Long-run inflation expectations*

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March 2023

Abstract

We estimate a model of *individual* long-run inflation expectations when inflation follows a trend-cycle time series process with panel data from the U.S. Survey of Professional Forecasters. We use our model to study *average* long-run expectations when individual forecasters know the inflation process, observe inflation and receive common and idiosyncratic signals about long-run inflation. We find coordination of sentiments around the inflation target prevented expectations from becoming unanchored in the face of inflation running persistently below target in the 2010s. We apply our model to study the case of a U.S. central banker setting policy in December 2015 when inflation had been running below target for many years, and in December 2022 when it had been running very hot for a year and a half. We find that if the projections from the Fed' December Summary of Economic Projections were realized they would be inconsistent with preventing long-run inflation expectations from become unanchored. This is so even with sentiments coordinated in a manner consistent with their historical behavior. In the most recent episode we find that the common signal is relatively imprecise and so it is even harder for sentiments about long-run inflation to be coordinated.

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

JEL classification: *E31, C83, D84*

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1 Introduction

Inflation-targeting central bankers look at a variety of indicators to assess their progress in maintaining price stability including average and median long-run inflation expectations from surveys.[1] While survey data on long-term inflation expectations are plentiful, the information that gets aggregated into them and the factors that can cause them to remain stable or drift away from the central bank's target are not well understood.[2] In this paper we use panel data from the U.S. Survey of Professional Forecasters (SPF) to estimate a model of expectations formation to understand better how *individual* forecasters respond to new information and the implications of this behavior for *average* long-run inflation expectations.

Average long-run inflation expectations in the SPF declined over the course of the 1990s, remained stable over the 2000s and early 2010s, and then decline very gradually from the mid 2010s until the onset of the pandemic. A vast amount of heterogeneity in the cross section of forecasters underlies these aggregate trends. This heterogeneity manifests itself in a variety of ways. Generally there is wide dispersion among forecasts. Some forecasters have forecasts that are highly erratic while others have forecasts that evolve more smoothly. In some periods forecast revisions tend to move together while in others they appear more disconnected. Our model of expectations formation aims to capture these patterns.

In our model forecasters have rational expectations but limited information. Forecasting occurs within an environment in which inflation follows a time-varying-parameter trend-cycle time-series process that is known by the forecasters. Forecasters face a signal extraction problem to track the unobserved trend component of inflation which they then use to form their long-run expectations.

We assume forecasters observe one public and two private signals about the inflation trend. The public *inflation signal* is the current inflation rate that updates the history of inflation. This signal captures everything forecasters can learn about long-run inflation from observing

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

[2]The the U.S. surveys that include longer term inflation expectations include Blue Chip Economic Indicators, the Atlanta Fed' Business Inflation Expectations, the Livingston survey, Michigan Survey of Consumers, and the Survey of Professional Forecasters.

inflation's historical behavior. The private signals are both subject to *sentiments shocks* that are orthogonal to the fundamentals that drive inflation. The *common signal* captures factors that coordinate long-run expectations that are not already reflected in the historical inflation dynamics. Such coordination might reflect the central bank's communications regarding how it will seek to achieve its inflation objective, changes in public trust regarding the central bank's ability to stabilize inflation around its target, and animal spirits. The precision of the common signal can vary to account for the fact that the degree of co-movement in inflation forecasts changes over time. We also allow the precision of the common signal to vary across forecasters to account for heterogeneity in how individual forecasts co-move with the average. The *idiosyncratic signal* captures other factors that underlie the heterogeneity we find.

We estimate the model in two steps. In the first step, we estimate the trend-cycle model using CPI inflation over the sample period 1959q1 to 2019q4. We combine this estimated model with the three signals just described to calculate the laws of motion of the individual forecasters' long-run inflation expectations. In the second step, we estimate this law of motion using the time series of CPI inflation, trend inflation estimated in the first step, and our panel of SPF CPI long-term inflation forecasts which covers the sample after 1991.

While we do not observe the common and idiosyncratic signals, they can be identified from revisions to forecasters' expectations that cannot be explained by the historical behavior of inflation alone. This identification is facilitated by our assumption that we as econometricians observe trend inflation when we estimate the laws of motion for individual expectations, but forecasters do not. Identification of the common signal relies on the degree of co-movement among the forecasts, while the idiosyncratic signal is identified from the cross-sectional variability. Periods in which forecast revisions co-move a lot are interpreted by the model as times when the common signal is relatively precise and so forecasters update their expectations more rapidly in response to it. When forecast revisions are more dispersed and co-move by little, the common signal will be less precise and forecasters will put more weight on the idiosyncratic signal when updating their expectations.

We find time-varying sensitivity of individual long-term inflation expectations to the signals. The median elasticity of individual expectations to the inflation signal averages under 10 percent, is a-cyclical, and does not vary much across forecasters. There is much more heterogeneity in the sensitivity of forecasters to the common signal and it tends to be somewhat larger and pro-cyclical. Reflecting the heterogeneity in the SPF, forecasters are much more responsive to the idiosyncratic signal — the median sensitivity is about 30 percent — but there is wide disperson.

The cross section is crucial to these findings. If we assume forecasters are identical and assign them the average forecast, we find virtually no responsiveness to the inflation signal and very high pass through of the common signal. This has important implications for the role of common sentiments in affecting average expectations. Our findings are an example of the necessity of accounting for the cross section to understand aggregate expectations from surveys that is emphasized by Engelberg, Manski and Williams (2010).

The generally slow rate of learning reflected in the responsiveness to the signals provides a partial explanation for why the stabilization of average expectations over the 1990s and their subsequent decline were such long lasting episodes. Our model suggests coordination of sentiments also played a central role. In particular this coordination kept average expectations relatively stable in the face of inflation running persistently below target from the early 2010s and the resulting decline in trend inflation. We interpret this role for sentiments coordination as reflecting effective Fed communications.

In addition to providing a characterization of past individual and 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-run inflation expectations are likely to be anchored going forward from a particular date. Its parameters determine how quickly individual forecasters respond to incoming information. Therefore we can use the model to project how average inflation expectations might evolve under different scenarios for future inflation and sentiments.

We apply our model to the case of a U.S. central banker setting policy in December 2015 and December 2022. In the former case inflation had been running below target for four years, while in the latter it had been running very hot for over a year. We find that in both cases, if the inflation projected in the Fed's Summary of Economic Projections (SEP) were realized, it would be inconsistent with preventing long-run inflation expectations from become unanchored.[3] This is so even with sentiments coordinated in a manner consistent with their historical behavior. In the most recent episode we find that the common signal is relatively imprecise and so it is even harder for sentiments about long-run inflation to be coordinated.

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 expectations through the lens of our estimated model. In the penultimate section we discuss our anchoring experiments, and then we conclude.

2 Relation to the literature

Goldstein and Gorodnichenko (2022) estimate a model where forecasters receive noisy signals about the future using the cross-sectional distribution of SPF *short-term* forecasts of CPI inflation. They find that forward-looking signals are critical to explain these data. While it is in principle possible to extend our model to allow signals to convey forward information about long-run inflation, in practice doing so is computationally challenging.[4] A key difference with Goldstein and Gorodnichenko (2022) is our focus on explaining SPF forecasts about *long-run* CPI inflation. It is also important to notice that in our model signals are about trend inflation that is estimated with a two-sided filter and, therefore, partially reflects *future* information about low-frequency movements in inflation as well.

Patton and Timmermann (2010) use a signal extraction model to understand the sources

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

[4] In a previous version of this paper in which the parameters of the time-series model of inflation were assumed to be constant we allowed forecasters to observe signals about future trend inflation (four- and eight-quarters ahead.) We found that allowing for forward information did not change our results materially. This may be due to our focus on long-run inflation forecasts instead of short-run forecasts.

of disagreement in Consensus Economics forecasts of US real GDP growth and CPI inflation for the current and subsequent calendar year. They find that dispersion among forecasters is highest at long horizons where private information is of limited value. In contrast, Andrade, Crump, Eusepi and Moench (2016) find that disagreement about CPI inflation in the Blue Chip Financial Forecasts survey is basically flat across horizons up to ten years. Our focus is on detecting when forecasters agree in the sense that their long-run inflation forecasts are coordinated due to common sentiments. Disagreement about long-run inflation is accounted for by the idiosyncratic signals.

Our trend-cycle model builds on Stock and Watson (2007) and Chan, Clark and Koop (2018) and is also related to the models studied by Mertens and Nason (2020), Cogley, Primiceri and Sargent (2010), and Hasenzagl, Pellegrino, Reichlin and Ricco (2020).[5] The papers with trend-cycle models that are closest to ours link trend inflation to expectations from survey data to learn about the implications of changes in the inflation process for inflation forecasts and the anchoring of inflation expectations. Henzel (2013), Mertens and Nason (2020), and Nason and Smith (2021) study average short run inflation forecasts from the SPF. They treat trend inflation as the long-run forecast of inflation, but long-run inflation expectations themselves do not feature as an observable in model estimation. Mertens (2016) estimates Beveridge-Nelson decompositions to obtain estimates of trend inflation. His paper uses information from inflation rates, survey forecasts of inflation, and long-term interest rates. Our framework can be extended to a multivariate setting but we leave that for future research. All of these papers use average expectations from survey data. We show the central importance of using cross-section information to understand average expectations.

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, for example Nakamura and Steinsson (2018), Gürkaynak, Sack and Swanson (2005), and Campbell, Evans, Fisher and Justiniano (2012). We interpret coordination of sentiments about the long run as central bank communications. Sentiments are identified in our model from the private signals received by individual forecasters about

[5]Faust and Wright (2013) review of the earlier literature on trend-cycle models.

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) and Coibion, Gorodnichenko, Knotek and Schoenle (forthcoming) 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.

A large and growing literature has documented that professional forecasters' short-run expectations about a large array of macro variables violate the Full Information Rational Expectations (FIRE) assumption, for example Coibion and Gorodnichenko (2015), Bordalo, Gennaioli, Ma and Shleifer (2020), Kohlhas and Walther (2021), and Bianchi, Ilut and Saijo (2023). Our model deviates from the FIRE assumption since forecasters learn about trend inflation via a number of imperfect signals following the tradition of noisy information models. In addition, this literature documenting the violation of the FIRE assumption in survey data has primarily looked at short-run forecasts whereas our focus is on long-run inflation expectations. When we test the SPF long-run CPI inflation expectations, we find evidence of overreaction to recent realizations of CPI inflation. However, the extent to which SPF long-run inflation expectations overreact to current inflation is an order of magnitude smaller than the overreaction characterizing SPF short-run inflation expectations documented by Kohlhas and Walther (2021).[6]

Our paper also is connected to the large literature on the anchoring of inflation expectations. Broadly speaking this 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 use this concept. The papers in this literature that are closest to ours study a representative agent who learns about the central bank's inflation objective. Some key work in this area includes Carvalho,

[6]These results beyong the scope of this paper, but are available upon request.

Eusepi, Moench and Preston (2023), Beechey, Johannsen and Levin (2011), and Orphanides and Williams (2005). These papers consider signal extraction problems where agents seek to learn 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. We find the information in the cross section to be vital to our identification of the sensitivity of forecasts to new information.

The second concept of anchoring 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.

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 being in a certain range of the inflation target as measured by survey expectations. 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 new information. Our approach has several advantages. First, it allows us to distinguish between changes in the aggregate sensitivity of expectations to signals about long-run inflation from idiosyncratic sensitivities of an individual forecaster compared to other forecasters. Second, by estimating heterogeneous sensitivities we can control for compositional effects. Accounting for compositional effects is particularly important in light of the critique of conditional mean forecasts highlighted by Engelberg, Manski and Williams

(2010). Heterogeneity arises in our environment through the precision of the common signal and the variance and serial correlation of the idiosyncratic sentiments. Nechio (2015) studies composition in terms of the distribution of forecasters' root mean inflation forecast error.

3 Model and estimation

This section describes the data generating process for inflation and specifies how our panel of forecasters form long-run inflation expectations when they understand that inflation follows this process. We then discuss our notion of inflation anchoring within this framework and how we estimate the model.

3.1 The inflation model

Forecasters form their long-term inflation expectations believing that inflation outcomes are driven by a time-varying parameter trend-cycle model which for tractability is assumed to be univariate. The model of inflation, π_t is:

$$\pi_t = \bar{\pi}_t + \varepsilon_t + \sigma_\omega \omega_t; \tag{1}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \sigma_{\lambda,t} \lambda_t; \tag{2}$$

$$\varepsilon_t = \phi_t \varepsilon_{t-1} + \sigma_{\eta,t} \eta_t. \tag{3}$$

Inflation is decomposed into a trend component ($\bar{\pi}_t$), a cyclical component (ε_t), and an i.i.d. component (ω_t). Trend inflation reflects the long-run drivers of inflation that are already incorporated into the behavior of inflation. These presumably include perceptions of the behavior of the central bank.[7] The cyclical component of inflation captures persistent variation of inflation around its long-term trend, for example due to Phillips curve dynamics. The i.i.d component captures high frequency variation in inflation that does not have persistent effects, for example due to food and energy prices. The random variables ω_t, λ_t, and η_t are i.i.d. $\mathcal{N}(0, 1)$ and σ_ω, $\sigma_{\lambda,t}$, and $\sigma_{\eta,t}$ are all strictly positive.

[7] In a New Keynesian model trend inflation would be incorporated into long-run inflation expectations of price setters, $E_t \pi_\infty$, as described by Hazell, Herreño, Nakamura and Steinsson (2022).

The variances of the innovations to the trend and cycle components, $\sigma^2_{\eta,t}$ and $\sigma^2_{\lambda,t}$, follow log random walk processes:

$$\ln(\sigma^2_{\eta,t}) = \ln(\sigma^2_{\eta,t-1}) + \gamma_\eta \omega_{\eta,t}; \tag{4}$$

$$\ln(\sigma^2_{\lambda,t}) = \ln(\sigma^2_{\lambda,t-1}) + \gamma_\lambda \omega_{\lambda,t}, \tag{5}$$

where $\omega_{\eta,t}$ and $\omega_{\lambda,t}$ are i.i.d. $\mathcal{N}(0,1)$. The cyclical component's auto-regressive parameter (ϕ_t) is also stochastic and is modelled similarly:

$$\phi_t = \phi_{t-1} + \gamma_\phi \omega_{\phi,t}, \tag{6}$$

where $\omega_{\phi,t}$ is distributed $\mathcal{N}(0,1)$ and $\phi_t \in (0,1)$ so innovations to ϕ_t are drawn from truncated standard normal distributions with thresholds $-\phi_{t-1}/\gamma_\phi$ and $(1-\phi_{t-1})/\gamma_\phi)$ that ensure stationarity.

3.2 Forecasters' long-run inflation expectations

Forecasters have rational expectations but make their long-run inflation forecasts based on limited information. They know the inflation model and its parameters, the history of inflation, and receive three signals that inform their beliefs about long-run inflation. The public *inflation signal* is received by all the forecasters and simply updates the history of inflation to include its current value. The other two signals are private and provide information about the inflation trend. The *common signal* includes a random variable term that is perfectly correlated across the forecasters. This variable is orthogonal to the fundamentals of the inflation process ($\bar{\pi}_t$, ϵ_t, and ω_t) and so we refer to it as *sentiments*. The *precision* of the common signal is forecaster-specific. The *idiosyncratic signal* includes sentiments as well, but these are independently distributed across forecasters.

Denoting the inflation, common and idiosyncratic signals by $s_{1,t}$, $s_{2,t}(i)$ and $s_{3,t}(i)$ where i denotes a particular forecaster, the signal structure faced by the forecasters is given by

$$s_{1,t} \quad = \quad \pi_t; \tag{7}$$

$$s_{2,t}(i) = \bar{\pi}_t + \alpha(i) v_{c,t}; \tag{8}$$

$$s_{3,t}(i) = \bar{\pi}_t + v_t(i); \tag{9}$$

$$v_{c,t} = \rho_c v_{c,t-1} + \sigma_{c,t} \nu_{c,t}; \tag{10}$$

$$v_t(i) = \rho(i) v_{t-1}(i) + \sigma_v(i) \nu_{v,t}(i), \tag{11}$$

where $\alpha(i)$ and $\sigma_{c,t}$ are strictly positive and $\nu_{c,t}$, $\omega_{c,t}$, and $\nu_{v,t}(i)$ are i.i.d. $\mathcal{N}(0,1)$.

