhs
$\sigma_{\nu,\text{prior}}$	Calibrated	0.2

Table 2: Parameter values for panel estimation

6.2 Panel estimates

We estimate the state-space model in equations (11)-(12) over the sample period 1991Q3-2020Q3 assuming $h = 4$. The first period where the 10-year CPI inflation expectations are available is 1991Q4. Since forecasters in the SPF do not observe contemporaneous inflation when they submit their forecasts, we shift the SPF data one period forward. For instance, in 1991Q3, we are using inflation and the estimated inflation drift in 1991Q3 and the SPF expectations for 1991Q4. If a forecaster enters the Survey after 1991Q4, its initial beliefs are updated by the Kalman filter assuming omitted observations. Appendix C describes how we set the initial conditions. These initial conditions are set so that we as the econometricians have the same priors about the initial state as the forecasters.

In Table 2 we summarize the priors and estimated parameters of the panel estimation. As indicated in the table the prior for $\sigma^2_{\nu,t}$ is a Gaussian random walk. This prior should induce a smooth change in the forecasters' common attention to news about inflation drift over time, which reflects our belief that drastic changes in overall attention are not likely *a priori*. In the baseline we set $\sigma_{\nu,\text{prior}}$ – the standard deviation of the Gaussian random walk prior – to 0.2, but we also show the robustness to alternative values. The initial condition for the variance $\sigma^2_{\nu,0}$ is assumed to be distributed as inverse gamma with moments shown in Table 2.

Table 2 shows we estimate a persistence of around .4 for the v_t process. The time series of $\sigma_{\nu,t}$ is shown in the left of Figure 3. From the estimated initial value there has been an upward trend with a large drop around the Great Recession. This indicates that attention to long-term inflation generally has declined as inflation became more stable. During the turbulent developments of the Great Financial Crisis and the ensuing Great Recession, attention to long-run inflation increased to levels not seen since the late 1990s. The right chart in Figure 3 plots the distribution of forecaster-specific attention to news, σ_z. This distribution suggests that the level of attention across forecasters is quite heterogeneous.

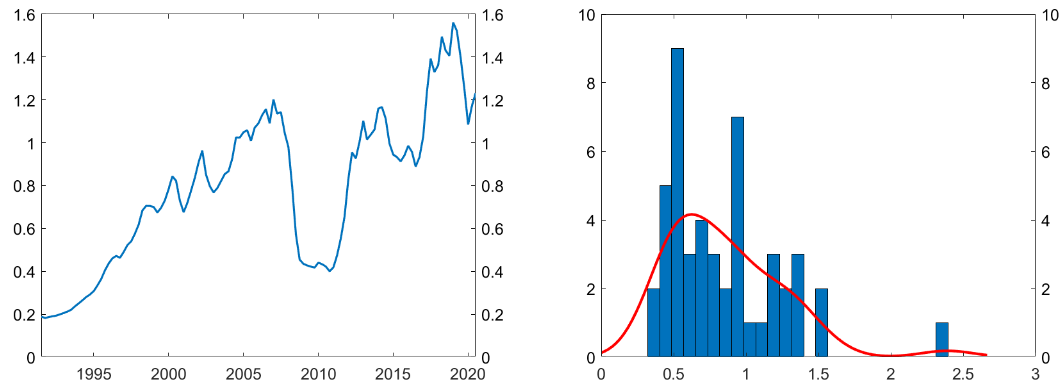

Figure 3: Time series of $\sigma_{\nu,t}$ (lhs) and histogram of σ_z (rhs)

7 Inflation expectations through the lens of the model

This section describes the implications of our model for the attention of forecasters over time and across forecasters based on the estimated Kalman gain matrices. The Kalman matrices allow us to compute the impulse responses to study the effect of the model's different shocks on forecasters' long term inflation expectations. Third, we analyze the historical contribution of the different shocks to the evolution of long-term inflation expectations over time and the anchoring and de-anchoring of average US inflation expectations over the last 30 years.

7.1 Estimates for forecasters' attention

As described in the previous section, a key ingredient of the panel estimation is the Kalman gain matrix for each forecaster. The Kalman gain matrix is based on the solution of the signal extraction problem of each forecaster and is a $(h + 3) \times 2$ matrix (see derivation in Appendix B, equation (17)). The different rows correspond to the state variables and the two columns to the signals. The elements of this matrix tell us how much each forecaster learns from the two signals about the state variables. A large Kalman gain reflects that a forecaster pays a lot of attention to a given signal and learns a lot about the underlying state variable. Our main interest is in the third row of the Kalman gain matrix which corresponds to the Kalman gain for the inflation drift h period ahead and shows how much a given forecaster adjusts her long-term inflation expectations in response to changes in the two signals.

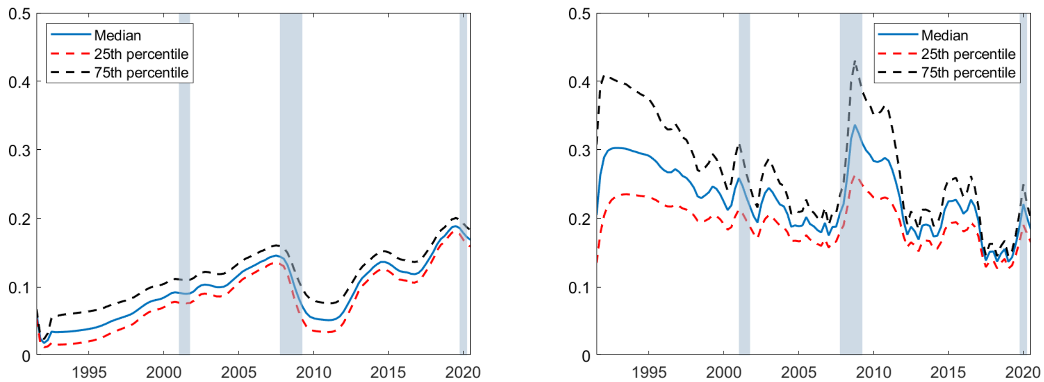

Figure 4: Kalman gains for the inflation drift due to the inflation (lhs) and news (rhs) signals
Notes: Shaded areas indicate NBER recession dates.

Figure 4 plots the distribution of the Kalman gain regarding the inflation drift over time. The left figure shows the Kalman gain from observing the inflation rate. The right figure plots the Kalman gain from receiving news about long-term inflation. There are a number of things we can learn from this figure.

First, the median Kalman gain for inflation is smaller than for news. News about an increase in trend by 100 basis points moves average long-term inflation expectations by about 25 basis points on average compared to 10 basis points for the inflation signal. This suggests that news plays a larger role in shaping professional forecasters' long-run inflation expectations in the sample period. Forward-looking information is more important for forecasters to form beliefs about the long-term. Nevertheless, the difference between the Kalman gains has fallen in recent years as the Kalman gain for the inflation signal has a positive trend in the sample period.

