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

Jonas Fisher[†]   Leonardo Melosi[‡]   Sebastian Rast[§]

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Abstract

We use panel data from the U.S. Survey of Professional Forecasters to estimate a model of individual forecaster behavior in an environment where inflation follows a trend-cycle time series process. Our model allows us to estimate the sensitivity of forecasters' long-run expectations to incoming inflation and news about future inflation, and measure the coordination of beliefs about future inflation. We use our model of individual forecasters to study *average* long-run inflation expectations. Short term changes in inflation have small effects on average expectations; the sensitivity to news is over twice as large, but is still relatively small. These findings provide a partial explanation for why the anchoring and subsequent de-anchoring of average inflation expectations over 1991 to 2020 were such long-lasting episodes. Our model suggests coordination of beliefs also played a role, slowing down but not preventing the pull on average expectations from inflation running persistently below target. We apply our model to the case of a U.S. central banker setting policy in September 2021. Our results suggest the high inflation readings of mid-2021 would have to be followed by overshooting of the Fed's target generally at the high end of the Fed's Summary of Economic Projections to re-anchor long term expectations at their pre-Great Recession level.

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

JEL classification: *E31, C83, D84*

1   Introduction

To assess their progress in maintaining price stability inflation-targeting 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] We describe a method to use panel data to estimate the sensitivity of forecasters' long term inflation expectations to incoming inflation and to news about future inflation, and measure the coordination of beliefs about future inflation. We estimate our model using panel data from the U.S. Survey of Professional Forecasters (SPF) and apply it to explore the historical drivers of average inflation expectations from 1991 to 2020, and to consider inflation anchoring from the stance of a hypothetical policymaker at the September 2021 meeting of the Federal Open Market Committee (FOMC).

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 and cycle components of inflation which they use to form 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 captures forward-looking information or *news* about long-run inflation not already captured in the historical behaviour of inflation. It is specified as the sum of future trend inflation and common and idiosyncratic shocks. The common shock coordinates beliefs about future inflation. Such coordination might reflect the central bank's communications regarding how it will seek to achieve its inflation objective, changes in public trust regarding

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

[2]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, and the Survey of Professional Forecasters. The New York Fed Survey of Consumer Expectations has medium term expectations.

the central bank's ability to stabilize inflation around its target, and animal spirits or sentiment. The variance of the common shock is time-varying to capture episodes when expectations are particularly sensitive or insensitive to the signals. The idiosyncratic shock has a forecaster-specific variance to capture the forecasters' heterogeneous sensitivity the signals.

We take this model to the data in two steps. First, we estimate the trend-cycle model using core CPI inflation over the sample period 1959q1 to 2020q3.[3] We combine this estimated model with the two signals just described to calculate the laws of motion of the individual forecasters' 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 is identified by revisions to forecasters' expectations that cannot be rationalized by the historical behavior of inflation alone. This identification is facilitated by our assumption that we observe trend inflation when we estimate the laws of motion of individual forecasters' expectations, but forecasters do not. By making this assumption we can isolate the importance of news about trend inflation that is not yet reflected in historical inflation. The idiosyncratic component of the beliefs is identified by the cross-section of the SPF.

We estimate time-varying sensitivity of forecasters' long term inflation expectations to incoming inflation and news about future inflation. Forecasters' expectations respond little to incoming inflation. Averaging over the panel, they adjust their long-term expectations by only 10 basis points in response to a 100 basis point change in inflation. Forecasters are more than twice as sensitive 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.

The slow rate of learning reflected in these low elasticities provides a partial explanation for why the anchoring and subsequent de-anchoring of average inflation expectations over the period 1991 to 2020 were such long lasting episodes. Our model suggests coordination

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[3]The end of the sample period is the last quarter before the implementation of the Fed's new long run framework for monetary policy. This is discussed further below.

of beliefs also played a role, slowing down but not preventing the pull on average long term expectations from inflation running persistently below target from the early 2000s. The greater sensitivity to news than to actual inflation suggests that coordination of beliefs through 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.

In addition to providing a characterization of past average inflation expectations, our model can be used as a guide to central bankers looking to the future, and in particular those operating within an inflation targeting regime. The goal of such a regime is to anchor long term inflation expectations at the inflation target. Our estimated model can be used to study whether and under what conditions average long term inflation expectations will be anchored going forward from the end of the sample period. Its parameters determine how quickly individual forecasters respond to incoming inflation and news about future inflation. Therefore we can use it to project average inflation expectations under different scenarios for the future paths of inflation and news.

We apply our model to the case of a central banker considering the stance of U.S. monetary policy in September 2021. At this time inflation had been running substantially above the inflation target for over half a year after a long period of running below target and average long term expectations drifting near to our sub-target estimate of trend inflation by 2020q3. But in the face of the high inflation readings in mid-2021 long term inflation expectations were rising too. These conditions presented the Fed with a key test of its credibility. In August 2020 Fed Chair Powell had announced a new long run framework for guiding US monetary policy. This framework is articulated in the Fed's Statement on Longer Run Goals and Monetary Policy, which includes the following passage: "In order to anchor longer-term inflation expectations at this level [2 percent PCE inflation], the Committee seeks to achieve inflation that averages 2 percent over time, and therefore 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."[4] How much overshooting of the target does our

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[4]See https://www.federalreserve.gov/monetarypolicy/files/fomc_longerrungoals.pdf.

model say the Fed should have been striving to achieve to implement this strategy as it set policy in September 2021?

In our model, expectations can be re-anchored if inflation runs for some time above the Fed's inflation target and the Fed coordinates beliefs by communicating that it will use policy to ensure this overshooting outcome. Our model's parameters determine how quickly individual forecasters respond to incoming inflation and news about future inflation. Therefore we can use it to project average inflation expectations under different scenarios for the future paths of inflation and news.

We explore two experiments to shed light on the overshooting question. In the first we calculate average long term inflation expectations implied by the highest, median, and lowest paths of inflation taken from the Fed's September 2021 Summary of Economic Projections (SEP).[5] Expectations in this experiment are determined solely by realized inflation and there is no role for the coordination of beliefs. We find that in all three cases average long term expectations fall persistently below 2.5 percent despite the sharp increase in inflation in mid-2021.

In the second experiment we find values of the permanent, cyclical, and news shocks that deliver paths for inflation and the inflation drift from 2021q4 that re-anchor average long term CPI inflation expectations at 2.5%, the level of anchoring before the Great Recession.[6] We find that inflation need only come in at the high end of the SEP projections to re-anchor expectations due to the coordination of beliefs on higher inflation in the future. We interpret this as suggesting a role for policy communications. By signalling that inflation will come in higher than warranted by the underlying trend the central bank does not need as much of an inflation overshoot to re-anchor expectations.

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, the data we use, and our estimates. We then examine the history of inflation

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[5]The SEP are available at https://www.federalreserve.gov/monetarypolicy/fomc.htm.

[6]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. We assume a 50 basis point wedge between the two measures 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. Accounting for compositional effects is particularly important in light of the critique of conditional mean forecasts highlighted by Engelberg, Manski and Williams (2010). Our fixed effect is the variance of the forecaster-specific beliefs. Nechio (2015) studies composition in terms of the distribution of forecasters' root mean inflation forecast error.

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.

Finally, our work is related to the literature studying the dynamics of inflation with a trend-cycle model with unobserved components (Stock and Watson (2007)). Building on the idea by Beveridge and Nelson (1981), trend inflation in these models can be viewed as the long-run level of expected inflation. The papers in that field closest to ours link trend inflation with expectations from survey data to learn about the implications of changes in the inflation process for inflation forecasts and to study the anchoring of inflation expectations. This includes Henzel (2013), Mertens (2016), Mertens and Nason (2020) and Nason and Smith (2021). Two notable differences between those papers and our paper is the focus on long-run inflation expectations and on the cross-sectional dimension of the survey data.

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 believing inflation outcomes are driven a particular trend-cycle time series model.[7] 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

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[7]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.

inflation from its long-run trend. Trend inflation reflects the long-run drivers of inflation that are already incorporated into the historical behavior of inflation. According to this process the expected value of inflation at long horizons equals the trend, $\bar{\pi}_t$.[8]

Forecasters make their long term forecast in each period with an information set that includes knowledge of the trend-cycle model, the history of inflation, and two signals. The *inflation signal* is received by all the forecasters and simply updates the history of inflation to include its current value.[9] The second signal $y_t(i)$ is given by:

$$y_t(i) = \bar{\pi}_{t+h} + u_t(i), \quad h > 0. \tag{4}$$

This signal is private as it depends on the identity of the forecaster, denoted i. The dependence on the identity of the forecaster reflects differences in their beliefs, $u_t(i)$, given by

$$u_t(i) \equiv v_t + z_t(i). \tag{5}$$

The forecaster-specific component is $z_t(i) \sim \mathcal{N}(0, \sigma_z^2(i))$ and the common component v_t is driven by

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

with $\nu_t \sim \mathcal{N}(0, \sigma_{\nu,t}^2)$. The shocks $z_t(i)$ are homokedastic and orthogonal to each other and ν_t.[10] Since the private signal provides news about the future long-run dynamics of inflation we refer to it as the *news signal*. The forecasters are assumed to know the parameters of the signals.

The news signal $y_t(i)$ is designed to gauge the importance of news or forward-looking

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[8]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, Herreño, Nakamura and Steinson (2020).

[9]The forecasters in the SPF do not know inflation in the quarter they are surveyed because they submit their forecasts in the second month of each quarter. We address this by lagging SPF forecasts when we estimate the model. For example, we measure long term expectations in the 2020q3 using forecasts from the November 2020 survey.

[10]In principle the forecast-specific component of beliefs 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 beliefs.

information about long-term inflation in forecasters' inflation expectations. 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 (4) 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 (4), $u_t(i)$, includes common and idiosyncratic shocks that affect the forecasters' beliefs about long term inflation which may or may not come to pass. Since these shocks are autonomous (i.e. orthogonal to the variables in equation 7), they can be thought of as animal spirits or sentiments. Sentiments that coordinate beliefs about long term inflation (ν_t) may be triggered by central bank communications and media influencing public opinion about long-run inflation in a particular direction, for instance by criticizing or backing the strategy of the central bank. The idiosyncratic shock $z_t(i)$ affects the beliefs of a specific forecaster i. This shock accounts for compositional effects in average inflation expectations due to forecasters with different idiosyncratic variances moving into and out of our survey sample.