The common and idiosyncratic sentiments $v_{c,t}$ and $v_t(i)$ are both AR(1) and hence the private signals can deviate from the inflation trend persistently. The innovations to common sentiments ($\nu_{c,t}$) are heteroskedastic with variance $\sigma^2_{c,t}$. The time-varying volatility of the innovation to common sentiments captures episodes when long-term expectations of *all* the forecasters are particularly sensitive or insensitive to the common signal. The precision of the common signal for forecaster i is determined by $\alpha(i)$. For example, if $\alpha(i)$ is close to zero the signal for forecaster i is almost perfectly revealing about the inflation trend. The idiosyncratic sentiments $v_t(i)$ have forecaster-specific auto-correlation coefficients $\rho(i)$ and innovation standard deviations $\sigma_\nu(i)$. The forecaster-specific parameters $\alpha(i)$, $\rho(i)$, and $\sigma_v(i)$ provide the flexibility that is necessary to address the large amount of heterogeneity in the inflation forecasts in terms of their co-movement, persistence, and volatility. Forecasters are assumed to know the parameters of the signals.

The sentiments terms in the two private signals are an essential feature of our framework. Common sentiments $v_{c,t}$ capture factors that coordinate expectations. These might include 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. Idiosyncratic sentiments $v_t(i)$ affect the expectations of specific forecasters and help to capture the myriad of factors that underlie the heterogeneity in the SPF.

At each date t forecasters observe the signals with knowledge of the history of inflation and the trend-cycle model of inflation summarized by (1)–(6). 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 that govern the dynamics of

$\bar{\pi}_t$. 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 and this is what we assume they do. 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 variances of the two sentiments shocks $\nu_{c,t}$ and $\nu_{v,t}(i)$ help to determine the magnitudes of the Kalman gains on the private signals and therefore the sensitivity of individual expectations to the private 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 from the SPF to changes in the inflation trend. If the sentiments in either private signal are correctly understood to always equal zero, forecasters know $\bar{\pi}_t$ perfectly and their long-term inflation expectations will respond one for one with the inflation trend. If the sentiments terms are very volatile the private signals are close to useless. In this situation forecasters rely almost exclusively on the historical behavior of inflation to form their long-term inflation expectations.

3.3 Inflation anchoring in the model

Forecasters' inflation expectations are considered anchored when average long-term expectations do not drift away persistently from the central bank's inflation target. Conversely, de-anchoring occurs when average long-term inflation expectations drift away from the target on a persistent basis. Note that the inflation trend $\bar{\pi}_t$ is different from the concept of an inflation target. However, it is crucial to determining the risks to anchored expectations as inflation expectations tend toward the trend.

How might de-anchoring occur in our framework? One way is when the central bank lets inflation run away from its target persistently. Sooner or later the inflation trend will start diverging from the target and de-anchoring occurs as forecasters learn that the trend is changing. The role played by the inflation and private signals in this type of de-anchoring is quite different. As the inflation trend keeps deviating from the central bank's target, the inflation signal reveals a persistent deviation of inflation from the target. Absent countervailing effects from the private signals, this leads to a progressive de-anchoring of inflation expectations as the forecasters learn that the trend has drifted away from the target.

The private signals also contain information about the inflation trend and so they influence the rate of learning about it. However due to the sentiments terms they have different effects on anchoring. The idiosyncratic sentiments $v_t(i)$ are crucial to accounting for the heterogeneity in expectations, but because they are independently distributed across forecasters they should not affect average inflation expectations if the number of forecasters is sufficiently large. If common sentiments $v_{c,t}$ are highly volatile, the common signal plays essentially no role and forecasters' average expectations are updated at a pace consistent with them only observing the behavior of inflation and their idiosyncratic signals. If the volatility of common sentiments is smaller, long-run inflation expectations move more autonomously from the observed dynamics of inflation. As a result, the common signal can either accelerate or decelerate de-anchoring. 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. In our set-up this would correspond to $v_{c,t} < 0$. However, if forecasters' trust in the central bank's ability or willingness to quash the rising inflation is waning, the common signal can even accelerate the de-anchoring as this would coincide with $v_{c,t} > 0$.

It should be noted that common signals that keep expectations anchored may turn out to be wrong. For example, this would be the case if the central bank failed to tighten monetary policy as expected when inflation is running persistently above target. However, assessing the accuracy of the signals can be done only with the benefit of hindsight, i.e. after having observed or estimated the future shocks to the inflation drift.

3.4 Estimation

We follow a two-step approach to estimate forecasters' long-term inflation expectations resulting from their signal extraction problem. In the first step we estimate the parameters of the trend-cycle model (σ_ω, γ_η, γ_λ and γ_ϕ) summarized by equations (1)–(6) using only inflation as an observable and standard Bayesian state-space methods. This allows us to obtain estimates of the trend, cycle and i.i.d components of inflation conditional on all the sample observations using the Kalman smoother.

In the second step, we estimate a panel model in which forecasters know the the trend-cycle model estimated in the first step, understand the signal structure summarized by equations (7)–(11), and observe the three signals. We as econometricians observe inflation, the trend and cycle components of inflation obtained from the first step, and individual long-run inflation forecasts, but we do not observe the private signals. Therefore, we estimate a state space model that combines equations (1)–(6) with N sets of equations corresponding to the updating of the N forecasters' expectations about the state via the Kalman filter. This yields estimates of the signal process (ρ_c, $\sigma_{c,t}$, $\alpha(i)$, $\rho(i)$, and $\sigma_v(i)$, $i = 1, 2, \ldots, N$). As the trend-cycle model implies that the expected value of inflation at long horizons equals the trend, $\bar{\pi}_t$, we identify forecasters' long-run inflation expectations at a point in time with their contemporaneous expectations about $\bar{\pi}_t$. We obtain estimates of the private signals using the Kalman smoother.[8]

4 Data

This section describes the inflation and inflation expectations data that 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 (PCE) index, which is the inflation measure currently targeted by the Fed. We use data on quarter over quarter CPI inflation from the U.S. Bureau of Labor Statistics spanning the sample 1959q1–2019q4 to estimate the trend-cycle model. Our sample includes the Great Inflation which we expect to be informative when we study the implications of the surge of inflation in 2021-2022 for long-run expectations. We exclude the most recent data from our estimation of the trend-cycle model as the 2021-2022 surge of inflation will unduly influence our smoothed measure of the trend. We will use the more recent data in our anchoring experiments.

Since we identify forecasters' long-run inflation expectations with the inflation trend, ideally we would use data on long-run expectations that excludes near term forecasts driven by the

[8] Appendix A describes the state-space model we use for the panel estimation in detail.

cyclical and high frequency components of inflation. Moreover, we seek panel data that covers as long a sample period as possible. The measure that most closely matches our ideal is the SPF forecasts of average CPI inflation six to ten years ahead. However, these data only become properly available in 2011.[9] To maximize the length of our sample we splice these data to forecasts of average CPI inflation over the next ten years that go back to 1991. If the cyclical term in the inflation data generating process is sufficiently small and short lived (ϕ_t and $\sigma_{\eta,t}$ are small) the 10 year expectations should be a good approximation to our ideal measure. The forecasters in the SPF do not observe 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 2018q4 using forecasts from the survey that was conducted in February 2019.

To have a sufficient number of observations to measure the variance and serial correlation of the idiosyncratic sentiments we consider only those forecasters with at least 32 forecasts. This leaves us with an unbalanced panel of 51 forecasters. Note that in some cases there are gaps in the time series of forecasts for individual forecasters.[10] In Appendix C we show that average and median long-term expectations in our sample of forecasters corresponds closely to their values in the complete SPF sample.

Figure 1 shows some key features of our measure of long-term inflation expectations over the sample 1991q3 to 2022q3. The top left panel shows average and median long-term inflation expectations at the beginning of the 1990s were near 4 percent. 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 percent until the Great Recession after which there was again a downward trend, towards 2 percent. In 2022q3 amidst high inflation long-term inflation expectations remained relatively low. In the top right panel we see that behind these aggregate dynamics there is substantial heterogeneity across forecasters. The standard deviation is high in the

[9]Starting in 2011 the Philadelphia Fed included a "consistency check" which shows forecasters their implied 5y5y forward inflation.

[10]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.

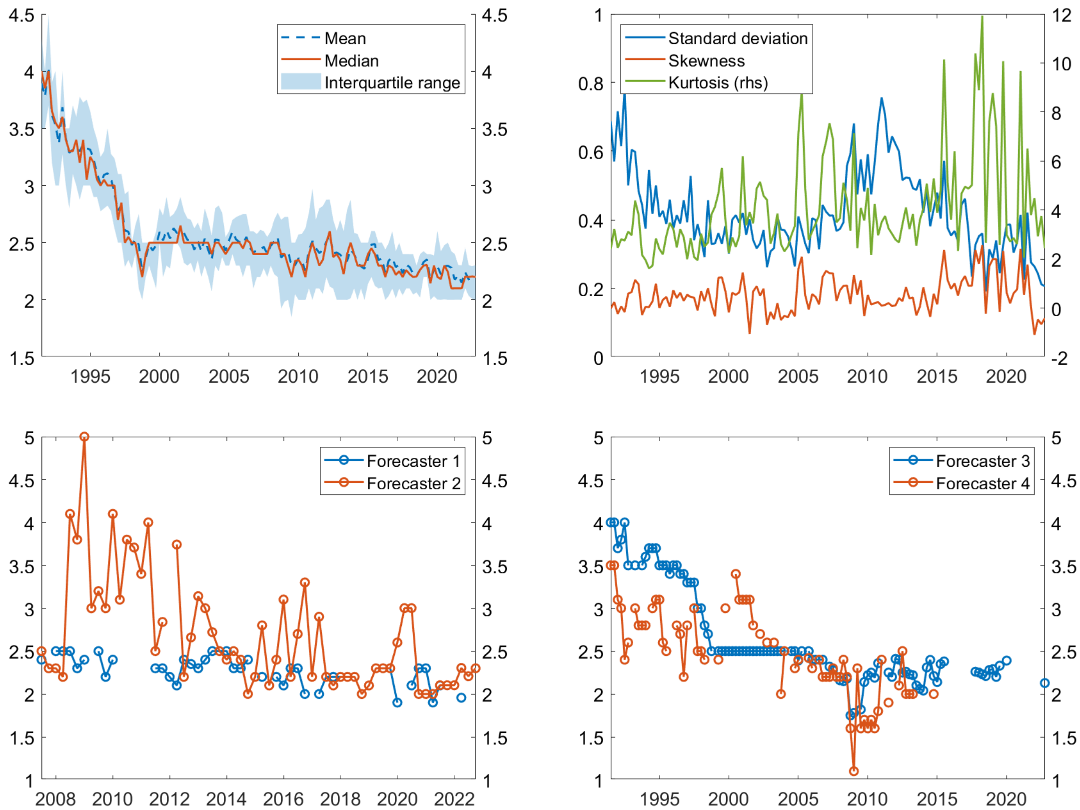

Figure 1: Time series summary of long-term CPI inflation expectations

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.

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 long-term expectations for 4 selected forecasters. We use these plots to highlight three points. First, there can be substantial differences in the level of expected inflation. Second, some forecasters have episodes of fairly stable inflation expectations and only adjust smoothly (blue lines) while the other forecasters change their expected inflation in nearly every period. Third, there is some degree of co-movement in expectations across the forecasters. This is an important source of identification of the common sentiments.

5 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 study inflation anchoring.

5.1 Estimates of the inflation model

The priors and estimated posterior modes for the time-invariant parameters of the trend-cycle model are shown in Table 1.[11] The time-varying parameters are shown in Figure 2. Figure 2 is particularly interesting. It shows that the volatility of the trend component of inflation peaks during the Great Inflation at 36 basis points (bp) and declines fairly quickly over the ensuing 20 years, leveling off around 22 bp around 2000. The volatility of the cyclical shock is much larger. It peaks in 1980 and again during the Great Recession. The persistence of the cyclical component is also high around the peak of the Great Inflation, topping out around .8. Persistence falls gradually thereafter and settles at about .25 in the middle of the 2000s. Overall this seems like a plausible characterization of inflation over the last 60 years.

	Prior				Posterior
	Shape	Scale	Mean	[5%, 95%]	Mean
γ_η^2	5	0.04	0.01	[0.004,0.02]	0.0497
γ_λ^2	5	0.04	0.01	[0.004,0.02]	0.0104
γ_ϕ^2	5	0.004	0.001	[0.0004,0.002]	0.0014
σ_ω^2	3	0.2	0.1	[0.032,0.245]	0.1520

Table 1: Prior and posterior for parameters distributed as Inverse Gamma (Shape,Scale)

Once the model is estimated, we use the Kalman smoother to obtain estimates of the inflation trend. The top left chart of Figure 3 shows the time series of CPI inflation and our estimate of the inflation trend over the full estimation sample. The shaded area shows the sample period we use to estimate the panel model. The inflation trend reaches its peak of around 5 percent in 1980 and ends the sample at close to 2 percent.

[11] We describe how we initialize the state vector in Appendix B. Following Chan et al. (2018) and Stock and Watson (2007) we assume the initial value of the trend is zero and allow a very wide initial uncertainty so the trend in the second period of the sample is relatively unconstrained.

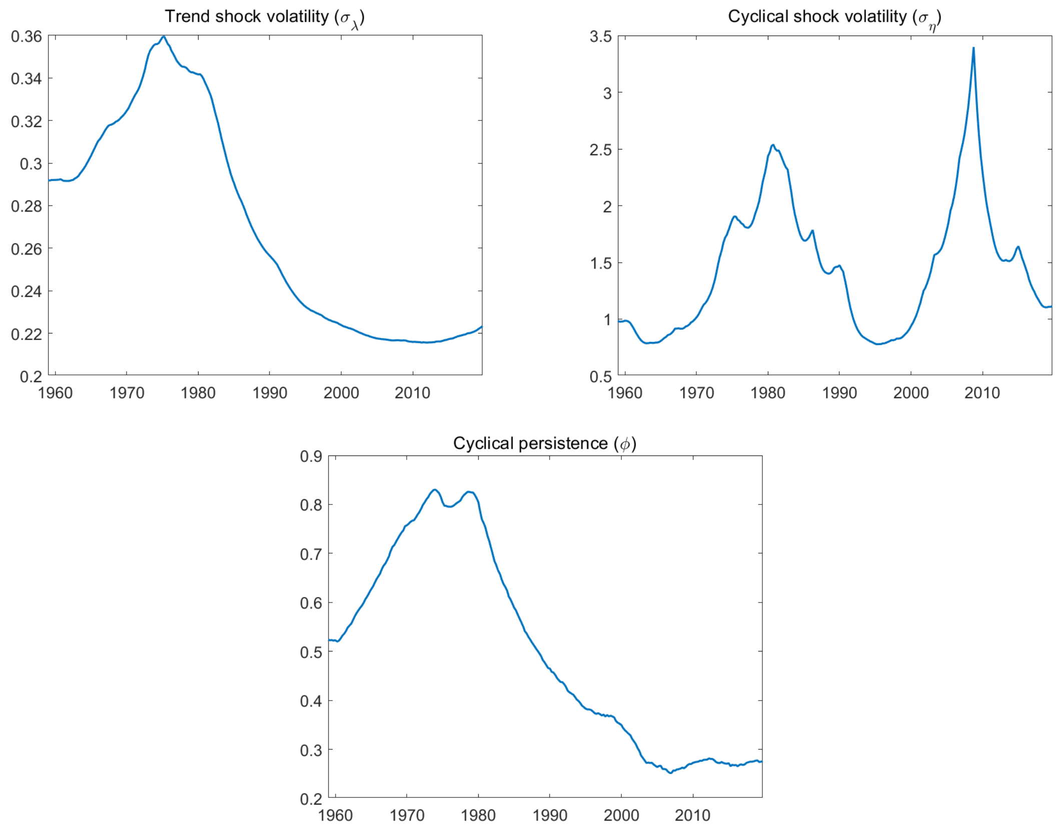

Figure 2: Time-varying parameter estimates (posterior means)

The right chart in Figure 3 shows average long-run CPI inflation expectations from the SPF along with the estimated inflation trend over the period of our panel estimation. In the first part of the sample average expectations lag the decline in the trend.[12] From around 2000 to 2007 the two series are in alignment and roughly stable at about 2.5%, suggesting expectations were anchored, although the Fed did not have a formal inflation target at this time. With the trend following along with average expectations there was less risk of expectations becoming unanchored. The alignment of average expectations with the estimated inflation trend in this period is striking given that the expectations are not used to identify the trend. We view this to be a partial validation of our assumption that the forecasters use the trend-cycle model to inform their expectations about long-run inflation.

[12] As described in section 4 we rely on average 1 to 10 year ahead expectations for our measure of long-run inflation expectations over this period. If inflation is anticipated to decline slowly over the following 10 years then there will be an upward bias to long-term inflation expectations during this period.