Second, attention varies over time and in opposite ways for the two signals. The shaded areas in Figure 4 indicate NBER recessions dates and illustrate that while attention to the historical dynamics of inflation is pro-cyclical, attention to forward-looking factors is counter-

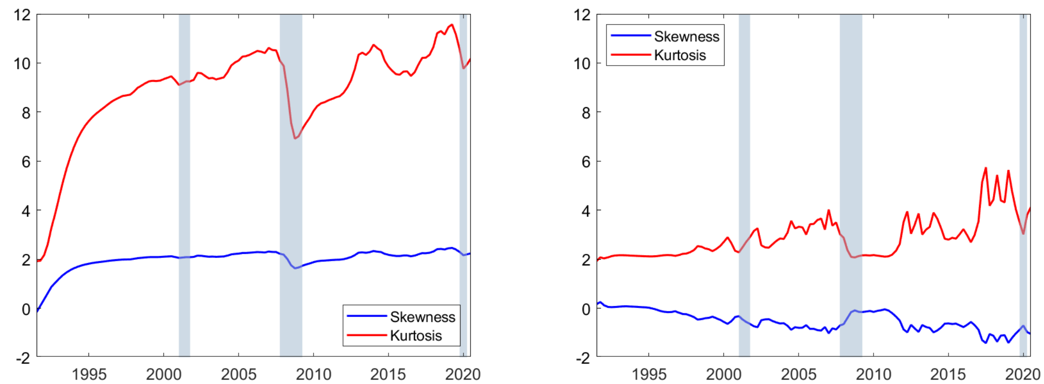

Figure 5: Higher moments of Kalman gain distribution for inflation drift: inflation signal (lhs), news signal (rhs)

Notes: Shaded areas indicate NBER recession dates.

cyclical. This is especially noteworthy during the Great Recession where we observe a large increase in the median Kalman gain for the news signal. This finding implies that average inflation expectations are particularly responsive to news about long-run inflation during recessions and when the interest rate reaches its effective lower bound. During such times the central bank has to rely more on other monetary policy tools including forward-looking communication about how to stabilize inflation. The relative size of the estimated Kalman gain from the inflation and news signals suggests that central bank communication can be an effective tool for anchoring long-term inflation expectations in large recessions.

Third, heterogeneity in attention to the news signal is counter-cyclical as indicated by the widening in the 25th and 75th percentile bands in the recessions, particularly the Great Recession.

Figure 5 shows the skewness and the kurtosis of the distributions of Kalman gains from the inflation signal (left panel) and from the news signal (right panel) across forecasters. While the distribution of Kalman gains from the inflation signal is positively skewed, the distribution of Kalman gains from the long-run inflation news is generally negatively skewed. Both distributions became more symmetric during the past two recessions. The kurtosis of both distribution of Kalman gains is counter-cyclical, suggesting that the tails of the distribution of Kalman gains become thinner in recessions.

7.2 The effects of the different shocks on inflation expectations

Our model allows us to estimate how forecasters' inflation expectations respond to the different shocks. Figure 6 plots the impulse response functions to one-time one standard deviation shocks to each of the four shocks of the model. All model parameters are set to the estimated values except for the time-varying parameter $\sigma_{\nu,t}$ which we set to the average value estimated over time which is 0.79. We assume that inflation and the inflation drift are both equal to the value of the inflation drift in 1991Q3. Moreover, we simulate the model for several burn-in periods to make sure that initial conditions do not affect the Kalman gain and the parameter matrices in equation (11) anymore.

Each chart shows the impulse response function of inflation expectations for a forecaster with σ_z calibrated to the median, the 25th-percentile and the 75th-percentile estimated value of σ_z, respectively. We study shocks to the cyclical component η, permanent component λ, communication ν, and composition z.

The top left chart shows the response to a transitory shock to inflation η. The transitory shock leads to a very small temporary rise in long-term inflation expectations. Note that a one standard deviation shock in η increases actual inflation by more than 60 basis points. The magnitude in this chart shows that this increase only partly feeds through to long-term inflation expectations with a peak effect of around 5 basis points.

The top right chart plots the response to a permanent shock to inflation λ that leads to a jump in the inflation drift $h = 4$ periods ahead by around 30 basis points. Forecasters learn about this change fairly slowly over time. Inflation expectations of the median forecaster rise by 7 basis points in the period when the shock materializes and within the first 6 quarters they complete half of their adjustment. After around 7 years the median forecaster has learned the new level of trend inflation.

The bottom two charts depict the impulse response functions for shock to the common the news signal ν_t (left plot) and to a change in the idiosyncratic news $z_t(i)$ (right plot). In both cases, a one standard deviation shock moves median inflation expectations away from the inflation drift by slightly more than 15 basis points. The effects of these shocks are a

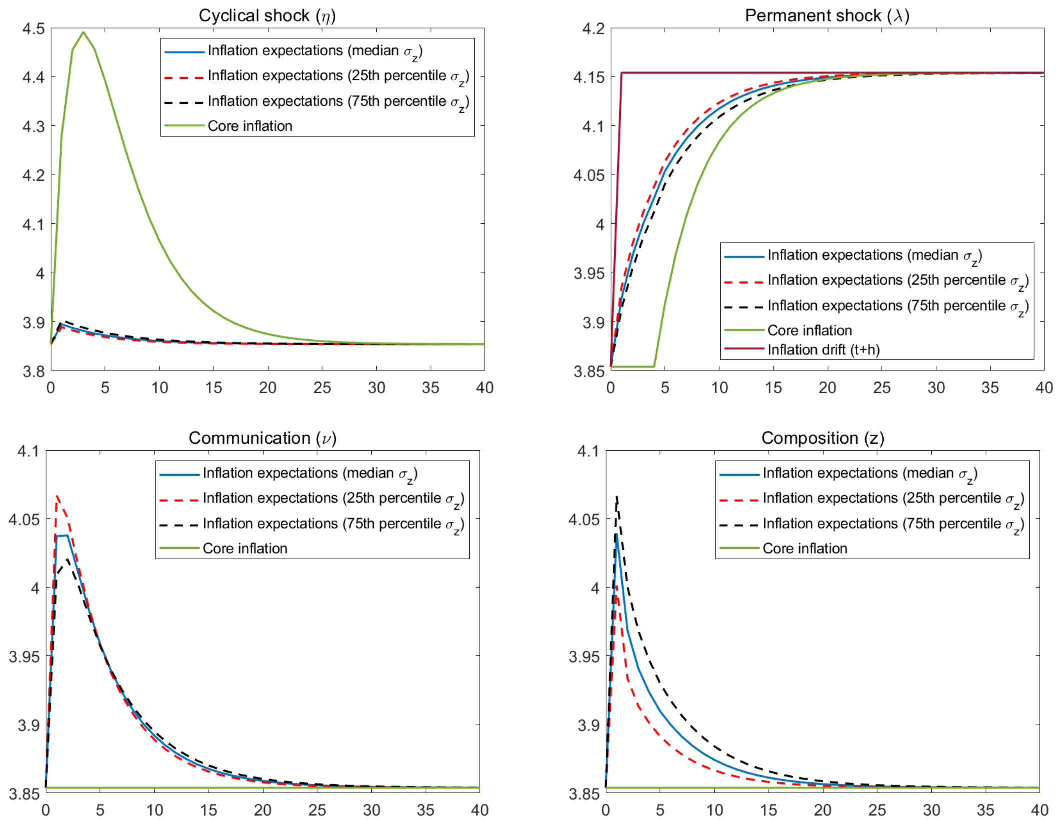

Figure 6: Impulse response functions to one standard deviation shocks

Notes: IRFs to one time shock that happens in period 1. The blue and red/black dashed lines correspond to the IRFs of inflation expectations of forecaster with median and 25th/75th percentile of the distribution of estimated σ_z, respectively. The green and the dark red line show the IRF of core inflation and the inflation drift, respectively.

similarly persistent. This illustrates that purely noise or sentiment driven shocks can move away median inflation expectations for a significant period of time from the inflation drift.

7.3 Historical drivers of long-term inflation expectations

In this section we use our model to learn more about the historical drivers of long-term inflation expectations. Figure 7 shows the historical shock decomposition of forecasters' average inflation expectations together with the inflation drift. We study the role of the cyclical and permanent shocks, communications, and composition effects by considering the effect of one shock at a time assuming all the other shocks are set to zero. The detailed procedure to obtain the historical shock decomposition is described in Appendix G.