The volatility of $u_t(i)$ (which depends on the variances of ν_t and $z_t(i)$) influences the sensitivity of expectations to the two signals. 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 respond one for one with the drift. If the volatility of $u_t(i)$ is very high, the news signal is close to useless. In this situation forecasters rely almost exclusively on the historical behavior of inflation to form their

long-term inflation expectations.

Note that the standard deviation of the innovations to the common component of beliefs, $\sigma_{\nu,t}$, is time-varying and the same across forecasters while the standard deviation of the idiosyncratic component, $\sigma_z(i)$, is constant and specific to each forecaster.[11] The volatility of common beliefs captures episodes when long term expectations of *all* the forecasters are particularly sensitive or insensitive to the signals. The volatility of idiosyncratic beliefs captures forecaster-specific sensitivity to the signals.

At each date t forecasters observe the signals with knowledge of the history of inflation and the trend-cycle model. They use this information to update their expectations about $\bar{\pi}_t$ using Bayes rule. We assume their objective is to minimize the variance in their estimates of the underlying state variables. Given our model is linear and its shocks are normally distributed this implies that it is optimal for forecasters to update their expectations using the Kalman filter. It is important to note that the resulting expectations do not feedback into the trend-cycle model and so do not affect the dynamics of inflation.

The volatilities of the two shocks ν_t and $z_t(i)$ help determine the magnitudes of the Kalman gains and therefore the sensitivities of individual expectations to the two signals. These variances cannot be estimated directly because we do not observe the realizations of the shocks. Rather, they are identified from the observed sensitivity of average and individual expectations to current and future changes in the drift. In this sense, these shocks can be thought of as shocks to average and individual expectations.

3.2 Forecasters' long-run inflation expectations

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

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

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

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[11] For the majority of forecasters in our data the null hypothesis of homoskedasticity for $z_t(i)$ is not rejected.

where

$$\xi_t = [\pi_t, \varepsilon_t, \bar{\pi}_{t+h}, \bar{\pi}_{t+h-1} \cdots, \bar{\pi}_{t+1}, v_t]'$$

$$e_t = [\eta_t, \lambda_{t+h}, \nu_t]'$$

$$s_t(i) = [\pi_t, y_t(i)]'.$$

Here $\boldsymbol{\Phi}$ 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. We assume they seek a linear rule that minimizes the variance in the estimated states. Given the Gaussian structure of our shocks this 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:

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

where $\xi_{t|t}(i) \equiv \mathbb{E}(\xi_t | s_t(i), \pi^{t-1})$ denotes forecaster i's expectations conditional on their signals 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 belief, v_t. If the volatility of this component is large, the news signal plays essentially no role and forecasters' expectations are updated at a pace consistent with only 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 wrong, 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 parameters of the trend-cycle model (ρ, ϕ, σ_η, and σ_λ) 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 the a panel model assuming that forecasters know the trend-cycle model estimated in the first step and observe inflation and their private signals $y_t(i)$. We as the econometricians observe inflation, the inflation drift obtained from the first step, and a measure of long term inflation expectations, but we do not observe the private signals. Therefore, we estimate a state space model that combines equations (1)-(3) with N equations corresponding to equation (10) for each of the N forecasters in our sample. This yields estimates of (ρ, $\sigma_{\nu,t}$, and $\sigma_z(i)$, $i = 1, 2, \ldots, N$).

The transition equation we use in our panel estimation reads

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

where $\overrightarrow{\xi}_{t|t}$ and $\overrightarrow{z}_t$ are column vectors stacking $\xi_{t|t}(i)$ and $z_t(i)$ of every forecaster and the matrices $\widetilde{\boldsymbol{\Phi}}_t$ 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

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

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. Our choices are guided by the fact that CPI inflation forecasts from the SPF are available for a longer period than forecasts of inflation in the personal consumption expenditure index, which is the inflation measure targeted by the Fed. We use data on year over year core CPI 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 1991Qq–2021Q4. We use the 10-year average CPI inflation forecasts to measure long-term inflation expectations in our model.[12] This measure does not directly correspond to the long-term inflation expectations $\bar{\pi}_{t+h}$ in our

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[12]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 inflation forecasts which are only available starting from 2005.
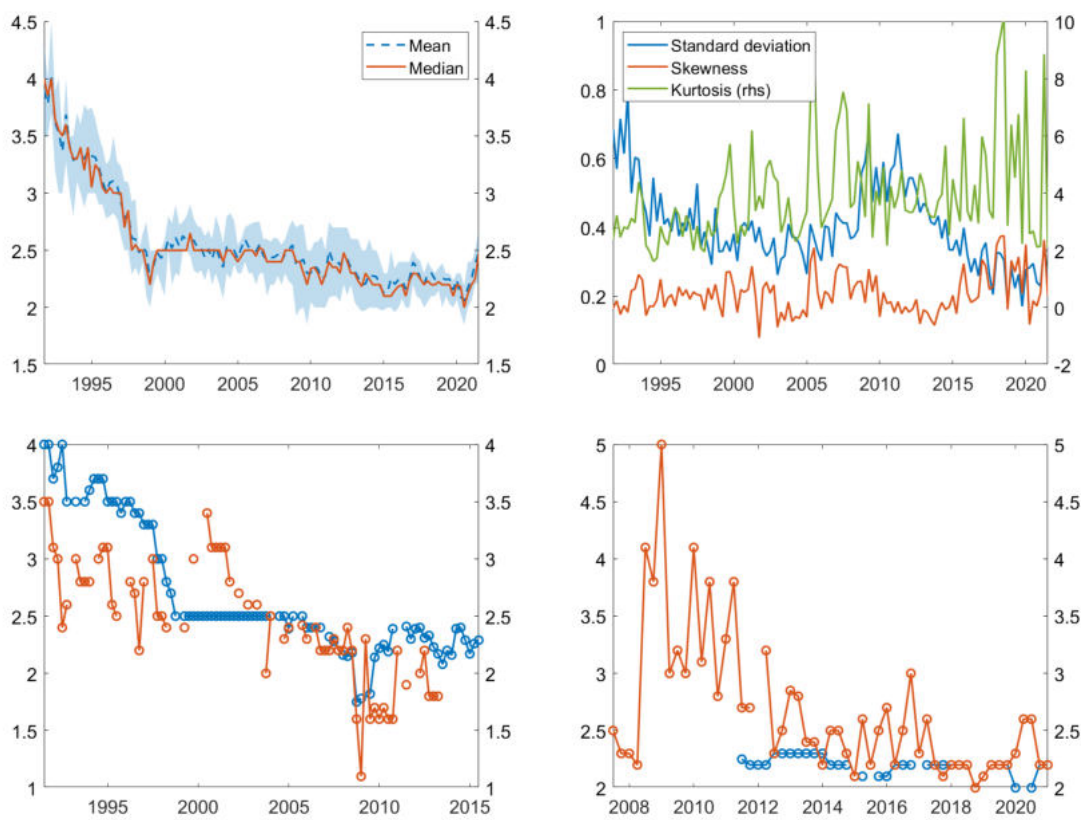
Figure 1: Time series summary of 10-year CPI inflation expectations

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.

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 beliefs 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.[13] 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.

The top row in Figure 1 shows how the the distribution of long-term inflation expectations

[13]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.

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 average 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.[14] 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 inflation drift, $\bar{\pi}_t^{est}$. Figure 2 shows the time series of core CPI inflation and our estimate of

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

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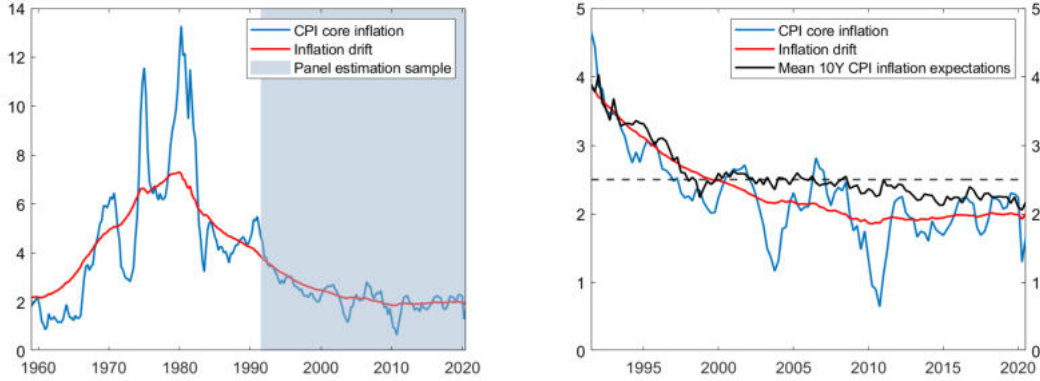| Parameter	Prior	Posterior mode
ρ	Beta(0.5,0.2)	0.785
ϕ	Beta(0.5,0.2)	0.623
σ_η	Inverse Gamma (0.25,4)	0.427
σ_λ	Inverse Gamma (0.25,4)	0.300
$\bar{\pi}_{t_0}$	Uniform	2.187

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.

the inflation drift over the full estimation sample. The shaded 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.

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.

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

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 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

submit their forecasts, we shift the SPF data one period backward. 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 $\sigma_{\nu,t}^2$ 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 $\sigma_{\nu,0}^2$ is assumed to be distributed as inverse gamma with moments shown in Table 2.