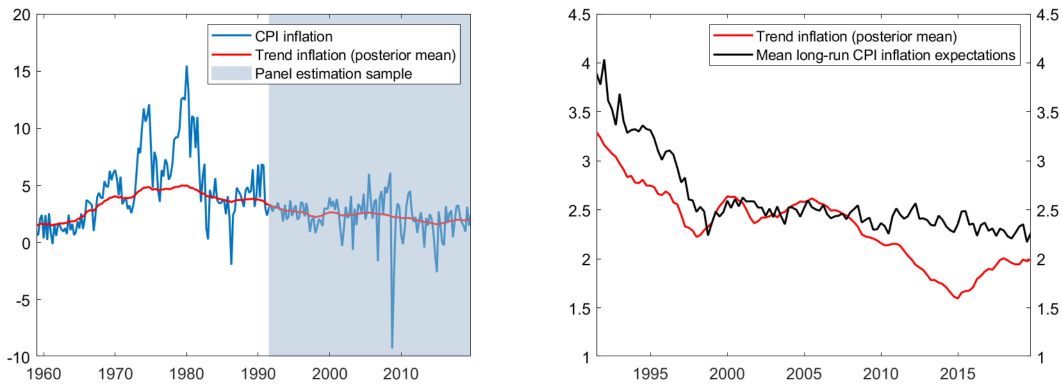

Figure 3: Inflation, inflation trend, and long-run inflation expectations

Notes: The shaded area in the left chart indicates the sample period for the panel estimation.

Just prior to the Great Recession the trend begins a long downward drift to its nadir of 1.6 percent in 2015. The trend turns the corner in 2015 and rises to 2% by 2017 where it remains until the end of the sample in 2019q4. Assuming a wedge of 30 bp between PCE and CPI inflation this is below the Fed's inflation target.[13] Average expectations begin to trend down after the Great Recession. By the end of the sample they are consistent with the Fed's target based on our assumption of the size of the wedge between PCE and CPI inflation. However, given that the inflation trend had been stable at 2 percent for several years, our model suggests there was a additional risk of de-anchoring at the end of 2019 as average expectations tend toward the trend in our panel model.

5.2 Panel estimates

We estimate the panel model over the sample period 1991q3-2019q4.[14] In Table 2 we summarize our priors and the resulting parameter estimates. The random walk prior for $\ln(\sigma^2_{c,t})$ should induce a smooth change in the volatility of common sentiments, which reflects our *a priori* view that the sensitivities of forecasters' expectations to the common signal are unlikely to change quickly. The estimation drives the auto-correlation of common sentiments, ρ_c, to one.

[13]That there is a wedge is well known, but the size of the wedge is uncertain. Our choice of 30 bp is in line with the behavior of the two inflation measures in the ten years prior to the end of our estimation sample.

[14]We assume that forecasters have been receiving signals for several periods before they enter our sample so that the initial state and uncertainty correspond to the individual forecaster's steady state values.

Parameter	Prior	Posterior mode
$\alpha(i)$	Inverse Gamma(3,1)	see Figure 4
ρ_c	Beta(0.5,0.2)	.99
$\sigma_{c,t}$	$\ln \sigma^2_{c,t} \backsim \mathcal{N}\left(\ln \sigma^2_{c,t-1}, .25\right)$	see Figure 4
$\rho(i)$	Beta(0.5,0.2)	see Figure 4
$\sigma_v(i)$	Inverse Gamma (3,1)	see Figure 4

Table 2: Parameter values for panel estimation

From hereon we assume common sentiments are a random walk, i.e. $\rho_c = 1$.

The time series of $\sigma_{c,t}$ is shown in the top left plot of Figure 4. This plot shows that the volatility of common sentiments is highly cyclical. The volatility doubles leading up to both of the recessions and falls during the recessions, dramatically so in 2001. Common sentiments are least volatile in the period 2013–2015, but they become more volatile toward the end of the sample, ending up somewhat higher than at the beginning of the sample.

The other three plots in Figure 4 show the distributions of the idiosyncratic parameters. These plots demonstrate the considerable heterogeneity among the forecasters in terms of the precision of the common signal and the persistence and volatility of idiosyncratic sentiments. These distributions suggests that the degree of sensitivity to the signals is quite heterogeneous.

6 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' long-run inflation expectations to the signals varies over time and across forecasters based on the estimated Kalman gains. Next we use impulse responses to study the effects of the model's different shocks on average long-run inflation expectations. Finally, we analyze the historical contribution of the different shocks to the evolution of average long-run inflation expectations over the last 30 years.

6.1 Forecasters' sensitivity to the signals

A key output of the panel estimation is the Kalman gains on the signals. The Kalman gains are based on the solution to the signal extraction problem of each forecaster. They tell us how

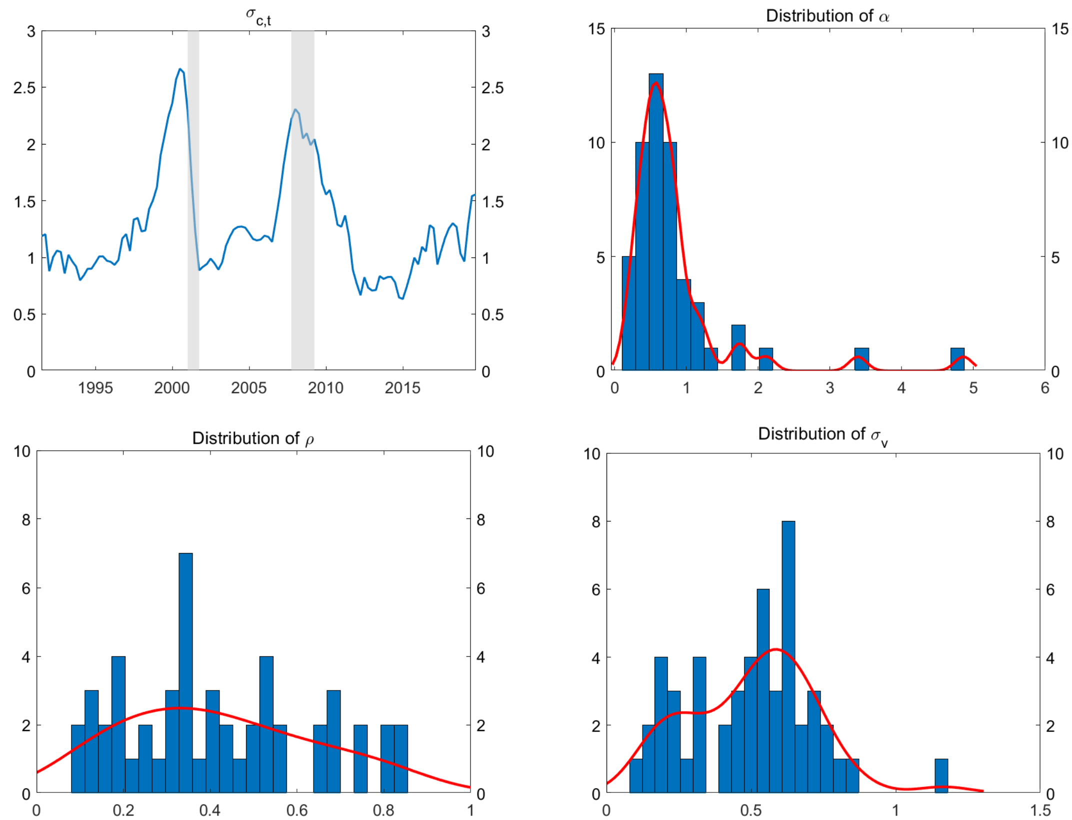

Figure 4: Panel model estimates

Notes: Grey shaded areas indicate NBER recession dates. Red lines are kernel density estimates.

much each forecaster updates, or learns about, their long-run expectations after observing the signals. A larger Kalman gain reflects a higher degree of sensitivity to a signal and faster learning about the inflation trend.

Figure 5 shows the distribution of the Kalman gains for the three signals. The top plot shows the Kalman gains associated with observing the inflation rate and the bottom two plots shows the Kalman gains associated with observing the private signals. The solid blue lines correspond to the medians of the forecasters' gains while the blue shading indicates 90 percent credibility bands. (The dotted lines will be discussed later.) Note that the Kalman gains vary over time due to the the time-varying parameters of the trend-cycle model $\sigma_{\lambda,t}$, $\sigma_{\eta,t}$, and ϕ_t, as well as the time-varying volatility of common sentiments $\sigma_{c,t}$. They vary across forecasters due to the idiosyncratic parameters $\alpha(i)$, $\rho(i)$ and $\sigma_v(i)$.

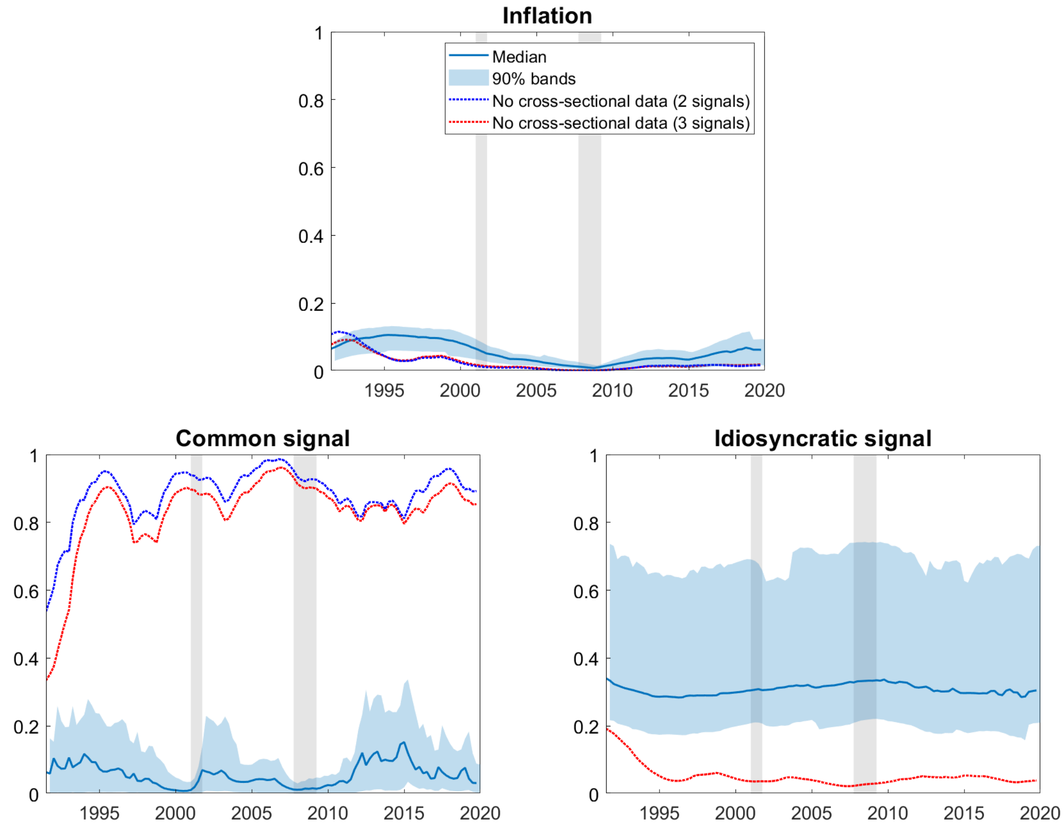

Figure 5: Kalman gains for the inflation (top) and private (bottom) signals

Notes: Grey shaded areas indicate NBER recession dates. Blue lines and shading correspond to estimates based on our panel of forecasters. The red line corresponds to the case where we assume a representative forecaster and ignore the cross-sectional data.

The median Kalman gains are much lower for the inflation and common signals compared to the idiosyncratic signal. The gains for the inflation signal are generally slow moving and vary little across forecasters. There is little evidence of cyclicality. Interestingly during the Great Recession forecasters were in broad agreement that there was essentially no information about long-run inflation in the inflation signal. Outside of that period the Kalman gains are small but not negligible. They were largest before the 2001 recession with the median about .1. The median responsiveness to the inflation signal was rises after 2015 but is still low at the end of the sample — a 100 bp increase in inflation would increase long-run expectations by just 6 bp.

There is more heterogeneity in the sensitivity of long-run expectations to the common signal, both across time and forecasters. The median gains are generally larger than for the inflation signal, but still small, peaking at about .15 in 2015. Like the inflation signal most forecasters saw little information in the common signal during the Great Recession. However, during the period of low inflation in the 2010s the median forecaster was more sensitive to the common signal than the inflation signal. To the extent that the common signal reflects Fed communications this suggests that forecasters were "listening" more closely than at other times.

The median Kalman gain for the idiosyncratic signal averages around .3 and there is a huge amount of heterogeneity with the 90 percent range roughly .2 to .75. The relatively high Kalman gains and the huge amount of variation in them reflects the vast heterogeneity in our data combined with the relatively low degree of co-movement in the forecast revisions.

Does accounting for the heterogeneity in the cross section of forecasters matter for the sensitivity of average expectations to the signals? To assess the importance of heterogeneity we consider the hypothetical case of a representative forecaster. This is equivalent to assuming that all forecasters are identical and receive the same signals. We assume that their forecasts are captured by the average SPF forecast.[15] The Kalman gains for the representative forecaster are shown in Figure 5 with the red and blue dotted lines. The difference between the red and blue dotted lines is whether or not we include the idiosyncratic signal.[16]

The Kalman gains associated with the representative forecaster suggests that accounting for heterogeneity matters a lot as they are radically different from those we estimate with the cross section of forecasters. Except for the early part of the sample the sensitivity of expectations to the inflation signal assuming forecasters are identical is essentially zero. The sensitivity of the representative forecaster to the common signal is particularly striking as from 1995 onward it hovers in the range .8 – 1 range compared to less than .2 for the large majority of forecasters in our sample. These large Kalman gains reflect the relatively high degree of co-movement

[15] This case does *not* correspond to any particular forecaster in our sample.

[16] The representative forecaster's Kalman gain on the idiosyncratic signal is a little hard to interpret. In the representative forecaster case both signals are common in the sense that all forecasters receive the same signal. The difference between the signals is that the common signal has time-varying volatility while the parameters of the idiosyncratic signal are constant. Including the idiosyncratic signal does not make much of a difference to the sensitivity of representative forecaster's expectations to the common signal.

between average expectations and the inflation trend evident in the right-hand plot of Figure 3. Under the interpretation that the common signal in part reflects Fed communications, assuming a representative forecaster would suggests those communications are powerful. Overall these findings demonstrate the importance of using the information in the cross section to correctly identify the sensitivity of expectations to new information.

6.2 The effects of the shocks on average expectations

Our framework allows us to estimate how average inflation expectations respond to shocks via the Kalman gains of the individual forecasters. Figure 6 plots impulse response functions associated with one-time one standard deviation shocks to the permanent and cyclical components of the inflation process (λ_t and η_t) and the sentiments in the two private signals ($\nu_{c,t}$ and $\nu_{v,t}$). Each plot shows five lines corresponding to when the shocks are assumed to occur. That is they are based on the values of the time-varying parameters and the idiosyncratic parameters of the forecasters in the sample at the dates indicated in the legends. In all cases we average the responses of the individual forecasters. With idiosyncratic sentiments it is the average response of a forecaster to a shock to its own idiosyncratic sentiments.[17] Note the scales are the same in each plot. To gauge magnitudes Figure 7 shows the responses of inflation to the permanent and cyclical shocks.

The top left plot of Figure 6 shows responses to a permanent shock to inflation λ_t that leads to an immediate jump in inflation of around 22 bps (left plot of Figure 7). This shock feeds directly into all three signals. However, because the Kalman gains are typically small, forecasters learn about this change fairly slowly no matter when the shock is assumed to occur — it takes around 3 years before the average forecast matches to the new level of trend inflation.

The top right plot of Figure 6 shows the response of the average long-run forecast to a transitory shock to inflation η_t. This shock only affects the inflation signal which has very small Kalman gains associated with it. Consequently, while the shocks leads to large changes in inflation (from 75 bps to 230 bps as shown in the right hand plot of Figure 7), the response of

[17]Interestingly our results for all four shocks are very similar if we shock a single forecaster that is assigned the average of the idiosyncratic parameters (not shown).