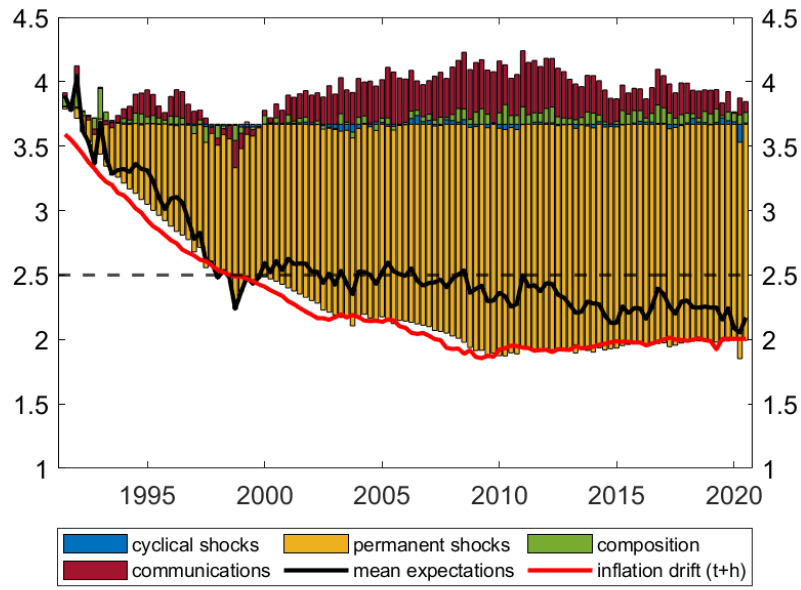

Figure 7: Historical decomposition of average inflation expectations

Notes: Simulation of model based on smoothed estimates with different shocks active.

The historical shock decomposition highlights that the persistent decline in inflation in the 1990s as depicted by the red line has been accompanied by a decline in average long-term inflation expectations. During these years primarily permanent shocks to inflation λ_t led average inflation expectations to become anchored. From the 2000s inflation declined further but inflation expectations remained fairly stable. The main driver behind this discrepancy between trend inflation and average inflation expectations is news not yet reflected in current inflation, ν_t. This stream of news led forecasters to keep their average inflation expectations stable and close to the Fed's objective.[11]

This result is important as it suggests that communication has played an important role in stabilizing long-term inflation expectations around the Fed's target notwithstanding the low inflation rates observed over the last two decades. However, at the onset of the Great Recession long-term inflation expectations started to fall slowly below the value they settled around at the end of the disinflation period. By the end of the post-Great Recession recovery,

[11] In this paper, we assume that core CPI inflation at 2.5% is consistent with price stability. This is because long-term CPI inflation expectations have settled around that level following the long US disinflation until the beginning of the Great Recession. See the left plot of Figure 2.

the gap between average inflation expectations and the sub-target estimated trend of inflation has shrunk considerably.

In line with the results described in subsection 7.1, cyclical shocks to inflation played a minor role as drivers of inflation expectations in the last 30 years. The composition of the SPF panel through idiosyncratic noise $z_t(i)$ has had a mainly positive effect on long term expectations. Absent these composition effects the post Great Financial Crisis de-anchoring of average long term expectations would have come earlier and faster.

In Appendix G, we show the historical decomposition of individual expectations for a subset of forecasters. The forecaster-specific noise $z_t(i)$ plays an important role as a driver of inflation expectations at the forecaster level. As shown in Figure 7, this source of noise may also contribute to explain average inflation expectations given that the number of forecasters in our sample is finite.

8 Re-Anchoring U.S. Inflation Expectations

Before the pandemic, CPI inflation ran below average inflation expectations from the SPF for two decades. This persistent deflationary bias led to progressive declines in the mean and median long-run CPI inflation expectations to below their pre-Great Recession level (2.5%), as seen in the right plot of Figure 2. At the onset of the pandemic recession, SPF long-run inflation expectations are quite close to the estimated sub-target trend level of inflation that we estimate. As shown in the previous section, central bank's forward-looking communications seems to have slowed down the fall in SPF inflation expectations.

If inflation keeps running below 2.5% for more years, our model predicts that the de-anchoring of inflation expectations will become more severe because the drift $\bar{\pi}_t$ will keep declining.[12] In our model, the de-anchoring can be averted if inflation runs for some time above the FOMC's average inflation target. The new framework adopted by the Federal Reserve aims to achieve exactly that: "In order to anchor longer-term inflation expectations at this level, the Committee seeks to achieve inflation that averages 2 percent over time, and therefore

[12] Bianchi et al. (2021) show that in New Keynesian models, a low interest rate environment can bring about deflationary spirals when the risk of hitting the ZLB becomes pervasive.

judges that, following periods when inflation has been running persistently below 2 percent, appropriate monetary policy will likely aim to achieve inflation moderately above 2 percent for some time."

We now use our model to investigate for how long and by how much inflation must overshoot the Fed's inflation target to bring average CPI long-run inflation expectations from the SPF back to their pre-Great Recession level, 2.5%, on a persistent basis. Our estimated model is ideally suited to such an investigation because it provides an empirical grounding to how quickly individual SPF forecasters respond to incoming inflation and news about future inflation. We now consider an experiment that uses our model of SPF forecasters to address the overshooting question.[13]

We start our analysis in 2020Q4, which coincides with the announcement of the new operating framework by the Federal Reserve Chair Jerome Powell and the end of our estimation sample. The experiment is designed to quantify the inflation necessary to cement average expectations at 2.5%, the most recent reading from the SPF, if the underlying drift is assumed to return only gradually to 2.5% by the end of 2024. We answer the question: what inflation would be necessary given this path of the drift if the Fed wants to keep long term expectations at 2.5%?

The assumed paths for the drift and average expectations are shown as the red and black dashed lines in the left plot of Figure 8 respectively. The dashed blue line in the right plot of the same figure is the path of inflation that reconciles the assumed paths of the drift and expectations. We calculate this as follows. First, we impose in the measurement equations that the average long-run expectations of the forecasters is equal to the assumed path for average expectations. We then use the Kalman filter to back out inflation and values of the news signals and cyclical shocks that rationalize the joint behavior of the drift and expectations. Since $\bar{\pi}_{t+h}$ is predetermined by our assumed path for the drift the path of the news signal $y_t(i)$ is pinned down by v_t, that is communication.

The right plot of Figure 8 shows that inflation must overshoot 2.5% by 150 to 50 bps through to mid 2023 to cement expectations at 2.5%. It turns out that this already substantial

[13]See Appendix H for details of the calculations underlying these experiments.