Table 2 shows we estimate a persistence of around 0.4 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 suggests that the sensitivity of expectations to the news signal has declined as inflation became more stable. During the turbulent developments of the Great Financial Crisis and the ensuing Great Recession, the exogenous common beliefs were substantially less volatile suggesting greater sensitivity to news. The right chart in Figure 3 plots the distribution of the variance of forecaster-specific beliefs, $\sigma_z(i)$. This distribution suggests that the degree of sensitivity to the signals is quite heterogeneous.
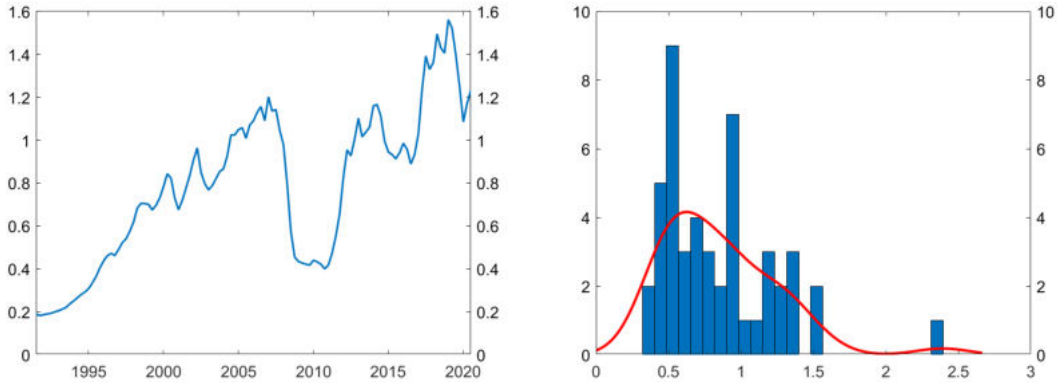
Figure 3: Time series of $\sigma_{\nu,t}$ (lhs) and histogram of σ_z (rhs)

7 Inflation expectations through the lens of the model

This section discusses three aspects of the historical behavior of inflation expectations. We first describe how the sensitivity of forecasters to the signals varies over time and across forecasters based on the estimated Kalman gain matrices. Next we use the Kalman matrices to compute impulse responses to study the effect of the model's different shocks on forecasters' long term inflation expectations. Finally, 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 Forecasters' sensitivity to inflation and news

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 a high degree of sensitivity to the inflation and news signals and fast learning about the underlying state variables. Our focus is on 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

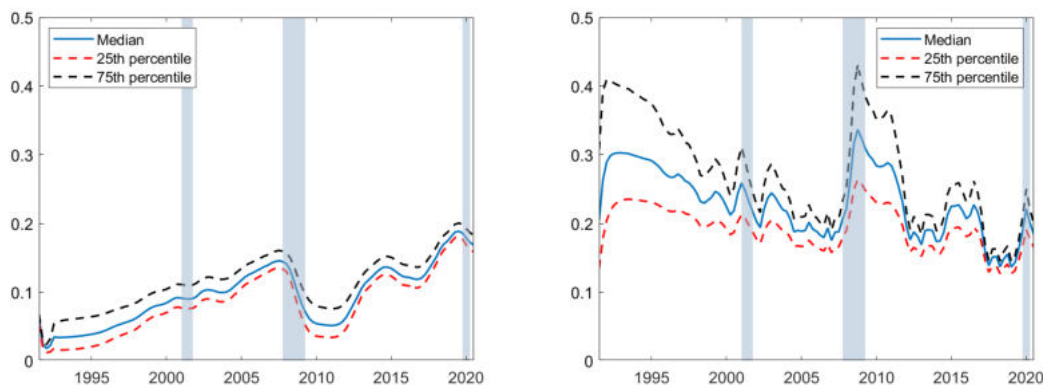inflation expectations in response to changes in the two signals.

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 while it is roughly stationary for news.

Second, the gains vary over time and generally in opposite directions. The shaded areas in Figure 4 indicate NBER recessions dates and illustrate that while the sensitivity of expectations to the inflation signal is pro-cyclical, it is counter-cyclical for news. This is especially noteworthy during the Great Recession where we observe a large increase in the median Kalman gain for the news signal. These findings suggest that individual and therefore average inflation expectations are particularly responsive to news about long-run inflation during recessions and
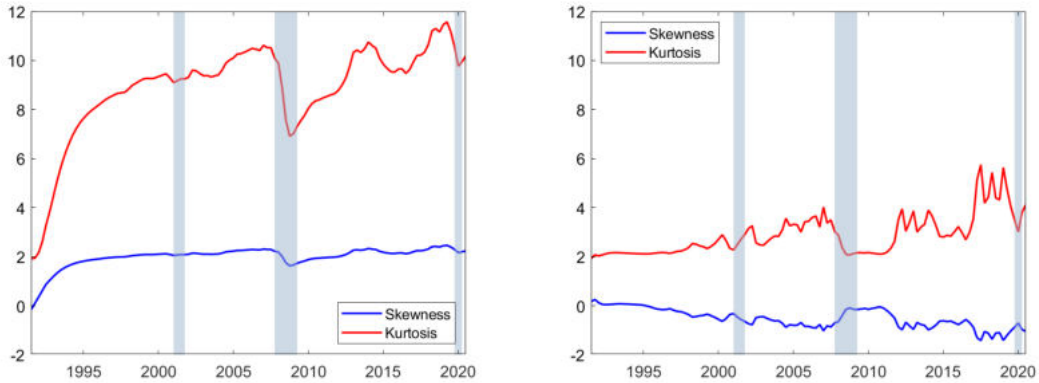
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Figure 5: Higher moments of Kalman gain distribution for inflation drift: inflation signal (lhs), news signal (rhs)

Notes: Shaded areas indicate NBER recession dates.

when the Federal Funds 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, meaning that the tails of the distribution of Kalman gains become thinner in recessions.

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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. In addition, 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, common beliefs ν, and idiosyncratic beliefs, z, which is indicative of how important the composition of the survey is to average inflation expectations.

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 shocks to the common beliefs ν_t (left plot) and to the idiosyncratic beliefs $z_t(i)$ (right plot). In both cases, a one standard deviation shock moves median inflation expectations away from the inflation drift by about 20 basis points. The effects of these shocks are a similarly persistent. This illustrates
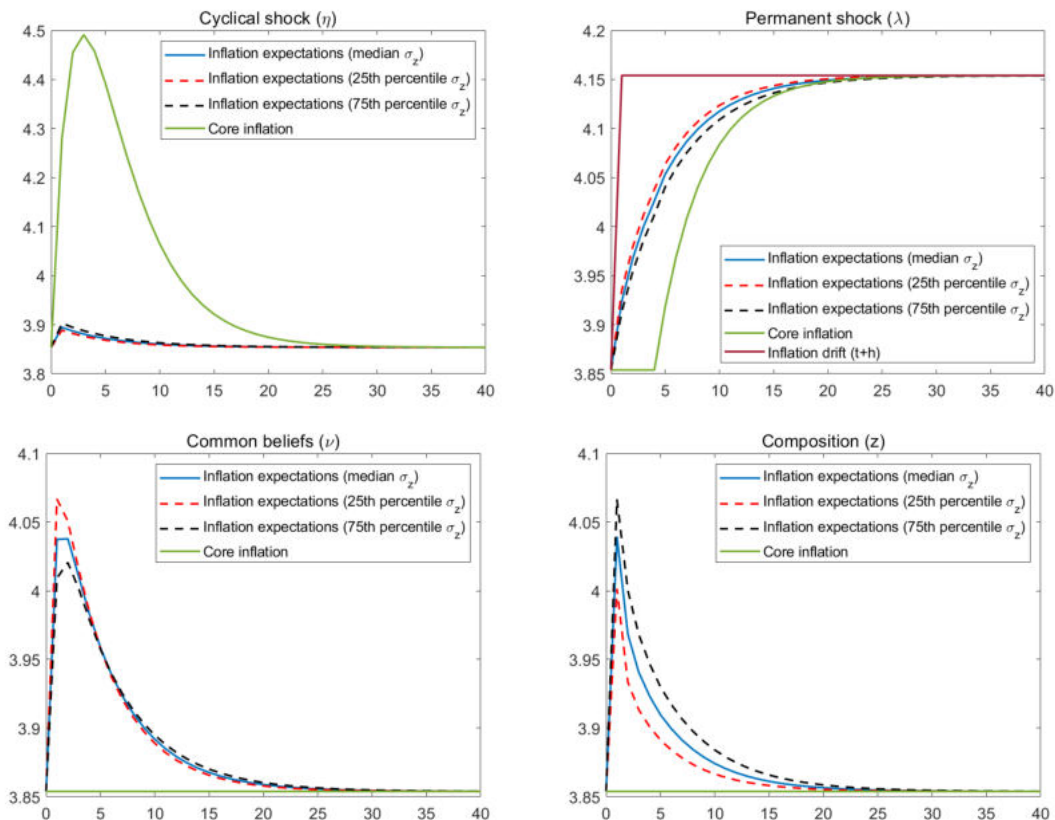
Figure 6: Impulse response functions to one standard deviation shocks

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.

that shocks to beliefs can move away median inflation expectations for a significant period of time from the inflation drift. The similarity of the responses to the idiosyncratic shock suggests that composition is likely to have a relatively small effect on average inflation expectations.

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, common beliefs, and composition 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
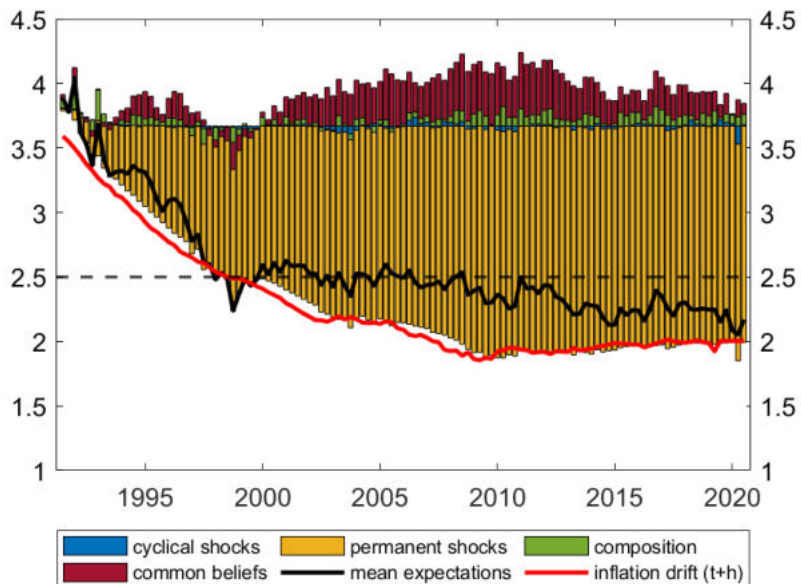
shock decomposition is described in Appendix F.