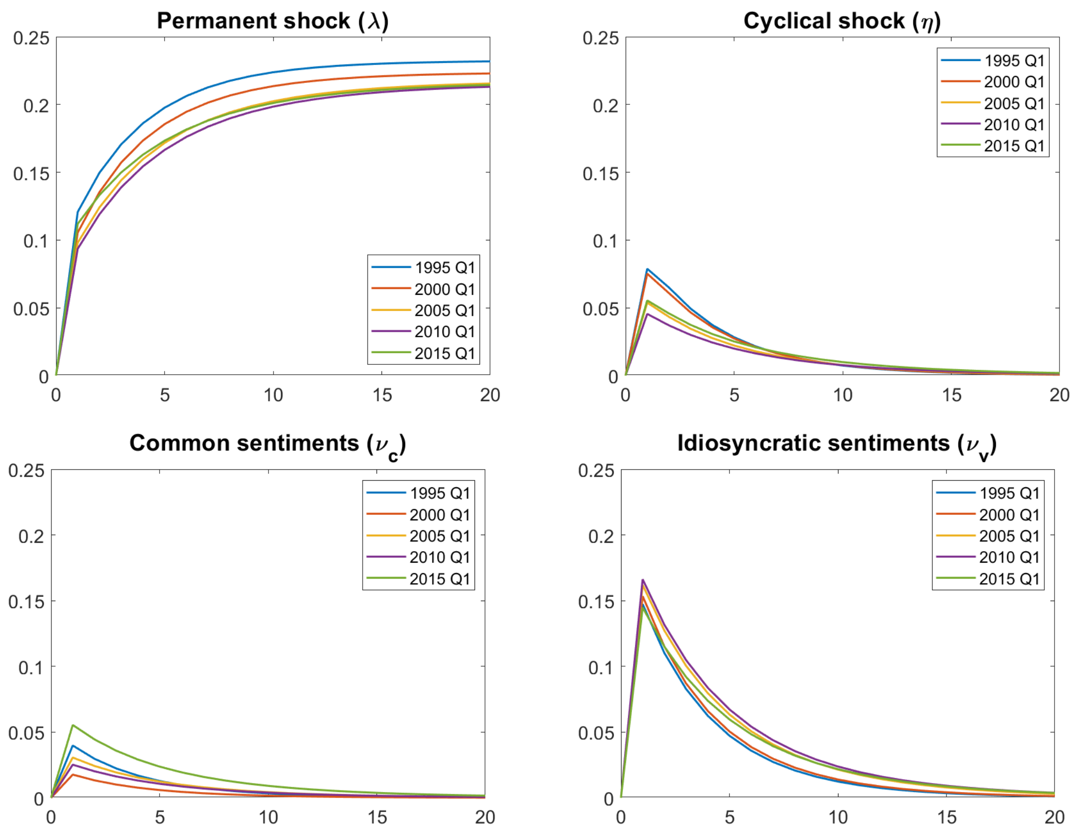

Figure 6: Impulse response functions for average long-run inflation expectations to one standard deviation shocks

Notes: Impulse response functions of average expectations to a one standard deviation shock that happens in period 1 (after 20 periods of burn in so the Kalman gains are at their steady state values). The different lines correspond to different values of the time-varying parameters taken from the dates indicated in the legends and averages over responses of forecasters in the sample at the same dates.

average expectations is never more than 8 bps. However the response of average expectations is more persistent than the response of inflation.

The bottom two plots depict the impulse response functions for one standard deviation shocks to common sentiments $\nu_{c,t}$ (left plot) and idiosyncratic sentiments $\nu_{v,t}(i)$ (right plot). Since these shocks only appear in the signals they have no impact on inflation. The common sentiments shock only affects the common signal. So, while it is a permanent shock ($\rho_c = 1$), the response is transitory. As forecasters update their expectations they learn from the inflation and idiosyncratic signals that there has not been a change in the inflation trend and so the effect on average expectations dies out fairly quickly. The small values of the responses

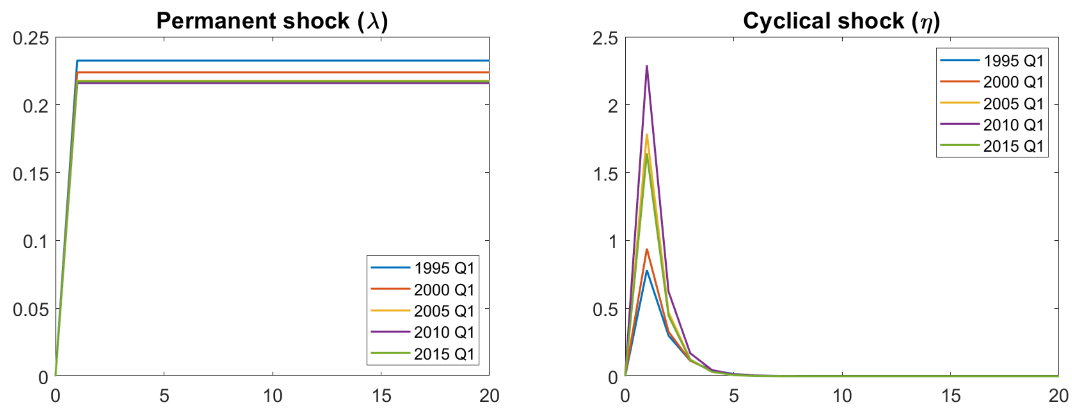

Figure 7: Impulse response functions for inflation to one standard deviation shocks

Notes: Impulse response functions to a one standard deviation shock that happens in period 1. The different lines correspond to different values of the time-varying parameters taken from the dates indicated in the legends.

to common sentiments reflect the small Kalman gains associated with the common signal. The average response to an idiosyncratic sentiments shock is much larger than for common sentiments and two to three times larger than for the cyclical shock that only impacts the inflation signal, reflecting the larger Kalman gains for the idiosyncratic signals.

6.3 Historical drivers of average long-run inflation expectations

In this section we use our model to investigate the historical drivers of average long-run inflation expectations. Figure 8 shows the historical shock decomposition of average inflation expectations together with the inflation trend.[18] We study the role of the permanent (yellow) and cyclical (blue) shocks, common sentiments (red), and idiosyncratic sentiments (green) 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 D.

Figure 8 shows the primary driver of the long term decline in average inflation expectations is permanent shocks to inflation λ_t (yellow). The main driver behind the discrepancies between trend inflation and average inflation expectations discussed in subsection 5.1 is common sentiments, $v_{c,t}$. Common sentiments keep expectations higher than the inflation trend in the

[18] Appendix D shows the historical decompositions for each forecaster in our sample.

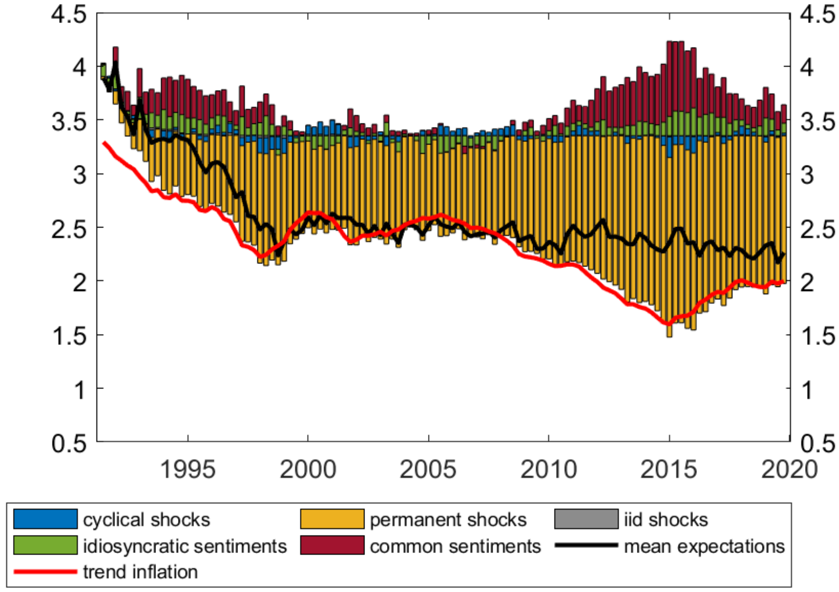

Figure 8: Historical decomposition of average inflation expectations

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

1990s.[19] Common sentiments prevent average expectations from following the decline in trend inflation in the 2010s. They keep inflation expectations relatively stable as low inflation pulls down the trend.

The role of common sentiments in the 2010s may seem puzzling given the magnitude of the impulse responses to common sentiments shocks shown in Figure 6. The estimated common sentiments shocks are not particularly large in this period. However, their empirical distribution is heavily skewed to the right and is therefore inconsistent with our assumption of a mean zero normal distribution. This likely reflects specification error and could be an indication of non-rational expectations on the part of the forecasters. For instance, suppose forecasters assume that common sentiments follow a stationary process while the true process is a random walk. Under these conditions forecasters would more frequently confuse a shock to common sentiments with a shock to the trend. We conjecture this would whiten the estimated shocks to common sentiments.

[19] This could reflect bias in the forecasts due to the decline in the trend and using 10 year average expectations to measure long-run inflation expectations in this period.

We interpret the effects of common sentiments in the 2010s as reflecting that communications have played an important role in stabilizing average expectations near the Fed's target notwithstanding the low inflation rates at the time. However, around the time of the Great Recession average expectations started to fall slowly below the value they settle at the end of the 1990s disinflation. By the end of the estimation sample the gap between average inflation expectations and the sub-target estimated trend of inflation shrinks considerably. This is largely a result of common sentiments having a declining effect on expectations which might indicate forecasters' waning confidence in the Fed's ability to combat low trend inflation.

Cyclical shocks to inflation have only a small impact on average inflation expectations over the last 30 years (blue) and if anything they make the wedge between average expectations and the inflation trend harder to explain. Idiosyncratic sentiments (green) account for a significant share of the wedge in the early and later parts of the sample. This reflects that the samples of forecasters in these periods have upwardly biased forecasts relative to the trend.[20] Absent these composition effects the apparent de-anchoring of average long-term expectations over the last decade or so would have come earlier and faster.

7 Anchoring U.S. Inflation Expectations

The previous section shows that our model provides a reasonable characterization of the historical behavior of average long-term inflation expectations from the SPF. Our model can also be used as a guide for central bankers looking to the future, and in particular central bankers 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 any particular date. The model's parameters determine how quickly individual forecasters respond to the three signals via the Kalman gains shown in Figure 5. This makes it possible to use it to project average inflation expectations under different scenarios for the future paths of inflation and sentiments.

[20] The average shock to idiosyncratic sentiments is 4 bp and the distribution is close to normal.

We apply our model to the case of a U.S. central banker setting policy in December 2015 and December 2022. From the late 1990s to the Great Recession average long-term CPI inflation expectations were stable near 2.5 percent and close to the inflation trend (Figure 3). However, after the Great Recession inflation ran persistently below target. In the four years leading up to December 2015 CPI inflation averaged just 1.2 percent. This dragged the inflation trend down to 1.6 by 2015q3. Long-run inflation expectations had stayed relatively stable near 2.5 percent (see Figure 3) but the low value of the inflation trend threatened to drag expectations lower. In December 2022 inflation had been running very hot for a year and a half. Estimating the time varying parameters and states of the inflation model from 2020q1 to 2022q3 we find that the inflation drift had risen to close to 3 percent by 2022q3. Remarkably long-run inflation expectations had actually fallen a little — by 2022q3 (as measured in November 2022) average long-run inflation expectations were 2.2 percent in our sample of forecasters. However, in this case the high level of the inflation trend threatened to pull long-run inflation expectations up. What paths of inflation should the Fed have been striving to achieve going forward from December 2015 and December 2022 to prevent expectations from becoming unanchored? What role could coordination of sentiments, or communication, have to play to ensure long-run expectations remained stable? We now consider two kinds of experiments with our model to address these questions.[21]

7.1 Alternative paths of inflation

We consider the evolution of average expectations under alternative paths of inflation taken from the Fed's December 2015 and December 2022 SEP. To calculate paths for average inflation expectations implied by the panel model we require paths for inflation and the inflation trend. The December SEPs report q4 over q4 PCE inflation for the current year and three years ahead. We assume a 30 bp wedge between the long-run levels of CPI inflation and PCE inflation to translate the SEPs into CPI equivalents. We then smooth the annual projections into quarterly values.

Given a path for inflation we use our time-series model to obtain the inflation trend using

[21] See Appendix F for details of the calculations underlying these experiments.

the Kalman smoother. In the case of December 2015, we take the parameter values and states of the time-series model in 2015q3 that are based on the full sample estimation and then run the Kalman smoother from the end of the SEP projection period in 2018q4 back until 2015Q4 to obtain the trend. In the December 2022 experiment we take the parameter values and states of the time series model in 2019q4 that are based on the full sample estimation and run the Kalman smoother from 2025q4 back until 2020q1 to obtain the trend.[22]

With inflation and the drift in hand we use our estimated panel model to infer the forecasts of individual forecasters from which we calculate average long-run inflation expectations, launching from 2015q4 and 2022q4.[23] The December 2015 experiment conditions on CPI inflation in 2015q3, average inflation expectations in 2015q3 (since we lag SPF expectations this corresponds to the November 2015 survey so forecasters have yet to see the December 2015 SEP), the SEP inflation paths from 2015q4, and the inferred inflation trend. Similarly, the December 2022 experiment conditions on CPI inflation in 2022q3, the November 2022 SPF, the SEP inflation paths from 2022q4, and the inferred inflation trend. Note that these steps are the same as those we followed to estimate the panel model except for the fact that we do not use the distribution of SPF inflation expectations, i.e. only inflation and the inflation trend are used and individual forecaster expectations are treated as missing values. This means there are no sentiments shocks in these experiments.

Figure 9 shows the paths of inflation corresponding to lowest, median, and highest projections along with the estimated inflation trends. The top row corresponds to December 2015 and the bottom row to December 2022. The key takeaway from the 2015 case is that all three paths of the drift adjust very slowly to near 2 percent. This slow convergence means that in all three scenarios the inflation trend exerts a downward bias to average inflation expectations. In the 2022 case the sharp rise in inflation over the previous year and a half lifts the inflation trend to near 3 percent and it falls only slightly over the projection period.[24] This exerts an upward bias to expectations.

[22] Appendix F displays the inflation trend and historical decomposition for the 2020q1–2022q3 period.

[23] We calculate the average using the sample of forecasters that submit a forecast at least once during the two years leading up to the start of the experiment.

[24] If we exclude the SEP projections from our estimation of the inflation trend in 2022q3 it is 25 bp higher.

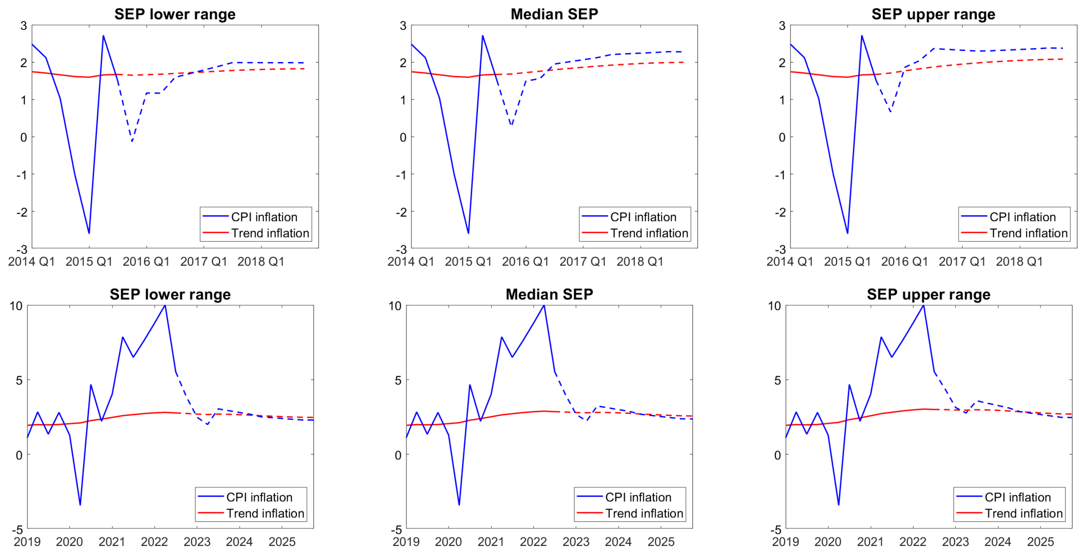

Figure 9: Inflation path and estimated inflation drift based on December 2015 (top row) and December 2022 (bottom row) SEP for lower range (lhs), median (middle) and upper range (rhs)

Figure 10 illustrates the impact of these paths of inflation and trend inflation on the predicted paths of average inflation expectations. The December 2015 case shows that the slow rise of the trend toward 2 percent keeps expectations 10 to 40 bp below the Fed's inflation target (about 2.3 percent in CPI units) for the following three years.[25] The December 2022 experiment shows the opposite – expectations rise 20 – 30 bp above target. Note however that these paths assume that there is no influence of common or idiosyncratic sentiments — realized inflation is the influence on expectations.

7.2 Paths of inflation consistent with stable long-run expectations

Now we solve for the paths of inflation that would keep average expectations at their most recent value (about 2.5 percent in 2015q3 and 2.2 percent in 2022q3), allowing for the possibility that sentiments can be coordinated. In these experiments we hold fixed the volatility of common sentiments at its most recent value. In 2015q3 the volatility is .86, close to its lowest value of .63 in 2015q1, which translates to a historically large Kalman gain on the common

[25]The sharp initial drop reflects the removal of common sentiments which keep expectations elevated in 2015q3 — see Figure 8.