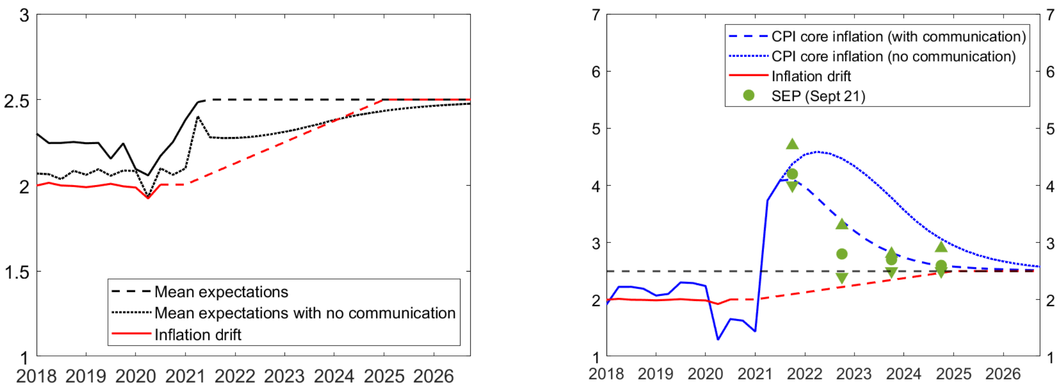

Figure 8: Projected inflation path (rhs) under gradual inflation drift increase and anchored expectations (lhs)

Notes: SEP (Sept 21) corresponds to the Summary of Economic Projections from September 2021 and is the core PCE inflation forecast for the fourth quarter of 2021-2024, rescaled by 50 basis points to be consistent with core CPI inflation. The dots correspond to the median projections and the arrows to the upper and lower range projections, respectively.

overshooting is held down by communication. That is, the news signals need to come in stronger ($v_t > 0$) than justified by the path of the drift alone. This can be seen in the left plot where the black dotted line shows the path of expectations when we set $\nu_t = 0$.[14] Without communication expectations stay below 2.5% through to the end of 2026 (left plot). By promising inflation higher than warranted by the drift the central bank does not need as much of an overshoot. The blue dotted line in the right plot shows the path of inflation that would be necessary in the absence of communication to keep expectations at 2.5%. This is the case where the signal correctly indicates the path of the drift. Without the lift from communication forecasters must see actual inflation much higher to revise their expectations so they remain at 2.5%. This highlights the crucial role communication has to play in re-anchoring expectations if underlying inflation, that is the drift, moves only slowly back to 2.5%. Absent the communication the overshooting must be much larger and longer lasting.

To gauge the magnitude of overshooting that is required in this experiment the right plot of Figure 8 shows projections from the September 2021 Summary of Economic Projections, with the markers indicating high, median, and low SEP projections. Without communication the

[14]This means essentially that until 2021Q2 central bank communication is active but afterwards not. Due to the serial correlation in v_t this means the role of communication vanishes over time.

path of inflation must exceed *all* FOMC participants' projections in 2022 and 2023, exceeding the highest projections by about 100 bps in both years. The case with communication more closely aligns with the SEP although inflation must come in 50 bps higher than the median projection in 2022.

9 Conclusion

In this paper, we show how to use panel survey data to estimate forecasters' allocation of attention when learning about long-run inflation and how sensitive their expectations are to incoming inflation and news about inflation going forward. We apply our method to the U.S. Survey of Professional Forecasters and find that observed changes in inflation have small effects on long term inflation expectations. News has larger effects but they are still relatively small. These features of our estimated model provide an explanation for why the anchoring and subsequent de-anchoring of average long term inflation expectations over the period 1991 to 2020 were long lasting episodes.

Professional forecasters pay more attention to news about long-run inflation that are not fully reflected by the historical behavior of inflation. This type of news includes public trust regarding the central bank's commitment to its inflation target and communications about how the central bank will seek to achieve price stability in the long run. We find that this type of news has been playing an important role to keep inflation expectations anchored over the past two decades.

We also show that while the high inflation readings of 2021 boosted average inflation expectations close to values unseen since the onset of the Great Recession levels, expectations are predicted to fall quickly if inflation will retrench to target too quickly. We use our model to assess the degree of overshooting necessary to re-anchor long term expectations at pre-Great Recession levels where they had stood for 10 years. Generally inflation must be at least as large as the upper bound of the SEP inflation projections in 2022 and 2023. Our model suggests effective central bank communications can reduce the size of overshooting necessary to re-anchor expectations.

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A Definition of matrices in subsection 3.2 and section 4

The matrices in equations (8) and (9) are defined as follows:

$$\xi_t = \begin{bmatrix} \pi_t \\ \varepsilon_t \\ \bar{\pi}_{t+h} \\ \bar{\pi}_{t+h-1} \\ \vdots \\ \bar{\pi}_{t+2} \\ \bar{\pi}_{t+1} \\ v_t \end{bmatrix}, \ \mathbf{\Phi} = \begin{bmatrix} \rho & \phi & 0 & 0 & \dots & 0 & 1-\rho & 0 \\ 0 & \phi & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & \rho_v \end{bmatrix}, \ \mathbf{R}_t = \begin{bmatrix} \sigma_\eta & 0 & 0 \\ \sigma_\eta & 0 & 0 \\ 0 & \sigma_\lambda & 0 \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \sigma_{\nu,t} \end{bmatrix}$$

$$e_t = \begin{bmatrix} \eta_t \\ \lambda_{t+h} \\ \nu_t \end{bmatrix}, \ \mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}, \ \Psi(i) = \begin{bmatrix} 0 \\ \sigma_z(i) \end{bmatrix}$$

The matrices in equation (11) are defined as follows:

$$\widetilde{\mathbf{\Phi}}_t \equiv \begin{bmatrix} \mathbf{\Phi} & \mathbf{0}_{k\times k} & \mathbf{0}_{k\times k} & \dots & \mathbf{0}_{k\times k} \\ \mathbf{K}_t(1)\mathbf{D\Phi} & (I-\mathbf{K}_t(1)\mathbf{D})\Phi & \mathbf{0}_{k\times k} & \dots & \mathbf{0}_{k\times k} \\ \mathbf{K}_t(2)\mathbf{D\Phi} & \mathbf{0}_{k\times k} & (I-\mathbf{K}_t(2)\mathbf{D})\mathbf{\Phi} & \dots & \mathbf{0}_{k\times k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{K}_t(N)\mathbf{D\Phi} & \mathbf{0}_{k\times k} & \mathbf{0}_{k\times k} & \dots & (I-\mathbf{K}_t(N)\mathbf{D})\mathbf{\Phi} \end{bmatrix}$$

$$\widetilde{\mathbf{R}}_t = \begin{bmatrix} \mathbf{R}_t & \mathbf{0}_{k\times 1} & \mathbf{0}_{k\times 1} & \dots & \mathbf{0}_{k\times 1} \\ \mathbf{K}_t(1)\mathbf{DR}_t & \mathbf{K}_t(1)\mathbf{\Psi}(1) & \mathbf{0}_{k\times 1} & \dots & \mathbf{0}_{k\times 1} \\ \mathbf{K}_t(2)\mathbf{DR}_t & \mathbf{0}_{k\times 1} & \mathbf{K}_t(2)\mathbf{\Psi}(2) & \dots & \mathbf{0}_{k\times 1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{K}_t(N)\mathbf{DR}_t & \mathbf{0}_{k\times 1} & \mathbf{0}_{k\times 1} & \dots & \mathbf{K}_t(N)\mathbf{\Psi}(N) \end{bmatrix}$$

B Model derivations

Based on equations (8)-(9) the Kalman filter recursion is given by:

$$\xi_{t|t-1}(i) = \Phi\xi_{t-1|t-1}(i) \tag{13}$$

$$P_{t|t-1}(i) = \Phi P_{t-1|t-1}(i)\Phi' + R_t R_t' \tag{14}$$

$$s_{t|t-1}(i) = D\xi_{t|t-1}(i) \tag{15}$$

$$F_{t|t-1}(i) = DP_{t|t-1}(i)D' + \Psi(i)\Psi(i)' \tag{16}$$

$$\xi_{t|t}(i) = \xi_{t|t-1}(i) + \underbrace{P_{t|t-1}D'\left[F_{t|t-1}(i)\right]^{-1}}_{K_t(i)}\left[s_t(i) - D\xi_{t|t-1}(i)\right] \tag{17}$$

$$P_{t|t}(i) = P_{t|t-1}(i) - P_{t|t-1}(i)D'\left[F_{t|t-1}(i)\right]^{-1}DP_{t|t-1}(i) \tag{18}$$