Figure 7: Historical decomposition of average inflation expectations

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

Figure 7 shows the primary driver of the long term decline in average inflation expectations is permanent shocks to inflation λ_t. After the drift reached 2.5 percent in the late 1990s it declined further but inflation expectations remained fairly stable. The main driver behind this discrepancy between trend inflation and average inflation expectations is common beliefs, news not yet reflected in current inflation, ν_t. This pattern of common beliefs led forecasters to keep their average inflation expectations stable and close to the Fed's objective.[15]

We interpret this result as suggesting indicating that communication has played an important role in stabilizing average 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, the gap between average inflation expectations and the sub-target estimated

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[15]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.

trend of inflation has shrunk considerably.

In line with the results described in subsection 7.2, 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 beliefs $z_t(i)$ has had a mainly positive and small effect on long term expectations. Still, absent these composition effects the post Great Financial Crisis de-anchoring of average long term expectations would have come earlier and faster.

In Appendix F, we show the historical decomposition of individual expectations for a subset of forecasters. The forecaster-specific beliefs $z_t(i)$ plays an important role as a driver of inflation expectations at the forecaster level. As shown in Figure 7, this source of volatility 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

The previous section shows that our model provides a plausible characterization of the historical behavior of average long term inflation expectations. Our model can also be used as a guide for central bankers looking to the future, and in particular those operating within an inflation target regime. The goal of such a regime is to anchor long term inflation expectations at the inflation target. Our estimated model can be used to study whether and under what conditions average long term inflation expectations will be anchored going forward from the end of the period data are available. Its parameters determine how quickly individual forecasters respond to incoming inflation and news about future inflation. Therefore we can use it to project average inflation expectations under different scenarios for the future paths of inflation and news.

We now apply our model to the case of a central banker considering the stance of US monetary policy in the third quarter of 2021. From the late 1990s to the Great Recession SPF average long term CPI inflation expectations appear to have been anchored at 2.5 percent. However for the two decades prior to the pandemic CPI inflation almost always ran below these expectations. This persistent deflationary bias led to progressive declines in the inflation

drift and in average expectations. By 2020q3 long term CPI inflation expectations had fallen to near 2 percent, roughly the same level as our estimated inflation drift, as shown in the right plot of Figure 2. In mid-2021, as the economy emerged from the pandemic recession, year-on-year core CPI inflation rose sharply from a near pandemic low of 1.5 percent in 2020q1 to 3.9 percent in 2021q2 and 4.1 percent in 2021q3. These high readings coincided with a substantial increase in SPF average long term inflation expectations from 2.1 percent in the May survey, 2.4 percent in the August survey, and 2.6 percent by the time of the November survey.[16] These conditions presented the Fed with a key test of the credibility of its new long run framework for guiding U.S. monetary policy announced by Fed Chair Powell in August 2020. This framework tries to commit the Fed to overshooting its target if necessary to re-anchor expectations. How much overshooting of the target does our model say the Fed should have been striving to achieve to implement this strategy as it set policy in September 2021? We now consider two experiments with our model to address this question.[17]

8.1 Alternative paths of inflation

In the first experiment we consider the evolution of average expectations under alternative paths of inflation taken from the Fed's September 2021 SEP. We obtain our model's predictions for average long term inflation expectations conditional on alternative paths of inflation in two steps. In the first step we use our estimated trend-cycle model to calculate the inflation drift with inflation data from 2020q4 (the quarter after the end of our estimation sample and the announcement of the Fed's new long run framework) through 2021q3 and September SEP inflation projections from 2021q4 through 2024q4. In addition we linearly interpolate inflation to 2.5 percent in 2025q5 where it stays until 2026q4. The latter step facilitates the calculation of the drift through 2025q4 which we need to construct the news signal in 2024q4 (with $h = 4$).[18] In the second step we use our estimated model of individual inflation

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[16]These expectations do not correspond exactly to the SPF headline rates because they are averages not medians and because they are based on our sample of forecasters which is a subset of the survey's sample.

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

[18]The September 2021 SEP reports FOMC participants' projections (under their individual views about appropriate monetary policy) for the q4 over q4 inflation rate in 2021q4, 2022q4, 2023q4, and 2024q4. We linearly interpolate between projections to obtain quarterly values.

forecasters to calculate average long-run inflation expectations launching from 2021q3 and conditioning on core CPI inflation in 2021q3, the November 2021 SPF (recall we lag SPF projections to account for the timing of the survey), the SEP inflation paths from 2021q4, and the inflation drift estimated in the previous step. Note that these steps are the same as those we followed to estimate our model of individual forecasters except for the fact that we do not use the distribution of SPF inflation expectations as they are not available.

Estimation of the inflation drift in the first step is complicated by the sharp rise in inflation in mid-2021. This rise in inflation appears to be a result of a surge in aggregate demand from fiscal and monetary stimulus and negative shocks to aggregate supply coming from a contraction in labor supply and disruptions to the supply of goods. Our linear and Gaussian setup is unlikely to properly capture these unusual developments. Consequently we adapt the method Lenza and Primiceri (2020) propose to estimate VAR models with samples that include the pandemic-driven wild swings in data starting in 2020q2.[19] In particular, we scale the variances of the cyclical and permanent components starting in 2021q2 by the factor β that decays at rate γ. When we calculate average inflation expectations we assume the forecasters know this scaling. We estimate values of β near 4.75 and γ near 0.1 (meaning the scaling factor falls quickly back to 1) using uniform priors taken as given paths of inflation from 2021q4 to 2026q4. With these coefficients in hand we calculate the inflation drift from 2020q4 to 2024q4 by running the Kalman smoother backward from 2024q4.
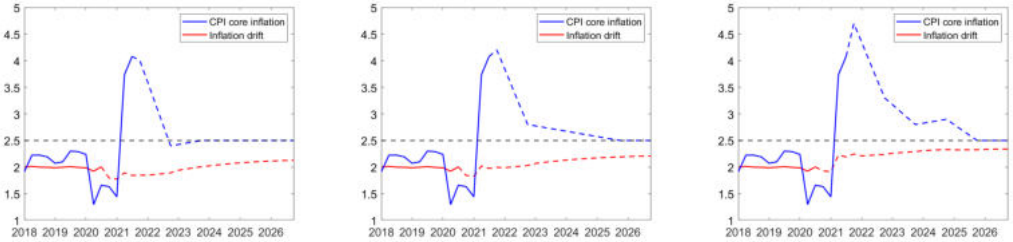

Figure 8: Inflation path and estimated inflation drift based on SEP lower range (lhs), median (middle) and upper range (rhs)

From left to right Figure 8 shows the paths of inflation corresponding to lowest, median, and highest projections along with the inflation drifts implied by these paths. The key takeaway

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[19]See Ferroni et al. (2020) for a related approach to estimating DSGE models with unusual shocks.

from this figure is that all three paths of the drift adjust very slowly back toward 2.5 percent.[20] This slow convergence means that in all three scenarios the drift exerts a downward bias to average inflation expectations.

Figure 9 illustrates the impact of this on the predicted paths of average inflation expectations. In all three cases these drop quickly below 2.5 percent, stay low, and end up between 2.1 and 2.4 percent in 2024q4. Evidently, according to our model, the inflation projected by FOMC participants in September 2021 should not have been projected to re-anchor expectations at 2.5 percent.
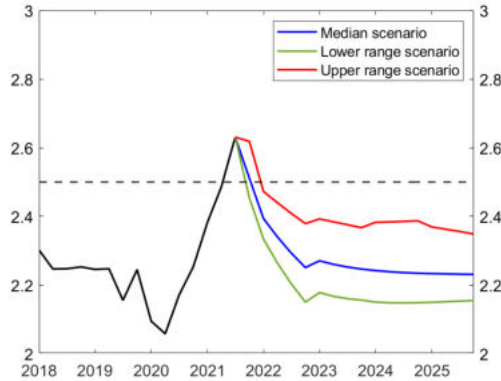

Figure 9: Mean inflation expectations under different SEP inflation scenarios

8.2 The path of inflation consistent with re-anchoring expectations

In the second experiment we study the path of inflation that would re-anchor average expectations at their pre-Great Recession level of 2.5 percent starting from 2021q4.[21] We impose in the measurement equations that the average long-run expectations of the forecasters are equal to 2.5 percent from 2021q4-2025q4. We then assume an initial path for the inflation drift from 2020q4 to 2026q4 and find the values of the permanent and cyclical shocks to inflation and the shocks to beliefs, that deliver a path for inflation from 2021q4 and rationalize the joint behavior of the drift and expectations. Since $\bar{\pi}_{t+h}$ is predetermined by our assumed path for

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[20]Note that if the variances of the cyclical and permanent shocks do not change, the drifts in all three scenarios rise quickly to above 2.5 percent in 2021q2 and stay at or above that level throughout the remainder of the projection period (not shown).