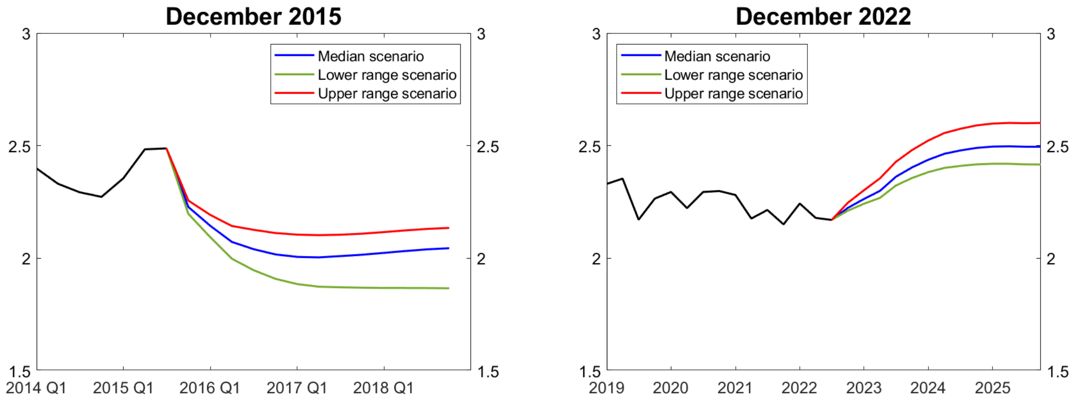

Figure 10: Mean inflation expectations under different SEP inflation scenarios from the December 2015 (lhs) and December 2022 (rhs)

signal. In 2022q3 the volatility is larger (1.36) and the Kalman gain on the common signal commensurately smaller. The different magnitudes of the volatilities and gains across the two time periods reflects the pattern of the cross section of forecasts at the time. Leading up to 2015q3 there was relatively little heterogeneity and a relatively high degree of co-movement. In 2022q3 the forecasts had been more dispersed and co-moving less.

We consider two cases, one with "communication" and one without. The case with communication has all three signals active and common sentiments $v_{c,t}$ are allowed to vary to keep expectations stable. The no communication case assumes forecasters only receive the inflation and idiosyncratic signals. In both cases we set the shocks to idiosyncratic sentiments $\nu_{v,t}$ to zero to isolate the role of common sentiments.

We solve for the paths of inflation as follows. First, we assume an initial path for the inflation trend and find the values of the permanent and cyclical shocks to inflation (the i.i.d. component is set to zero) and the shocks to common sentiments that deliver paths for inflation that rationalize the joint behavior of the assumed paths of the trend and average expectations. Given the calculated path of inflation we can infer a path of the trend as we do in subsection 7.1. The resulting path of the trend will not necessarily equal the path we assumed initially. We iterate on the assumed path of inflation until it converges.

Figure 11 displays our findings. These plots show that, according to our model, the SEP inflation projections are either too low (December 2015) or too high (December 2022)

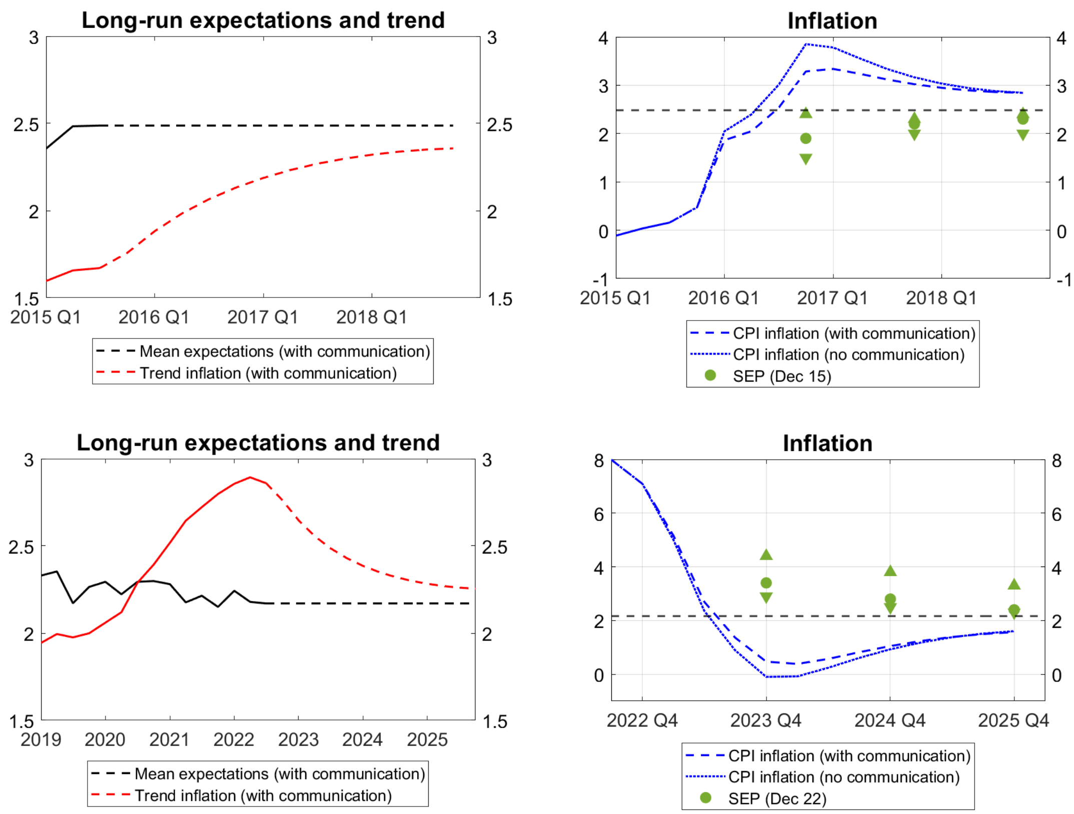

Figure 11: Inflation paths consistent with keeping average long-term inflation expectations steady over the SEP forecast horizon from the December 2015 and December 2022 FOMC meetings.

Notes: The rhs dashed lines show the path of *year-on-year* inflation consistent with steady expectations within four years from December 2015 (top) and December 2022 (bottom) with no constraints on signals. The lhs black dashed lines show the assumed path of steady average expectations and the red line shows the inflation trend consistent with the inflation path on the rhs. The dotted lines in the rhs plot show the case when we constrain the common signal to be not used. The dots correspond to the median SEP projections and the arrows to the highest and lowest projections.

to stabilize long-run inflation expectations. The plots show year-on-year inflation to be comparable with the SEP. The blue dashed lines in the right hand plots show the inflation that is consistent with stabilizing inflation expectations at the level indicated by the black dashed lines in the left hand plots. The inflation trend corresponding to the inflation path with communication is shown with the red dashed line in the left hand plots. The blue dotted lines in the right hand plots are the no communication inflation paths. The top and bottom rows correspond to the 2015 and 2022 experiments respectively.

The 2015 experiment reveals that with communication a fairly substantial overshooting of inflation — peaking around 3.3 percent – is required to stabilize inflation expectations. Notice that the inflation path far exceeds the range of SEP projections in December 2015 (green triangles and circle). Without communication inflation would need to be up to 57 bp higher as the absence of the common signal forces inflation along to do the job of stabilizing expectations.

Actual inflation did not come in nearly as high as the path of inflation we solve for in this experiment, at least not on a persistent basis. Perhaps because of this average long-run inflation expectations drifted down from 2.5 percent in 2015q3 to 2.2 percent by the end of 2018. Furthermore, the estimated trend at the end of the projection period is a touch below 2 percent while in the experiment with communication it rises to 2.4 percent. This suggests that the failure of inflation to overshoot the Fed's target left the economy vulnerable to a further downward drift of inflation expectations.

In the December 2022 experiment communication has less of an impact since we estimate the variance of the common sentiments shock to be relatively high and so the Kalman gains on the common signal are small. With the common signal having relatively little influence on expectations, the model implies inflation will need to come in persistently lower than 2 percent starting in 2023 to keep expectations stabilized. The expectations-stabilizing path dips below .5 percent and is much lower than the SEP projections. This reflects the high level of the inflation trend we estimate for 2022q3 and the diminished role for communication due to the high variance on common sentiments at that time. In Appendix F we show a version of this experiment that assumes the variance of common sentiments is the lower value we use in the December 2015 experiment (which is near the lowest value we estimate). This might reflect more aggressive communication by the Fed.[26] In this case common sentiments, or communication, stabilizes long-run inflation expectations without inflation having to fall as low — the trough is .8 percent instead of .4 percent.

8 Conclusion

In this paper, we estimate a model of long-run inflation expectations formation with panel data from the SPF and use it to measure how the coordination of sentiments influences long-run inflation expectations. We find that common sentiments about future inflation play an important role keeping long-run inflation expectations relatively anchored over the 2010-2019 period in the face of low inflation and a concomitant drop in the inflation trend. We interpret these common sentiments as reflecting the forecasters' trust in the central bank's commitment and ability to maintain its inflation target in the long-run and the effectiveness of its communications about how it will seek to achieve price stability.

In addition to providing a characterization of long-run 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 U.S. central banker setting policy in December 2015 when trend inflation was running below the inflation target, and December 2022 when the trend was running far above the target. In both cases our model predicts the most likely outcome if inflation were to come in as projected in the SEPs at the time would be for long-run inflation expectations to become unanchored even with sentiments coordinated in a manner consistent with their historical behavior. This is particularly so in the most recent episode as we find that the common signal is relatively imprecise and so it is harder for sentiments about long-run inflation to be coordinated. Fed communications would need to be unusually effective at coordinating sentiments around the inflation target to prevent

[26] Indeed the FOMC may have been attempting to do this when it inserted "The Committee is highly attentive to inflation risks" in its May 2022 post-meeting statement. This phrase was a feature of the post-meeting statements for the remainder of 2022.

expectations from becoming unanchored.

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A Model derivations

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

$$\begin{aligned}\xi_t(i) &= \mathbf{\Phi_t}(\mathbf{i})\xi_{t-1}(i) + \mathbf{R_t}(\mathbf{i})e_t(i) && (12)\\ s_t(i) &= \mathbf{D}(\mathbf{i})\xi_t(i) + \mathbf{\Psi}u_t && (13)\end{aligned}$$

where

$$\begin{aligned}\xi_t(i) &= [\varepsilon_t, \bar{\pi}_t, v_{c,t}, v_t(i)]'\\ e_t(i) &= [\eta_t, \lambda_t, \nu_{c,t}, \nu_t(i)]'\\ s_t(i) &= [s_{1,t}, s_{2,t}(i), s_{3,t}(i)]'\\ u_t &= [\omega_t, \omega_{2,t}, \omega_{3,t}]'.\end{aligned}$$

Here $\mathbf{\Phi_t}(\mathbf{i})$ is a $k \times k$ matrix which depends on ϕ_t, ρ_c and $\rho(i)$, where $k = 4$ is the number of state variables; $\mathbf{R_t}(\mathbf{i})$ is $k \times 4$ and depends on $\sigma_{\eta,t}$, $\sigma_{\lambda,t}$, $\sigma_{c,t}$, $\sigma_v(i)$; $\mathbf{D}$ is a $3 \times k$ matrix and $\mathbf{\Psi}$ is 3×3 and depends on σ_ω. The measurement errors $\omega_{2,t}$ and $\omega_{3,t}$ are just added for completeness but their variance is zero so they are irrelevant. The detailed definitions are as follows:

$$\mathbf{\Phi_t}(\mathbf{i}) = \begin{bmatrix} \phi_t & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & \rho_c & 0\\ 0 & 0 & 0 & \rho(i)\end{bmatrix}, \ \mathbf{R}_t(i) = \begin{bmatrix} \sigma_{\eta,t} & 0 & 0 & 0\\ 0 & \sigma_{\lambda,t} & 0 & 0\\ 0 & 0 & \sigma_{c,t} & 0\\ 0 & 0 & 0 & \sigma_v(i)\end{bmatrix}$$

$$\mathbf{D}(\mathbf{i}) = \begin{bmatrix} 1 & 1 & 0 & 0\\ 0 & 1 & \alpha(i) & 0\\ 0 & 1 & 0 & 1\end{bmatrix}, \ \mathbf{\Psi} = \begin{bmatrix} \sigma_\omega & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0\end{bmatrix}$$

The Kalman filter recursion for forecaster i is given by:

$$\begin{aligned}\xi_{t|t-1}(i) &= \mathbf{\Phi_t}(\mathbf{i})\xi_{t-1|t-1}(i) && (14)\\ P_{t|t-1}(i) &= \mathbf{\Phi_t}(\mathbf{i})P_{t-1|t-1}(i)\,\mathbf{\Phi_t}(\mathbf{i})' + \mathbf{R}_t(i)\mathbf{R}_t(i)' && (15)\\ s_{t|t-1}(i) &= \mathbf{D}(\mathbf{i})\xi_{t|t-1}(i) && (16)\\ F_{t|t-1}(i) &= \mathbf{D}(\mathbf{i})P_{t|t-1}(i)\,\mathbf{D}(\mathbf{i})' + \Psi\Psi' && (17)\\ \xi_{t|t}(i) &= \xi_{t|t-1}(i) + \underbrace{P_{t|t-1}(i)\mathbf{D}(\mathbf{i})'\left[F_{t|t-1}(i)\right]^{-1}}_{K_t(i)}\left[s_t(i) - \mathbf{D}(\mathbf{i})\xi_{t|t-1}(i)\right] && (18)\\ P_{t|t}(i) &= P_{t|t-1}(i) - P_{t|t-1}(i)\,\mathbf{D}(\mathbf{i})'\left[F_{t|t-1}(i)\right]^{-1}\mathbf{D}(\mathbf{i})P_{t|t-1}(i) && (19)\end{aligned}$$

Re-arrange the Kalman filter recursions as follows to obtain equation:

$$\begin{aligned}\xi_{t|t}(i) &= \xi_{t|t-1}(i) + K_t(i)\left[s_t(i) - D(i)\xi_{t|t-1}(i)\right] && (20)\\ &= \left[\mathbf{I}_4 - K_t(i)\,D(i)\right]\mathbf{\Phi_t}(\mathbf{i})\xi_{t-1|t-1}(i) + K_t(i)\,s_t(i) && (21)\end{aligned}$$

$$= \quad [\mathbf{I}_4 - K_t(i)\, D(i)]\, \mathbf{\Phi_t(i)} \xi_{t-1|t-1}(i) + K_t(i)\, [D(i)\xi_t(i) + \Psi u_t] \tag{22}$$

$$= \quad [\mathbf{I}_4 - K_t(i)\, D(i)]\, \mathbf{\Phi_t(i)} \xi_{t-1|t-1}(i) + K_t(i)\, [D(i)(\Phi_t(i)\xi_{t-1}(i) + R_t(i)e_t(i)) + \Psi u_t] \tag{23}$$

Putting the trend-cycle model and the combined the signal extraction problems of all forecasters together gives our state space model of the econometrician.

The transition equation we use in our panel estimation reads

$$\begin{bmatrix} \xi_t \\ \overrightarrow{\xi}_{t|t} \\ \omega_t \end{bmatrix} = \widetilde{\mathbf{\Phi}}_t \begin{bmatrix} \xi_{t-1} \\ \overrightarrow{\xi}_{t-1|t-1} \\ 0 \end{bmatrix} + \widetilde{\mathbf{R}}_t \begin{bmatrix} \eta_t \\ \lambda_t \\ \nu_{c,t} \\ \overrightarrow{\nu_{v,t}} \\ \omega_t \end{bmatrix} \tag{24}$$

where $\overrightarrow{\xi}_{t|t}$ and $\overrightarrow{\nu_{v,t}}$ are column vectors stacking $\xi_{t|t}(i)$ and $\nu_{v,t}(i)$ of every forecaster. Note that ξ_t contains the idiosyncratic sentiments processes for all forecasters, i.e.

$$\xi_t = \begin{bmatrix} \varepsilon_t & \bar{\pi}_t & v_{c,t} & \overrightarrow{v_t} \end{bmatrix}'$$

.

The measurement equations for our panel estimation are

$$\begin{bmatrix} \pi_t^{cpi} \\ \varepsilon_t^{est} \\ \bar{\pi}_t^{est} \\ \mathbb{E}_t \pi_t^{long}(1) \\ \mathbb{E}_t \pi_t^{long}(2) \\ \vdots \\ \mathbb{E}_t \pi_t^{long}(N) \end{bmatrix} = \begin{bmatrix} \mathbf{D_{CPI}} & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & \sigma_\omega \\ \mathbf{1}_1 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 \\ \mathbf{1}_2 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 \\ \mathbf{0}_{1\times k} & \mathbf{1}_2 & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 \\ \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \mathbf{1}_2 & \dots & \mathbf{0}_{1\times k} & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{1}_2 & 0 \end{bmatrix} \begin{bmatrix} \xi_t \\ \xi_{t|t}(1) \\ \xi_{t|t}(2) \\ \vdots \\ \xi_{t|t}(N) \\ \omega_t \end{bmatrix}, \tag{25}$$

where $\mathbf{D_{CPI}}$ is a zero row vector of length N+k-1 with elements 1 and 2 equal to 1. $\mathbf{1}_n$ 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 (25) include an empirical measure of inflation such as CPI inflation, π_t^{cpi}, our estimates of the cyclical component, ε_t^{est}, trend inflation, $\bar{\pi}_t^{est}$, and an empirical measure of long-term inflation expectations of forecasters, $\pi_t^{long}(i)$.