Then, re-arrange the Kalman equation as follows to obtain equation (10):

$$\begin{aligned}
\xi_{t|t}(i) &= \xi_{t|t-1}(i) + K_t(i)\left[s_t(i) - D\xi_{t|t-1}(i)\right] && (19)\\
&= \left(\mathbf{I}_{h+3} - K_t(i)\,D\right)\xi_{t|t-1}(i) + K_t(i)\,s_t(i) && (20)\\
&= \left(\mathbf{I}_{h+3} - K_t(i)\,D\right)\xi_{t|t-1}(i) + K_t(i)\left[D\xi_t + \Psi(i)z_t(i)\right] && (21)\\
&= \left(\mathbf{I}_{h+3} - K_t(i)\,D\right)\xi_{t|t-1}(i) + K_t(i)\left[D(\Phi\xi_{t-1} + R_t e_t) + \Psi(i)z_t(i)\right] && (22)
\end{aligned}$$

C Initial conditions for estimation

Define the state vector of the trend-cycle model as $\xi_t = [\pi_t, \epsilon_t, \bar{\pi}_t]'$. We initialize the state as follows:

$$\xi_{0|0} \equiv E\left(\begin{bmatrix} \pi_0 \\ \epsilon_0 \\ \bar{\pi}_0 \end{bmatrix}\right) = \begin{bmatrix} \pi_{t_0} \\ 0 \\ \bar{\pi}_{t_0} \end{bmatrix}$$

$$\mathbf{P}_{0|0} \equiv E\left(\begin{bmatrix} \pi_0 \\ \epsilon_0 \\ \bar{\pi}_0 \end{bmatrix}\begin{bmatrix} \pi_0 & \epsilon_0 & \bar{\pi}_0 \end{bmatrix}\right) = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{\sigma_\eta^2}{1-\phi^2} & 0 \\ 0 & 0 & \varsigma \end{bmatrix}$$

where t_0 denotes the last quarter before the estimation starts. We set π_{t_0} to the CPI core inflation rate in the last quarter before the estimation starts (1958Q4) and ς is set to σ_λ^2.[15] The expected initial level of trend inflation, $\bar{\pi}_{t_0}$, is dealt with as parameter to be estimated.

The initial conditions for the panel estimation are assumed to be

$$\begin{aligned}
\tilde{\xi}_{0|0} &\equiv E\left(\begin{bmatrix} \xi_0 \\ \overrightarrow{\xi}_{0|0} \end{bmatrix}\right) = \mathbf{1}_{(N+1)\times 1} \otimes \bar{\xi}_{0|0} \\
\widetilde{\mathbf{P}}_{0|0} &\equiv E\left(\begin{bmatrix} \xi_0 \\ \overrightarrow{\xi}_{0|0} \end{bmatrix}\begin{bmatrix} \xi_0 & \overrightarrow{\xi}_{0|0} \end{bmatrix}\right) = \mathbf{I}_{(N+1)\times 1} \otimes \bar{\mathbf{P}}_{0|0}
\end{aligned}$$

where $\mathbf{1}_{(N+1)\times 1}$ is a $(N+1)\times 1$ vector of ones, $\mathbf{I}_{N+1}$ is the $(N+1)\times(N+1)$ identity matrix and

$$\bar{\xi}_{0|0} \equiv E\left(\begin{bmatrix} \pi_0 \\ \epsilon_0 \\ \bar{\pi}_{0+h} \\ \bar{\pi}_{0+h-1} \\ \vdots \\ \bar{\pi}_{0+2} \\ \bar{\pi}_{0+1} \\ v_0 \end{bmatrix}\right) = \begin{bmatrix} \pi_{t_0} \\ 0 \\ \bar{\pi}_h \\ \bar{\pi}_{h-1} \\ \vdots \\ \bar{\pi}_2 \\ \bar{\pi}_1 \\ 0 \end{bmatrix} \quad \text{and}$$

$$\bar{\mathbf{P}}_{0|0} \equiv E\left(\begin{bmatrix} \pi_0 \\ \epsilon_0 \\ \bar{\pi}_{0+h} \\ \bar{\pi}_{0+h-1} \\ \vdots \\ \bar{\pi}_{0+2} \\ \bar{\pi}_{0+1} \\ v_0 \end{bmatrix}\begin{bmatrix} \pi_0 & \epsilon_0 & \bar{\pi}_{0+h} & \bar{\pi}_{0+h-1} & \ldots & \bar{\pi}_{0+2} & \bar{\pi}_{0+1} & v_0 \end{bmatrix}\right)$$

[15] The estimated parameters are robust to alternative values for ς.

$$= \begin{bmatrix} 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & \frac{\sigma_\eta^2}{1-\phi^2} & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \varsigma & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 0 & \varsigma & 0 & 0 & 0 & 0 \\ \vdots & 0 & 0 & 0 & \ddots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & \varsigma & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & \varsigma & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & \frac{\sigma_{\nu,0}^2}{1-\rho_v^2} \end{bmatrix}$$

where π_{t_0} is set to the core inflation rate in 1991 Q2 (the last quarter before the start of the panel estimation sample) and $\bar{\pi}_0$ corresponds to the inflation drift in 1991 Q2 and $\bar{\pi}_1$, etc. are set accordingly.

The interpretation of these initial conditions is that they are set so that we as the econometricians have the same priors about the initial state as those about the forecasters' initial beliefs. Therefore, forecasters' initial beliefs at the beginning of the sample, i.e. 1991Q3, are denoted by $\bar{\xi}_{0|0}$ and $\bar{\mathbf{P}}_{0|0}$. If a forecaster enters the Survey after 1991Q4, its initial beliefs are updated by the Kalman filter assuming omitted observations. Recall that forecasters are heterogeneous in their level of attention, the Kalman filter will assign different prior uncertainty $\bar{\mathbf{P}}_{t-1|t-1}(i)$ across forecasters who enter the Survey in the same quarter.

D Selection of forecasters

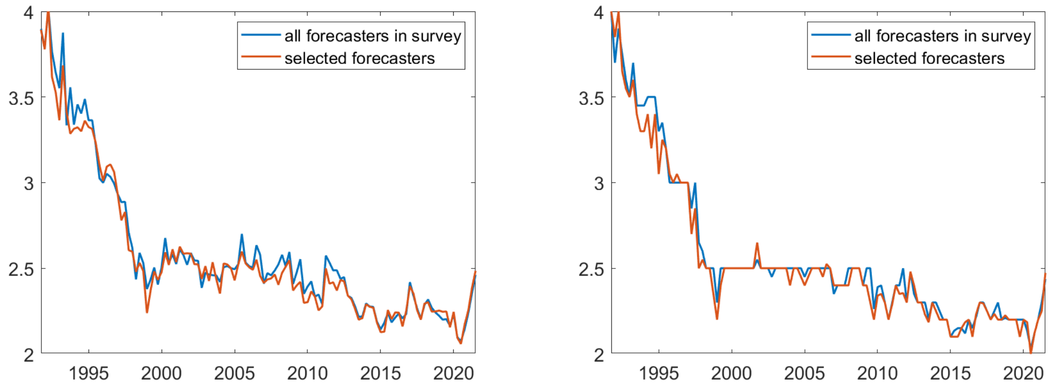

Figure 9: Time series of inflation expectations: mean (lhs) and median (rhs)

E Volatility of Expectations

In order to understand better what determines the estimated parameters we analyze their relationship with the inflation expectations data. As illustrated by Figure 10 the estimated parameters of the process $u_t(i) \equiv v_t + z_t(i)$ in equation (5) are related to the second moment of the distribution of inflation expectations. The left chart shows that forecasters with a higher standard deviation of expectations over time tend to have a higher σ_z. This result suggests that periods in which the average cross-sectional volatility increases, the likelihood selects a larger volatility of the idiosyncratic noise, $z_t(i)$. The right chart plots the estimated σ_ν as a function of the standard deviation across forecasts at a given point in time and points to a negative relationship between the standard deviation of expectations across forecasts and the volatility of the forward-looking component v_t. If the volatility of the forward-looking component is low, forecasters pay more attention to the information coming from news about long-run inflation (the second signal) and consequently, expectations react more to news (larger Kalman gains).