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

the drift, the path of the news signal $y_t(i)$ is pinned down by $u_t(i)$, that is the common and idiosyncratic beliefs. Since we only impose a restriction on the mean of the forecasts and the sample of forecasters is unchanged, $z_t(i)$ plays essentially no role. Given the calculated path of inflation we can infer a path of the drift as we do in the first experiment. The resulting path of the drift will not necessarily equal the path of the drift we assumed initially. We iterate on the assumed path of the drift until it converges.
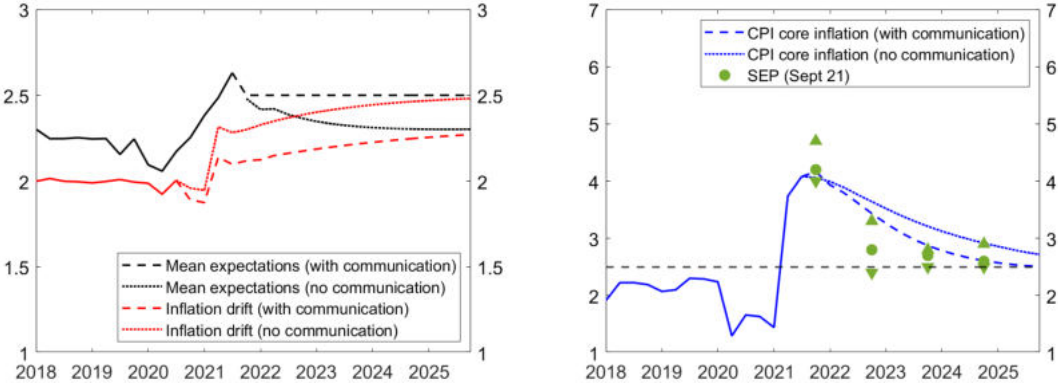

Figure 10: Inflation consistent with re-anchoring average long-term inflation expectations at 2.5 percent from 2021q4.

Notes: SEP (Sept 21) corresponds to the Summary of Economic Projections from September 2021 and is the year over year core PCE inflation projection 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 highest and lowest projections.

Figure 10 displays our findings. The blue dashed line in the right hand plot shows the inflation that is consistent with anchoring mean inflation expectations at 2.5 percent. The corresponding inflation drift is shown in the left hand plot. This experiment reveals that to re-anchor expectations inflation must overshoot 2.5 percent by 150 to 50 basis points in 2022 and 2023. To gauge the magnitude of this overshoot the right hand plot also shows the largest, median, and smallest inflation projection from the SEP (solid arrow heads and circle). We can see that the overshoot is close to the upper range of the SEP inflation in 2022 and 2023.

How can we square this finding with the declines in expectations observed in Figure 9? The reason is common beliefs. The news signals need to come in stronger ($v_t > 0$) than justified by the path of the inflation drift alone. This can be seen in the left plot of Figure 10 where the

black dotted line shows the path of expectations when we set $\nu_t = 0$.[22] Absent the common beliefs expectations would fall below 2.5 percent much as they do in Figure 9. The blue dotted line in the right plot shows the inflation that would be necessary to re-anchor expectations without the lift from beliefs (the red dotted line in the left hand plot shows the implied value of the drift). This is notably higher than the path with common beliefs. We interpret this finding as indicating a potential role for forward looking communication by the FOMC in re-anchoring expectations while ensuring inflation returns to 2.5 percent faster than otherwise.

9   Conclusion

In this paper, we show how to use panel survey data to estimate how sensitive forecasters' long term inflation expectations are to incoming inflation and news about future inflation, and measure the coordination of beliefs about future inflation. 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 a partial 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. Our model suggests coordination of beliefs also played a role, slowing down but not preventing the pull on average expectations from inflation running persistently below target.

Professional forecasters' inflation expectations respond to news about long-run inflation that is not fully reflected by the historical behavior of inflation. This type of news affects common and idiosyncratic beliefs about future inflation. We interpret the common beliefs we estimate as reflecting the forecasters trust regarding the central bank's commitment to its inflation target and effect communications about how the central bank will seek to achieve price stability in the long run. We find that common beliefs that the Fed would attain its target played an important role keeping inflation expectations anchored over the past two decades.

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[22]This means that until 2021Q3 common beliefs are active but afterwards not. Due to the low serial correlation in v_t this means the role of beliefs vanishes quickly.

In addition to providing a characterization of past average inflation expectations, our model can be used as a guide to central bankers looking to the future, and in particular those operating within an inflation targeting regime. We apply our model to the case of a central banker considering the stance of U.S. monetary policy in September 2021. We consider two experiments with our model. With the first we find that while the high inflation readings of mid-2021 boosted average inflation expectations close to the seemingly anchored values from before the Great Recession, the September SEP projections imply expectations would fall back down to pre-pandemic levels because they return to target too quickly. In our second experiment we use our model to assess the degree of overshooting of the inflation target that is necessary to re-anchor long term expectations at pre-Great Recession levels. Generally inflation must be at least as large as the highest SEP inflation projections in 2022 and 2023. Our model suggests that effective central bank communications that coordinate beliefs about future inflation reduces 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:

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

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

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

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

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

B Model derivations

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

$$
\xi_{t|t-1}(i) = \Phi \xi_{t-1|t-1}(i) \tag{13}
$$
$$
P_{t|t-1}(i) = \Phi P_{t-1|t-1}(i) \Phi' + R_t R_t' \tag{14}
$$
$$
s_{t|t-1}(i) = D \xi_{t|t-1}(i) \tag{15}
$$
$$
F_{t|t-1}(i) = D P_{t|t-1}(i) D' + \Psi(i)\Psi(i)' \tag{16}
$$
$$
\xi_{t|t}(i) = \xi_{t|t-1}(i) + \underbrace{P_{t|t-1}D'\left[F_{t|t-1}(i)\right]^{-1}}_{K_t(i)}\left[s_t(i) - D\xi_{t|t-1}(i)\right] \tag{17}
$$
$$
P_{t|t}(i) = P_{t|t-1}(i) - P_{t|t-1}(i) D'\left[F_{t|t-1}(i)\right]^{-1} D P_{t|t-1}(i) \tag{18}
$$

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

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

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.[23] 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

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

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

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

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

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

---

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

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

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.
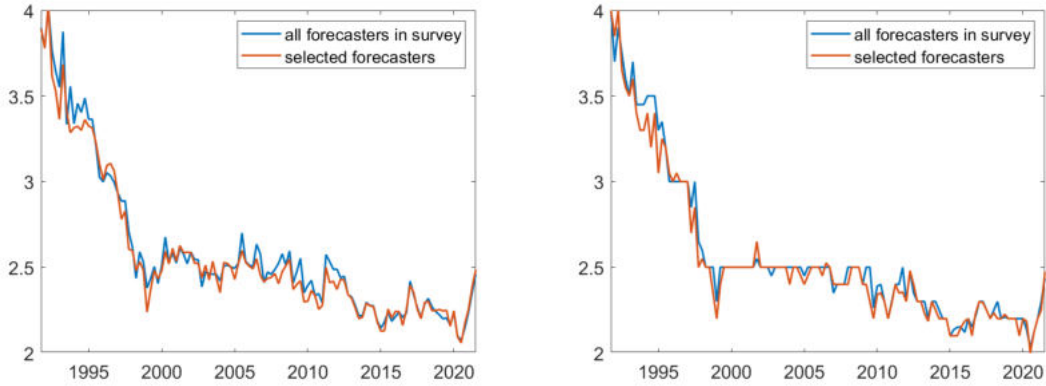
D Selection of forecasters

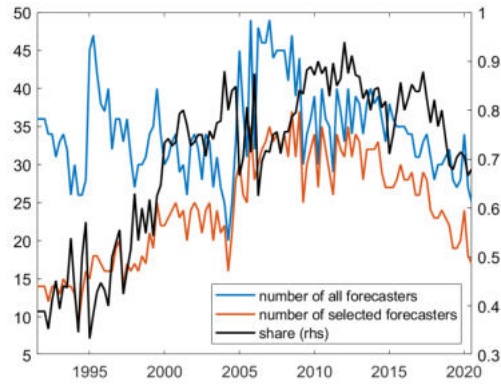Figure 11: Time series of inflation expectations: mean (lhs) and median (rhs)

Figure 12: Number of total and selected forecasters in the US SPF survey

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 13 the estimated parameters of the process $u_t(i) \equiv v_t + z_t(i)$ in equation (4) 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 beliefs, $z_t(i)$. 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).
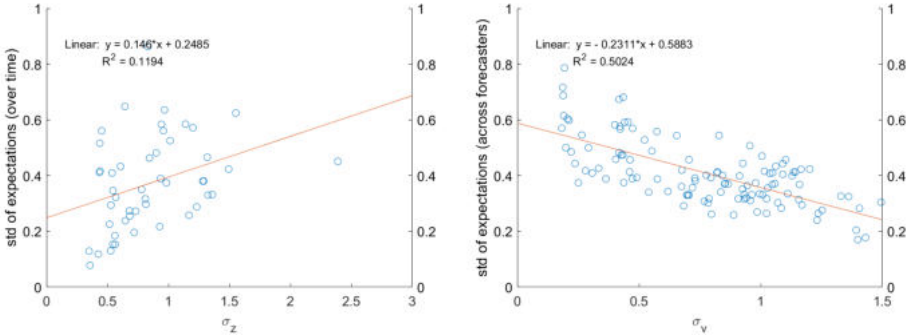

Figure 13: Relationship of estimated parameters with distribution of expectations

F   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 14 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.
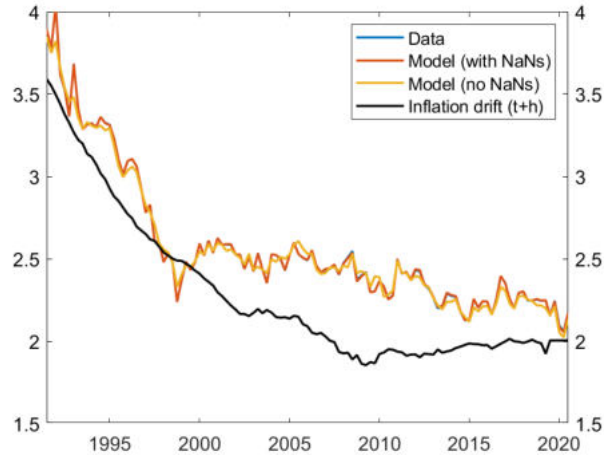