B Initial conditions for estimation

Initial conditions of inflation model

We initialize the state equations of our inflation model as described in equations (1)-(3) as follows: $\epsilon_0 = 0$, $\bar{\pi}_0 = 0$. The initial uncertainty is set to the unconditional variance for ϵ_0 and to 1e6 for $\bar{\pi}_0$. The time-varying parameters are initialized as $\ln(\sigma^2_{\eta,1}) \sim N(0,\kappa)$, $\ln(\sigma^2_{\lambda,1}) \sim N(0,\kappa)$, $\phi_1 \sim N(0,\kappa)$ where κ=1e6.

Initial conditions of forecaster model

As usual in the literature on factor models the relative scale of loadings and factors is indeterminate and requires a normalization. We set $\log(\sigma^2_{c,0}) = 0$.

We assume that for each forecaster the initial variance-covariance matrix $P_{0|0}(i)$ in equation (15) is at the "steady-state"[27] level given the initial parameter values. To compute this steady-state matrix we start from the following matrix

$$P_{0|0}(i) = \begin{bmatrix} \frac{\sigma^2_{\eta,1991Q2}}{1-\phi^2_{1991Q2}} & 0 & 0 & 0 \\ 0 & 100 & 0 & 0 \\ 0 & 0 & 100 & 0 \\ 0 & 0 & 0 & \frac{\sigma^2_v(i)}{1-\rho(i)^2} \end{bmatrix} \tag{26}$$

and we iterate over equations (15), (17), (19) to get the "steady-state". The values from 1991q2 are used since our first period of the panel model is 1991q3.

Initial conditions of panel model

The initial conditions for the transition equation defined in equation (24) are as follows:

$$\xi_0 \equiv \begin{bmatrix} \epsilon_{1991Q2} \\ \bar{\pi}_{1991Q2} \\ 0 \\ \mathbf{0}_{N\times 1} \end{bmatrix} \tag{27}$$

$$\mathbf{P}_0 \equiv \begin{bmatrix} 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ 0 & 0 & 100 & \mathbf{0}_{1\times N} \\ \mathbf{0}_{N\times 1} & \mathbf{0}_{N\times 1} & \mathbf{0}_{N\times 1} & \mathbf{I}_{N\times N} \overrightarrow{\frac{\sigma^2_v}{1-\rho^2}} \end{bmatrix} \tag{28}$$

The zeros in the upper left 2×2 part mean that we do not want the panel estimation to change the initial estimate of trend and cycle that we got from the time series estimation. The common sentiments process is non-stationary, so we assume an initial value of zero but with large uncertainty.

Denoting with $\xi^*_{0|0}(i)$ the initial condition of the econometrician for the state estimate of

[27] Intuitively, this implies that forecasters have already received some signals before and are not completely uninformed about the history of inflation. Alternatively, we could assume that forecasters have never received any signals before, including inflation, and impose a wide/uninformative initial uncertainty. This would lead to large initial spikes in the Kalman gains since forecasters react a lot to the first few signals but results for rest of the sample are little affected.

forecaster i, we assume

$$\xi^*_{0|0}(i) \equiv \begin{bmatrix} \epsilon_{1991Q2} \\ \bar{\pi}_{1991Q2} \\ 0 \\ 0 \end{bmatrix}, \quad \forall i \tag{29}$$

ω_0 is set in line with the estimate of the iid component for 1991q2.

The initial covariance matrix is based on deriving the variance of $\xi_{t|t}(i)$ and is given by

$$\begin{aligned}
\Sigma_t(i) &= var(K_t(i)s_t(i)) && (30)\\
&= K_t(i)var(D(i)\xi_t(i) + \Psi u_t)K_t(i)' && (31)\\
&= K_t(i)[D(i)var(\xi_t(i))D(i)' + \Psi\Psi']K_t(i)' && (32)\\
&= K_t(i)[D(i)P_{t|t}(i)D(i)' + \Psi\Psi']K_t(i)' && (33)
\end{aligned}$$

We can evaluate this at time 0 using $P_{0|0}(i)$ and the corresponding $K_0(i)$ as defined above, so that

$$\mathbf{P}^*_{0|0}(i) \equiv \Sigma_0(i), \quad \forall i \tag{34}$$

The remaining elements of the initial covariance matrix for equation (24) are assumed to be zero.

C Selection of forecasters

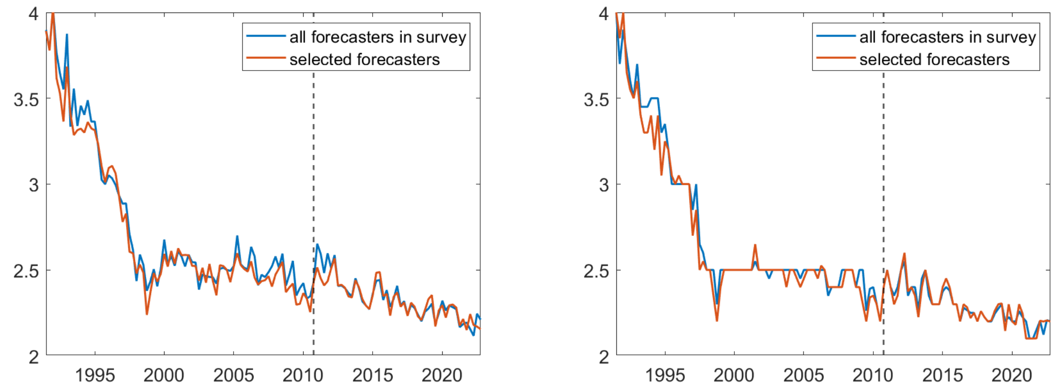

Figure 12: Time series of inflation expectations: mean (lhs) and median (rhs)

Note: Dashed vertical line indicates 2011Q1 before which we use 10Y and afterwards 5Y5Y expectations.

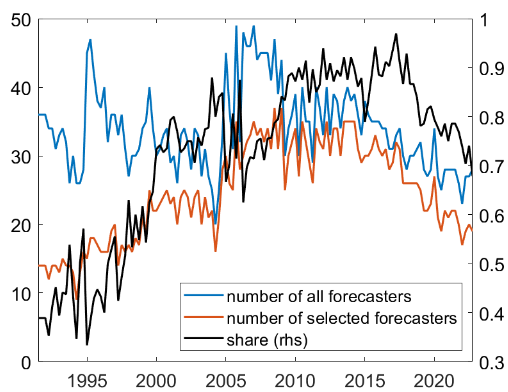

Figure 13: Number of total and selected forecasters in the US SPF survey

D Historical decomposition

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

(i) We append all the shock series as state variables to the model in equation (24) 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 8.

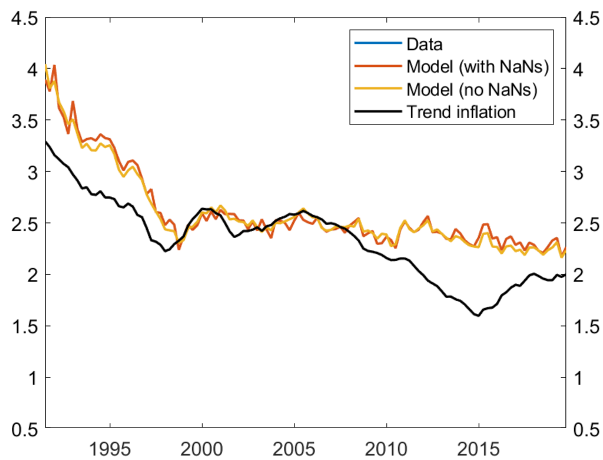

Figure 14: Average inflation expectations: data vs model

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.

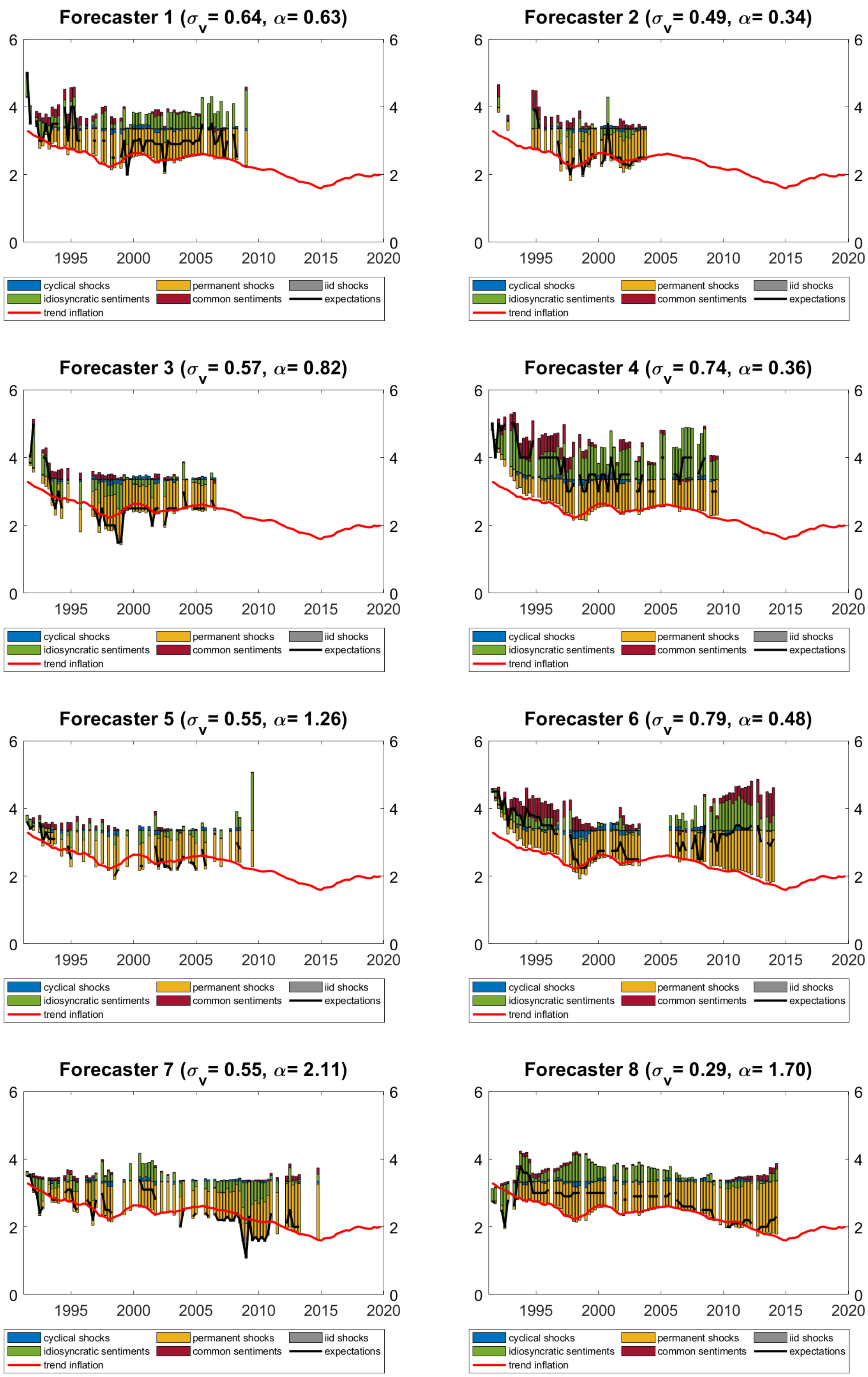

Figure 15: Historical decomposition of individual forecaster's expectations

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

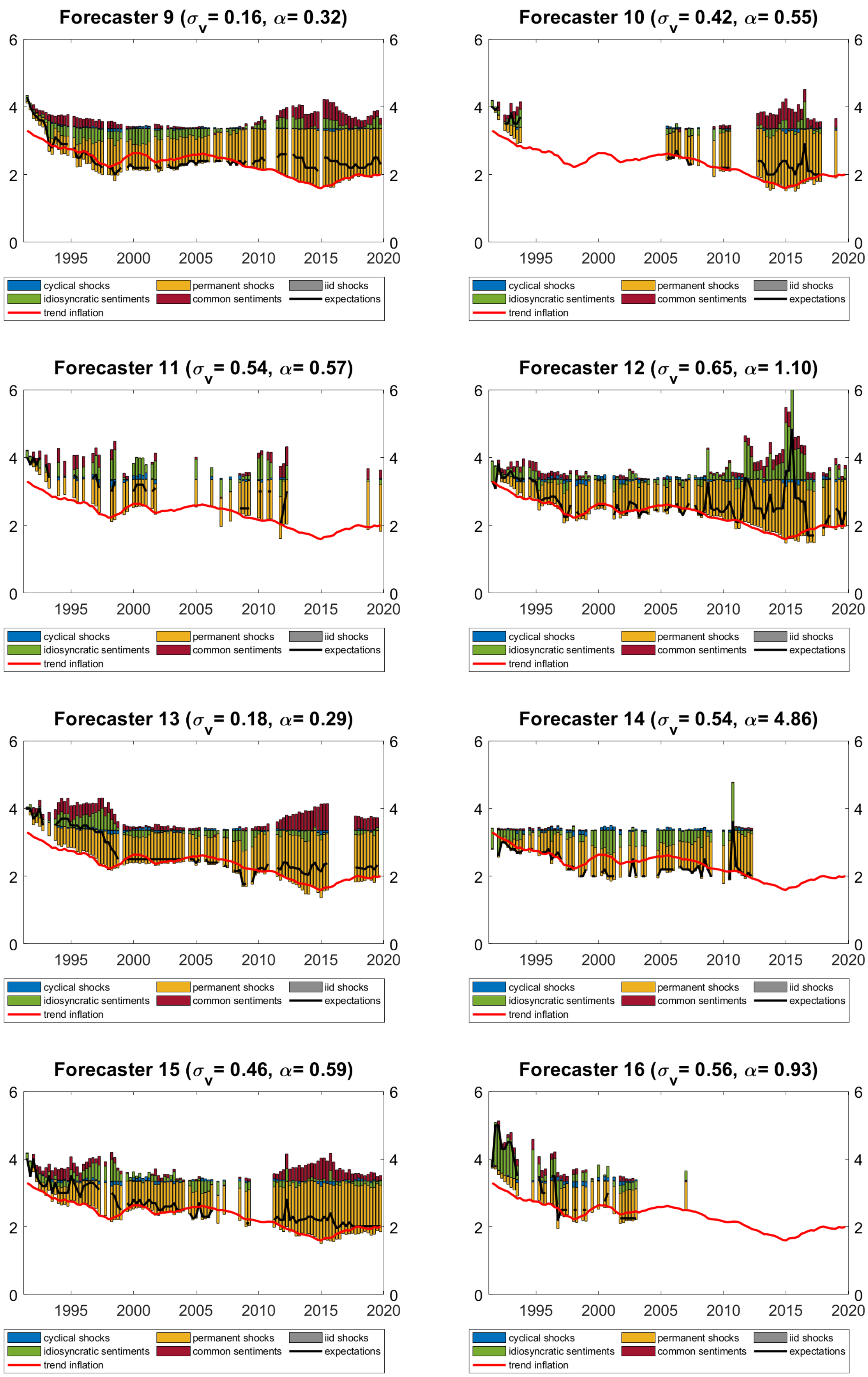

Figure 16: Historical decomposition of individual forecaster's expectations (continued)