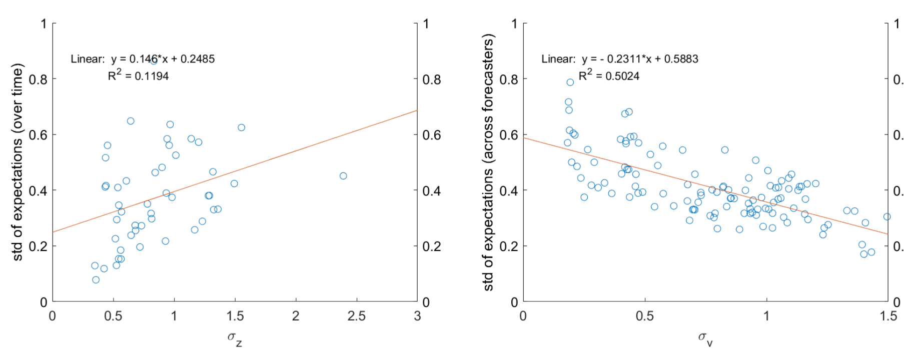

Figure 10: Relationship of estimated parameters with distribution of expectations

F Robustness of panel estimates

(1) Baseline

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.384
$\sigma_{\nu,t}$	$\ln \sigma_{\nu,t}^2 \backsim \mathcal{N}\left(\ln \sigma_{\nu,t-1}^2, \sigma_{\nu,\text{prior}}^2\right)$	see Figure 11, top
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.220
$\sigma_z(i)$	Inverse Gamma (0.5,4)	see Figure 11, bottom
$\sigma_{\nu,\text{prior}}$	Calibrated	0.2

(2) h=8

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.428
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.233

(3) ρ_v=0

Parameter	Prior	Posterior mode
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.233

(4) $\sigma_{\nu,\text{prior}} = 0.4$

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.369
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.249
$\sigma_{\nu,\text{prior}}$	Calibrated	0.4

(5) Select forecasters with at least 16 quarters

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.387
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.210

(6) Select forecasters with at least 48 quarters

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.446
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.230

(7) larger prior mean of $\sigma_z(i)$

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.381
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.223
$\sigma_z(i)$	Inverse Gamma (**0.75**,4)	see Figure 11, bottom

(8) Larger prior standard deviation of noise

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.396
$\sigma_{\nu,0}$	Inverse Gamma (0.5,**8**)	0.257
$\sigma_z(i)$	Inverse Gamma (0.5,**8**)	see Figure 11, bottom

Table 3: Robustness of parameter values for panel estimation

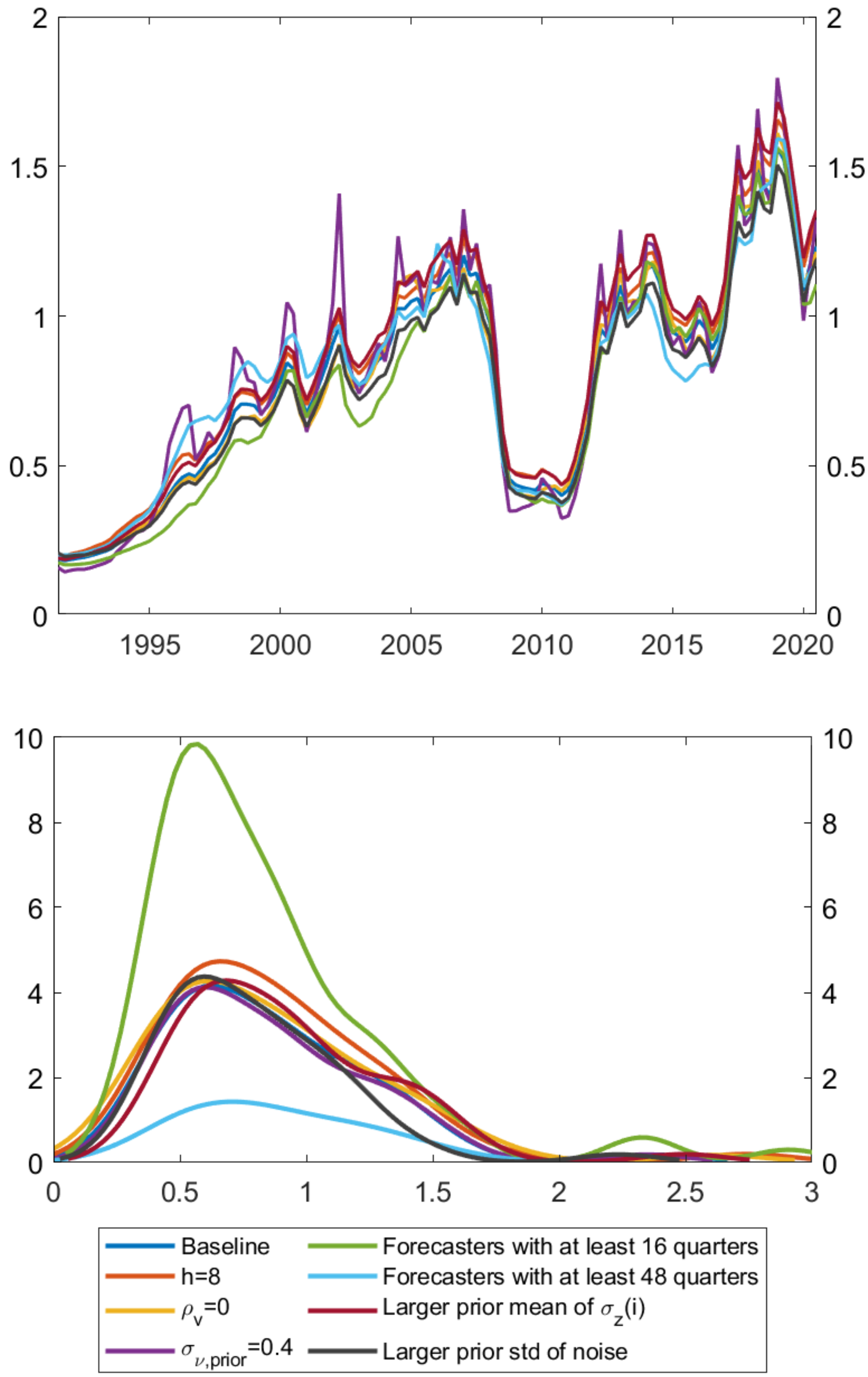

Figure 11: Robustness of $\sigma_{\nu,t}$ (top) and $\sigma_z(i)$ (bottom)

Notes: Bottom chart shows kernel-smoothing distribution fitted to histogram with 25 bins.

G Historical decomposition

The following describes the procedure to obtain the historical shock decomposition:

(i) We add the shock series $z_t(i)$ and ν_t as state variables to the model in equation (11) and then use the Kalman smoother to obtain the smoothed estimates of all shock series.