Figure 14: Average inflation expectations: data vs model

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.
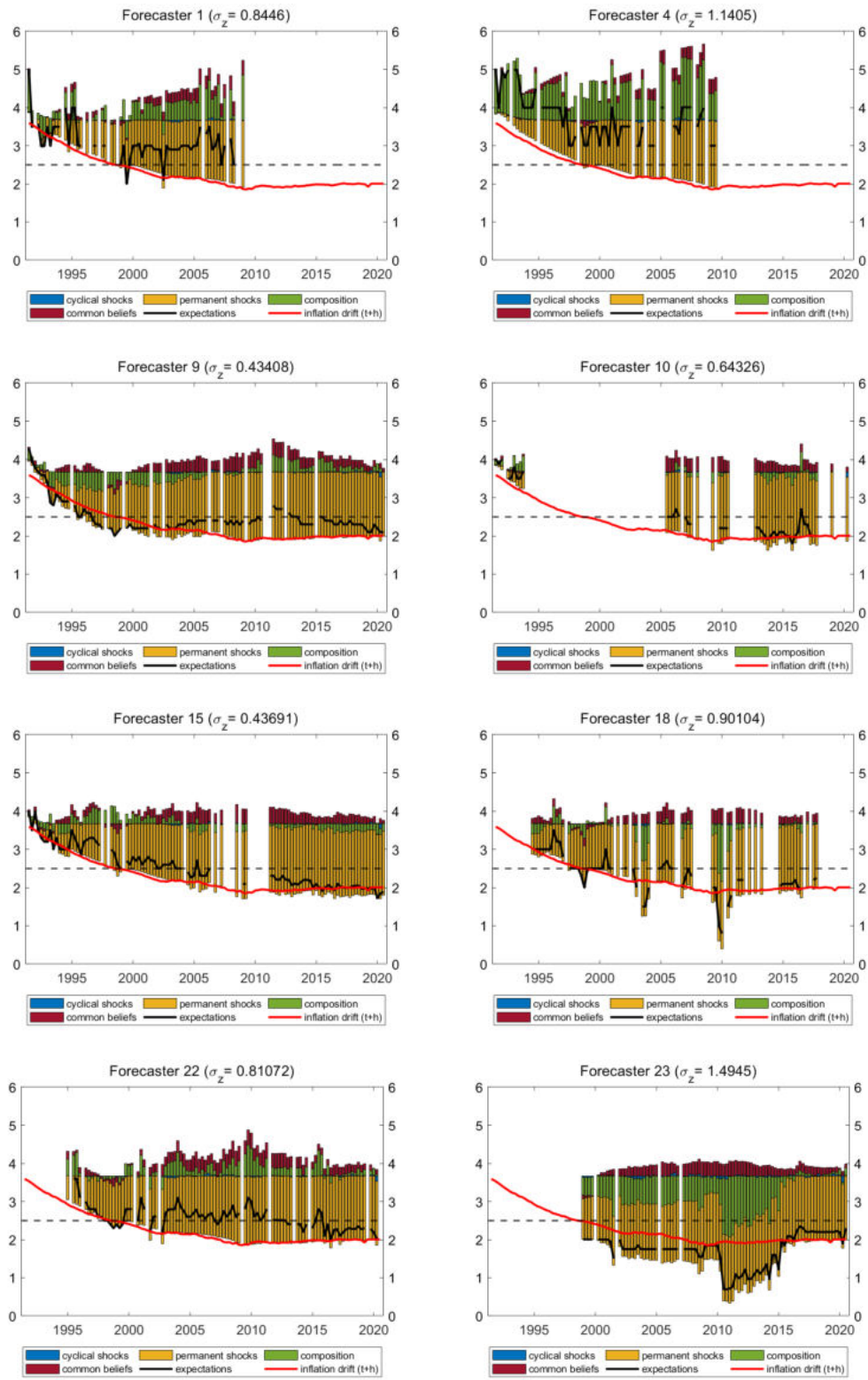
Figure 15: Historical decomposition of inflation expectations for different forecasters

Notes: Simulation of model based on smoothed estimates with different shocks active.
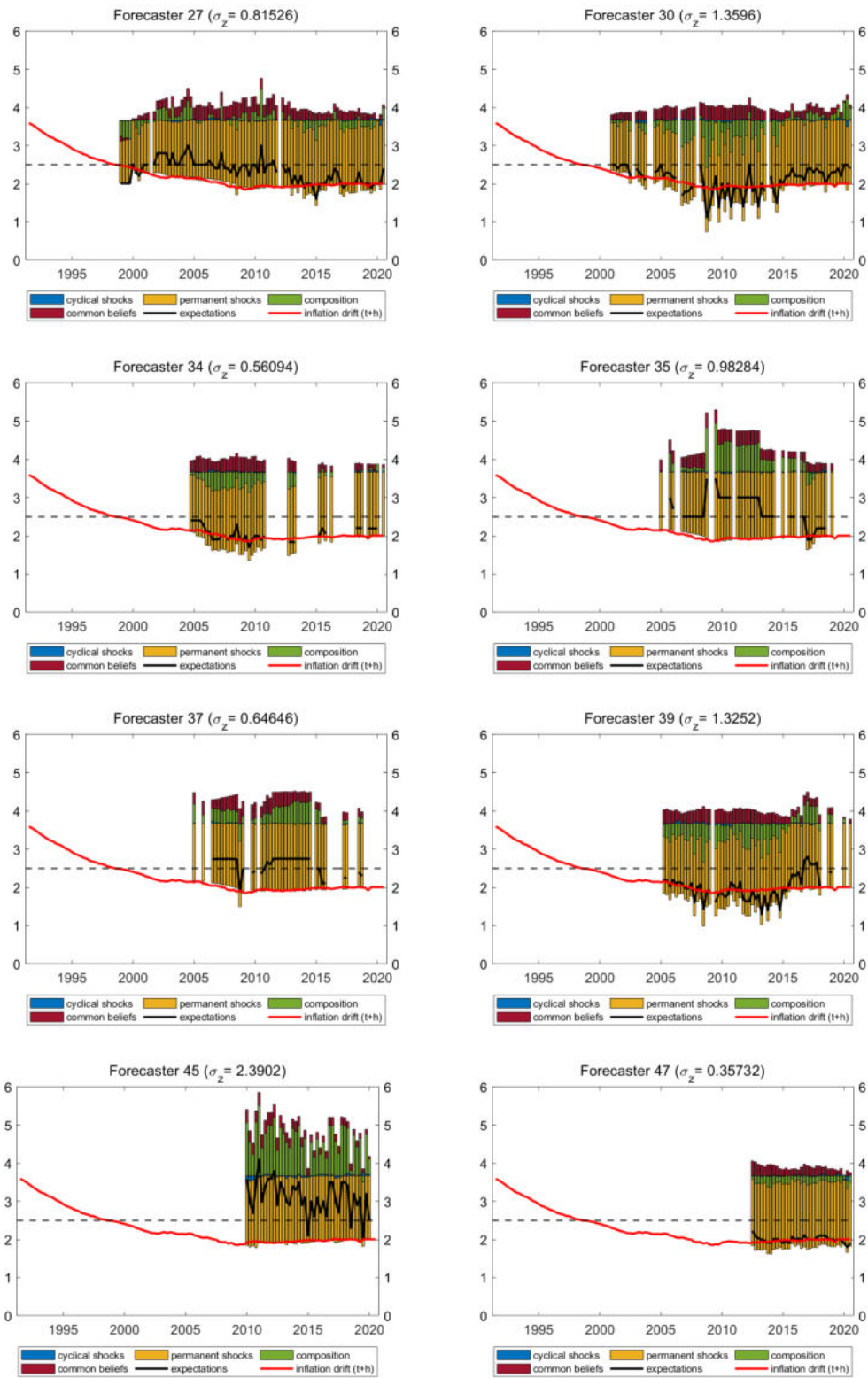
Figure 16: Historical decomposition of inflation expectations for different forecasters (continued)

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

G Robustness of panel estimation

This section shows some robustness analysis of the panel estimates (see Table 3 and Figure 17), the implied Kalman gain for the inflation drift (see Figure 18 and Figure 19) and the historical decomposition of average inflation expectations (see Figure 20). Our results are robust to setting h=8, no serial correlation in the common belief component (v_t), alternative prior specifications and different forecasters selections. The different robustness analyses are defined in the table below from (2)-(8).

(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 17, top
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.220
$\sigma_z(i)$	Inverse Gamma (0.5,4)	see Figure 17, 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 17, bottom

(8) Larger prior standard deviation of beliefs		
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 17, bottom