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

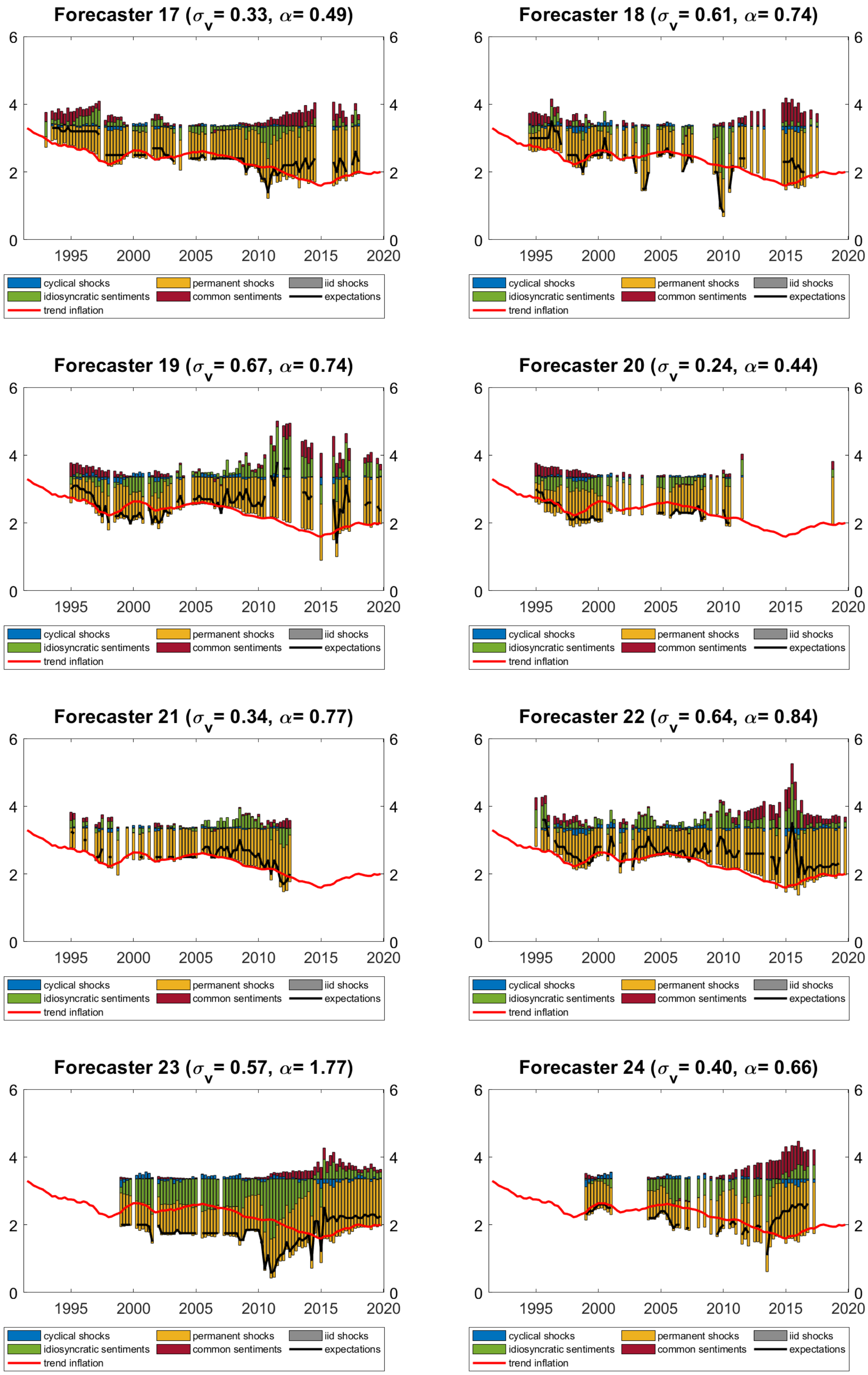

Figure 17: Historical decomposition of individual forecaster's expectations (continued)

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

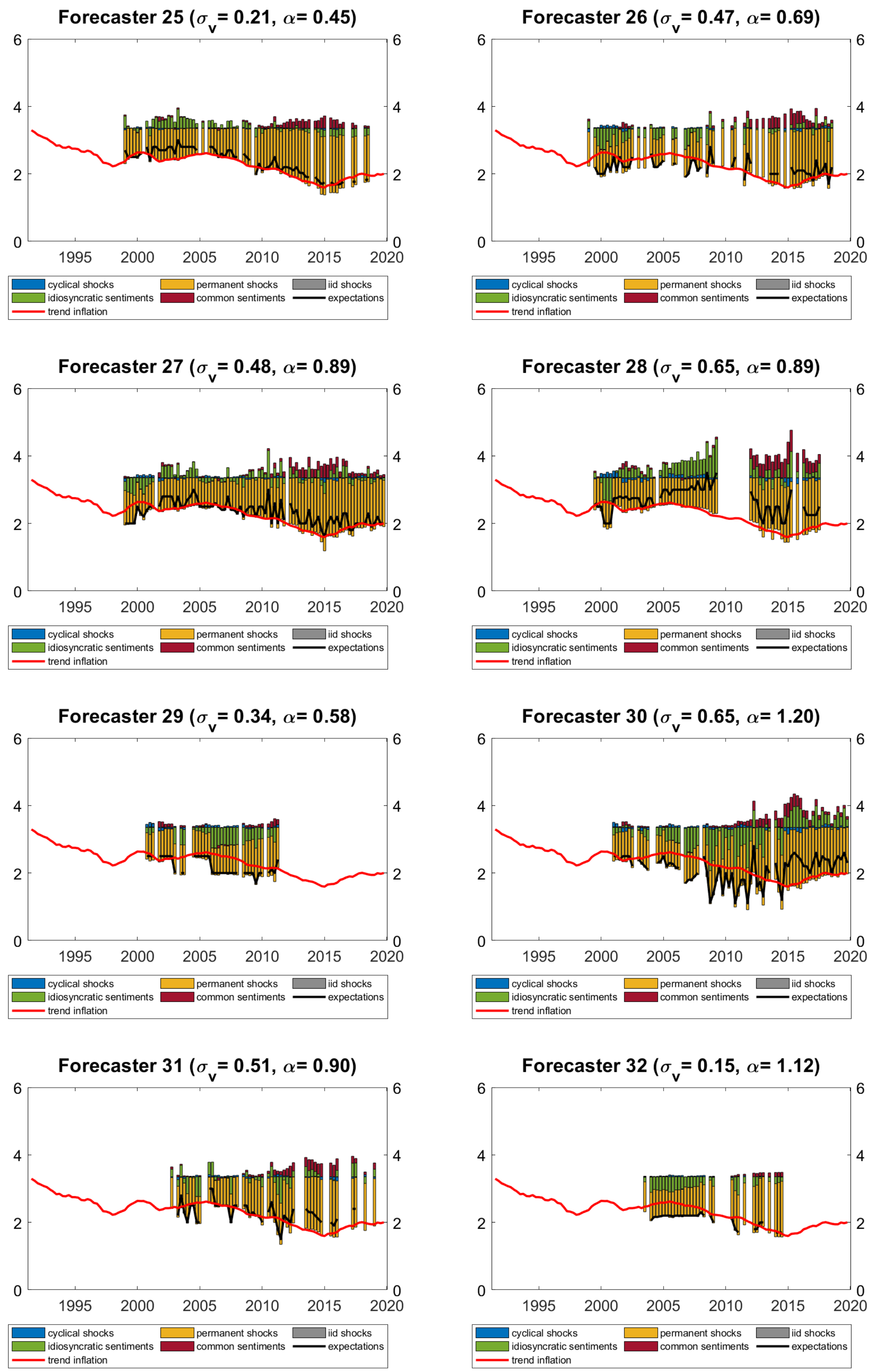

Figure 18: Historical decomposition of individual forecaster's expectations (continued)

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

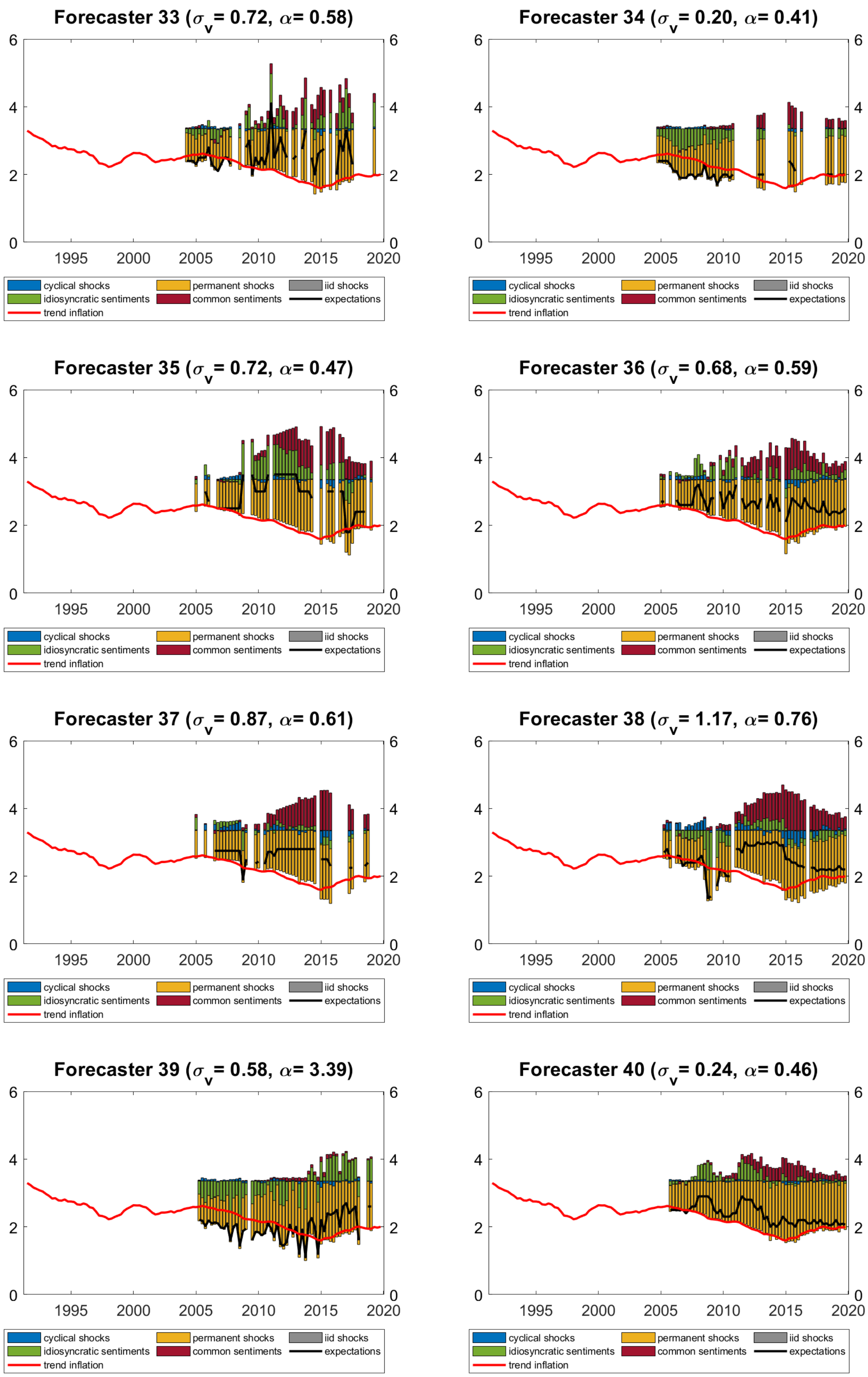

Figure 19: Historical decomposition of individual forecaster's expectations (continued)

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

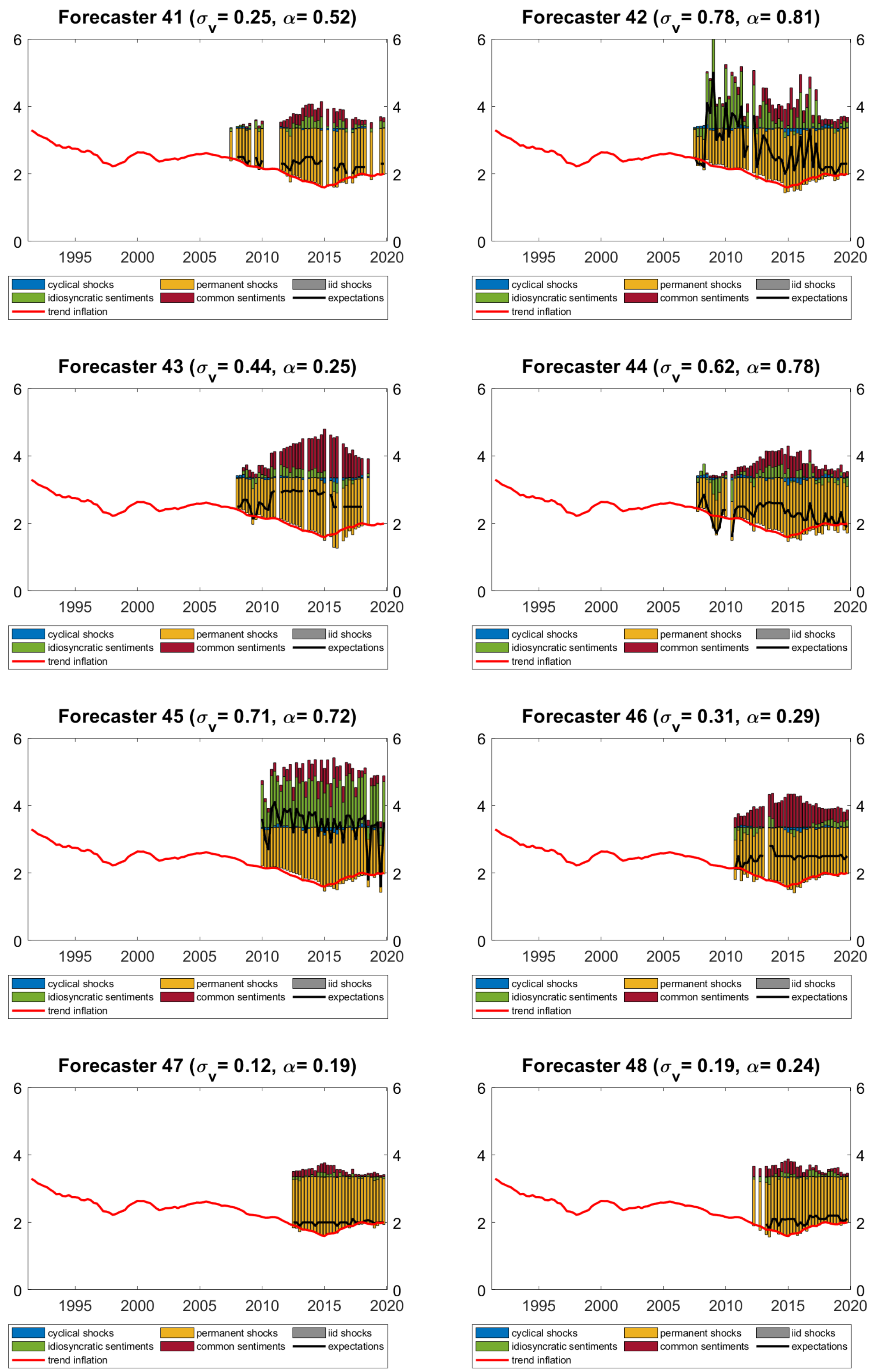

Figure 20: Historical decomposition of individual forecaster's expectations (continued)

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

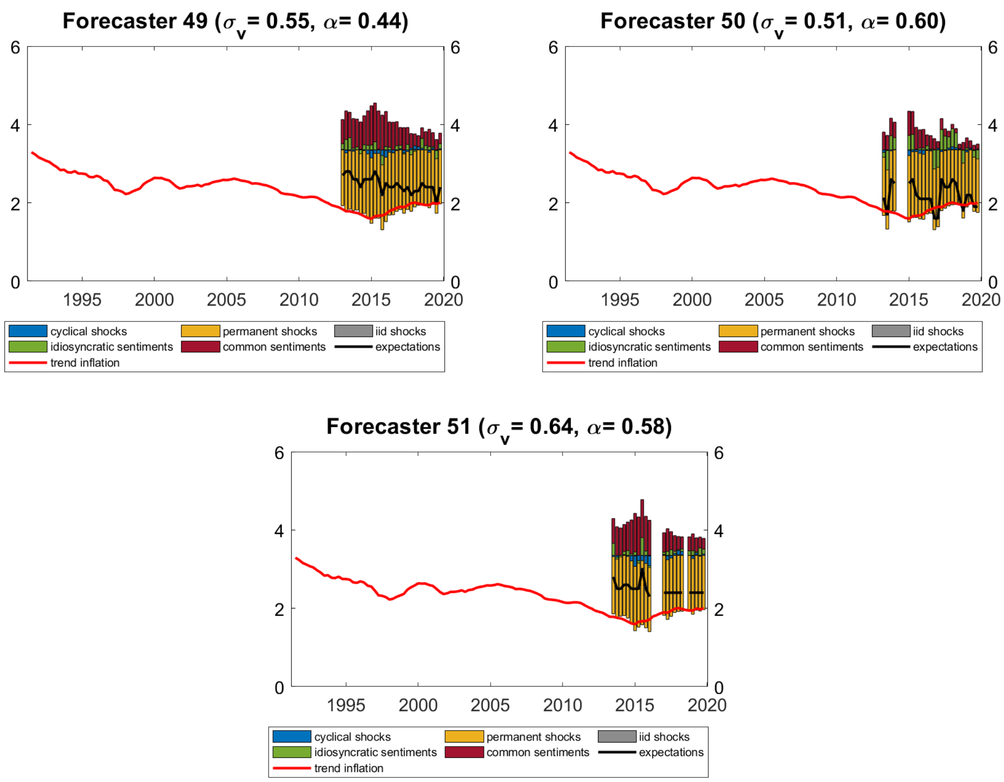

Figure 21: Historical decomposition of individual forecaster's expectations (continued)

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

E Robustness of panel estimation

This section shows some robustness analysis of the panel estimates to our calibration choice of γ_c. In our baseline we set $\gamma_c = 0.5$. Below we report some of our key results for $\gamma_c = 0.1$.