(ii) We derive the initial states in period 0 by inverting the transition equation for period 1 and using the smoothed estimates for the parameter matrices and shock series from period 1 in this equation to get the initial states in period 0.

(iii) We simulate the model based on the smoothed estimates of the parameter matrices and shock series. Figure 12 shows the simulated average inflation expectations together with the average inflation expectations in the data and the inflation drift.

(iv) We replace the smoothed estimates of all shock series by zero and simulate the model to obtain the series of inflation expectations in the absent of any shocks.

(v) We simulate the model by allowing one shock to be non-zero at the time and then compute the deviation of this simulated series of inflation expectations from the series obtain in step (iv) before.

(vi) For each shock, we compute the average of these deviations across forecasters to obtain the bars in Figure 7.

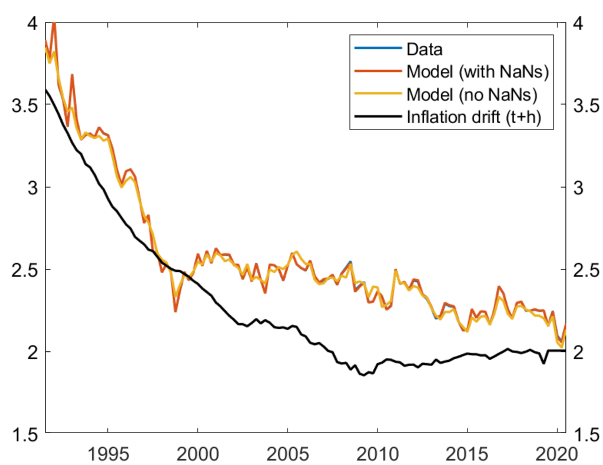

Figure 12: Average inflation expectations: data vs model

Notes: Data corresponds to average inflation expectations by all forecasters. Model (with NaNs) corresponds to the average of the model simulated inflation expectations where periods without forecasts are replaced by missing values. Model (no NaNs) corresponds to the average of the model simulated inflation expectations where periods without forecasts are filled by the Kalman smoother.

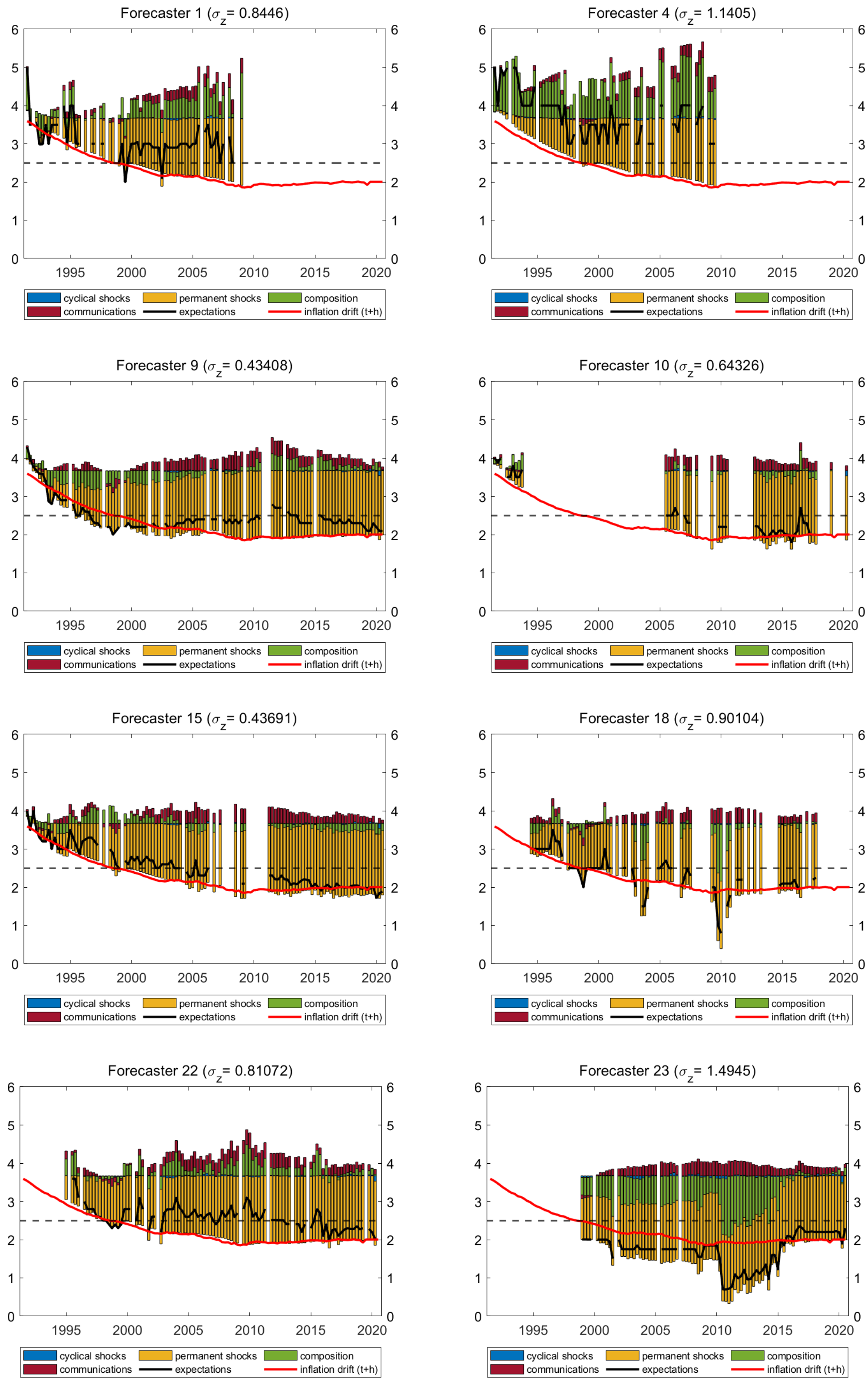

Figure 13: Historical decomposition of inflation expectations for different forecasters

Notes: Simulation of model based on smoothed estimates with different shocks active.