Table 3: Robustness of parameter values for panel estimation
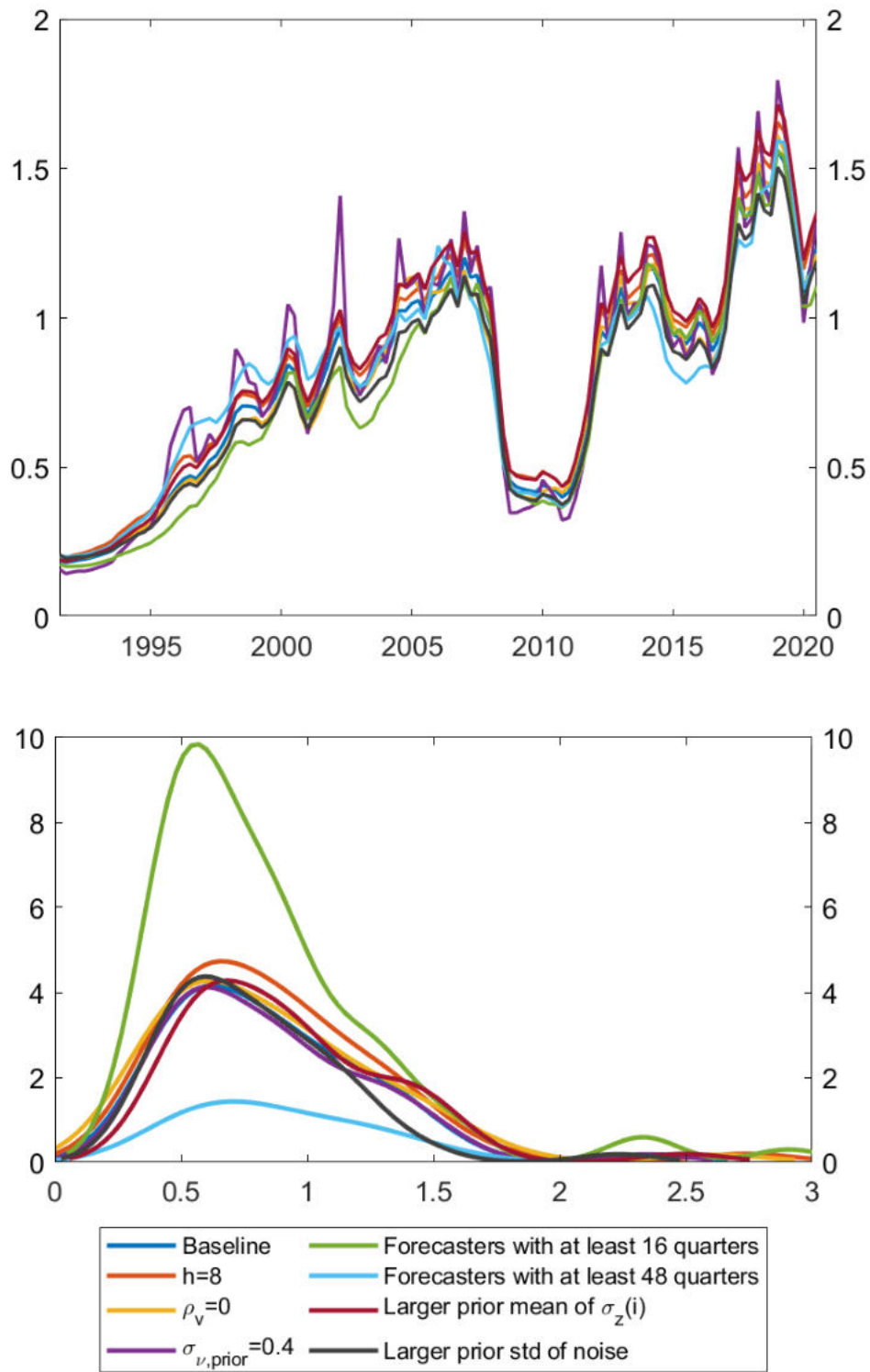
Figure 17: Robustness of $\sigma_{\nu,t}$ (top) and $\sigma_z(i)$ (bottom)

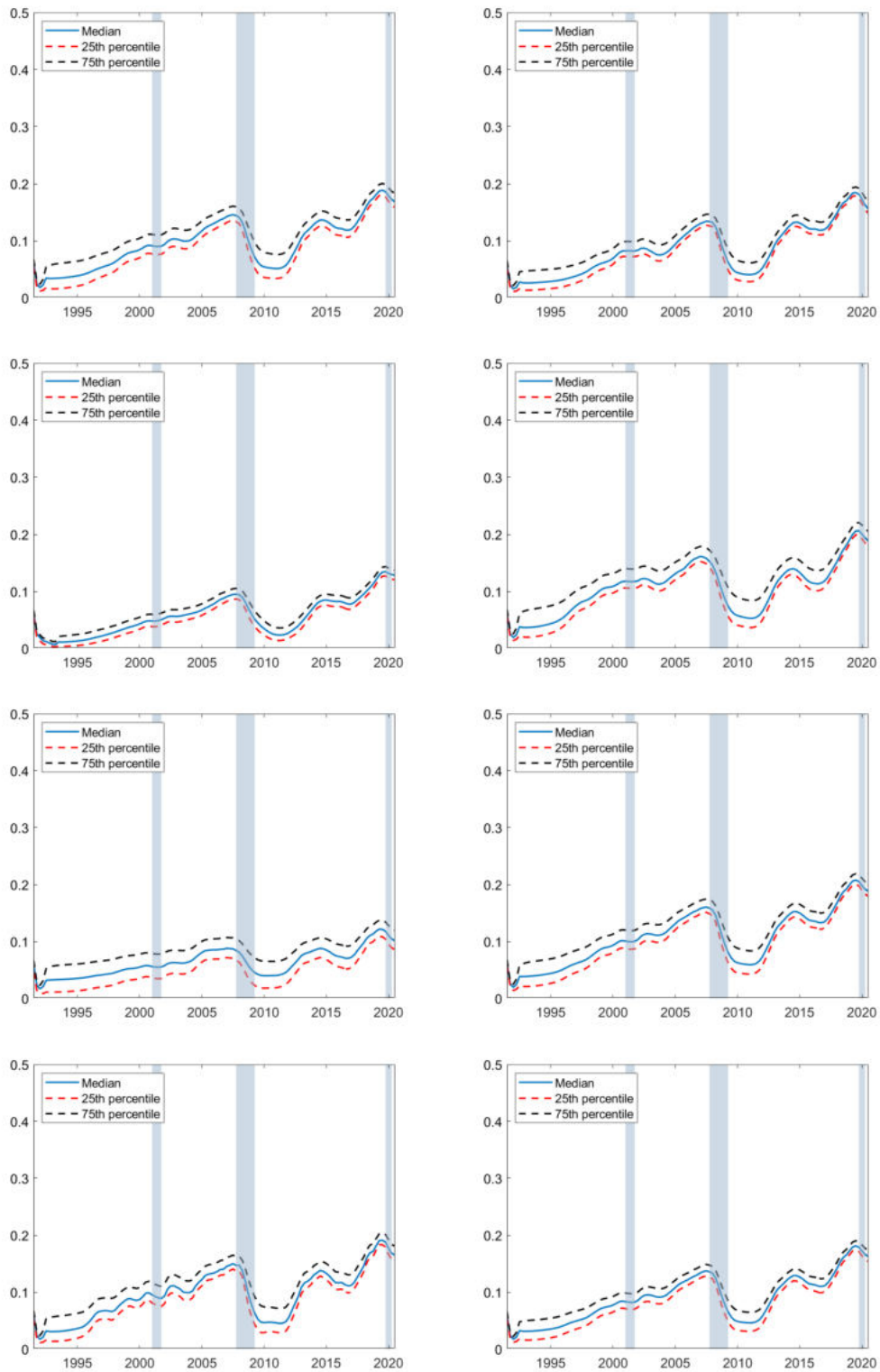Notes: Bottom chart shows kernel-smoothing distribution fitted to histogram with 25 bins.