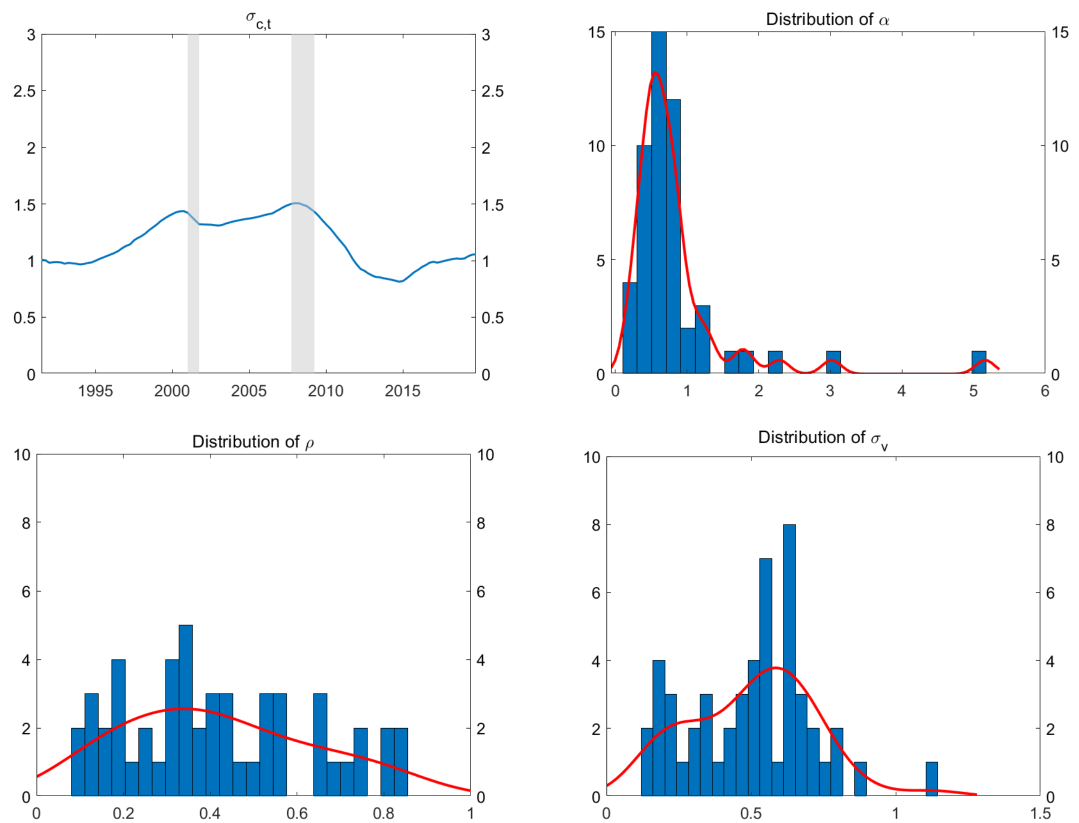

Figure 22: Panel model estimates

Notes: Grey shaded areas indicate NBER recession dates. Red lines are kernel density estimates.

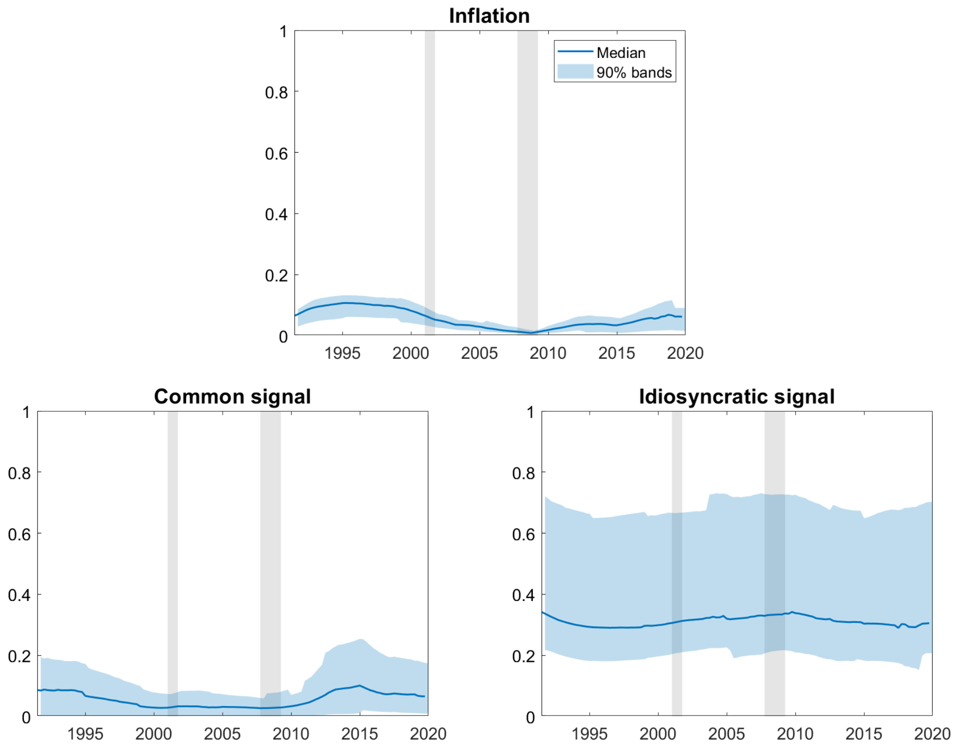

Figure 23: Kalman gains for the inflation (top) and private (bottom) signals

Notes: Grey shaded areas indicate NBER recession dates. Blue lines and shading correspond to estimates based on our panel of forecasters. The red line corresponds to the case where we assume a representative forecaster and ignore the cross-sectional data.

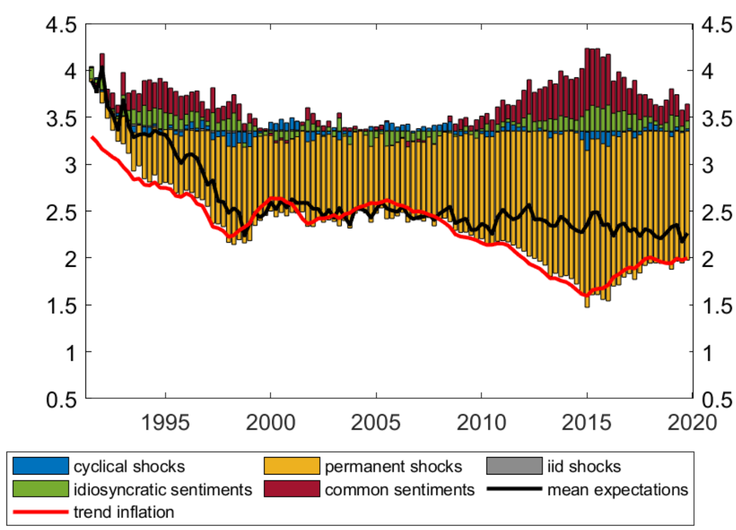

Figure 24: Historical decomposition of average inflation expectations

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

F Projection exercise

In the following we describe the detailed procedure underlying the projection exercise in section 7. We focus on the projection exercise for December 2022. The December 2015 exercise proceeds similarly.

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

(i) Construction of **inflation paths** from 2020Q1-2025Q4:

  (a) 2020Q1-2022Q3: We use the realized CPI inflation rate.

  (b) 2022Q4-2025Q4: We use the median, lower or upper range path for PCE inflation from the December 2022 Summary of Economic Projections (SEP). For each year from 2023-2025, the forecasts refer to the year-on-year growth rate of the fourth quarter. We apply these year-on-year growth rates to the CPI index and linearly interpolate the missing quarters. Then we compute quarter-on-quarter annualized growth rates and add 30 bps to be consistent with CPI inflation being on average 30 bps higher than PCE inflation. Finally, we apply a 4-quarter moving average to that projection path to avoid jumps generated by the fact that we only have one SEP projection per year.

(ii) Estimation of **trend inflation**: For each inflation path from (i) we estimate trend inflation using the trend-cycle model in equation (1)-(3). The sample goes from 2020Q1-2025Q4 and we initialize the Gibbs sampler with the estimates from 2019Q4. The estimated trend inflation paths together with the corresponding inflation paths are shown in Figure 9.

(iii) Estimation of **inflation expectations**: For each of the three SEP scenarios, we use the inflation and trend inflation series obtained in the previous two steps as observables in the state-space model of the econometrician (see equations (24)-(25)).

  (a) 2020Q1-2022Q3: We use the observed SPF inflation expectations and estimate the panel model to get estimates for the time-varying parameter $\sigma_{c,t}$. The time-invariant parameters are kept as in our baseline estimation. The estimates of this extended sample together with the Kalman gain and historical decomposition is shown in subsection F.1.

  (b) 2022Q4-2025Q4: Inflation expectations are treated as missing, so we apply the Kalman smoother to obtain estimates of all the state variables. $\sigma_{c,t}$ is fixed at the last estimated value from 2022Q3. We compute the average inflation expectations across forecasters who have been in the sample during the two years prior to December 2022[28] and plot these in Figure 10.

The projection exercise for December 2015 proceeds similarly except that we do not need step (a) in steps (i) and (iii).

[28] Alternatively, we could compute the mean across the inflation expectations of all forecasters. However, there is a significant number of forecasters who have been in the sample during earlier years of our sample but they dropped out before the end and including them in this exercise might therefore bias results.

Part 2: Inflation path required to keep expectations steady at their current level

(i) **Initial guess for trend inflation**: We follow steps (i)-(ii) in Part 1 to estimate trend inflation based on the SEP median inflation projection path.

(ii) Same as step (iii), (a) in Part 1 but just for the inflation path based on the SEP median projection.

(iii) **Estimate of inflation path**: We obtain estimates of the inflation path from 2022Q4-2025Q4 by applying the Kalman smoother to the state-space model as defined in equations (24)-(25) except that the measurement equations are modified as follows:

- Inflation: For 2022 Q4 we impose a "nowcast" for inflation (based on the SEP median path) but afterwards the path of inflation is treated as missing.
- Trend inflation: We set trend inflation equal to the initial guess from step (i)
- Iid component of inflation: We set the iid component to zero
- Expectations: Individual inflation expectations are not available and since we want to **keep expectations steady at their current value** we impose that average inflation expectations are equal to the average value from the 2022 Q4 SPF round. Again, this is only imposed for forecasters who have been in the sample during the two years prior to December 2022.
- Idiosyncratic sentiments: We set the shocks to idiosyncratic sentiments to zero. The idea is to focus only on the role of common sentiments vs inflation in this exercise.

The state-space model is initialized using the estimated states in 2022Q3 from step (ii). We apply the Kalman smoother to obtain estimates of the inflation path for two cases:

(a) **with communication:** all three signals are on as in our baseline model.

(b) **no communication:** the common signal is turned off by setting the corresponding column of the Kalman gain matrix to zeros.

(iv) The inflation path from the previous step is not necessarily consistent with the initial guess for trend inflation. Therefore, we apply the Kalman smoother on the trend-cycle model going forward from 2022Q4 to obtain a new trend estimate that is consistent with the inflation path from step (iii).[29] With this new trend estimate we restart from step (iii) and solve for a "fixed point" by iterating over steps (iii)-(iv) until convergence in the inflation path for each of the two cases with and without communication.

The projection exercise for December 2015 proceeds analogously except that step (ii) is not needed.

[29] For simplicity we assume that the trend estimate before 2022Q4 remains unchanged and we keep all the parameters fixed at their 2022Q3 values. In line with (iii) we impose that the iid component is zero.

F.1 Extended sample results

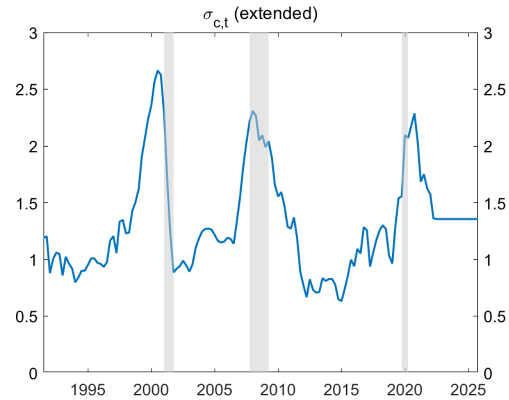

Figure 25: Extended estimate of $\sigma_{c,t}$

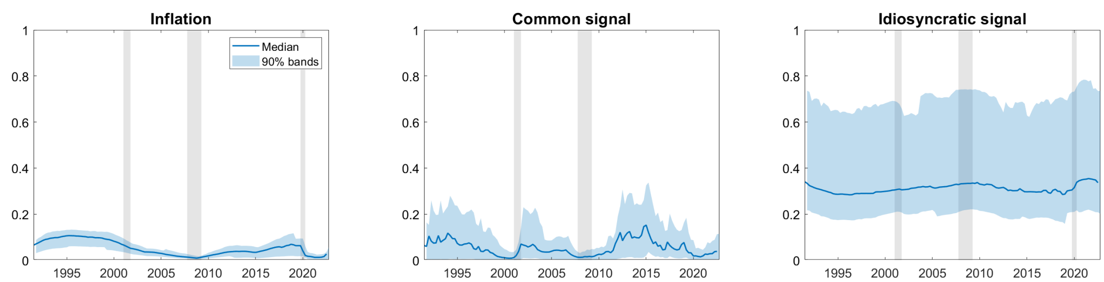

Figure 26: Kalman gains for the inflation (lhs) and private (middle and rhs) signals

Notes: Grey shaded areas indicate NBER recession dates.

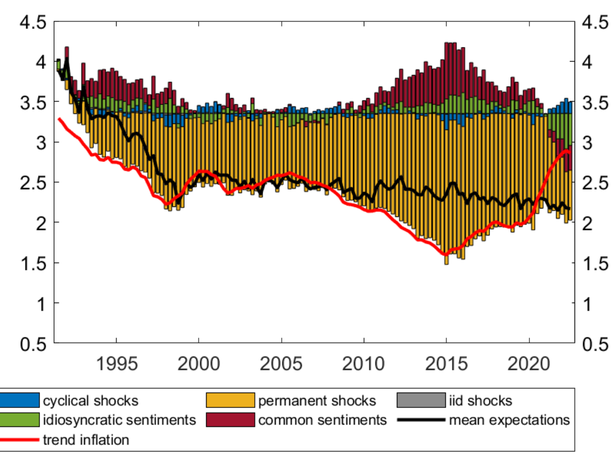

Figure 27: Historical decomposition of average inflation expectations

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

F.2 December 2022 exercise with low $\sigma_{c,t}$

In Figure 11 we have assumed that the value of $\sigma_{c,t}$ is estimated between 2020Q1 and 2022Q3 but then kept constant at the last value from 2022 Q3 (see Figure 25). Below we illustrate the role of $\sigma_{c,t}$ by assuming that instead from 2022 Q4 onwards it takes the same value as in the December 2015 exercise which is only around 0.86. Under this case, the gap between the inflation path with and without communication is up to twice as large as in Figure 11.

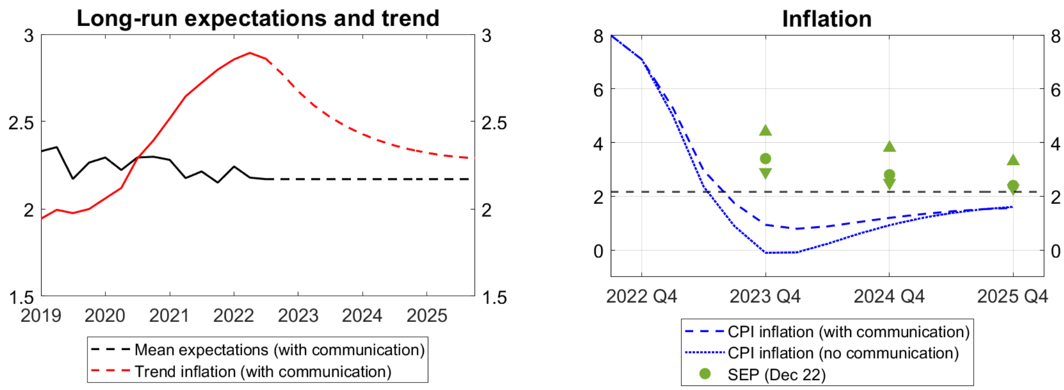

Figure 28: Inflation paths consistent with keeping average long-term inflation expectations steady over the SEP forecast horizon from the December 2022 FOMC meetings, *low* $\sigma_{c,t}$.

Notes: The rhs dashed lines show the path of *year-on-year* inflation consistent with steady expectations within four years December 2022 with no constraints on signals. The lhs black dashed lines show the assumed path of steady average expectations and the red line shows the inflation trend consistent with the inflation path on the rhs. The dotted lines in the rhs plot show the case when we constrain the common signal to be not used. The dots correspond to the median SEP projections and the arrows to the highest and lowest projections.