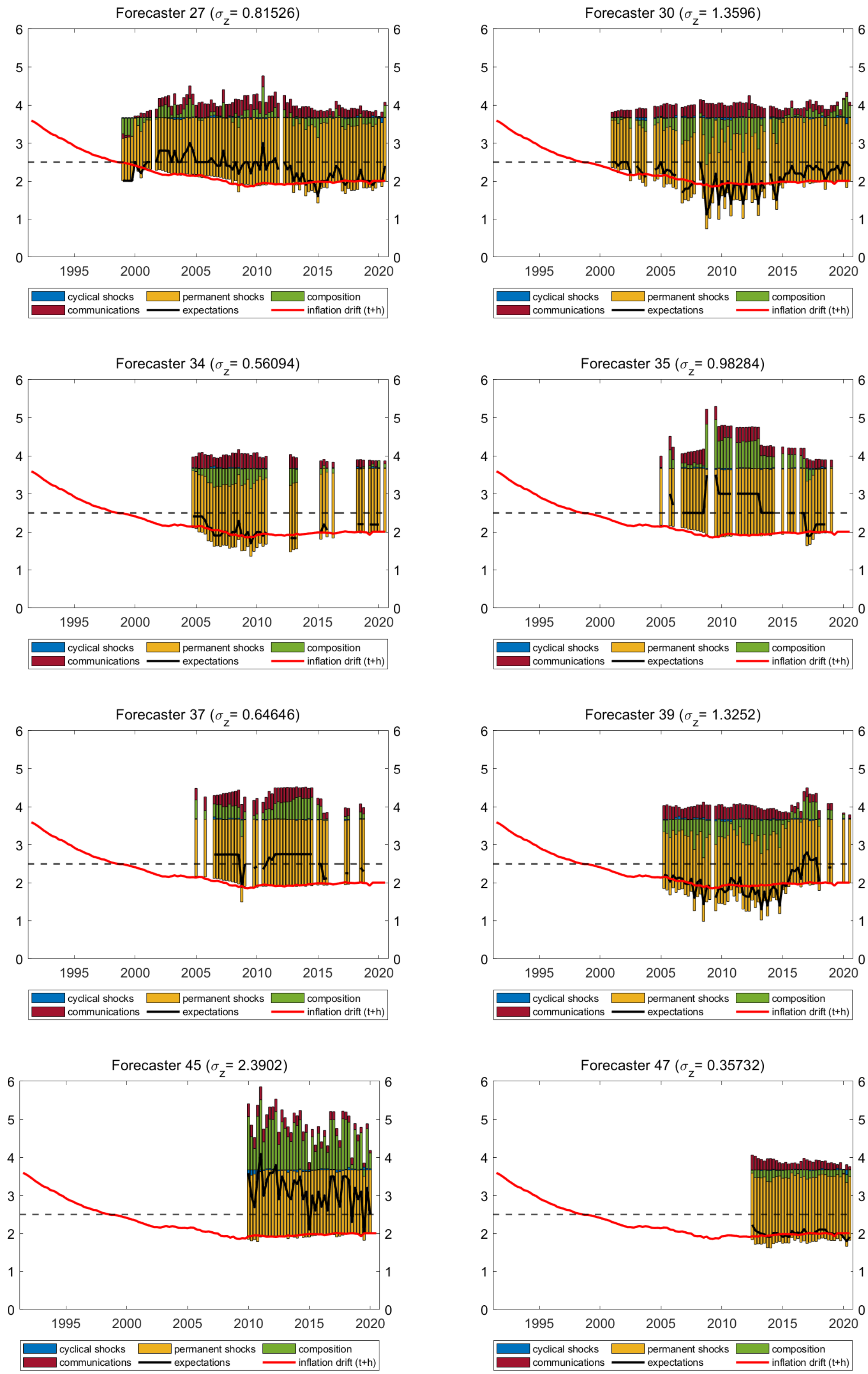

Figure 14: Historical decomposition of inflation expectations for different forecasters (continued)

Notes: Simulation of model based on smoothed estimates with different shocks active.

H Projection exercise

In the following we describe the detailed procedure underlying the projection exercise in section 8. The projection exercise starts in 2020Q4 since our estimation sample goes until 2020Q3.

Inflation path required to cement expectations at 2.5% (anchoring)

(i) Set **inflation drift path**: We assume re-anchoring from 2025 and choose a smooth path of $\bar{\pi}_t$ from 2020Q4 through 2026Q4 such that

   (i) $\bar{\pi}_t = \bar{\pi}_{2020Q3}$ for $t = \{2020Q4, 2021Q1\}$

   (ii) $\bar{\pi}_{2025Q1} = \bar{\pi}_{2025Q2} = ... = \bar{\pi}_{2026Q4} = 2.5\%$ (Re-anchoring successful from 2025Q1 and on)

   (iii) From 2021Q2 through 2024Q4 we assume that the targeted path $\bar{\pi}_t$ evolves linearly

(ii) Using the drift from step (i), we have all the data for our observables in the panel estimation available from 2020Q4 until 2021Q2. We use the Kalman filter of the state space of the econometrician as defined in Equation (11)-(12) to obtain filtered estimates of the state variables. We assume $\sigma_{\nu,t}$ is equal to the value estimated for 2020Q3.[16]

(iii) Now we use the states from the previous step as initial conditions to run the Kalman filter from 2021Q3 until 2026Q4. We observe the inflation drift from step (i) for the whole sample and realized inflation for 2021Q3 only. Inflation expectations are not available and since we want to cement expectations at 2.5% we impose that average inflation expectations are equal to 2.5%.[17] We use the same state space model as defined in Equation (11)-(12) except that we append the shocks as state variables and then we use two scenarios for communication that imply the following measurement equations:

   (i) **with communication:**

$$\begin{bmatrix} \hat{\pi}_t \\ \bar{\pi}_{t+h} \\ 2.5N \end{bmatrix} = \begin{bmatrix} \mathbf{1}_1 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & ... & \mathbf{0}_{1\times k} & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{1}_3 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & ... & \mathbf{0}_{1\times k} & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{0}_{1\times k} & \mathbf{1}_3 & \mathbf{1}_3 & ... & \mathbf{1}_3 & 0 & 0 & 0 & \mathbf{0}_{1\times N} \end{bmatrix} \begin{bmatrix} \xi_t \\ \xi_{t|t}(1) \\ \xi_{t|t}(2) \\ \vdots \\ \xi_{t|t}(N) \\ \epsilon_t \\ \lambda_{t+h} \\ \nu_t \\ \overrightarrow{z}_t \end{bmatrix}$$

[16] The projected inflation path is similar for alternative values of $\sigma_{\nu,t}$.

[17] In 2021Q2 mean inflation expectations are very close to 2.5. The exact value is 2.485.

(ii) **no communication (ν_t=0):**

$$\begin{bmatrix} \hat{\pi}_t \\ \bar{\pi}_{t+h} \\ 2.5N \\ 0 \end{bmatrix} = \begin{bmatrix} \mathbf{1}_1 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{1}_3 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{0}_{1\times k} & \mathbf{1}_3 & \mathbf{1}_3 & \dots & \mathbf{1}_3 & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 & 0 & 1 & \mathbf{0}_{1\times N} \end{bmatrix} \begin{bmatrix} \xi_t \\ \xi_{t|t}(1) \\ \xi_{t|t}(2) \\ \vdots \\ \xi_{t|t}(N) \\ \epsilon_t \\ \lambda_{t+h} \\ \nu_t \\ \overrightarrow{z}_t \end{bmatrix}$$

(iv) The estimated $\hat{\pi}_t$ from step (iii) are plotted in the rhs of Figure 8 together with the inflation drift and SEP projections.

(v) In order to assess the contribution of communication to mean average inflation expectations we estimate the historical decomposition of inflation expectations using the Kalman smoother based on the measurement equations defined in the case with communication above (see also Appendix G). The historical decomposition is shown in Figure 15. The black dotted line in the lhs of Figure 8 is computed as the mean expectations minus the contribution of communication (red bars).

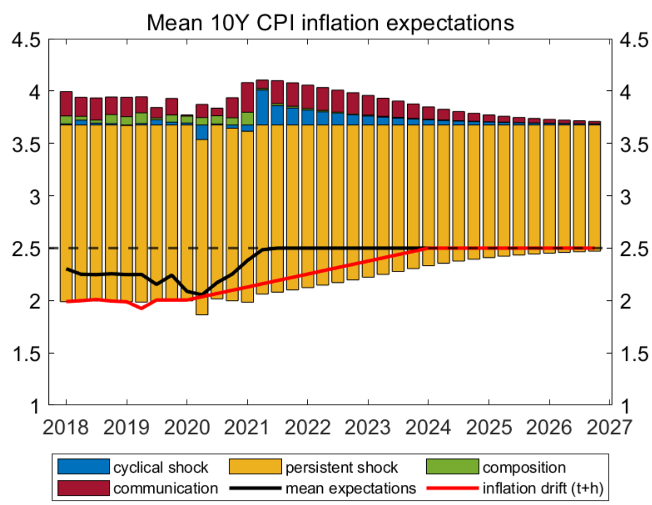

Figure 15: Historical decomposition of mean expectations under projection exercise