Figure 18: Robustness of estimated Kalman gains for the inflation drift due to inflation signal. (1)-(4) are shown in left column and (5)-(8) in right column.
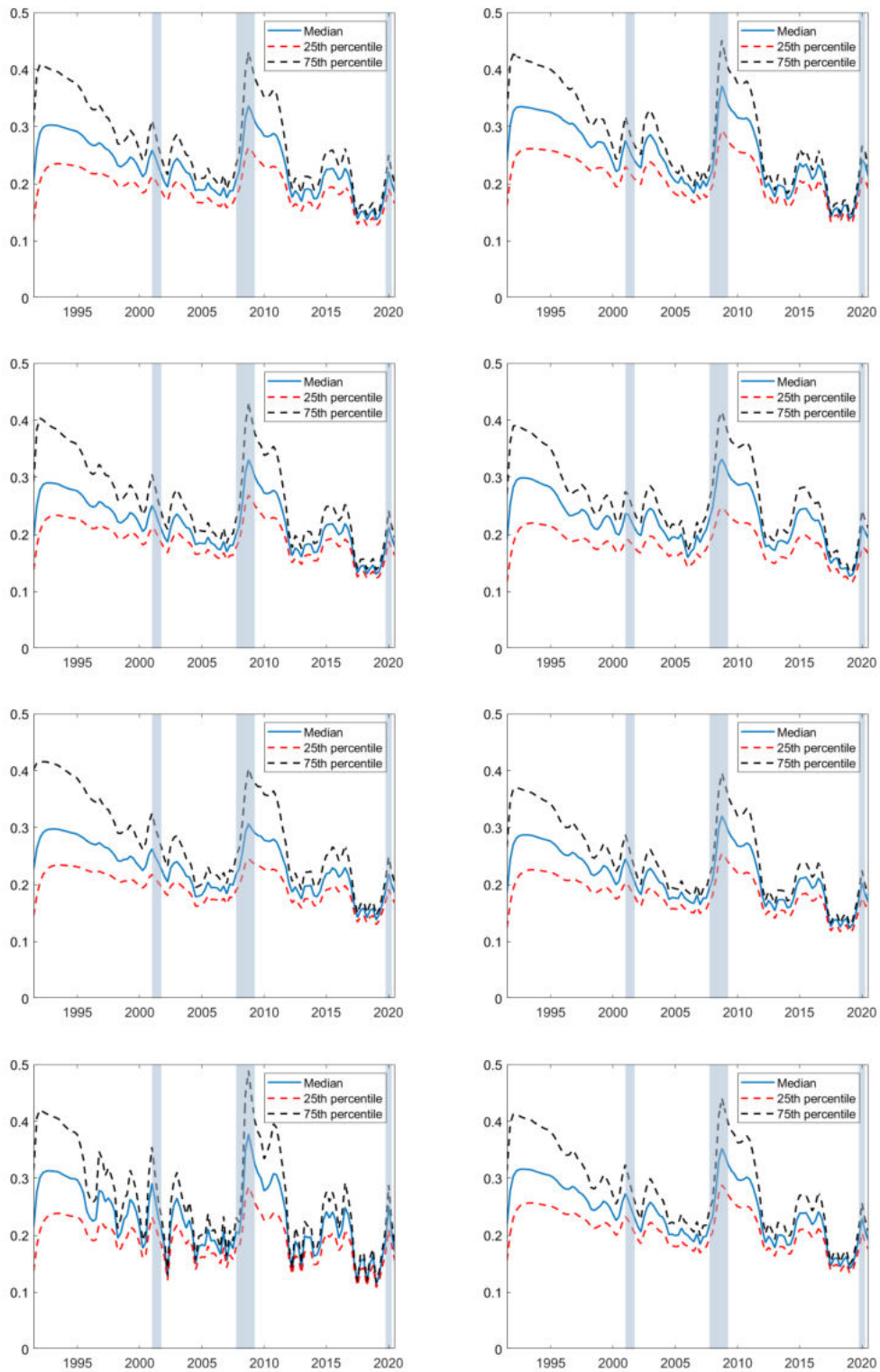
Figure 19: Robustness of estimated Kalman gains for the inflation drift due to news signal. (1)-(4) are shown in left column and (5)-(8) in right column.
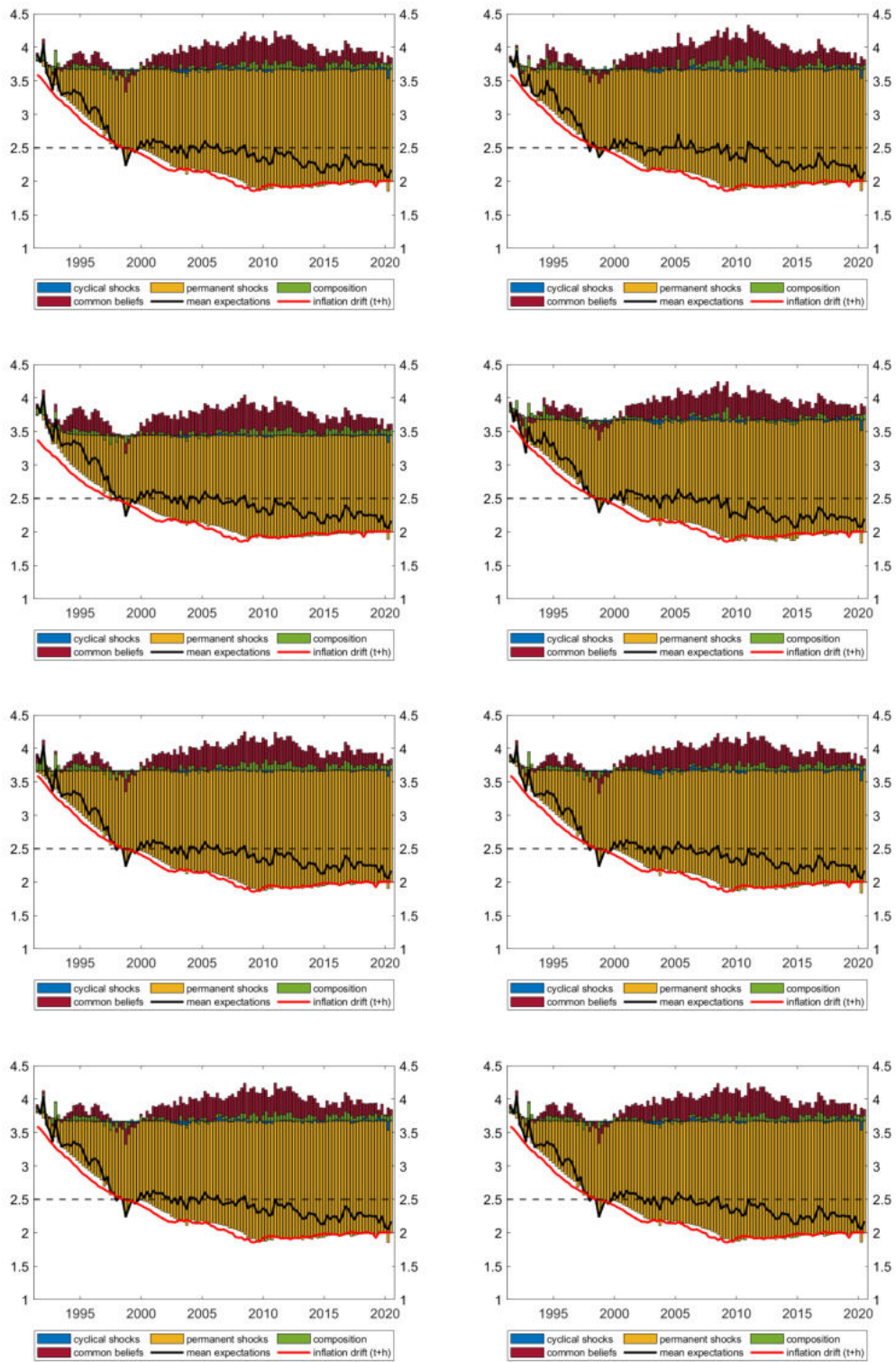
Figure 20: Robustness of estimated historical decomposition of average inflation expectations. (1)-(4) are shown in left column and (5)-(8) in right column.

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.

Part 1: Path of inflation expectations based on SEP inflation paths

  (i) Construction of **inflation paths** from 2020Q4-2026Q4:

  (a) 2020Q4-2021Q3: we use the realized core CPI inflation rate

  (b) 2021Q4-2026Q4: we use the median, lower or upper range path for PCE core inflation from the September 2021 Summary of Economic Projections. For each year from 2021-2024, the forecasts refer to the year-on-year growth rate of the fourth quarter and we rescale the forecasts by 50 basis points to be consistent with core CPI inflation. From 2025Q4 onwards we assume that inflation is equal to the longer run projection of 2% rescaled again by 50 basis points to be consistent with core CPI inflation. For the missing quarters we obtain the inflation path based on linear interpolation.

 (ii) Estimation of **inflation drift**: We estimate the inflation drift using the estimated trend-cycle model in equation (1)-(3). The sample goes from 2020Q4-2026Q4 and we use the parameter estimates from the time series estimation and the estimates of the state and co-variance matrix in 2020Q3 as initial conditions. In order to handle the extremely large shock in 2021Q2, we follow the approach by Lenza and Primiceri (2020) and allow for a rescaling of the shock volatilities σ_η and σ_λ. Denoting the scaling factor by s_t, $s_t = 1$ before 2021Q2, $s_{2021Q2} = \beta$ and from 2021Q3 onward $s_{2021Q2+j} = 1 + (\beta - 1)\gamma^j$ with j>0. We estimate the parameters s_0 and ρ using uniform priors. For the median SEP scenario we obtain β=4.758 and γ=0.088. Finally, we use the Kalman smoother to obtain an estimate of the unobserved inflation drift. The estimated inflation drifts together with the corresponding inflation paths are shown in Figure 8.

(iii) Estimation of **inflation expectations**: We use the inflation and inflation drift series obtained in the previous two steps as observables in the state-space model of the econometrician (see equations (11)-(12)). Note that the sample goes until 2025Q4 but we only observe SPF inflation expectations until 2021Q3. Afterwards they are treated as missing values. We keep all parameter estimates equal to the estimated values shown in Table 2 and assume $\sigma_{\nu,t}$ is equal to the value estimated for 2020Q3 until the end of the sample. Applying the Kalman smoother we obtain estimates of all the state variables. We compute mean inflation expectations across forecasters as plotted in Figure 9.[24]

---

[24]Note that we compute the mean across the inflation expectations of all forecasters even if they have only been in the survey many years ago. Computing just the mean across forecasters who have been active in the survey in 2021 yields very similar results.

Part 2: Inflation path required to cement expectations at 2.5% (anchoring)

(i) Estimation of **inflation drift**: We follow steps (i)-(ii) in Part 1 but only focus on the SEP median inflation path.

(ii) Using the drift from step (i), we have all observables in the panel estimation available from 2020Q4 until 2021Q3. We use the Kalman filter of the state-space model 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.

(iii) Now we use the states from the previous step as initial conditions to run the Kalman filter from 2021Q4 until 2025Q4. We only observe the inflation drift from step (i) for the whole sample. Individual 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%.[25] 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:**

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

(ii) **no communication (ν_t=0):**

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

(iv) Using the Kalman smoother we obtain smoothed estimates of $\hat{\pi}_t$ from step (iii) for both cases.

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[25]In 2021Q2 and 2021Q3 mean inflation expectations are close to 2.5 with values of 2.485 and 2.631, respectively.

(v) Since these inflation paths are not necessarily consistent with the inflation drift used as input we apply a bisection algorithm to solve for a "fixed point". Using the obtained inflation path as input to step (i) we iterate over steps (i)-(iii) until convergence for each of the two cases with and without communication.[26] The implied inflation paths are plotted in the rhs of Figure 10 together with the SEP projections. The estimated inflation drift paths are plotted in the lhs of the same figure.

(vi) In order to assess the contribution of communication to average inflation expectations we estimate the historical decomposition of average inflation expectations using the Kalman smoother based on the measurement equations defined in the case with communication above (see also Appendix F). We start from 2021Q3 as initial condition. The historical decomposition is shown in Figure 21. Then, the black dotted line in the lhs of Figure 10 is computed as the mean expectations minus the contribution of communication (red bars).
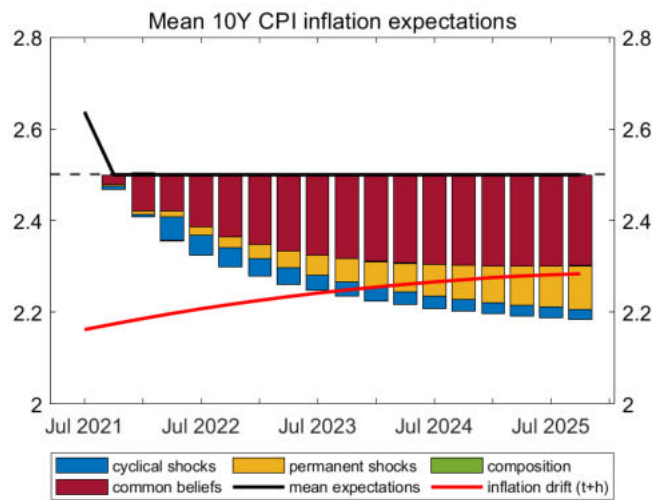

Figure 21: Historical decomposition of mean expectations under projection exercise

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[26]Since we need an inflation path until 2026Q4 for step (i) we assume that inflation in 2026Q1-2026Q4 is the same as in 2025Q4.